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User-led decentralized thermal comfort driven HVAC operations for improved efficiency in office buildings

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ABSTRACT

Thermal comfort is one of the main driving factors in defining the operational settings of HVAC systems, and it greatly impacts energy efficiency in buildings. Lack of information about human related variables results in using unrepresentative operational settings, which in turn could bring about low efficiency in HVAC operations. In this paper, the implementation and evaluation of a framework that integrates building occupants' personalized thermal profiles into the HVAC control logic is presented. The framework enables occupants to communicate their preferences for indoor thermal conditions through a user interface, leveraging a participatory sensing approach. The framework learns occupants' comfort profiles, using a fuzzy predictive model, and controls the HVAC system using a complementary control strategy, which enables the framework to be implemented in existing centrally controlled HVAC systems with minimum intrusion. Evaluation of the framework in a real building setting showed user comfort improvement. Moreover, the results showed a 39% reduction in daily average airflow when the HVAC system conditions the rooms at occupants' desired temperatures. Airflow is proportional to the energy consumption of HVAC system components. Consequently, the implementation of the framework shows improvements in the efficiency of the HVAC system's performance for centrally controlled office buildings.

1. Introduction

Buildings are major consumers of energy in the U.S. (about 42% of total annual energy consumption [1]) and all around the world (i.e., 20–40% of annual energy consumption [2]). In general, heating, ventilation, and air conditioning (HVAC) systems are the largest contributors to the energy consumption in buildings. In the U.S., these systems account for almost 43% of energy consumption [1]. Thermal comfort is one of the driving factors in the design and operation of HVAC systems and therefore, one of the key factors in determining energy demand of these systems. Determination of the operational settings of HVAC systems plays an important role in the efficiency. Efficiency, in this context, is described as the performance of an HVAC system in providing and maintaining satisfactory indoor thermal conditions, while reducing energy expenditures related to the system operations. In order to provide satisfactory indoor thermal conditions, HVAC operational settings are usually determined based on the recommendations of industry standards. These standards, in the simplest form, recommend satisfactory temperature ranges for different seasons. For example, ISO EN 7730, 2005 recommends an indoor environment with the temperature range of 23.5–25.5 °C in order to have 94% of building occupants comfortable in the summer while the recommended range for indoor environment temperature is 21.0–23.0 °C to have 94% of the occupants comfortable in the winter [3]. More advanced thermal comfort models in standards are based on heat budget models. The PMV-PPD (Predicted Mean Vote-Predicted Percentage of Dissatisfied) is the prevalent thermal comfort model that has been used by the standards since its introduction by Fanger [4] in 1970s. Thermal comfort is defined as the "*condition of mind, which expresses satisfaction with the thermal environment*" [5] and it is affected by different indoor environmental and human related variables, which makes it a complex variable to be quantified for individual users.

Although the heat budget models account for some of the human related factors such as clothing values and metabolic rates, determination of user related factors is usually a challenging task. Thus, these factors are usually estimated as constant values based on standards' recommendations. Accordingly, the application of the standard recommended settings, in the absence of contextual user information, could potentially result in dissatisfactory experiences.

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Several research studies have pointed to the occupants' dissatisfaction with thermal indoor conditions [6,7]. The preliminary studies conducted by the authors in three HVAC operated buildings in Southern California, where HVAC systems usually operate in cooling mode, also showed that a large percentage of occupants perceive the indoor environment as cool to cold. Out of 294 votes in two of the buildings in fall and summer seasons, about 60% of the votes perceived the indoor environment as cool to cold. In the third building, also the test bed building of this study, 34% of the occupants reported dissatisfaction and in 49% of the cases, occupants perceived their environment somewhat cool to cold.

Dissatisfaction with the indoor environment brings about low efficiency in the HVAC system operations. Moreover, mitigating solutions that some occupants might use to compensate for the discomfort, such as using portable space heaters in buildings, where the indoor environment is cooler than the desired, could cause excessive operations of HVAC systems, aggravating the discomfort problem and consuming more energy, and therefore leading to lower efficiencies. The temperature in the room, where the portable space heater is used, rises which in return increases the temperature in the thermal zone. This issue results in the HVAC system to compensate for the excessive heat load. As a result, the temperature in all of the rooms in the thermal zone drops, affecting all of the occupants in that zone.

Moreover, research studies showed that thermal comfort is also a complex context dependent quantity. Occupants' thermal comfort zone has been shown to vary with seasonal variations, regional and cultural contexts, implying that thermal comfort is time, location, and context dependent [8–10]. Accordingly, in this study, we propose and validate a framework for integrating building occupants' thermal preference profiles into the HVAC control logic to avoid using unrepresentative predefined HVAC operational settings. The proposed framework is founded on the hypothesis that it is possible to learn occupants' thermal preference profiles, integrate them into the control logic of HVAC systems, and improve system efficiency in existing buildings. The framework enables occupants to continuously communicate their thermal preferences to a building management system (BMS) through a participatory sensing approach for HVAC system operations. The proposed framework provides the ground for minimally intrusive personalized HVAC control in commercial buildings as it includes a complementary and non-intrusive control algorithm, which enables an HVAC system to provide and maintain the preferred indoor thermal conditions. The complementary controller works with the existing legacy HVAC controller, which controls the flow rate, air temperature and ventilation in the building.

In order to test the above-mentioned hypothesis, the proposed framework has been deployed and evaluated in a real building setting with permanent occupants. The evaluation is performed assessing the efficiency of the HVAC system performance by exploring the effect of the framework on occupants' comfort and the associated energy consequences. The paper is structured as follows: A review of the literature is presented in Section 2. Section 3 describes the components of the proposed framework. In Section 4, the implementation of the framework in the experimental test bed is described. Section 5 presents the experiments, validation metrics, and findings of the framework evaluation. Finally, conclusions are presented in Section 6.

2. Review of literature on thermal comfort and HVAC control

Advanced HVAC control algorithms with comfort and energy multivariable objective functions have been extensively studied. Quantification of comfort ranges is a critical component of a control loop in operating HVAC systems. The PMV index has been used in several studies as the metric for user comfort integration [11–17]. As noted in the literature, the PMV index depends on a number of parameters including environmental and human related variables. Assumptions for human related variables are used in the absence of information about building occupants [15,16]. Incorporation of these assumptions causes the index to be less representative of the dynamic occupancy characteristics in buildings. Furthermore, the calculation of the PMV requires a number of indoor environmental variables. These variables are temperature, humidity, air velocity, and radiant temperature. Measurement of these variables requires a customized sensing system, which compounds the calculation of this index. A number of studies proposed sensor network solutions for increasing the accuracy of the PMV calculation [18,19]. However, due to the complexity of these sensor networks deployment, practical applications of these sensor systems for building control are limited [20]. Therefore, a number of studies proposed using user provided information to obtain a metric for thermal comfort integration to the control logic of building systems. Guillemin and Morel used occupants' preferences in the form of temperature set points through custom keyboards in each room [13]. Murakami et al. used user input for combination of binary preferences of warmer and cooler along with ASHRAE thermal sensation scale through a user interface [21]. Daum et al. used user input in the form of too hot/too cold complaints along with a probabilistic approach for determination of user comfort profiles [20]. Controlling building systems through user provided set points has the drawback that set points in buildings are not necessarily equal to the perceived room temperatures. Moreover, user defined set points might not always lead to user comfort. Accordingly, a number of studies proposed mechanisms for learning users' comfort ranges. Based on their observation, Guillemin et al. [13] proposed that an alternative algorithm is needed as occupants were not able to propose set points that bring about their comfortable conditions. Daum et al. [20] proposed an approach to update a default probabilistic representation of user comfort profiles using user-provided information obtained through the above-mentioned binary buttons. In another approach, Bermejo et al. [17] proposed to use static fuzzy rules for the PMV and update the thermal comfort index as occupants interact with the thermostats in their rooms.

The application of thermal comfort metrics needs to be coupled with control mechanisms in order to enable conditioning of indoor environments. Due to the fuzzy nature of thermal comfort, several studies proposed fuzzy logic controllers to enable the provision of thermal comfort in buildings [11,16,22–26]. Additionally, multi-agent simulations [27] and neural network based computing methods [28,29] have been investigated for advanced building controls. Adaptive fuzzy controllers, as well as, genetic and gradient-based algorithms have been used for multi-objective optimization of occupant comfort and building energy consumption [30–33]. As noted above, the majority of these advanced control mechanisms focused on standard thermal comfort index, namely the PMV or other indoor air quality indices, as control variables. However, the integration of human related variables still remains a challenging problem, for which constant assumptions are used in majority of the cases. In many of the cases, the proposed advanced control algorithms require retrofits to the HVAC system components, making it difficult to implement in practice. Despite these difficulties, the application of advanced algorithms has shown improvements in HVAC system operations. However, they are better suited for new buildings, where customization of the HVAC components is more feasible.

Evaluation of the proposed strategies for improving thermal comfort in buildings is another important aspect to consider. As noted above, many of the proposed approaches require modifications to the building system components, which introduce a challenge for evaluations in real building settings. Accordingly, simulations [12,15–17,34,35], experimental chamber studies [11], and studies in limited areas such as one or two rooms [13,16] are commonly used for validation of the algorithms. Although simulation is a well-established approach, and is extensively used in studies, many challenging aspects of the control strategies might not be observed in simulations. Moreover, building component characteristics, occupant characteristics as well as various unpredicted conditions in buildings could affect indoor environments, and they are usually difficult to be modeled accurately in simulation. A number of studies evaluated their proposed control algorithms in larger scales. Kolokotsa et al. [14] implemented a fuzzy controller in two buildings in different seasons of the year for different comfort indices, including thermal, visual, and air quality related comfort and showed more than 30% of reduction in energy consumption. Murakami et al. [21] evaluated their proposed algorithm for improving user comfort in an open plan office setting. Their proposed approach, which set daily set points, was evaluated through a collective voting by a group of 50 occupants and showed that the energy consumption was almost the same before and after the implementation. Considering the above mentioned challenges of personalized thermal comfort driven HVAC operation, in the remaining sections, a framework is proposed and evaluated (in a real building setting) towards addressing some of these challenges.

3. User-led decentralized thermal comfort driven framework

Considering the above noted challenges of thermal comfort, the proposed user-led thermal comfort driven HVAC control framework seeks a number of objectives: (1) integrating the context dependent information of building occupants in the control mechanisms of HVAC systems through participatory sensing; (2) learning occupants thermal comfort profiles to be used in HVAC operations; (3) controlling the HVAC system to provide and maintain thermal preferences, and (4) providing a solution, which could be implemented in existing buildings with minimum intrusion. The core components of the framework are its ability to learn personalized thermal comfort profiles over time and its ability to operate the HVAC set points based on the learned personalized comfort profiles by implementing a complementary decentralized (room based control as opposed to thermal zone based) control strategy, which is integrated with the legacy HVAC system.

3.1. Acquiring personalized thermal preferences

Many factors can drive comfort preferences of occupants in a building including physical, physiological, psychological, and cultural factors. A number of studies have demonstrated that prediction methods in standards, such as the ones in the ASHRAE 55, tend to overestimate or underestimate a user's thermal comfort votes [36–39]. We use a participatory sensing approach to obtain context-dependent information from building occupants. The participatory sensing approach relies on the increasing application of ubiquitous computing devices such as portable computers, smartphones, and tablets. Participatory sensing provides the opportunity for capturing contextual information, which inherently embraces all different driving factors such as local changes in heat loads, varied sensitivity of users, etc. However, participatory sensing also requires a well-designed interface, which facilitates accurate, fast, and frequent data acquisition to avoid user fatigue during data provision. In the thermal assessment studies, a number of thermal comfort sensation scales have been proposed for assessment of building occupants' perceptions. These scales include the ASHRAE thermal sensation scale, the Bedford comfort scale, the McIntyre

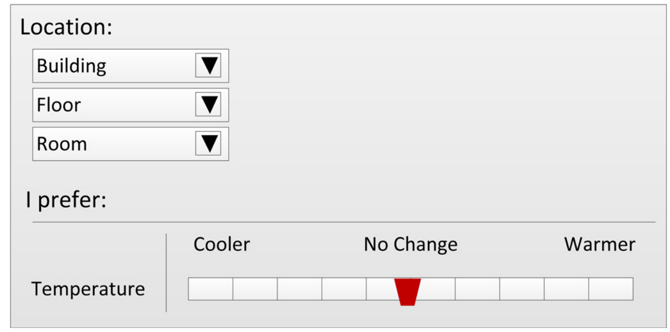


Fig. 1. Components of the proposed user interface and thermal preference scale.

3-point preference scale, and the acceptability scale. Due to the complex nature of thermal comfort, using a combination of these scales has been recommended [40] to ensure that an accurately representative occupant comfort is obtained. However, the use of combined scales requires a user to go through a multiple-thread interface, which potentially results in confusion and the data analysis becomes complicated.

To address these issues, we used a novel thermal preference scale, (1) integrating the functionality of thermal sensation scale and preference scale into one scale with a range of intensity; and (2) increasing the consistency of the user input. Consistency is defined as users' capability to be consistent in reporting their own individual preferred thermal conditions. The proposed scale is a graduated slider with snapping capabilities (only accepting discrete values on the slider graduation lines) as depicted in Fig. 1. Details of the user interface design and evaluation could be found in [41]. By moving the slider to the left or right, users express their preferences and at the same time their perception of the indoor environment is captured. The numeric values associated with the slider button position, which in this context are called *thermal perception index* (*TPI*), show the intensity associated with a user's vote. This scale along with a user location module was implemented into a single page user interface for different platforms (including smartphones and web browsers).

Capturing the variation in indoor environmental conditions and correlating it with user provided votes are needed to obtain the personalized thermal comfort profiles. Therefore, sensing infrastructure is a required component of the proposed framework. Usually, legacy HVAC systems in buildings monitor temperature variations at the thermal zone level. However, the sensor is commonly located in one room of a zone and does not provide a representative measure for distribution of indoor environmental conditions in all rooms. Accordingly, a combination of sensors was installed in each room of a zone to determine the effective environmental variables on users' votes using room level sensor readings. Room level sensing provides a better representation of the indoor environmental condition for each user. A field study was conducted and a correlation analysis was carried out to investigate driving factors for user comfort votes. Temperature, humidity, carbon dioxide (as a measure of air ventilation in the room), and light intensity (as a measure of solar heat gain) values were studied and the temperature values were found to be the most effective driving factor in user comfort votes. Details of this study could be found in [41].

3.1.1. Learning personalized thermal comfort profiles

Through the user interface, occupants report their preferences under different indoor environmental conditions. After a period of data collection, the user provided data and associated temperature values (obtained through the sensor network) are matched. A typical data collected from a user is shown in Fig. 2. The horizontal axis shows the values on the thermal preference scale (*TPI* values,

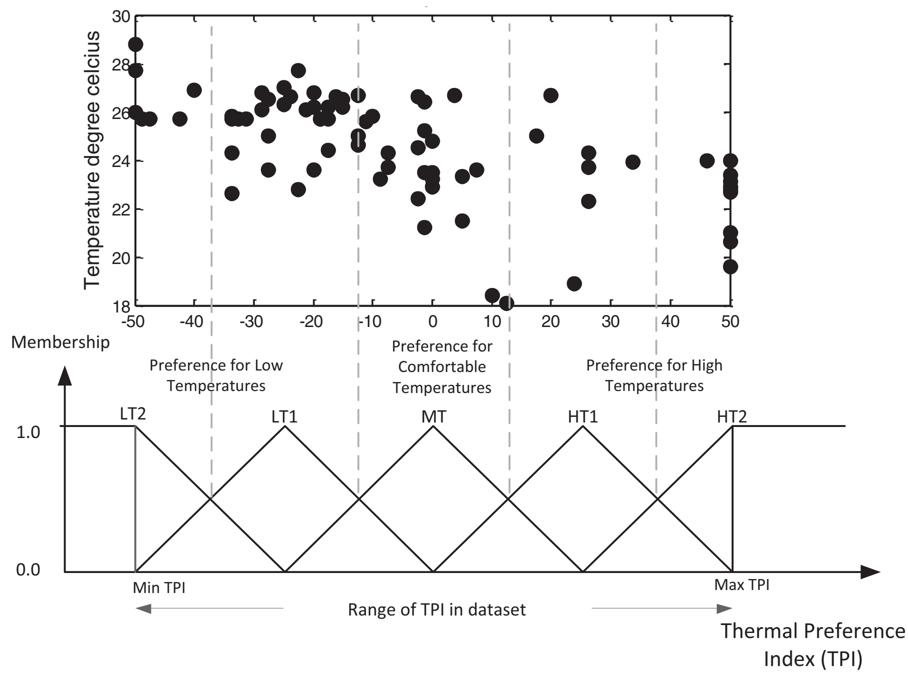


Fig. 2. Typical data set for one user and assigned fuzzy sets on the thermal preference ranges.

ranging from −50 to 50) and the vertical axis shows the associated temperature values. As noted, each reported preference vote is associated with a range of temperature and the data has a fuzzy pattern due to the complex nature of comfort perception. We use a fuzzy pattern recognition approach in order to extract the underlying pattern in the data. This pattern includes the temperature ranges associated with different reported votes (thermal perception ranges) and a customized scale for each user's preferences. Although the attire level is one of the main driving factors in users' perception of the environment, measuring the attire level requires continuous information provision by users and is not a feasible solution in long term. Thus, the proposed learning approach benefits from users' adaptiveness once they are provided with control over the environment. Accordingly, users could adjust their preferences for indoor thermal conditions with their attire level.

In order to extract the patterns in the user provided data, M fuzzy sets P^l, $l = 1, \ldots, M$ are assigned to the thermal preference votes (*TPI* values on the slider) that each user reported. These fuzzy sets represent different thermal comfort perception ranges. Upon assigning the fuzzy sets, Wang–Mendel fuzzy pattern recognition approach [42] is used to determine the temperature ranges associated with the fuzzy sets for each user and to develop a descriptive model. Fig. 2 shows a typical fuzzy set assignment for one occupant's vote data.

For each (TPI_i,t_i) data point a membership value ($\mu_{P^q}(TPI)$) is computed using the definitions of the assigned fuzzy sets. Each data point is then used to generate an IF-THEN rule for the fuzzy set with a maximum membership value ($\mu_{P^{l*}}(TPI) \geq \mu_{P^l}(TPI)$ for all $l = 1, \ldots, M$) in the following form:

IF TPI_i is in P^{l*} THEN t is centered at t_i
and the weight of the rule (w) is equal to $\mu_{P^{l*}}(TPI)$. The rules are generated for all N data points and then these N rules are divided into M groups, which share the same IF part to be combined and form a single rule:

IF TPI_i is in P^l, THEN t is in T^l

where T^l is the triangular fuzzy set for the combined rule. In each group N_l initial rules are combined. The representative temperature (t^l_{av}) associated with the combined rules are:

$$t^l_{av} = \frac{\sum_{k=1}^{N_l} t^l_k \cdot w^l_k}{\sum_{k=1}^{N_l} w^l_k}$$

which is a weighted average of the temperature values in each fuzzy set, assigned to thermal preferences. In order to determine the comfort ranges and the custom scale, a predictive model ($f(TPI)$) is obtained by using singleton fuzzifier, product inference engine as fuzzy inference engine, and center-average defuzzifier:

$$f(TPI) = \frac{\sum_{l=1}^{M} t^l_{av} \cdot \mu_{P^l}(TPI)}{\sum_{l=1}^{M} \mu_{P^l}(TPI)}$$

Using the predictive model, temperature values are assigned to the boundaries between M fuzzy sets, originally assigned to the *TPI* values. The personalized thermal comfort profile, which determines the temperature ranges for various *TPI* values, is obtained. The predictive model is used as a personalized scale for each user to determine the requested temperature change.

3.2. Complementary control strategy

The control loop of a typical large centrally controlled HVAC system relies on one thermostat per zone and the proximity of the thermostat to the air diffusers determines the distribution of air and temperature in the rooms. Most often, temperature distribution in all rooms of a thermal zone is not uniform, which could bring about dissatisfaction. In some cases, it may not be physically possible to change the indoor room temperature to meet with the user-preferred temperature by only relying on the legacy HVAC system control mechanism. This happens when the BMS sensor is close to the diffusor in one room and the HVAC system is controlled by the temperature in that specific room, as the output of the BMS sensor drives the temperature in all rooms of that zone. We use a complementary control strategy, which relies on the additional

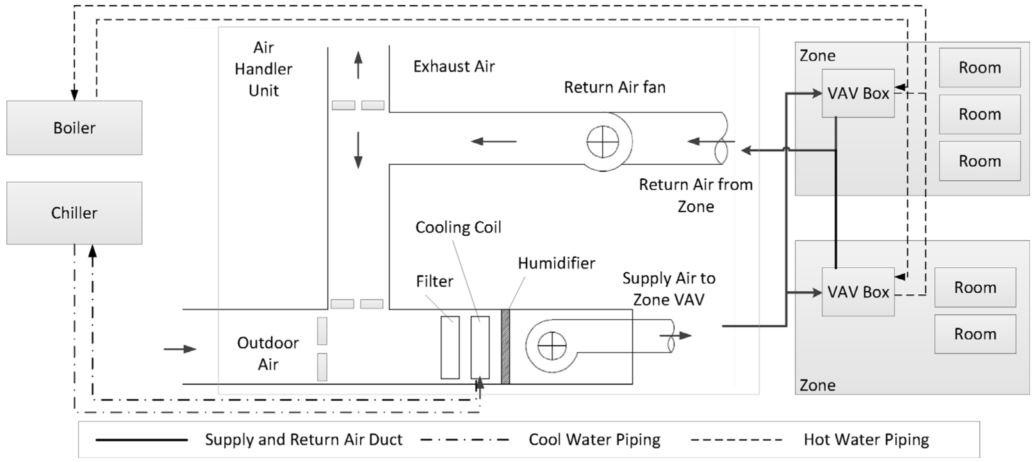


Fig. 3. HVAC system component schematics in the test bed building.

temperature sensor network for receiving feedback from the environment. The application of the distributed sensor system in each room enables the controller to keep the thermal condition in each zone closer to all of the zone's occupants' thermal comfort profiles. Optimum placement of the sensors calls for an extensive study of indoor microclimate and is not in the scope of this study. However, since both the user preference acquisition process and the control process use the same sensor system, the proposed sensing network provides a better representation of a room's microclimate.

As mentioned above, ambient temperature has been found to be the most effective factor in driving users' thermal preference votes. This fact enables us to use the HVAC temperature set point as a control parameter. The control strategy is as follows:

$$\min_{s_p} \quad \delta = \frac{1}{N_r}\sum_{i=1}^{N_r} T_r^i - T_{pr}^i$$

$$\text{s.t.}\, S_{p_{\min}} \leq S_p \leq S_{p_{\min}}$$

$$\Delta S_p = k_p \cdot \delta \leq \Delta S_{p_{\max}}$$

where N_r is the number of rooms in one thermal zone, T_r^i is the temperature reading from room i sensor, T_{pr}^i is the preferred temperature in room i, S_p is the zone VAV (variable air volume) box temperature set point, $S_{p_{\min}}$ and $S_{p_{\max}}$ determine the range of set point variations to avoid excessive temperature change in a thermal zone. The algorithm is a proportional algorithm, which minimizes δ, the sum of deviations from the preferred temperatures in all rooms of a zone. The optimum S_p is proportionally achieved by adjusting ΔS_p as the step change of the set point by using k_p as proportional coefficient. $\Delta S_{p_{\max}}$ determines the maximum step change in each iteration.

4. Framework implementation

The implementation of the framework is an extension to the legacy HVAC management system (BMS (building management system) hereafter) by incorporating the above-mentioned components into an integrated system. The framework, which is called HBI-TC (Human Building Interaction for Thermal Comfort), is integrated into the operational logic of a centrally controlled HVAC system, for which occupants have no control on the operation of the BMS. The implementation was carried out in an operational office building on University of Southern California campus.

4.1. Test bed building

The test bed building is a three-story building, which houses offices, classrooms, and conference rooms. The building has 60 permanent occupants (office workers) and about 2000 temporary residents (students) per semester. The building is equipped with a centralized HVAC system, which is typical in modern office buildings in the United States. The HVAC system is centrally controlled with a state-of-the-art BMS. Two Air Handling Units (AHUs) serve the building with Variable Air Volume (VAV) boxes in each zone. Fig. 3 illustrates a schematic drawing of the HVAC system in the test bed building.

The supply air fans in the AHU circulate the air through the VAV boxes. The supply air is conditioned to ~13 °C by the AHU. The return air fan applies a negative pressure to collect the air from each zone. The return air is mixed with the outside air in the AHU and is conditioned to a constant temperature by passing it through cooling coils. The VAV boxes control the zone level thermal conditions by variable volume of air with a constant temperature. A minimum air flow for thermal zone is enforced in order to ensure proper ventilation for maintaining the indoor air quality. The test bed has been equipped with 55 HBI-TC sensor boxes in the offices of permanent occupants in the second and third floor of the building. Sensor boxes include the temperature sensors and a number of other ambient sensors, used for occupancy detection, which is not part of the scope of this paper. Therefore, sensor boxes were installed close to the door of each room at a height of 4–5 feet. MaxDetect, RHT03 temperature/humidity sensor was used. Temperature measurement accuracy is ±0.2 °C and the resolution (sensitivity) is 0.1 °C. The sensor system uses an Arduino Black Widow stand-alone single-board microcontroller with integrated support for 802.11 WiFi communications.

4.2. HBI-TC framework system integration

At the core of the framework is the HBI-TC server, which manages the flow of data between the sensor nodes and the BMS. The server hosts a relational database, in which all data with time stamps are stored. Occupants in the building can access the user interface either through a URL on a web browser or by installing the smartphone application, available on Apple Store and Google Play. The prototype, used in this study, is the snapping thermal preference scale with five degrees both in warmer and cooler sides with *TPI*s from −50 to 50. The user provided data, including user location and preference votes, are matched with the closest data from

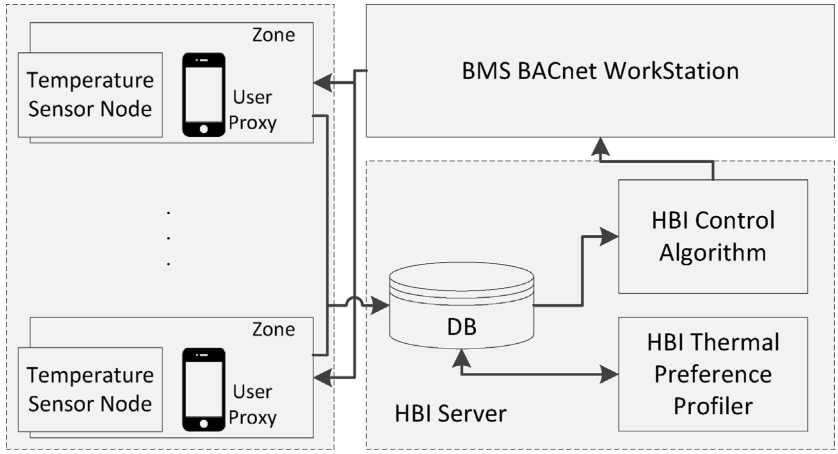


Fig. 4. Data flow in the HBI-TC framework implementation.

the temperature sensors through the HBI-TC server. The complementary control resides on the HBI-TC server and is fed by the real time data from the temperature sensors in the building and users' comfort profile data that reside on the server. The server communicates to the BMS BACnet workstation to adjust the system set points dynamically and in real time. Fig. 4 shows the flow of data in HBI-TC framework.

The process starts with a training period during which occupants interact with the system in order for HBI-TC to capture their preferences and associated ambient temperature values. During the training process the early morning temperature is set at different values so that occupants could experience different temperature ranges and react accordingly. During the training period, the requested change in temperature is calculated based on a linear relationship between the *TPI* values and temperature changes. Upon completion of the training period, the HBI-TC profiler retrieves the data set for each occupant and the comfort profiles are generated using the fuzzy predictive model described in Section 3.1. From this point on, the HBI-TC controller uses the preferred temperature values for each user and adjusts the zone temperature accordingly. In this way, instead of using a static set point during the day, the set point is dynamically set and reacts to variations of different sources of heating or cooling loads in each zone. During this stage, user requested temperature changes are determined according to the personalized scale for each user profile. The HBI-TC control algorithm reacts to a user's requests to address local discomfort; however, it returns room control temperature to the user preferred (desired) temperature after a short period of time. This period depends on the time that the HVAC system takes to adjust indoor conditions. In our test bed, this time was set to 30 min. The IDEF0 diagram of the framework process is illustrated in Fig. 5.

5. Framework evaluation

5.1. Experiments

In order to evaluate the performance of the HBI-TC framework, an experimental study was conducted. For the purpose of this experiment, four adjacent zones of the test bed building in the third floor were selected. Before the activation of the HBI-TC prototype in the building, an email was sent to all permanent occupants of the test bed, describing the objectives of the study as well as the instructions for accessing the user interface. The occupants were asked to provide their votes during the day for at least four times. This preliminary data collection process continued for two weeks. Occupants that showed more interest in participating (based on the number of votes) were selected as participants in the long-term study. Fig. 6 shows the plan view of the selected four zones: two zones with two rooms and two zones with three rooms. The rooms are on the south and north sides of the building

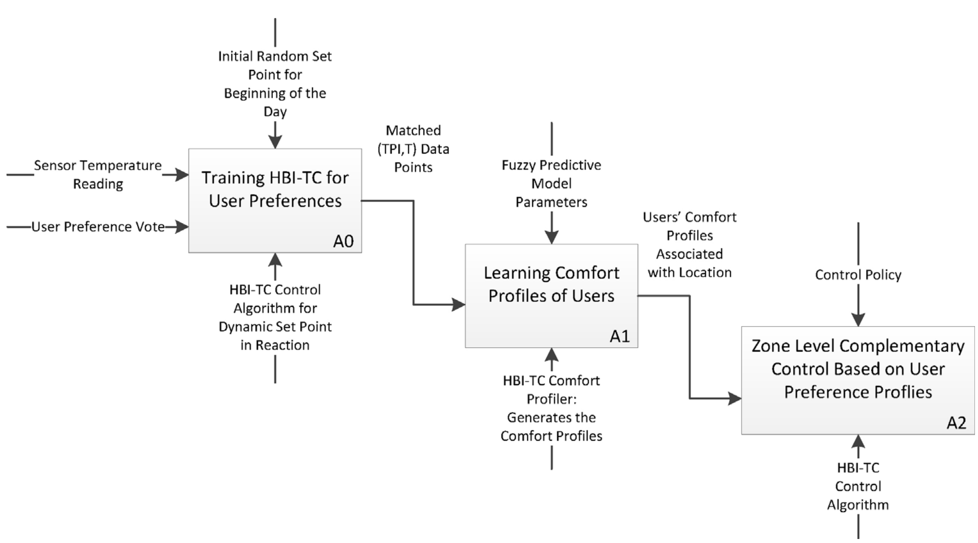


Fig. 5. IDEF0 representation of the proposed HBI framework.

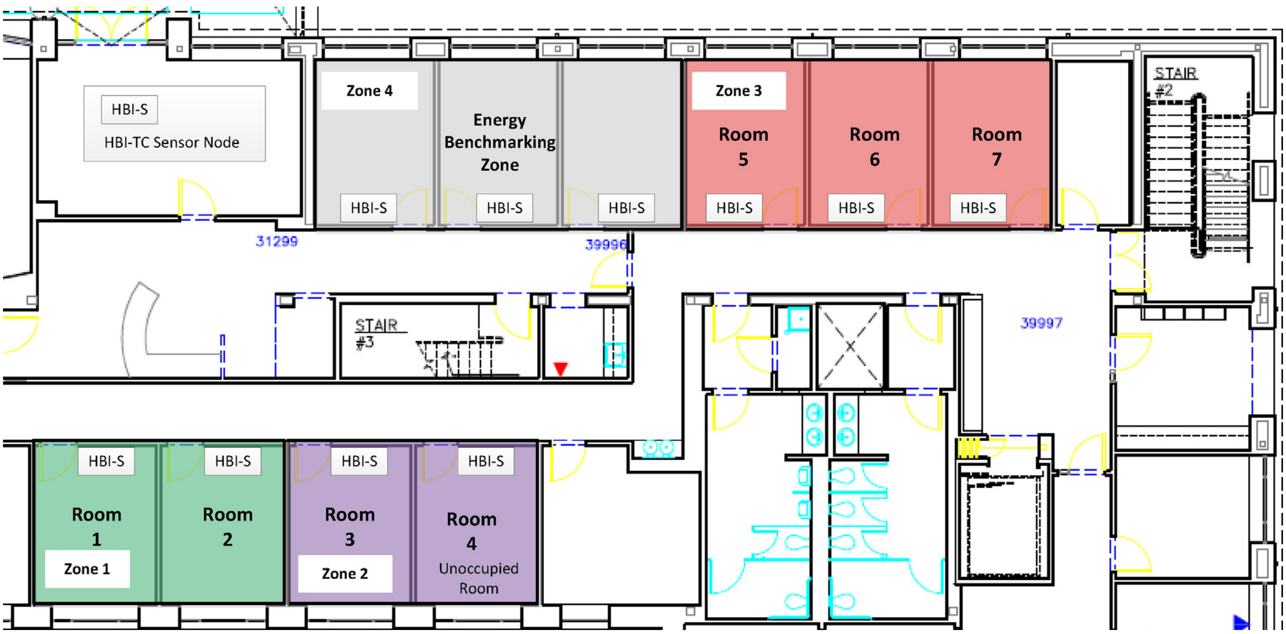


Fig. 6. Floor plan of the zones that are included in the experimental study.

and all of the rooms have large windows with controllable blinds. The rooms are single occupancy rooms with permanent occupants. An Institutional Review Board (IRB) approval was obtained for the study.

Three control modes were tested for operating the HVAC system and comparing the framework's impact on energy consumption and occupant comfort. The *first* mode is HVAC control by the BMS (i.e., the existing legacy control mode). In this mode, the VAV box operational set points were set to a constant temperature (~22.8 °C) for all of the targeted zones – it is called "BMS-22.8" hereafter. The *second* mode is HVAC control by the HBI-TC controller (i.e., the proposed control algorithm) that uses personalized comfort profiles. In this mode, the set point, in each zone, is dynamically set by the HBI-TC controller – it is called "HBI-desired" hereafter. The *third* mode is HVAC control by the HBI-TC controller using the predefined constant temperature set point (~22.8 °C) for all of the targeted zones – it is called "HBI-22.8" hereafter. The reason behind having three modes is that the BMS controller cannot provide and maintain a uniformly distributed temperature in every room of a zone and the temperature distribution is dependent on the location of the BMS sensor in the zone and the proximity of the sensor to the diffusor. Therefore, we hypothesized that using distributed HBI-TC sensors in the zones and using the complementary HBI-TC controller facilitate the provision and maintenance of a uniformly distributed thermal conditions at the room level, which results in thermal comfort improvements. Accordingly, for the *evaluation of the comfort consequences* of the HBI-TC framework, the HBI-desired and BMS-22.8 are compared (proposed control vs. legacy HVAC control). For the *evaluation of the energy consequences* of the HBI-TC framework, two operational modes are compared: (1) HBI-desired and BMS-22.8 to compare the proposed framework with the legacy HVAC control; and (2) HBI-desired and HBI-22.8 to compare the energy consequences of controlling the zones with two different policies for the same controller-preferred (desired) temperature versus predefined temperature set points. All modes controlled the targeted zones during the operational hours (6:30–21:00).

One out of the four zones was used as a benchmarking zone. In the other three zones, six occupants out of seven rooms participated in the experiments. The seventh room (Room 4 in Fig. 6) was unoccupied. The first test period was from October 15th 2012 to December 20th 2012. The objectives of this test period were to evaluate the comfort consequences through user interactions with the HBI-TC enabled control and to explore the energy consumption consequences of the BMS-22.8 and HBI-desired modes. During this test period, two weeks were used for the training and after the training; the zones were controlled based on the learned thermal comfort profiles until the end of the experiment. In the second test period, the experiment was conducted for four weeks during April 2013 to June 2013. In this test period, the targeted zones were controlled by the HBI-desired for two weeks and HBI-22.8 for another two weeks. The learned thermal comfort profiles of the occupants in the first period were used for the second period.

5.2. Evaluation metrics

As noted, the main objective of the HBI-TC framework is to improve the efficiency of centrally controlled HVAC systems. As defined earlier, efficiency is evaluated through measuring occupant comfort and calculating the energy consumption consequences of the HBI-TC implementation. Thermal comfort is "*a condition of mind, which expresses satisfaction with the thermal environment*" and is therefore, subjective. Measuring biological signals from a user's body or asking for a user's subjective opinions are two possible methods for measuring comfort. The former was not a viable option for this study due to its intrusive nature. Subjective opinions could be measured implicitly through counting the number of votes from users or explicitly through interviews. Due to the fact that users were reminded to provide their feedback during the training period, comfort measurement through counting the number of feedback votes could result in biased conclusions. Accordingly, user interviews at different stages of the experiments were used for assessing comfort consequences of the framework. During these interviews, participants were asked to determine their satisfaction with their indoor environment on a scale of 1–10, 1 being the lowest satisfaction and 10 being the highest satisfaction. The interviews were conducted three times: (1) before enabling the framework; (2) at the end of the two week training period (the first period); and (3) at the end of the period when the zones were controlled based on users' personalized thermal comfort profiles (i.e., the HBI-desired mode or the second period).

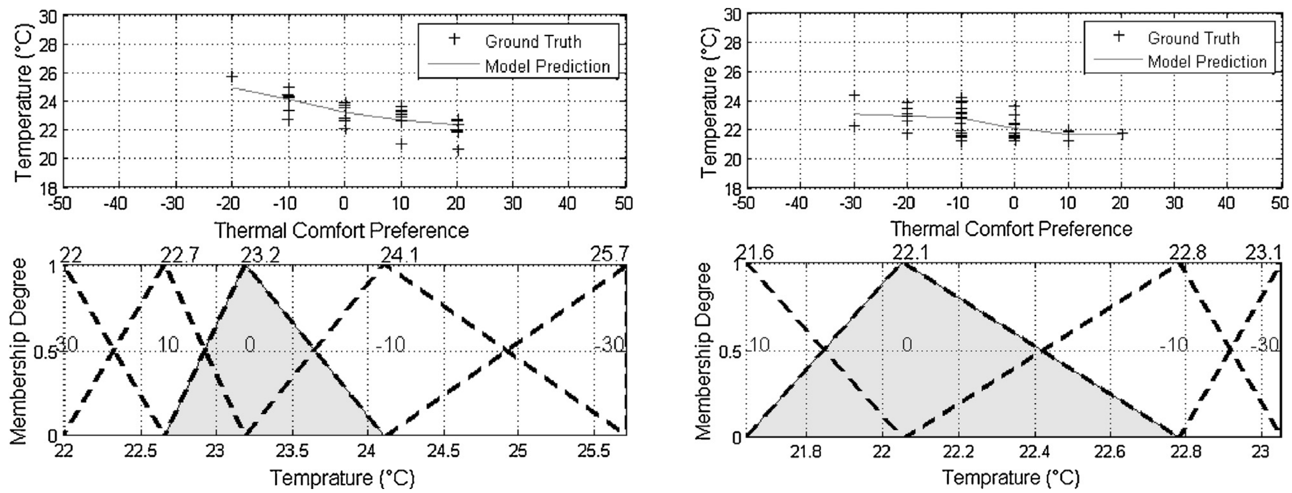


Fig. 7. The learned thermal comfort profiles of two participants.

Cooling process in the AHU, positive pressure applied through the supply air fans, possible heating process in the VAV boxes, and negative pressure applied through the return air fan are contributing processes in energy consumption of an HVAC system. The cool and hot water that is used for cooling and heating processes is conditioned in a central plant, which could serve a number of buildings (which is also the case for the test bed building). The accurate measurement of the HVAC energy consumption requires sub-metering of AHU electricity consumption as well as sub-metering of heating and cooling energy that is associated with specific AHUs and VAV boxes. However, this requires metering of all of the zones that an AHU is serving. To find a metric for measuring energy in individual zones an approximated measure is considered for energy consumption for temperature change and the energy consumed in air fans. The required energy for temperature variation could be obtained by:

$$Q = \dot{m} C_a \Delta T$$

where Q is the energy for change in temperature, $\dot{m}$ is the air flow, C_a is the air heat capacity, and ΔT is the temperature change before and after heating or cooling. The cooling is performed by mixing the return air and outside mixed air. Temperature of the mixed air depends on the volume and the temperature of the air coming from each source. The volume of each source is usually determined by the HVAC economizer, which seeks optimized energy consumption for cooling. Accordingly, determining the temperature for energy calculation is a challenging task. However, the contribution of each zone in the cooling energy consumption is proportional to the airflow of each zone based on the continuum equation. Heating process, which is performed at the VAV level, is also proportional to the zone airflow. For the supply and return fan the power consumption is also proportional to the airflow passing through the fans. Therefore, in this study, airflow variation is used as the evaluation metric since comparison between different operational modes is carried out using relative changes in the energy consumption.

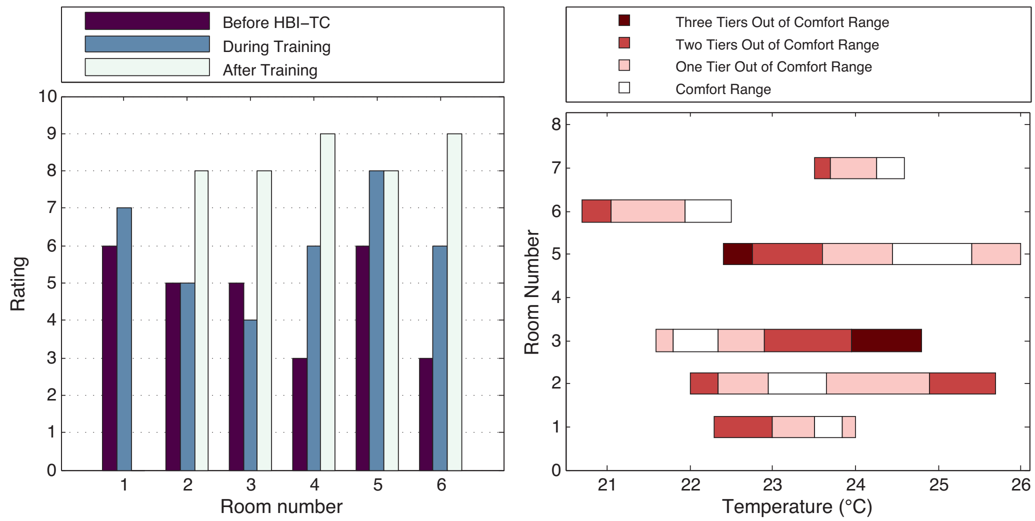
5.3. Findings

5.3.1. Comfort consequences

Upon training for two weeks, the thermal comfort profiles of the participants of the six rooms were generated and used for the HBI-TC control algorithm. The parameters of the comfort profile learning algorithm were set based on an extensive assessment done for improving the accuracy of the comfort profiles. Details of these assessments could be found in [43]. Fig. 7 illustrates the comfort profile of two participants. As it could be seen in this figure, the comfort profile has two components: (1) the comfort ranges (lower part of the figures), which are defined based on the fuzzy predictive model and the assigned fuzzy sets for the *TPIs*; (2) the customized scale (upper part) for each user. As the scales in Fig. 7 show participants have different levels of sensitivity to different conditions of temperature variations. These scales are used for reacting to users' feedback after the training period is over. Different fuzzy sets in the comfort profiles determine different ranges of users' comfort. The central fuzzy set with gray shade determines the preferred temperature zone for each user. In this study, the temperature in the center of this fuzzy set is used as preferred (desired) temperature for control purposes.

The comfort profiles of six users in the targeted zones were used as the default operating desired temperature ranges during the post-training period. Once the personalized comfort profiles were obtained, upon the receipt of a new request, the requested change in temperature was calculated using the customized scale of each user's comfort profile and the temperature change was passed to the controller as the desired temperature for that user. The change was reversed after 30 min to the default value. The observations of the HVAC system reaction time were used in determining this 30-min interval. After receiving a vote from a user, new requests from the same user were ignored for 30 min to ensure that user local discomfort does not cause excessive changes in the HVAC system. In the preliminary testing of the HBI-TC framework and before enabling the framework in the building, the observations in the targeted zones showed that it is not possible to reach the temperature that a user might ask because of the minimum airflow setting of the VAV boxes. The reason was that the minimum airflow for the VAV boxes was set to ∼5.7 m^3/min. This airflow has been set to ensure that a conservative cool environment could be achieved. Therefore, the minimum airflow of the zones were reduced and set to ∼3 m^3/min for the HBI-TC framework. The reduction of the air flow was considered in accordance with the Ventilation for Acceptable Indoor Air Quality (ASHRAE standard 62.1–2007). A 59% of air flow reduction in HVAC operations in BMS mode was observed after minimum airflow adjustment. However, as it is illustrated in Fig. 10, the BMS mode with reduced minimum air flow results in an undercooled indoor environment.

Fig. 8 shows the thermal comfort ranges of the participants (Fig. 8b) and the results from the comfort assessment (Fig. 8a). The participant in room 1 stated that his presence was intermittent in the room after the training period and he preferred not to rate the performance of the system for the post-training period. As this figure shows, the average of the rating before training is 4.7



a) User rating for thermal comfort evaluation

b) Users' comfort ranges extracted from each profie

Fig. 8. Users' thermal comfort ranges and their ratings for the HBI-TC framework performance.

out of 10 possible points. During the training period, user comfort was slightly improved to an average of 6 out of 10 possible points, and during the post-training period the average vote increased to 8.4 out of 10 possible points, which shows potential for user comfort improvements for the experimental group although the difference is not statistically significant for statistical generalization. The sensitivity analysis showed that a larger sample of 20 or more participants is required for statistical significance. Large-scale experiments are among the future directions of the authors. In addition to quantitative subjective ratings, the participants stated their satisfaction with the implemented framework and they expressed their enthusiasm about keeping the framework active in the building. Moreover, the improved user experience implicitly supports the users' adaptive abilities.

The performance of the HBI framework in providing the desired thermal condition is shown in Fig. 9. In this figure, the variation of room temperatures in each room, the users' preferred (desired) comfort temperature, lower bound desired temperature and upper bound desired temperature for a sample day are illustrated. As it could be seen in zones 1 and 2, the room temperature variations were in the comfort zone limit of the users. As mentioned before, room 4 was vacant. In zone 3, the related profile for room 6 was disabled in the HBI-TC control algorithm as the occupant of room 6 was not in the office (for the day of the presented data), and the temperature time series for rooms 5 and 7 are shown. The average temperature for room 5 is out of the comfort range for half a degree Celsius, which is due to the averaging policy that is used in the HBI-TC control algorithm. Improving the control algorithm for maximizing the comfort score for all occupants in each zone is among the future research directions of the authors. However, as the subjective votes show, the user in room 5 expressed a considerable improvement for his/her thermal comfort levels. This is due to the fact that the thermal condition provided by the new HBI-TC controller is closer to the user's thermal preference range compared to the time that HVAC was solely controlled by the BMS.

Fig. 10 shows the comparison between different operational modes (i.e., BMS-22.8, HBI-22.8, and HBI-desired) to explore the possibility of improving the temperature distribution and keeping the temperature close to the users' preferences with the HBI-TC control algorithm. The graphs show a sample day for each condition, and the temperature time series are average temperatures of all the rooms in each zone. Mean lower bound and upper bound are the average of desired temperature range lower and upper bounds for the occupants of one zone. As it is shown, using the BMS-22.8 mode resulted in high temperatures in the rooms. This happened due to the changes in the minimum airflow setting of the VAV boxes. Accordingly, to achieve lower temperatures, the minimum airflow should have been increased in order to cope with the improper location of the BMS sensors. This is the reason behind the dissatisfaction of occupants and their perception of the indoor environment as somewhat cool to cold before HBI-TC implementation. Fig. 10 also shows the performances of HBI-desired and HBI-22.8. As it could be seen, the HBI-desired is successfully conditioning zones' indoor environment to be compatible with users' preferences. The improvement in performance of the HVAC is achieved through application of room level sensors and the complementary HBI-TC controller.

5.3.2. *Energy consumption consequences*

In proportional controllers, tuning of the proportional coefficient is an essential step to avoid excessive oscillations, which could result in excessive energy consumption in HVAC system operations. Accordingly, as a first step, the tuning of the k_p coefficient was performed to find the best coefficient. In this process 0.25, 0.4, 0.6, and 1 were used for the coefficient and the HBI-TC control algorithm was run for a day with each one of these coefficients. Fig. 11 shows the airflow variations in zone 1 as an example. As it is shown in this figure, $k_p = 0.4$ was found to be the best coefficient among the tested ones, with decreased oscillation. The increase in the airflow at the beginning of the day is part of the scheduled operation of the BMS for the initial conditioning of the indoor environment.

The energy consequences of the complementary control algorithm were evaluated by studying two comparative cases. The first comparison was done between the HBI-desired and the BMS-22.8. For the comparison, the data from October to December of 2011 was used. Many factors could affect the airflow variations including outside temperature and activities in the zones. The comparison was performed between the days with similar outside temperature ranges. Since the length of the period of comparison is relatively long and the same occupants used the rooms in both years with almost similar activity patterns, we compared the daily average airflow variations directly. Table 1 shows the results of the comparison with an overall 39% reduction in daily average airflow. It is emphasized that in this comparison air flow values for the BMS mode

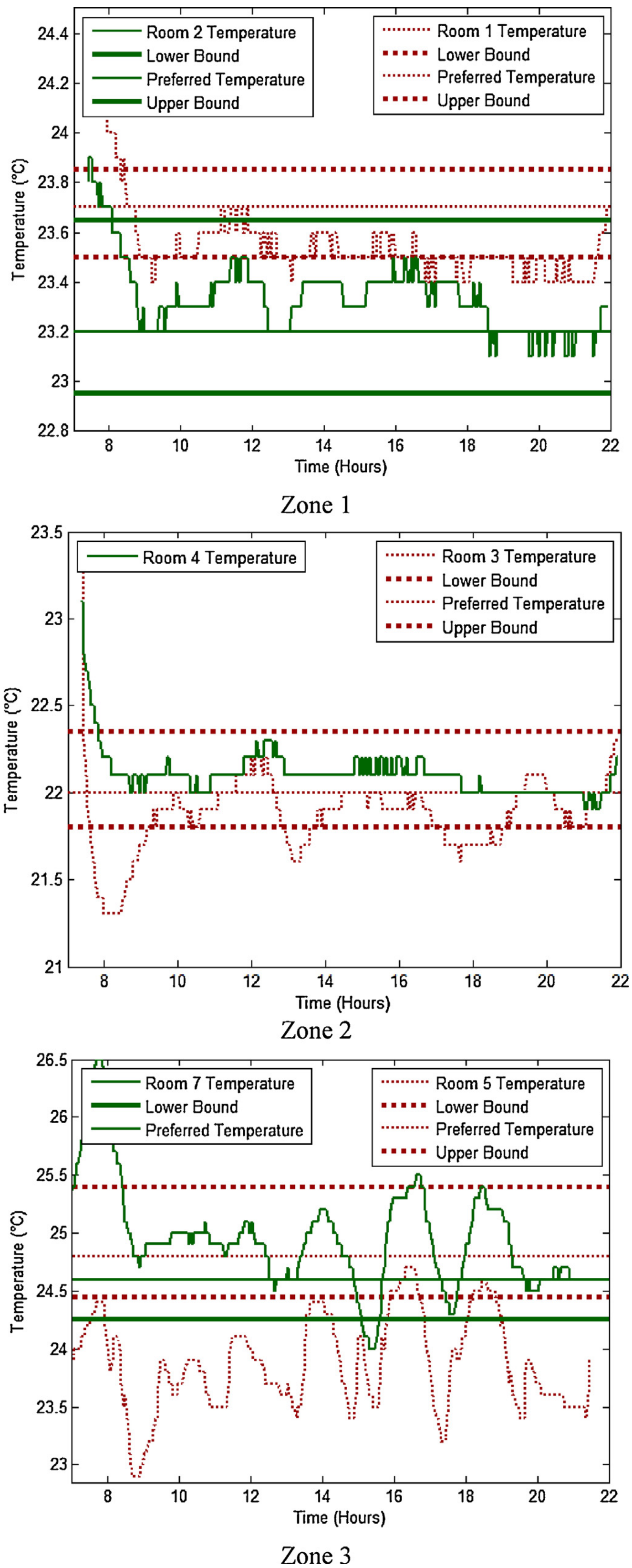


Fig. 9. Targeted rooms' temperature time series and the users' comfort profiles' margins.

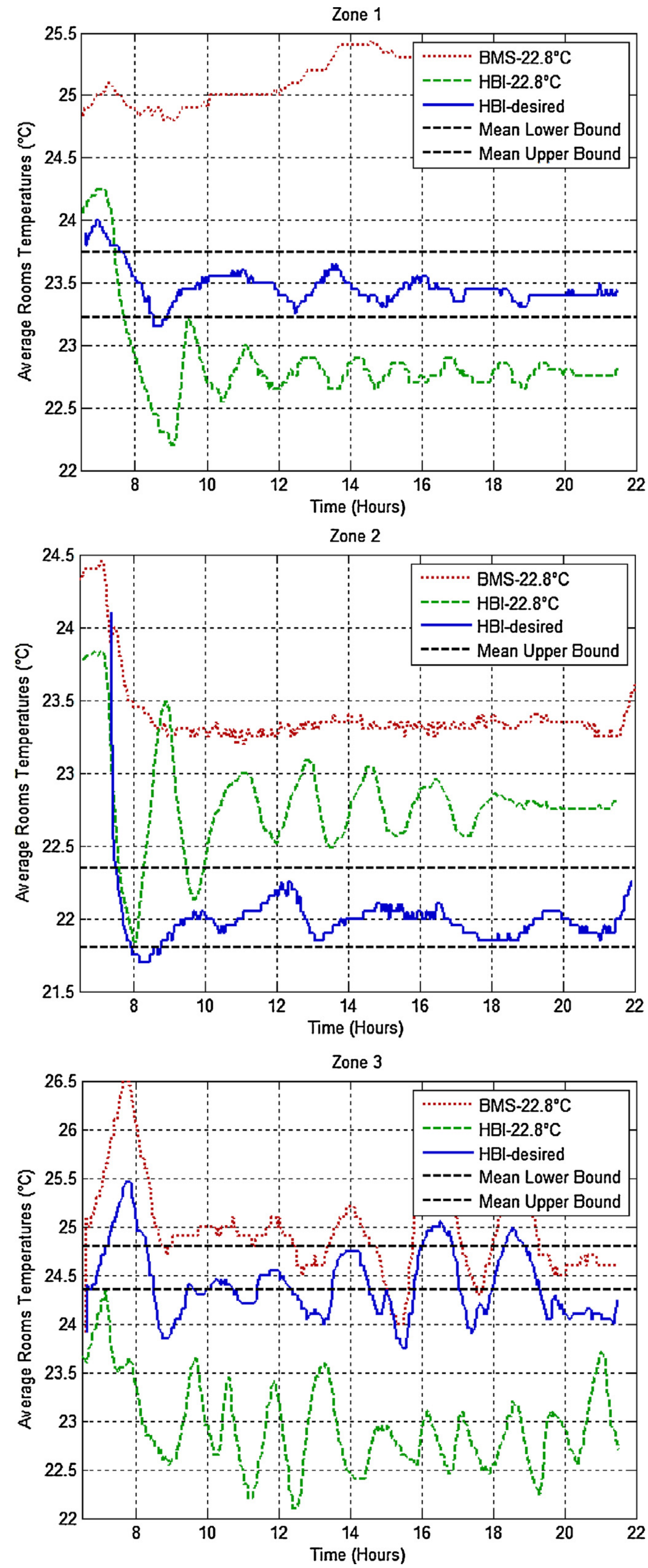


Fig. 10. Temperature time series for three sample operation days of the HVAC system under three operating modes for three experimental zones.

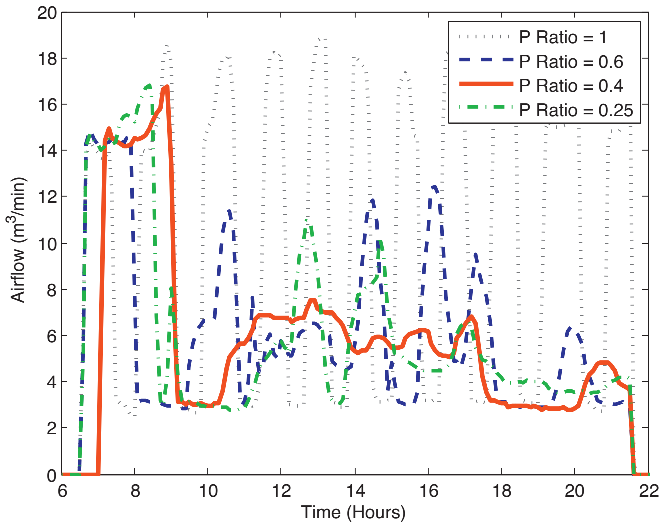


Fig. 11. The variation of air flow for different values of k_p.

Table 1
The comparison of average daily air flow variation between HBI-desired and BMS-22.8.

Mode	Zone 1	Zone 2	Zone 3	Overall
2012 HBI-desired	5.14	8.21	5.42	6.26
2011 BMS-22.8	9.48	9.51	11.69	10.23
Variations	−46%	−14%	−54%	−39%

was collected before implementation of the HBI-TC and therefore the minimum air flow was higher. As it is shown in Fig. 10, the reduction in minimum air flow results in undercooling condition in case of operating in the BMS mode. This is the reason behind the higher energy consumption in the BMS mode operation. In order to illustrate the reason for the observed savings, in Fig. 12, the comparison between daily average airflows for a period of 30 days in 2011 and 2012 are presented. Taking the performance of the BMS mode in Figs. 10 and 12 into account shows the lower efficiency of the BMS operational mode. The comparison shows high rate of airflow in 2011 compared to the airflow values of the HBI-desired operational mode in 2012. The energy impact of heating at VAV boxes for the HBI-desired and BMS modes was investigated by comparing the

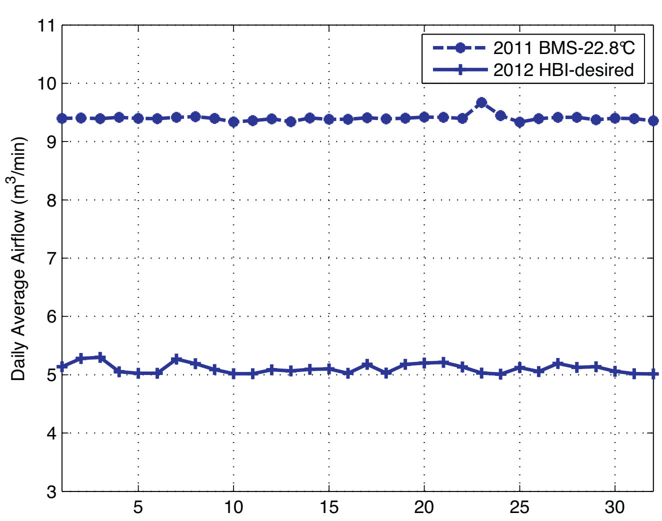


Fig. 12. The comparison between variation of daily average air flow in 2011 (BMS-22.8) versus 2012 (HBI-desired).

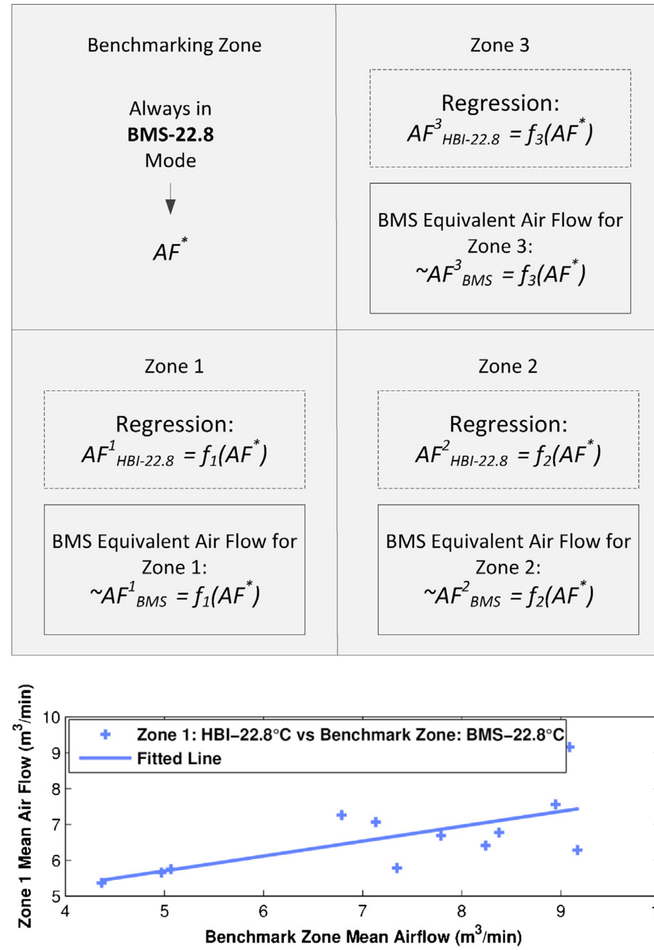


Fig. 13. The benchmarking process and a sample inter-zone regression analysis.

average percentages of the time that the VAV heating valves were open. These percentages are 7.32% in zone 1, 4.12% in zone 2, and 0.9% in zone 3 for HBI-desired operational mode, and 2.84% in zone 1, 1.66% in zone 2, and 0.35% in zone 3 for the BMS operational mode. As it could be seen the heating system of the VAV boxes was not active in majority of the operational periods for either of the strategies. As a result, airflow variation was considered as the main metric for comparisons between different modes of operation.

The second comparison was done between the HBI-desired and HBI-22.8. The comparison was carried out in different modes for four weeks: two weeks using the HBI-desired mode and two weeks using the HBI-22.8 mode. In order to conduct a fair comparison between the two control modes, a benchmarking approach was adopted. Zone 4, which is in close proximity to the experimental zones, was used as the benchmark zone. In the benchmarking process, the daily average airflow of each one of the zones in the HBI-22.8 mode was mapped to an equivalent daily average airflow of the BMS-22.8 mode (shown as $_{\sim}AF^{z}{}_{BMS}$ in Fig. 13). Zone 4 was always operated in the BMS-22.8 mode. When the targeted zones are operated based on HBI-22.8 mode, a regression analysis was carried out to obtain the relationship between the daily average airflow in the benchmarking zone and the other zones (depicted as $AF^{z}{}_{HBI} = f_z(AF^{*})$ in Fig. 13). Using the regression curves for comparison, the equivalent daily average airflow of the zones in the HBI-22.8 mode for the period of the HBI-desired operation mode was obtained. Fig. 13 also shows the results of the linear regression analysis between zone 1 and the benchmark zone as an example.

The airflow variations are presented in Table 2 by benchmarking and calculating the energy consumption of the HBI-22.8 and

Table 2
Variation of average daily airflow in targeted zones for the HBI-22.8 mode versus HBI-desired mode.

Mode	Zone 1	Zone 2	Zone 3	Overall
HBI-22.8	8.42	6.38	16.4	10.4
HBI-desired	5.48	9.45	8.08	7.67
Variations	−35%	48%	−51%	−26%

HBI-desired modes. The overall airflow in the HBI-desired mode has been decreased by 26%. The HBI-22.8 mode is the mode that a more uniform distribution of conditioned air is possible (due to the HBI-TC sensor boxes in each room) for predefined temperature set points. As mentioned in Section 2, a high percentage of the occupants were dissatisfied, perceiving their indoor environments as cool to cold. Accordingly, the HBI-TC framework could potentially reduce energy consumption in the building by learning all permanent occupants' thermal comfort profiles.

6. Limitations

In this study, the proposed framework has been designed and evaluated for office buildings with closed office spaces equipped with a centrally controlled HVAC system. However, in buildings with open plan offices, in the absence of partitioned spaces, provision and maintenance of different microclimates could be a challenging task, which requires a comprehensive study of the microclimates in open plan offices and development of novel strategies for implementation of personalized thermal driven HVAC control. The HBI-TC framework is more suited for permanently occupied offices, where thermal comfort profiles for occupants could be established. In this study, the objective function focused on thermal comfort by using thermal preferences' zone level average. The energy efficiency of the HVAC system could be improved through the multi-objective optimization of energy and comfort and introduction of more advanced policies in HVAC operations. Detection of occupancy patterns and integration of occupancy related information into the operational loop and improvements to the control policies to improve zone level preferred temperature calculations are among the future directions of the authors. Development of policies to prevent users from gaming the control strategies and optimization of the sensor locations in zones are also two areas of future research.

7. Conclusions

This study presents the results from the implementation and evaluation of a framework that integrates occupants' preferences in the operation of HVAC systems. The paper tested the hypothesis that by operating the HVAC system based on occupants' comfort profiles the system efficiency could be improved. Three zones of an office building were used for the validation of the hypothesis. The proposed framework uses a participatory sensing approach for user-BMS communications and learns user's comfort profiles, using a fuzzy predictive model, as users interact with the system to achieve their preferred indoor thermal conditions. The user comfort profiles are then utilized through a complementary control strategy at the zone level. The comfort and energy consumption implication of the proposed framework was evaluated through experimental studies. Interviews with the participants showed improvements in user satisfaction with their thermal comfort. Although the framework showed potential to improve comfort while reducing energy consumption, to achieve statistically significant results a larger-scale experiment is needed. The evaluation of energy consumption of the proposed framework showed promising results for saving energy. The results showed a 39% reduction in daily average airflow rates (compared to the legacy HVAC system operations with predefined temperature set points). The comparison between the proposed framework control modes for users' desired temperatures versus predefined temperatures also showed a reduction in daily average airflow rates by 26%.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.enbuild.2013.11.066.

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