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# Occupancy-based HVAC control using deep learning algorithms for estimating online preconditioning time in residential buildings

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ABSTRACT

This paper presents a rule-based (RB) heating, ventilation, and air-conditioning (HVAC) control system using a multi-layer perceptron network, a deep learning algorithm, for estimating dynamic preconditioning time in residential buildings. The proposed system takes advantage of occupancy, indoor temperature, and weather data to make control decisions in buildings. The system performance is evaluated in terms of financial, demand-side management, energy-efficiency, and occupants' thermal comfort. The proposed approach considers the perfect occupancy prediction assumption to remove the impact of the uncertainty associated with occupancy prediction and to estimate an upper bound limit for the system performance. The system performance is compared with that of conventional rule-based control approaches to show its effectiveness. To select the optimal control system, the TOPSIS method, as a multi-criteria decision-making approach, is employed. The sensitivity of the proposed system to the temperature setback is also assessed by considering conservative, medium, and deep setback bounds. It is demonstrated that the proposed system outperforms other alternatives when the deep and medium bounds are utilized. This study reveals two limitations of occupancy-based control systems by investigating their performance from financial and peak-demand points of view. First, these systems can cause peak-demand issues and increase the on-peak energy consumption by up to 10%. Secondly, employing a conservative setback can significantly decrease the financial merits of the system, leading to a discounted payback period of 10.87 years for implementing smart thermostats.



## 1. Introduction

Space heating and cooling demands account for more than half of the building energy consumption worldwide [1,2]. As discussed in Ref. [3], almost 39% of this amount could be wasted due to conditioning vacant zones, over-conditioning, air leakages, and the use of appliances with low efficiency. This huge amount of energy waste highlights the necessity of implementing more efficient control systems to optimize building energy consumption and cost. In 1906, the first types of programmable thermostats were produced as a solution to energy waste, caused by conditioning unoccupied spaces [4]. It was previously estimated that a considerable amount of energy saving could be achieved through properly programmed thermostats [5]. However, many studies reported that such thermostats practically suffer from being inappropriately programmed by users and do not lead to significant energy saving in real cases [6]. To deal with this issue, reactive control was proposed and investigated [5,7-13]. This control system automatically infers occupancy states using sensor networks and utilizes a setback temperature in vacant spaces, which can result in higher energy efficiency and cost reduction. However, it is essential to implement a conservative setback temperature to minimize the occupants' thermal discomfort upon arrival [14].

Earlier research studies investigated predictive control, as an alternative to reactive control, by integrating future occupancy predictions with control systems. Knowing future occupancy patterns in advance provides HVAC systems with enough time to precondition the building before occupants' arrival. Theoretically, using such proactive control systems allows the use of deeper setback to save more energy during unoccupied periods while maintaining thermal comfort when occupants are present.

Rule-based (RB) control has been one of the most utilized occupancy-based predictive control strategies in the literature [15]. In RB control, a set of rules is implemented to define setpoint/setback schedules as a function of future occupancy states, forecasted by occupancy models. Most earlier research studies developed RB control by approximating a static preconditioning time, also named preheating time or HVAC lag time, as the prediction horizon of occupancy models (i.e. how far the models predict

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**Nomenclature**

*Abbreviations*

| | |
|---|---|
| *AESR* | Annual energy saving ratio, % |
| API | Application programming interface |
| ATCSR | Annual total cost saving ratio, % |
| CAD | Canadian Dollar |
| CRB | Conventional rule-based |
| DBMS | Database management system |
| DPB | Discounted payback period, year |
| HVAC | Heating, ventilation, and air conditioning |
| IRR | Internal rate of return, % |
| MAE | Mean absolute error |
| MLP | Multi-layer perceptron |
| MPC | Model predictive control |
| MSE | Mean square error |
| NIS | Negative ideal solution |
| NPV | Net present value, CAD |
| PIS | Positive ideal solution |
| PRB | Proposed rule-based control |
| RB | Rule-based |
| ReLU | Rectified linear activation function |

*Symbols*

| | |
|---|---|
| $B_{ann}$ | Annual benefits, CAD |
| $C_{cap}$ | Capital cost, CAD |
| $C_{op}$ | Operating cost, CAD |
| $C_{tier1}$ | Electricity cost in the first tier, CAD |
| $c_{tier1}$ | Electricity tariff in the first tier, CAD/kWh |
| $C_{tier2}$ | Electricity cost in the second tier, CAD |
| $c_{tier2}$ | Electricity tariff in the second tier, CAD/kWh |
| d | Discount rate, % |
| $d_i^{NIS}$ | Distance from NIS point |
| $d_i^{PIS}$ | Distance from PIS point |
| E | Electricity consumption, kWh |
| $E_{tier1}$ | Electricity consumption in the first tier, kWh |
| $E_{tier2}$ | Electricity consumption in the second tier, kWh |
| f | Inflation rate, % |
| i | Market interest rate, % |
| m | Number of alternatives in the decision matrix |
| n | Life span, year |
| N | Elements of the nondimensionalized decision matrix |
| p | Number of criteria in the decision matrix |
| $R_i$ | Relative closeness |
| t | Tax rate, % |
| x | Elements of the decision matrix before normalization. |

occupancy profiles in advance). However, the actual preconditioning time often differs from this static average value, which can cause inaccuracies in the control system and result in energy waste or thermal discomfort. To be more specific, on the one hand, after a long unoccupied period when the temperature can fully drift to the setback, it naturally takes more time than the average value to precondition a building before occupants' arrival. On the other hand, after a short unoccupied period, using the average preconditioning time can cause a waste of energy owing to unnecessarily conditioning unoccupied spaces. Additionally, the preconditioning time can also depend on weather conditions that need to be considered for more accurate modeling. For instance, it takes much longer to preheat a building on a cold day than on a day with moderate temperature, and as a consequence, neglecting this dependency might also cause imprecisions in the control system. However, to the best of the authors' knowledge, no earlier studies investigated the integration of online preconditioning-time estimations with RB control systems.

Model predictive control (MPC) has been proposed as an alternative to RB control. Such control systems take advantage of accurate building models, weather data, and robust online optimization algorithms, as well as occupancy models to make optimal sequences of control decisions to maximize energy saving and thermal comfort [16]. On account of using building models in optimal control, the optimization algorithm can dynamically estimate the preconditioning time during the decision-making process. However, there are some limitations on the use of such algorithms that prevented them from being widely applied in the building sector [17]. The limitations include its relatively low potential for being generalized in different cases, the need for high skills in the development stage, and the high computational power requirement. Additionally, as discussed in Refs. [18,19], the amount of energy saving achieved by using MPC might not compensate for the complications added to the control problem.

Another limitation of the earlier research works is that they mainly focused on energy efficiency and thermal comfort when evaluating the performance of RB control systems, neglecting other factors such as financial benefits and demand-response management. However, these criteria are of great importance when evaluating a control strategy in buildings. Financial indicators are the most effective incentives for many building owners and project managers to replace the old thermostats with new ones. Furthermore, in many regions, power plants are struggling with covering the energy demand of users during the peak periods [20,21]. In such cases, the timing of energy consumption can be as important as the amount of total consumption, and the main focus is given to demand-response management programs. Hence, there is a need for considering all these factors when studying occupancy-based control systems.

This paper proposes an RB control system, aiming to address the limitations of earlier studies by predicting preconditioning time online. The proposed control system is expected to outperform conventional RB control systems while avoiding the complexities of optimal control. To this end, a multi-layer perceptron (MLP) network, as a deep learning algorithm, is developed using the historical data for outdoor weather, indoor temperature, and the lag time of HVAC systems. The performance of the proposed control system is evaluated and compared to that of conventional RB systems with static preconditioning time. As well as energy-efficiency and thermal comfort merits, the performance is evaluated in terms of economic and demand-response management. A comprehensive financial analysis is performed to quantify the economic benefits that can be obtained by using occupancy-based HVAC control systems. Different financial indicators, such as the internal rate of return (IRR), discounted payback period (DPB), net present value (NPV), and annual total cost saving ratio (ATCSR) with the consideration of tax and inflation rates, are considered in this analysis. The TOPSIS (Techniques for Order Preferences by Similarity to the Ideal Solution) method, as a multi-criteria decision-making approach, is employed to provide the trade-off between the conflicting criteria for selecting the best control method among the proposed and the conventional control systems. In addition, the sensitivity of the control systems to setback temperature is evaluated using conservative, medium, and deep setback bounds. The main limitations of earlier work and the contributions of this study can be summarized as follows:

- The dynamic nature of the preconditioning time was ignored in conventional occupancy-based RB control systems implemented in previous research works. This study proposes a novel RB control system using online estimation of the preconditioning time, as a function of indoor operative temperature and weather conditions, via deploying deep neural networks.
- Previous research works mainly focused on the energy and thermal comfort merits of occupancy-based HVAC control systems while neglecting the financial factors and demand-response management potential of the systems. In this paper, a comprehensive financial analysis is carried out to assess the economic gains achieved from replacing old thermostats with smart ones. Furthermore, the impact of using occupancy-based HVAC control systems on the peak-demand profiles of buildings is also investigated.

The rest of the paper is structured as follows: Section 2 provides a literature review on the related research works and discusses the methodologies implemented for occupancy-based control. In Section 3, the proposed RB control system is described in detail. The building simulation tool used for evaluating the proposed algorithm is discussed in Section 4. Section 5 describes the performance evaluation criteria utilized in this study. The results are presented in Section 6, and finally, the conclusions and main findings are discussed in Section 7.

## 2. Background

Among different types of occupancy-based HVAC control methods, RB control has been the most utilized system in the literature [15]. RB control systems are cost-effective and require relatively low computational power. Lee et al. [22] conducted an experimental study to evaluate the performance of an RB control system in terms of energy saving using occupancy information collected from smartphones. They approximated a static preconditioning time of almost 22 min for increasing the temperature by an average of 2.5 °C in different case studies. According to the results, this system decreased the energy consumption by 26% in comparison with an always-on control system as the baseline. Erickson et al. [23] developed an RB control system, called OBSERVE, which used the information from a network of cameras to detect occupancy and accordingly regulated setback temperature and ventilation rates with a preconditioning time of almost one hour. Using a simulation approach, they demonstrated that this system was able to save 42% of energy annually. Dong and Andrews [24] also reported up to 30% energy saving when they applied occupancy-based RB control to a conference hall.

As well as energy-efficiency indicators, some earlier works studied the performance of RB control from a thermal comfort viewpoint. Beltran et al. [25] applied RB control to regulate temperature and ventilation rates in an office building, using a fixed preconditioning time of one hour. They reported that this system resulted in 24.8% annual energy saving; however, it caused temperature deviation from the setpoint during occupancy hours with a mean square error (MSE) of almost 0.4 °C. Koehler et al. [26] developed an RB control, called TherML, based on a preconditioning time of 59 min using 5-week historical data for the lag time of HVAC systems to increase the temperature from 15.5 to 20.6 °C. They demonstrated that TherML could lead to almost 22 h of correct temperature setting (i.e. maintaining setpoint temperature during occupied periods and setback temperature during vacant periods). Gluck et al. [14] developed an RB control using a fixed one-hour prediction horizon and three different setback bounds with 10, 5, and 2 °C deviations allowed from the setpoint during the vacancy. They reported that using the same temperature bounds, reactive control always outperformed the RB controller in terms of energy saving. However, they assumed a more relaxed setback range for the predictive control and showed that the RB control provided almost 21% more energy saving than the reactive one. In addition, RB control demonstrated the ability to reduce MissTime (i.e. how long occupants encounter a space in which the actual temperature deviates from the desired setpoint temperature) of reactive control by up to 180 min per day. Nägele et al. [27] studied and compared the operation of reactive and RB control from energy-efficiency and thermal-comfort viewpoints using occupancy data from smartphones and building simulation. They reported that the reactive control led to the highest energy saving by almost 26%, whereas RB control accounted for the lowest MissTime of approximately 28 h. Iyengar et al. [28] proposed iProgram as an opportunity to upgrade current programmable thermostats to become occupancy-aware without the need for additional infrastructure. Through simulating 100 homes as virtual test cases, they reported 0.42 kWh daily energy saving and an average MissTime of around 15 min.

As discussed in Ref. [15], MPC has been one of the most popular optimal control approaches utilized for occupancy-based HVAC operation. By considering future disturbances such as weather and occupancy changes, as well as using optimization algorithms and building models, MPC is able to dynamically estimate preconditioning time. MPC often showed superior performance than RB control systems [29]. Refs. [30,31] implemented an MPC algorithm to minimize the thermal discomfort of occupants and energy consumption. The optimization algorithm in the control system utilized a setback temperature when no one was present while preheating the building before the arrival time to improve thermal comfort. It was shown that the system led to 8% energy saving and kept the thermal comfort within the acceptable range. Turley et al. [32] demonstrated that utilizing MPC algorithms could decrease building energy consumption by almost 13%, compared with reactive control with an assumption of perfect occupancy prediction. Killian et al. [31] investigated the performance of occupancy-based MPC in terms of the ability to reduce the temperature deviation from the desired setpoint. Results showed that using MPC decreased temperature violation by around 33%. A number of researchers demonstrated that despite the superior performance of occupancy-based MPC, it causes too much complexity in developing the control system. Goyal et al. [18,19] demonstrated that including occupancy information in the control system can lead to almost 50% energy saving. However, they argued that the energy saving achieved by MPC algorithms might not compensate for the complexity induced in the control system compared with the conventional control algorithms.

## 3. Methodology

### 3.1. System description

The schematic diagram of the RB control system utilized in this study is demonstrated in Fig. 1. In this framework, occupancy information is collected using occupancy detection and monitoring networks, such as PIR sensors [7,11], Wi-Fi networks [8], cameras [23], or environmental sensors [33]. The occupancy data are continuously stored using database management systems (DBMS). The real-time and historical occupancy data are, then, utilized to train an occupancy model. As the control system makes online decisions, the occupancy model should be regularly updated using the most recent data. Next, the predicted occupancy patterns are

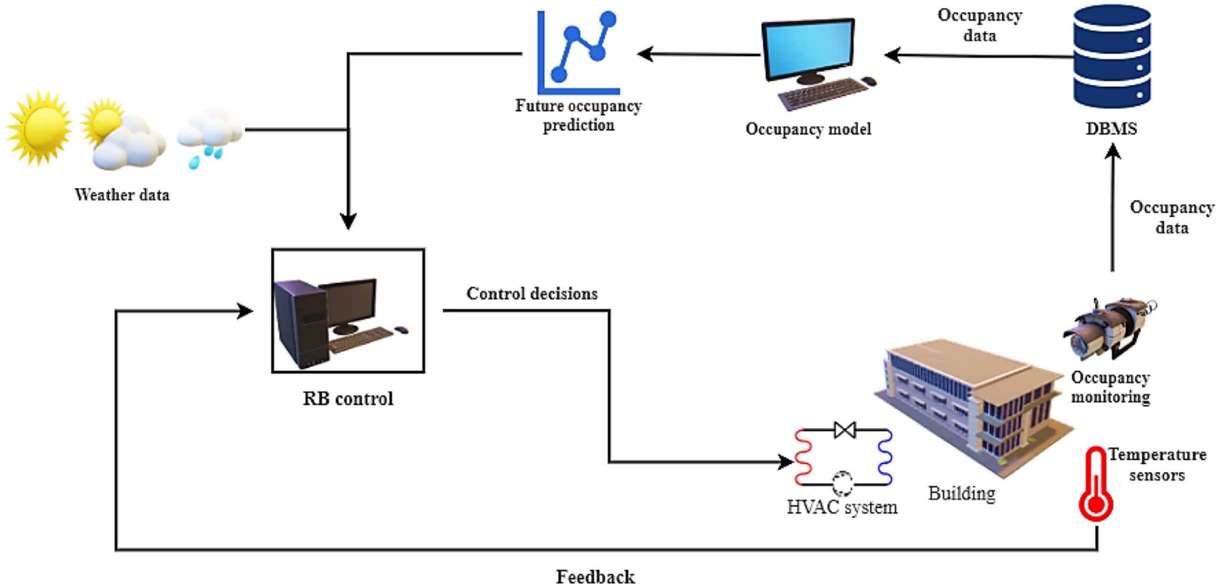


**Fig. 1.** Schematic diagram of the proposed RB control framework.

utilized as an input to the RB controller. In contrast to conventional RB systems, which are independent of weather conditions, the proposed system receives weather data as input. The weather parameters as well as indoor operative temperature, as a feedback signal received from temperature sensors, are employed to make control decisions. The control decisions are utilized in the HVAC system to regulate setback/setpoint temperature in the monitored spaces. This process is repeated in each time step and the control decisions are updated continuously.

### *3.2. Occupancy database and model description*

A real occupancy database, gathered from five residential units [34,35], is utilized in this study to develop and evaluate the control systems. It is worth noting that because of privacy issues that might be caused for the households due to the monitoring process, there are a few occupancy databases available for use, among which the selected database provides the most reliable and validated information [34,35]. More specifically, the occupancy monitoring system consisted of a relatively large number of PIR sensors, which is expected to improve the accuracy of occupancy detection in buildings [36]. 13 PIR sensors were implemented in each unit: two sensors were used in the living rooms, five sensors in corridors, and one sensor in each kitchen, bathroom, and bedroom.

The data were originally gathered at one-minute time intervals; however, the resolution is transformed to 30-min time intervals in the preprocessing step. One of the reasons for changing the resolution of occupancy data is linked with the data collection method using motion detectors. More specifically, the accuracy of PIR sensors for occupancy detection is dependent on the number and positioning of the sensors as well as on the mobility of the occupants. For example, the sensors might report no occupancy during some events when the mobility of the occupants decreases (i.e., while watching TVs or taking a nap). As mentioned in Ref. [36], changing the resolution to 30-min intervals can help with addressing such errors associated with PIR sensors. It is worth noting that using more complex occupancy monitoring systems such as cameras, fine time intervals can also be adopted. However, such systems are rarely used in residential buildings due to privacy and cost issues. Besides, using 30-min time intervals rather than the original one minute can enhance the control system computational efficiency. Occupancy data at each interval can accept 0 or 1, respectively demonstrating the occupancy states. A time interval shows an occupied state if at least one motion is detected by one of the sensors during this period. The raw data include some missing values for motion detectors in different records. During such periods when no signals are recorded, the building is assumed to be occupied to ensure that the thermal comfort of occupants is not compromised. The data are stored in MySQL databases and are pre-processed using MySQL workbench [37].

As shown in Ref. [36], the accuracy of occupancy prediction models mainly varies in the range of 60–90% depending on the model and case study. Due to the rapid improvements in artificial intelligence and data analysis techniques, many different occupancy models have been proposed in the literature and their performance has been improved during the last decade. Hence, the performance of the control system might depend on the applied occupancy model. Furthermore, the performance can also depend on the size of the occupancy database; long-term monitoring might result in improved prediction performance of the occupancy model. To remove the dependency of the control system performance on the selection and development of the occupancy model, a perfect occupancy prediction assumption is made in this study. Perfect occupancy prediction was also utilized in earlier studies [32,38] to achieve an ideal upper bound performance of the control system.

### *3.3. Rule-based control*

Fig. 2 demonstrates the flow diagram of the proposed rule-based (PRB) control framework. As can be observed, first, current indoor temperature and weather data are utilized as the input of the preconditioning-time model, described in Section 3.4. This model provides an estimation of the time required to reach the desired setpoint temperature as a function of input variables. Then, the estimated preconditioning time is utilized as the prediction horizon of the occupancy model. It means that the occupancy model forecasts the future occupancy states in a period that is equal to the preconditioning time. If a building is going to remain vacant during this period, the HVAC system is turned off, allowing the current temperature to approach the setback. Otherwise, the control algorithm initiates the HVAC operation to bring back the

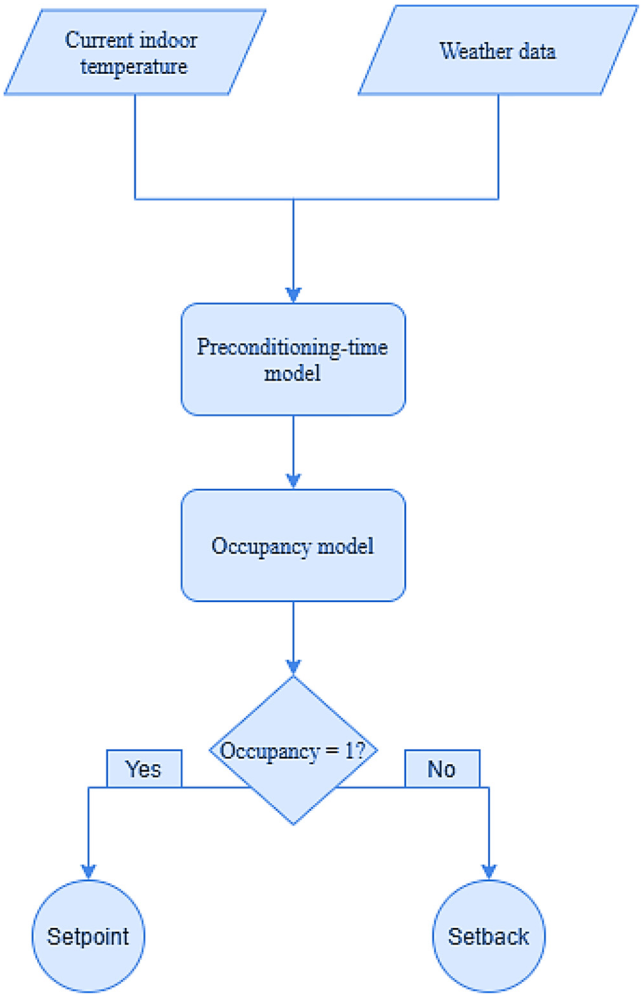


**Fig. 2.** The flow diagram of the RB control system proposed in this study.

setpoint temperature before the occupant arrival. In this study, a minimum prediction horizon of one hour is considered to ensure that the thermal comfort conditions are met in most cases. This process is repeated in each time step to update the control decision.

In this study, to evaluate the effectiveness of the proposed control strategy, its performance is compared with that of two types of conventional control systems. The first one is the always-on thermostat, which is selected as the baseline. It maintains the setpoint temperature regardless of the occupancy patterns or any other factors. Conventional RB (CRB) control systems utilized in the literature, operating based on static preconditioning time, are also investigated in this study. Three CRB systems with different fixed preconditioning times of 60, 90, and 120 min are considered to investigate the impact of preconditioning time on the system performance.

### 3.4. Preconditioning-time model

As mentioned earlier and demonstrated in Fig. 2, a model in the PRB control system is developed to provide an online estimation of the HVAC lag time. This model should be computationally cost-effective to be feasible for online control systems. However, using building simulation software is not the optimal approach due to its relatively low computational speed, required building physics knowledge, model development expertise, and relatively poor generalization potential. Data-driven models have attracted great attention because of their promising ability to address these issues and as a result, are implemented to predict preconditioning time. In this study, a multi-layer perceptron (MLP) network as a deep learning algorithm is employed. As shown in Table 1, seven candidate features, including indoor temperature as well as outdoor environmental attributes such as solar radiation and temperature, which can affect the prediction performance are selected for developing the model. In order to remove irrelevant features, a Pearson correlation coefficient as a filter feature selection method is adopted. The correlation coefficients among each variable and the output are demonstrated in Table 1. The correlation coefficients in the range of −0.3–0.3 are considered weak and eliminated from the feature set [39]. Fig. 3 shows that four features among the potential feature set; indoor temperature, outdoor temperature, horizontal solar radiation, and diffuse solar radiation are selected to develop the model As the changes in the weather condition are mostly small in the relatively short-term periods of preconditioning time, the impact of the weather changes on the prediction performance is neglected.

To construct the dataset required for training the MLP network, the energy simulation tool and the test case described in Section 4, are utilized. A complete simulation is performed for from November 1st to March 31st (a five-month period) to cover the entire heating period. In this simulation, temperature schedules are defined using a programmable thermostat, in which the HVAC system initiates the preconditioning process at 15:00 every day. A maximum duration of 6 h (i.e. from 15:00 to 21:00) is associated with the preheating process. Over the rest of the day, the HVAC system remains off to provide enough time for the building to reach a deep setback. However, a minimum temperature of 10 °C is assumed to preserve the building from possible issues such as pipe freezing. A dataset with 217,440 elements is constructed using the mentioned simulation. It is noted that more simulations with different setback/setpoint schedules can be utilized for making a larger dataset to obtain a more accurate model [40]. However, in real-world applications, it takes several years to provide such a comprehensive dataset; thus, in this study, only one simulation is considered to provide an estimation of the system performance close to that of real ones.

The entire database is randomly divided into three parts: training, validation, and testing datasets, with a ratio of 80:10:10. The training and validation parts are utilized for the hyperparameter tuning process using a random-search method. The number of hidden layers, number of neurons in each layer, batch size, and the learning rate are determined in this process. After finding the optimal hyperparameters, the model is trained using both training and validation datasets and is applied to the testing set to achieve unbiased results for the model performance.

For training the model, the number of epochs is considered 20,000. In order to prevent the model from overfitting, an early stopping methodology is employed to stop the training procedure after 500 epochs when no improvement in the performance is observed. Rectified linear activation function (ReLU) is imple-

**Table 1**
Pearson correlation coefficients between the input variables and the output.

| Variable | Pearson correlation coefficient |
|---|---|
| Indoor operative temperature | −0.86 |
| Outdoor dry bulb temperature | −0.52 |
| Horizontal solar radiation | −0.43 |
| Diffuse solar radiation | −0.35 |
| Direct solar radiation | −0.27 |
| Precipitation | −0.08 |
| Wind speed | −0.02 |

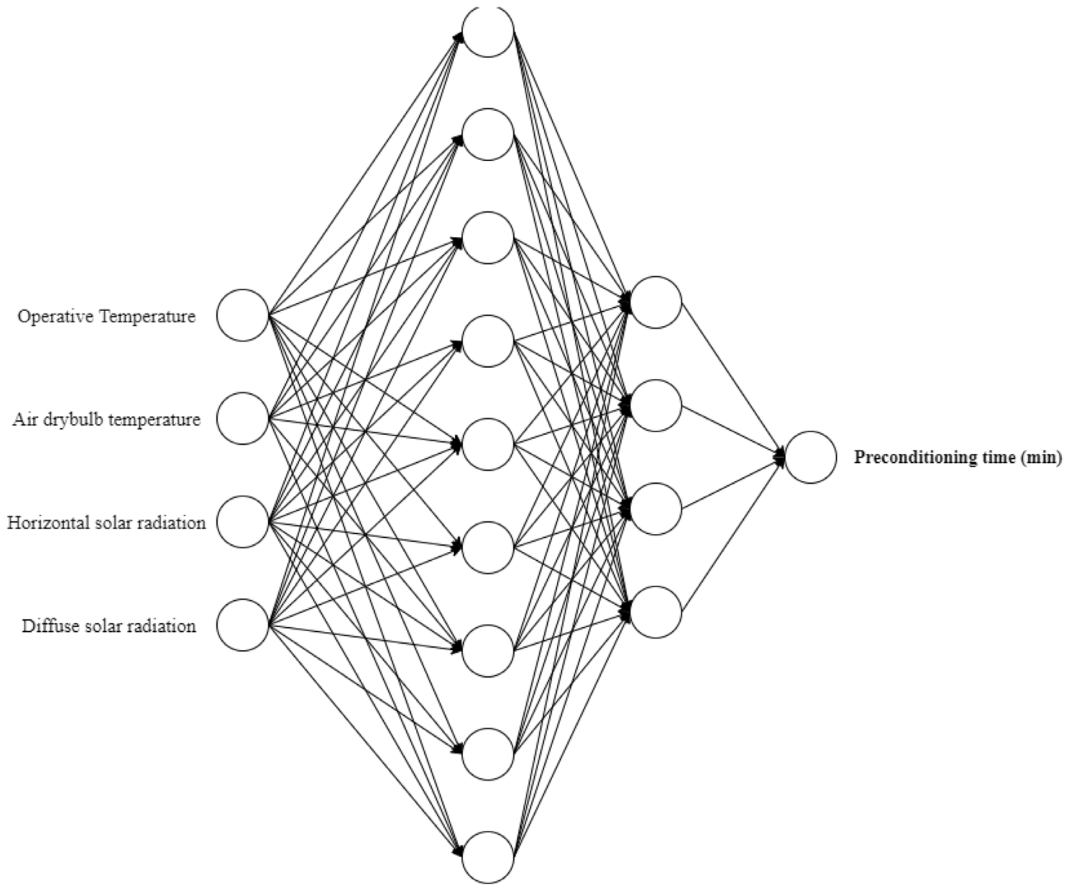


**Fig. 3.** The diagram of a sample multi-layer perceptron network implemented for preconditioning time estimation.

mented for each neuron, and an Adam optimizer is selected to minimize MSE for finding the optimal weights of the network. The model is developed using Keras library in Python [41].

## 4. Building simulation

The developed control system is applied to a case study to evaluate its performance and effectiveness. As no HVAC data are available for the original residential building discussed in Section 3.2, a hypothetical building is considered in this study as a virtual testbed based on the floor plan of the original one. EnergyPlus is used to construct a reliable energy model. EnergyPlus is an energy simulation tool, which has been widely validated against many testbeds such as those demonstrated in ASHRAE standard 140 [42]. It has been made as bug-free as possible [43] and can provide reasonable accuracy by considering detailed heat transfer models. However, the appropriate selection of input variables is essential to develop a reliable energy model. To this end, the input variables, including construction materials of the building, are selected based on ASHRAE standards [44] available as OpenStudio libraries and EnergyPlus weather data [45].

The 3D model as well as the 2D plan of the building, designed in the SketchUp software [46], are demonstrated in Fig. 4. The 3D model is imported into EnergyPlus via OpenStudio plug-in [47]. As discussed in Section 3.2, five occupancy datasets collected from different residential units are implemented in five separate building simulations to consider the influence of occupancy behavior on the system's performance. Electric baseboard heaters are considered as the heating equipment and as a result, electricity is the main source of providing heating demand. The size of the heating equipment is determined using the auto-sizing feature in EnergyPlus for the always-on control scenario. Then, the determined size is also utilized for other control systems.

It is noted that in each time step of the simulation, indoor temperature and weather data are required for estimating the preconditioning time, which is, then, utilized to make control decisions for regulating the setpoint temperature in the following step. In other words, after completing the simulation in each time-step, the setpoint for the following time-step needs to be determined and manipulated in EnergyPlus. Additionally, the results need to be retrieved and stored before starting the simulation for the next step. This process cannot be performed as a one-time simulation that is conventionally utilized in the literature. To deal with this task, EnergyPlus/Python application programming interface (API) [48] is employed, which provides flexibility for the users to manipulate EnergyPlus variables from the Python environment. This API also makes it possible to retrieve and store EnergyPlus results in Python after completing each simulation. The interactions between software and different libraries are demonstrated in Fig. 5.

## 5. Performance evaluation criteria

### *5.1. Financial indicators*

The economic merits of the proposed control system could be the most important decision-making criteria for many owners. It is because one of the main barriers to retrofitting the buildings with smart thermostats is often their relatively high cost. Knowing about the long-term economic gains achieved through this investment can be a great incentive in such cases. In this section, a com-

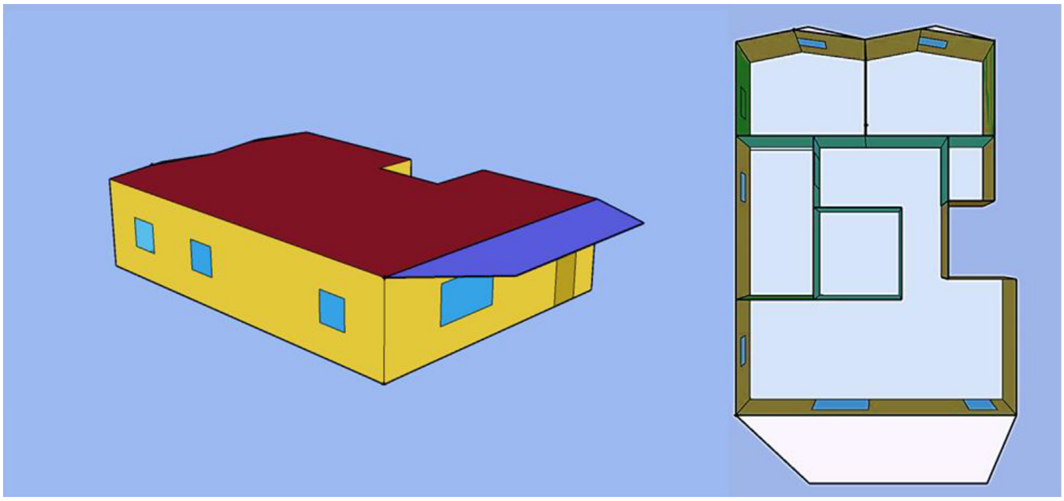

**Fig. 4.** The designed model of the simulated building as the case study.

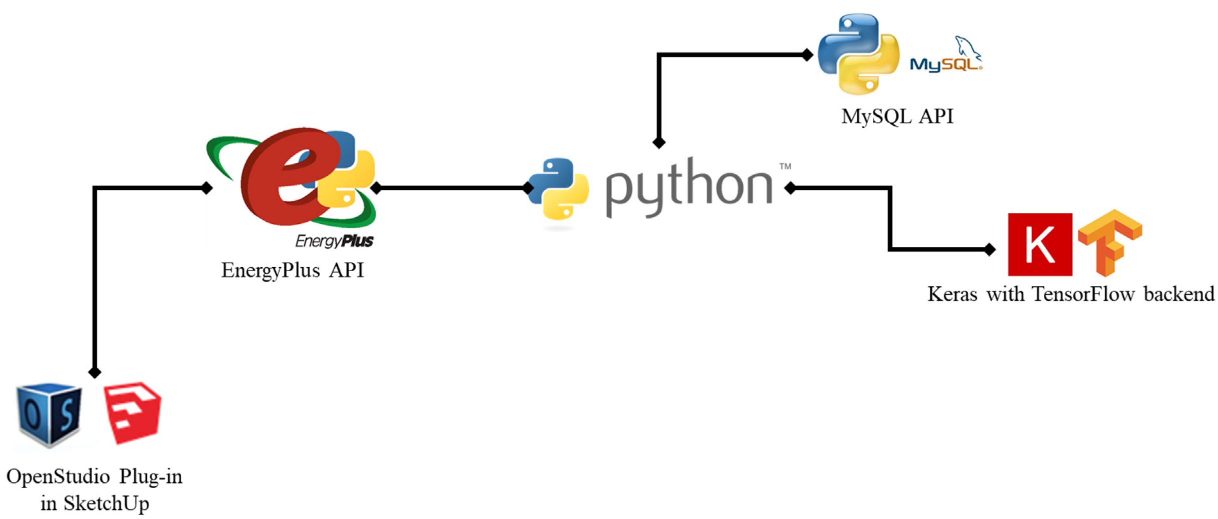


**Fig. 5.** Interactions between different applications and libraries used in this study.

prehensive financial analysis of the system is performed by estimating the main economic indicators, including IRR, ATCSR, DPB, and NPV associated with replacing old thermostats with smart ones.

To estimate the annual operating cost of each system, it is assumed that the operating cost equals the utility cost, which is estimated according to the local electricity tariffs for residential buildings [49]:

$$C_{op} = C_{tier1} + C_{tier2} \tag{1}$$

where $C_{tier1}$ and $C_{tier2}$ indicate the electricity cost in the first and second tier, respectively. In this two-tiered pricing, the electricity price per kWh varies based on the total amount of electricity consumption. More specifically, if the total electricity consumption by customers during a billing period, E, is less than the first-tier limit, $E_{tier1}$, they are billed based on the electricity tariffs in the first tier, $c_{tier1}$. If their consumption exceeds this limit, the balance, $E - E_{tier1}$, is billed based on the electricity tariffs in the second tier, $c_{tier2}$, which is higher than that in the first tier. Accordingly, the electricity costs in each tier can be calculated using the following relationships:

$$\begin{aligned} C_{tier1} &= c_{tier1}.\max(E, E_{tier1})\,(1+t) \\ C_{tier2} &= c_{tier2}.\max(0, E - E_{tier1})(1+t) \end{aligned} \tag{2}$$

where c is the cost of electricity per kWh in each tier, E denotes the amount of electricity consumption, $E_{tier1}$ represents the energy consumption limit associated with the first tier, and t denotes the tax rate.

Smart thermostats are expected to reduce the annual operating costs by saving energy, compared with the conventional thermostats. In this regard, the annual benefits, $B_{ann}$, is defined using the following relationship to quantify the amount of annual cost saving:

$$B_{ann} = C_{op} - C_{op,baseline} \tag{3}$$

where $C_{op,baseline}$ denotes the operating cost associated with the always-on control. Using the annual benefits, NPV can be calculated. NPV demonstrates the difference between the initial investment cost, $C_{cap}$, of smart thermostats and the equivalent present value of future benefits. A positive NPV shows that the project is profitable and negative values show net loss associated with the current project. NPV can be defined as [50]:

$$NPV = \frac{B_{ann}}{CRF} - C_{cap} \tag{4}$$

The first term represents the present value of the future benefits, in which CRF denotes the capital-recovery factor and is defined as follows:

$$CRF = \frac{d(1+d)^n}{(1+d)^n - 1} \tag{5}$$

where d is the discount rate (also called interest rate), and n is the life span of the system. In order to consider the annual inflation rates, that can lead to an increase in the future electricity prices, the discount rate is defined based on the market interest rate, i, and inflation rate, f, as follows [51]:

$$d = \frac{i-f}{1+f} \tag{6}$$

Based on Eq. (4) for NPV, IRR can be defined as the discount rate that can make NPV equal to zero. IRR is utilized as another indicator to quantify profitability by estimating the expected yearly rate of return. It can be calculated by solving the following equation through trial and error [52]:

$$\frac{(1+IRR)^n - 1}{IRR(1+IRR)^n} - \frac{C_{cap}}{B_{ann}} = 0 \tag{7}$$

Having the annual benefits and the capital costs of each system, the DPB can also be estimated. DPB estimates the time it takes for a project to break even. In other words, it shows the point in time when the future benefits fully cover the capital cost while respecting the time value of money. DPB can be estimated using the following equation [5]:

$$DPB = \frac{\ln\left(\frac{B_{ann}}{B_{ann} - C_{cap} d}\right)}{\ln(1+d)} \tag{8}$$

ATCSR is utilized as an indicator to estimate how much the total cost can be saved annually by replacing conventional systems with smart thermostats. ATCSR can be estimated using the following equation [53]:

$$ATCSR = \frac{ATC - ATC_{baseline}}{ATC_{baseline}} \tag{9}$$

where ATC is the system total annual cost. It is noted that ATC considers the investment costs as well as the annual operating cost. For this purpose, the capital recovery factor is utilized to calculate an equivalent annual cost for the initial investment as follows [54]:

$$ATC = C_{capital} \times CRF + C_{op} \tag{10}$$

The parameters required for the financial analysis are summarized in Table 2.

**Table 2**
The economic parameters utilized for the financial analysis .

| Parameter | Unit | Value | Ref. |
|---|---|---|---|
| Market interest rate, i | % | 5.0 | |
| Life span, n | Year | 20 | [55] |
| Capital cost, $C_{cap}$ | CAD | 250[1] | |
| Electricity price in the 1st tier, $c_{tier1}$ | CAD/kWh | 0.0608 | [49] |
| Electricity price in the 2nd tier, $c_{tier2}$ | CAD/kWh | 0.0938 | [49] |
| 1st tier limit for electricity consumption, $E_{tier1}$ | kWh/day | 40 | [49] |
| Tax rate, t | % | 14.975 | [56] |
| Inflation rate, f | % | 2.0 | [57] |

[1] The average price of smart thermostats available in the market including tax.

### 5.2. Energy and peak-demand management indicators

Energy-efficiency has been the most popular indicator for evaluating the performance of occupancy-based HVAC operations [15]. In this study, the annual energy saving ratio (AESR) is utilized to quantify the systems energy-efficiency performance. This indicator demonstrates the annual amount of energy that can be saved using smart thermostats:

$$AESR = \frac{AE - AE_{baseline}}{AE_{baseline}} \tag{11}$$

where AE denotes the annual energy consumed for covering the heating demand in kWh associated with each system using different setback temperatures. One of the limitations of this definition is that it does not consider the timing of energy consumption when evaluating the performance and consequently, cannot reflect the potential of demand-response management. To address this issue, the annual energy saving is also calculated for mid- and on-peak periods, as defined in Fig. 6.

### 5.3. Thermal comfort metrics

As providing the thermal comfort requirement is the main purpose of using HVAC systems, it is of essential importance to include comfort criteria when evaluating the system perormance. For this purpose, MissTime, which is defined as the period when occupants encounter a temperature that deviates from the desired setpoint is employed in this study [14]. In other words, any period when occupants are present, and the temperature is less than the setpoint is considered as thermal discomfort. In this study, an operative temperature of 21.5 °C is considered as the setpoint (i.e. desired temperature).

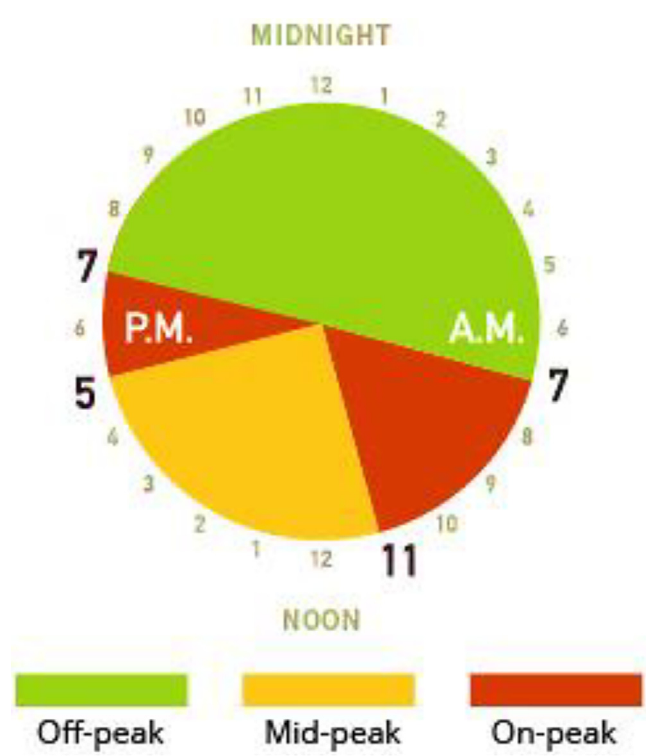


**Fig. 6.** Off-, mid-, and on-peak periods considered for evaluating the peak-demand performance of the systems [58].

**Table 3**
The range of hyperparameters used in the tuning process as well as the optimal values obtained.

| Parameter | Range | Selected value |
|---|---|---|
| Number of layers | [1-4] | 2 |
| Number of neurons | [2, 6, 16, 32, 64, 128, 256] | First layer: 65<br>Second layer: 256 |
| Learning rate | [0.005, 0.01, 0.05, 0.1] | 0.05 |
| Batch size | [5,000, 10,000, 15,000] | 5,000 |

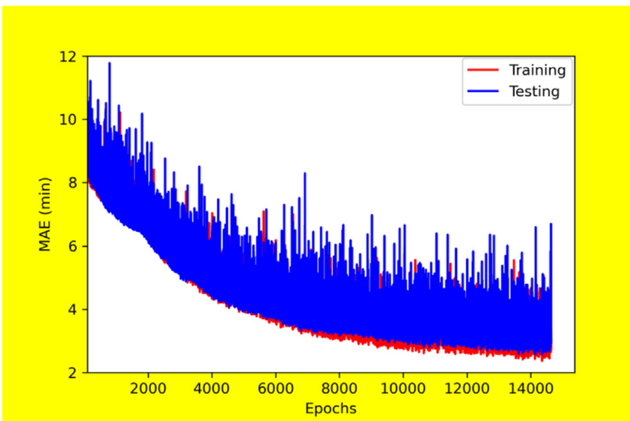


**Fig. 7.** The performance of the final MLP model after each epoch of the training process.

## 6. Results

### 6.1. Performance of the preconditioning-time model

To determine the optimal structure of the MLP model, a random search-based method for tuning the hyperparameters is implemented. In this process, the number of hidden layers, the number of neurons in each layer, the batch size, and the learning rate in the optimization algorithm are explored as hyperparameters. This method is an iterative technique that randomly tries different values of these hyperparameters from predefined ranges, represented in Table 3. An MLP model is trained based on the selected hyperparameter in each iteration and its performance in terms of MSE is evaluated and recorded. This process is repeated at every iteration and stops when the maximum number of iterations, which is 100 iterations in this study, is reached. The hyperparameters that result in the best model, providing the lowest MSE, are chosen to train the final preconditioning-time model. The optimal values for the parameters obtained in this process are shown in Table 3.

Using the optimal hyperparameters, the final MLP model is trained using both the training and validation sets. Then, the model is applied to the test set to obtain unbiased results for evaluating the performance. Fig. 7 represents MAE after each epoch for training and testing datasets. It is observed that the training process is completed before completing 15,000 epochs of training, due to early stopping conditions explained in Section 3.4. Ultimately, the model provides a test MAE of 2.68 min. As the control decisions

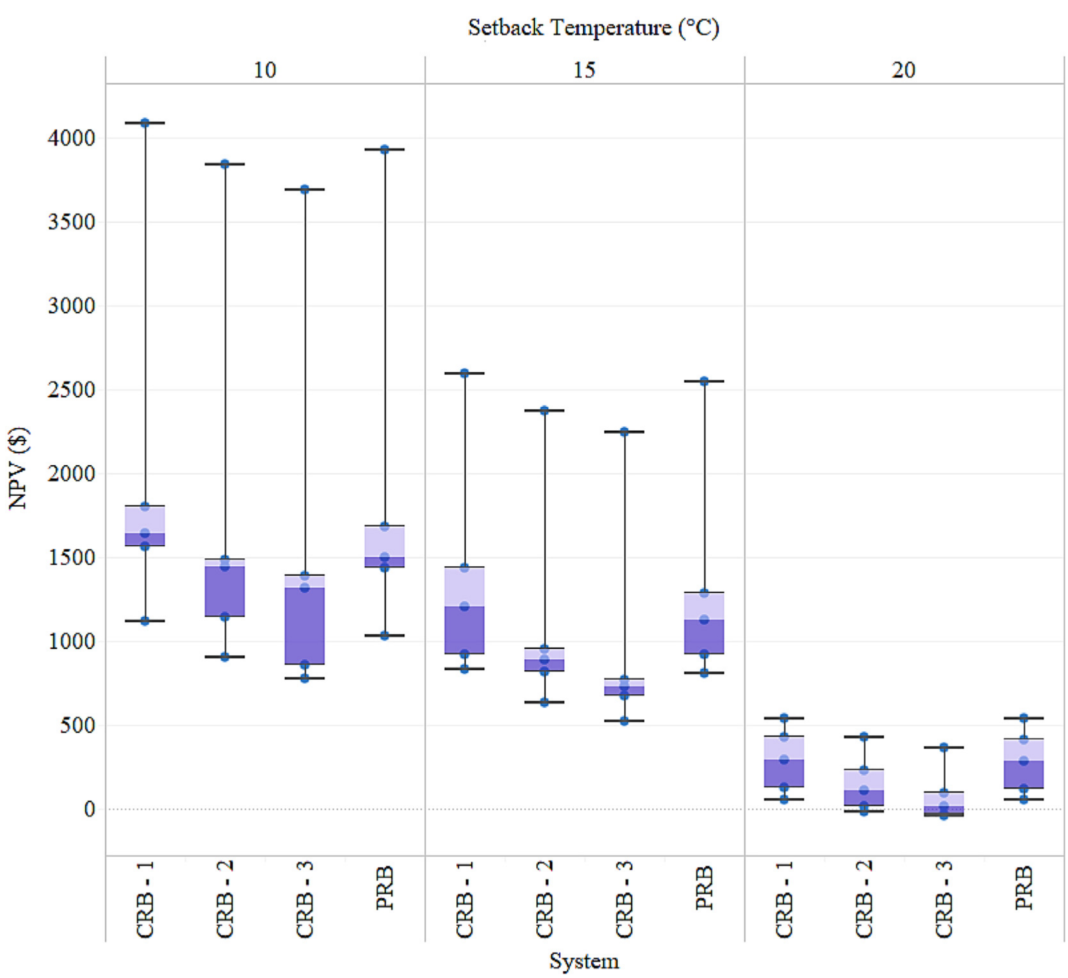


**Fig. 8.** The distribution of NPV for the RB control systems in different setback bounds.

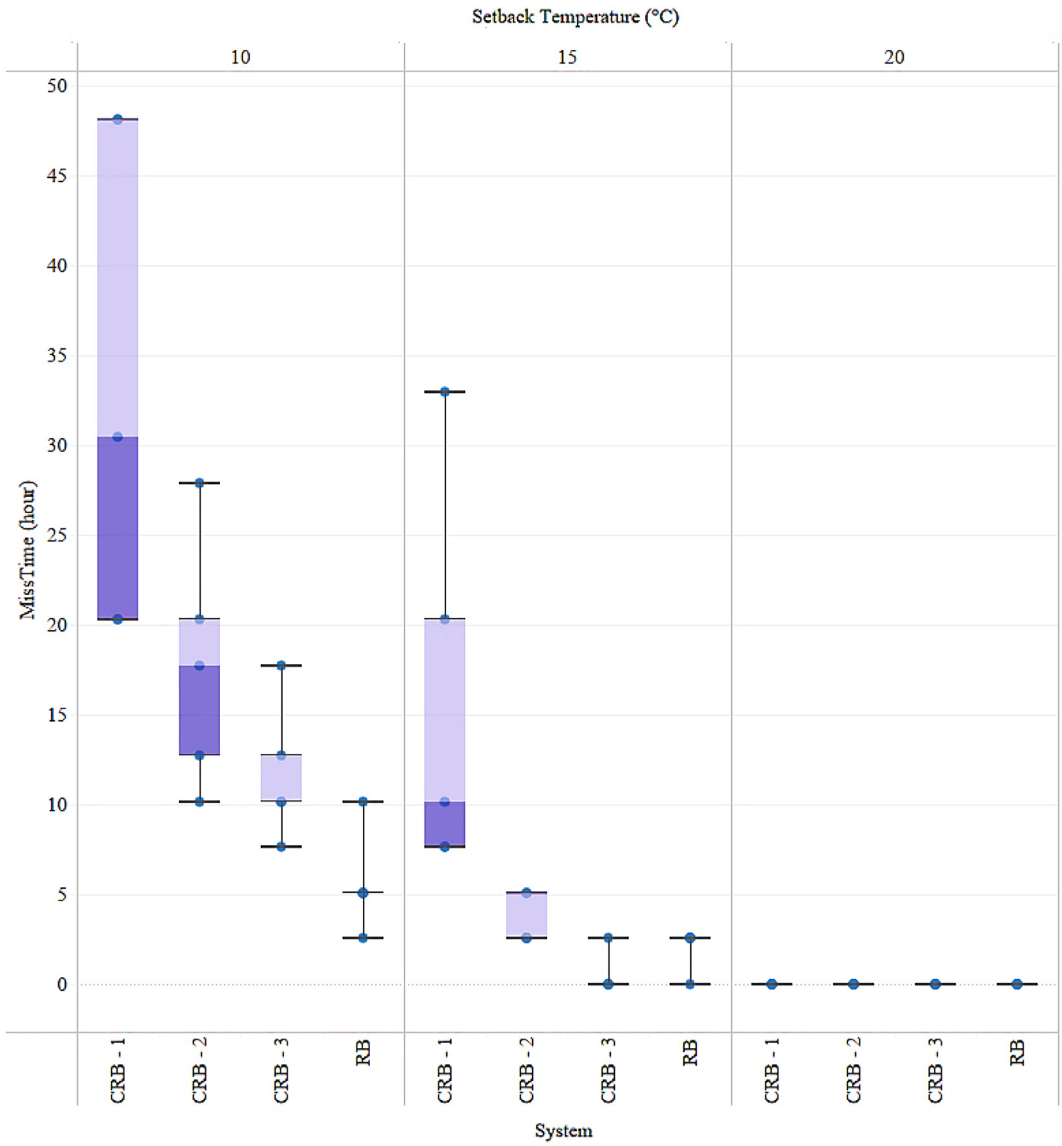


**Fig. 9.** The distribution of MissTime for RB control systems in different setback temperature bounds.

**Table 4**
The mean NPV and MissTime for RB control systems used in the decision-making process as well as the relative closeness index achieved from the TOPSIS method.

| System | Deep setback | | | Medium setback | | | Conservative Setback | |
|---|---|---|---|---|---|---|---|---|
| | MissTime (hour) | NPV ($) | R | MissTime (hour) | NPV ($) | R | MissTime (hour) | NPV ($) |
| CRB-1 | 33.44 | 2,045 | 0.5 | 15.71 | 1,400 | 0.5 | 0 | 289 |
| CRB-2 | 17.73 | 1,765 | 0.46 | 3.55 | 1,135 | 0.56 | 0 | 153 |
| CRB-3 | 11.65 | 1,607 | 0.43 | 0.51 | 990 | 0.5 | 0 | 79 |
| PRB | 5.57 | 1,937 | 0.84 | 2.03 | 1,325 | 0.85 | 0 | 283 |

are made at 30-min intervals, the performance of the MLP algorithm is considered reasonable in this control framework.

### 6.2. Multi-criteria decision making

This section is devoted to selecting the best-performing RB control among the conventional and proposed systems. As the energy-efficiency and financial merits are consistent, using NPV as an indicator among these factors suffices for the decision-making process. NPV associated with each RB system in different setback bounds is demonstrated in Fig. 8. In this figure, CRB-1, CRB-2, and CRB-3 respectively denote the conventional RB control systems with 60-minute, 90-minute, and 120-minute preconditioning time. It is observed that CRB-1 resulted in the highest economic benefits in all temperature bounds with a median NPV of up to $1643. Naturally, when the preheating time increases in CRB systems, the economic merits decrease as well, as more energy is consumed for preheating the space. Using a longer preheating time can even lead to a negative NPV in the conservative setback range with a median NPV of as low as $13. It shows that replacing old thermostats might not be profitable in some cases. In all the temperature bounds, CRB-1 is followed by the PRB system, with a median

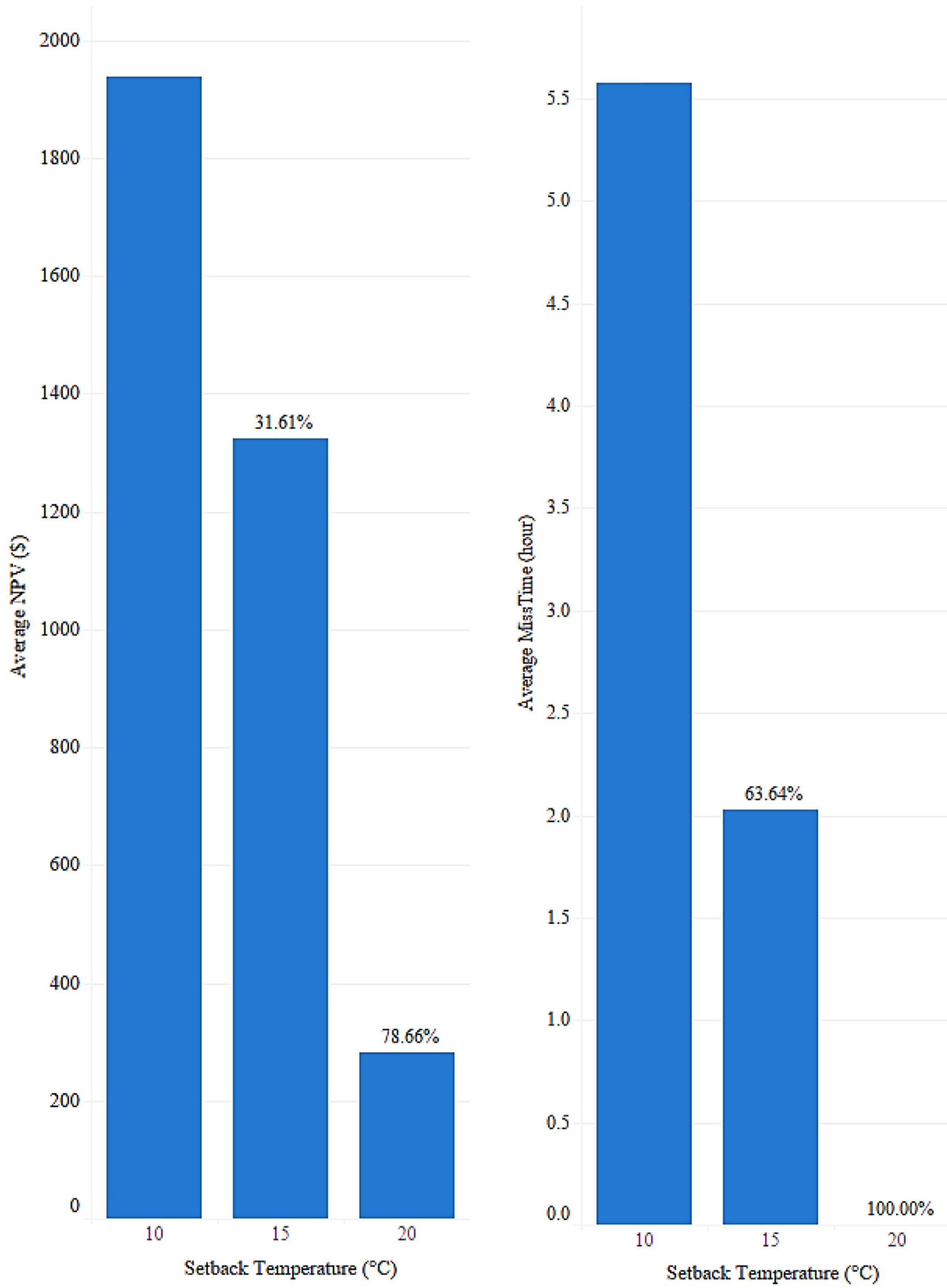


**Fig. 10.** Average MissTime and NPV for the selected RB control systems based on the allowed setback temperature.

NPV of up to $1545 for the deepest setback and a median NPV of $289 for using a conservative temperature. It is observed that employing the PRB system always leads to a positive NPV in all cases.

Fig. 9 illustrates the distribution of MissTime for the control systems in different temperature setback bounds. In contrast to the economic merits, CRB-1 provides the lowest MissTime at a median of up to almost 30 h. Increasing the preconditioning time for the conventional control strategies clearly reduces the MissTime due to using longer preconditioning time that helps the HVAC system to reach the setpoint prior to occupants' arrival. The PRB control provides the shortest MissTime in the deep setback range at a median time of 5 h. As for the setback temperature of 15 °C, CRB-3 and PRB systems result in the same performance with no thermal discomfort in most cases. For a conservative setback, using all control systems causes no thermal discomfort for the all cases.

As demonstrated above, economic and thermal comfort objectives are mostly conflicting for the RB control systems. In other words, none of the systems outperform other alternatives regarding both objectives, except for using a conservative temperature bound, in which CRB-1 provides the best MissTime and NPV.

Therefore, there is not a unique optimal control system for deep and medium setback bounds. To systematically choose the best system among these alternatives, TOPSIS (Techniques for Order Preferences by Similarity to the Ideal Solution) method, a multi-criteria decision-making approach, is employed. The first step in the decision-making process is constructing an m × p matrix, called a decision matrix [59], in which m indicates the number of alternatives (i.e. the candidate solutions in the decision-making process) and n is the number of criteria. As represented in Table 4, there are four different alternatives and two decision-making criteria in this problem for each temperature bound, and as a result, the decision matrix has a shape of 4 × 2. Next, the matrix is normalized using the following relationships [59]:

$$N_{ij} = \begin{cases} \frac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}} & NPV\ criterion,\ j = 1 \\ \frac{\max\limits_i x_{ij} - x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}} & MissTime\ criterion,\ j = 2 \end{cases},\quad i = 1, \ldots, m \tag{12}$$

where N and x respectively indicate the elements of the normalized and original matrices. The optimal alternative has the smallest distance from the Positive Ideal Solution (PIS) and the largest distance from the Negative Ideal Solution (NIS) [60]. In this study, PIS is a point that has the highest NPV while having the least MissTime, and NIS is the opposite point to PIS. Having PIS and NIS, the distances of all the alternatives from these two points are measured using the traditional Euclidean metric. In order to find the best point in terms of their distances from PIS and NIS, a relative closeness indicator, $R_i$, for each alternative is defined as follows:

$$R_i = \frac{d_i^{NIS}}{d_i^{PIS} + d_i^{NIS}},\quad i = 1, \ldots, m \tag{13}$$

where $d_i^{NIS}$ and $d_i^{PIS}$ are the distances of the $i^{th}$ alternative from the NIS and PIS, respectively. The alternative with an $R_i$ closest to 1 is selected as the solution. The values of the relative closeness for the alternatives are represented in Table 4. As can be observed, the PRB control provides the highest R at 0.84 and 0.85, respectively for deep and medium bound setback and is selected as the optimal RB systems.

**Table 5**
The average performance indices for the selected RB control systems in different setback bounds.

| Performance indicator | Unit | Setback temperature | | |
|---|---|---|---|---|
| | | 10 °C | 15 °C | 20 °C |
| AESR | % | 12.24 | 8.92 | 3.29 |
| ATCSR | % | 12.91 | 8.81 | 1.83 |
| Electricity consumption | kWh/day | 64.24 | 66.67 | 70.80 |
| DPB | Year | 2.72 | 3.63 | 10.87 |
| IRR | % | 45.12 | 32.75 | 10.25 |
| NPV | CAD | 1,937 | 1,325 | 283 |
| MissTime | Hour | 5.57 | 2.03 | 0 |

### 6.3. Impact of setback temperature

Fig. 10 demonstrates the impact of setback temperature on the MissTime and NPV of the selected RB control systems. It is observed that increasing the setback from 10 °C to 15 °C can lead to a 31.61% fall in the NPV while improving the MissTime by 63.64%. Similarly, using a conservative setback can cause a 78.66% further reduction in the financial profitability of the system and a 100% decrease in the MissTime. Table 5 summarizes the average values of performance indicators for the PRB control systems based on different setback bounds. It can be observed that implementing an RB control using conservative setback temperature does not provide compelling economic performance. It leads to a payback period of 10.87 years, which is approximately three times longer than that obtained for using a medium setback. It also provides an ATCSR of 1.83%, which is one-fifth of that for using a medium setback bound. In terms of energy-efficiency, this system results in almost 3.29% energy saving without compromising thermal comfort. By relaxing the constraints on setback temperature and using a setback of 15 °C, the economic performance considerably increases; it leads to a payback period of 3.63 years, reduces annual total cost by 8.81%, and decreases annual energy consumption by 8.92%. By decreasing the setback to 10 °C, the performance of the system, except for the MissTime, can be further improved. It

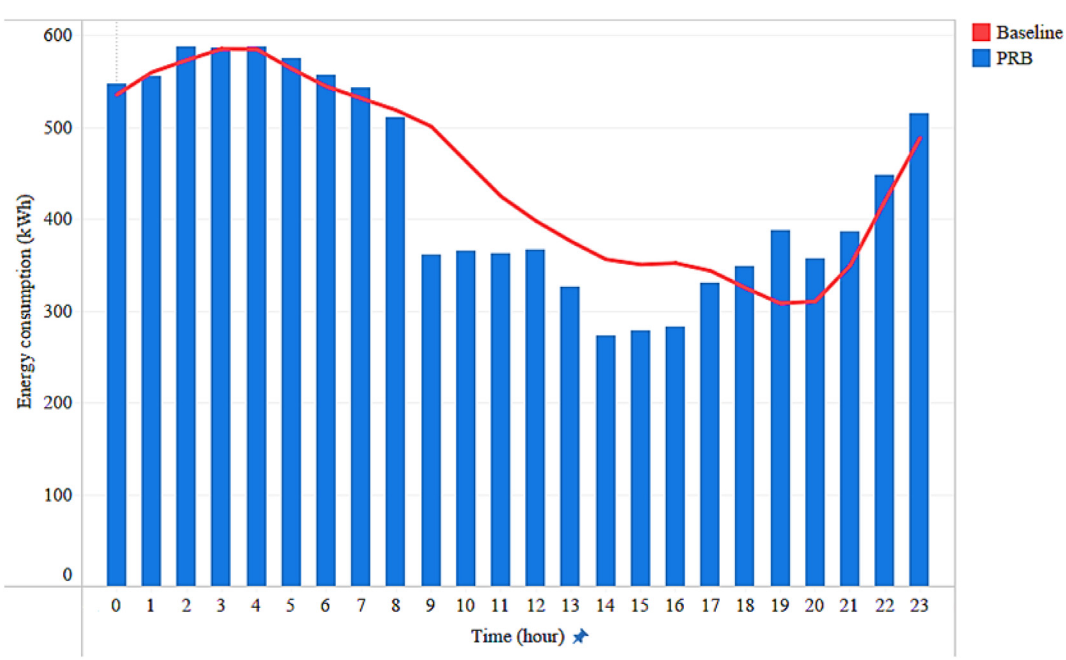


**Fig. 11.** Average hourly energy consumption of the PRB system using the medium setback.

**Table 6**
On-peak and mid-peak energy consumption using RB control with different setback temperatures.

| Setback | 7:00–11:00 peak period | | 11:00–17:00 mid-peak period | | 17:00–19:00 peak period | |
|---|---|---|---|---|---|---|
| | Energy consumption (kWh) | Energy saving | Energy consumption (kWh) | Energy saving | Energy consumption (kWh) | Energy saving |
| 10 | 1652 | 18% | 1850 | 19% | 734 | −10% |
| 15 | 1682 | 17% | 1877 | 18% | 720 | −8% |
| 20 | 1871 | 8% | 2132 | 7% | 703 | −5% |
| Always on | 2029 | – | 2295 | – | 669 | – |

results in a payback period of 2.72 years, which is almost a 23% improvement compared with that of the medium setback. A closer look at this table reveals that the improvements achieved by the transition from the conservative to medium setback temperature are much higher than those obtained from the medium to deep setback. The reason is linked with the thermal mass of the building, which can store energy and resist temperature reduction. Due to this passive energy storage, long vacancy periods are required to reach a setback temperature of less than 15 °C. However, as occupants often use the building for most of the time, the temperature can rarely decrease to a deep setback range.

### 6.4. Peak-demand performance

To study the impact of using occupancy information in the control systems on the peak-demand performance, the average hourly energy consumption of the baseline and PRB control systems for a sample case is depicted in Fig. 11. It shows that during the off-peak period, from midnight to 7:00, both the baseline and the PRB control system consume almost the same amount of energy. It is because of the fact that during this period, the occupants are often sleeping and occupying the buildings. However, the PRB control starts to save energy during the morning on-peak period, 7:00 – 11:00. As summarized in Table 6, the PRB control can save energy by 17% during this period using a medium setback range. The highest amount of energy saving happens during the mid-peak when people usually leave, and the building is likely to be vacant; the PRB control can save energy by 18% during this period with the medium setback. However, in the on-peak period, from 17:00 to 19:00, the baseline system considerably outperforms the PRB control. More specifically, using occupancy-based control can cause an 8% increase in the peak energy demand using a medium setback. It is because when people leave their homes during the day, the indoor temperature gradually decreases towards the setback. Hence, before the arrival time, there would be a sudden change in the HVAC operation (energy consumption) to preheat the building and provide the thermal comfort condition as soon as possible. Such sudden changes can significantly increase the on-peak demands during this period. The energy consumption of PRB control still remains slightly higher than that of the baseline during the period between 19:00 and 23:00. It is because although occupants have mostly returned home during this period, the temperature of the building envelopes often remains low. Therefore, an extra amount of energy is typically consumed during this period to recharge the thermal mass of the building.

## 7. Conclusion

In this paper, an RB control system, using dynamic estimations of preconditioning time and future occupancy patterns, is proposed, and its performance is assessed in terms of economic, energy, peak-demand management, and thermal comfort metrics. In contrast to conventional RB control systems that use static preconditioning time for regulating indoor temperature, the proposed system takes advantage of a deep learning algorithm to provide online estimations as a function of indoor temperature and outdoor environmental features. To evaluate the impact of setback temperature on the system performance, deep, medium, and conservative setback ranges are considered. The main findings can be summarized as follows:

1. The MLP model is able to provide reasonable performance for estimating the preconditioning time with an MAE of 2.68 min,
2. Using the TOPSIS method, it is shown that employing dynamic estimations of preconditioning time in RB control can improve the overall performance of the system in deep and medium setback bounds. However, no improvement is observed when a conservative setback is concerned,
3. The financial analysis demonstrates that replacing old thermostat with smart ones can result in up to 12.91% saving in annual total cost, 2.72 years of payback period, and $1,937 net present value,
4. Implementing conservative setback temperature in the control systems can significantly decrease the profitability of the thermostats, leading to a median DPB of 10.87 years. In some cases, negative NPV is obtained, showing that using such thermostats can cause net loss,
5. It is revealed that occupancy-based control systems can inversely impact the on-peak energy consumption. It is demonstrated that it can increase the on-peak energy consumption by up to 10% due to the sudden rises in the HVAC energy consumption prior to occupants' arrival. This negative impact highlights the necessity of taking peak-demand management into account while developing occupancy-based control systems.

It is noted that although using a building block or a district as a case study can provide more generalizable results in terms of financial, energy saving, and peak demand performance, this study was limited to consideration of a single house as the case study to evaluate the performance of the proposed system. Hence, more comprehensive case studies can be considered for investigating the RB control systems in future work. Additionally, the occupancy-based control systems are examined with an assumption of perfect occupancy prediction, and as a result, this study provides an upper bound level of the system's performance. Implementing actual occupancy models in the control systems is proposed as future work to evaluate the impact of occupancy prediction errors on system behavior.

## CRediT authorship contribution statement

**Mohammad Esrafilian-Najafabadi:** Methodology, Conceptualization, Writing – original draft, Writing - review & editing. **Fariborz Haghighat:** Project administration, Funding acquisition, Conceptualization, Methodology, Supervision, Writing - review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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