frontiers | Frontiers in Energy Research

TYPE Original Research
PUBLISHED 24 April 2025
DOI 10.3389/fenrg.2025.1542107

Check for updates

OPEN ACCESS

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RECEIVED 09 December 2024
ACCEPTED 07 April 2025
PUBLISHED 24 April 2025

CITATION
Yang Y, Bjørnskov J and Jradi M (2025) Optimizing HVAC systems with model predictive control: integrating ontology-based semantic models for energy efficiency and comfort.
Front. Energy Res. 13:1542107.
doi: 10.3389/fenrg.2025.1542107

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Optimizing HVAC systems with model predictive control: integrating ontology-based semantic models for energy efficiency and comfort

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Building systems are dynamic and non-linear. In HVAC systems, independently controlled modules interact, creating complex interdependencies that challenge optimizing energy savings and thermal comfort. Model predictive control (MPC) has emerged as a promising strategy to address these challenges effectively since its inception. In this study, MPC is applied to optimize indoor performance by integrating the district heating and ventilation systems using an ontology-based semantic model, with the objective of minimizing heating energy consumption while maintaining indoor comfort. A data-driven energy model was developed for a single floor of a hospital building, comprising 12 conditioned zones and incorporating data from 45 measuring devices. Two rooms with differing thermal performance and control strategies were selected for analysis. The results demonstrate that the implementation of the MPC reduces heating energy consumption by 7.3% and 8.5% in the respective rooms while also increasing the indoor thermal comfort time by 3.17% and 86.51%, respectively. Integrating MPC with an ontology-based semantic model creates a robust framework for advanced building energy management. This approach facilitates seamless communication and interoperability among HVAC subsystems, enabling cohesive control within a digital twin platform. The semantic model standardizes and contextualizes diverse data, enhancing the accuracy and responsiveness of the MPC.

KEYWORDS

model predictive control, building energy optimization, thermal comfort, HVAC, digital twin

1 Introduction

Buildings consume around 40% of primary energy (Yang et al., 2020). Their operations not only result in very high energy consumption but also lead to substantial environmental concerns due to greenhouse gas emissions (Huang et al., 2021). Traditionally, building energy systems have been managed using Rule-Based Control (RBC), such as on/off or bang-bang control, and Proportional-Integral-Derivative (PID) controllers. These methods are favored for their simplicity and low computational requirements (Mork et al., 2022). In recent years, a number of advanced control strategies, such as extremum seeking control (ESC) (Li and Tong, 2021), reinforcement learning (RL) (Wang and Hong, 2020), mixed-integer quadratic programming (MIQP) (Killian et al., 2018), and model predictive control (MPC) (Zhan and Chong, 2021), have been developed to enhance building energy management, leading to significant improvements in energy efficiency (Mariano-Hernández et al., 2021). The implementation of these building control strategies alone has been shown to achieve an estimated annual energy savings of 30% across various building types (Fernandez et al., 2017). Specifically, applying advanced control strategies to HVAC systems can reduce energy consumption by 25% while maintaining a satisfactory indoor environment (Afroz et al., 2018). Optimizing the operation of building energy systems offers a promising and efficient approach to rapidly reducing emissions from the existing building stock (Stoffel et al., 2023).

Maximizing user comfort and minimizing energy costs are common optimization objectives in modern smart homes within the building energy systems optimization problem (Haider et al., 2016). Among the advanced control strategies developed in recent years, MPC has shown promising potential to address these challenges in both application and energy savings due to its distinct advantages (Faedo et al., 2017). Firstly, MPC can derive optimal control actions for the present moment by predicting and accounting for future system conditions. Additionally, it effectively manages trade-offs between conflicting yet interconnected objectives through co-optimization. Moreover, MPC can be easily integrated into existing building control systems, functioning as supervisory control. Consequently, numerous studies have explored and proposed MPC applications in building energy management (Yao and Shekhar, 2021). For example, Hua et al., (2024) applied MPC to an office meeting room in Espoo, achieving a 2.8% reduction in energy consumption while enhancing the system's hydrodynamic stability by 50%. Zhang et al. (2023) developed an MPC strategy for private offices with controllable variable air volume (VAV) systems, demonstrating energy savings ranging from 28% to 35%. Ascione et al. (2023) investigated a nearly zero-energy building located in Benevento, featuring an efficient air-source multi-split system for cooling. Their MPC implementation ensured similar comfort performance while achieving cost savings of around 28%. Taheri et al. (2024) proposed a cloud-based MPC scheme for controlling the HVAC systems of educational buildings. Langner et al. (2024) devised an MPC strategy for the efficient management of distributed energy resources, including photovoltaic power generation and storage, thermally controlled loads, and smart appliances.

However, HVAC systems vary across buildings; therefore, the focus of MPC for HVAC systems also differs. For instance, due to varying weather conditions caused by geographic differences (Yang et al., 2024a), HVAC systems may operate solely for cooling or only for heating (Wang J. et al., 2023; Wang H. et al., 2023). As a result, the focus of MPC for HVAC systems exhibits geographic variability. Since Denmark is located in the northern part of Europe, the primary energy demand in buildings comes from heating. Therefore, this study will focus on optimizing the performance of heating systems. Additionally, heating systems differ across building types (Yang et al., 2024b). In some buildings, rooms are heated using VAV systems (Wang and Dong, 2024), whereas in others, heating is provided through district heating (DH) (Xu et al., 2017). In this study, data from an actual hospital heated by both VAV and DH systems have been collected, and the MPC will be implemented by combining both systems.

Since MPC controls the system by determining a sequence of control actions through the optimization of a specific objective function over a future time horizon—while applying only the first control action at each time instance (Yao and Shekhar, 2021)—a model capable of predicting the building's future performance is essential for the optimization process. Building energy models are typically developed using tools such as TRNSYS (Thermal Energy System Specialists, LLC, 2024), EnergyPlus (Yang et al., 2024c), or Modelica (Magni et al., 2021), as well as through data-driven methods (Smarra et al., 2018). In this study, a comprehensive building model employing an ontology-driven approach based on Python is used to accurately represent the complex dynamics of the building systems (Bjørnskov and Jradi, 2023). Additionally, since programming software offers an excellent environment to implement advanced algorithms and serves as a suitable tool for designing MPC controllers (Blum et al., 2022), an MPC controller is developed in Python. This study contributes to the growing body of knowledge in building energy management by presenting a novel integration of MPC with an ontology-based semantic model, specifically applied to optimize the performance of HVAC systems in complex building environments. The approach can address key challenges associated with the dynamic and nonlinear interactions between subsystems within an HVAC framework, such as DH and ventilation systems. The contributions and advancements to existing literature are outlined as follows:

- Ontology-Based Semantic Integration: Unlike traditional MPC approaches that often rely on static or standalone models, this study employs an ontology-based semantic model to provide a standardized, interoperable framework for data integration. This ensures that diverse data sources, including 45 measurement devices, are utilized effectively, offering enhanced context-awareness and adaptability in control strategies.
- Comprehensive Zone-Level Analysis: The research targets a specific hospital floor with 12 conditioned zones, offering a granular analysis of individual room performance. By focusing on two rooms with differing thermal behaviors and control strategies, the study captures insights into the interplay between zone-specific parameters and overarching control objectives, which is often overlooked in broader studies.
- Energy Efficiency and Comfort Optimization: The implementation of the proposed MPC approach yielded measurable energy savings of 7.3% and 8.5% in the analyzed rooms, accompanied by improved thermal comfort. This dual achievement of energy efficiency and occupant wellbeing is a significant improvement over existing studies, which often prioritize one goal at the expense of the other.
- Scalability and Applicability: By demonstrating the feasibility of coupling MPC with an ontology-based model, the research highlights its scalability for implementation in other building types and operational contexts. The methodology aligns well with the trends in smart building technologies, making it a versatile solution for future energy management systems.
- Bridging a Gap in Digital Integration: While most existing literature emphasizes either advanced control techniques or semantic modeling independently, this study bridges the gap by

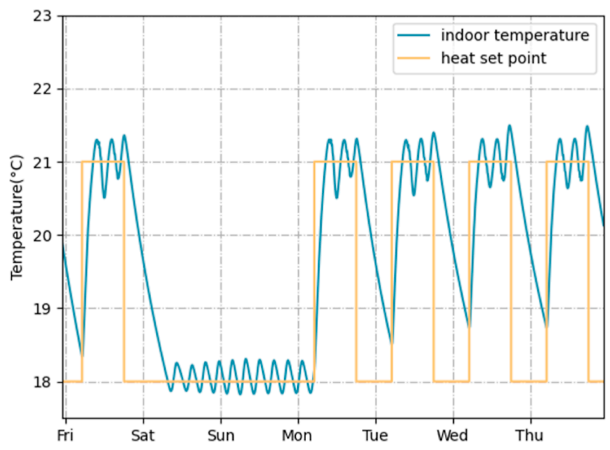

FIGURE 1
Indoor temperature and heating set point profile of thermally comfortable room over 1 week.

integrating the two into a unified framework. This integration not only enhances the decision-making capabilities of control systems but also enables smoother adoption within modern building management paradigms.

2 Methodology

2.1 Case description

As depicted in Figure 1, the first floor of the building consists of six office spaces ranging from 18 m^2 to 31 m^2, each furnished with desks, computers, monitors, and multiple lighting sources. Occupancy varies from single-person offices to shared spaces accommodating up to six individuals. Two 46 m^2 meeting rooms, separated by a folding wall, can be combined into a larger space as needed. The floor also includes two changing rooms of 21 m^2 and 42 m^2, containing two and six enclosed toilet stalls, respectively. Additionally, an 82 m^2 shared staff accommodation area features a kitchenette. Other amenities, such as a stairwell, elevator, and multiple single-stall restrooms, are present but excluded from the demonstration. Table 1 summarizes the spaces, detailing their areas, functions, and occupancy. Each space is equipped with sensors monitoring temperature, CO_2 levels, radiator valve positions, and damper positions, except for Space two, which lacks temperature, CO_2, and valve position sensors.

As indicated in Table 1, demand-controlled ventilation (DCV) is implemented in most rooms, adjusting air supply flow through damper actuation via proportional-integral (PI) controllers to maintain CO_2 concentrations within comfortable levels. With the exception of Space 2, all areas are equipped with radiators and motorized valves, which are also regulated by PI controllers. Additionally, most dampers function in an on-off mode, facilitating heating within a 0%–30% opening position range.

The first room selected for this study is Space eight, where the ventilation system is controlled by a CO_2 setpoint with a constant value of 900 ppm. The temperature profile and heating setpoint for this room are shown in Figure 1. For this meeting room, the heating setpoint is set to 21°C during working hours and 18°C during off-hours. As shown in Figure 1, the indoor temperature follows the setpoint closely, and thus, this room is referred to as a thermally comfortable room.

The second room selected for this study is Space 4, where the ventilation system is jointly controlled with the DH system based on a heating setpoint. Since this room serves as a changing room, it is assumed that occupants wear fewer clothes, meaning that a higher temperature is required to satisfy thermal comfort. As shown in Figure 2, the heating setpoint for this room is 22°C during working hours and 21°C during non-working hours. However, it can be observed that the indoor temperature fails to reach the setpoint during both working and non-working hours. The damper and valve openings of the ventilation system and DH system are also shown in Figure 2, and it is evident that both systems are already operating at maximum capacity. For this reason, this room will be referred to as a thermally uncomfortable room in the following discussion.

2.2 Energy model development

To implement effective model predictive control, a comprehensive building model was developed using an ontology-driven approach. This approach leverages semantic models to capture the building's physical structure, system relationships, and equipment characteristics, enabling automatic generation of simulation models suitable for MPC. By structuring the model this way, we ensure it remains adaptable and maintainable while accurately representing the complex dynamics of the building systems. The energy modeling framework adopted in this work, and the details of the model generation and calibration process are described in earlier work by the authors (Bjørnskov et al., 2025; Bjørnskov et al., 2025).

The model predictive control implementation uses a component-based modeling framework. The building system is divided into individual components representing thermal zones, controllers, dampers, valves, and sensors. Some components are implemented in Python, while others are exported as Functional Mock-up Units (FMUs) from Modelica models to utilize both platforms' capabilities.

2.2.1 Component models

The modeling framework is built on component models that represent specific aspects of building behavior. A key example is the thermal zone model implemented in Modelica, shown in Figure 3. This component represents room dynamics with heat transfer through the building envelope, thermal storage in room air and furniture, heat addition from the space heater, and air exchange through the ventilation system.

The thermal zone model interfaces with other building systems through defined connection points. These interfaces include.

- Air handling connections for supply and exhaust flows
- Heating circuit ports for hot water distribution
- Environmental inputs for outdoor conditions and solar gains
- Control signal connections for valve and damper positions

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TABLE 1 General information on the spaces included in the demonstration case (Bjørnskov et al., 2025).

				Measuring devices				Climate control	
Space	Area [m^2]	Type	Occupancy	Temperature	CO_2	Valve position	Damper position	Temperature	DCV
1	82.2	Accommodation		x	x	x	x	x	x
2	15.6	Storage/Copy					x		
3	23.1	Office	3	x	x	x	x	x	x
4	20.7	Showers		x	x	x	x	x	
5	23.1	Office	1	x	x	x	x	x	x
6	41.2	Showers		x	x	x	x	x	
7	46.6	Meeting room	9	x	x	x	x	x	x
8	46.6	Meeting room	9	x	x	x	x	x	x
9	23.1	Office	1	x	x	x	x	x	x
10	23.1	Office	1	x	x	x	x	x	x
11	17.5	Office	1	x	x	x	x	x	x
12	30.7	Office	6	x	x	x	x	x	x

TABLE 2 The relationship between the PMV values and the thermal comfort.

PMV	−3	−2	−1	0	1	2	3
Thermal sense	Cold	Coo1	Slightly cool	Neutral	Slightly warm	Warm	Hot

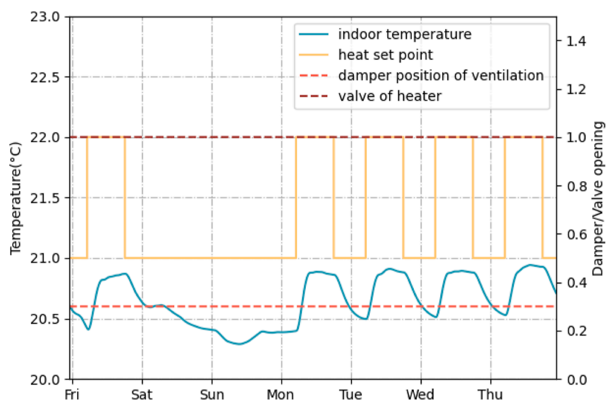

FIGURE 2
Indoor temperature, heating setpoint, damper opening of the ventilation system, and valve opening of the DH system of the thermally uncomfortable room over 1 week.

- Sensor outputs for temperature and CO_2 measurements

2.2.2 Full simulation model

The complete simulation model, shown in Figure 4, integrates individual components into a comprehensive representation of the building floor. The model consists of 152 interconnected components, representing the building's thermal behavior and control systems. The network includes several space models that represent individual thermal zones, with the thermally comfortable room and thermally uncomfortable room highlighted in the blue and red boxes in Figure 4, respectively. Details of the ontology-driven model generation can be found in our previous study (Bjørnskov et al., 2025).

Component connections reflect the physical building's system topology. For example, in the thermally comfortable room, the model includes the current heating capacity constraints, enabling the MPC to account for these limitations when coordinating heating and ventilation systems.

2.3 MPC framework

To optimize the energy performance of the room, an MPC controller is designed for the HVAC system. In the original RBC, the heating and ventilation systems are controlled independently. However, in real life, the operation of the ventilation system impacts the indoor air temperature. In other words, the performance of the heating system is coupled with the ventilation system to some extent. Therefore, the MPC controller is designed to integrate the heating system controller with the ventilation controller.

Since MPC is a multi-objective optimization process, the initial step is to define the targets for implementing these control strategies. The objectives for the optimization will be discussed in the following subsections.

2.3.1 Parameters for optimization problems

2.3.1.1 Energy

In the field of building energy management, the ultimate optimization goal is to reduce overall energy consumption and eventually achieve net-zero energy buildings. In buildings, energy can be used for heating, cooling, lighting, and various other purposes. In this study, since the energy used to maintain indoor temperature accounts for the primary energy consumption during the winter in Denmark, the primary objective is to minimize the heating energy consumption ($Energy_{all}$) of the DH system ($Energy_h$) and ventilation systems ($Energy_v$), which can be calculated by:

$$Energy_{all} = Energy_h + Energy_v \tag{1}$$

For the energy mentioned in Equation 1, $Energy_h$ is straightforward to measure, as it corresponds to the energy consumed by DH system maintain the indoor temperature. However, $Energy_v$ is more complex compared to the DH system. A schematic of the ventilation system can be seen in Figure 5. Outdoor air passes through the heat recovery unit and heating coil before being delivered to each room. Therefore, in this study, the energy consumption of the ventilation system for the target room refers to the energy consumed by the heating coil for the air supply to the target room, which can be calculated using Equation 2, as follows:

$$Energy_v = \left(t_{supply} - t_{hc.out}\right) m_{supply} c_{p.air} \tag{2}$$

where t_{supply} is the supply air temperature (°C), $t_{hc.out}$ is the air temperature after the heat recovery unit (°C), m_{supply} is the supply air flow rate (kg/s), and $c_{p.air}$ is the thermal capacity of the air (J/(kg·°C)).

2.3.1.2 Thermal comfort

Reducing energy consumption can often be achieved at the expense of indoor comfort, which is undesirable for the occupants. Therefore, the objective of this MPC is to minimize the heating energy usage for DH and ventilation systems while maximizing indoor thermal comfort.

Serval indices can be used to quantify the indoor thermal comfort. Among them, the most common used are Predicted Mean Vote (PMV) and the Predicted Percentage Dissatisfied (PPD) (Thapa and Kr. Panda, 2015). As highlighted in Table 2, the PMV provides a quantitative estimate of the thermal sensation experienced by a

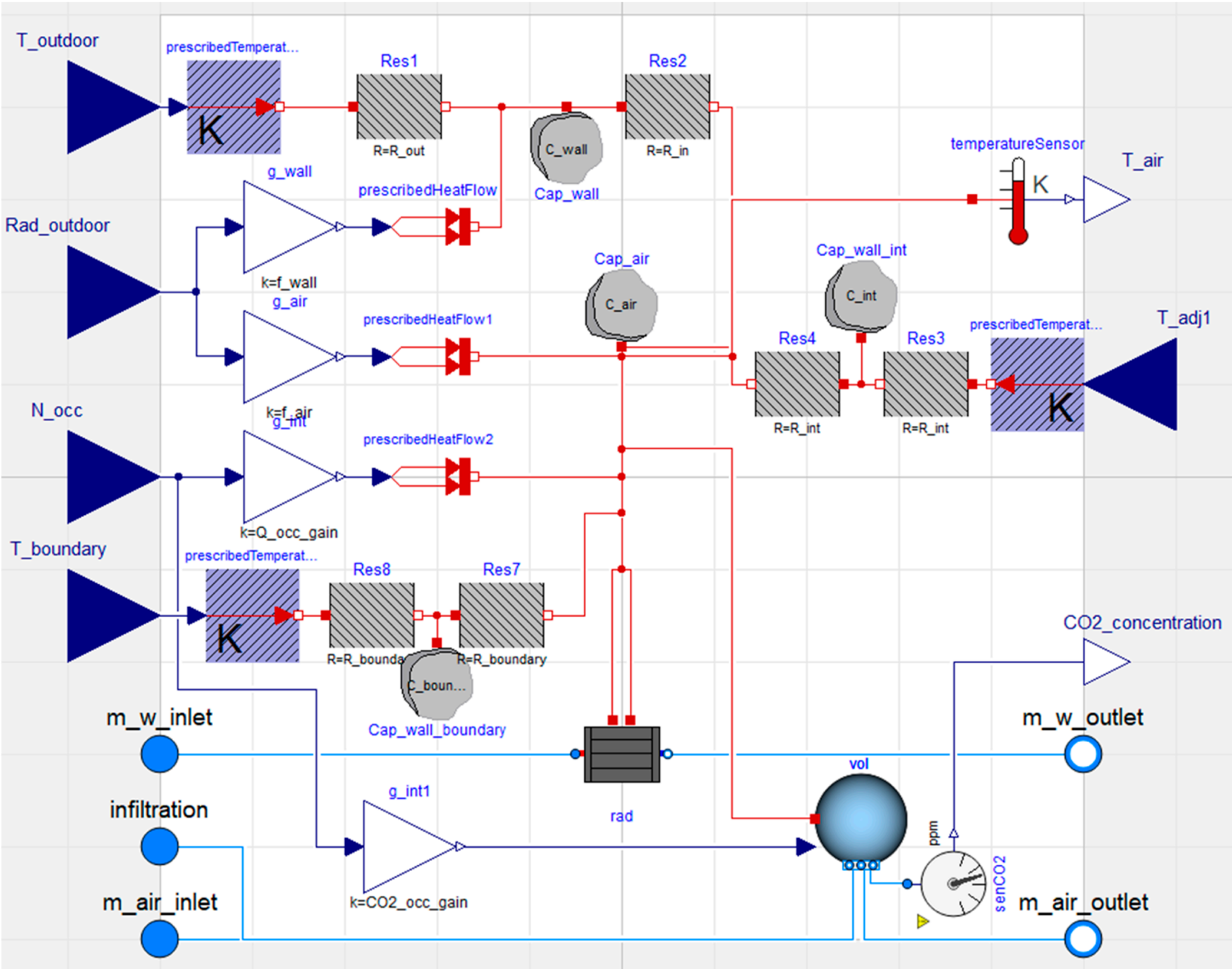

FIGURE 3
Example component model of a space.

group of individuals in a particular thermal environment, which can be calculated by Equation 3:

$$
\begin{aligned}
PMV =& \left(0.303e^{-0.036M} + 0.028\right) \times ((M - W) - 3.05 \\
& \times 10^{-3}(5733 - 6.99(M - W) - P_a) - 0.42((M - W) - 58.15) \\
& - 1.7 \times 10^{-5} M(5867 - P_a) - 1.4 \times 10^{-3} M(34 - t_a) - 3.96 \\
& \times 10^{-8} f_{cl}\left((t_{cl} + 237)^4 - (t_r + 273)^4\right) - f_{cl} h_c (t_{cl} - t_a)) \quad (3)
\end{aligned}
$$

where M represents the metabolic rate (W/m^2), while W represents the effective mechanical power (W/m^2). P_a represents the partial pressure of water vapor (Pa) and t_a represents the ambient air temperature (°C). t_{cl} represents the clothing surface temperature (°C), whereas t_r represents the mean radiant temperature (°C). f_{cl} represents the ratio of the surface area of the clothed body to that of the unclothed body is denoted, and h_c represents the convective heat transfer coefficient (W/m^2·K). And the relationship between the PMV values and the thermal comfort can be seen in Table 1 (Zhang et al., 2019).

Based on the PMV, the PPD can be calculated by Equation 4 (Song et al., 2024).

$$PPD = 100 - 95 \exp\left(-0.03353PMV^4 - 0.2179PMV^2\right) \quad (4)$$

The critical threshold for judging indoor thermal comfort based on PPD is 10%. When the PPD is below 10%, the indoor thermal environment is considered comfortable. Since a higher PPD represents a greater level of dissatisfaction with the indoor environment, the second objective of our MPC in this multi-objective optimization is to minimize the indoor PPD. Furthermore, the maximum hourly value of PPD during the examined period is preferred to the average value as objective function, because it allows a more rigorous and punctual control of thermal comfort. Indeed, the choice of maximum hourly value of PPD ensures that the hourly PPD does not fall below the maximum hourly value of PPD provided by the optimization study during the whole examined period (Ascione et al., 2016).

2.3.1.3 Indoor air quality

In addition to thermal comfort, other indoor parameters, such as CO_2 levels, also significantly impact occupant wellbeing.

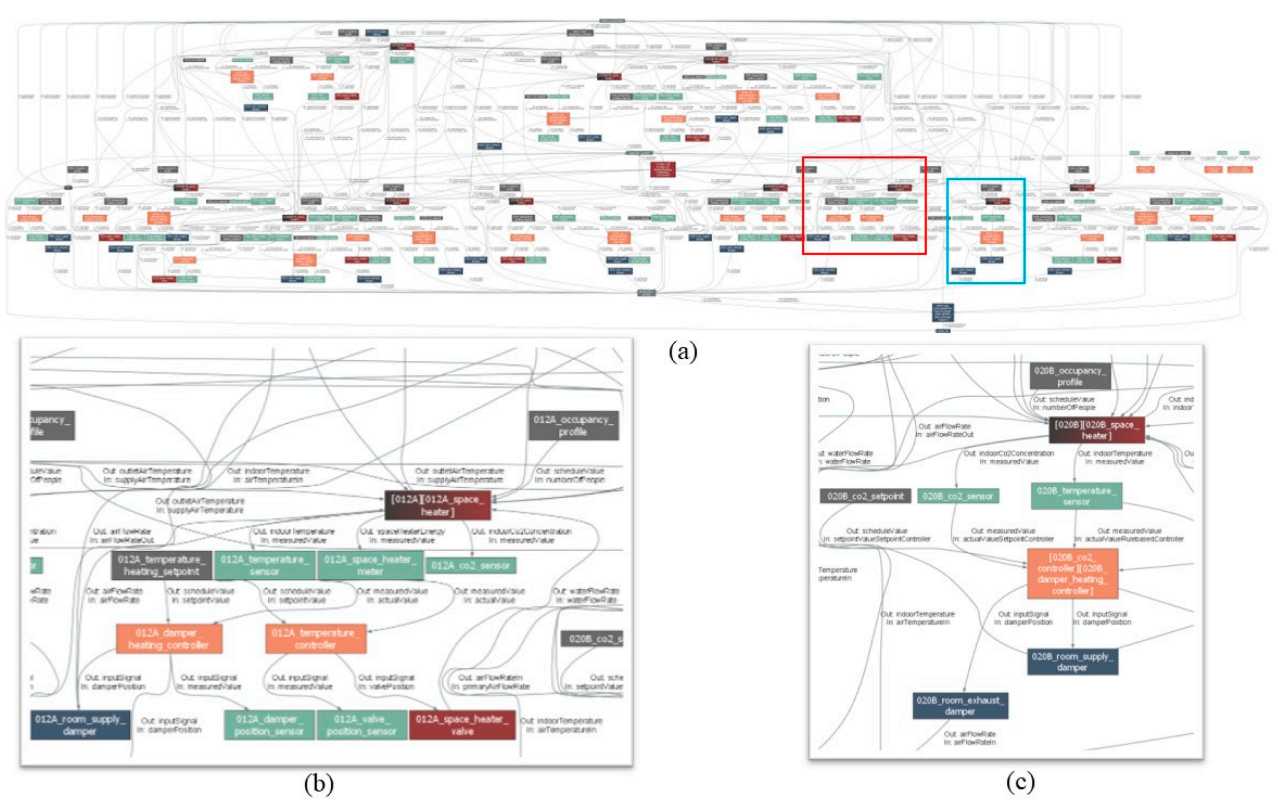

FIGURE 4
(A) Simulation model of the hospital case, automatically generated from the semantic model (Bjørnskov et al., 2025; Bjørnskov et al., 2025), with the room case study highlighted in **(B)** the red frame and **(C)** the blue frame.

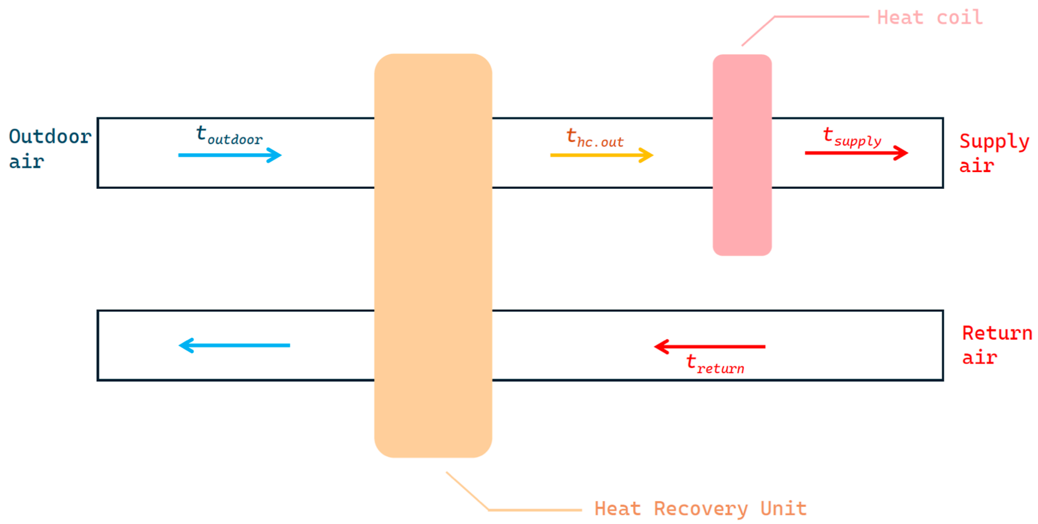

FIGURE 5
Schematic of the ventilation system in the considered case study.

In some rooms, the ventilation system is controlled by CO_2 setpoints, and its operation directly influences indoor CO_2 concentrations. Consequently, for rooms where the ventilation system is controlled by CO_2 setpoints, indoor air quality (IAQ) is used as a metric to evaluate the system's effectiveness in maintaining a healthy indoor environment. According to the European Standard EN 13779, IAQ is categorized into four levels based on CO_2 concentration (EN, 2025).

- Class A (High Quality): CO_2 levels above outdoor air by no more than 350 ppm.
- Class B (Medium to High Quality): CO_2 levels above outdoor air by 350–500 ppm.
- Class C (Moderate Quality): CO_2 levels above outdoor air by 500–800 ppm.
- Class D (Low Quality): CO_2 levels above outdoor air by more than 800 ppm.

In this study, the outdoor CO_2 concentration is assumed to be approximately 400 ppm, and IAQ is considered in the MPC for rooms where the ventilation system is controlled by CO_2 setpoints.

2.3.2 Model for multi-objective optimization problems

To implement the MPC with the ontology-based semantic model, the model is first used to standardize diverse data sources and generate a simulation model. This simulation model acts as a black-box representation to predict the target room's parameters based on different control signals. The predicted outputs are then utilized in the MPC framework to perform multi-objective optimization, ensuring effective control decisions.

As mentioned in Section 2.1, two rooms with different thermal performance—namely, thermally comfortable and thermally uncomfortable—using different control strategies were selected for this study. For the former, the ventilation system is controlled based on the CO_2 setpoint. Consequently, the optimization problem for the MPC in this room can be formulated as shown in Equations 5–7:

$$minF\left(sp_t, sp_{CO_2}\right) = \left[Energy, PPD_{max}, C_{CO_2.max}\right] \tag{5}$$

Subject to:

$$sp_{t.min} \le sp_{t.n} \le sp_{t.max} \tag{6}$$

$$sp_{CO_2.min} \le sp_{CO_2.n} \le sp_{CO_2.max} \tag{7}$$

where *Energy* refers to the heating energy consumption by the DH system and ventilation systems during the optimization period. PPD_{max} and $C_{CO_2.max}$ represent the maximum hourly *PPD* and hourly CO_2 concentration, respectively. *sp* refers to the setpoint of the control system, with the subscript *t* indicating temperature, CO_2 referring to CO_2, and *n* representing the hour within the optimization period. For sp_t, the setpoint boundary is 18°C–22°C, while sp_{CO_2} is set between 750 ppm and 900 ppm. These constraints have been defined based on the recommendation and feedback from the building operators. This model is built using Python and solved with the pymoo package (Blank and Deb, 2020).

For the thermally uncomfortable room, the ventilation system is jointly controlled with the DH system based on the heating setpoint. Specifically, the operation of both the DH system and the ventilation system is determined by the heating setpoint. While the operation of the ventilation system does influence IAQ, it cannot assertively control IAQ. Therefore, IAQ is not considered an optimization target for the MPC, as the ventilation system lacks the capability for precise IAQ control. Besides, as it can be seen in Figure 2, since the fully opening valve of the ventilation system and fully opening the damper of the heating system cannot make the indoor temperature to reach the heat setpoint, the supply air temperature from the ventilation system, t_{supply}, is also utilized in the MPC optimization process to increase the indoor air temperature. Consequently, the optimization problem for the MPC in this room can be formulated as expressed in Equations 8–10:

$$\mathrm{minF}\left(sp_t, sp_{t.supply}\right) = \left[Energy, PPD_{max}\right] \tag{8}$$

Subject to:

$$sp_{t.min} \le sp_{t.n} \le sp_{t.max} \tag{9}$$

$$sp_{t.supply.min} \le sp_{t.supply} \le sp_{t.supply.max} \tag{10}$$

The heating setpoint sp_t for this room varies between 21°C and 22°C, while the supply air temperature $sp_{t.supply}$ ranges from 19°C to 30°C. Also, in this case, the constraints have been set based on feedback from the building operators.

2.3.3 Solution for the multi-objective optimization problem

In multi-objective optimization problems, a key challenge is defining the solutions. From a theoretical mathematical perspective, these problems do not have a single optimal solution; instead, they yield a collection of solutions known as the Pareto front. The Pareto front represents a set of non-dominated solutions that form the boundary of the feasible solution space, where trade-offs between objectives occur.

Once a set of non-dominated solutions is obtained, the next challenge is to narrow it down to a few or even a single solution. This decision-making process in multi-objective problems is referred to as Multi-Criteria Decision Making (MCDM). To perform MCDM for the ultimate control, multi-objective problems must be transformed into single-objective problems. For this purpose, the Weighted Sum Method is applied, as shown below:

$$Minimizei \sum w_i f_i(x) \tag{11}$$

where w_i are the weights for objective $f_i(x)$

For different objectives $f_i(x)$, the lower and upper bounds would be very different, therefore, normalization for different objectives is required.

3 Results and discussion

3.1 MPC for the thermally comfortable room

3.1.1 Decision making for the MPC

For this room, there are three objectives for optimization, forming a 3D solution space. The distribution of these solutions is shown in Figure 6. However, for MPC, only one solution is needed for the final control strategy, meaning a single solution must be selected from the Pareto front using MCDM. In this study, the weighted sum method is applied. However, determining the appropriate weights to achieve the desired control outcomes is not straightforward. Therefore, the range of weights is tested. The primary requirement is to ensure indoor comfort when the room is occupied. The final MCDM result is shown in Figure 6, represented

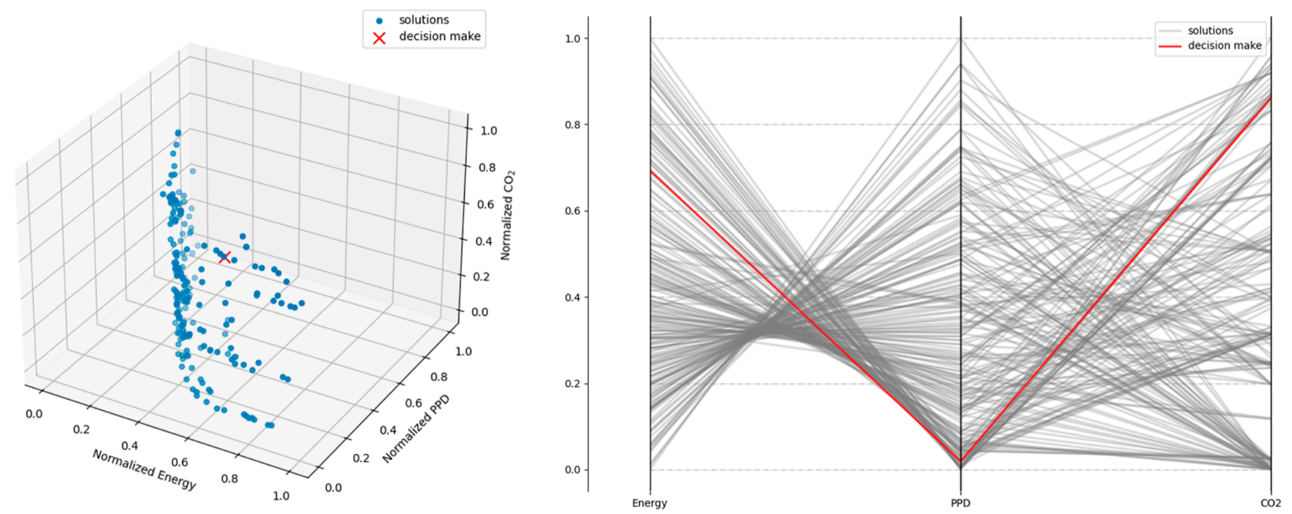

FIGURE 6
Distribution of the solutions and the decision made by the multi-objective optimization for the first hour of December in 3D scatter plot and parallel coordinates plot.

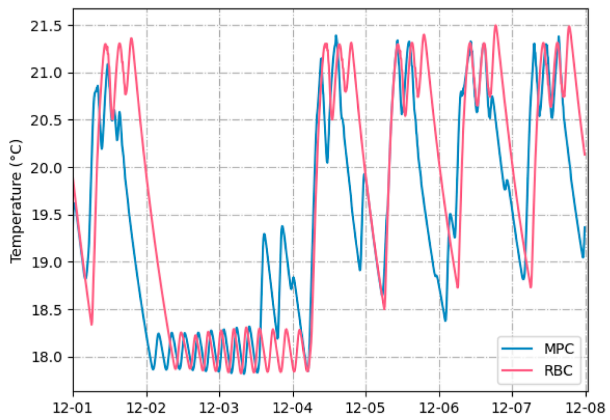

FIGURE 7
Room temperature controlled by MPC and RBC during the first week of December.

by the red line, with the highest emphasis placed on indoor thermal comfort, followed by energy consumption, and the least emphasis on CO_2 concentrations.

3.1.2 Comparison between RBC and MPC

To observe the performance difference between the room controlled by RBC and MPC, Figure 7 illustrates the indoor temperature managed by these two strategies during the first week of December. During weekdays, compared to RBC, it can be observed that MPC initiates preheating in the morning, raising the indoor temperature in advance to ensure thermal comfort when people arrive. Additionally, since occupancy ends at 17:00, MPC lowers the indoor temperature earlier in the afternoon than RBC, thereby saving energy. Throughout working hours on weekdays, the indoor temperatures achieved by MPC and RBC are at comparable levels.

On Saturday, both control strategies display a similar temperature trend. However, on Sunday, MPC, which bases control decisions on the next 24-h forecast, also accounts for Monday's working hours when thermal comfort is needed. As a result, the indoor temperature maintained by MPC on Sunday is observed to be higher than that of RBC, as it is shown in Figure 7.

Based on the indoor environment parameters, the thermal comfort index, PPD, can be calculated. Figure 8 presents the PPD statistics of the room during the first week of December, showing both the PPD for the entire period and the PPD during times when the room is occupied. For the entire period, it can be observed that the average PPD for both MPC and RBC is at a similar level, with values of 7.72% and 7.46%, respectively. Additionally, the upper quartile for MPC is lower than that for RBC, with values of 10.04% and 10.31%, respectively. Since a PPD of 10% is the threshold distinguishing comfort from discomfort, the MPC shows slightly better performance than RBC in maintaining indoor thermal comfort for most of the time, which increase the indoor thermal comfort time by 3.17%. During the period when the room is occupied, the PPDs for both MPC and RBC are maintained within 5%–6%. Therefore, both control strategies effectively ensure thermal comfort when people are present indoors.

Since both control strategies ensure indoor thermal comfort, the focus shifts to the energy performance difference of the HVAC system managed by MPC and RBC. Figure 9 shows the daily heating energy consumption of the DH systems and ventilation systems controlled by MPC and RBC during the first week of December. On working days, the use of MPC reduces the overall heating energy consumption of both systems. Although preheating the room increases energy consumption, adjusting the indoor air temperature according to occupancy behavior leads to greater energy savings. On non-working days, the MPC slightly increases overall energy consumption. However, for the entire week, the use of MPC results in a 7.32% energy savings compared to RBC. In other

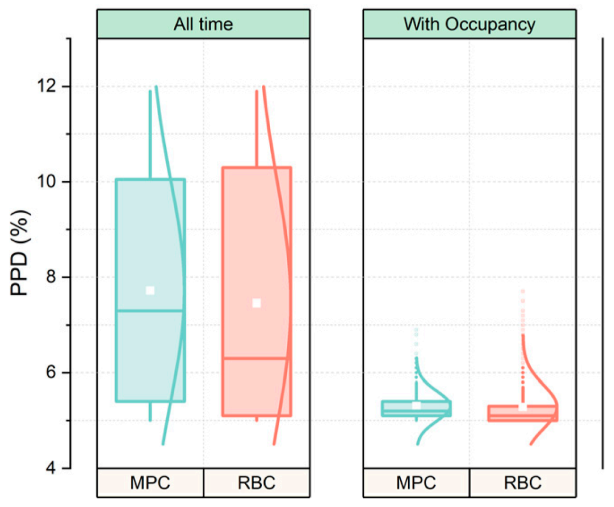

FIGURE 8
PPD distribution under MPC and RBC during the first week of December, for both the entire time period and the time with occupancy.

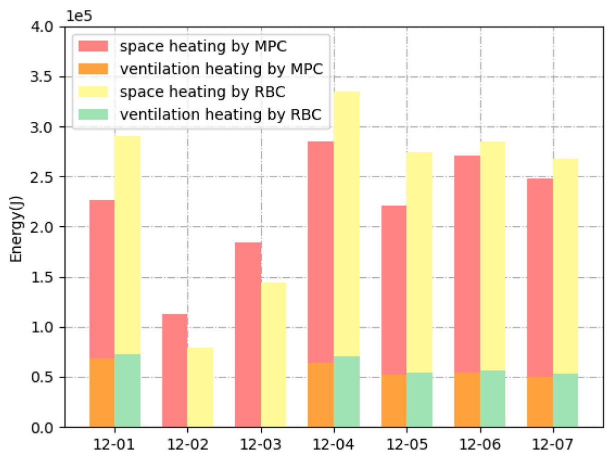

FIGURE 9
Daily heating energy consumption by DH system and ventilation system by MPC and RBC during the first week of December.

words, the MPC achieves energy savings while maintaining indoor thermal comfort.

Moreover, since the ventilation system in this room is controlled by a CO_2 setpoint, the application of MPC results in changes to the indoor CO_2 concentrations. Figure 10 illustrates the CO_2 concentrations controlled by MPC and RBC during the first week of December, with light blue representing high-quality IQA (class A) and blue indicating medium to high-quality IQA (class B). For both control strategies, the IQA of the room during non-working hours remains at class A, with no fluctuations in CO_2 concentrations due to the absence of indoor CO_2 sources during this period. During working hours, the MPC increases the indoor CO_2 concentration by an average of 31.72 ppm over the week compared to the RBC. However, it is important to note that even with this increase, the IQA

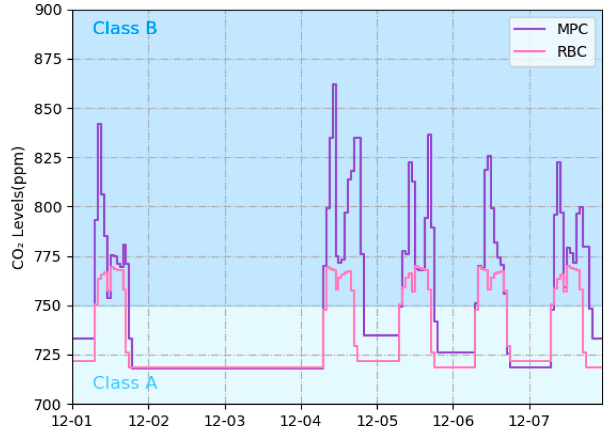

FIGURE 10
Room CO_2 concentration controlled by MPC and the RBC during the first week of December.

under MPC remains within class B, the same level of IQA maintained by RBC. Overall, the application of MPC achieves similar IQA while meeting energy-saving objectives.

3.2 MPC for the thermally uncomfortable room

3.2.1 Decision making for the MPC

For the thermally uncomfortable room, both the ventilation system and heating system are controlled by the heating setpoint. In other words, although the operation of the ventilation system affects the CO_2 concentration, the indoor CO_2 concentration is not directly controlled by the ventilation system. Therefore, the optimization objectives for this room are limited to energy consumption and the thermal comfort index, PPD. Figure 11 illustrates the distribution of solutions and the decision made by the multi-objective optimization for the first hour of December in the thermally uncomfortable room. The solutions form a well-defined non-dominated area, reflecting the characteristics of the Pareto front. Based on these solutions, the decision marked by a red "x" slightly prioritizes thermal comfort over energy consumption.

3.2.2 Comparison between RBC and MPC

The temperature profile managed by the MPC for the first week of December, based on the MCDM strategies, is shown in Figure 12, along with the temperature profile controlled by the RBC. For this room, the heating setpoint is adjusted between 21°C and 22°C, as indicated by the yellow background in Figure 12. Under the original RBC, the indoor temperature consistently fails to reach the heating setpoint. However, after applying the MPC, the indoor temperature during working days is successfully maintained within the range of 21°C–22°C, achieving the setpoint. It is worth noting that during the weekend, the indoor temperatures controlled by both the RBC and MPC fail to reach the heating setpoint, particularly on Sunday. This can be attributed to the similar heating setpoints for adjacent rooms. As shown in Figure 13, this room is adjacent

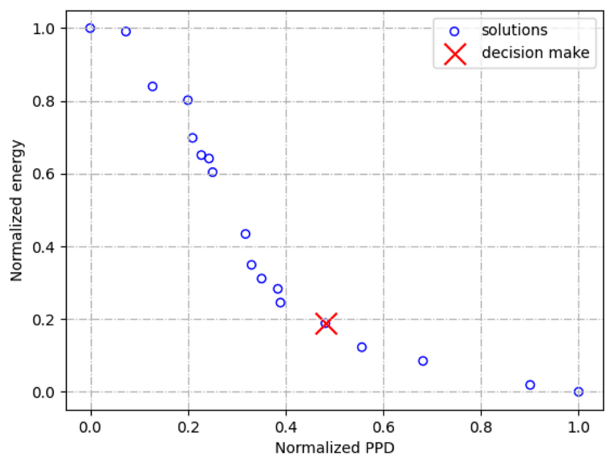

FIGURE 11
Distribution of the solutions and the decision made by the multi-objective optimization for the first hour of December.

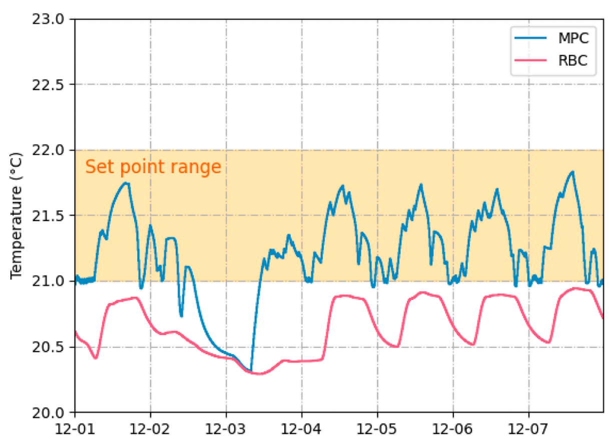

FIGURE 12
Room temperature controlled by MPC and RBC during the first week of December.

to staff accommodation area (Space 1) and the corridors, which share the same temperature setpoint as the thermally comfortable room (Space 8). During the weekend, the indoor temperatures in the adjacent rooms, as illustrated in Figure 7, remain around 18°C. This temperature difference results in increased heat transfer to the adjacent rooms, making it difficult to maintain the indoor temperature of the target room at its setpoint. This can be addressed by extending the MPC implementation to the adjacent rooms.

One objective of the MPC for this room is to ensure thermal comfort. Therefore, the PPD distribution under MPC control and the original RBC during the first week of December, for both the entire time period and the occupancy period, is shown in Figure 14. Under the original RBC, the PPD remains consistently above 10% throughout the entire time period, indicating that the room is always thermally uncomfortable. However, after the application of the MPC, the PPD for the entire time period shows significant improvement. The upper quartile falls below 10%, meaning that the room is thermally comfortable 75% of the time. In general, the implementation of the MPC increases the thermal comfort time by 86.51%. During the occupancy period, the PPD distribution under RBC control still remains above 10%, demonstrating that even during working hours, the basic thermal comfort requirements are not met. In contrast, the PPD distribution under MPC control improves further, with the upper quartile dropping to approximately 9%. This indicates that thermal comfort is better maintained during occupancy with MPC control. Thus, the application of MPC effectively enhances indoor thermal comfort compared to the original RBC.

Another objective of the MPC for this room is to ensure the efficient use of energy for heating. The daily heating energy consumption for this room under MPC and RBC control is shown in Figure 15. Typically, improving indoor thermal comfort results in increasing heating energy consumption. However, as shown in Figure 15, the energy consumption under MPC, which achieves better thermal comfort (as seen in Figure 14), is actually lower than that under RBC, which results in less thermal comfort. After applying the MPC, overall heating energy consumption was reduced by 8.5% compared to the RBC. This reduction is due to the building's ventilation system, which supplies air at a constant temperature of 19°C across the entire floor. For this room, the heating setpoint ranges from 21°C to 22°C, meaning the ventilation system effectively acts as a cooling source. Under the original RBC, the ventilation system is controlled by the heating setpoint, which causes the valve to remain open to maintain the indoor temperature. However, because of the low supply air temperature, this places additional strain on the DH system. This paradoxical process leads to high energy consumption without ensuring adequate indoor thermal comfort. In contrast, the MPC increases the supplied air temperature, resolving this paradoxical issue. By doing so, the MPC reduces energy consumption while simultaneously maintaining indoor thermal comfort.

3.3 Discussion

The application of MPC demonstrated clear advantages over RBC in optimizing indoor comfort and energy efficiency across two room scenarios. For the thermally comfortable room, MPC balanced indoor comfort with energy efficiency, leveraging MCDM to select optimal solutions from the Pareto front. It maintained acceptable IAQ within Class B standards, though CO_2 levels slightly increased, comparable to RBC. In the thermally uncomfortable room, MPC addressed design inefficiencies, improving thermal comfort and reducing energy consumption. Dynamic heating adjustments resolved issues with the ventilation system's low supply air temperature, reducing discomfort and enhancing overall comfort metrics compared to RBC.

Overall, MPC outperformed RBC, achieving energy savings and enhanced comfort, especially in scenarios where the original strategy failed. The study highlights MPC's ability to balance competing objectives, adapt to varying conditions, and address system inefficiencies. A multi-objective framework enabled MPC to minimize energy use while ensuring thermal comfort and acceptable IAQ, with weighted objectives prioritizing comfort during occupancy and efficiency during unoccupied periods.

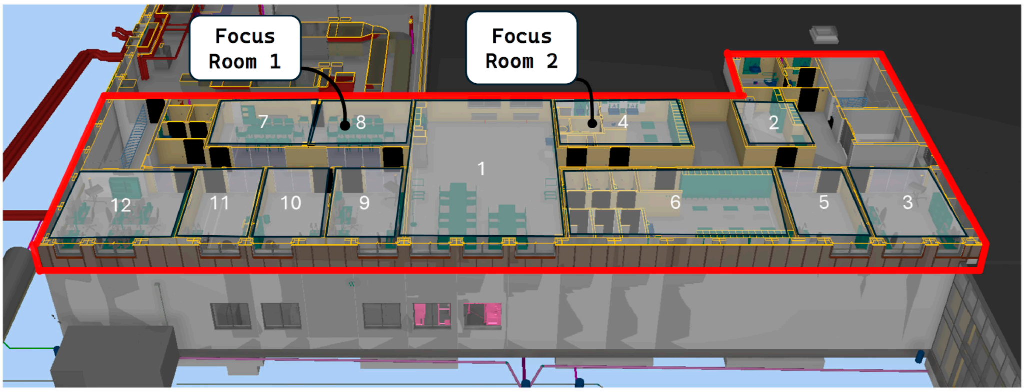

FIGURE 13
Floor plan of the considered case, including the modeled spaces (Bjørnskov et al., 2025; Bjørnskov et al., 2025).

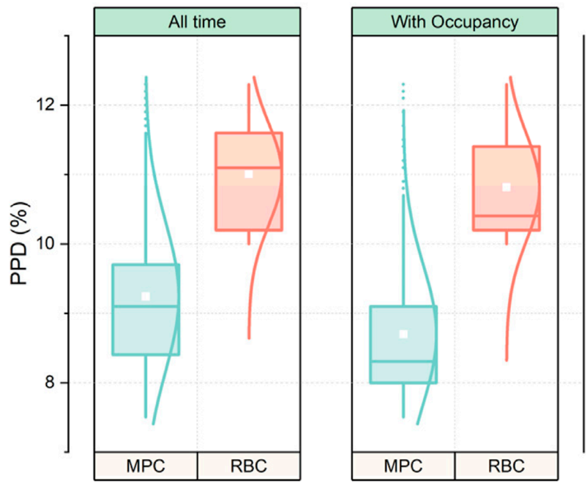

FIGURE 14
PPD distribution under MPC and RBC during the first week of December, for both the entire time period and the time with occupancy.

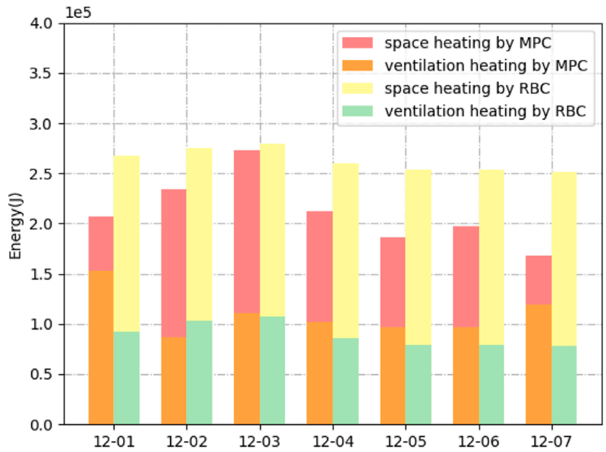

FIGURE 15
Daily heating energy consumption by DH system and ventilation system by MPC and RBC during the first week of December.

System constraints ensured realistic control strategies, maintaining comfort and IAQ within thresholds despite aggressive energy-saving measures. This was particularly effective in addressing design challenges in the thermally uncomfortable room. The scalability of MPC to larger buildings and its reliance on high-resolution data further emphasizes its potential. Future studies could explore integrating factors like humidity and weather, extending applicability to broader contexts and seasonal variations.

The study's focus on specific scenarios and operational periods highlights its broader applicability. While demonstrating MPC's effectiveness in winter, similar principles could be adopted for summer cooling or mixed-mode ventilation, where different constraints prevail. Expanding the analysis to include transitional seasons or variable occupancy patterns would provide a more comprehensive view of MPC's adaptability and year-round performance.

4 Limitations of the research

The MPC is applied to a digital twin model of the hospital for energy saving and thermal environment maintenance in this study. However, currently, the digital twin model can only consider the certain indoor parameters which are used for indoor thermal environments control such as temperature and CO_2 levels. For the hospital, some other indoor parameters are equally important such as humidity, velocity and cleanliness for the Assessment of the indoor environment.

5 Conclusion

In this study, MPC was applied to optimize energy consumption and indoor comfort in a room by considering both the heating and ventilation systems. A whole-floor model was developed using an ontology-based semantic model, and two rooms with differing ventilation control strategies and thermal performance were selected from this floor for the MPC analysis. A Python-based MPC optimizer was integrated with the ontology-based semantic model to enhance the room's performance. The main conclusions are as follows

1) The implementation of the MPC resulted in a reduction in energy consumption for both rooms. For the thermally comfortable room, energy consumption decreased by 7.32%. Meanwhile, for the thermally uncomfortable room, energy consumption was reduced by 8.5%.
2) The application of the MPC not only saves energy but also improves indoor thermal comfort. For the room that already met thermal comfort requirements, the weekly PPD under MPC control slightly outperformed that under RBC control. However, during occupied periods, the two control strategies showed similar thermal comfort levels. For the room that previously did not meet thermal comfort standards, the implementation of the MPC significantly improved indoor thermal comfort compared to original RBC.
3) In the room that already met thermal comfort requirements, the ventilation system was controlled by CO_2 setpoints. For this room, the improvement in energy performance while maintaining indoor thermal comfort came at the expense of an increase in indoor CO_2 concentrations. However, despite the rise in CO_2 concentrations, the IAQ for both the original RBC and MPC remained the same, staying within Class B standards.
4) In the room that did not meet thermal comfort requirements, the ventilation system and heating system were jointly controlled by the heating setpoints. However, the flawed design of the ventilation system made it difficult to achieve the original setpoint. Therefore, the MPC was utilized to address the inefficiencies caused by the unreasonable design and allocation of the jointly controlled system.

The findings of this study have broader implications for the deployment of MPC in real-world scenarios. Energy savings and comfort improvements achieved through MPC validate its potential as a robust tool for advancing sustainability goals in building management. The study also underscores the necessity for MCDM approaches to handle trade-offs effectively, such as balancing CO_2 levels against energy consumption.

However, challenges remain. The digital twin model used in this study currently considers only a limited set of indoor parameters for controlling the thermal environment, such as temperature and CO_2 levels. In hospital settings, maintaining optimal humidity levels is crucial for preventing airborne pathogen transmission and ensuring occupant wellbeing. While humidity control was not explicitly modeled in this study, it can be integrated into future HVAC optimization frameworks, potentially using coupled temperature and humidity control strategies. Additionally, airflow velocity and air cleanliness are typically managed through ventilation and filtration strategies, which can be incorporated into future work to develop a more holistic approach to HVAC optimization.

Furthermore, the robustness of MPC to system parameter uncertainties requires further investigation. While MPC effectively handles constraints and disturbances, its sensitivity to modeling errors and dynamic changes must be addressed. Implementing robust or stochastic MPC can improve resilience by accounting for worst-case scenarios or probabilistic uncertainties. Additionally, adaptive strategies that update model parameters in real time could enhance accuracy. Sensitivity analysis can help assess the impact of parameter variations on performance and stability. Future research should evaluate MPC under varying uncertainties using Monte Carlo simulations or real-world experiments to better understand its reliability in practical applications.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YY: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review and editing. JB: Data curation, Investigation, Software, Validation, Visualization, Writing – original draft, Writing – review and editing. MJ: Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review and editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was carried out under the "DanRETwin: A Digital Twin solution for optimal energy retrofit decision-making and decarbonization of the Danish building stock" project, funded by the Danish Energy Agency (Energistyrelsen) under the Energy Technology Development and Demonstration Program (EUDP), ID number: 640222-496754.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

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