Building and Environment 96 (2016) 118–130

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Effect of technology-enabled time-of-use energy pricing on thermal comfort and energy use in mechanically-conditioned residential buildings in cooling dominated climates

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ARTICLE INFO

Article history:
Received 14 August 2015
Received in revised form
28 October 2015
Accepted 11 November 2015
Available online 21 November 2015

Keywords:
Building energy modeling
Response surface methodology
Thermal comfort
Time-of-use pricing

ABSTRACT

The effects of automatic indoor set point temperature setbacks using smart thermostats in response to time-of-use (TOU) electricity rates structures on occupant thermal comfort are evaluated for representative single family residential buildings located in 3 climate zones with dominant cooling loads. Building energy models (BEM) of single family homes are evaluated using a full factorial experimental design to create a response surface which provides a continuous function to evaluate the impact of four design variables on long-term thermal comfort indices, including Average Percent of People Dissatisfied (*Average PPD*), and Percentage Outside Thermal Comfort Zone (*POS*). These design variables include indoor set point temperature, degrees of setback temperature in cooling mode, building thermal mass, and air exchange rate for each climate zone. These are compared to the relative energy savings resulting from TOU thermostat setbacks while considering other design variables. A second-order response surface is found to provide a reasonable fit to BEM simulation in- and out-of-sample data. The set point temperature is the most influential of the variables studied in decreasing long-term thermal comfort, while reducing HVAC electricity use. The thermostat setback has the strongest influence on thermal comfort in a hot-dry climate, while the most HVAC energy savings is able to be achieved in the mixed-humid climate zone. The results are tabulated for weighing the costs and benefits of TOU electricity rates for homes with different characteristics, in climate zones with air conditioning-dominate energy consumption.

1. Introduction

In residential buildings, in which people spend on average 69% of their time [1], it is important to maintain a comfortable indoor environment. The properties of this indoor environment, including thermal comfort, have been linked to the health and productivity of occupants [2,3]. In mechanically-conditioned residential buildings which represent 83% of all residential buildings in the United States [4], the indoor environment is highly dependent on the operation of the heating, ventilation and air conditioning (HVAC) system. This is particularly important in the extreme warm and cold seasons in which the desired indoor conditions are much different than the outdoor weather conditions.

As a result, in part, of the high penetration and use of residential HVAC systems, particularly in warmer climate zones, the electric grid in these locations experiences large fluctuations in the electricity demand (MW) during the summer months. A graph of a summer electricity demand profile (MW) [5] is shown in Fig. 1a for the ERCOT (Electric Reliability Council of Texas) electric grid, which includes hot, warm and mixed climate zones 2, 3 and 4 respectively as defined by the ASHRAE climate zones regions [6]. A significant portion of the peak loads in these areas is due to residential energy use, including HVAC systems. In ERCOT over 50% of summer peak electricity loads (Fig. 1b) can be attributed to residential buildings [7].

To address the variability in electricity demand, many electric utility companies have piloted or offer time-of-use electricity pricing (TOU) strategies for residential buildings, many of which are summarized in Newsham and Bowker (2010) [8]. Historically electricity rates schedules for residential buildings have not varied

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http://dx.doi.org/10.1016/j.buildenv.2015.11.012
0360-1323/

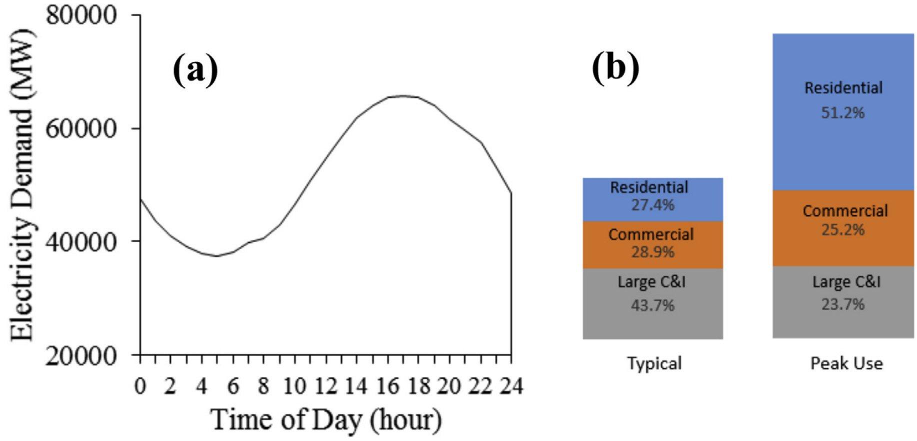


Fig. 1. (a) Example of hourly fluctuation in electricity demand in ERCOT (Electric Reliability Council of Texas), which includes ASHRAE climate zones 2, 3 and 4, for a summer (cooling) season day (data: [5]); (b) Comparison of a typical electricity demand (MW) in ERCOT (Electric Reliability Council of Texas) for a typical day, and a summer day (left) during a peak-use time (right), indicating over 50% of peak demand is from residential buildings (data: [7]).

by time of use, but rather may be a constant rate, or tiered based on the amount of total electricity used throughout a one month period. TOU rates vary based on the time of day in which the electricity is used. These pricing structures include a lower "off-peak", and a higher "on-peak" rate ($/kWh), with some rate structures also including a mid-level rate between the off- and on-peak times. Some also vary depending on whether it is a weekday or weekend. The TOU pricing trials that have achieved the highest energy savings and peak load reduction have been with homes that have "enabling technology", or technology that enables automatically reduction in electricity use when sent a pricing signal [8], rather than relying only on occupant-dependent changes. A common enabling technology is a smart thermostat, which is a programmable thermostat that communicates with the utility company pricing signals via two-way radio. This thermostat reduces electricity consumption during on-peak times by automatically introducing a setback in the set point temperature of the thermostat. Additional enabling technologies include smart home appliances, which can also reduce or defer electricity demand by altering their time-of-use of operation, discussed in Cetin et al. [9]. Since the change in HVAC system operation has a direct effect on indoor thermal comfort, this research is focused on smart thermostat-enabled HVAC operational changes.

For the adoption of TOU pricing structures, it is important that energy and/or cost savings are achieved to obtain participation from residential customers. However, it is also important to consider the effects these changes have on occupant comfort. In changing thermostat set point temperatures, thus changing the operation of the HVAC system, this also alters indoor environmental conditions. This includes both the indoor temperature and humidity, which affect occupant comfort [10]. The thermal comfort of occupants is a measure of occupant satisfaction with the indoor environmental conditions. A commonly used and widely accepted mathematical model of thermal comfort was developed by Fanger [11,12]. It is a function of dry-bulb air temperature (°C), mean radiant temperature (°C), air speed (m/s), and humidity (%), metabolic rate (met), and clothing insulation (clo) [10,13]. These factors are time dependent, but thermal comfort is assessed assuming steady-state conditions. This model uses these input parameters to predict the predicted mean vote (PMV) and the percent of people dissatisfied (PPD), with an acceptable PMV between −0.5 and 0.5 on a scale of −3 to 3, and a maximum acceptable PPD of 10% on a scale of 1–100%. Outside of these conditions is considered outside of the thermal comfort zone.

This model based on Fanger [11,12] is included in many national and international standards, including ASHRAE Standard 55 [10], International Standards Organization (ISO) 7730 [13], and EN 15251 [14]. A European adaptive thermal comfort model and an American adaptive thermal comfort model have been developed and included in EN 15251 and ASHRAE 55, respectively. The European adaptive thermal comfort model is based on either an exponentially weighted running mean of the daily outdoor air temperature, while the American adaptive thermal comfort model is based on the mean monthly outdoor temperature. As discussed in Attia and Carlucci [15], the standards generally agree with the suggestion of adoption of Fanger's model for mechanically heated and cooled buildings, while providing the option to use adaptive comfort models in naturally ventilated buildings [10] or in buildings without mechanical cooling [14]. As the large majority of residential buildings in the United States are mechanically conditioned, particularly in the hot summer periods, for this reason Fanger's PMV/PPD was chosen as the focus of this study. This model, however, only evaluates the thermal comfort for a single point in time.

Methodologies for defining the level and severity of thermal comfort or discomfort over a period of time have been proposed by a number of authors, many of which are summarized by Carlucci and Pagliano [16]. These include indices that evaluate the (a) percentage of time in or outside a threshold comfort range (e.g. [13,17–19]]), (b) cumulative indices (e.g. Refs. [13,20]) in which thermal comfort values are added up over time, and (c) averaging indices (e.g. Ref. [21]) which calculate an average metric over a period of time.

Each long-term evaluation methodology has advantages and disadvantages. The *Percent Outside Thermal Comfort Zone (POS)* methodology (a), is able to capture upper and lower exceedances from the thermal comfort ranges; however, it suffers from the discontinuity occurring at the proposed thermal comfort zone limits. This implies an abrupt change in comfort perception of the occupants at this threshold, which is inconsistent with reality. This methodology also does not measure the severity of discomfort, only its occurrence. This methodology has been used significantly in previous studies (e.g. Refs. [16–18,22]) and is a simple way to evaluate long-term thermal comfort. Cumulative indices such as *Accumulated PPD* [13] do not have a discontinuity at the thermal comfort zone boundary. However, the value requires defining a reference cumulative value of what is an acceptable level of comfort over the given period of time. *Average PPD,* the average value of the PPD over the time period considered, also does not have a discontinuity at the thermal comfort zone boundary and can be compared to the existing ASHRAE 55 [10] defined recommended limit for acceptable PPD. It is calculated by averaging all of the measured PPD values over the time evaluated. Based on these advantages and disadvantages, for comparison to previous studies, *POS* is used in this research, and because *Average PPD* can be compared to current recommended thermal comfort limits, *Average PPD* is also utilized. The *PPD* can be related to the *PMV* using the equations defined by the Fanger model [12]. No known additional relationship between the different long-term thermal comfort indices, however, are known to have been developed.

To evaluate the effect of changes of building operations on thermal comfort, Cetin et al. [19] proposed a five-step methodology that uses building energy modeling simulations to develop a response surface (RSM) [23] that models the change in the *POS* response of a residential building due to operational and physical changes as a continuous function polynomial function. In this study this methodology was applied to assess a building's *POS* due to a 1-h demand response event in which the HVAC system is turned off. This study found that the RSM provided a reasonable fit to in-sample and out-of-sample BEM simulation data. The lower-order RSM function provides a model that enabled a quick evaluation of thermal comfort response of a building within a range of values of each of the design variables. Compared to running a building energy model simulation for each possible combination of variables desired to be studied, this methodology provides a way to quickly evaluate the effect of the change in a design variable of the building rather than running additional BEM simulations. Additionally, the function is used to take into account the inherent uncertainty in the design variables, by using Monte Carlo simulation to evaluate the probability that a given situation will exceed a given threshold values of acceptable thermal discomfort of the occupants. Cetin et al. [19] applied the proposed methodology to evaluate the thermal comfort response of a residential building to a 1-h demand response event but the methodology could be used to evaluate other the thermal comfort response of a building for other scenarios as well. Additionally, the methodology could be improved by evaluating multiple long-term thermal comfort indices, and also by comparing the trade off between energy use in comparison to the effect on occupant comfort.

Various techniques, including the RSM, have been proposed to simplify the evaluation of BEM by defining the relationship between a measured response and a set of design (input) variables. Specifically, the response surface methodology has been used in recent studies for the modeling of buildings and their components (e.g. Refs. [24–26]). Other methodologies include a simplified normative model [26], reduced order models [27,28], and artificial neural networks [29–31]. The response surface results in a function that can easily be used as input into probabilistic modeling, such as Monte Carlo simulation. In addition after its initial development, obtaining a model response is extremely fast. Also it has previously been shown to provide good agreement with in and out of sample data in building applications. For these reasons this methodology is used in this research in the evaluation of TOU pricing on different building types in different climate zones, on thermal comfort.

There are three main objectives of this study. The first main objective is to evaluate the use of the RSM constructed from BEM simulation data to determine long-term thermal comfort effects on a residential building. In this research, this methodology is applied to determine the effect of technology-enabled time-of-use pricing on thermal comfort in the cooling season (summer) for a range of climate regions, and building and operational characteristics. The studied homes have a smart thermostat that automatically sets back the thermostat set point temperature during peak energy price time periods. As a long-term thermal comfort index, this study uses the *Average PPD* index, and also, it compares this to the *POS* index. Second, this study seeks to utilize the results of the RSM and probabilistic analysis to understand the influential design variables on long-term occupant thermal comfort. Third, this study aims to compare the thermal comfort levels resulting from the smart thermostat and TOU pricing, to the electricity use reductions that results from this change in operations. The results of this research are intended to be used for evaluating the costs (thermal discomfort) and benefits (energy reduction) due to TOU pricing for residential buildings with the flexibility of a model that provides a continuous function to evaluate thermal comfort changes due to operational and physical property changes within a specified range.

This research is organized into several sections. The Methodology section discusses the climate zones studied, baseline characteristics of the building energy models used, and the input design variables chosen. Each step of the five-step methodology used to evaluate the effects of TOU on long-term thermal comfort is then discussed. The Results and Discussion section describes the results of this methodology and analysis to achieve the three discussed objectives. To achieve the first objective, this section includes a check of the accuracy of the model developed by this methodology for in- and out-of-sample data. To achieve the second objective, this section then compares the level of influence of the studied variables on the thermal comfort indices and on the probability of exceeding a threshold level of discomfort using this model. Finally, to accomplish the third objective, the HVAC energy use is compared to the long-term thermal comfort indices, to show the relationship between energy use and comfort in each of the studied climate zones. This research concludes with Limitations and Conclusions sections, in which the limitations of the study and a summary of the findings, respectively, are discussed.

2. Methodology

To evaluate the effects of TOU on thermal comfort in different climate zones a building with same geometry was modeled while considering specifics of each climate. The five-step evaluation methodology includes: (1) design variable definition, (2) building energy modeling (BEM), (3) response surface development, (4) probabilistic evaluation using the response surface, and (5) result interpretation; each are discussed in order below.

Three climate zones are evaluated, including ASHRAE climate zone 4a (mixed-humid), 3a (hot-humid), and 2b (hot-dry) [6]. A representative location was chosen within each of these climate zones for evaluation. These climates zones represent a significant portion of the residential buildings in the U.S. in warm and hot climate zones, totaling 63.1 million U.S. residential households. A summary of the descriptive characteristics of these locations is included in Table 1. The average number of cooling degree days (CCD) and average outdoor relative humidity in these climate zones throughout the year and in the summer period was determined based on Typical Meteorological Year (TMY) datasets developed using Class I weather station data [32]. The most recent set of TMY data was used, TMY3, which was created using the most recently available weather and solar data. This weather data source is commonly used for building energy modeling.

To represent a typical building, a single-story 204 m^2 single family home with a forced-air central air conditioning system was used to evaluate the effects of HVAC operational changes on thermal comfort. This size is equal to the average size of a U.S. single family home based on the Residential Energy Consumption Database [4] for the three studied climate zones.

In the development of a building energy model, the building envelope properties, HVAC system specifications, and internal loads and schedules need to be defined. The properties of the

Table 1
Climate zones characteristics and U.S. residential buildings.

Climate zone	ASHRAE climate zone[a]	Residential buildings (millions)[b]	Location of study in climate zone	Annual CCD (10 °C)[c]	Summer[d] CCD (10 °C)[c]	Summer[d] average RH (%)[e]
Mixed-humid	4a	32.8	Baltimore, MD	2169	1870	70
Hot-humid	3a	17.0	Austin, TX	3046	2537	71
Hot-dry	2b	13.3	Phoenix, AZ	4064	3368	27

[a] As defined by ASHRAE 90.1–2013 [6].
[b] From Residential Energy Consumption Survey [4].
[c] CCD = Cooling Degree-Days with a reference temperature of 10 °C.
[d] Summer is defined as May 1 to September 30.
[e] From Typical Meteorological Year (TMY) weather data [32]. RH = Relative Humidity (%).

building envelope were defined using the International Energy Conservation Code (IECC) [33], and include the insulation values for the walls, ceiling, and fenestrations, and the solar heat gain coefficient of the windows. These characteristics represent the minimum prescriptive values required by the IECC, thus the building model represents the characteristics common to newer buildings. Additional building properties were defined based on the Building America House Simulation Protocol [34] for new buildings. Previous research has also cited the need to adjust the moisture absorption capacity assumption of building energy model, particularly when evaluating indoor thermal comfort [34–36]; based on this research a value of 15 was used in the building energy model. The building systems include a single-stage residential HVAC system with external compressor and condenser unit and indoor air handling unit, with an air distribution system and duct system in the attic space. Cooling and heating are electric-based from a heat pump. Since the building is a single story house, the HVAC control is a single zone with standard on/off compressor and air handling unit fan [34]. The size of the HVAC system was fixed based on Manuel J [37] sizing calculations for each of the studied climate zones assuming a constant cooling set point and the mean values of the properties of the studied variables listed in Table 4. Internal loads are based on typical occupancy schedules and internal load schedules for residential buildings from the Building America Energy Simulation Protocol [34]. These building envelope and system properties are summarized in Table 2.

To define the time-of-use rate schedule, since time-of-use rates are implemented with the purpose of incentivizing peak load reduction, only the cooling period of the year is when TOU is applied. Based on the studied TOU pricing trials occurring in hot and warm climate zones, the length of study was limited to May 1st to September 30th for the cooling season (summer), paralleling many of the TOU rate schedule periods for the cooling season (summer) in the studied areas [8]. Of the studied TOU pricing trials, both two- and three-tier electricity pricing structures were used. In the chosen cities for use in this study, the optional time-of-use rate structures offered for residential buildings generally have a peak TOU summer rate that begins between 10:00 am and 2:00 pm, and ends at 8:00 pm. To parallel this timing, but to limit overestimation of the effect on thermal comfort, a two-tier rate structure was chosen such that the peak use rate occurs between 2:00 pm and 8:00 pm and the off-peak rate occurs between 8:00 pm and 2:00 pm. The time-of-use rate versus the standard rates used are shown in Table 3.

Table 3
Time-of-use and standard summer electricity rate schedule (May 1-September 30).

Time-of-use		Standard	
Off-peak	8 pm–2 pm	All times	12 am–12 am
On-peak	2 pm–8 pm		

2.1. Design variable definition: building operations variables

To develop a response surface several design variables $\mathbf{X} = \{X_1, X_2, \ldots X_n\}$ are considered, including the degrees of indoor temperature setback in cooling mode during on-peak times. These design variables are used as inputs to build and define the response surface. It is desired that the model allow for adjustments for a range of occupant-controlled parameters, as these parameters are adjustable without making modifications to the building structure. These parameters include the thermostat cooling (summer) set point temperature (°C), the degrees of setback temperature (°C) during on-peak times, and the air exchange rate (hr^{-1}). The set point temperature and degrees of setback temperature can be adjusted by changing the thermostat; the air exchange rate varies based on the natural and mechanical ventilation, and the weatherization of a home. The thermal mass of the home is the fourth design variable. Thermal mass can vary depending on the type of building construction and the amount, thickness of the interior partition walls and amount of objects or furniture placed and the home. Variations in the thermal mass of a building can affect how quickly a building's indoor environmental conditions respond to set point temperature changes, and thus are important to also include in this study. The effect of thermal mass on buildings has been discussed in previous research [38–41], however, most have focused on commercial rather than residential building applications.

Each design variable requires an upper and lower bounds of

Table 2
Residential building construction and system properties by climate zone.

Climate zone (#)	Ceiling[a]	Wall[a]	Window[a]	SHGC[a]	Exterior boundary conditions	Window area (%)[b]	HVAC size (kW)[c]	SEER[d]
Mixed-humid (4a)	R-38	R-13	U-0.35	–	All exterior walls	15%	12.3	13
Hot-humid (3a)	R-30	R-13	U-0.50	0.30			15.8	
Hot-dry (2b)	R-30	R-13	U-0.65	0.30			19.3	

[a] Minimum building construction properties per requirements in International Energy Conservation Code [33].
[b] Percentage of total exterior wall surfaces.
[c] HVAC is sized according to Manual J calculations by climate zone [37].
[d] SEER rating is the minimum value for a residential system per ASHRAE 90.1 [6].

Table 4
Design variables used to create thermal comfort response surface model.

Type	Variable	Lower bound $x_{i,low}$	Upper bounds $x_{i,high}$	(Geometric) mean μ_i	(Geometric) standard deviation	Distribution
Operational	Summer (cooling) set point temp. (°C)[a]	21.1	29.4	25.1	1.7	Normal
	Thermostat setback temp (°C)[b]	0	4.5	1.8	1.3	Normal
	Air exchange rate (ACH) (1/hr)[a,c]	0.10	1.0	(0.26)	(1.04)	Lognormal
Structural	Internal thermal capacitance (kJ/°Cm²)[d]	26.4	39.3	35.1	4	Normal

[a] Pecan Street Research Institute; Dataset on building energy audits and survey performed in 2013 and 2014 on residential buildings in Texas [44].
[b] Siemann 2014 [42].
[c] Offermann [43].
[d] Building America Building Simulation Protocol [34].

which the variable is evaluated and the model is valid in the developed response surface. The upper $(x_{i,high})$ and lower $(x_{i,low})$ bounds of the set point temperatures were chosen to be within the limits of the summer thermal comfort zone as defined by ASHRAE 90.1 [6]. The degrees of setback temperature was chosen to represent the extreme minimum (no setback), to maximum setback from previously conducted demand response and time-of-use rate trials [42]. The upper and lower bounds of the air exchange rate were chosen to cover a range of values common in newer buildings [43]. Thermal mass varies depending on the amount of interior walls and furniture inside a residential building. The values used are measured in kJ/°C-m^2 and include interior drywall used for the external and internal walls and ceiling. The lower bound of the thermal mass equates to 13 mm drywall on the interior side of the exterior walls, on the ceilings and on the interior partition walls. These variables are summarized in Table 4.

2.2. Building energy modeling (BEM)

Using BEM software EnergyPlus version 8.1 [45], the response of the studied building was evaluated using a 3^n full factorial experimental design for the four sets of design variables. For each climate zone, this amounts to 81 trials, or a total of 243 BEM simulations. This includes a simulation at each combination of the n design variables (X_i; $i = 1$ to n) at three design points $x_{i,high}$, $x_{i,low}$ and a center point. The output variables of BEM, including indoor temperature, T_a (°C), mean radiative temperature, T_{MR} (°C), operative temperature T_o, (°C) and humidity ratio HR (%) are used to evaluate the values of *Average PPD* (Eq. (1a)) and the *POS* (Eqs. (1b) and (c)) for all simulations. In these equations k is the climate zone, h is the hour being evaluated, and h_{tot} is the total number of hours. Within the thermal comfort zone ($c_h = 0$) is defined as a PPD value of less than 10 or a PMV between −0.5 and 0.5 per ASHRAE 55 (2010). PPD, a function of the input variables, was calculated based on the equations in by ASHRAE 55 in Appendix D [10]. The output of the BEMs was combined and a MATLAB code was developed to calculate *Average PPD* and *POS* for each trial.

$$Average\ PPD_k = \left(\frac{\sum_1^{h_{tot}} PPD(T_a, T_{MR}, T_o, HR)_h}{h_{tot}} \right)_k \tag{1a}$$

$$POS_k = \left(\frac{\sum_1^{n} c_h}{h_{tot}} \right)_k \tag{1b}$$

$$c_h = \begin{cases} 1 \leftarrow (\text{outside thermal comfort zone}) \\ 0 \leftarrow (\text{inside thermal comfort zone}) \end{cases} \tag{1c}$$

2.3. Response surface development

Based on the results of the building energy modeling simulations, a response surface $S(\mathbf{X})$ (Eq. (2)) is created. This response function is defined using linear and nonlinear terms made up of the n design variables $\mathbf{X} = \{X_1, X_2, \ldots X_n\}$ listed in Table 5, and a set of coefficients, b_i ($i = 1$ to n) for linear variation and b_{ij} ($i,j = 1$ to n) for quadratic variation. These are discussed in Meyer et al. [46], and Khuri and Mukhopadhyay [47]. Least-squares regression is used with the selected design variables and the results of the BEM simulations to develop the nonlinear, second-order response surface function. To evaluate the goodness of fit of the model, the R^2 (coefficient of determination) value is used. Evaluation of goodness of fit was conducted on both in-sample and out-of-sample data which are within the range of the upper and lower bounds of the design variables considered. Out-of-sample data was developed using a random number generator to create values for each of the design variables between the upper and lower bounds, $x_{i,high}$, and $x_{i,low}$, then BEM was evaluated for each of these trials and compared to the model-predicted values. Terms in $S(\mathbf{X})$ that have a significant influence on the response surface are defined as those in which the p-value is less than 0.0005.

$$S(\mathbf{X}) = b_o + \sum_{i=1}^{n} b_i X_i + \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij} X_i X_j \tag{2}$$

2.4. Probabilistic evaluation using the response surface

The response surface model developed following BEM simulations is an approximate representation of a real-world based situation based on assumptions and approximations. To address uncertainty in the design variables, Monte Carlo simulation [48] is used with the distributions of the design variables specified in Table 4 to determine the *Average PPD* for each of the three climate zones for the typical home studied. The distribution parameters for each of the design variables were determined based on data collected from previous studies, as summarized in Table 4. An Anderson-Darling test was performed to determine the best distribution fit for the data for each of the design variables based on the collected data. This is compared to a threshold acceptable level of PPD, PPD_{acc}, to determine the probability that the *Average PPD* will exceed this threshold value (Eq. (3)), where $S(\mathbf{X})$ is the response surface function developed in Step 3. In this evaluation it is assumed that all the design variables are independent random variables. The PPD_{acc} is evaluated as 5%, 10% and 15%. The accuracy of P_f estimates based on MC simulations increases with the number of simulations, which was set at a maximum of 100,000 simulation.

$$P_{f,\ PPD} = PPD_{acc} - S(\mathbf{X}) \tag{3}$$

Table 5
Average PPD[a] and POS[b] coefficients and p-values of the second-order response surface model.

	Cli-mate	Inter-cept	T_{SP} (°C)	T_{SB} (°C)	TM (kJ/°C-m^2)	ACH (1/hr)	T_{SP}*T_{SB}	T_{SP}*TM	T_{SP}*ACH	T_{SB}*TM	T_{SB}*ACH	TM*ACH	T_{SP}[b]	T_{SB}[b]	TM[b]	ACH[b]
Average percent of people dissatisfied (PPD)																
Coefficient	2b	452.72	−40.10	−1.514	−0.501	3.421	0.110	−0.001	0.161	0.006	−0.342	0.063	0.912	−0.051	0.005	1.732
	3a	291.4	−27.4	−0.122	−0.718	11.034	0.010	−0.003	0.005	0.015	−0.528	0.038	0.662	−0.003	0.009	0.027
	4a	78.995	−8.640	0.521	−0.020	26.248	−1.4E-04	−0.002	−1.312	0.001	0.018	−0.004	0.245	−0.051	0.000	2.944
P-value[c]	2b	**0.000**	**0.000**	0.081	0.409	0.434	**0.000**	0.929	0.477	0.449	0.006	0.401	**0.000**	0.430	0.559	0.278
	3a	**0.000**	**0.000**	0.904	0.317	**0.000**	0.725	0.858	0.968	0.116	**0.000**	0.398	**0.000**	0.971	0.376	0.957
	4a	**0.000**	**0.000**	0.442	0.967	**0.000**	0.994	0.848	**0.000**	0.932	0.919	0.944	**0.000**	0.320	0.981	0.021
Percent of time outside thermal comfort zone (POS)																
Coefficient	2b	−18.85	1.442	0.093	0.003	0.014	−0.004	−7.8E-06	0.005	−3.7E-05	−0.002	−3.4E-04	−0.026	0.005	−3.6E-05	0.002
	3a	−19.14	1.502	−0.002	−0.024	0.074	1.2E-04	−2.0E-05	1E-04	−0.001	−0.005	0.001	−0.027	-4E-05	0.001	0.009
	4a	−14.13	1.081	0.032	0.329	−0.001	−0.001	0.000	−0.020	2.9E-05	0.002	0.000	−0.019	0.001	3.5E-06	0.081
P-value[c]	2b	**0.000**	**0.000**	**0.000**	0.815	0.894	**0.000**	0.983	0.403	0.848	0.465	0.849	**0.000**	0.001	0.864	0.952
	3a	**0.000**	**0.000**	0.909	0.070	0.123	0.815	0.952	0.963	**0.000**	**0.000**	0.458	**0.000**	0.976	**0.000**	0.293
	4a	**0.000**	**0.000**	0.010	**0.000**	0.925	**0.000**	0.785	**0.000**	0.799	0.500	0.926	**0.000**	0.165	0.977	0.001

The bold values indicate a P-value of less than 0.0005.

[a] Average Percent of People Dissatisfied (as defined by Eq. (1a)).

[b] Percent of time Outside Thermal Comfort Zone (as defined by Eqs. (1b) and (c)). T_{SP} = Set point temperature, T_{SB} = Setback temperature, TM = thermal mass, ACH = air exchange rate. 2b = Hot-dry (Phoenix, AZ), 3a = hot-humid (Austin, TX), 4a = mixed-humid (Baltimore, MD).

[c] If less than 0.0005, the p-value is shown as a zero value.

3. Results and discussion

The results of research are divided into three different sections to specifically address each of the three objectives. The first section addresses the evaluation of the RSM to create a continuous function that represents the long-term thermal comfort performance of a building due to changes in the considered design variables. The second section utilizes the resulting model and probabilistic analysis to evaluate the influence of the design variables and the terms in the RSM model on long-term thermal comfort. The third section compares HVAC energy use with the long-term thermal comfort indices to evaluate the costs and benefits of smart thermostat technology-enabled time-of-use pricing.

3.1. Model evaluation to predict thermal comfort

The coefficients for the response surfaces built for each of the studied climate zones is included in Table 1. The second order response surface model shows a stronger fit than a first order model, with a coefficient of determination (R^2) value of 0.995–0.997 for in-sample data fitting in each of the studied climate zones. Table 5 shows the coefficients and p-values for each of the terms for each of the three locations of study for both the *Average PPD* and the *POS*.

In predicting the *Average PPD* and the *POS*, the response surface provides a strong fit to in-sample data (Fig. 2a and c). For out-of-sample data, a set of values for the design variables was created using a random number generator within the range of the minimum ($x_{i,low}$) and maximum ($x_{i,high}$) limits of the experimental design and compared to the predicted values using the response surface. This also shows the strong fit between the model-predicted and the actual values. Parity plots showing the fit of out-of-sample data are shown in Fig. 2b and d. For the out-of-sample data, the *Average PPD* models show a strong fit, with the model for Climate Zone 2a and 4b over-estimating the value of *Average PPD* slightly (1% and 3% respectively). The out-of-sample data for the *POS* generally fits the predicted the values, however it generally is shown to under-predict POS values greater than 20%.

3.2. Influential variables and RSM terms on thermal comfort

In all of the studied climate zones, increases set point temperature and increases in the thermostat setback temperature also increase the *Average PPD* and *POS* long-term thermal comfort indices. Increased discomfort due to increased set point temperatures is consistent with ASHRAE 55 (2010) [10], in which the percent of people dissatisfied increases with increasing indoor temperatures. In all of the studied climate zones, an increase in thermal mass over the range of values studied has little effect on the *Average PPD* and *POS*. A home with a larger thermal mass has a lower rate of increase in indoor temperature because a higher thermal mass introduces a thermal lag or time delay in the flow of heat from exterior to interior. Thus if the thermostat is setback it can take more time for a higher thermal mass building to increase in temperature to where the occupants are uncomfortable. However, the thermal mass in the modeled buildings represents the typical thermal mass of a newly built home. This thermal mass and variation in thermal mass is small in comparison to what has been used to effectively affect rate of increase in temperature, and in effect the thermal comfort in residential buildings in previous studies (e.g. Refs. [49–51]). In all of the studied climate zones an increase in air exchange rate, increases the *Average PPD* and *POS*. This is consistent with previous findings (e.g. Refs. [52,53]). If an increased amount of unconditioned outdoor air enters into the indoor environment due to a higher air exchange rate, this can increase indoor temperatures faster, resulting in a longer period of time at a higher temperature.

The most significant second-order RSM terms vary by the climate zone in which the building is located. Terms in the response surface with significant influence (p-value less than 0.0005) on the thermal comfort indices are shown to have a p-value of 0.000 in Table 5. The set point temperatures and squared set point temperature were significant influences for both *Average PPD* and *POS* in all of the studied climate zones. The degree of setback term was significant for the *POS* in climate zone 4a (mixed-humid), and thermal mass term in climate zone 2b (hot-dry). Air exchange rate has the most influence in Climate Zones 3a and 2b. Additionally several of the reaction terms were significant.

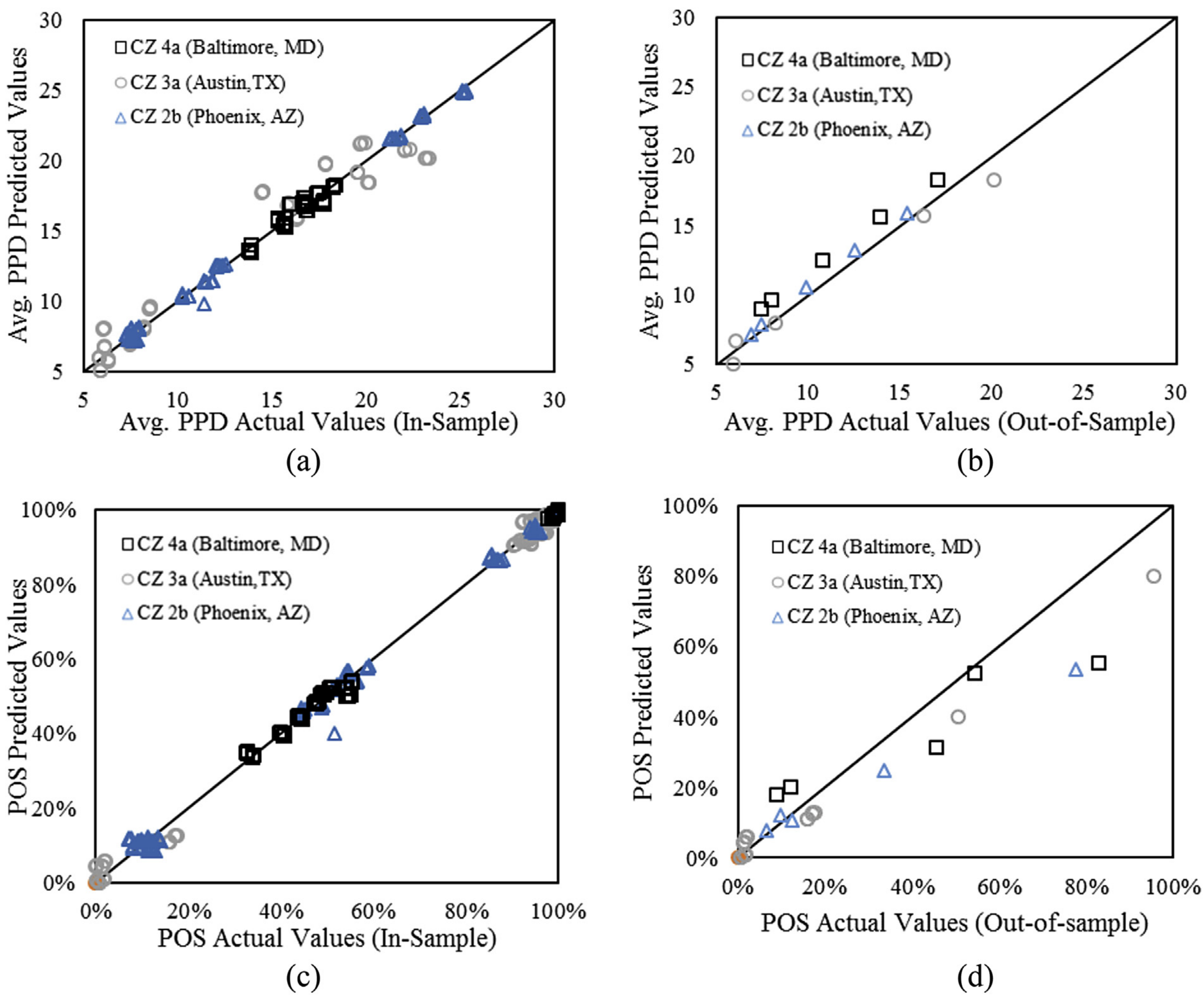


Fig. 2. Parity plots comparing the model-predicted values of the Average PPD and POS for in-sample (a and c) and out-of-sample (b and d) data. Note: CZ = climate zone, PPD = Percent of people dissatisfied, POS = percent outside the thermal comfort zone.

3.3. Degrees of setback and set point temperature influence on thermal comfort

In evaluating the influence of the degrees of setback on thermal comfort, the *Average PPD* and the *POS* are compared with a constant set point temperature with zero degrees of setback, at each of the different design scenarios. At a degree of setback of zero, this represents a constant set point temperature regardless of the peak pricing. Fig. 3 shows that the number of degrees of setback has non-linear influence on the long-term thermal comfort indices. Each of the lines in Fig. 3 represents a different set point temperature and is labeled as such.

The degrees of setback during the on-peak times most strongly influences the thermal comfort indices in Climate Zone 2b (hot-dry). A 4° setback increases the *Average PPD* by 3.5%–4.5%, and 5%–10% for the POS in this climate zone. In a hot climate with the highest number of cooling degree days in comparison to the other studied climates, this is a reasonable result. With a higher outdoor temperature, this will cause the building's indoor temperatures to increase faster during the setback times, as the building absorbs more solar radiation and transfer heat to the interior with a higher interior to exterior temperature gradient. The greatest change in the *Average PPD* is due to changes in the degrees of setback temperature when the set point temperature is lower, while the greatest difference in *POS* occurs at higher set point temperatures. This represents a difference in results that varies based on the long-term thermal comfort index being used, and is discussed further in the comparison of the two thermal comfort indices in the section below.

Changes to the set point temperature have the strongest influence on thermal comfort in the hot climate zones (2b, hot-dry and 3a, hot-humid) (Fig. 3). The *Average PPD* varies by approximately 17% across a range of 5 °C in set point temperature for Climate Zone 2b (hot-dry), and 19% for Climate Zone 3a (hot-humid). These variations in thermal comfort are 56% and 77% more, respectively, than for Climate Zone 4a (mixed-humid). Similarly, the POS varies by approximately 69% across the evaluated indoor set point temperatures for Climate Zone 2b (hot-dry), and 65% for 3a (hot-humid). These variations are 27% and 20% more, respectively than for Climate Zone 4a (mixed-humid).

This also shows that an indoor set point of 22 °C–24 °C at varying setback temperatures will generally ensure that the indoor environmental conditions will remain below the threshold value of *Average PPD* of 10%, as defined by ASHRAE 90.1 [6]. Thermostat set point temperatures greater than 24 °C, a common thermostat set point for the summer (cooling) season for a mechanically-conditioned home, were above the 10% threshold with varying ranges of degrees of setback temperatures.

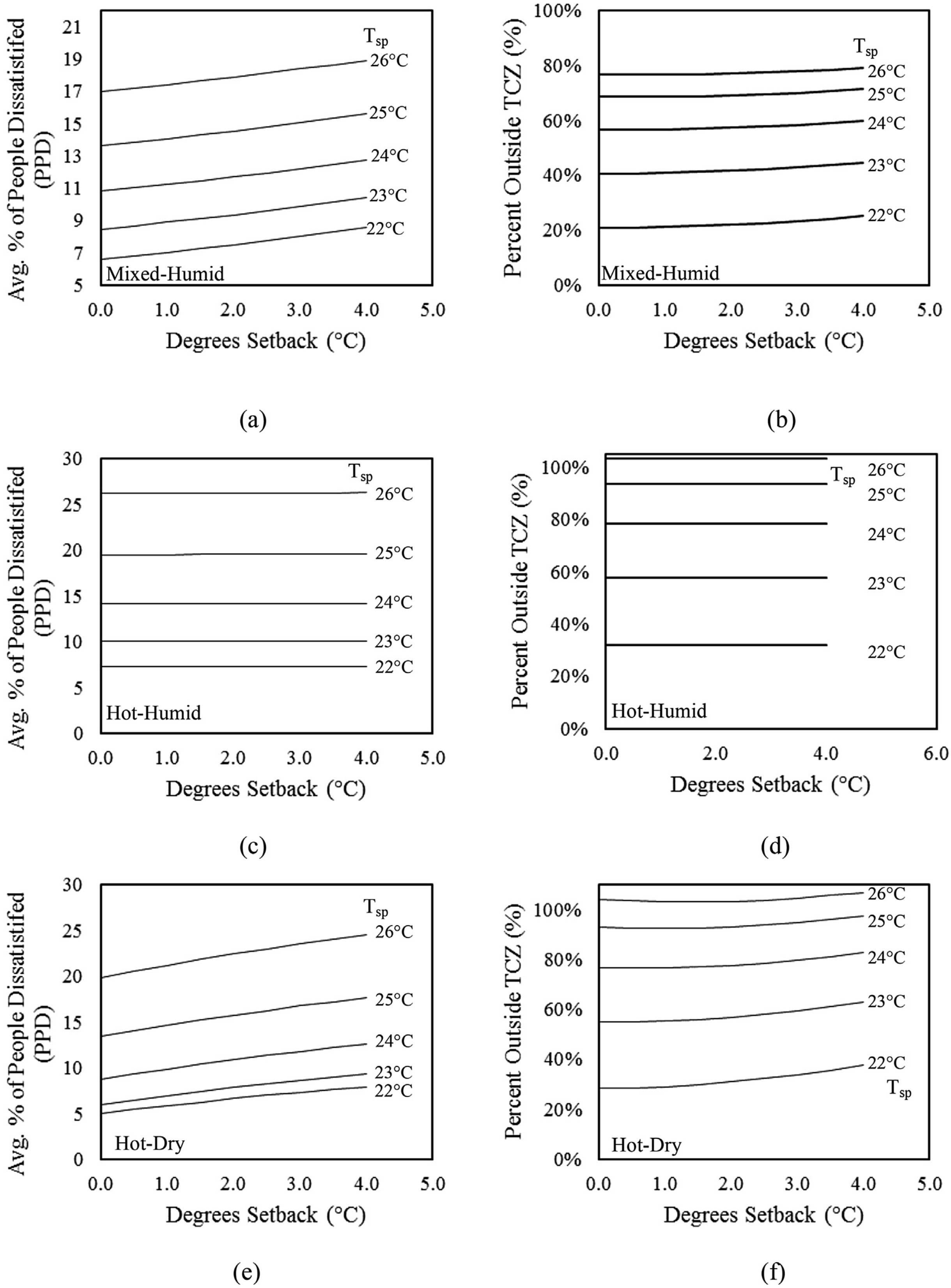


Fig. 3. Influence of degrees of setback temperature on the *Average PPD* and *POS* at a range of indoor set point temperatures for Climate Zone 4a (mixed-humid) (a,b), 3a (hot-humid) (c,d), and 2b (hot-dry) (e,f). Note: Each line represents a set point temperature; a constant value for ACH of 0.4 h^{-1} and thermal capacitance of 35 kJ/°C-m^2 are used in the creation of these graphs.

3.4. Probability analysis: probability of exceeding threshold acceptable level of discomfort

To look at the effects of a large-scale implementation of time-of-use pricing, probabilistic analysis allows for evaluation of the effects on a set of homes with a distribution of setback temperatures, and the other studied design variables. Assuming an adoption rate of the degrees of setback temperature for time-of-use pricing from Siemenn [42], and the probability distributions of the design variables specified in Table 2, Monte Carlo simulation results are shown in Fig. 4. For homes in the hot-dry climate zone a lower percentage of the homes meets the suggested maximum 10% PPD as compared to the mixed-humid and mixed-hot climates. For homes in the hot-dry climate zone approximately 35% and 60% of single family homes have an *Average PPD* of 10% and 15% respectively, where as in the hot-humid and mixed-humid climate zones, 45–65% and 80% of homes have an *Average PPD* of 10% and 15%. The hot climate zones also have a longer tail of homes at high values of *Average PPD* than the mixed climate zone.

3.5. Comparison of thermal comfort indices

In the development and evaluation of the effect of the considered design variables on *Average PPD* and *POS*, the use of one thermal comfort index versus another is important to consider. Fig. 5a shows a comparison of the thermal comfort indices at an ACH of 0.4 h^{-1} and a thermal mass of 35 kJ/°C-$m^{2,}$ with variations in set point temperature and degrees of setback. Fig. 5b shows the results of the BEM simulations used to create the response surface. The threshold acceptable level of PPD per ASHRAE 55 [10] is equal to 10%, which equates to a *POS* of between approximately 45 and 80% depending on the climate zone and the values of the design variables used. This also shows that the *POS* evaluation can only evaluate thermal comfort up to the equivalent *Average PPD* of 26–27%. After this level, the *POS* is nearly 100% or slightly over predicts the 100% value, whereas the *Average PPD* can continue to differentiate the level of thermal comfort at higher ranges of indoor temperature conditions.

3.6. Comparison of energy use and thermal comfort

The energy use of the HVAC system servicing the studied residential building is compared with the two long-term thermal comfort indices for each of the studied climate zones. Similarly using the response surface methodology, HVAC use is related to the studied design variables. The values of these coefficients and p-values are included in Table 6. Similar to the thermal comfort indices, HVAC use is most influenced by the set point temperature in all of the studied climate zones.

Fig. 6 shows the comparison of the HVAC energy use to the *Average PPD* and *POS* at an ACH of 0.4 h^{-1} and a thermal mass of 35 kJ/°C-$m^{2,}$ with variations in set point temperature and degrees of setback. Each cluster of data points has a set point temperature and are labeled as such. The variation in the values in the clusters is due to the change in degrees of setback temperature (0–4 °C) with the highest degree of setback being the points with the highest thermal comfort dissatisfaction.

In Climate Zone 2b (hot-dry), the HVAC energy use is highest, followed by Climate Zone 3a (hot-humid) and 4a (mixed-humid). This is consistent with the values of the cooling degree days listed in Table 1. The thermal comfort of occupants decreases as the HVAC use increase, however this trend is not linear and depends on which long-term thermal comfort index is used. As the indoor set point temperature increases, and the degrees of setback increases, the amount of HVAC energy use decreases. An increase in the number of degrees of setback causes the greatest decrease in HVAC energy use in the mixed-humid climate as compared to the other studied climate zones. This is likely due to the less extreme outdoor temperatures and solar radiation in the mixed-humid climate that would not heat the residential building as quickly during the peak use time when the set point temperature is higher. An increase in set point temperature also causes the least increase in occupant dissatisfaction in the mixed-humid climate zone compared to the other studied climate zones.

4. Study limitations

There are several limitations to this study. This research is limited to the study of the thermal comfort of mechanically-conditioned, residential buildings. In support of the selected type of buildings, mechanically conditioned residential buildings are most commonly found in the United States, and represent a large majority of the residential building stock [4]. Air conditioning use is also predicted to increase in use in future years throughout the world [54]. Naturally ventilated buildings are also common, particularly in European countries, and can be evaluated using the adaptive thermal comfort model. Due to the lack of an HVAC system it is likely that these buildings are more strongly affected by building construction characteristics and climate variations, however, the focus of this study is on the effects of changes in HVAC operations and resulting thermal comfort due to TOU pricing. Since HVAC loads are a significant portion of the peak energy use in the United States and are often targeted for TOU pricing, focusing on mechanically conditioned buildings is justifiable.

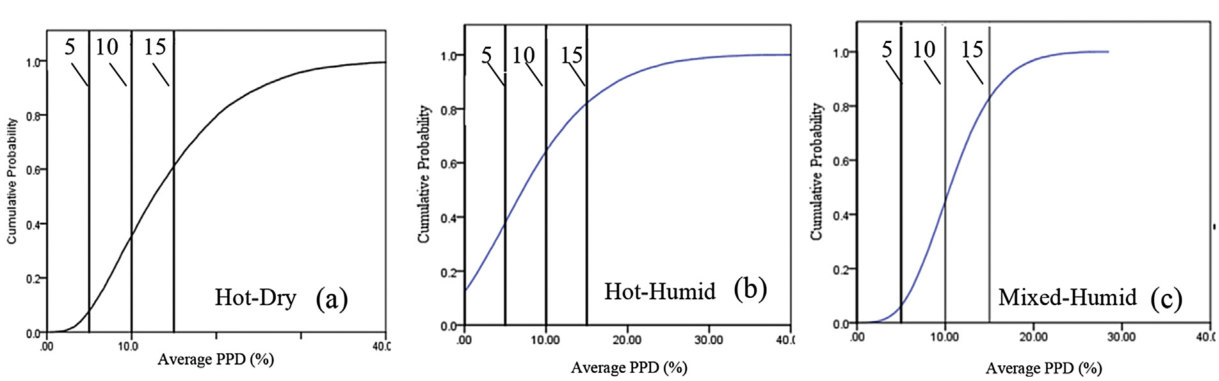
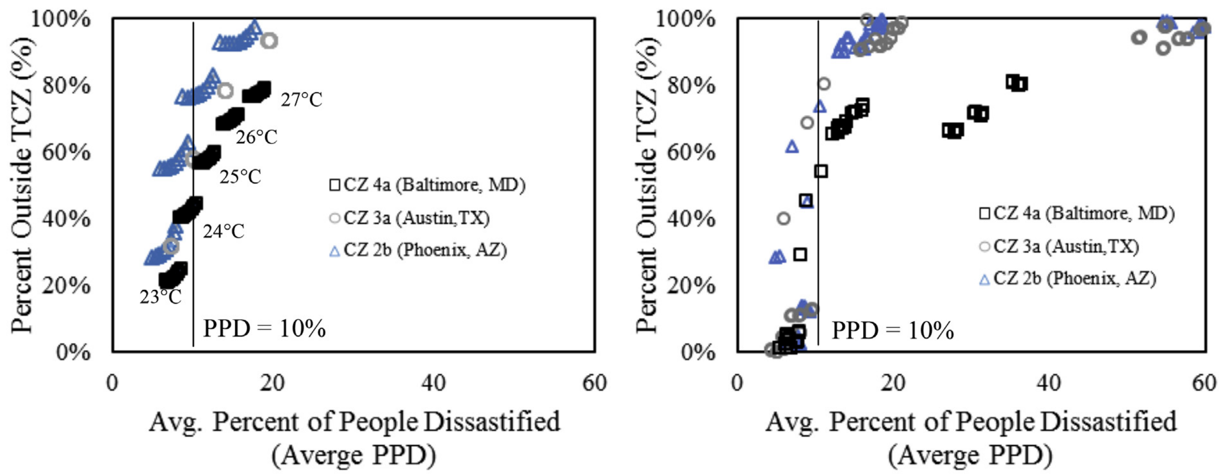


Fig. 4. Cumulative probability of the Average Percent of People Dissatisfied (*Average PPD*) (%) for Climate Zone (a) 2b (hot-dry), (b) 3a (hot-humid), and (c) 4a (mixed-humid) resulting from Monte Carlo Simulation.



(a) (b)

Fig. 5. Comparison of Percent of People Dissatisfied (%) and Percent Outside the Thermal Comfort Zone for Climate Zone 4a (mixed-humid), 3a (hot-humid), and 2b (hot-dry) using the RSMs (a), and for all data points used to develop the RSM from building energy modeling (b). Note: In Fig. 5a each cluster of points has a set point temperature as labeled; the variation in the values in the clusters is due to the change in degrees of setback temperature with a higher degree of setback temperature representing the points on the right of each cluster; a constant value for ACH of 0.4 h^{-1} and thermal capacitance of 35 kJ/°C-m^2 are used.

This study is also focused on single family homes rather than multi-family properties. Single family homes were chosen for this research as they are the most common form of the mechanically conditioned residential building stock in the U.S. Differences between single family and multi-family include that multi-family residential buildings do not interface with the exterior on all sides and thus may affect the HVAC performance characteristics [55] and resulting thermal comfort. The single family home size and dimensions are also constant and not varied, as are other variables that are assumed as constant values in this study. The addition of an increasing number of design variables using a full factorial design significantly increases the number of BEM simulations needed to create the response surface. This study is limited in the design variables evaluated. However, this study targeted design variables that can have an effect on thermal comfort and that vary across the residential building stock, without suggesting occupant schedule change requirements, or the need to modify occupant behavior. Factors of the building's construction, systems, occupancy schedules, and internal loads, and different time-of-use rate schedules may be evaluated as additional design variables in future work".

Additional limitations also arise from the use of building energy modeling, as a building energy model is a simplification of a real-world building. However, significant effort has been done to validate the assumptions in the building energy model [34]. It assumes a single zone HVAC model in which a single temperature represents the temperature of the interior space when this may not necessarily be the case. This does not take into account temperature distributions or stratification which may affect thermal comfort within the studied zone [56–58]. If this methodology is applied to a commercial building or residential building with multiple HVAC systems and zones, multiple zones' thermal comfort would need to be considered. It is also assumed that the velocity of the cooling air provided by the HVAC is within the acceptable range per ASHRAE 55 [10]. It is also assumed that the HVAC system is functioning properly without any faults or inefficiencies and is properly sized using Manual J. An improperly sized HVAC system or an HVAC system with faults may affect the energy use and length of time the HVAC is on [55,59].

The performance of an HVAC system and a building is highly dependent on external conditions. The TMY3 weather files [32] were used to evaluate the effect of thermal comfort. TMY weather files are the most commonly used form of weather data for energy modeling and were thus deemed appropriate for use in this study. However, TMY weather data does not take into account extreme weather conditions that have been found to be increasingly common occurrence, due to climatic changes [56]. This may affect that TOU pricing setbacks' influence on thermal comfort.

The thermal comfort model and long-term indices used also have limitations, many of which are discussed in Carlucci et al. [16]. The amount of clothing worn by occupants and the level of activity affect the location of the thermal comfort zone and thus the predicted level of comfort experienced by occupants. The thermal comfort model chosen for this research, based on the Fanger model [11,12] also assumes steady-state conditions. With a change in the indoor set point temperature due to a setback in temperature when the HVAC is in cooling mode, a residential building may not necessarily be operating under steady-state conditions. More recently, it has been suggested that other methodologies may be used to evaluate thermal comfort. However, as pointed out in Wong et al. [62], there are limited available models that provide a similar predictor of thermal sensation. Adaptive thermal comfort models, including those previously discussed, the American and European adaptive thermal comfort models in standards ASHRAE 55 [10] and EN 15251 [14], are based on the outdoor daily or monthly temperatures, and do not assume steady-state conditions. While these models are generally applied to naturally conditioned spaces, in the context of the use for a residential building where the indoor set point is changed, the application of this thermal comfort model may be appropriate. Adaptive thermal comfort models for commercial and residential buildings under TOU pricing have been discussed in recent literature (e.g. Refs. [60,61]). If an adaptive thermal comfort model was used as the basis for the thermal comfort long-term indices in this research, most likely the level of thermal discomfort experienced by occupants would be predicted to be lower. This comparison of thermally comfortable indoor conditions is well described and shown in Fig. 10 of Attia and Carlucci [15].

Table 6
HVAC energy use (kWh) coefficients and p-values[a] of the second-order response surface model.

	Climate	Intercept	T_{SP} (°C)	T_{SB} (°C)	TM (kJ/°C-m^2)	ACH (1/hr)	T_{SP}*T_{SB}	T_{SP}*TM	T_{SP}*ACH	T_{SB}*TM	T_{SB}*ACH	TM*ACH	T_{SP}[b]	T_{SB}[b]	TM[b]	ACH[b]
Coefficient	4a	21382	−1440	−221.5	2684.2	−2.679	6.228	0.041	−91.89	0.055	−14.99	0.170	24.40	9.77	0.006	−46.82
	3a	32984	−1880	36.9	−201.3	7578	−1.819	−0.441	7.126	2.974	−229.8	−13.198	28.642	2.224	1.717	−205.7
	2b	21647	−965.4	−47.91	14.309	7406	−5.731	0.154	−21.77	−0.293	−231.5	−1.397	10.775	24.941	−0.128	−6.599
P-value	4a	0.000	0.000	0.000	0.000	0.922	0.000	0.952	0.000	0.881	0.148	0.960	0.000	0.001	0.988	0.517
	3a	0.000	0.000	0.705	0.004	0.000	0.507	0.798	0.584	0.002	0.000	0.003	0.000	0.762	0.085	0.000
	2b	0.000	0.000	0.281	0.646	0.000	0.000	0.844	0.065	0.481	0.000	0.719	0.000	0.000	0.775	0.936

[a] If less than 0.0005, the p-value is shown as a zero value.
[b] T_{SP} = Set point temperature, T_{SB} = Setback temperature, TM = thermal mass, ACH = air exchange rate. 2b = Hot-dry (*Phoenix, AZ*), 3a = hot-humid (*Austin, TX*), 4a = mixed-humid (*Baltimore, MD*).

The thermal comfort indices also evaluates the indoor thermal comfort of the household at all times of the day, regardless of whether or not a building may be occupied. If a building is not occupied during the time that the thermostat setbacks are in place any uncomfortable indoor environmental conditions that may results will not affect occupants until the building is occupied. However, additional information and evaluation is needed to further investigate and quantify these potential differences and influences.

Finally, while this research focuses on assessing the potential energy savings achieved through reduced HVAC use and compares this to the thermal comfort indices, it does not discuss how this translates to cost savings to the consumer. Depending on the pricing strategy of electricity utilized, including both the off-peak and on-peak electricity costs, and the relative difference between the two, the energy savings achieved may translate to a range of cost savings to the residential consumer. The range in energy prices in the U.S. varies by more than 20 cent/kWh. Similarly, there is a significant range in the possible price difference between on-peak and off-peak pricing. The pricing of electricity may also affect occupant behavior. An in-depth economic analysis is needed to assess these variations in costs and such an analysis is considered a subject for future work.

Acknowledging the discussed limitations, this research provides information that is valuable in evaluating the effects of TOU pricing on thermal comfort for different climate zones, and homes with different characteristics, and compares these effects to energy use. In addition it expands upon the use of the RSM methodology beyond previously research.

5. Conclusions

One of the main purposes of time-of-use pricing is to encourage changes in building operations to reduce peak load on the electric grid. This study focuses on residential buildings with smart thermostats that can automatically setback the thermostat of the HVAC during the on-peak period. This reduces demand on the electric grid and also reduces energy use. The following conclusions can be drawn from this study.

1) A second-order response surface provides a good fit to in-sample and out-of-sample data in predicting the *Average PPD* for a residential building energy model using a 3^n full factorial design. This is consistent across all climate zones studied. For the percent of time outside the thermal comfort zone (*POS*), the second-order response surface provides a good fit to in-sample data, and slightly under-predicts out-of-sample values.
2) The strongest influencing factor on the long-term thermal comfort indices studied is the indoor set point temperature, of the four studied design variables (thermal mass, setback temperature, set point temperature, and air exchange rate). Air exchange rate and thermal mass are less influential on thermal comfort. Increasing the set point temperature by one degree increases the *Average PPD* by 2–7%, and *POS* by 8–17%.
3) An increase in the degrees of setback temperature generally decreases the thermal comfort of occupants. This influence is

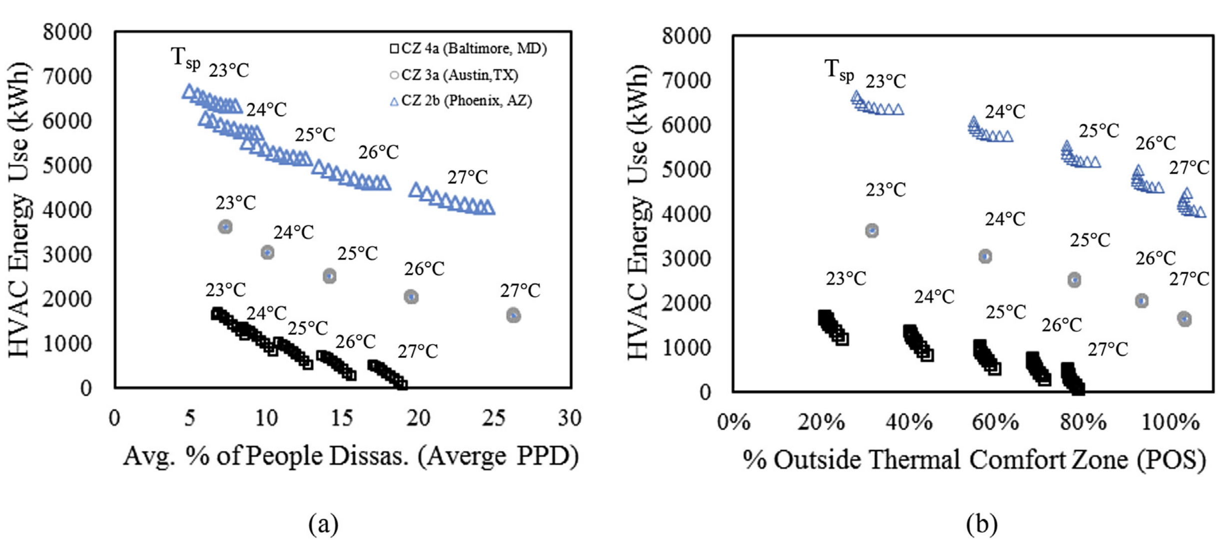


Fig. 6. HVAC energy use compared to the long-term thermal comfort indices *Average PPD*(a) and *POS* (b) for Climate Zone 4a (mixed-humid), 3a (hot-humid), and 2b (hot-dry). Note: Each cluster of points has a set point temperature as labeled; the variation in the values in the clusters is due to the change in degrees of setback temperature; a constant value for ACH of 0.4 h^{-1} and thermal capacitance of 35 kJ/°C-m^2 are used.

greatest in the hot-dry climate zone (2b) of the three climate zones studied. Compared to a constant set point temperature in which the temperature is constant even during on-peak times, the *Average PPD* increases 2%–4.5%, and the *POS* increases 5%–10%.

4) Probabilistic analysis demonstrates, based on the distributions of design variables of new, single family residential buildings, that the mixed climate zone will maintain a threshold 10% *Average PPD* more easily than the hot climate zones in the implementation of TOU pricing.
5) Regarding HVAC use, the set point temperature is an important influencing factor in all climate zones. A one degree increase in set point temperature decreases the HVAC energy use by 300–400 kWh (24–31%), 400–600 kWh (17–19%), and 500–600 kWh (9–10%) in climate zones 4a, 3a and 2b respectively. The decrease in HVAC energy use achieves the greatest energy savings in the hot-dry climate zone, but the largest percent savings in the mixed-humid climate zone.
6) HVAC use is negatively correlated with the *Average PPD* and *POS*, meaning a decrease in HVAC use increases the *Average PPD* and *POS*, negatively affecting occupants. In general the HVAC energy use decreases 100–130 kWh for each degree of increase in *Average PPD*, and 21 to 30 kWh decrease for each additional percent outside the thermal comfort zone (POS). This decrease in energy use per *POS* and *Average PPD* is highest in the hot-dry climate (2b) as compared to the other studied climates.
7) In choosing which thermal comfort index is appropriate for use in evaluating long term thermal comfort of the two studied, the *Average PPD* can capture a wider range of thermal discomfort as compared to the *POS*. *POS* also does not measure severity of the discomfort. Over an equivalent level of *Average PPD* of 26%, the *POS* is at 100%, after which any additional changes to the indoor environment will not be captured by this *POS* index.

The results of this research are helpful in understanding the influencing factors on occupant comfort for buildings operating under time-of-use pricing, and their relationship to HVAC use. This type of analysis could be used by utility companies to determine what the potential savings would be achieved in implementing smart thermostat-enabled time of use pricing schedule, and the anticipated effect on thermal comfort.

Acknowledgments

This work was supported by the National Science Foundation IGERT Grant no. DGE-0966298. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] N.E. Klepeis, W.C. Nelson, W.R. Ott, J.P. Robinson, A.M. Tsang, P. Switzer, W.H. Engelmann, The national human activity pattern survey (NHAPS): a resource for assessing exposure to environmental pollutants, J. Expo. Anal. Environ. Epidemiol. 11 (3) (2001) 231–252.
[2] L. Schellen, W.D. van Marken Lichtenbelt, M.G.L.C. Loomans, J. Toftum, M.H. De Wit, Differences between young adults and elderly in thermal comfort, productivity, and thermal physiology in response to a moderate temperature drift and a steady-state condition, Indoor Air 20 (4) (2010) 273–283.
[3] T. Akimoto, S.I. Tanabe, T. Yanai, M. Sasaki, Thermal comfort and productivity-Evaluation of workplace environment in a task conditioned office, Build. Environ. 45 (1) (2010) 45–50.
[4] United States Energy Information Administration, RECS, Residential Energy Consumption Survey, U.S. Department of Energy, Washington D.C., U.S.A, 2009.
[5] Electric Reliability Council of Texas (ERCOT) Hourly Load Data Archives, ERCOT Hourly Load Data, 2014. http://www.ercot.com/gridinfo/load/load_hist/.
[6] ASHRAE. ANSI/ASHRAE/IES Standard 90.1-2013, Energy Standard for Buildings Excet Low-rise Residential Buildings, 2013.
[7] P. Wattles, Demand Response and ERCOT Grid Reliability, Energy Efficiency Forum – Arlington, TX, May 23, 2012.
[8] G.R. Newsham, B.G. Bowker, The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: a review, Energy Policy 38 (7) (2010) 3289–3296.
[9] K.S. Cetin, P.C. Tabares-Velasco, A. Novoselac, Appliance daily energy use in new residential buildings: use profiles and variation in time-of-use, Energy Build. 84 (2014) 716–726.
[10] ASHRAE, Standard 55-2013 – Thermal Environmental Conditions for Human Occupancy, 2013.
[11] P.O. Fanger, Calculation of thermal comfort, introduction of a basic comfort equation, ASHRAE Trans. 73 (2) (1967). III-4.
[12] P.O. Fanger, Thermal Comfort, McGraw Hill, New York, 1972.
[13] International Standards Organization, ISO 7730 – Ergonomics of the Thermal Environment – Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria, International Organization for Standardization, Switzerland, 2005.
[14] EN 15251, Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings-addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics, 2006.
[15] S. Carlucci, S. Attia, Impact of different thermal comfort models on zero energy residential buildings in hot climates, Energy Build. 102 (2015) 117–128.
[16] S. Carlucci, L. Pagliano, A review of indices for the long-term evaluation of the general thermal comfort conditions in buildings, Energy Build. 53 (2012) 194–205.
[17] J.L. Hensen, R. Lamberts, Building Performance Simulation for Design and Operation, Spon Press, New York, 2012.
[18] B.W. Olesen, G.S. Brager, A better way to predict comfort: the new ASHRAE standard 55-2004, ASHRAE J. 8 (2004) 20–26.
[19] K.S. Cetin, L. Manuel, A. Novoselac, Thermal comfort evaluation for mechanically conditioned buildings using response surfaces in an uncertainty analysis framework, Sci. Technol. Built Environ. (2015), http://dx.doi.org/10.1080/23744731.2015.1100022 in press.
[20] S. Borgeson, G.S. Brager, Comfort exceedance metrics in mixed-mode buildings, in: Proceedings of Conference: Adapting to Change: New Thinking on Comfort Cumberland Lodge, Windsor, 2010.
[21] J.F. Nicol, J. Hacker, B. Spires, H. Davies, Suggestion for new approach to overheating diagnostic, in: Proceedings of Air Conditioning and the Low Carbon Cooling Challenge, Cumberland Lodge, July 2008, pp. 27–29. Windsor, UK.
[22] J.S. Sage-Lauck, D.J. Sailor, Evaluation of phase change materials for improving thermal comfort in a super-insulated residential building, Energy Build. 79 (2014) 32–40.
[23] G.E. Box, K.B. Wilson, On the experimental attainment of optimum conditions, J. R. Stat. Soc. Ser. B 13 (1) (1951) 1–45.
[24] V. Khalajzadeh, G. Heidarinejad, J. Srebric, Parameters optimization of a vertical ground heat exchanger based on response surface methodology, Energy Build. 43 (6) (2011) 1288–1294.
[25] S.C. Kang, H.M. Koh, J.F. Choo, An efficient response surface method using moving least squares approximation for structural reliability analysis, Probab. Eng. Mech. 25 (4) (2010) 365–371.
[26] B. Eisenhower, Z. O'Neill, V.A. Fonoberov, I. Mezić, Uncertainty and sensitivity decomposition of building energy models, J. Build. Perform. Simul. 5 (3) (2012) 171–184.
[27] S. Goyal, P. Barooah, A method for model-reduction of non-linear thermal dynamics of multi-zone buildings, Energy Build. 47 (2012) 332–340.
[28] W.J. Cole, E.T. Hale, T.F. Edgar, Building energy model reduction for model predictive control using OpenStudio, IEEE Am. Control Conf. (2013) 449–454.
[29] B. Yuce, H. Li, Y. Rezgui, I. Petri, B. Jayan, C. Yang, Utilizing artificial neural network to predict energy consumption and thermal comfort level: an indoor swimming pool case study, Energy Build. 80 (2014) 45–56.
[30] Y.C. Chang, J.T. Lu, Y.C. Liu, C.H. Wang, Using artificial neural network to execute demand response considering indoor thermal comfort and forecast load-shedding, Appl. Mech. Mater. 716 (2015) 1399–1408.
[31] A. Ashtiani, P.A. Mirzaei, F. Haghighat, Indoor thermal condition in urban heat island: comparison of the artificial neural network and regression methods prediction, Energy Build. 76 (2014) 597–604.
[32] S. Wilcox, National Solar Radiation Database 1991-2005 Update: User's Manual (No. NREL/TP-581-41364), National Renewable Energy Laboratory (NREL), Golden, CO, 2007. http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/.
[33] International Code Council, International Energy Conservation Code, 2009.
[34] R. Hendron, C. Engebrecht, Building America House Simulation Protocol, National Renewable Energy Lab, 2010.
[35] X. Fang, J. Winkler, D. Christensen, Using EnergyPlus to Perform Dehumidification Analysis on Building American Homes, 2011. NREL/JA-5500–49899.
[36] J. Woods, J. Winkler, D. Christensen, Moisture modeling: effectives moisture penetration depth versus effective capacitance, in: Thermal Performance of the Exterior Envelopes of Whole Buildings XII International Conference, 2013.
[37] Air Conditioning Contractors of America, Residential Load Calculations: Manuel J, 2011.
[38] K.R. Keeney, J.E. Braun, A simplified method for determining optimal cooling

control strategies for thermal storage in building mass, Int. J. HVAC&R Res. 2 (1) (1996) 1–20.
[39] K.R. Keeney, J.E. Braun, Application of building precooling to reduce peak cooling requirements, ASHRAE Trans. 103 (1) (1997) 463–469.
[40] G.P. Henze, D. Kalz, S. Liu, C. Felsmann, Experimental analysis of model-based predictive optimal control for active and passive building thermal storage inventory, Int. J. HVAC&R Res. 11 (2) (2005) 189–214.
[41] G.P. Henze, C. Felsmann, A.R. Florita, M.J. Brandemuehl, H. Cheng, C.E. Waters, Optimization of building thermal mass control in the presence of energy and demand charges (1313-RP), ASHRAE Trans. 114 (2) (2008) 75–84.
[42] M. Siemann, Performance and Application of Residential Building Energy Grey-box Models, University of Maryland, 2013. Dissertation.
[43] F.J. Offermann, Ventilation and Indoor Air Quality in New Homes, 2009. Califorina Energy Commission PIER Collaboration Report.
[44] Pecan Street Research Institute. Dataport: Residential Building Energy Consumption Database. https://dataport.pecanstreet.org/.
[45] U.S. Department of Energy. EnergyPlus Version 8.2 Energy Simulation Software. http://apps1.eere.energy.gov/buildings/energyplus/.
[46] R.H. Meyer, D.C. Montgomery, C.M. Anderson-Cook, Response Surface Methodology: Process and Product Optimization Using Designed Experiments, 2011.
[47] A.I. Khuri, S. Mukhopadhyay, Response surface methodology, Wiley Interdiscip. Rev. Comput. Stat. 2 (2) (2010) 128–149.
[48] J.M. Hammersley, D.C. Handscomb, Percolation Processes, Monte Carlo Methods Springer, Netherlands, 1964, pp. 134–141.
[49] C.A. Balaras, The role of thermal mass on the cooling load of buildings. An overview of computational methods, Energy Build. 24 (1) (1996) 1–10.
[50] P. La Roche, M. Milne, Effects of window size and thermal mass on building comfort using an intelligent ventilation controller, Sol. Energy 77 (4) (2004) 421–434.
[51] D.M. Ogoli, Predicting indoor temperatures in closed buildings with high thermal mass, Energy Build. 35 (9) (2003) 851–862.
[52] B.M. Berardi, E. Leonie, B. Marchesini, D. Cascella, G.B. Raffi, Indoor climate and air quality in new offices: effects of a reduced air-exchange rate, Int. Arch. Occup. Environ. Health 63 (4) (1991) 233–239.
[53] H.B. Rijal, P. Tuohy, M.A. Humphreys, J.F. Nicol, A. Samuel, J. Clarke, Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings, Energy Build. 39 (7) (2007) 823–836.
[54] M. Isaac, D.P. Van Vuuren, Modeling global residential sector energy demand for heating and air conditioning in the context of climate change, Energy Policy 37 (2) (2009) 507–521.
[55] K.S. Cetin, A. Novoselac, Single and multi-family residential central all-air HVAC system operational characteristics in cooling-dominated climate, Energy Build. 96 (2015) 210–220.
[56] H. Zhang, C. Huizenga, E.A. Arens, T. Yu, Modeling thermal comfort in stratified environments, in: Proceedings from Indoor Air, 2005, pp. 133–137. Beijing, China.
[57] D.P. Wyon, M. Sandberg, Vertical Temperature Gradients, Mean Room Temperatures and Their Effects on Thermal Discomfort, National Swedish Institute for Building Research, 1993.
[58] B.W. Olesen, M. Scholer, P.O. Fanger, Discomfort Caused by Vertical Air Temperature Differences, Indoor Climate, Danish Building Institute, Copenhagen, 1979.
[59] J.D. Rhodes, B. Stephens, M.E. Webber, Energy audit analysis of residential air-conditioning systems in Austin, Texas, ASHRAE Trans. 118 (1) (2012) 143–150.
[60] G. Henze, J. Pfafferott, S. Herkel, C. Felsmann, Impact of adaptive comfort criteria and heat waves on optimal building thermal mass control, Energy Build. 29 (2007) 221–235.
[61] L. Peeters, R. De Dear, J. Hensen, W. D'haeseleer, Thermal comfort in residential buildings: Comfort values and scales for building energy simulation, Appl. Energy 86 (5) (2009) 772–780.
[62] L.T. Wong, K.W. Mui, C.T. Cheung, Bayesian thermal comfort model, Build. Environ. 82 (2014) 171–179.