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Adaptive Setpoint Optimization for Developing Energy Usage Strategies to Alleviate Energy Poverty

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ABSTRACT

Thermostat settings in residential buildings impact both energy bills and health. While residents can only control indoor temperature through thermostats, there is a lack of understanding about the impacts of adjusting thermostat settings on energy consumption and thermal comfort. This knowledge gap makes it challenging to balance cost-effective and thermally comfortable behaviors, which could ultimately exacerbate disparities in dwelling conditions. This study presents a framework to optimize adaptive temperature setpoint schedules through parametric building energy modeling and explore energy usage strategies that reconcile energy reduction with thermal comfort for residents. The study consists of 1) defining simulation scenarios, 2) optimizing adaptive setpoint schedules in building energy models, and 3) developing energy usage strategies. By providing expected utility fees and thermal sensation levels for each strategy, this study assists residents in making informed decisions regarding adaptive thermostat settings for balancing economic and health challenges. This study promotes a sustainable and equitable built environment by equipping all populations, especially low-income households, with adaptable and actionable approaches.

Keywords: Building energy modeling, Temperature setpoints, Residential building, Energy usage strategy, Energy poverty

1. INTRODUCTION

Extreme outdoor temperatures impact the operations of indoor heating and cooling systems, necessitating costly adaptive responses to these severe weather conditions. According to the U.S. Energy Information Administration (EIA), nearly one-third of U.S. households face challenges paying their energy bills [1]. This financial strain often compromises their ability to maintain safe and healthy indoor temperatures [2, 3].

Adjusting temperature setpoint schedules instead of maintaining a fixed setpoint can reduce building energy consumption. However, these changes can adversely affect thermal comfort [4], especially for those facing health vulnerabilities and energy poverty. Therefore, it is essential to jointly analyze the impacts of temperature setpoint profiles on both energy consumption and thermal comfort and understand how setpoint modifications influence these metrics [5].

Although previous studies [6, 7] and associated energy assistance programs [8] recognize the importance of addressing energy poverty in low-income households, there is still a lack of understanding regarding the impact of indoor temperature control on energy bills and thermal comfort. Specifically, it remains unclear how adjustments in temperature setpoint schedules can affect energy costs compared to a fixed setpoint in residential buildings and what trade-offs exist between energy use and thermal comfort when residents control indoor temperatures through thermostats.

Therefore, this paper uses simulation-based and data-driven methods to explore energy usage strategies, considering energy consumption and occupants' thermal comfort. It aims to provide a comprehensive understanding of the implications of setpoint temperature adjustments on energy bills and thermal comfort, ultimately contributing to more effective energy management strategies for low-income households.

2. LITERATURE REVIEW

2.1 Adaptive setpoint temperatures

This is a paper for the 16th International Conference on Applied Energy (ICAE2024), Sep. 1-5, 2024, Niigata, Japan.

Several studies have shown that adjusting indoor temperature setpoints offers significant potential for energy savings [9, 10, 11, 12]. Since additional savings can especially be achieved through optimal selections [13], researchers are increasingly focused on investigating how HVAC system operations can be optimized under specific climate or occupancy conditions [13, 14, 15]. Despite the progress in commercial and office buildings, there is a noticeable gap in research focusing on residential settings. There is also a lack of goals and strategies for addressing energy conservation and occupant comfort from the perspective of energy poverty. Therefore, it is necessary to research optimizing setpoint temperatures under various climate conditions and occupancy information, considering different scenarios for alleviating energy poverty.

2.2 Multi-objective optimization

A multi-objective optimization (MOO) problem requires the simultaneous satisfaction of numerous different objectives [16]. Due to the inherently conflicting nature of these objective functions, an MOO problem has no unique solution but rather a set of non-dominated, Pareto optimal solutions [17]. Pareto optimality can be defined as the state where resources are allocated as efficiently as possible so that improving one criterion will not worsen other criteria [18].

Genetic Algorithms (GAs) are a heuristic search and optimization technique inspired by natural evolution. GAs can facilitate the discovery of more efficient and optimized solutions by starting from non-optimized ones, combining them, and introducing random disorder elements until converging into optimal solutions [19]. Building energy simulations coupled with GAs has proven promising in identifying optimal solutions to complex energy efficiency problems [20, 21, 22, 23]. Within Rhino and Grasshopper, various plugins (e.g. Galapagos and Octopus) can be utilized to perform simulation optimization. However, using them, research has primarily focused on optimizing building design elements according to specific objectives. This study shifts the focus from building form to optimizing time-specific setpoints, bringing energy-efficient and thermally comfortable behavior options directly to residents' fingertips.

3. MATERIAL AND METHOD

This study is composed of 1) defining simulation scenarios, 2) optimizing adaptive setpoint schedules in building energy models, and 3) developing energy usage strategies for energy poverty. Figure 1 shows the overall research framework.

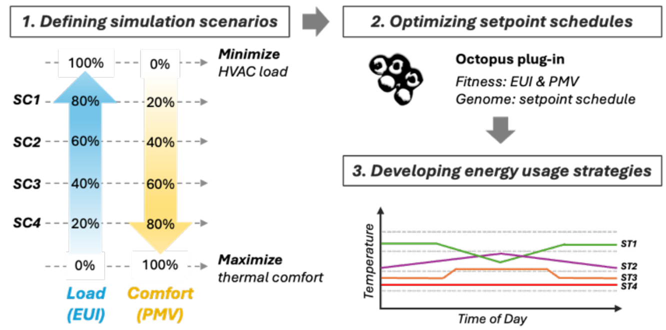


Figure 1. Research framework

3.1 Defining simulation scenarios

Various simulation scenarios were established based on energy bills and indoor thermal comfort. Energy bills are measured by EUI (Energy Use Intensity, kWh/m²), and indoor thermal comfort is assessed using PMV (Predicted Mean Vote) values. EUI is a crucial measure, reflecting the total energy consumed by the building, normalized to its area, allowing for comparisons across different building types and designs. In addition, PMV is an index estimated based on indoor space conditions such as air temperature, relative humidity, and air velocity, predicting the mean value of votes of a group of occupants on a seven-point thermal sensation scale. Within the PMV index, +3 indicates too hot, while -3 indicates too cold. Setting different target EUI and PMV values for each scenario allows residents to choose between energy usage and comfort based on their economic situations. The ultimate goal is to derive each scenario's optimal time-of-day heating and cooling setpoints.

3.2 Optimizing adaptive setpoint schedules in building energy models

A parametric energy model was developed to optimize and simulate the energy performance of a building under various adaptive setpoint schedules. Using Rhino and Grasshopper, along with Honeybee and Ladybug plugins, the model incorporates the EUI and PMV metrics to assess energy efficiency and thermal comfort [24].

A multi-objective optimization approach is adopted using the Octopus tool in Grasshopper to address the trade-offs between energy efficiency and thermal comfort. Octopus is a plug-in for applying evolutionary principles to parametric design and problem-solving [25]. It allows the search for many goals at once, producing a range of optimized trade-off solutions between the

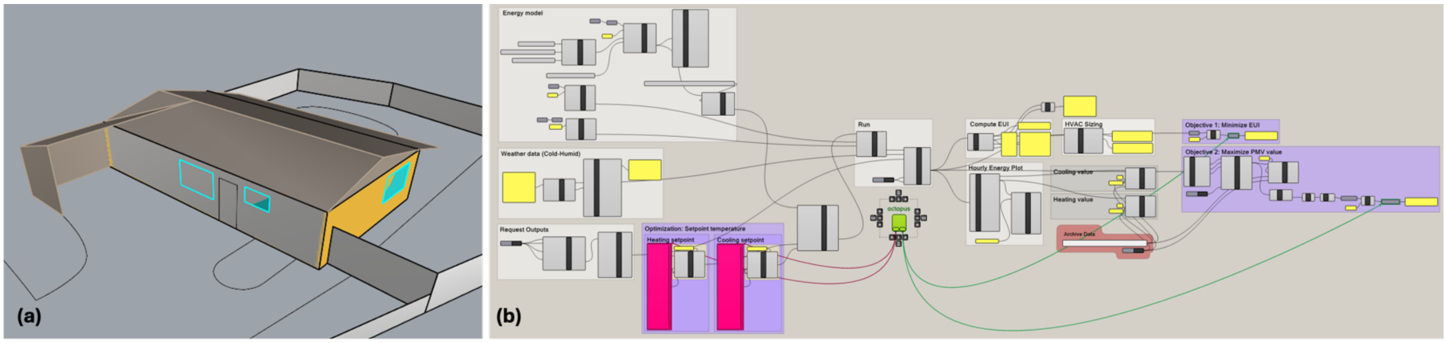


Figure 2. Sample modeling

extremes of each goal. EUI and PMV values were linked to the Octopus for multi-objective search and optimization. The EUI was determined by summing only the annual heating and cooling loads. The PMV was calculated by averaging the values for a year and then converting them to an absolute value, as a PMV closer to zero indicates better thermal comfort. Therefore, the primary objective of using the Octopus plugin was to minimize EUI and PMV values in this study.

We applied weighting factors to the objectives to account for the different priorities in each scenario. For example, in Scenario 1, a weight of 0.2 was applied to the EUI and 0.8 to the PMV. The gene pool, generating random values for setpoints by time according to the objective, was also linked to the Octopus genome.

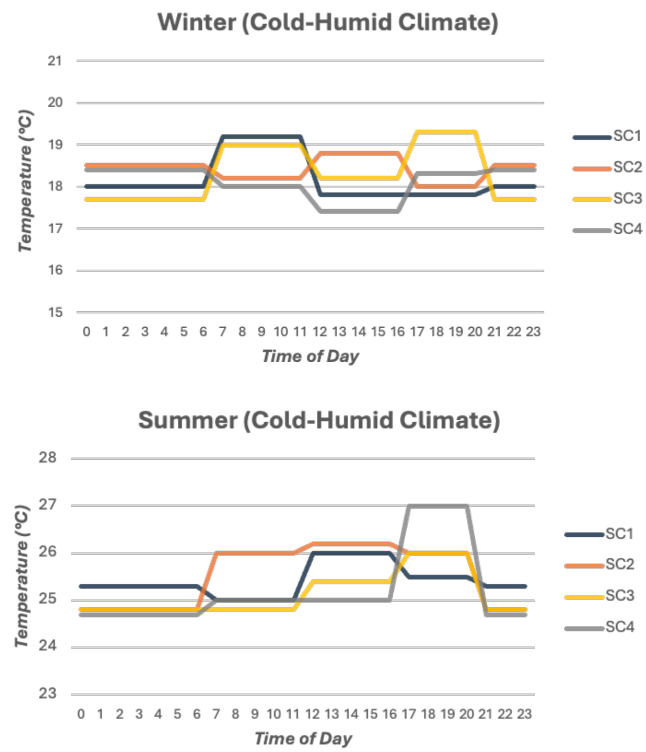
3.3 Developing energy usage strategies

Based on the simulation results, we proposed energy usage strategies, including heating and cooling setpoint schedules for each scenario. These schedules also presented the expected utility costs and the thermal sensation level. Following these strategies, residents can adjust their thermostats according to their economic situation, balancing energy consumption and thermal comfort.

4. RESULTS

A sample simulation was conducted for total scenarios under Cold-Humid climate conditions (Figure 2b). The single-family sample building model from Honeybee GitHub was used for the simulation [26] (Figure 2a). The population size and maximum generation numbers in Octopus were set to 10 and 50, respectively. The heating setpoint range was set between 15 to 21°C, and the cooling setpoint range was set between 23 to 28°C. Among the generated results, the setpoint schedule that most closely approached the two objectives simultaneously was selected.

As a result, the setpoint schedule was visualized as a graph for winter (heating) and summer (cooling). To address setpoint fluctuations throughout the day, we divided the time into four periods—night and early morning, morning, afternoon, and evening—and calculated the average setpoints for each period. Specifically, the periods were defined as follows: night and early morning from 9:00 PM to 6:00 AM, morning from 7:00 AM to 11:00 AM, afternoon from 12:00 PM to 4:00 PM, and evening from 5:00 PM to 8:00 PM. Additionally, the expected utility costs and thermal sensation levels were presented alongside the schedules to make them easier for residents to understand (Figure



Expected utility fee	**Thermal sensation**
ST1: $ 243.35/month	ST1: Slightly comfort
ST2: $ 245.74/month	ST2: Comfortable
ST3: $ 246.91/month	ST3: Moderately comfortable
ST4: $ 248.58/month	ST4: Most comfort

Figure 3. Energy usage strategies

3). The building model used in this study has an area of 145 m², and the US electricity rate of $0.178 (price per kWh) was applied for the calculation [27].

5. DISCUSSION

We compared the EUI and PMV values between adaptive and fixed setpoints under the same conditions (Table 1). When the heating setpoint was fixed at 21°C and the cooling setpoint at 23°C, the results showed an EUI of 153.81 kWh/m² and an average PMV of 0.87 (the corresponding predicted percentage of dissatisfied (PPD) is 21%). Conversely, when the heating setpoint was fixed at 15°C and the cooling setpoint at 28°C, the EUI was 73.34 kWh/m², with an average PMV of 1.73 (PPD is 63%). The simulation results for fixed setpoints achieve only one objective: either a PMV close to 0 or a low EUI. In contrast, the adaptive setpoints proposed in this study demonstrate the ability to meet both objectives simultaneously, as set for each scenario.

Table 1. Comparison of EUI and PMV values

	Fixed setpoints	**Adaptive setpoints**			
		SC1	SC2	SC3	SC4
EUI	153.81 73.34	113.09	114.21	114.75	115.53
PMV (PPD)	0.87 (21%) 1.73 (63%)	1.24 (37%)	1.23 (37%)	1.22 (36%)	1.21 (36%)

The optimized heating and cooling setpoints demonstrated in the results can reduce energy consumption and improve building energy management. This leads to lower energy costs for residents, which is crucial in areas with high energy prices or environmental sensitivities. The schedules are also designed to maintain a thermally comfortable indoor environment, enhancing resident satisfaction in both heating and cooling scenarios. This approach supports a healthy indoor climate while conserving energy.

However, the EUI values calculated in this study are relatively high, inevitably leading to very large utility fees in the proposed strategy. This reflects a limitation stemming from the lack of detailed HVAC system design. The default EUI values calculated based on the fixed setpoints presented earlier are also notably high. Therefore, modeling an HVAC system that is finely tuned to the specifics of residential buildings would make it possible to achieve more appropriate EUI values and utility fees. Additionally, a more detailed assessment of thermal sensation is needed. Detailed descriptions of thermal sensation could be provided, tailored to each season or occupant schedule. For example, a description for Strategy 1 might state, "Suitable for occupants who are mostly active indoors in the morning or evening and are away during the midday hours."

The findings of this study can be integrated into smart home automation systems, allowing optimized setpoints to be automatically applied via smart thermostats. This enables residents to achieve optimal energy efficiency without manual adjustments and provides a foundation for systems that monitor and adjust energy use in real time. For this, additional simulations across various climates and building profiles are needed to refine the strategy further. By considering occupant schedules, more personalized and occupant-centered strategies can be developed. The parametric nature of the model allows for easy modification and expansion, facilitating the efficient development of optimal solutions for different scenarios.

6. CONCLUSIONS

This study explores energy usage strategies for residents by optimizing adaptive temperature setpoint schedules through parametric building energy modeling and a multi-objective optimization approach. By providing expected utility costs and thermal sensation levels for each strategy, the research aids residents in making informed decisions that improve their indoor environment while conserving energy. This study contributes to a more sustainable and equitable built environment by offering practical and adaptable strategies for managing indoor temperatures across diverse populations. Future research should focus on implementing these strategies in real-world settings, accounting for different climate conditions and building types, to validate the modeling results.

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