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Energy Trade Off Analysis Of Optimized Daily Temperature Setpoints

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Abstract

We introduce a systematic approach for analyzing the energy consumption of four control policies (i.e., zone level daily optimal control, zone level annual optimal control, building level daily optimal control, building level annual optimal control), which differed based on their temporal and spatial control scales. In order to integrate occupant thermal comfort requirements, we defined uniformly distributed random constraint functions on the setpoints. We used the DOE reference small office building in three U.S. climate zones for simulating the performances of control policies, using EnergyPlus. Among the four control policies, the building level annual control policy showed close to the highest energy efficiency (27.76% to 50.91% (average of 39.81%) savings depending on the climate) with comparatively small training data requirements. In addition, the building level daily optimal setpoint selection, subject to thermal comfort constraints, leads to 17.64 – 38.37% (average of 26.61%) energy savings depending on the climate. We also demonstrate that temporal scale of the policies have a statistically significant impact on the small office building's energy consumption while spatial scale's impact is insignificant.

Keywords: HVAC system; setpoint control; building energy optimization; spatiotemporal scale; occupant comfort; optimal control

1. Introduction

Commercial and residential buildings account for approximately 30% of the total energy consumption in the world and contribute substantially to the climate change, i.e., 30% of the global greenhouse gas emissions [1]. This share is larger (about 40% of the total energy consumption [2] in the developed countries. The growth in the population, the increasing demand for better building services and improved comfort, in addition to the rise in the time spent in buildings, result in an ever increasing building energy consumption [3]. HVAC systems, which are responsible for providing comfortable thermal conditions and acceptable air quality in buildings, account for the largest share in energy usage and gas emissions (about 50% of the consumption in the developed countries [3]

Majority of the HVAC system controllers work with a negative feedback control loop based on indoor air temperature [4, 5]. In this control logic, the error between a target state (i.e., a temperature setpoint) and the feedback (i.e., a thermostat reading) should not exceed a threshold (i.e., deadband).

HVAC systems often use fixed control parameters in compliance with the standards (e.g., ASHRAE Standard 55 [6], ASHRAE Standard 62.1 [7]), which assume thermal comfort is static over time. However, it has been shown that dynamic environmental variables (e.g., outside temperature [8]) and user related variables (e.g., physical acclimation [9]) influence thermal comfort, making it dynamic over time [10-13]. For example, occupants prefer higher setpoints in the summer compared to the winter [11], and buildings also consume less energy at higher setpoints in the summer compared to the winter. Therefore, smart selection of higher setpoints in the summer and lower setpoints in the winter provide an opportunity to not only conserve energy, but also improve thermal comfort. However, it is important to note that the highest or lowest setpoints are not always the most energy efficient setpoints [14, 15].

In a previous study, we demonstrated that a control policy that selects optimal setpoints on a daily basis with a fixed spatial scale (i.e., one setpoint for the entire building) considerably reduces the energy consumption compared to a control policy that selects an optimal setpoint on an annual scale [14]. The savings ranged from 6.78 to 37.03% depending on the climate and building size with an average of 16.4%. However, consideration of the impact of other factors on HVAC performance, such as the internal heat exchange between the zones, might provide opportunities to optimally select zone level optimal control parameters to improve the energy efficiency at the building level. Therefore, a control policy that optimizes the HVAC performance on a daily basis at the zone level could potentially improve the overall building energy efficiency. In addition, imposing thermal comfort constraints on the selection of the optimal control parameter selection impacts the effectiveness of the control policies. Understanding the impacts of spatial (i.e., building level and zone level) and temporal (i.e., annual and daily) scales of the controllers on the overall HVAC system energy consumption under thermal comfort constraints is the primary gap explored in this paper.

Thus, we introduce a systematic approach for analyzing four control policies, which differ based on their temporal and spatial scales: (1) building level annual optimal control policy, (2) zone level annual optimal control policy, (3) building level daily optimal control policy (introduced and validated in a previous study [14]), and (4) zone level daily optimal control policy. The first and the third control policies assign optimal control parameters at the building level, while the second and fourth operate at the zone level. Therefore, the focus of this study is to compare optimization of a single value for a cluster of setpoints with multiple values for setpoints. The first and second control policies select optimal parameters on an annual basis, while the third and fourth policies select optimal parameters on a daily basis. In order to represent the impact of personal comfort on these control policies, we used a uniformly distributed noise generating function to simulate occupants comfort and constraint the optimal control parameters and compared the energy consumption of these control policies with each other. We used the small size office building reference simulation model developed by the Department of Energy (DOE) [16] for comparing the four control policies in three United States climate zones.

The paper is organized as follows. A review of the recent studies on optimal controllers and control policies for comfort driven HVAC operations is presented in Section 2. We explain the design and implementation of the four control policies, discretization of the simulation factors, and data analysis in Section 3. We present the energy simulation models and procedures in Section 4. Section 5 provides the results of the comparison of the four control policies. Limitations on the generalization of the findings and future steps of the research are presented in Section 6. Finally, Section 7 provides a summary of the results and conclusions of the paper.

2. Literature review

An HVAC thermal zone level controller operates based on two control parameters defined as a setpoint (target value) and deadband (performance relaxation range around the setpoint). The higher value on the deadband is referred to as the cooling setpoint and the lower value on the deadband is referred to as the heating setpoint. Extending both heating and cooling setpoints increases the deadband. Since it is well known that maximizing the deadband always results in energy efficiency because it increases the no-operation margin around the setpoint, this paper focuses on the smart selection of setpoints rather than the impact of increasing the deadband.

Control policies for optimizing HVAC setpoints can be divided into two categories: (1) control policies that are complementary to the existing HVAC control logic and that influence the performance of HVAC systems by solely adjusting the indoor air temperature setpoints [14, 17, 18], and (2) operational policies that intervene existing HVAC control logics (e.g., order, condition, and loop) and that require the dynamic control of local subsystems [19]. In this paper, we focus on the techniques in the first category due to the fact that these techniques could be easily generalized, they work for any type of HVAC system and do not require a model of an HVAC system (making them model free). However, optimizing the operation of HVAC systems solely for setpoints might result in thermally uncomfortable conditions for building occupants. For example, an occupant might prefer a cool environment while the optimal control parameters result in a much warmer thermal environment than the desired level. Therefore, we also narrowed down our review to the techniques that allow for integration of dynamic personal thermal comfort requirements into HVAC control loop.

Researchers have proposed various personalized and real-time comfort sensing approaches, which can potentially be used in existing buildings. A model predictive control (MPC) optimization environment, introduced in [20], couples the environment to a building automation system, allowing real-time optimization, considering operator overrides and updated weather forecasts to predict optimal building control strategies. Through determining hourly HVAC cooling setpoints and supply water temperature for minimizing the daily energy cost, 5 to 54% energy savings and improvement in occupants' comfort were achieved. The setpoints were fixed across the building systems and only varied over time (i.e., temporal scale). Authors of [17] developed a multi-objective genetic algorithm for optimizing a building's mechanical systems performance. The optimization algorithm operates complementary to a building's central control system. The optimization process strives to maximize energy efficiency and thermal comfort by searching the supervisory control strategy setpoints, such as supply air temperature, supply duct static pressure, chilled water supply temperature, minimum outdoor ventilation, reheat (or zone supply air temperature). HVAC system steady-state models, developed and validated against the monitored data of the existing VAV system, were used for energy use and thermal comfort calculations. Comparing actual and optimal energy use, the authors demonstrated that the proposed control strategy could save energy by 16% for two summer months while satisfying minimum zone airflow rates and zone thermal comfort. It was then concluded that the proposed control strategy with required constraints could improve the operating performance of the existing HVAC system. Similar to the previous study, the setpoints were uniform across building for each subsystem and it solely varied over time (i.e., temporal scale). A methodology for optimizing building supervisory control in simulation has been introduced in [21]. Their stochastic model predictive control (SMPC) architecture is capable of incorporating different levels of variability in building performance due to occupant behavior and provided control setpoints which lead to more conservative building performance. A set of time windows enabled the use of complex building models in energy simulations. The case study results showed that stochastic optimization led to a more conservative and more reliable 33% performance improvement compared to the 50% performance improvement of deterministic optimization. Similar to two previous studies, the setpoints were uniform across the building for each subsystem and it solely varied over time (i.e., temporal scale). Authors in [22], applied computational intelligence algorithms to solve the non-parametric model for minimization of HVAC energy consumption and room temperature ramp rate Through real-world implementation of the methods, their results indicated that particle swarm optimization and harmony search algorithms are suitable for solving the proposed optimization model. The computational results demonstrated that energy savings could be achieved by optimizing the settings for the supply air static pressure set point and discharged air temperature set point on a temporal scale. Authors in [23] applied a novel control method using multi-dimensional interpolation between optimized control configurations for various steady-state load distributions on a system with arbitrary steady-state and transient load distributions. Applying the method on a two-room HVAC system predicts power savings for an arbitrary steady load that is nearly equivalent to that using a Variable-Air-Volume air condition system with chiller modulation. However, the new method provides 19% energy savings over an uncontrolled system compared to energy savings of 6% for a VAV with chiller modulation for arbitrary transient loads. This method applied the control strategy mainly on a spatial scale and did not consider the implications of temporal scale.

Although extensive research has been conducted to improve HVAC system energy efficiency through customizing the control of setpoints based on comfort requirements, all of the above mentioned studies have focused either on the temporal control scale or on the spatial control scale-- not on both temporal and spatial control scales simultaneously [24]. Understanding the impacts of both temporal and spatial scales in an integrated control policy would shed light on the type of overall architecture of control policies that provide higher efficiencies as it helps clarifying the trade-off between a controller complexity in terms of control nodes on a spatial scale and commands per unit time on a temporal scale. Optimizing the energy efficiency of HVAC systems, by finding the optimal control parameters, could be studied via hourly, daily, seasonal, or annual (i.e., temporal scale) or at the zone level and at the building level (i.e., spatial scale). In this paper, we focused two extreme temporal scales (i.e., daily and annual) and assessed the energy implications of spatiotemporal scales of an optimal HVAC control policy briefly described in an earlier effort [14] under dynamic factors, such as weather variations and the simulated occupants thermal comfort constraints.

3. Methodology

To address the above mentioned gap, we first define the control policies based on temporal and spatial control scales. For the temporal scale, we selected two levels for the comparison: annual scale and daily scale. In the annual scale, the setpoint that minimizes the energy consumption for the entire year is selected. In the daily scale, the setpoints, which minimize the energy consumption on a daily basis, are selected and may vary over time due to the impact of dynamic factors. For the spatial scale, we selected two levels for the comparison: building level and zone level. At the building level, a single setpoint that minimizes the energy consumption for the entire building is selected, while at the zone level, a vector of zone setpoints that minimizes the total building energy consumption is selected. Consequently, four control policies are formulated as: (1) building level annual optimal control policy, (2) zone level annual optimal control policy, (3) building level daily optimal control policy, and (4) zone level daily optimal control policy. We followed a systematic approach for quantifying the energy consumption of these control policies. We then compared these control policies to a baseline control policy where the setpoint and the deadband are fixed to 22.5 °C and 3K, respectively, for the entire year during the on-hour mode for all of the zones in a building. Accordingly, for the baseline control policy, the heating and cooling setpoints were established as 21 °C and 24 °C, respectively. These control parameters are also the default values on the reference building models provided by the DOE.

As previously mentioned, the previous research has shown extending the deadband would in all cases reduce the energy consumption as it relaxes the system operations [14, 25]. Consequently, we only study the zone level air temperature setpoints as the control parameters to find the optimal settings. Since setpoint is a continuous variable, we need to first discretize it. Although the granularity of the setpoint as a variable improves the control performance and savings, it also increases the computational costs. For our investigations, we selected 1 °C as the granularity for the setpoints. The setpoints space range was selected as 19.5 to 25.5 °C. These setpoints span a wider range than the ranges studied in existing studies [26, 27].

We specifically focus on the office buildings due to the fact that office buildings have the largest share of commercial building stock in the United States both in terms of number (18%) and the floor space (18%) [28]. In addition, office buildings accommodate 38% of total occupants in commercial buildings [28]. The small office buildings, provided by the DOE as one type of reference buildings, has five zones. Therefore, we have 7 (number of setpoints)^5(number of zones) (i.e., 16,807) cases of zones/setpoints combinations for a small size office building. In order to reduce the number of simulations to be carried out we narrowed down the climates from 16 to 3 (i.e., a hot climate (Miami, Florida (1A)), a mild climate (Chicago, Illinois (5A)), and a cold climate (Fairbanks, Alaska (8)). We focused on the buildings that were built after 2004, as they are in compliance with the new building control standards, which allow for the technology for autonomous zone level setpoints selection to be implemented. In other words, the control policies, studied in this paper, require building management systems to allow for dynamic assignment of temperature setpoints. The reference building model was assigned with different schedules, based on weekdays (HVAC system operations from 6:00 AM to 10:00 PM), Saturdays (HVAC system operations from 9:00 AM to 5:00 PM), and Sundays and holidays (HVAC system is off the entire day). Due to the influence of occupancy on the system performance [29], we only used the weekdays in this analysis.

Simulation duration also plays an important role on validity and generalizability of the results. The DOE has provided a 1 year simulation period built in their simulation models. However, simulation models can be used for a shorter duration (e.g., daily, monthly, and seasonal) depending on the desired functionalities, which are determined based on the building stakeholder priorities. Since we are interested in the whole building energy consumption comparison, one-year duration was assigned on the simulation models for all conditions to eliminate the bias to a hot season or cold season. We run the energy simulations via MATLAB programming language for all combinations of factors. We located the factors in the building energy simulation model file (.idf file) and replaced them with the target values for each combination. The simulation outputs included energy consumption, internal and external variables for the entire simulation period on an hourly basis. We excluded the first 28 days of the simulations due to the effects of warm-up days [30], which is the period EnergyPlus uses to tune and calibrate the internal model parameters.

The next step after running the simulations and storing the results is the comparison of the energy usage for the four mentioned policies to the baseline. Simulations provide daily energy consumption as a function of the setpoint. In each control policy, the setpoints that minimize the energy consumption based on the objective function (Table 1), were selected and the associated value of the objective functions were stored in a database.

Table 1. Optimal setpoint calculation for control policies

Control Policy	Spatial	Temporal	Optimal setpoint calculation
1	Building level	Annual	$\sum_{i=1}^{n} E_i(sp)$
2	Zone level	Annual	$\sum_{i=1}^{n} E_i(sp)$
3	Building level	Daily	$\sum_{i=1}^{n} E_i(sp)$
4	Zone level	Daily	$\sum_{i=1}^{n} E_i(sp)$

Where, E_i is energy consumption of building for day i and it is either a function of a scalar setpoint (sp) for building level control policies or vector setpoint (sp) for zone level control policies. n is the number of days. In all of the control policies, the optimal setpoints were calculated through an exhaustive search of the setpoint-building energy space, which was derived via extensive simulations.

As mentioned before, it is necessary to explore the sensitivity of these four policies to comfort requirements. Here, we construct our constraint-generating method based on two facts: (1) humans adapt to weather variations over seasons and consequently they prefer higher setpoints in the summer compared to the winter [11], and (2) buildings also consume less energy at higher setpoints in the summer compared to the winter [27]. These facts suggest that we can model potential comfort preferences using a deviation from the optimal setpoints of the building. In other words, if the optimal setpoint for a certain day in the summer is high (a value in the acceptable range is defined), the occupants thermal comfort can be modeled as a deviation from that optimal setpoint. We define a uniformly distributed distribution as a deviation level (σ) for representing the amount of deviation of occupant preferences from the optimal setpoints. Accordingly, we studied the impact of varying σ for 0, 1, 2, 3, and 4 °C. 0 °C represents no integration of personal comfort requirements into the control loop. 4 °C is the highest value and since it is symmetrical around the setpoint, it covers a range of 8 °C. We chose to limit our investigations to 4 °C as occupants are less likely to perceive comfort beyond 8 °C range around the setpoint. The constraint function follows a uniformly distributed probability distribution function. This distribution is conservative, as it assigns similar probabilities to any deviation values. In order to calculate the energy consequences of enforced constraints, we used the optimal setpoints (Table 1) and applied the constraints in terms of uniformly distributed deviations from the optimal setpoints. Table 2 demonstrates the formulation of the energy metrics for the comparison of the control policies. Since the comfort constraints are at the zone level, we used the same optimal setpoint in the case of control policies 1 and 3 for all of the zones. Consequently, we applied the zone level comfort constraints for all of the control policies.

Table 2. Energy metrics for the comparison of the control policies

Control Policy	Spatial	Temporal	Energy Metric
1	Building level	Annual	$\sum_{i=1}^{n} E_i(sp^{opt} + \sigma)$
2	Zone level	Annual	$\sum_{i=1}^{n} E_i(sp^{opt} + \sigma)$
3	Building level	Daily	$\sum_{i=1}^{n} E_i(sp_i^{opt} + \sigma)$
4	Zone level	Daily	$\sum_{i=1}^{n} E_i(sp_i^{opt} + \sigma)$

Next, we studied the impacts of four potentially influential factors (i.e., control policy spatial scale, control policy temporal scale, thermal comfort constraints, and the climate) on the annual energy consumption. Control policy spatial scale is a categorical variable with two states (i.e., building level and zone level). Control policy temporal scale is also a categorical variable with two states (i.e., annual and daily). Thermal comfort constraints can be modeled as an integer variable holding five states associated with different values of σ: 0, 1, 2, 3, and 4 °C. Climate is a categorical variable holding 3 states (i.e., Miami, Chicago, and Fairbanks). We used an n-way analysis of variance (ANOVA) to statistically quantify and compare the impacts of the factors. The p-value from an ANOVA analysis varies between 0 and 1 and tests the null hypothesis that the data from all the factors (variables dimension) have a statistically significant impact on the energy consumption. The F-values (ratio of the mean squares of the factors) and the degrees of freedom from the ANOVA analysis are used to calculate the P values. The larger the F value, the higher probability that the variation among factor means could not have happened by chance, and consequently the greater the importance of the factor on the energy consumption. Standard deviations of energy consumption based on the factors and percentages of deviation with respect to the average energy consumption were calculated to better understand the impact of the factors. The larger the deviation, the higher the impact of the factor have on the energy consumption.

4. Simulation models

The small office building is a single floor building with five thermal zones. The temperature in each zone is controlled by a thermostat. The total floor area of the building is 511 m^2 with an aspect ratio of 1.5 and the floor-to-floor height is 3.05 m. The windows glazing fraction ratio is 0.21. The roof of the building is completely insulated above the deck and the roof insulation and 1.6cm gypsum board made up the attic roof with wood joist. While steel frame was used for the wall construction, exterior walls have wood-frame with 2.5cm stucco and 1.6cm gypsum board. The wall insulation is 1.6cm gypsum board. The cooling equipment is Packaged Air Conditioning Unit and a furnace was the heating equipment in the building. The building's air Distribution equipment is Single-Zone Constant Air Volume (SZ CAV).

The occupancy density used in the simulation model is 18.6 m^2/person [16]. Figure 1 shows the small office building model used in this study.

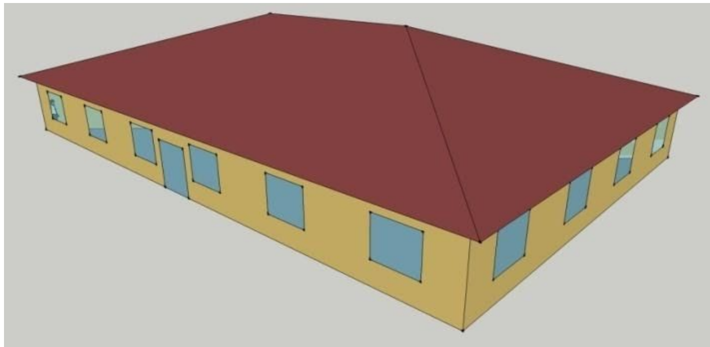

Fig 1. Small office building simulation model

The cities studied are Miami, FL, Chicago, IL, and Fairbanks, AL, representing 1A, 5A and 8 climate zones, respectively. The cities are the most populated cities in each climate zone presented in Figure 2. Climate 1A represents the hottest, and climate 8 represents the coldest. We chose climate 5A Chicago because the climate experience both cold and hot conditions during a year.

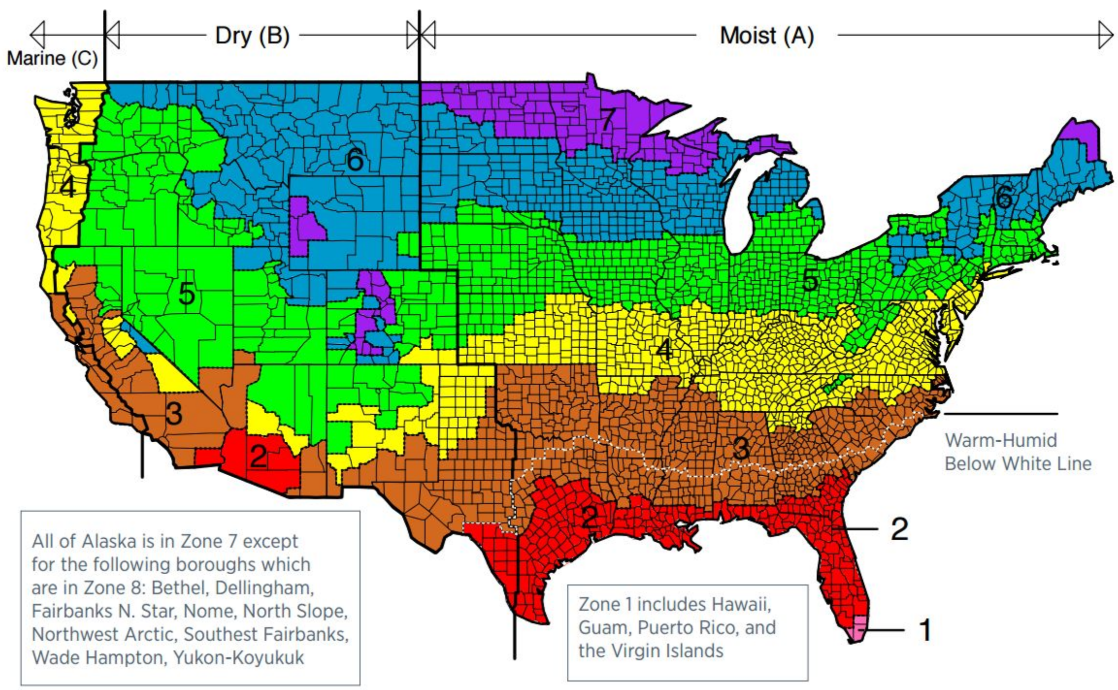

Fig 2. Climate zone classification ([31])

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The outputs of the simulations were stored in a CSV file. The data were then processed to calculate the energy consumption over a single day and a year via summing the hourly energy consumptions. The stored internal and external variables included the simulation settings (e.g., setpoint, city, and occupancy schedule) and outside temperature associated with daily simulation results.

5. Results

For the optimal control policy 1 (building level annual), we present the annual optimal setpoints in each climate and the annual energy savings compared to the baseline in Table 3. For the optimal control policy 2 (zone level annual), the setpoints for different zones were allowed to vary, but they were fixed for the entire year. The vector of the optimal setpoints and the associated annual energy savings for control policy 2 are also shown in Table 3. In the optimal control policy 3 (building level daily), the setpoints were selected at the building level (one setpoint for all zones), but they varied on a daily basis. Figure 3 shows the setpoint variations over time based on the control policy 3 for all three climates. In the optimal control policy 4 (zone level daily), the setpoints for different zones were allowed to vary (each zone had their own setpoint) and they also varied on a daily basis. In addition, the energy consumption of all control policies were compared to the baseline control policy (i.e., setpoint of 22.5 °C) in order to understand how temporal and spatial control policy scales impact the energy consumption (Table 3).

Table 3. Setpoint selections and energy savings compared to the baseline policy

		Miami, Florida (1A)	**Chicago, Illinois (5A)**	**Fairbanks, Alaska (8)**
Baseline policy	Setpoint (°C)	22.5	22.5	22.5
Control policy 1 (building level annual)	Optimal setpoint (°C)	25.5	21.5	19.5
	Savings (%)	50.67	1.56	19.81
Control policy 2 (zone level annual)	Optimal setpoints (°C)	[25.5 25.5 25.5 25.5 25.5]	[22.5 21.5 22.5 21.5 21.5]	[19.5 19.5 19.5 19.5 19.5]
	Savings (%)	50.67	1.84	19.81
Control policy 3 (building level daily)	Savings (%)	50.83	40.06	27.63
Control policy 4 (zone level daily)	Savings (%)	50.91	40.76	27.76

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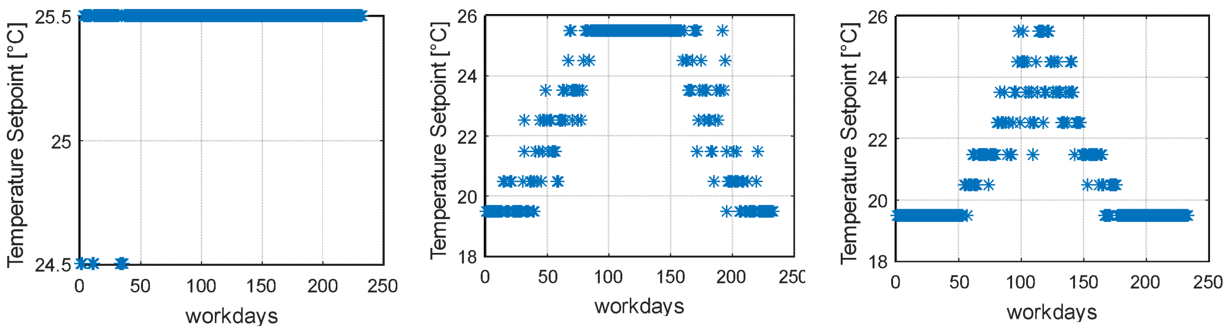

a) Miami, Florida (1A) b) Chicago, Illinois (5A) c) Fairbanks, Alaska (8)

Fig 3. Optimal building level setpoints based on control policy 3

As it can be seen in Table 3, for the climate zone 1A (the hottest climate) for control policy 1, the highest setpoint (25.5°C) in the searched setpoint space, was selected for the entire year. Similarly, the set of highest zone setpoints was selected in control policy 2. As it can be seen in Figure 3a, the daily optimal setpoints in control policy 3 did not vary considerably (standard deviation of 0.17 °C) over the year for the climate zone 1A due to the fact that the outside thermal environment in this climate consistently results in a heat gain. Consequently, the energy consumption of the control policies 1 and 2, in zone 1A, were only slightly (~ 0.2%) worse than the control policies 3 and 4, but was considerably (50.67%) better than the baseline (Table 3).

In the climate zone 5A for control policy 1, 21.5 °C was selected as the optimal setpoint for the entire year. The set of optimal zone setpoints were around 21.5 and 22.5 °C with minor deviations in control policy 2 (Table 3). As it can be seen in Figure 3b, the daily optimal setpoints in control policy 3 varied considerably over the year due to the fact that outside thermal environment results in heat gain for cases of positive temperature gradient of indoor versus outdoor and heat loss in cases of negative temperature gradient of indoor versus outdoor. Consequently, the energy consumption of control policy 1 was considerably (around 40%) worse than the control policies 3 and 4, and was only slightly (1.56 %) better than the baseline. This finding points to the fact that the selection of optimal daily setpoints (zone level or building level) in climates that experience both cold and hot conditions during a year brings about substantial savings.

In the climate zone 8 (the coldest climate) for control policy 1, the lowest setpoint 19.5 °C was selected as the optimal setpoint for the entire year in the control policy 1. In this climate zone, the set of optimal zone setpoints was also 19.5 °C in the control policy 2. As it can be seen in Figure 3c, the daily optimal setpoints in control policy 3 slightly varied over the year (standard deviation of 1.80 °C) due to the fact that outside thermal environment resulted in a heat loss for majority of cases where a positive temperature gradient of indoor versus outdoor existed. Consequently, the energy consumption of control policies 1 and 2 were (~7.8%) worse than control policies 3 and 4, and were considerably (19.81%) better than the baseline.

An interesting finding is, in none of the climate zones, control policies 3 and 4 did not have considerable differences in terms of energy efficiency (maximum of 0.7% for climate 5A). Considering the fact that the highest or lowest setpoints are most often the optimal daily setpoints in very hot or cold climates, respectively, daily selection of optimal setpoints in extreme climates did not considerably

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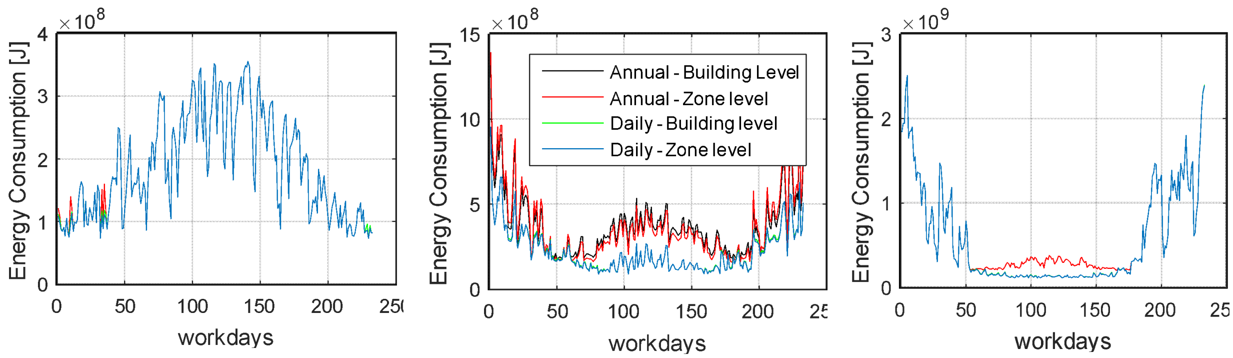
improve the energy efficiency. On the other hand, the daily selection of the optimal setpoints for milder climate considerably improved the energy efficiency, demonstrating the fact that the highest and lowest setpoints are not often the optimal setpoints in milder climates. The savings come from lowering the heat transfer between the building's interior and the outdoor environment as an HVAC controller strives to minimize the error between the temperature measurements and setpoints. Another interesting observation is that the zone based selection of the optimal setpoints only slightly reduced the energy consumption in both annual and daily optimal control policies. A reason contributing to this finding could be the fact that the size of the building was small and therefore it was impacted by outdoor environment conditions rather than heat exchange between the zones. To the best of our knowledge, this is the first time a trade-off analysis for spatial (i.e., zone based) optimization has been quantitatively studied according to the DOE reference energy simulation models. The daily energy consumption for all control policies are demonstrated in Figure 4 for three climates.



Miami, Florida (1A) Chicago, Illinois (5A) Fairbanks, Alaska (8)

Fig 4. Daily energy consumption based on different control policies

Table 4 shows the energy savings for each control policy with different levels of thermal comfort enforcements (σ), as explained in Section 3. Thermal comfort requirements might result in deviations of zone setpoints from the optimal setpoints. Consequently, we quantified the sensitivity of the control policies when thermal comfort requirements were enforced. In addition, the energy consumption for each case was compared to the baseline control policy, which did not integrate any comfort requirements.

Table 4. Energy savings of the control policies with different levels of thermal comfort requirements

		Energy savings compared to the baseline (%)			
	σ (°C)	**Miami, Florida (1A)**	**Chicago, Illinois (5A)**	**Fairbanks, Alaska (8)**	**Average**
Control policy 1 (building level annual)	0	50.67	1.56	19.81	24.01
	1	46.95	-0.56	18.77	21.72
	2	42.95	-5.91	17.21	18.08
	3	38.48	-10.52	15.15	14.37
	4	33.62	-16.12	12.31	9.94
Control policy 2	0	50.67	1.84	19.81	24.11

(zone level annual)	1	46.95	-0.16	18.77	21.85
	2	42.95	-5.17	17.21	18.33
	3	38.48	-11.05	15.15	14.19
	4	33.62	-16.53	12.31	9.73
Control policy 3 (building level daily)	0	50.83	40.06	27.63	39.51
	1	46.98	36.48	24.89	36.12
	2	42.88	30.63	21.34	31.62
	3	38.37	23.82	17.64	26.61
	4	33.48	16.31	13.42	21.07
Control policy 4 (zone level daily)	0	50.91	40.76	27.76	39.81
	1	47.06	36.92	24.95	36.31
	2	42.94	30.87	21.41	31.74
	3	38.42	23.97	17.72	26.7
	4	33.5	16.42	13.53	21.15

As it can be seen in Table 4, the energy savings for all control policies reduce with the increase in σ representing the applied comfort constraints. The reduction in the savings follow a non-linear relation with a monotonically increasing gradient based on the σ. This points out the fact that the impact of the variations in the optimal setpoints results in higher inefficiencies due to the imbalanced heat exchange between the zones. In addition, we can observe that annual control policies for milder climates result in negative savings under occupants thermal comfort constraints. This also demonstrates that solely optimizing the setpoints for thermal comfort when the controller does not have a temporal scale for setpoint selection results in energy inefficiency. However, controllers with a temporal scale, such as daily setpoint selection in our case, could meet occupants comfort requirements while still saving energy – an important observation.

In average, the increase rates in the energy consumption for control policy 1 were 2.29% for the σ =1 °C (24.01 - 21.72), 5.93 % for the σ =2 °C, 9.64% for the σ =3 °C, and 14.08% for the σ =4 °C. Somewhat similar variations were observed for the control policy 2: 2.29 % for the σ =1 °C, 5.78% for the σ =2 °C, 9.91% for the σ =3 °C, and 14.38% for the σ =4 °C. It is interesting to point that for smaller values of comfort constraints (σ), the savings for control policy 2 for the milder climate was larger, but it was below control policy 1 for σ greater than 2 °C. A larger increase was observed for control policy 3 as 3.39 % for the σ =1 °C, 7.89 % for the σ =2 °C, 12.90. % for the σ =3 °C, and 18.44 % for the σ =4 °C. A similar behavior to control policy 2 was observed for control policy 4. 3.5 % decrease in savings for the σ =1 °C, 8.07 % for the σ =2 °C, 13.11 % for the σ =3 °C, and 18.66 % for the σ =4 °C were observed as depicted in Table 4.

In this study, the setpoints space range was selected as 19.5 to 25.5 °C, which represents a variation of 3 °C around the baseline setpoint and resulted in energy savings ranged between 27.76 – 50.91%

(average of 39.81%). It is important to note that when σ was 3 °C, the energy usage only increased by 9.64 – 13.11% in all of the control policies. It demonstrates that a control strategy utilizing a temporal scale for selecting temperature setpoints subjected to a uniformly distributed comfort constraints would results in a considerable energy saving.

We also studied the impacts of the control policies at the spatial and temporal scales, under the thermal comfort constraints, and based on the climate for the annual energy consumption. In Table 5, we present the F and *p* values of the ANOVA analysis. The factors are sorted based on the level of influence on the target variable (i.e., energy consumption).

Table 5. Results of ANOVA analysis for the potentially influential factors

Potential Influential Factors	States	F-value	*p*-value
Climate	1A, 5A, 8	921.78	9.26e-41
Control policy temporal scale	Annual, Daily	38.83	8.88e-08
Thermal comfort constraints (σ)	0 °C, 1 °C, 2 °C, 3 °C, 4 °C	10.75	2.15e-06
Control policy spatial scale	Building level, Zone level	0.05	0.82

The climate has the largest and statistically significant (p-value below 0.05) impact on the energy consumption with an F-value of 921.78. Meaning, different choices of control policies can be selected depending on the climate. For example, the annual setpoint selection would result in considerable energy efficiency in extreme climates (i.e., very hot or cold climates) throughout the year; the highest setpoints in the hot climates and the lowest setpoint in the cold climates. However, in climates where the temperature gradient between the building interior and outdoor environment changes its direction throughout the year (i.e., milder climates), more granular temporal scale of control policy would result in higher energy efficiency. Climate was followed by the statistically significant factors of temporal scale and thermal comfort constraints, and not statistically significant factor of spatial scale. The fact that the temporal scale had a greater contribution compared to the thermal comfort constraints was consistent with the observation in our previous analysis (i.e., optimal daily selection of setpoints in the space range of 19.5 to 25.5 °C which represents a variation of 3 °C around the baseline improve the energy efficiency under all values of the thermal comfort constraints).

Another important observation was that the spatial scale did not significantly impact the overall energy consumption, however, the temporal scale had a significant impact on the overall energy consumption. At the same time, the zone level optimal control policies required more training data for finding the optimal setpoints compared to the building level control policies, due to the fact that the search space for the zone level optimal setpoints are exponentially larger than the building level control policies. For example, the search space for the setpoint space of 19.5, 20.5, 21.5, 22.5, 23.5, 24.5, and 25.5 °C is only 7 states for the building level optimal setpoints and 7^5 states for the zone level optimal

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setpoints. Considering the fact that the zone level control policies only slightly improved the energy efficiency and the fact that their training processes required substantially greater data points, building level control policy seem to be a more viable choice. In addition, as pointed out earlier, annual control policies for milder climates result in negative savings under occupants thermal comfort constraints. Although the annual control policies performed better for extreme climates, among the four studied control policies and across all climate types, the building level daily control policy is the best control policy considering the thermal comfort constraints because this policy has the added efficiency improvements and simpler learning requirements. In the case of control policy 3 (building level daily), between 17.64 – 38.37% (average of 26.61 %) energy savings were achieved by using a control policy that selects optimal setpoints while maintaining thermal comfort.

6. Discussion

This paper used the DOE small office building reference simulation model to investigate the temporal and spatial setpoint control policies for individual zones for HVAC system energy efficiency. The proposed method is not restricted to the office buildings, VAV HVAC systems or building sizes and can be applied to other building types/sizes and HVAC systems, as the basic idea to optimize heating/cooling setpoint control based on occupant comfort remains the same [32, 33]. In this study, we only used the workday results for eliminating the variable of occupancy. The impact of dynamic occupancy on the control policies should be investigated in a future study. Having access to real-time information on the occupants thermal comfort allows HVAC system controllers to minimize the overall energy consumption while providing comfortable thermal conditions [35].

The daily selection of optimal setpoints in climates with relatively high (i.e., Miami Florida (1A)) or low (i.e., Fairbanks, Alaska (8)) outside temperatures does not considerably improve the energy efficiency in comparison to the annual selection of the setpoints. However, the daily selection of optimal setpoints for a milder climate (i.e., Chicago, Illinois (5A)) considerably influences the energy consumption. These findings suggests that energy savings from a more complex control policy highly depends on the dynamic variations of the external factors [36, 37].

Considering the fact that the setpoints were solely selected based on the temporal scale (i.e., daily and annual) and the fact that a finer scale (e.g., hourly) can potentially improve the energy efficiency of HVAC systems, there is a trade-off between the computation costs and complexity of the HVAC controller and the associated energy savings, which requires further investigations [36, 38-40]. In cases, where there are a large number of permutations of operational settings for finding the optimal parameters in real buildings' HVAC systems, it is often not feasible to search all conditions because of the associated costs and potential occupant discomfort [41]. For example, implementing a zone level strategy in real-world via exhaustive search could be very costly. However, this study aimed to use brute-force method to compare such cases which are difficult to be validated via a real-world case. To address this issue, we plan to develop techniques that allow for searching and learning optimal setpoints that are subject to dynamic influential variables in an online learning paradigm. The presented study on spatial and temporal control policies with thermal comfort as a constraint is one strategy, which included an analysis of potential energy savings. However, since a generalized model of human thermal comfort is not yet established [42-45], thermal comfort constraints were modeled as uniformly distributed random variables, which are conservative based on the fact that human thermal preferences change based on seasonal weather variations.

To integrate such control strategy into control loop of HVAC systems, a stream of the input data (e.g., building energy usage data and occupancy) needs to be collected in a database. These inputs are used to calculate an optimal setpoint at the building level on a daily basis. Different algorithms could be used to learn optimal daily setpoints such as a hybrid metaheuristic [32]. Given the daily optimal setpoints, a control would select a setpoint for each building zone, as close as possible to the optimal setpoint subject to the thermal comfort constraints on the zone setpoints. To integrate personal comfort constraints, recent advancements in thermal comfort learning techniques (e.g., participatory sensing of comfort or using physiological measurements for learning comfort) [12, 46, 47], which provide real-time access to the thermal comfort of occupants, can be used.

7. Conclusions

In this study, we followed a systematic approach for analyzing the impact of temporal and spatial variations and thermal comfort requirements on HVAC system control policies. The control policies, studied in this paper are: (1) building level annual control policy, (2) zone level annual control policy, (3) building level daily control policy, and (4) zone level daily control policy. In all of the control policies, the optimal setpoints were calculated through an exhaustive search of the setpoint-building energy space, which was derived via extensive simulations. We used the DOE reference small office building simulation model in three climates (1A, 5A, and 8) to compare the four control policies. In order to represent actual building operations, we added occupants' thermal comfort requirements, as uniformly distributed random constraint functions, on the setpoints to model thermal comfort requirements. Through our statistical analysis, we demonstrated solely optimizing the setpoints for thermal comfort (without a temporal optimization of setpoints for energy) results in energy inefficiencies. Therefore, controllers with a temporal scale, such as daily setpoint selection, is needed to meet occupants comfort requirements while still saving energy. We also found that in a milder climate, the control policies that have dynamic adjustment of setpoints achieved more energy efficiency, while for extreme climates (hot/cold climates), a fixed setpoint for the entire year provided close to highest energy efficiency. Our results demonstrate that the optimal building level daily energy control policy result in average savings of 27.76% to 50.91% (average of 39.81%) depending on the climate. In addition, if thermal comfort requirements were uniformly distributed, the daily optimal setpoint selection, subject to thermal comfort constraints, led to 17.64 – 38.37% (average of 26.61%) energy savings, depending on the climate. These savings are conservative as thermal comfort preferences are often skewed toward energy efficient setpoints. Among the four control policies, the building level daily control policy had the highest energy efficiency with comparatively small training data rudiments. Finally, we ranked the potentially influential factors on the control policies as the climate, temporal scale, and thermal comfort constraints with statistically significant impacts, and spatial scale with a statistically not significant impact. The results of this study could be used by building stakeholders to define and implement more efficient control policies, depending on the accessibility to training data, desired efficiency, and controllability of building systems.

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