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Adaptive Fuzzy Logic Control for Optimizing HVAC Setpoints to Enhance Energy Efficiency in Urban Buildings

Mojtaba Safdari[1], Mohammad Al Janaideh[2], Kamran Siddiqui[3], Amir A. Aliabadi[1]

[1] *School of Engineering, University of Guelph, Guelph, Ontario, Canada, msafdari@uoguelph.ca*
[2] *School of Engineering, University of Guelph, Guelph, Ontario, Canada, maljanai@uoguelph.ca*
[3] *Department of Mechanical and Materials Engineering, Western University, London, Ontario, Canada, ksiddiq@uwo.ca*
[1] *School of Engineering, University of Guelph, Guelph, Ontario, Canada, aaliabad@uoguelph.ca*

ABSTRACT

This paper presents a Weather-Responsive Fuzzy Control (WRFC) strategy to dynamically adjust temperature and humidity setpoints for energy-efficient HVAC operation in urban buildings. WRFC integrates external weather data, electricity prices, and occupancy levels to adapt HVAC setpoints, aligning indoor conditions with outdoor temperature and humidity variations. Using a Fuzzy Logic Controller (FLC), a control variable (w) is calculated to optimize setpoints, balancing energy use and occupant comfort. Compared to fixed setpoint strategies, WRFC significantly reduces heating and humidification demands, especially under high Air Changes per Hour (ACH) conditions. While cooling and dehumidification demands increase in summer, WRFC achieves annual energy savings of 274 [kW-hr m^{-2} year^{-1}] for a typical residential house. Sensitivity analysis highlights WRFC's effectiveness across diverse building types, particularly older and less airtight structures. These results demonstrate that weather-responsive setpoint control enhances HVAC sustainability and energy efficiency in urban environments.

Keywords: Building Energy Modeling, Fuzzy Control, Sensible and Latent Loads.

INTRODUCTION

The growing need for energy-efficient technologies underscores the importance of optimizing Heating, Ventilation, and Air Conditioning (HVAC) systems, which are major energy consumers and vital for maintaining indoor comfort and health. Temperature and humidity, the most critical parameters for Indoor Environmental Quality (IEQ) and thermal comfort must be carefully managed. Proper control prevents damage to buildings and HVAC equipment while adapting operations to occupancy and external conditions . Setpoint control, which involves maintaining target temperature and humidity levels, plays a key role in HVAC performance. Optimizing these setpoints allows operators to reduce energy use without compromising indoor conditions [5].

Control strategies for building energy management include On/Off, PID, MPC, and FLC . PID and On/Off are simple but struggle with nonlinearities and tuning issues. MPC is more advanced but limited by high computational demands. FLC handles uncertainties and nonlinearities effectively, making it suitable for dynamic environments. Hybrid methods like Fuzzy-PID and NN-MPC combine strengths to improve performance. Recent works [3] show FLC's potential in energy-efficient temperature and humidity control [4].

Most existing controllers and smart building research focus on systems that adjust setpoints based on occupancy detection [10]. These systems often overlook other environmental factors. The concept of a physically intelligent building that adapts setpoints based on occupancy, outdoor conditions, electricity pricing, and latent heat remains under explored, but it could significantly enhance energy efficiency and comfort. Traditional HVAC control strategies typically rely on fixed setpoints, missing opportunities to use favorable outdoor conditions and reduce HVAC loads.

This study proposes a Weather-Responsive Fuzzy Control (WRFC) strategy that dynamically adjusts temperature and humidity setpoints using real-time data, including outdoor conditions, occupancy, and electricity prices. WRFC continuously adapts to optimize HVAC performance in both peak occupancy and energy-saving modes, reducing energy use while maintaining comfort. It integrates both sensible and latent loads, improving energy efficiency and occupant comfort, advancing HVAC setpoint decision-making and creating a physically intelligent building.

1. METHODOLOGY

1.1. Model Description

This study simulates urban physics using the Vertical City Weather Generator (VCWG v3.0.0), a multi-physics model that integrates processes for momentum, heat, humidity, and water exchanges through urban surfaces, soil, and the atmosphere. VCWG uses models like the Resistance Capacitance thermal network, Navier-Stokes transport, and Monin-Obukhov Similarity Theory (MOST) [1] to predict urban climate and building performance. For weather boundary conditions, the Vatic Weather File Generator (VWFG v1.0.0) provides data using the ERA5 datasets. VCWG's results for a base building were validated against real-world data from London, Ontario [9]. This paper extends the model by integrating a Fuzzy Logic Controller (FLC) and running it for Toronto in 2020. For more details, refer to earlier publications [7, 2, 8].

Figure 1 shows the arrangement of single detached residential buildings considered in this study. Such houses are prevalent in North America and account for 52.6% and 64% of residential building stock in Canada and the United States, respectively. The building features for each city are based on common codes and standards such as the National Energy Code of Canada for Buildings (NECB), the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) 62.1, ASHRAE 62.2, ASHRAE 90.1, and ASHRAE 90.2.

1.2. Weather-Responsive Fuzzy Control (WRFC)

This study introduces a novel real-time control strategy known as Weather-Adaptive Fuzzy Control (WRFC), designed to dynamically manage indoor temperature and humidity setpoints within a building. This method has been integrated with the VCWG software according to the flowchart in figure 3. The core principle of this method is to closely track external conditions and adjust the indoor setpoint accordingly whenever feasible. For instance, when outdoor conditions fall outside the human comfort range but occupancy levels are low, the system gradually adjusts the indoor setpoint to align with the outdoor temperature or humidity, provided it remains within predefined setback limits. Conversely, if outdoor conditions are within the comfort zone, the indoor setpoint

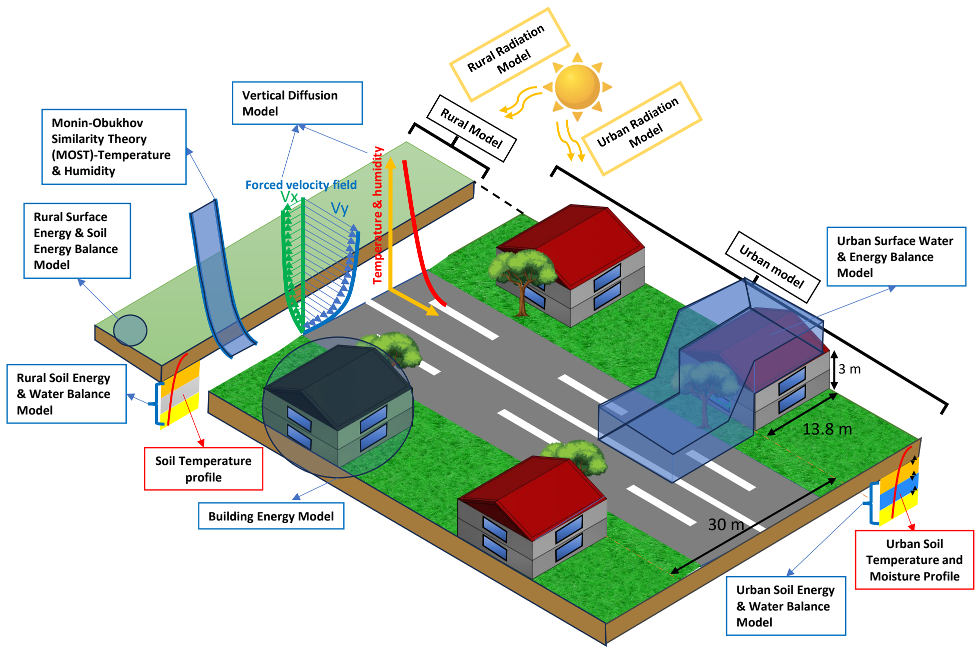

Figure 1. Illustration of the Vertical City Weather Generator (VCWG v3.0.0) model and the constituent sub-models.

is maintained in close proximity to the external conditions to eliminate the need for HVAC system operation. A basic description of the algorithm can be found in the flowchart in Figures 3 and 8. Another innovative aspect of this approach involves an integration of a fuzzy inference system that uses linguistic variables to evaluate the impact of external, uncontrollable factors, enabling a more refined and adaptive control of indoor environmental conditions for higher energy savings. The comfort ranges are defined in Figure 2 for humidity and temperature. It should also be noted that the basic thermostat mode for cooling setpoint is 27 °C and for heating setpoint is 22 °C.

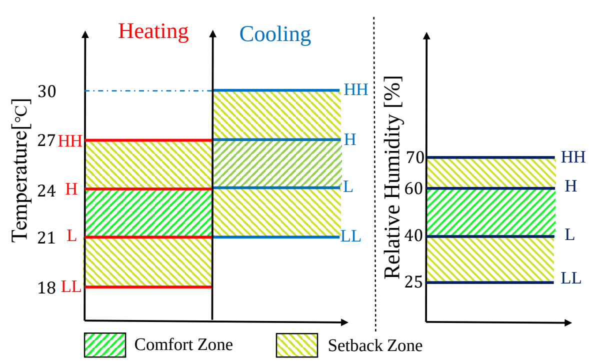

Figure 2. Illustration of the comfort and setback ranged for indoor temperature and humidity.

According to the FLC process diagram illustrated in the Figure 3 which follows Mamdani's Fuzzy Inference System (FIS) [6] the controller employs FLC to determine the *w* parameter, which governs the adaptation of setpoints by creating an adjustment value based on current input values.

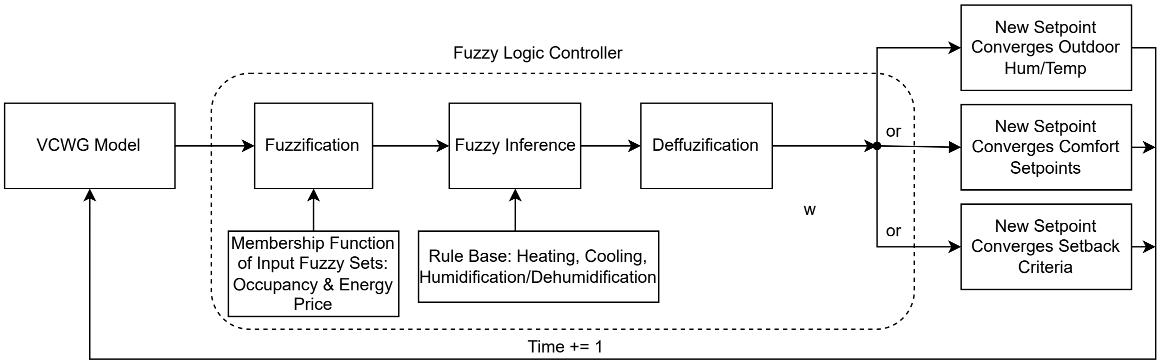

Figure 3. Flowchart illustrating the integration of the Weather-Adaptive Fuzzy Control (WRFC) with the Vertical City Weather Generator (VCWG) software

To do so, first the system uses predefined membership functions to assess the input's degree of membership. The controller uses two fuzzy variables as occupancy level [Person m^{-2}], and time of day [hr]. It is assumed in this study that three persons are living in a residential detached house of 100 m^2 with membership functions defined for low, medium, and high that any density more than 0.03 Person m^{-2} would be considered as a high occupancy level. For electricity price we have used the Time-Of-Use (TOU) pricing scheme in Ontario, Canada, as an example reflecting different electricity costs during different periods of the day and season. It is important to note that the differences in electricity prices between Winter and Summer, as well as between weekdays and weekends, have been accounted for in this study. These two inputs, with their respective levels in Figures 4 and 5, are mapped using trapezoidal and triangular membership functions to capture the varying degrees of occupancy and TOU.

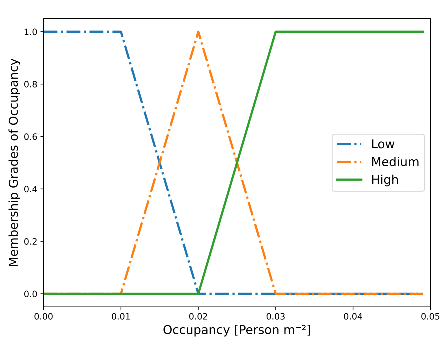

Figure 4. Fuzzy membership functions for the occupancy variable in the building.

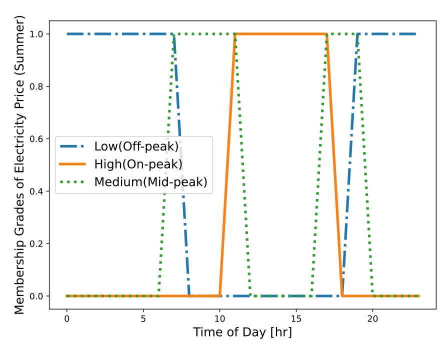

Figure 5. Fuzzy membership functions for the price variable in Summer.

Following the fuzzy inference process, we apply the fuzzy rules defined in Table 1 to the fuzzified input variables (electricity price and occupancy level) to determine the output variable *w*. These rules differentiate between weekday and weekend strategies for the Summer and Winter. Specifically, weekend rules do not account for electricity price fluctuations since rates remain constant throughout the day and night. In contrast, heating and humidification rules are not dependent on electricity price fluctuations, as these processes utilize natural gas in the HVAC system. Given

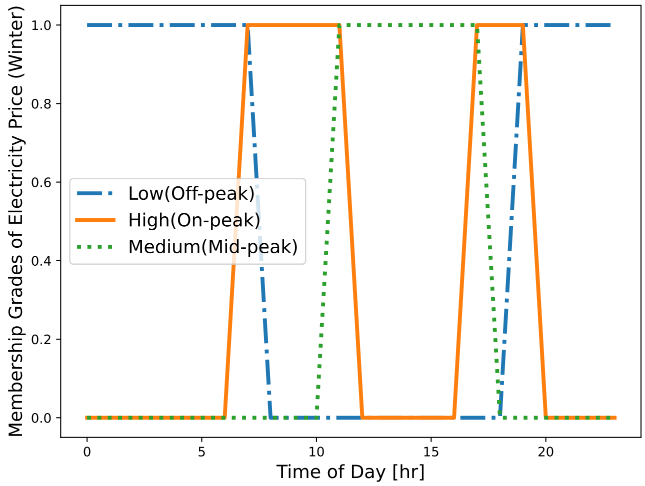

Figure 6. Fuzzy membership functions for the price variable in Winter

that gas prices remain constant throughout the day and night in Canada, gas price has not been considered a fuzzy input for these processes. Conversely, cooling and dehumidification require a refrigeration cycle, and thus electricity, so the corresponding rules depend on electricity price. In this table N means the setpoints should converge to outdoor condition, P means the setpoints should converge to comfort levels, and Z means no change.

Regarding Table 1 for cooling during weekdays, when occupancy is low and electricity price is low, medium, or high, the system should attempt to converge to the outdoor conditions, which is likely higher than the indoor and comfort setpoints. This corresponds to the linguistic variable N in our rule definition. In this scenario, energy efficiency takes precedence over comfort considerations when occupancy is low. Subsequently, when occupancy is medium and the price is low, the system converges to the comfort level P, while a medium price results in no change Z, and a high price increases convergence to the outdoor level N. Finally, high occupancy with low, medium, and high prices prompts convergence to the comfort level P. It should be noted that in this study Max operator has been used for decision-making process [11]. With the Max operation method, the output value for the linguistic variables corresponds directly to the highest activation levels.

In this step, the fuzzy outputs obtained earlier are converted into a crisp value (w) that can be utilized to adjust the setpoints.

The fuzzy output membership function employed in this study is a triangular membership function designed to calculate w, which controls the heating, cooling, humidification, or dehumidification setpoints (Figure 7). It includes three categories: N, Z, and P, ensuring a consistent and adaptable control strategy across all of these processes. The P and N values of these membership functions determine whether the smart setpoint should follow outdoor conditions or adhere to predefined comfort setpoints, dynamically adjusting the setpoints based on real-time input data.

The defuzzification process utilizes the centroid method, also known as the center of gravity or center of area method, to compute a specific numerical output for the w variable (Figure 8).

Table 1. Combined rules for HVAC adjustments based on occupancy presence, electricity price, and day type (weekdays and weekends): N: Converging to outdoor, Z: No change, P: Converging to comfort setpoint

Function	Day Type	Occupancy	Electricity Price	*w* Adjustment
Cooling/Dehumidification	Weekday	Low	Low	N
		Low	Medium	N
		Low	High	N
		Medium	Low	P
		Medium	Medium	Z
		Medium	High	N
		High	Low	P
		High	Medium	P
		High	High	P
	Weekend	Low	-	N
		Medium	-	Z
		High	-	P
Heating/Humidification	All Days	Low	-	N
		Medium	-	Z
		High	-	P

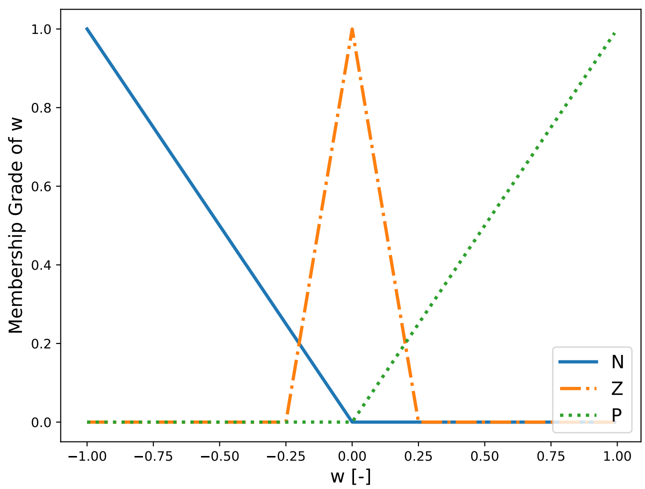

Figure 7. Fuzzy membership functions for temperature and humidity setpoints' adjustments. Both temperature and humidity adjustments use similar membership functions categorized into Negative (N), Zero (Z), and Positive (P) to guide the control of HVAC system setpoints.

2. RESULTS AND DISCUSSION

2.1. Performance of the Weather-Responsive Fuzzy Control (WRFC)

The model was run for a full year with a runtime of about 30 minutes on a single CPU, demonstrating its efficiency for a comprehensive urban physics simulation. Results for selected months with Air Changes per Hour (ACH) set at 1.5 hr^{-1} highlight its operation.

In May, a shoulder season with mixed heating, cooling, and neutral modes, the system's response is complex. Figure 9 (a) shows temperature behavior, while Figure 9 (b) illustrates the corresponding sensible heating and cooling loads. Early in the month, the system predominantly heats the building, keeping indoor temperatures within the comfort and setback thresholds (blue lines) during high occupancy. As outdoor temperatures rise later in the month, the system occasionally

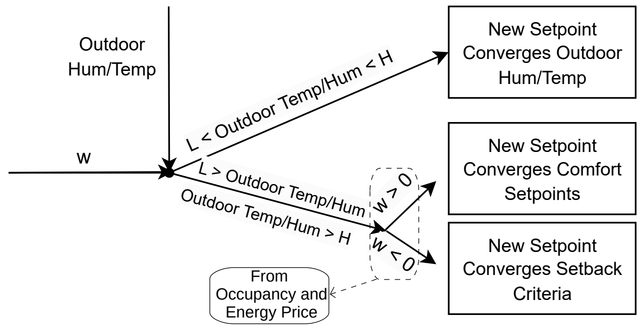

Figure 8. Decision tree illustrating how a value of *w* forces the smart setpoint to move toward comfort or outdoor conditions by adjusting the setpoint accordingly.

enters neutral mode, requiring no heating or cooling, with indoor temperatures naturally aligning within the comfort zone. When occupancy is low, indoor temperatures are allowed to drift outside comfort limits, prioritizing energy efficiency.

The system dynamically adjusts to outdoor temperature fluctuations. Around 700 hr, the outdoor temperature rises to 28°C, and the indoor temperature aligns with the comfort range (L to H). As outdoor temperatures exceed the H threshold, indoor conditions follow until occupancy increases, prompting the system to maintain comfort. This adaptive behavior repeats, balancing comfort and energy efficiency.

Smart humidity control also adapts effectively to dynamic conditions. Figure 10 (a) shows relative humidity (RH) behavior, while Figure 10 (b) displays humidification and dehumidification loads. When outdoor RH exceeds comfort thresholds, indoor RH adjusts to conserve energy during low occupancy. Conversely, when conditions demand, the system prioritizes comfort by maintaining indoor RH within acceptable ranges, showcasing its flexibility in balancing efficiency and comfort.

3. CONCLUSION

This study evaluated the impact of smart thermostat and humidistat configurations on building energy efficiency, focusing on seasonal variations in heating, cooling, humidification, and dehumidification under different air change rates (ACH). By integrating a Fuzzy Logic Control (FLC) system into the Vertical City Weather Generator (VCWG v3.0.0), we simulated a detached residential building in Toronto over a full year (2020). The findings highlight both the potential and the limitations of dynamic setpoint adjustments based on environmental, occupancy, and energy price inputs.

- Smart control yielded significant energy savings, reducing heating loads by up to 132.8 [kW-hr m^{-2} $year^{-1}$] during colder months and saving 141.5 [kW-hr m^{-2} $year^{-1}$] for humidification by aligning indoor relative humidity (RH) with outdoor conditions, particularly in leakier buildings.
- During peak summer months, cooling demand increased by 31.4 [kW-hr m^{-2} $year^{-1}$], and dehumidification demand rose by 5.3 [kW-hr m^{-2} $year^{-1}$], due to fluctuations and higher mass loads. These results indicate reduced effectiveness of the smart control in warm sea-

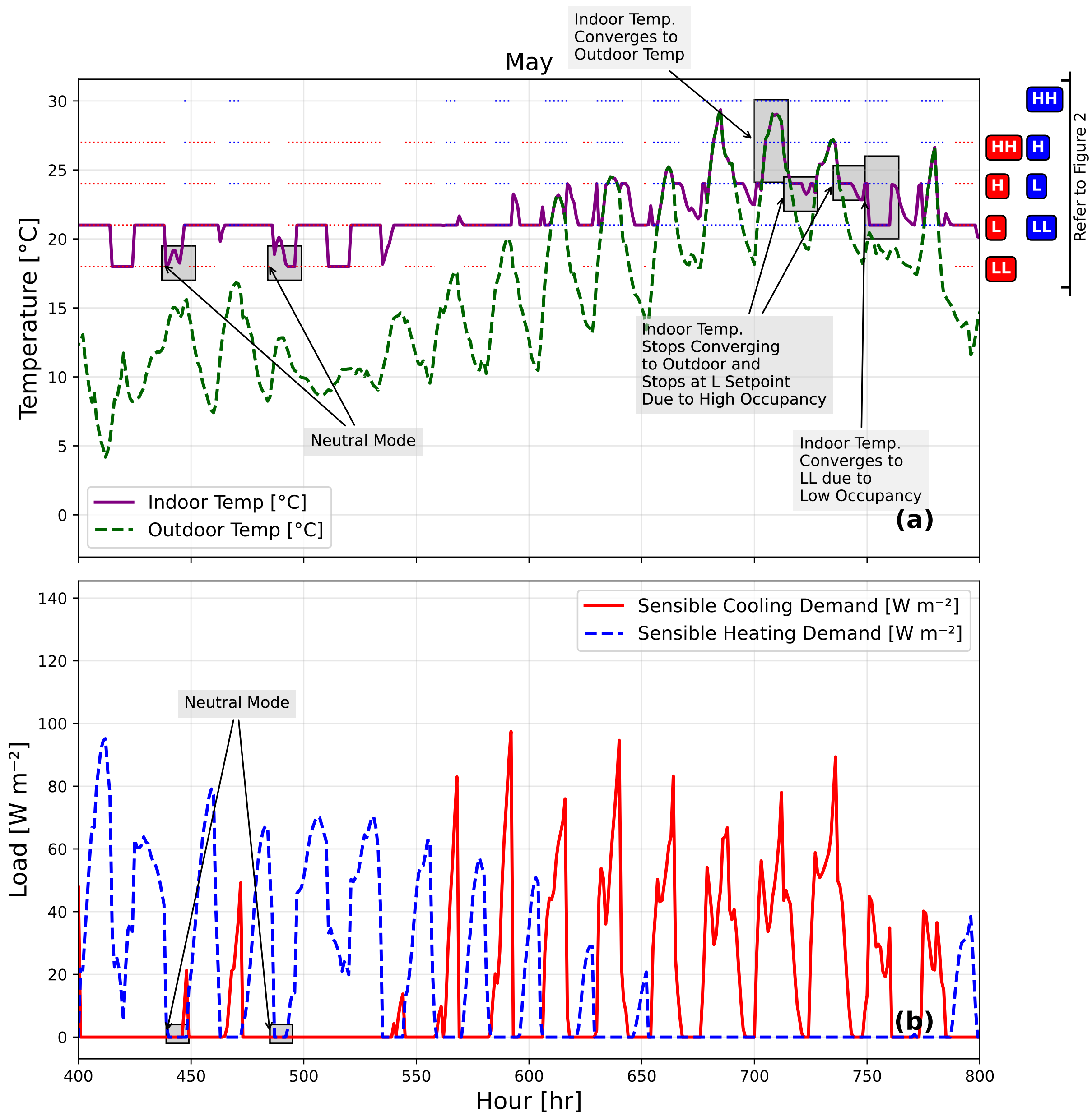

Figure 9. (a) Indoor temperature variations and (b) sensible heating and cooling load variations, both for May, showing the system's response to occupancy changes, electricity prices, and outdoor conditions.

sons.

- Year-round smart control achieved a net saving of 237 [kW-hr m^{-2} year^{-1}]. A hybrid approach, disabling smart features in summer, increased savings to 274 [kW-hr m^{-2} year^{-1}], demonstrating the advantages of a seasonal, adaptive strategy.
- Unlike conventional systems requiring airtightness, this approach proved effective in older, leakier buildings, reducing energy loads through better air exchange management.

In summary, while the smart control strategy excelled in heating and humidification, challenges

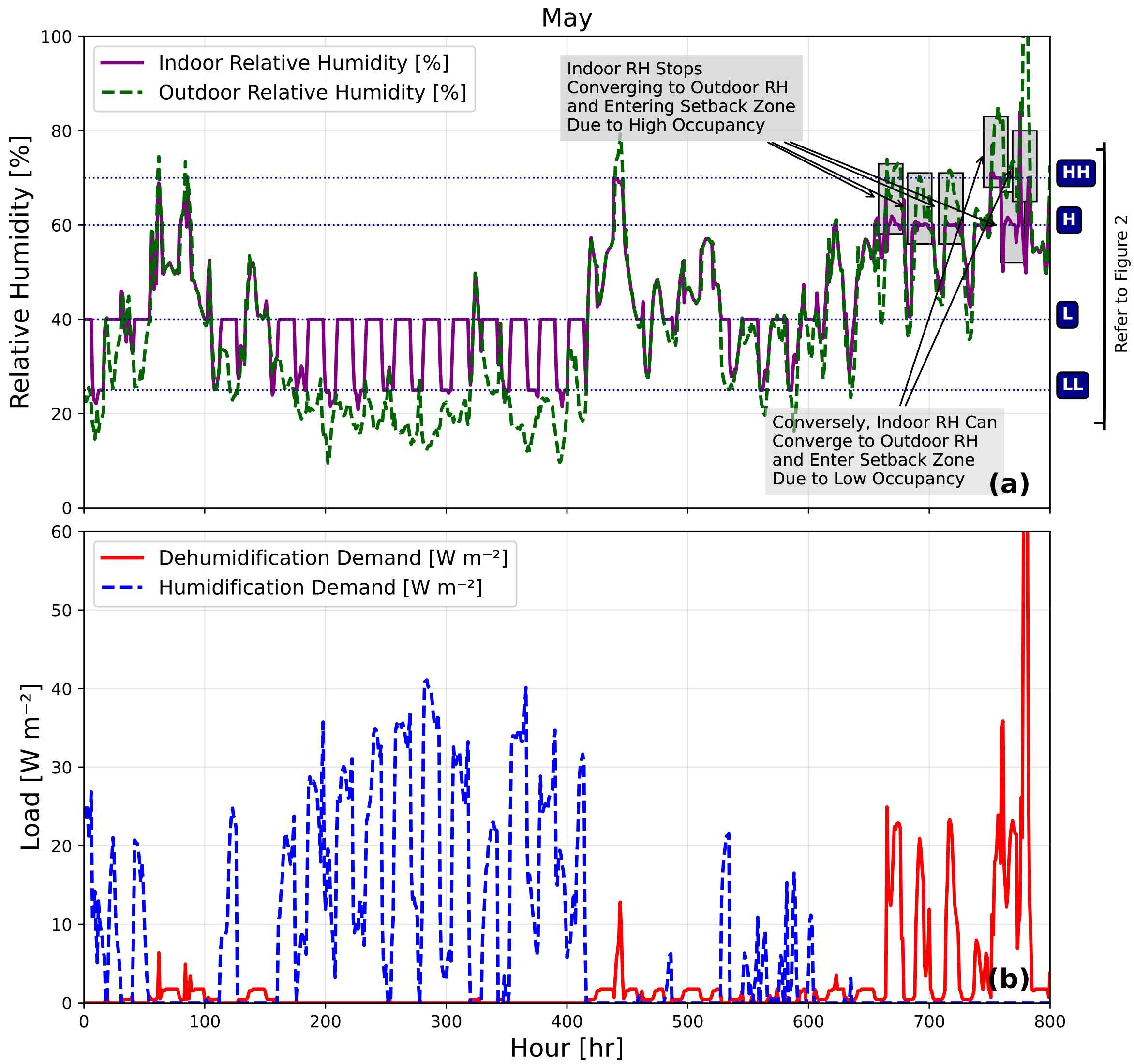

Figure 10. (a) Indoor RH variations and (b) latent (Humidification/Dehumidification) load variations, both for May, showing the system's response to occupancy changes, electricity prices, and outdoor conditions.

in cooling and dehumidification suggest the value of a hybrid approach, applying smart features selectively by season. This adaptable strategy enhances energy efficiency in diverse building types and supports sustainable HVAC energy management. Future research could extend these findings to other climate zones and building configurations.

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