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QUANTIFYING THE INFLUENCE OF TEMPERATURE SETPOINTS, BUILDING AND SYSTEM FEATURES ON ENERGY CONSUMPTION

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ABSTRACT

HVAC systems are the major energy consumers in commercial buildings in the United States. Selection of setpoints impacts the amount of energy consumed by these systems. However, the influence of temperature setpoints on energy consumption and the potential energy savings are not yet fully identified. Through simulation this paper provides a systematic approach for quantifying the influence of different factors (i.e., construction category, climate, setpoint, and deadband) on building energy consumption. We implemented the approach on the medium-sized DOE reference office building of three construction categories in five climates using the EnergyPlus software. N-way ANOVA analysis ranked the factors as from the most influential to the least influential as: (1) construction category, (2) climate, (3) deadband, and (4) setpoint. Further analyses showed extending the deadband from 3 K to 6 K reduces energy consumption by 16.2%. Optimal annual setpoints varied across climates, and could lead to 6.63% average savings.

1 INTRODUCTION

Commercial buildings account for 18.9% of the energy consumption and 19.59% of the total greenhouse gas emissions in the United States (Book 2010; U.S. Energy Information Administration 2011). Heating, Ventilation, and Air Conditioning (HVAC) systems account for the largest share of the energy usage and gas emissions (43% of the commercial building energy consumption) (Book 2010; U.S. Energy Information Administration 2011). HVAC systems are primarily responsible for providing satisfactory thermal conditions and indoor air quality for building occupants. The common practice of defining operational settings for the HVAC systems is to use fixed setpoints, which assume occupants have static comfort requirements. However, it is proven that humans perceive comfort in a range of environmental thermal conditions (Nicol and Humphreys 2002). In addition, many dynamic environmental related variables (e.g., weather (Nicol and Humphreys 2002)) and human (e.g., acclimation related variables (Wenger 1988)) affect thermal comfort, and therefore, the individuals' thermal comfort ranges change over time (Guan et al. 2003; Jendritzky and de Dear 2009; Ghahramani et al. 2015). Given the range of comfortable conditions for an occupant, we can potentially control the service system to provide thermal conditions in that range while minimizing the overall energy consumption. However, there are several other factors, such as the building type and size, insulation and construction materials, HVAC system operation efficiency, climate, and occupant behavior, influence overall building energy consumption. The amount of energy savings related to comfort-aware HVAC setpoints with respect to different factors could be used as heuristics for building stakeholders to decide on the strategy for comfort-aware and energy-efficient HVAC operations (Ghahramani et al. 2014).

In this paper, we introduce a systematic approach for quantifying the effects of a number of factors (i.e., temperature setpoints, deadband, construction category, and the climate) on the overall building energy consumption. For our investigation, we used Department of Energy (DOE) Reference Commercial Building Models (Deru et al. 2011), which are EnergyPlus software simulation files. These models represent 70% of the commercial buildings stock in the United States. They provide the opportunity to compare different energy simulations with a baseline. In this study, we used medium-sized office and three construction categories (e.g., built after 2004, built after 1980 – before 2004, and built before 1980) in five locations (climate zones).

A review of the recent studies on quantification of the temperature setpoint influence on building energy consumption is presented in section 2. We introduce the systematical approach for identifying the influential factors on setpoint-energy consumption in section 3. The energy simulation models and simulation procedures are discussed in section 4. We present the results of the systematic approach in section 5. Section 6 provides a discussion on the generalization of the results and limitations of the simulation procedures. Finally, section 7 summarizes the results and concludes the paper.

2 LITERATURE REVIEW

HVAC system controllers often work with single temperature control loop (Freire et al. 2008; Haines and Myers 2009). A controller adjusts several internal variables to provide air with a certain flow and characteristics to keep the difference between thermostat readings with a setpoint in a certain range (i.e., half of a deadband value). The range around the setpoint at which no action is required from a system is called the deadband. HVAC systems, similar to any other mechanical system, require to have a non-negative deadband around the target setpoint to maintain stability. When the thermostat reading lies within the deadband range, the system only provides the minimum airflow to maintain acceptable air quality (ASHRAE Standard 62.1 (Ventilation for Acceptable Indoor Air Quality) (Standard)). The temperature at which the system begins heating is called the heating setpoint (associated with higher value on the deadband) and the temperature at which cooling starts is called the cooling setpoint (associated with lower value on the deadband). Previous research efforts have tried to quantify the influence of setpoints by extending the deadband (Hoyt et al. 2009; Hoyt et al. 2014). HVAC systems operate based on a single input / single output control logic (i.e., univariate control as opposed to bivariate control of both heating and cooling setpoints) (Haines and Myers 2009). Therefore adjusting solely the setpoint fits to this operation logic. In addition, heat transfer between a building and its environment works based on the heat gradient between indoor and outdoor environment and therefore, climate also influences the amount of energy consumption. Consequently, an energy saving technique, which performs well in a certain climate might not perform as well in another climate.

A study on the influence of widening deadbands on energy consumption of the medium-sized office DOE reference buildings built between 1980 and 2004 and built after 2004 was conducted by authors in (Hoyt et al. 2014). They carried out the study for 7 different cities (climate zones): Miami, Phoenix, Fresno, San Francisco, Baltimore, Chicago, and Duluth. The baseline setpoint range was 21.1 °C (heating setpoint) and 22.2 °C (cooling setpoint). The heating setpoint was extended to 17.7 °C and the cooling setpoint was extended to 30 °C. The results showed that through increasing the cooling setpoint of 22.2 °C to 25 °C, an average of 29% of the cooling energy and 27% of the total HVAC energy savings could be achieved. An 18.3-27.8 °C temperature range could save 32% to 73% of the total HVAC energy consumption depending on the climate. The authors also argued that the savings can be achieved through occupants' involvement in the control (Hoyt et al. 2014). The same authors in their previous studies (Hoyt et al. 2009) found that extending the setpoint range from 21.1-23.9 °C to 20.6-25 °C reduces between 13 to 28 % HVAC energy consumption on different types of medium-sized office buildings. In an another study on the large office DOE reference buildings (Fernandez and others 2012), the authors showed that extending the temperature setpoints range from 21.6 to 22.8 °C to 20.6 to 23.9 °C reduced the energy consumption by 9-20% depending on climate and time of the year.

Authors in (Kazanci and Olesen 2013) evaluated the effects of temperature setpoints and deadband on the HVAC system energy consumption and occupant thermal comfort in two cities (i.e., Copenhagen and Madrid). The setpoints ranged from 19 °C to 33 °C and the deadbands were ± 1 K and ± 2 K at 21 °C. The case study building was one story, single family house with an area of 66.2 m^2 and a conditioned volume of 213 m^3. The results showed that the deadband has a significant influence on the thermal comfort as they require occupants to adapt to a wider range of thermal environment. They also found that temperature setpoints have higher impacts on the energy consumption and the occupant thermal comfort. Potential 23% and 34% energy savings were realized during the heating season in Copenhagen and Madrid, respectively. In the cooling season, the potential savings were 17% and 10% in Copenhagen and Madrid, respectively. The authors concluded that understanding occupants actual comfort requirements is the key to use this potential savings from temperature setpoints.

However, these efforts have not statistically analyzed the savings from adjusting setpoints compared to other factors such as climate, construction category, and the deadband. In addition, there needs to be a systematic approach to help building stakeholders to compare the influence of different energy saving techniques.

3 METHODOLOGY

We followed a systematic approach for quantifying the influence of factors contributing to the HVAC energy consumption. In this approach, we first define the factors that must be studied. In this paper, we selected two control parameters (i.e., temperature setpoints, and the deadband), five climates (e.g., 2A: Houston, Texas – 3B: Los Angeles, California – 4A: Baltimore, Maryland – 5A: Chicago, Illinois – 6A: Minneapolis, Minnesota), and three construction categories (e.g., New construction (after 2004) Existing buildings (after 1980 – before 2004), Existing buildings (before 1980)). The detailed explanation of the climates and construction categories can be found in Section 4. Through defining the contributing factors, we identify the discrete (categorical) and continuous factors. In this case, two factors (i.e., climate, construction category) are discrete (categorical), and two factors (i.e., temperature setpoints and deadband) are continuous. However, in order to compare the significance of the factors on the energy consumption, we also need to discretize the continuous factors. Although there are various mathematical techniques for discretization, the granularity of discretized factors is highly dependent on the building stakeholder requirements. On the other hand, a more detailed analysis increases the computational cost by the order of parameters space size. In this paper, we study the setpoints and the deadband by assigning the granularity of 1 °C (i.e., K). We also define the range, in which the continuous parameters are likely to be chosen. This also depends on the consideration of occupant thermal comfort. In this study, we take the minimum and maximum temperature setpoints to be 19.5 and 26.5 °C, respectively. Considering a deadband of at a 6 K, the resulting cooling and heating setpoints covers a wide range of setpoints (16.5 °C to 29.5 °C, respectively). These setpoints are greater than values used in different studies (Hoyt et al. 2009; Hoyt et al. 2014; Fernandez and others 2012; Kazanci and Olesen 2013). For the deadband, we selected 2 K, 3 K (pre-set deadband on DOE reference buildings), 4 K, 5 K, and 6K. Various values of deadband can be studied based on stakeholders' preference, but values smaller than 2 K might be energy inefficient, and values greater than 6 K would require occupants to pursue individual adaptation procedures to perceive comfort. Table 1 summarizes all the conditions in which the simulation was carried out. As it can be seen there were 525 distinct cases for each permutation.

Table 1: Factors' categories used in the n-way ANOVA analysis.

Setpoint	Deadband	City (Climate)	Construction Category
19.5 °C	6K	Houston, Texas (2A)	New construction (after 2004)
20.5 °C	5K	Los Angeles, California (3B)	Existing buildings (after 1980 – before 2004)
21.5 °C	4K	Baltimore, Maryland (4A)	Existing buildings (before 1980)
22.5 °C	3K	Chicago, Illinois (5A)	
23.5 °C	2K	Minneapolis, Minnesota (6A)	
24.5 °C			
25.5 °C			

Through discretizing the continuous variables, we developed a set of feasible conditions that simulation models can provide insights into the factors' influence. The next step is to define the simulation period. Simulation models can be run for daily, monthly, seasonal, and yearly basis. The choice of the simulation period also depends on the stakeholder preferences. In this study, we set the duration to be a year. We chose a year period, because it includes climatic variations. Therefore, the results will not be biased to a specific season (e.g., hot season or cold season).

We then run the simulation models via a programming language (i.e., MATLAB software) for all permutations of factors. In order to do so, prior to the simulation for each permutation, we modify the building energy model file (i.e., .idf file). We search the model's text file for the location of the factor and replace the desired values in the location. The output of the simulation provides energy usage and other internal variables for one year on an hourly basis. For comparing the results of each permutation, we take the summation of all energy usage data and represent it as one value. In the summation process, we need to also consider the effects of simulation warm-up days, and we use a conservative warm-up days of 28 days (Garg et al. 2010).

Consequently, we have energy usage data for each permutation of factors. In order to understand the orderings of the factors, we use an N-way analysis of variance (ANOVA) to statistically analyze to influence of each factor. Through ranking the factors, we quantify how each factor contribute the overall energy consumption of the building.

In addition, we calculate the percentage difference of energy consumption over setpoints with respect to the baseline (setpoint: 22.5 °C, deadband: 3 K) for each construction category and city, and average them over cities to study influence of setpoints and deadband in each construction category. In order to understand which setpoint consume less energy in each city, we implemented a one-way ANOVA for the energy consumptions in a city and present the results in Section 6. We also calculate the percentage difference between average baseline energy consumption across different cities for each construction category to see how different building materials and characteristics would result in savings.

4 SIMULATION MODELS AND PROCEDURES

DOE divides office building energy simulation models into three categories based on the number of floors (small as single floor, medium as two to four floors, and large as more than four floors). The medium-sized buildings provided by DOE have three floors with floor-to-floor height of 3.96 m. The total floor area is 4,982 m^2 with the aspect ratio of 1.5. The glazing fraction is 0.33. The parking lot area is 8,067 m^2. The insulation for the roof construction is entirely above deck and the framing is steel frame for all three categories of the medium sized building. HVAC equipment for all construction categories are furnace for heating, packaged air-conditioned unit for cooling and single-zone constant air volume for air distribution. The occupancy measure was 18.6 m^2/person. Further information about the medium-sized building can be found in (Deru et al. 2011; Michaels and Leckey 2003).

The cities selected for this analysis were based on the weighting factors developed by authors in (Jarnagin et al. 2006), which were based on McGraw-Hill commercial building database. Weighting factors characterize the number of buildings that are similar to each reference building type in each location. Therefore, it allows the information from a reference building to be expanded to represent all buildings of this type in region or combined to represent the whole country (Deru et al. 2011). Due to the computational cost for simulation of buildings in different cities and the fact that we are only presenting the methodology of factor analysis in this paper, we selected five cities with highest weighting factors among the sixteen cities. These five cities are: Houston, Texas (climate: 2A), Los Angeles, California (Climate: 3B) – Baltimore, Maryland (Climate: 4A), Chicago, Illinois (Climate: 5A), Minneapolis, Minnesota (Climate: 6A). These cities represent the climate zones presented in Figure 1.

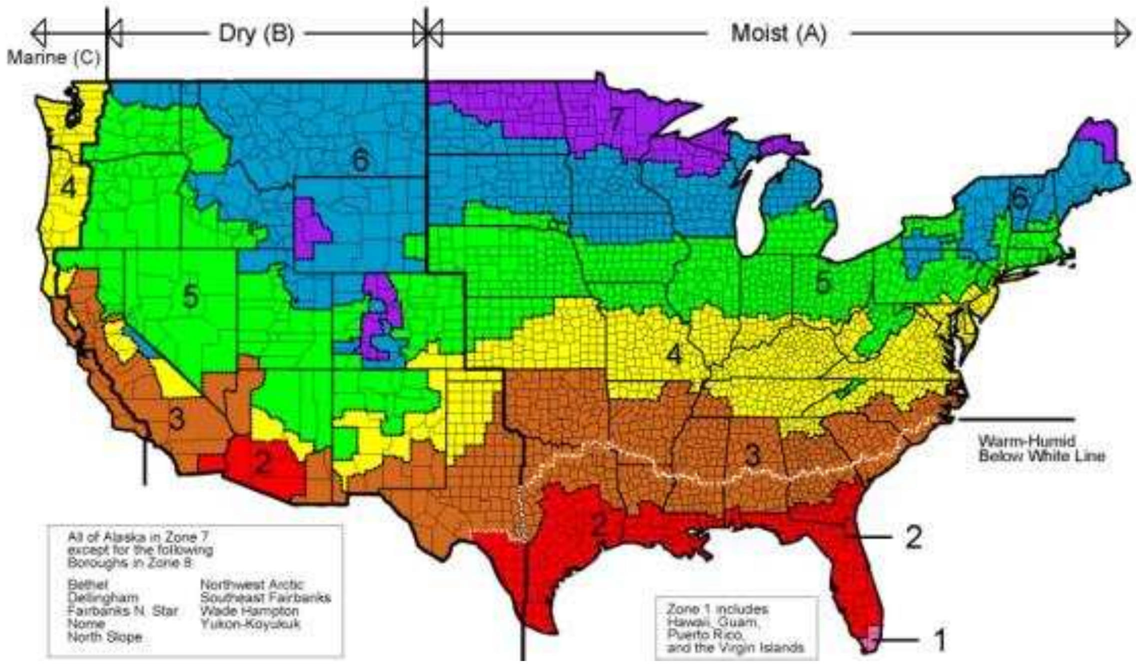

Figure 1: Climate zone classification ((Briggs et al. 2003).

The simulation models can be used in automated manner via programming language that can modify the text file (i.e., .idf file) of model and run the simulation. The simulation results are provided in several formats. One of the formats is CSV file that the programing language can process to calculate the sum of hourly energy consumption over the year. The simulation conditions (e.g., setpoint, deadband, city, construction category) are saved in a vector and associated with the sum in HVAC system and total building energy consumption.

5 RESULTS

The simulation results provide energy consumption over a year on an hourly basis. The daily HVAC system and the whole building energy consumption for a sample city (i.e., new construction (after 2004) in Minneapolis, Minnesota) over a year (with elimination of the first 28 days as described in Section 3) is presented in Figure 2. The baseline setpoint (22.5 °C) and deadband (3 K) were used in the simulation results provided in Figure 2. Whole building energy consumption includes all the electricity and gas used by in the building (e.g., lighting systems, HVAC system, and appliances). Figure 2 includes energy consumption for weekdays, weekend, and holidays. Therefore, there are days that HVAC did not consume any electricity or gas. There is no gas consumption during several days as gas is only used for heating.

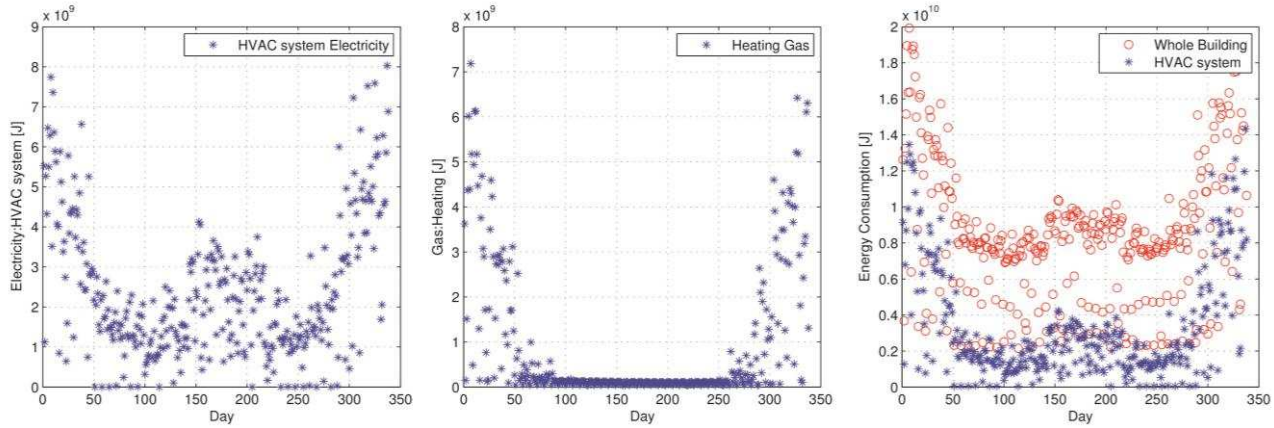

Figure 2: (a): HVAC system electricity use, (b) HVAC heating gas use, and (c) HVAC system (sum of HVAC electricity and gas) and whole building energy consumption for a medium-sized building in Minneapolis, Minnesota.

For a better presentation of daily energy consumption, we use average daily outside temperature. Figure 3.a present the daily energy consumption of Figure 2.c with respect to average daily outside temperature. In Figure 3.b we compare daily HVAC energy consumption of different construction categories in order to understand how construction categories influence the energy consumption. As it can be seen in the Figure 3.b, the newer the buildings, the smaller the energy consumption.

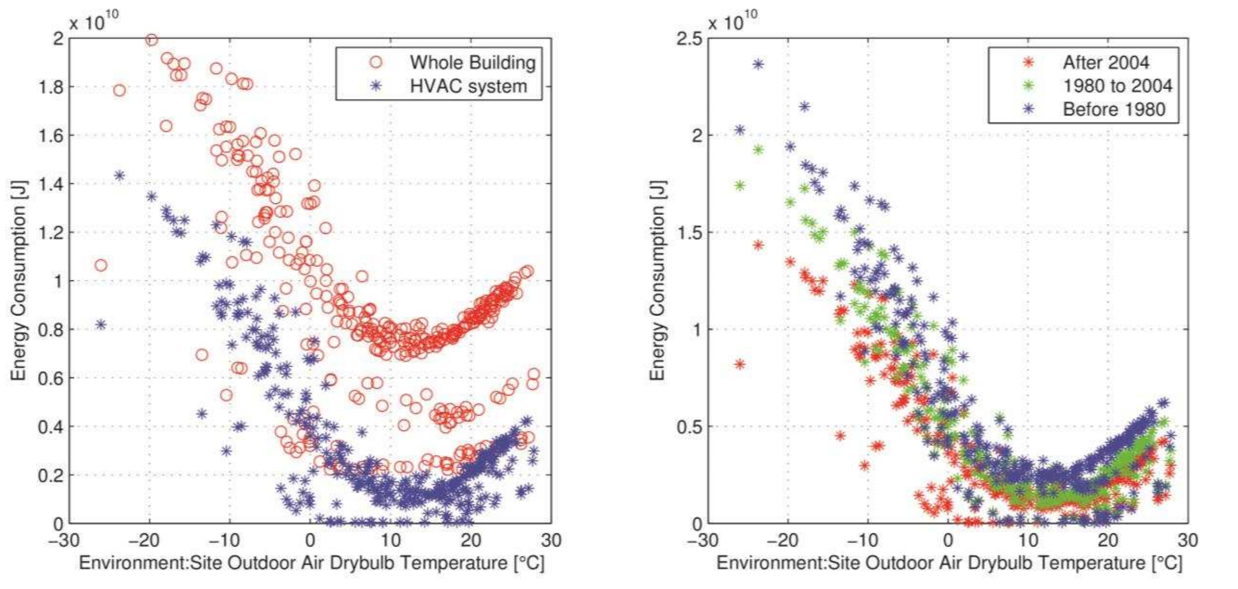

Figure 3: (a) HVAC system and whole building energy consumption with respect to outside temperature (b) HVAC energy consumption for different construction categories in the baseline setting.

Then we simulated 525 permutations and performed an n-way ANOVA analysis on the results. The factors which have p-values below 0.05 have an influence on the energy consumption with 95% probability. In addition, the smaller the p-value, the greater the importance of factor on the target variable. Table 2 summarizes the results of the ANOVA analysis for the HVAC system.

Table 2: N-way ANOVA results for different factors on the HVAC energy consumption.

Factor	F	p-value
Setpoint	25.45	$1.80*10^{-26}$
Deadband	103.34	$2.42*10^{-64}$
Climate	558.10	$2.52*10^{-184}$
Construction Category	1042.11	$1.65*10^{-180}$

Through comparison of the values of F values (i.e., statistical significance of factors) from ANOVA, the ranking of the influential factors from large to small are recognized: (1) Construction Category, (2) Climate, (3) Deadband, and (4) Setpoint. In order to better understand the influence of each factor on the HVAC energy consumption, we calculated the percentage difference between the average consumptions over different climates for each construction category with respect to the setpoints and deadbands (Tables 3, 4, and 5). Compared to the baseline (22.5 °C and 3K), selecting 19.5 °C, 20.5 °C, 21.5 °C, 23.5 °C, 24.5 °C, 25.5 °C as the setpoint would result in the following average percentages of energy usage for all construction categories and cities, respectively: 15.93%, 8.21%, 3.05%, -0.94%, 0.31%, and 3.01%. As the ANOVA analysis demonstrates, the deadband contributes more to the energy consumption rather than static setpoints. 3 K to 2 K, 4 K, 5 K, and 6 K would lead to 8.88%, -6.67%, -11.94%, and - 16.2% of average energy usage change in all construction categories, respectively.

Table 3: Percentage difference between average of HVAC energy consumption of different cities for new construction (after 2004).

	2K	3K	4K	5K	6K
19.5 °C	22.28	9.45	0.82	-5.34	-9.92
20.5 °C	15.59	4.03	-3.68	-9.35	-13.73
21.5 °C	12.05	1.19	-6.28	-11.70	-15.78
22.5 °C	10.33	0(baseline)	-7.12	-12.32	-16.21
23.5 °C	10.55	0.71	-6.25	-11.28	-15.13
24.5 °C	12.86	3.32	-3.64	-8.96	-13.93
25.5 °C	17.49	7.74	-0.31	-6.59	-11.49

Table 4: Percentage difference between average and standard deviation of HVAC energy consumption of different cities for existing buildings (after 1980 – before 2004).

	2K	3K	4K	5K	6K
19.5 °C	23.22	11.28	2.79	-3.67	-8.70
20.5 °C	17.24	5.97	-2.16	-8.33	-13.12
21.5 °C	12.91	2.19	-5.58	-11.43	-15.92
22.5 °C	10.07	0(baseline)	-7.33	-12.85	-17.15
23.5 °C	9.03	-0.32	-7.36	-12.75	-17.03
24.5 °C	10.19	1.17	-5.77	-11.34	-15.54
25.5 °C	13.40	4.36	-2.37	-7.37	-11.39

Table 5: Percentage difference between average and standard deviation of HVAC energy consumption of different cities for existing buildings (before 1980).

	2K	3K	4K	5K	6K
19.5 °C	36.79	27.06	18.56	10.78	3.90
20.5 °C	22.80	14.62	7.38	0.84	-5.00
21.5 °C	12.81	5.78	-0.50	-6.11	-11.16
22.5 °C	6.23	0(baseline)	-5.57	-10.65	-15.25

23.5 °C	2.61	-3.22	-8.44	-13.09	-17.35
24.5 °C	1.35	-4.18	-9.16	-13.65	-17.38
25.5 °C	2.44	-3.07	-7.70	-11.79	-14.98

The optimal annual setpoints for each city are presented in Table 6. Optimal setpoints are the setpoints that had the average lowest energy consumption across all the permutations of factors for each city. As it can be seen, the cities belonging to colder climates would consume less energy in relatively lower setpoints, but not necessarily at the lowest setpoint (i.e., 19.5 °C). The savings with respect to the baseline vary for different cities. The average savings were 6.63 %. In warmer climates such as 2A and 3B the savings are considerably greater.

Table 6: Optimal annual setpoints for different cities.

City (Climate)	Optimal Setpoint	Reduction with respect to 22.5 °C
Houston, Texas (2A)	25.5 °C	-14.41
Los Angeles, California (3B)	25.5 °C	-16.94
Baltimore, Maryland (4A)	23.5 °C	-0.79
Chicago, Illinois (5A)	22.5 °C	0
Minneapolis, Minnesota (6A)	21.5 °C	-0.99
Across all cities	22.5 °C	-6.63

In Table 7, the results for influence of construction category with respect to a baseline (i.e., before 1980) in each city are presented. As it can be seen, in average, retrofitting a building similar to buildings from before 1980 to buildings from 1980 to 2004 and after 2004 would considerably reduce energy consumption. The ANOVA results showed that construction category has the largest influence (Table 2). However, the costs associated with the retrofits might also be considerable. The selection of energy savings techniques are made by the building stakeholders and are not included in the scope of this study.

Table 7: Construction category energy consumption reduction percentage in different cities (baseline: before 1980).

City (Climate)	Existing buildings (after 1980 – before 2004)	New construction (after 2004)
Houston, Texas (2A)	30.87	76.51
Los Angeles, California (3B)	90.57	106.58
Baltimore, Maryland (4A)	31.02	83.23
Chicago, Illinois (5A)	38.54	67.06
Minneapolis, Minnesota (6A)	30.81	60.76
Across all cities	44.36	78.83

6 DISCUSSION

The statistical analysis presented in Section 5 are based on the annual energy consumption. However, we noted weather variations throughout a year highly influences the energy consumptions based on the setpoints. In other words, setting a high setpoint (i.e., 25.5 °C) would relatively consume less energy than baseline setpoint (i.e., 22.5 °C) in warm-hot seasons and consume relatively more energy than the baseline setpoint that in cool-cold conditions. In Figure 5, daily energy consumption for different setpoints with respect to daily outside temperature for a sample city (i.e., Minneapolis, Minnesota) for the baseline deadband (3 K) is presented.

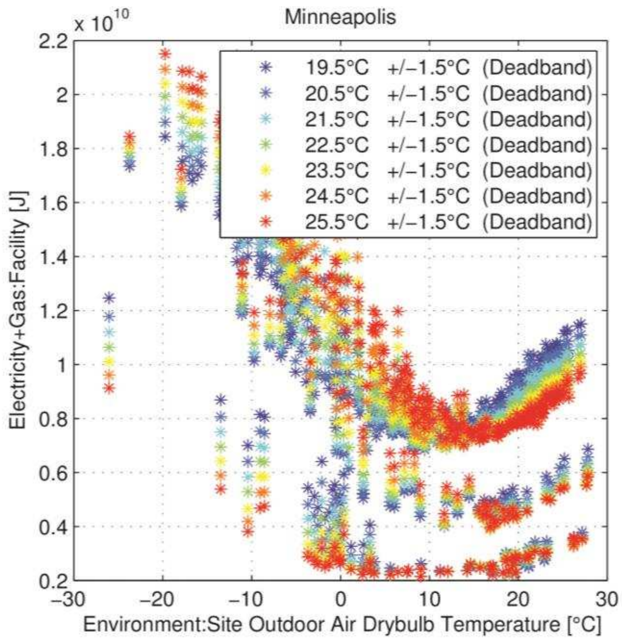

Figure 5: Daily energy consumption for different setpoints with respect to daily outside temperature for a sample city (i.e., Minneapolis, Minnesota) for the baseline deadband (3 K).

As it can be seen in Figure 5, selecting seasonal or daily setpoints can lead to energy consumption reduction although the sum of the energy consumption for different setpoints might not differ much. In other words, selecting daily setpoints for the HVAC system can lead to higher savings than solely setting a temperature setpoint for the entire year. Learning the optimal daily setpoint for a building, the interactions between the zones for selecting optimal zone-level setpoints, and how the potential savings from this approach would be ranked with respect to other factors (e.g., deadbands, climate, construction category) require further explorations which we plan to pursue it in a future study. In addition, we only studied 5 climates in this paper. We plan to extend our study to all 16 climates provided by the DOE as part of the reference buildings as well as to all types of office buildings (e.g., small, medium, and large office buildings). In these simulations, the effects of occupants were assumed to be constant as also defined in DOE models. However, occupancy presence, behaviors, and associated heat loads (Khosrowpour et al. ; Yang and Becerik-Gerber 2015; Yang and Becerik-Gerber 2014) also need to be studied in accordance with other factors. Moreover, we used a conservative warm-up period of 28 days as explained in Section 3. However, selection of the period can occur autonomously. We leave the process for measuring the number of warm-up days from simulation results to a future study. Furthermore, although learning the relationship between optimal setpoints and outside temperatures and the associated energy savings can lead the more energy efficient and comfort driven HVAC operations, it is not often feasible to implement an exhaustive search in real buildings HVAC controllers for learning optimal setpoints due to time, occupants comfort, and resource constraints. Therefore, one of future research steps in this research is the techniques for learning the optimal setpoints curves in real buildings.

7 CONCLUSIONS

There is a trade-off between the costs of implementing different energy retrofitting techniques and potential savings for HVAC systems in commercial buildings. Therefore, quantifying the potential savings from various retrofitting techniques can be used as heuristics for building stakeholders to make decisions. In this paper, we introduced a systematic approach to compare influential factors through the use of building energy simulation. As a demonstration, we compared 4 factors (i.e., temperature setpoint, deadband, city (climate), construction category) that potentially influence the energy consumption for a DOE reference medium-sized office building. Through simulations for each permutation of factors, their influence on HVAC energy consumption are ranked as the following from large influence to small influence: (1) construction category, (2) city (climate) (3) deadband (4) setpoints. In average, renovating a building with technologies from before 1980 to technologies and characteristics of buildings after 1980 to 2004 and after 2004 would lead to - 44.36 % and - 78.83% energy usage change, respectively. In average, variations of the deadband from 3 K to 2 K, 4 K, 5 K, and 6 K would lead to 8.88%, -6.67%, -11.94%, and - 16.2% energy usage change, respectively. Among the setpoints, 23.5 °C consumed the lowest energy consumption annually for all building types and climates. Compared to the baseline (22.5 °C), 19.5 °C, 20.5 °C, 21.5 °C, 23.5 °C, 24.5 °C, 25.5 °C had 15.93%, 8.21%, 3.05%, -0.94%, 0.31%, and 3.01% average energy usage change. Optimal annual setpoints differed between the studied climates, and results showed potential average energy usage change of - 6.63%. However, as explained in the discussion section, we observed that annual selection of a setpoint could be very energy inefficient. We plan to study the potential savings from a daily and seasonal setpoint selection strategy in our future research.

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