Human-Building Interaction Framework for Personalized Thermal Comfort-Driven Systems in Office Buildings

Farrokh Jazizadeh, S.M.ASCE[1]; Ali Ghahramani[2]; Burcin Becerik-Gerber, A.M.ASCE[3]; Tatiana Kichkaylo[4]; and Michael Orosz[5]

Abstract: Centrally controlled heating, ventilation, and air conditioning (HVAC) systems in commercial buildings are operated by building management systems (BMS) based on the predefined operational settings and a set of assumptions. Despite the high rate of energy consumption by HVAC systems in commercial buildings, observations showed that a significant portion of the occupants remain dissatisfied with thermal conditions. One of the main reasons is that HVAC systems do not take into account personalized comfort preferences in their operational rules. This study proposes a framework to integrate building occupants in the HVAC control loop, learn their comfort profiles, and control the HVAC system based on occupants' personalized comfort profiles. The framework fuses occupants' comfort perception indices (i.e., comfort votes provided by users and mapped to a numerical value), collected through participatory sensing, and ambient temperature data, collected through a sensor network, and computes occupants' comfort profiles by using a fuzzy rule-based descriptive and predictive model. The performance of the comfort-profiling algorithm was assessed using human subject data and synthetically generated data. For actuation, a BMS controller was proposed and tested in two zones of an office building. The BMS controller uses a proportional controller algorithm that regulates room temperatures to be equidistant from preferred temperatures of all occupants in the same thermal zone. Validation of the framework components demonstrated that the nonlinear underlying pattern of the thermal comfort sensation scale could accurately be recognized. Results of the BMS controller experiments revealed that the proportional controller algorithm is capable of keeping the thermal zones' temperatures in the ranges of preferred temperatures. **DOI: 10.1061/(ASCE)CP.1943-5487.0000300.**

Author keywords: Thermal Comfort; HVAC system; Human-building interaction; Commercial buildings; Learning; Energy.

Introduction and Motivation

Occupant thermal comfort is a dominant influence on building operations and a major criterion to evaluate the performance of building systems. In the United States, buildings consume about 40% of the energy, almost half of which is consumed by commercial buildings. About 43% of the energy in commercial buildings is consumed for heating, cooling, and ventilation purposes (Dept. of Energy 2010). Despite the high rate of energy used for indoor environmental conditioning, a significant portion of the occupants (i.e., 35% of building occupants) are still unsatisfied with code-defined indoor thermal conditions in commercial buildings (Guo and Zhou 2009; Jazizadeh et al. 2011), which may affect productivity and health of occupants (Guo and Zhou 2009; Seppanen et al. 2005). Dissatisfaction with indoor thermal conditions may also lead to the use of local heating and cooling sources, such as electrical heaters or fans. These local sources could potentially cause a thermal imbalance in subspaces of buildings, reduce overall satisfaction in a thermal zone, and increase energy consumption. For example, authors' observations showed that in the case of using electrical heaters, the HVAC system keeps blowing cooled air into a thermal zone to compensate for the added thermal load. This phenomenon results in an increase in energy consumption and a reduction of overall thermal satisfaction in a thermal zone by overcooling it.

Most building management systems (BMS) rely on industry standards, such as ASHRAE (American Society of Heating, Refrigerating, and Air-Conditioning Engineers) standards, using the predicted mean vote (PMV) as a thermal comfort index, to ensure and assess satisfactory environmental conditions during occupancy. The PMV index is used to quantify the average comfort perception of building occupants for whom a set of assumptions are made, such as their clothing levels, activity levels, and metabolic rates. These parameters as well as other indoor condition parameters, such as air temperature, radiant air temperature, humidity, and air speed, are adjusted to make sure that a specific minimum level of predicted percentage dissatisfied (PPD) (i.e., 20% of building occupants) is achieved. Accordingly, a typical centrally controlled HVAC system operates based on these predefined set points,

[1]Graduate Student, Sonny Astani Dept. of Civil and Environmental Engineering, Viterbi School of Engineering, Univ. of Southern California, KAP 217, 3620 S. Vermont Ave., Los Angeles, CA 90089-2531. E-mail: jazizade@usc.edu

[2]Graduate Student, Sonny Astani Dept. of Civil and Environmental Engineering, Viterbi School of Engineering, Univ. of Southern California, KAP 217, 3620 S. Vermont Ave., Los Angeles, CA 90089-2531. E-mail: aghahram@usc.edu

[3]Assistant Professor, Sonny Astani Dept. of Civil and Environmental Engineering, Viterbi School of Engineering, Univ. of Southern California, KAP 224C, 3620 S. Vermont Ave., Los Angeles, CA 90089-2531 (corresponding author). E-mail: becerik@usc.edu

[4]Computer Scientist, Information Sciences Institute, Viterbi School of Engineering, Univ. of Southern California, Suite 1001, 4676 Admiralty Way, Marina del Rey, CA 90292. E-mail: tatiana@isi.edu

[5]Assistant Director, Information Sciences Institute, Viterbi School of Engineering, Univ. of Southern California, Suite 1001, 4676 Admiralty Way, Marina del Rey, CA 90292. E-mail: mdorosz@isi.edu

Note. This manuscript was submitted on November 5, 2012; approved on February 15, 2013; published online on February 18, 2013. Discussion period open until June 1, 2014; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Computing in Civil Engineering***, Vol. 28, No. 1, January 1, 2014. © ASCE, ISSN 0887-3801/2014/1-2-16/$25.00.

assuming all occupants in one thermal zone, an individual indoor space or group of neighboring spaces with similar thermal loads, have the same comfort preferences (e.g., all occupants prefer 22.7°C).

Studies have shown weak and context-dependent correlations between standard-defined comfort ranges and occupant-reported comfort ranges (Barlow and Fiala 2007; Corgnati et al. 2007; Wagner et al. 2007). Studies have also showed that thermal comfort does not occur at thermal neutrality as defined by the standards (Van Hoof 2008). Often times, occupant comfort ranges are found to be larger and more forgiving than the predicted ranges implying a potential for reduced energy consumption by allowing more flexible and adaptive control of system set points (Hwang et al. 2009; Nicol and Humphreys 2009). Many factors could potentially contribute to the comfort preferences of each individual, for example, habits, differences in metabolic rates, sensitivity to airflow and temperature changes, and historic thermal experience. Moreover, under similar indoor environmental conditions, varying comfort preferences for one person could also be reported. Since many environmental and occupant variables are difficult to predict for a building population, field studies are common methods for assessing indoor environmental quality and occupant comfort. Field studies generally involve one time or periodic occupant surveys, which either ask participants to remember their comfort and summarize their experience over different seasons and times of day or ask participants to report only their current level of comfort, requiring multiple responses from each participant over a period of time (Buratti and Ricciardi 2009). The latter occupant survey type is usually limited to a few weeks or months due to the challenges with continuous and large-scale acquisition of human-contributed data (Ari et al. 2008). In comparison to the code-defined standards, field studies can often more accurately predict ambient comfort for a given population as they make no assumptions and take into account all contextual influences including climate, building characteristics, and culture. Yet these field studies also have limitations as they do not reflect real-time or context-dependent comfort of the occupants. There is no feedback about the occupants' comfort levels on an ongoing basis. Without any direct feedback other than infrequent complaints, building managers are forced to play it safe, resulting in suboptimal operations.

The building energy research community increasingly acknowledges the importance of human related information, including human presence, activities, behavior, and attitudes (Azar and Menassa 2011; Jain et al. 2012; Klein et al. 2012; Li et al. 2012; Peschiera et al. 2010; Peschiera and Taylor 2012) in building energy management. To involve humans and associated information in a building's operational loop, the authors' vision is to develop a framework for ubiquitous and real-time interactions between buildings and humans with a focus on increasing comfort, improving energy awareness, and reducing energy use in commercial buildings. In the envisioned human-building interaction (HBI) framework, buildings are not only shelters; they are entities that connect with their users and adapt to their needs. Humans (both end users and managers of buildings) play an important role in both the issue of increasing energy consumption by buildings and the proposed HBI vision. The goal for user-driven building controls is occupant satisfaction, for which an important criterion is the thermal comfort. Previous research has shown that reducing building energy consumption and increasing occupant comfort could be achieved concurrently (Barlow and Fiala 2007; Karunakaran et al. 2007; Klein et al. 2011). The HBI vision argues that operational strategies for commercial buildings should integrate occupant feedback into a building's operational logic and control of building systems as complementary information to the PMV-PPD indoor thermal condition baseline to improve comfort and potentially reduce building energy consumption. This study aims to assess the feasibility of learning personalized comfort profiles, obtained through occupants' real-time interactions with BMS, and operate HVAC based on the learned personalized comfort profiles.

The framework for human-building interaction for thermal comfort (HBI-TC) includes occupant-driven control of HVAC systems and personalized control of thermal comfort in office buildings. As part of this framework, the paper first describes an intermediary as a means of communication between humans and buildings, specifically, how occupants communicate their thermal comfort preferences to building systems. The intermediary is intended to be and validated as an indirect approach of collecting data from building occupants, while occupants adjust thermal settings to achieve their desired comfort levels. Feasibility of using a learning approach for profiling comfort preferences and comfort ranges as personalized sensation scales are explored. The underlying enablers of the proposed framework, algorithms for personalized comfort profile learning and building system control as well as the results from validation tests are presented.

Adaptive Building Control

Improved understanding of the complexities of occupant comfort has led to research in adaptive building control systems. To address the multivariable nature of preferred thermal and air quality conditions, fuzzy logic controllers have been proposed for operation of HVAC systems (Calvino et al. 2004; Duan Pei-yong and Hui 2010; Gouda 2005; Hamdi and Lachiver 1998; Kolokotsa et al. 2006; Ma Hong-Li and Zhu Bang-Tai 2005; Nowak and Urbaniak 2011). Additionally, multiagent simulations (Dounis and Caraiscos 2009) and neural network computing methods (Atthajariyakul and Leephakpreeda 2005; Ben-Nakhi and Mahmoud 2004) have been investigated for advanced building controls. Wireless sensor networks have been used for real-time ambient sensing of indoor environments for more informed control of HVAC and lighting systems (Guo and Zhou 2009; Marchiori and Han 2010; Singhvi et al. 2005; Tse and Chan 2008; Wen and Agogino 2008). Adaptive fuzzy controllers as well as genetic and gradient-based algorithms have been used for multiobjective optimization of occupant comfort and building energy consumption (Atthajariyakul and Leephakpreeda 2004; Bruant et al. 2001; Kolokotsa et al. 2001; Wen and Smith 2004). Despite these advances in building control strategies, the PMV index and the established visual comfort and air-quality thresholds are still consistently used to assess, maintain, and optimize occupant comfort without any validation of their representativeness of actual occupant preferences and comfort levels. Although most of these studies have proposed solutions for adaptive control to provide and maintain thermal comfort using the PMV index, the majority of these studies still assign predefined and constant human-related variables, such as metabolic rates, clothing values, and activity levels. Moreover, many advanced adaptive HVAC control solutions (which use PMV values as an objective variable) require sensing systems, which are capable of measuring multiple variables that affect the PMV value. These variables, such as air, radiant and surface temperature, humidity, and air speed, are used to capture variations in indoor environmental conditions. Sensing systems capable of measuring the above-mentioned variables exist, and they are used in research studies. However, their application in practical deployments in buildings may not be feasible (Daum et al. 2011) due to the large number and type of sensors needed. Accordingly, a relatively simple and cost-effective sensor system is needed.

J. Comput. Civ. Eng., 2014, 28(1): 2-16

Application of user-provided information for controlling HVAC systems has been explored in a number of research studies. Guillemin and Morel (2002) has proposed a self-adapting control system that learns specific occupant wishes through user input in the form of set points and an artificial neural network for thermal and lighting conditions (Guillemin and Morel 2002). In their approach, users were asked to provide operational set points directly for temperature and lighting through keyboards in each room. Based on their experimental study and conclusions, an alternative algorithm to learn users' preferences was needed to improve the performance of their proposed approach as comfort objectives were not met and occupants were not able to provide the set points they were comfortable with. Moreover, set points in buildings are not necessarily equal to the realized room temperatures. Murakami et al. (2007) proposed an approach for controlling the HVAC system based on user requests in an open office using an interface, through which users could ask for two options, warmer or cooler along with ASHARE sensation scale to represent their desired thermal sensations. Their proposed control logic for energy conservation, which adjusts a daily set point, was evaluated through a collective voting by a large group of people. The results of experiments in an open office with 50 occupants showed that energy used with comfort feedback was almost similar before and after the experiments (Murakami et al. 2007). Daum et al. (2011) has proposed a probabilistic measure of thermal comfort and applied it for controlling window blinds, using too hot/too cold buttons to improve thermal comfort and reduce energy consumption (Daum et al. 2011). Using artificial data, they have developed a default profile, which was updated based on the user data provided through the above-mentioned binary button. The profiles had three zones: comfortable, too cold, or too hot–allowing occupants to address (vote) the two extreme indoor conditions. Bermejo et al. (2012) applied static fuzzy rules to the PMV, which were calculated by using temperature and humidity sensor data, as well as assumptions for activity and clothing levels, as a thermal comfort index. The PMV was used in actuating room temperatures and was updated as occupants interacted with thermostats. Through experimental simulations, it was shown that the approach could be used as an online learning method for learning occupants' comfort (Bermejo et al. 2012). In addition to the achievements of previous research, the contribution of this study is a framework that complements existing building systems (designed based on the industry standards). The framework requires a minimum amount of sensing devices and no need for retrofitting HVAC system components. The framework learns users' individual preferences and develops a personalized sensation scale, which determines the sensitivity of each user to different thermal conditions. Learning of comfort profiles is carried out for each user without the need for any prior information or without using the PMV index, which has limitations as it requires advanced sensing infrastructure to be deployed in an environment and a set of assumptions to be made for human-related variables.

HBI-TC Framework for Personalized HVAC Operations

The HBI-TC framework uses comfort preferences information, obtained directly from each occupant through participatory sensing via an intermediary. Since occupants provide the comfort preference information while they are exposed to various ambient conditions, feedback inherently factors in potential drivers such as activity levels, clothing levels, metabolic rates, and other contextual factors that cause variations in comfort perceptions. This information is then used to control HVAC system operations by the BMS controller at the thermal-zone level based on the collective preferences of occupants of a zone. The objectives of this study include capturing the comfort profile of each individual through learning of personalized thermal comfort profiles, as well as new preferred temperatures. Learning of personalized comfort profiles is the foundation for the HBI-TC vision, which aims to improve thermal comfort for dissatisfied occupants, maintain thermal comfort for satisfied occupants, and efficiently control the HVAC system based on the comfort profiles. Fig. 1 illustrates the components of the HBI-TC framework.

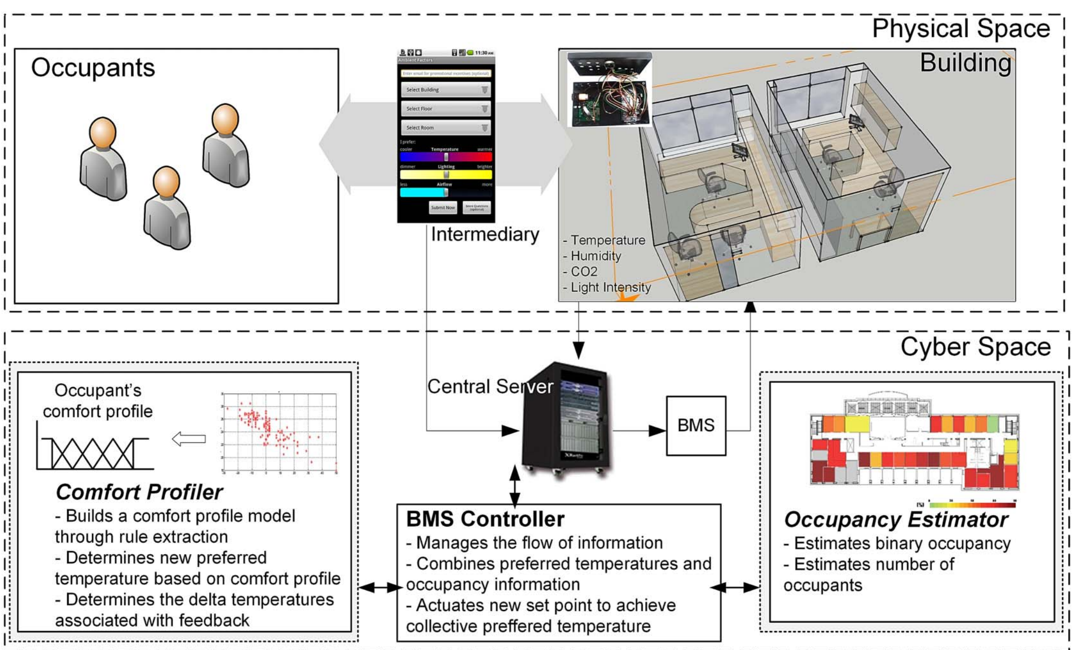
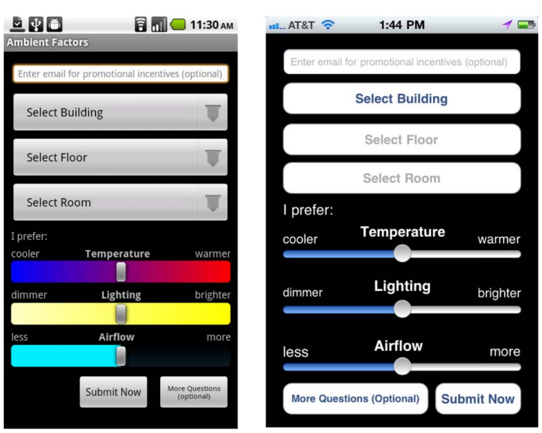


Fig. 1. Information flow in the HBI-TC framework and its components

Participatory Sensing Using an Intermediary

Participatory sensing provides an opportunity to track and act on information while enabling the mapping and sharing of local knowledge at a personal scale (Shilton et al. 2008). Participants use ubiquitous computing devices and interact with their environments. Having sensing nodes on participants allows the mobility of nodes and provides context-dependent information. To enable the HBI-TC framework, an intermediary was designed as a participatory sensing application for smartphones. The intermediary adopts participatory sensing principles for capturing real-time context-dependent perceptions and preferences of occupants regarding comfort by inherently incorporating their metabolic rates, clothing, and activity levels since the feedback reflects occupants' perception of ambient conditions given all these parameters. The objective was to design and test an application that contains a few focused questions to encourage fast and frequent input to building systems. The application allows occupants to express their preferences for three influential factors on comfort–temperature, light intensity, and air quality–that have the greatest impact on building energy consumption and occupant comfort (Zhang et al. 2011). The HBI-TC framework described in this study focuses on the temperature preferences as a tangible parameter for occupants to express their perceptions regarding their thermal comfort and to actuate the HVAC systems.

The interface of the intermediary was originally designed using an ASHRAE sensation scale. This scale for thermal comfort included seven degrees from −3 to +3 (corresponding to hot, warm, slightly warm, neutral, slightly cool, cool, and cold). The three middle degrees (−1, 0, 1) are considered satisfactory by ASHRAE; consequently, five levels (cold, cool, neutral, warm, hot) were incorporated in the design of the interface. The design verification tests showed that in some cases, occupants were still satisfied even if they indicated that they preferred warmer or cooler conditions. The optimum cognitive design of the intermediary was finalized through a series of task execution surveys and think-aloud experiments. The objective was to ensure that preference values, collected through the interface, reflected realistic preferences and perceptions of occupants. A series of prototypes were prepared and tested in multiple phases, which ultimately resulted in the final design of the application interface. As a result, a slider approach was introduced, for which the center was considered as neutral (satisfactory). By moving the slider to the left or right, occupants determine their preferences (Fig. 2) and at the same time, their perception of the indoor environment is captured. Values on the slider vary between −50 for the cooler side to 50 for the warmer side. These values are then used as indices for building comfort preferences. For example, if an occupant positions the slider on 20 (which is in the warmer side), it means that her/his perception of current ambient condition is cool/cold and he/she prefers warmer indoor environmental conditions. The slider that is used for capturing occupants' feedback is intentionally kept simple without a quantitative scale to avoid the requirement for occupants to have the knowledge of the relationship between their thermal comfort preferences and current ambient temperature. The intermediary has been developed as applications for iOS-based and Android-based smartphones and tablets. Moreover, a web application was also developed for users, who do not have access to smartphones.



Android version iPhone version

Fig. 2. Screenshots of different versions of the intermediary

Location and time of participation are contextual parameters that were also collected. User location, building name and room number, is provided by users, using the intermediary interface. For mobile devices such as smartphones or tablets, the five nearest buildings to a user's location are presented. To find the closest buildings, the last GPS-based location information (captured when user is outside the building) is used. User location is compared to the coordinates of all buildings on campus. In case the web application version of the intermediary is used, IP ranges of buildings are used for presenting the five nearest buildings to choose from. If no information is available, then an alphabetical list of buildings is provided. Then users navigate and scroll through the floors and rooms of their buildings using a drop-down menu. Reducing manual data entry facilitates sustained contribution and also reduces the entry of faulty data. All features of the intermediary interface are integrated into one page of application for ease of use.

Building Sensor Network

Ambient condition information at the room level is essential for the comfort profiler and BMS controller algorithms. Accordingly, the HBI-TC framework uses the data collected through an infrastructure of an ambient sensor network. The data from sensors is used for both comfort profiling and occupancy estimation; therefore, a combination of eight sensors was used. The sensors are encapsulated in a sensor box (Fig. 3) that has an Arduino Black Widow stand-alone single-board microcontroller computer with integrated support for 802.11 wi-fi communications. Each box hosts a temperature sensor, a relative humidity sensor, a CO_2 sensor, a light intensity sensor, a sound sensor, a motion sensor, a passive infrared sensor (detects objects as they pass through the door), and a door switch sensor (detects whether the door is open or closed). A sensor box is placed in each room of interest, and data is sampled every 1 min and stored in a central database.

Personalized Comfort Profiling

To compute models of user comfort preferences, subjective human data and objective sensor data are fused. To identify the most influential ambient condition parameters, a field experiment was conducted over a period of two months in four zones of an office building, equipped with sensor boxes. Among all ambient condition parameters (i.e., temperature, humidity, CO_2, and light intensity), temperature and humidity parameters were found to have stronger correlations (with higher correlation coefficients for temperature than humidity) with occupants' thermal preferences (Jazizadeh and Becerik-Gerber 2012). Based on this evaluation and the fact that the framework aimed to provide a nonintrusive approach (minimum additional hardware or no need for renovation), the temperature parameter was used. MaxDetect, RHT03

J. Comput. Civ. Eng., 2014, 28(1): 2-16

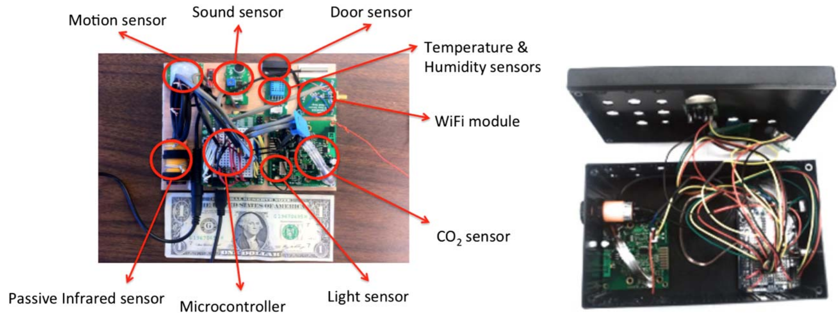


Fig. 3. Ambient sensors encapsulated in a sensor box (images by the authors)

temperature/humidity sensor was used in this study. Temperature measurement accuracy is $\pm 0.2°C$ and the resolution (sensitivity) is $0.1°C$. Occupants use the slider in the intermediary and send their feedback about their preferences using their subjective judgments, taking into account their instantaneous thermal comfort perceptions. The objective temperature data from the building sensor network is then used to obtain the equivalent ambient conditions when a request from an occupant is sent. The following sections discuss the computational methods used for representation of comfort models and the learning procedure for inferring them.

Learning Comfort Profiles

Upon the deployment of the framework in an office setting, occupants provide their thermal comfort feedback based on their perception of their environment. During the training period, HVAC system is operated according to occupants' feedback using a default relationship between their feedback (in the form of thermal perception indices) and requested temperature change (e.g., a linear relationship between comfort preference indices and preferred requested temperatures). Since each occupant's comfort scale is different, during the training process, occupants keep sending their feedback to achieve their optimum comfort; the feedback is then stored in the form of thermal perception indices and ambient temperatures. In other words, while occupants use the intermediary to control their HVAC system, they provide the data to be used for computing their personalized thermal sensation scales. Examples are illustrated in the scatter graphs of the data collected from four human subjects in a field experiment (Fig. 4). As it can be seen in this figure, for all of the occupants, each thermal perception index is associated with a range of temperature variations. When different zones of thermal perceptions are considered (along the y axis in the scatter graphs) for temperature variations, these zones have overlaps for all of the human subjects of this experiment. The margins between comfort perception zones blend, and each perception zone spans over a range of temperature. Based on these results, to detect the underlying patterns of data and categorize data points into overlapping thermal perception zones, the use of fuzzy representation was explored for comfort profile prediction and evaluated in this study. Through a fuzzy representation, assigned membership degrees to the input of each data point are used for extracting fuzzy rules to categorize the data points of the subjective feedback into different perception zones. Comfort profile in this context includes a thermal sensation scale, which is the relationship between a thermal perception index and the ambient temperature, as well as the thermal perception zones (very cold, cold, neutral, warm, and very warm) for each occupant.

In the case of thermal comfort management, occupants are the experts in determining their comfort ranges and therefore, they must control the HVAC system based on their desired thermal comfort. In the HBI-TC framework, this knowledge is used for autonomous control of an HVAC system. In other words, occupants provide the rules for controlling the system. An example of a rule for HVAC control is "if temperature is high then reduce the temperature by some degrees." Accordingly, in the fuzzy representation, occupants' perceptions versus temperature are defined in the form of if-then rules for the BMS controller. However, in the case of thermal comfort, occupants might not be completely aware of what associated temperatures are with their comfort range. Accordingly, the proposed framework uses the intermediary as proxies of occupants along with ambient sensor data. The underlying pattern of comfort profile is extracted from the captured data. Therefore, a fuzzy rule extraction was used to recognize the inherent patterns of the data provided by each occupant.

To satisfy the requested change in temperature, the BMS controller gets the temperature change as an input from the comfort profiler. Consequently, the problem is defined as a set of data points $[(tp_1, t_1), (tp_2, t_2), \ldots, (tp_N, t_N)]$ obtained via the intermediary from each occupant, where tp_i is the thermal perception index as input and t_i is the associated ambient temperature. The objective is to determine a mapping $(f{:}tp \rightarrow t)$ between thermal perception indices and ambient temperature as fuzzy rules, which categorize temperature ranges in the form of fuzzy sets and use the generated fuzzy rules for prediction. In other words, the thermal perception index membership function is labeled by ambient temperature values associated to each category as an outcome. To provide this mapping, underlying rules are extracted from the data using a learning algorithm. In recent years, various algorithms have been developed for extracting rule base as a supervised learning approach. In this study, the Wang-Mendel fuzzy rule extraction algorithm (Wang 2003; Wang and Mendel 1991), one of the well-known models, was adopted. A different number of fuzzy sets could be used for dividing the tp range. As an example, Fig. 5 shows the division into five fuzzy sets. Since the data is available only for the range of temperature that an occupant is exposed to, the fuzzy sets are defined between minimum and maximum tp. In dividing the tp range, zero is considered as the center of the neutral fuzzy set, and left and right of the neutral fuzzy set are divided into equal intervals.

Upon defining the fuzzy sets, for each (tp_n, t_n), an if-then rule is generated by selecting the fuzzy sets with a maximum membership function for tp_n. The then parts of rules' fuzzy sets are centered at t_n. Each rule is assigned a weight w_n, which is equivalent to the membership value of tp_n. Using the rule weights, the rules (with similar if parts) are combined to reduce the number of fuzzy sets with the then parts' fuzzy sets centered at weighted average (using the rule weights) of the t_n^g, where g denotes the group of rules

J. Comput. Civ. Eng., 2014, 28(1): 2-16

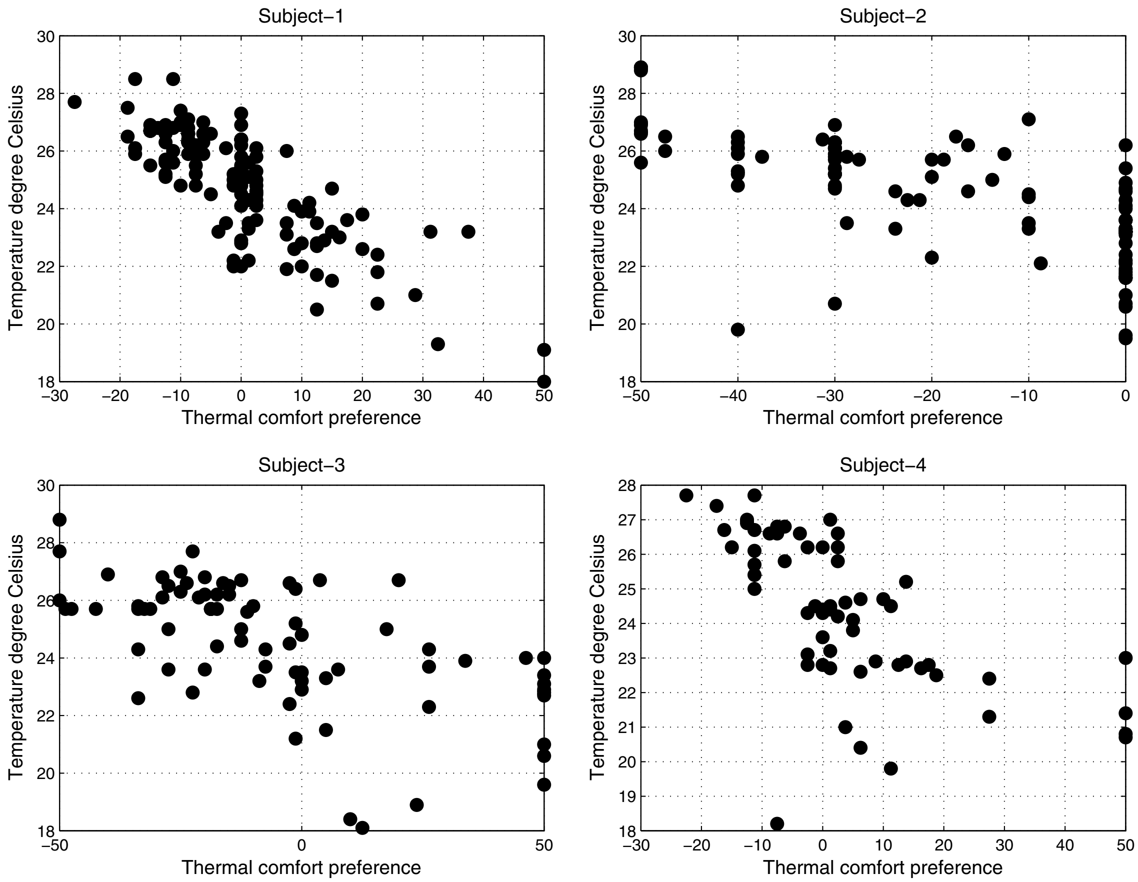


Fig. 4. Comfort preferences of four human subjects and associated temperature data

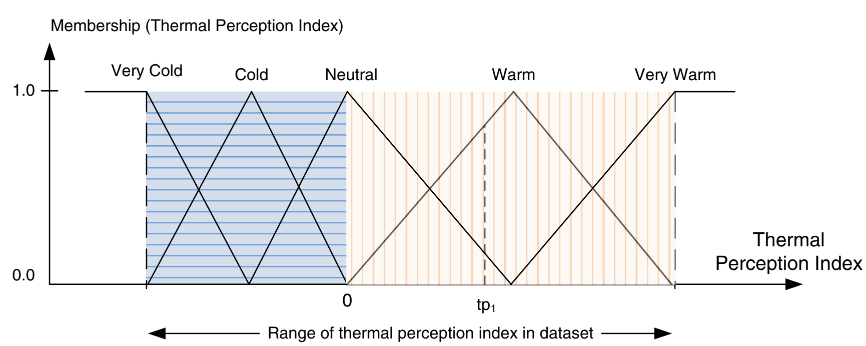


Fig. 5. The division of thermal perception index range into fuzzy sets membership functions

$$\mathrm{crc}^g = \frac{\sum_{n=1}^{N_g} w_n^g \cdot t_n^g}{\sum_{n=1}^{N_g} w_n^g}$$

in which, the crc^g = the weighted average of the t_n in each combined rule g (in total G combined rules); and N_g = the number of rules with similar if parts. Once the combined rules are generated a predictive model ($f{:}tp \to t$) is developed using product inference engine, the singleton fuzzifier, and center-average difuzzifier (Wang 2003)

$$f(tp) = \frac{\sum_{g=1}^{G} \mathrm{crc}^g.\mu^g(tp)}{\sum_{g=1}^{G} \mu^g(tp)}$$

where μ^g denotes the membership value for each of the combined fuzzy rules. Obtaining the fuzzy sets and associated predictive model, the comfort profile is generated.

Once a reliable comfort profile is obtained for an occupant, it is used by the BMS controller. The controller determines the preferred temperature of an occupant according to the learned comfort profiles. Default temperature for each occupant is determined based on the center of the neutral fuzzy set of his/her comfort perception. The equivalent ambient conditions (temperature in this study) are set as preferred temperature, and it is considered as a baseline for operation of an HVAC system. In the case of local discomfort, occupants adjust the desired indoor condition using the intermediary. Each new request and its equivalent ambient conditions are added to the data set and comfort profile model is updated. In this

J. Comput. Civ. Eng., 2014, 28(1): 2-16

way, while occupants adjust the operational settings of an HVAC system to achieve their preferred indoor condition, they also train the model to be used for autonomous control of the system.

Occupancy Estimation

One of the components of the framework is the operation of the HVAC system based on actual occupancy. At the thermal zone level, depending on the occupancy status of rooms, the comfort profile of occupants is activated (in case of positive occupancy) or remains inactive (in case of negative occupancy) by the BMS controller. Machine learning algorithms are used to estimate the occupancy load including binary occupancy detection and estimation of the number of occupants. Details of the occupancy estimation and the required policies for using occupancy estimation are reported in (Yang et al. 2012).

BMS Controller

The BMS controller of the HBI-TC framework controls BMS in operating an HVAC system. The goal of the controller is to keep temperatures of occupied rooms as close as possible to the preferred temperatures reported by the comfort model. At the core, the algorithm is a proportional controller. Several challenges are worth noting. First, the HBI-TC framework needs to work with existing BMS; therefore, it needs to extend rather than override. In this paper, this means that the only controllable parameter is thermostat setting (set point), while other operating parameters of a system, such as airflow, are set by the native BMS. Second, in a typical office building, multiple rooms are controlled by the same thermostat. BMS adjusts supply air temperature and air flow to make the reading of the thermostat sensor match the set point on the thermostat. In other words, thermostat controls one room in a group, leaving occupants of other rooms at the mercy of the thermostat owner. The comfort profiler algorithm takes into account preferences (T_p^i) and measured temperatures (T_r^i) from all rooms and chooses the set point to make all occupants as comfortable as possible. Note that due to the mechanical properties of a system, room locations, and other building and room features, it may not be possible to simultaneously provide all users with exactly their preferred temperatures, so the controller aims to minimize the sum of deviations from the preferred temperatures, which serves as the definition of error

$$\text{error} = \frac{\sum_{i=1}^{N_r}(T_r^i) - (T_p^i)}{N_r}, \qquad N_r = \text{number of rooms}$$

Third, the dynamic control mechanism inherently accounts for factors, such as heat loads in rooms, differences in solar heat gains, and temperature reading offsets due to the location of different sensors by dynamically driving the system control to minimize the error, as opposed to trying to compute a perfect set point. In fact, the thermostat set point that minimizes the error, SP_{opt}, may be quite different from the preferred temperatures of any of the occupants. The BMS controller reaches the SP_{opt} by proportionally adjusting the set point using $\Delta SP = k_p$. error, where k_p is the proportional coefficient, which is a tunable parameter. Finally, the controller needs to account for the slow response of the system. Once the set point is changed, it takes some time for the measurable room temperature changes to occur. Based on experimental results, a delay of 5 min was used before the next adjustment step to allow the room's temperature changes to take effect. The reciprocal of this delay serves the role of the parameter k_p of the proportional controller. In addition, the maximum magnitude of a single change was limited to 0.83°C (1.5°F). The value 0.83°C was chosen experimentally to obtain acceptable behavior of the controller (reasonably fast convergence with little oscillations). The ΔSP is applied to the most recent thermostat setting and the results truncated to lie between 18.33°C (65°F) and 26.67°C (80°F).

The BMS controller reacts to an input from an occupant in a room and ignores further input from the same occupant for 30 min. This delay in accepting a new request is considered to allow the previously requested changes to occur and for the occupant to perceive a new condition. If the new condition does not satisfy the occupant, further input is considered.

Framework Component Assessment

Prior to the deployment of the framework at the building level and assessment of its effectiveness in addressing the intended objectives, components of the framework, namely, the comfort profiler and the BMS controller were tested and assessed, and the results are presented in this paper. For the comfort profiler, the feasibility of the proposed framework in modeling personalized comfort profiles, which represent occupants' comfort preferences and thermal comfort zones, was explored. For the BMS controller, the feasibility of the proposed framework in factoring the preferred temperature of all occupants in one thermal zone and adjusting the set point of the zone to be equidistant from the preferences of all occupants was explored. The comfort profiler assessment was carried out through the validation of its performance using human subject data, collected through field experiments, in addition to the artificially generated data. The assessment of the actuator controller was conducted in a few zones of an operational office building with a prototype of the framework. An approval from the IRB was obtained for this study (UP-11-00020).

Comfort Profiler Assessment

Field Data Collection

A field experiment was conducted to collect data and simulate the comfort profiler's training period. The objectives were to assess the performance of the comfort profiler model and determine the sensitivity of the comfort profiler to different sample sizes and fuzzy sets as model parameters. The experiment was carried out in an office building with four human subjects. The building is located in the Southern California area, and the experiment was conducted at the beginning of the fall season; the outdoor temperature during the experiment was considered as warm (e.g., 27–29°C), in general. A single variable air volume (VAV) box controlled the target environment via a thermostat. Occupants were exposed to different temperature conditions. One of the key requirements in the experiment was to cover a wide range of temperatures to ensure that the algorithm was tested for different indoor environmental conditions.

Subjects downloaded the intermediary application (Fig. 2) to their smartphones. Data was collected for three weeks from early morning to late afternoon (about 8 h a day). To ensure each subject has been exposed to different ranges of temperature, temperature was set between 18 and 29°C on different days. Subject feedback was converted to temperature changes using a linear relationship between feedback value and the delta temperature. The average of the requested temperature changes were taken into account in adjusting the room temperature to encourage subjects to participate in the experiment. Scatter graphs of the collected data are shown in Fig. 6. In this figure, the horizontal axis shows the feedback submitted through intermediary, and the y-axis shows the ambient

J. Comput. Civ. Eng., 2014, 28(1): 2-16

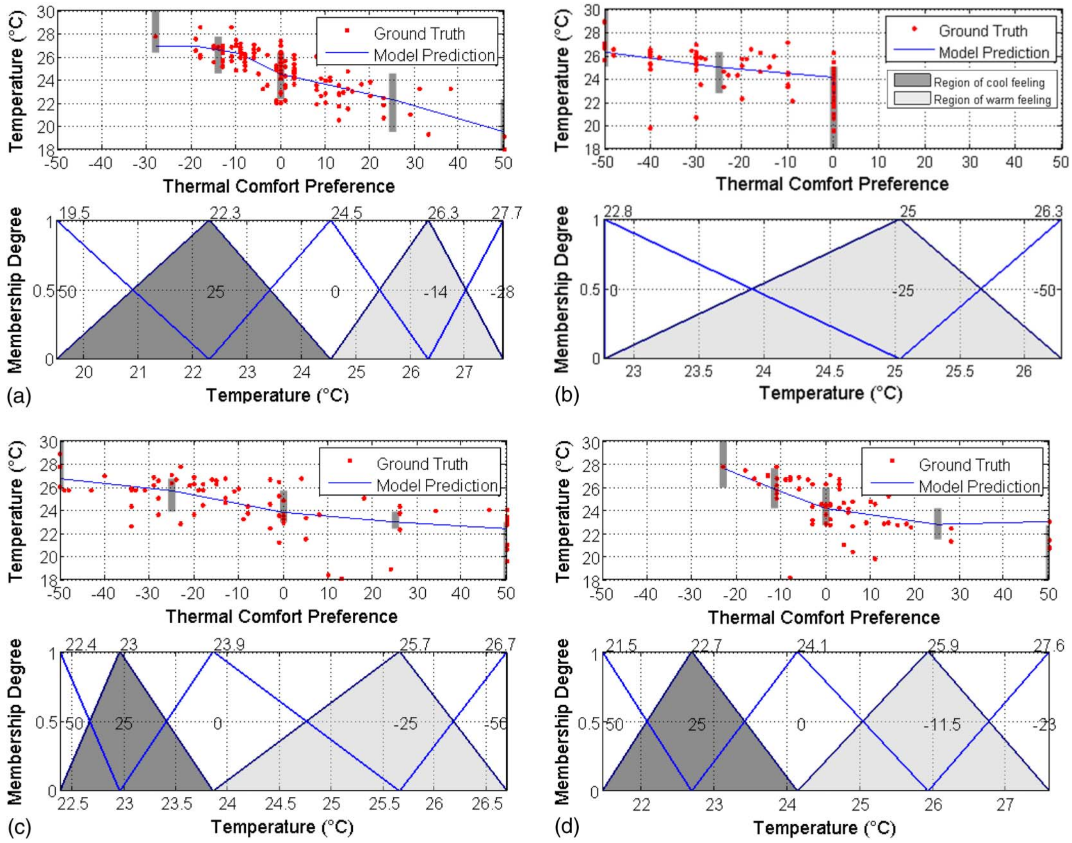


Fig. 6. Ground truth data, predicted models, and the calculated comfort profile fuzzy sets for each subject: (a) data set and comfort profile for Subject 1; (b) data set and comfort profile for Subject 2; (c) sata set and comfort profile for Subject 3; (d) data set and comfort profile for Subject 4

temperature in °C. A total of 114, 77, 76, and 61 data points were obtained from human subjects 1 to 4, respectively.

Comfort Profiler Validation

Performance of the comfort profiler was assessed using the error of the model in predicting the associated temperatures (ground truth collected in the field experiment) as the output of the model for comfort preference indices as the input to model. The entire data set was used as a training dataset and a 10-fold cross-validation was used in validating the performance of the model. The error of the model was the average of the mean of error over the 10-fold cross-validation runs. The average error values were calculated as 1.02, 1.21, 1.3, and 1.13°C with standard deviations of 0.31, 0.46, 0.43, 0.43°C for subjects 1 to 4, respectively. In predicting the comfort profile models, the number of fuzzy sets for dividing the input data was set to five. Five fuzzy sets divide the comfort preference indices space to five comfort zones, namely, very warm, warm, neutral, cold, and very cold. Fig. 6 illustrates the ground truth data, predicted models, and the fuzzy sets, which together illustrate the comfort profiles.

In each subfigure [Figs. 6(a–d)], the upper graph shows the ground truth data in addition to the predicted model for the slider value ranges (comfort preference indices). As it could be seen, the comfort profiler predicted model is a combination of linear models, which represent the nonlinear trend. The lower graphs show the fuzzy sets of the comfort feedback values with their associated temperature values predicted by the model. The values on top of the graphs are the predicted temperatures for the center of the fuzzy sets, and the values in the middle of the graph show the comfort preference index (feedback value) of the center of each fuzzy set. Zero on the intermediary slider is equivalent to a satisfactory condition. Accordingly, the temperature associated with zero on the comfort profile is considered as the preferred temperature for each human subject. This temperature is used as the preferred temperature in controlling the HVAC operations.

Comfort Profiler Sensitivity Analysis

Determination of the model sensitivity to the number of training data points and model hyper parameters is a key step for implementation of the framework at the building level. Hence, the optimum number of fuzzy sets as well as adequate number of training data points for obtaining a reliable comfort profile were assessed through sensitivity analyses on the data collected in the field experiments. To obtain the optimum number of fuzzy sets, the variation of the average model prediction errors for the data of four subjects was obtained through a 10-fold cross-validation for different numbers of fuzzy sets between 1 and 100. Large number of fuzzy sets increases the resolution of the fuzzy sets and consequently the number of rules. On the other hand, if the fuzzy sets are used as occupants' comfort ranges, the large numbers of fuzzy sets are not applicable. To see the trend of variation in error and determine the optimum number of fuzzy sets, 100 sets were selected as the maximum number of fuzzy sets. One of the research questions the authors want to explore in future studies is using the width of the neutral fuzzy set for any potential energy conservation, which has to be verified during building-level implementation of the framework. As it could be seen in Fig. 7, by increasing the number of fuzzy sets and moving toward five fuzzy sets, the model error decreases. For two of the subjects, the optimum error occurs at five fuzzy sets. Although the global optimum error for Subjects

J. Comput. Civ. Eng., 2014, 28(1): 2-16

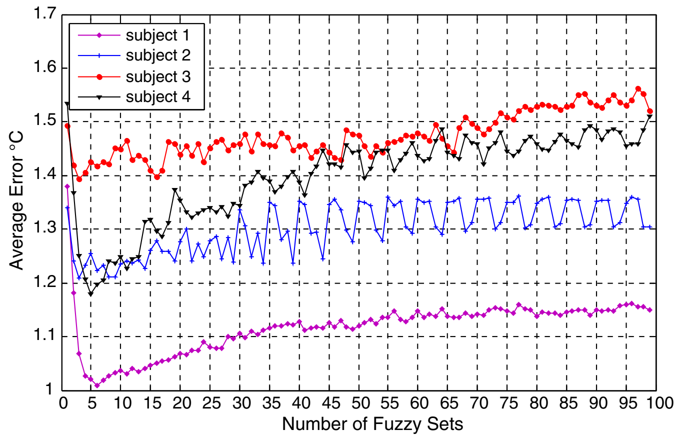


Fig. 7. Variations in average temperature prediction errors for 10-fold cross-validation versus different number of fuzzy sets

2 and 3 does not occur on five fuzzy sets, considering the trends in variation of error for all four subjects, the error in five fuzzy sets is very close to the global optimum error. Accordingly, five fuzzy sets are chosen as the optimum model hyper parameter for minimum error. Five fuzzy sets are also well-matched with five regions of the comfort zones, namely, very cold, cold, neutral, warm, and very warm.

To determine the sensitivity of the comfort profiler algorithm to the dataset size, an analysis of the model performance was carried out using different subsets of the ground truth data. Models were trained using 10 increments of data points for different subjects. The performance of the models with these datasets was assessed by comparing the test error for different number of training data points in samples. In addition, different numbers of fuzzy sets were also considered to ensure optimum error calculations. The down-sampled training datasets were selected based on chronological order from the original dataset to simulate the training process. Accordingly, the original dataset for each subject was divided into two subsets: training and testing. Ground truth dataset sizes were 114, 77, 76, and 61 for Subjects 1–4, respectively. Fig. 8 shows the comparison graphs of error values for different down-sampled datasets. As it is illustrated in all of the graphs in Fig. 8, by increasing the sample size, the prediction results improve until it reaches an almost constant error. The results of the sensitivity analysis show that the comfort profiler could be used early in the process of training and after collecting a sample of about 40 to 50 data points.

Comfort Profiler Validation with Synthetic Data

Even though field experiments were conducted to validate the performance of the comfort profiler in a real world setting, to consider the diversity of the occupants' characteristics, synthetic data were also used to create seven different personas for validation purposes. The synthetic data were generated as a combination of linear variation of perceived temperature as functions of comfort preference indices (shown below) as well as the noise to make sure that the data is compatible with real world data collection processes

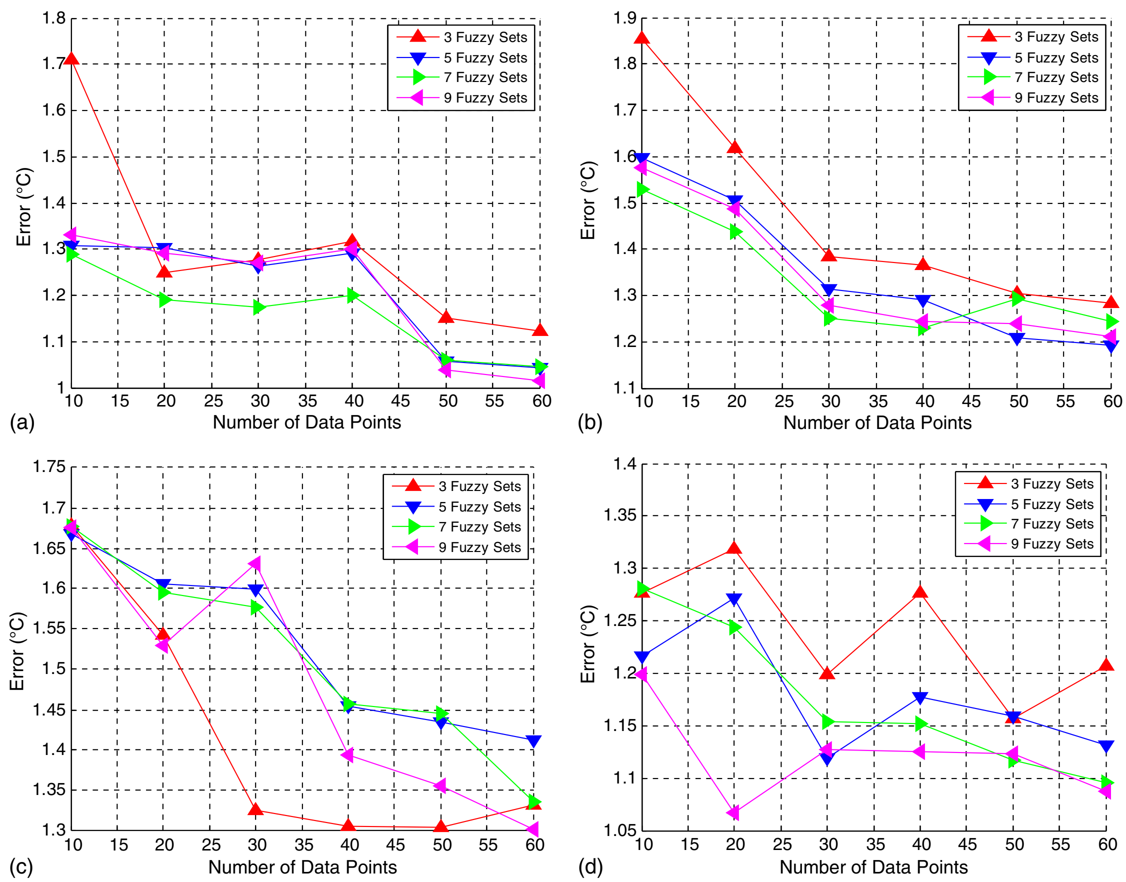


Fig. 8. Variations in average temperature prediction errors over different number of sample sizes: (a) Subject 1; (b) Subject 2; (c) Subject 3; (d) Subject 4

J. Comput. Civ. Eng., 2014, 28(1): 2-16

$$T = f(p) + \varepsilon \sim N(0, \sigma^2)$$

Noise was added by using a Gaussian distribution with zero mean and a variance, calculated by using the ground truth data. After fitting a linear model to the ground truth data and calculating the residual errors with respect to the fitted lines, the variance of residuals was calculated for different personas. The maximum variance (1.7°C), calculated from the data set, was used in generating the synthetic data sets. In validating the model using the synthetic data, 100 data points were used for each simulated persona. The number of fuzzy sets in inferring the underlying comfort profiles was set to five sets. Considering various conditions of sensitivity and also the symmetry in comfort profiles, seven personas were taken into account. The first persona is equally sensitive to warm and cold temperatures with uniformly distributed feedback data. The second persona is less sensitive to changes in temperature with equal reaction to both cold and warm conditions. The third persona is very sensitive and sets the slider to extreme values in case of temperature changes. The fourth persona is more forgiving toward cooler temperatures compared to the warmer temperatures. The fifth persona is very sensitive to warm temperatures but is more forgiving toward cooler temperatures. The sixth persona is very sensitive to warm conditions with normal reaction to cool indoor conditions. The seventh persona is extremely sensitive to warm conditions. In Fig. 9, Personas 1–7, the synthetically generated data, the underlying reference model (from which the synthetic data was generated), and the predicted model by comfort profiler are depicted. Fig. 9(h) shows the average and maximum error for a population of 100 for each persona–calculated through a 10-fold cross-validation. Errors in general are higher than the errors calculated for the human subjects. By increasing the bias of the data toward one side of the slider, the error in the model is increased.

The analysis of the data shows that the symmetry of data points over different ranges of temperature and preference feedback could be used as a guideline during participatory sensing to improve the prediction of comfort profiles since the symmetric datasets show a lower error value. Larger errors in the case of synthetic data are related to the fact that in generating the noise for the data, maximum variance of observations from the field tests was taken into account. The comparison between the underlying reference model and the comfort profiler predicted model shows the accuracy of the model in predicting the nonlinear underlying patterns, which have been introduced through generating noised-up samples.

BMS Controller Assessment

Field Tests

A key requirement for the feasibility of the HBI-TC framework is the connection between predicted comfort profiles and actuation of the HVAC system. Accordingly, the performance of the BMS controller in achieving the requested collective temperature changes in a thermal zone was tested in two thermal zones of an office building where the framework was deployed. Out of the two thermal zones, one of them covered three rooms (Zone A), and the other zone covered two rooms (Zone B). The HVAC system in the building was a centralized system. Each thermal zone was equipped with a VAV (variable air volume) box with dampers that are controlled centrally based on the temperature set points to maintain the temperature in the zone. The building was served by two air handler units (AHU). Both thermal zones' VAV boxes were fed by the same AHU. Zone A was located in the north side of the building and Zone B was located in the south side of the building. Both zones were on the same floor. All of the rooms were similar in terms of their areas, window sizes, and arrangements of furniture. The building was located in Southern California.

The rooms were equipped with sensor boxes, which were all placed close to the door, approximately in the same location in every room. Sensor boxes communicated the data through a wireless network to a centralized server, which controlled the flow of information and actuated the HVAC system (Fig. 1). In addition to the sensor boxes, each thermal zone had an existing temperature sensor (BMS sensor), which was part of the existing HVAC control system. The HVAC system controlled the indoor air temperature by comparing the set points and the temperature readings from the BMS sensor in each zone. The HVAC system was scheduled to operate from 6:30 a.m. to 9:30 p.m. for the entire week. Set point, set by facilities management for every zone of this building was 22.78°C. The HVAC system was shut off for nonoperational hours.

BMS Controller Validation Experiments

To validate the performance of the controller, a series of experiments were conducted. The performance of the controller in finding the optimum set point in each zone was evaluated by comparing the experimental results (variation of the temperature in the field) with the expected temperature changes. Fig. 10 shows the variation of different parameters in Zone B, in which only Room 1 is occupied. Since the objective was to test the performance of the BMS controller, in these experiments, comfort profiles of the actual occupants were not used. The BMS controller is activated from early morning at 6:00 a.m. (HVAC starts operating at 6:30 a.m.) by setting the preferred temperatures (T_p^i) for both rooms to 21.67°C.

Since the HVAC system was off and the room temperatures were larger than preferred temperatures, the BMS controller kept reducing dynamic set points and reached the lower boundary of 18.3°C around 6:30 a.m.. At 6:30 a.m., the HVAC started (the dashed line on Fig. 10) and reacted to the difference between the BMS-sensed temperature and current set point. The large jump in the airflow was the reaction to this difference. The airflow is controlled by the native BMS. The HVAC system kept discharging air with a value near the maximum airflow of the VAV box in that zone to reach the preferred temperatures in both rooms. At 7:30 a.m., the ΔSP reached a positive value as the room temperatures were 21.7°C in both rooms and preferred temperatures (calculated based on occupant feedback) were still 21.67°C. The BMS controller started increasing the set points to avoid further decrease in temperature in the zone. At 7:47 a.m., the occupant in Room 1 sent a request (slider value 0–no change requested) at room temperature of 21.6°C. The occupant feedback is depicted by a dot-dash line in Fig. 10. It resulted in the new preferred temperature for the room to be 21.6°C. As expected, this feedback did not affect the HVAC operations and consequently, the room temperature stayed the same.

The system reached a marginally stable condition around 8:00 a.m.. Oscillations were part of the regular HVAC operation as the system tried to keep the room temperature close to the preferred temperature. At 8:44 a.m., a request was sent with the value of +0.56°C resulting in the new preferred temperature to be 22.46°C ($T_p^1 = T_r^1 + 0.56$). As a result of this occupant request, a slight increase in the set point and a decrease in airflow over time were observed. At 9:44 a.m., a request from the occupant in Room 1 with the corresponding value of −1.11°C resulted in a new preferred temperature of 20.7°C ($T_p^1 = T_r^1 - 1.11$). The BMS controller reacted to this decrease and kept changing the set point for reaching a balance point, where ΔSP approached zero. At around

J. Comput. Civ. Eng., 2014, 28(1): 2-16

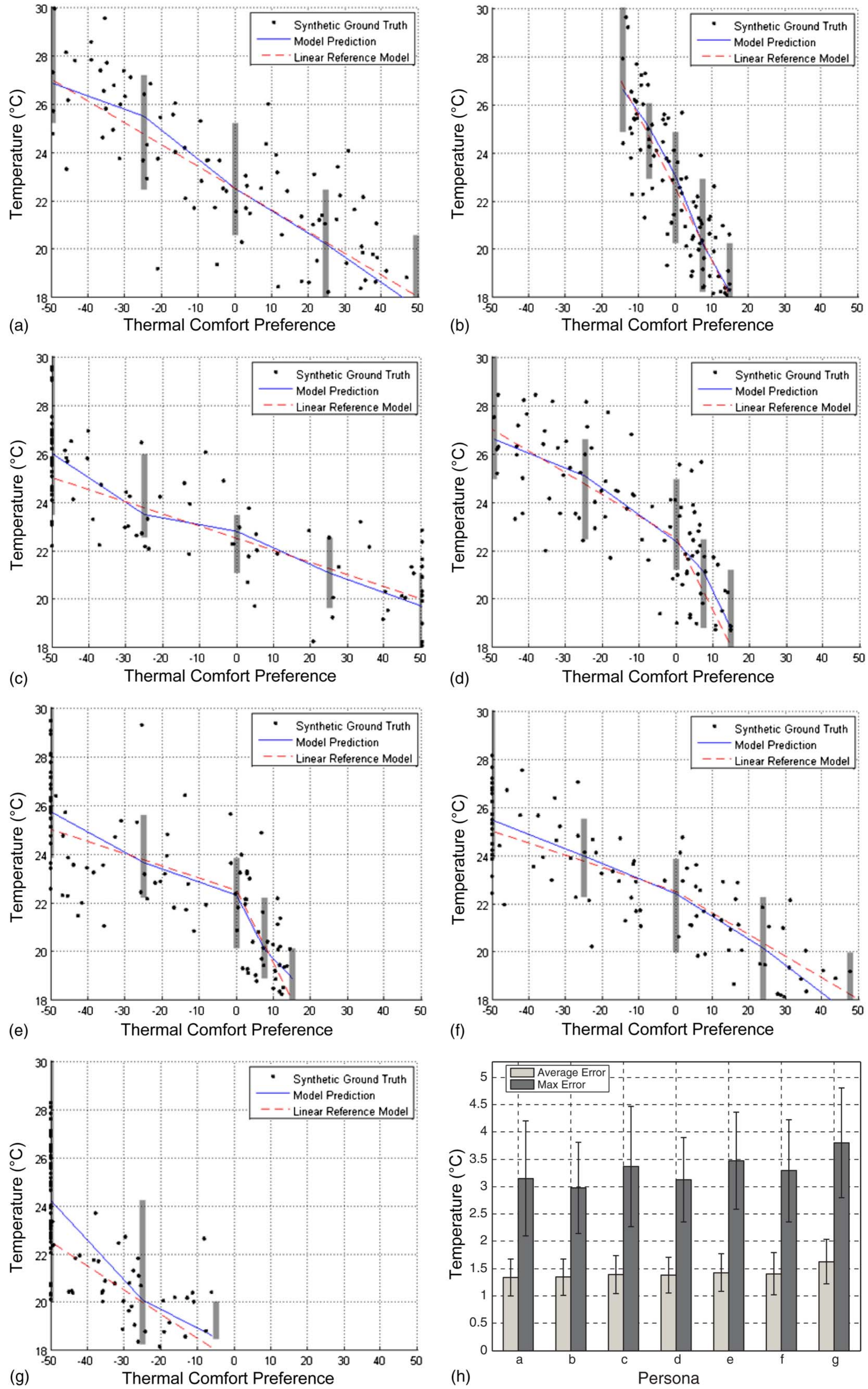


Fig. 9. Variations of synthetically generated preference feedback versus ambient temperature for different occupant profiles: (a) equally sensitive to all conditions; (b) less sensitive to temperature variations; (c) very sensitive to temperature variations; (d) normally sensitive to warm conditions and less sensitive to cool conditions; (e) very sensitive to warm conditions and less sensitive to cool conditions; (f) normally sensitive to cool conditions and very sensitive to warm conditions; (g) extremely sensitive to warm conditions; (h) average and maximum prediction error and their standard deviation

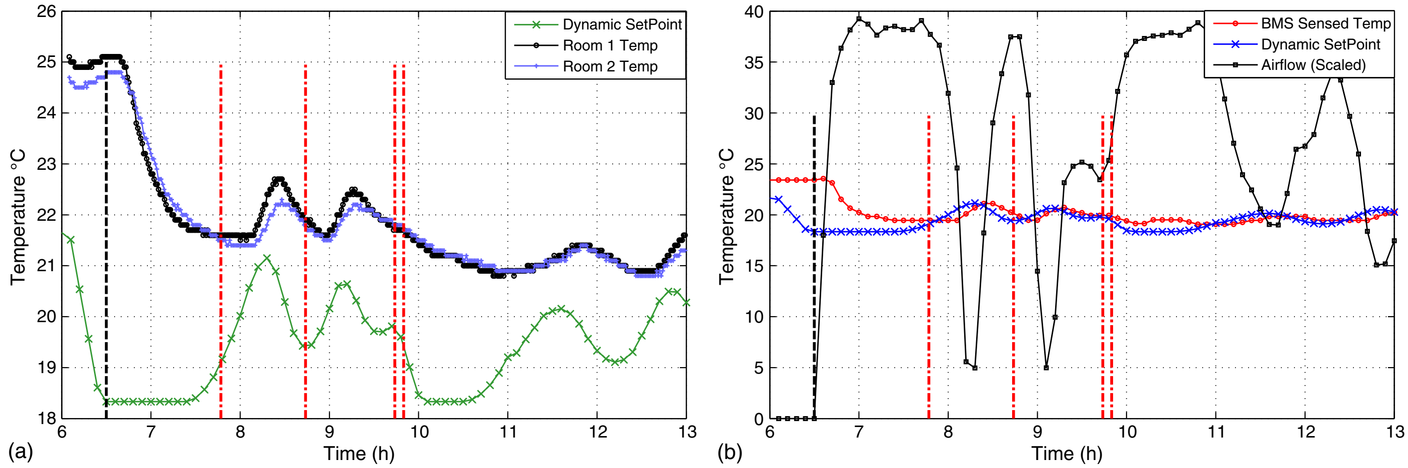


Fig. 10. Variation of ambient conditions in Zone B, controlled by the proposed framework: (a) variations of temperatures and set points; (b) variations of set points, HVAC system measured temperatures, and scaled airflow in the zone

10:35 a.m., the average temperature in both rooms reached the average of the preferred temperatures of both rooms thus set point started increasing. A few minutes later, a new request from the same occupant was ignored as the BMS controller considers a 30-min delay in accepting a new request. Comparing the room temperature trends and dynamic set points, a lag was observed after the peaks and falls of the dynamic set points and room temperatures. The lag was due to the time that takes for the HVAC system to change the indoor condition.

Fig. 11 shows the performance of the BMS controller in Zone A, where three occupants in the zone sent their feedback. The occupant in Room 3 (dot-dash line) sent a request (1.11°C) at 12:55 p.m. asking for warmer condition, resulting in the collective preferred temperature changes in the zone to be 0.37°C. The average temperature in all rooms was around 23.17°C before the request was received, then the average temperature increased to 23.8°C. The occupant in Room 1 (dot line) sent a request (0°C) at 1:23 p.m., which did not affect the system. The oscillations in temperatures and set points are part of the native BMS system. Another request, (1.67°C) from the occupant in the same room was sent at 5:48 p.m.. Based on this request, the new collective preferred temperature was 25.5°C ($T_p^1; = T_r^1 - 1.67$), and the BMS controller set the airflow to its required minimum value to adjust the condition for a higher temperature. The occupant in Room 2 (dashed line) sent a request, (slider value 10) at 5:56 p.m. asking for a warmer condition, but at the time, the system was already set to the maximum allowable set point value. Accordingly, no change in the set point occurred. As it can be seen from the experiments in both zones, the BMS controller was capable of modifying and maintaining the conditions based on the feedback from the occupants of the same zone. As the HVAC system was in the cooling mode during these experiments, a request for a warmer condition resulted in airflow reduction, which brought about energy conservation.

Discussion and Future Work

The proposed framework with its current features is for centrally controlled HVAC-driven office buildings. The BMS controller extends an existing HVAC control system without any retrofit to the system. However, access to the HVAC control system backend is required. Depending on the specifications of the native HVAC system's backend software, the proposed controller might need to be adjusted to comply with different system architectures and communication protocols. Deployment of the sensors in targeted rooms of a building is required. Sensors are critical for performance of all the

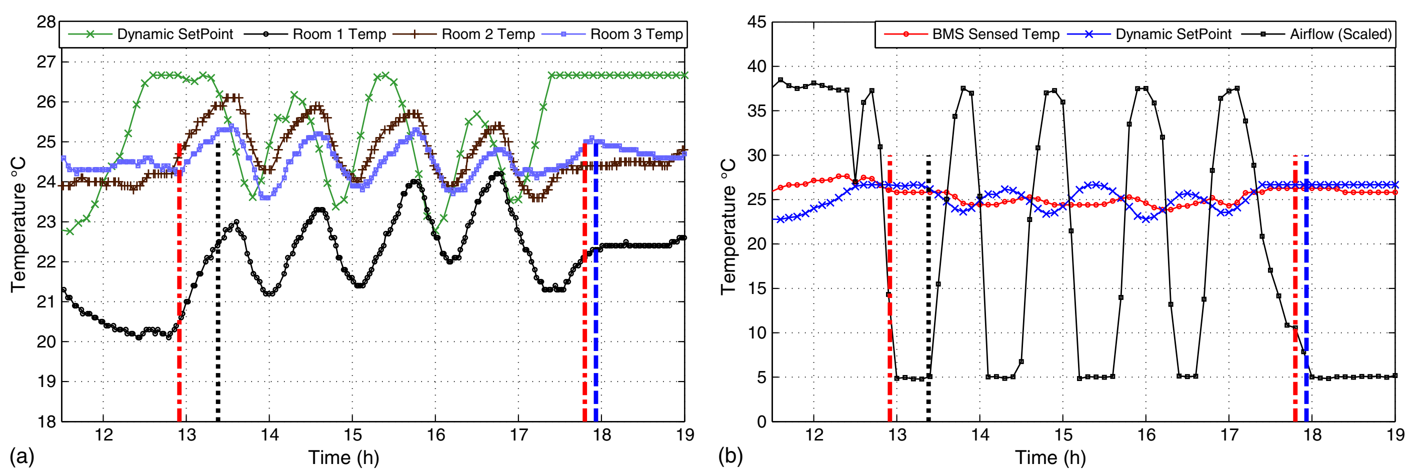


Fig. 11. Variation of ambient conditions in Zone A, controlled by the proposed framework: (a) variations of temperatures and set points; (b) variations of set points, HVAC system measured temperatures, and scaled airflow in the zone

J. Comput. Civ. Eng., 2014, 28(1): 2-16

components in the framework. Access to the wireless communication network in a building is required for a successful deployment. Moreover, accuracy of the occupancy estimation component depends on the adequacy of the algorithm training. Accordingly, development of a generalized model to handle occupancy in different types of rooms with minimum training is a requirement. Once the occupancy algorithms (for detecting binary occupancy) are set, integration of occupancy in the controller is carried out by transferring the binary occupancy value to the BMS controller.

Participation of the buildings' occupants is essential in learning their comfort profiles for personalized and comfort-driven HVAC operations. Since the intermediary has been designed for different platforms including smartphones, tablets, and personal computers and the framework has been proposed for office buildings, the majority of the permanent occupants of buildings would be able to provide their feedback. However, in the absence of personalized feedback, default set points, which are the set points set by facility managers are used so that the HVAC system does not ignore non-participating users. There might be a possibility of misusing the system. For example, users might provide comfort information for rooms other than theirs, or users might provide inaccurate information to increase the weight of their votes (e.g., give a higher warmer vote to cancel out their neighbor's cooler vote). To account for the former case, an outlier detection agent compares IDs of the devices used for sending feedback to the historical device IDs for a specific space. In the case of observing a mismatch, the feedback is not taken into account. For the later case, the underlying algorithms for operating the HVAC system, specifically the policies that are used for computing the collective vote for a zone, are not revealed to users. Therefore, there is a low possibility that users will submit an inaccurate vote to increase the weight of their own vote. Furthermore, users are not usually aware of their neighbor's vote. However, even in cases that a user tries to game the system, since the neighbors would not be satisfied with indoor conditions, they would provide their feedback, which will modify their comfort profiles and adjust the balance in the zone.

As noted, the focus of this study is on the design and assessment of the components of the HBI-TC framework. An important aspect of the study is the verification of the framework in improving occupant comfort. Therefore, a long-term building-level assessment of the framework in an office building with its occupants is planned as part of authors' future work. It is also the authors' plan to assess the proposed framework's effect on energy consumption in office buildings. Although the focus of this study is on enablers of thermal comfort improvement, the main objective of the HBI vision is the interaction between buildings and its occupants to improve comfort and, at the same time, to reduce energy consumption. Accordingly, a tradeoff study for using the HBI-TC framework in comfort improvement and energy consumption reduction in office buildings is needed. As it was demonstrated in previous sections, the width of the neutral zone in an occupant's comfort profile has the potential to be used for reducing energy demand in HVAC systems. Depending on outside temperature and occupants' comfort expectations, moving from the dissatisfied zone toward the comfort zone, without reaching the most comfortable temperature, may result in satisfaction of occupants. The authors are also planning to validate this hypothesis and assess the impact on energy conservation. The authors' observations in previous stages of the study showed that for the Southern California region, where HVAC systems predominately operate in a cooling mode, a majority of dissatisfied occupants complained about the cool to cold indoor environments (Jazizadeh et al. 2011). Accordingly, there is a potential for reducing energy consumption in buildings by introducing an adaptive system, which meets users' requirements. The preliminary results of the proposed solution's performance during the field experiments support the authors' initial observations. Finally, the authors plan to test the framework for assessing long-term comfort changes, the effectiveness of the framework in other building types and spaces (e.g., classrooms and open office spaces) and environments (e.g., colder climates), effectiveness of the framework in multioccupancy spaces and extend the framework to other ambient conditions, such as lighting and airflow.

Conclusion

This paper discusses a framework that facilitates human building interaction toward improving thermal comfort in office buildings. The framework uses a participatory sensing approach via a smartphone application as the intermediary for learning occupants' comfort profiles while occupants interact with the HVAC system. The intermediary enables occupants to provide their preferences about indoor air conditions using a slider to express their thermal comfort preferences. The provided feedback is then used for controlling HVAC system operations toward occupants' most comfortable temperatures. Occupant feedback is also used as an index of comfort perceptions. As occupants interact with the HVAC system, the comfort profiler learns their comfort profiles and their thermal comfort sensation scales using the thermal perception index (value stored from the intermediary slider) and the room temperature, which is sensed using a temperature sensor in each room. A fuzzy rule based algorithm is used to extract the underlying patterns in the data and develop a predictive model. The actuation component of the framework, the BMS controller, uses a proportional algorithm to adjust the thermal zone set point as the only parameter for HVAC control to integrate the feedback from occupants in different rooms and maintain the room temperature to be equidistant from multiple occupants' feedback in one thermal zone. The validation of the framework components demonstrated that by using the fuzzy rule based algorithm and appropriate number of fuzzy sets, the nonlinear underlying pattern of the thermal comfort sensation scale for intermediary slider values could accurately be calculated as personalized comfort profiles as well as the comfort ranges in the form of fuzzy membership functions. Sensitivity analysis was also used to determine the optimum number of fuzzy sets for comfort profiles. The results show that five fuzzy sets, which is also compatible with the number of comfort range intervals (very warm, warm, neutral, cold, and very cold), is the optimum hyper parameter for the proposed solution. The sensitivity analysis shows that 40 to 50 data points as training data that is evenly distributed could be used as the lower threshold for forming the comfort profiles. Finally, the results of the experiments of the BMS controller show that the proportional controller algorithm is capable of keeping the thermal zones' temperatures in the ranges of preferred temperatures. Verification of the framework's effectiveness in improving occupant's comfort as well as the implications of the framework on energy consumption in office buildings are two of the immediate objectives of authors' future studies.

Acknowledgments

This material is based upon work supported by the Department of Energy under grant No. DE- EE0004019 and the National Science Foundation under grant No. 1201198. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the Department of Energy or the National Science Foundation.

The authors would like to acknowledge the support of USC Integrated Media System Center (IMSC).

References

Ari, S., Wilcoxen, P., Khalifa, H. E., Dannenhoffer, J. F., and Isik, C. (2008). "A practical approach to individual thermal comfort and energy optimization problem." *Proc., NAFIPS 2008–Annual Meeting North Am. Fuzzy Info. Process. Soc.*, IEEE, Piscataway, NJ, 388–393.

Atthajariyakul, S., and Leephakpreeda, T. (2004). "Real-time determination of optimal indoor-air condition for thermal comfort, air quality and efficient energy usage." *Energy Build.*, 36(7), 720–733.

Atthajariyakul, S., and Leephakpreeda, T. (2005). "Neural computing thermal comfort index for HVAC systems." *Energy Conversion Manage.*, 46(15–16), 2553–2565.

Azar, E., and Menassa, C. (2011). "Agent-based modelling of occupants' impact on energy use in commercial buildings." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)CP.1943-5487.0000158, 506–518.

Barlow, S., and Fiala, D. (2007). "Occupant comfort in UK offices–how adaptive comfort theories might influence future low energy office refurbishment strategies." *Energy Build.*, 39(7), 837–846.

Ben-Nakhi, A., and Mahmoud, M. A. (2004). "Cooling load prediction for buildings using general regression neural networks." *Energy Conversion Manage.*, 45(13–14), 2127–2141.

Bermejo, P., et al. (2012). "Design and simulation of a thermal comfort adaptive system based on fuzzy logic and on-line learning." *Energy Build.*, 49, 367–379.

Bruant, M., Guarracino, G., and Michel, P. (2001). "Design and tuning of a fuzzy controller for indoor air quality and thermal comfort management." *Int. J. Sol. Energy*, 21(2–3), 81–109.

Buratti, C., and Ricciardi, P. (2009). "Adaptive analysis of thermal comfort in university classrooms: correlation between experimental data and mathematical models." *Build. Environ.*, 44(4), 674–687.

Calvino, F., La Gennusa, M., Rizzo, G., and Scaccianoce, G. (2004). "The control of indoor thermal comfort conditions: Introducing a fuzzy adaptive controller." *Energy Build.*, 36(2), 97–102.

Corgnati, S. P., Filippi, M., and Viazzo, S. (2007). "Perception of the thermal environment in high school and university classrooms: Subjective preferences and thermal comfort." *Build. Environ.*, 42(2), 951–959.

Daum, D., Haldi, F., and Morel, N. (2011). "A Personalized measure of thermal comfort for building controls." *Build. Environ.*, 46(1), 3–11.

Dept. of Energy. (2010). "Buildings energy data book." ⟨http://buildingsdatabook.Eren.Doe.gov/ChapterIntro1.Aspx⟩ (Sept. 2012).

Dounis, A. I., and Caraiscos, C. (2009). "Advanced control systems engineering for energy and comfort management in a building environment–a review." *Renew. Sustain. Energy Rev.*, 13(6–7), 1246–1261.

Duan, Pei-yong, and Hui, L. (2010). "A novel data-based control strategy of dynamic thermal comfort for inhabited environment." *Proc., 2010 8th World Congress Intelligent Control Automation (WCICA 2010)*, IEEE, Piscataway, NJ, 4865–4869.

Gouda, M. M. (2005). "Fuzzy ventilation control for zone temperature and relative humidity." *Proc., 2005 Am. Control Conf.*, IEEE, Piscataway, NJ, 507–12.

Guillemin, A., and Morel, N. (2002). "Experimental results of a self-adaptive integrated control system in buildings: A pilot study." *Solar Energy*, 72(5), 397–403.

Guo, W., and Zhou, M. (2009). "Technologies toward thermal comfort-based and energy-efficient HVAC systems: A review." *Proc., 2009 IEEE Int. Conf. Systems, Man and Cybernetics, SMC 2009*, IEEE, Piscataway, NJ, 3883–3888.

Hamdi, M., and Lachiver, G. (1998). "A fuzzy control system based on the human sensation of thermal comfort." *Proc., 1998 IEEE Int. Conf. Fuzzy Systems Proc. IEEE World Congress Computation. Intel.*, IEEE, Piscataway, NJ, 487–492.

Hwang, R., Cheng, M., Lin, T., and Ho, M. (2009). "Thermal perceptions, general adaptation methods and occupant's idea about the trade-off between thermal comfort and energy saving in hot-humid regions." *Build. Environ.*, 44(6), 1128–1134.

Jain, R. K., Taylor, J. E., and Peschiera, G. (2012). "Assessing eco-feedback interface usage and design to drive energy efficiency in buildings." *Energy Build.*, 48, 8–17.

Jazizadeh, F., and Becerik-Gerber, B. (2012). "Toward adaptive comfort management in office buildings using participatory sensing for end user driven control." *Proc., 4th ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, ACM, New York, 161–168.

Jazizadeh, F., Kavulya, G., Klein, L., and Becerik-Gerber, B. (2011). "Continuous sensing of occupant perception of indoor ambient factors." *Int. Workshop on Computing in Civil Engineering*, ASCE, Reston, VA, 161–168.

Karunakaran, R., Parameshwaran, R., and Iniyan, S. (2007). "Energy efficient controller for improving thermal comfort IAQ and energy saving in HVAC system." *Model., Measure. Control B*, 76(3–4), 31–49.

Klein, L., et al. (2012). "Coordinating occupant behavior for building energy and comfort management using multi-agent systems." *Autom. Constr.*, 22, 525–536.

Klein, L., Kavulya, G., Jazizadeh, F., Kwak, J., Becerik-Gerber, B., and Tambe, M. (2011). "Towards optimization of building energy and occupant comfort using multi-agent simulation." *Int. Symp. on Automation and Robotics in Construction (ISARC)*, IIT Madras, Chennai, India.

Kolokotsa, D., Saridakis, G., Pouliezos, A., and Stavrakakis, G. S. (2006). "Design and installation of an advanced EIB fuzzy indoor comfort controller using Matlab." *Energy Build.*, 38(9), 1084–1092.

Kolokotsa, D., Tsiavos, D., Stavrakakis, G. S., Kalaitzakis, K., and Antonidakis, E. (2001). "Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal-visual comfort and indoor air quality satisfaction." *Energy Build.*, 33(6), 531–543.

Li, N., Calis, G., and Becerik-Gerber, B. (2012). "Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations." *Autom. Constr.*, 24, 89–99.

Ma, H. L., and Zhu, B. T. (2005). "Application of self-adaptive fuzzy logic controller in building automation system." *J. Hebei Univ. Sci. Technol.*, 26(4), 68–71.

Marchiori, A., and Han, Q. (2010). "Distributed wireless control for building energy management." *Proc., 2nd ACM Workshop Embedded Sensing Syst. Energy-Efficiency Build., BuildSys'10*, ACM, New York, 37–42.

Murakami, Y., Terano, M., Mizutani, K., Harada, M., and Kuno, S. (2007). "Field experiments on energy consumption and thermal comfort in the office environment controlled by occupants' requirements from PC terminal." *Build. Environ.*, 42(12), 4022–4027.

Nicol, J. F., and Humphreys, M. A. (2009). "New standards for comfort and energy use in buildings." *Build. Res. Inf.*, 37(1), 68–73.

Nowak, M., and Urbaniak, A. (2011). "Utilization of intelligent control algorithms for thermal comfort optimization and energy saving." *Proc., 2011 12th Int. Carpathian Control Conf., ICCC'2011*, IEEE, Piscataway, NJ, 270–274.

Peschiera, G., and Taylor, J. E. (2012). "The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems." *Energy Build.*, 49, 584–590.

Peschiera, G., Taylor, J. E., and Siegel, J. A. (2010). "Response-relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data." *Energy Build.*, 42(8), 1329–1336.

Seppanen, O., Fisk, W. J., and Faulkner, D. (2005). "Control of temperature for health and productivity in offices." *Proc., American Soc. Heating, Refrig. Air-Condition. Eng., ASHRAE 2005 Annual Meeting*, Amer. Soc. Heating, Ref. Air-Conditoning Eng., 680–686.

Shilton, K., et al. (2008). "Participatory design of sensing networks: Strengths and challenges." *Proc., Participatory Design Conf., CPSR/ACM*, Indiana Univ., Indianapolis, IN.

Singhvi, V., Krause, A., Guestrin, C., James, H.,, Garrett, J., and Matthews, H. S. (2005). "Intelligent light control using sensor networks." *Proc., 3rd Int. Conf. on Embedded networked sensor systems*, ACM, New York, 218–229.

Tse, W. L., and Chan, W. L. (2008). "A distributed sensor network for measurement of human thermal comfort feelings." *Sens. Actuators A Phys.*, 144(2), 394–402.

J. Comput. Civ. Eng., 2014, 28(1): 2-16

Van Hoof, J. (2008). “Forty years of fanger’s model of thermal comfort: Comfort for all?.” *Indoor Air*, 18(3), 182–201.

Wagner, A., Gossauer, E., Moosmann, C., Gropp, T., and Leonhart, R. (2007). “Thermal comfort and workplace occupant satisfaction-results of field studies in german low energy office buildings.” *Energy Build.*, 39(7), 758–769.

Wang, L., and Mendel, J. M. (1991). “Generating fuzzy rules by learning from examples.” *Proc., 91CH3019-7*, IEEE, 263–8.

Wang, L. X. (2003). “The WM method completed: A flexible fuzzy system approach to data mining.” *IEEE Trans. Fuzzy Syst.*, 11(6), 768–782.

Wen, J., and Smith, T. F. (2004). “Development and validation of adaptive optimal operation methodology for building HVAC systems.” *Proc., SPIE-the Int. Society for Optical Engineering*, Vol. 5605, SPIE-Int. Soc. Opt. Eng, Z000005–Z000016.

Wen, Y., and Agogino, A. M. (2008). “Wireless networked lighting systems for optimizing energy savings and user satisfaction.” *Proc., 2008 2nd Annual IEEE Wireless Hive Networks Conf., WHNC*, IEEE, Piscataway, NJ.

Yang, Z., Li, N., Becerik-Gerber, B., and Orosz, M. (2012). “A non-intrusive occupancy monitoring system for demand driven HVAC operations.” *Proc., Constr. Res. Cong. 2012: Construction Challenges in a Flat World*, ASCE, Reston, VA, 828–837.

Zhang, H., Arens, E., and Pasut, W. (2011). “Air temperature thresholds for indoor comfort and perceived air quality.” *Build. Res. Inf.*, 39(2), 134–144.

J. Comput. Civ. Eng., 2014, 28(1): 2-16