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Occupancy-based HVAC control systems in buildings: A state-of-the-art review

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ABSTRACT

Intelligent buildings have drawn considerable attention due to rapid progress in communication and information technologies. These buildings can utilize current and historical data, collected from occupancy detection and monitoring networks, to predict occupancy profiles and adjust heating, ventilating, and air conditioning (HVAC) operations accordingly. This adjustment aims to minimize the energy consumption of HVAC systems while maintaining an acceptable level of thermal comfort and indoor air quality. To provide a trade-off between these conflicting objectives, a variety of occupancy-based control strategies have been proposed in the literature. The present article aims to review the research works concerning occupancy-based control systems, classify them based on the integration of occupancy information with control systems and identify their strengths and limitations. Finally, research gaps in this field are discussed from different aspects, including performance evaluation metrics, control methods, occupancy models and buildings types. Future research directions are also proposed to fill the identified gaps.

1. Introduction

1.1. Motivation for occupancy-based HVAC control

The upward trend of energy consumption in buildings has become a significant concern worldwide. Globally, buildings account for more than one-third of the total energy consumption, and it is even expected to increase in the future [1]. To deal with this issue, advanced controllers have drawn great attention as promising solutions to increase building energy performance [2]. In addition to energy saving, control strategies give particular attention to occupants' comfort, as people spend the majority of their time indoors [3]. However, energy saving objectives are often conflicting with the occupants' comfort and indoor air quality requirement, causing a challenging optimization problem [4]. To address this problem, researchers often apply strict constraints to the decision variables according to thermal comfort criteria or employ multi-objective optimization algorithms that can consider both energy and comfort objectives simultaneously. In order to make a trade-off between these objectives, information about occupant behavior plays an essential role in control systems [5]. Information about occupancy states (i.e. presence/absence states) can be employed for regulating appropriate setback temperature to save energy during unoccupied hours while providing an acceptable level of thermal comfort for occupants upon their arrival [6]. Indeed, conditioning vacant building indoor environment can bring about unnecessary run time of HVAC operation and consequently, cause energy waste [7]. Masoso et al. [8] emphasized the importance of unoccupied hours in overall energy consumption in offices and reported that more than half of the overall energy was consumed during unoccupied hours in their cases.

Despite the key role that occupancy information plays in improving the performance of buildings, analyzing studies on HVAC control systems reveals that dynamic occupancy patterns, as a kind of occupant behavior in buildings, have been mostly neglected by researchers in this field. Not taking this type of occupant behavior into account can cause unnecessarily conditioning during vacant hours, and over-ventilation due to maximum occupancy assumptions used in ventilation control [7,9]. Dynamic occupancy patterns are mostly ignored in commercial buildings by implementing static occupancy profiles as a function of building types and typical working hours [10]. In contrast to commercial buildings where facility managers often define occupancy schedules [11], in residential buildings, HVAC systems can be often adjusted to occupancy through direct interventions by occupants. However, users often mis-program their thermostats or entirely neglect the programming features, making such thermostats useless or even causing more energy consumption in many cases [12,13]. In addition, manually

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Nomenclature

ANN	Artificial neural networks
ARIMA	Auto regressive integrated moving average
DTW	Dynamic time warping
GPS	Global positioning system
GRU	Gated recurrent unit
HMM	Hidden Markov model
HVAC	Heating, ventilation and air conditioning
JSD	Jensen Shannon divergence
K-L	Kullback-Leibler
kNN	k-nearest neighbors
LSTM	Long short-term memory
MAE	Mean absolute error
MAPE	Mean absolute percentage error
ML	Machine learning
MPC	Model predictive control
MSE	Mean square error
NRMSE	Normalized root mean square error
PIR	Passive infrared sensor
PMV	Predicted mean vote
RB	Rule-based
RC	Resistance-capacitance
RBC	Rule-based control
RFID	Radio-frequency identification
RL	Reinforcement learning
RMSE	Root mean square error
RNN	Recurrent neural networks
SVM	Support vector machine

defined schedules by occupants often differ from the actual schedules, which can cause thermal discomfort, especially upon their arrival, and additional energy use [12,14]. For example, due to unexpected events that migh occasinally occure, occupants might return home before the preheating process is fulfilled, or long after the building is fully preconditioned based on the predefined temperature schedules, which could cause thermal discomfort or energy wast, repectively.

In order to overcome the mentioned shortcomings, control systems can automatically infer and predict occupancy patterns. Thanks to the Internet of Things (IoT) devices in smart buildings, capturing these relationships have become more possible by employing data mining and machine learning approaches [15]. One of the current trends of HVAC research is to make systems aware of current and future occupancy information through learning behaviors.

1.2. Previous literature reviews

Table 1 summarizes the review articles concerning occupant behavior-based HVAC control systems. Although these articles are high-quality reviews, there is still a gap for a review paper focusing on the state-of-the-art occupancy-based HVAC control systems. On one hand, some of these articles concentrated only on a few aspects of these systems. For example, articles [6,16–18] only focused on occupancy detection and modeling in buildings, neglecting the integration of occupancy information with control systems. These papers provided no insights into the challenges and limitations related to the control of occupancy-based HVAC systems. On the other hand, some other articles provided comprehensive reviews, covering various topics related to building control based on occupancy patterns, including lighting control, HVAC control, comfort-aware HVAC systems, occupancy detection methods, and occupancy models. It should be noted that these topics have been active research areas in recent years, and there have been a large number of papers published in this field. As a consequence, these review papers provided a general overview of the previously published papers in this field, and identifying the strengths and limitations of the methodologies were mostly neglected.

Table 1
Previously published review papers on the topics related to occupant behavior-based control in buildings.

Reference	Year	Research focus
Nguyen and Aiello [20]	2013	Intelligent buildings with occupancy models used for optimal control of lighting, HVAC, and appliances.
Mirakhorli and Dong [19]	2016	Control strategies in occupancy-centric buildings, focusing on model-based predictive control (MPC).
Shen et al. [6]	2017	State-of-the-art methodologies for occupancy detection and monitoring in office buildings.
Naylor et al. [16]	2018	Strengths and limitations of using different types of occupancy detection methods in buildings.
Salimi and Hammad [21]	2019	Occupancy detection techniques, occupancy models, and control of HVAC and lighting in office buildings.
Jung and Jazizadeh [22]	2019	Comfort-aware HVAC operation, occupancy detection, occupancy models, and occupancy-based control strategies.
Park et al. [23]	2019	Field evaluation studies on occupancy-centric control strategies.
Sun et al. [17]	2020	Occupancy measurement approaches with a focus on vision-based techniques.
Azar et al. [24]	2020	Design procedure of occupant behavior-based control strategies.
Dai et al. [18]	2020	Prediction of occupancy and window-opening behavior using machine learning algorithms.

Limited review work has focused on occupancy-based HVAC control systems. The closest review to this paper was done by Mirakhorli and Dong [19], where they reviewed the research works on occupancy-based model predictive control (MPC). However, they mostly ignored other types of occupancy-based control strategies, such as reactive and rule-based control. Additionally, this paper was published more than 4 years ago. As demonstrated in Fig. 1, since then, a relatively large number of research papers have been published in this field. This growing trend highlights the necessity of an updated review article to explore the recent state-of-the-art methods.

1.3. Contributions and paper structure

This paper aims to address the limitations of previous review papers by providing a focused review on the state-of-the-art occupancy-based HVAC control strategies. The ultimate target is to utilize the results of this thorough literature review to inspect the current research gaps in this field and accordingly, propose research directions for future work. For this purpose, the reviewed papers are first grouped into different categories according to the incorporation of occupancy information in control systems. The papers in each category are reviewed in detail from different perspectives, including performance evaluation methods, feature use for occupancy models, occupancy models, types of testbeds, and occupancy detection and monitoring techniques. Then, the reviewed papers are summarized and discussed from each perspective to reveal the research limitations from different dimensions.

The rest of this paper is structured as follows. In Section 2, the reviewed papers are classified into different categories for a detailed review. The research items are rigorously reviewed in Sections 3-5 and their limitations and strengths are discussed. Next, the main research gaps are identified and discussed in Section 6. In Section 7, conclusions are made by summarizing the findings and contributions.

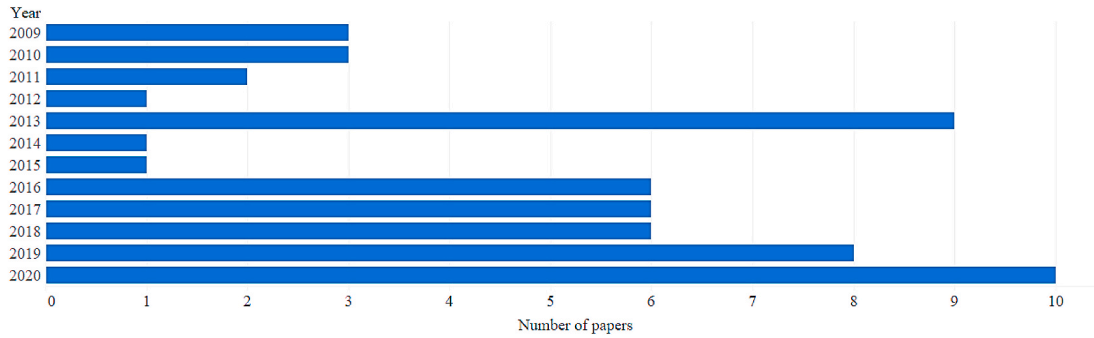

Fig. 1. Distribution of reviewed papers based on publication year.

2. Research classification

As shown in Fig. 2, occupancy-based HVAC control strategies are classified into two main categories based on the integration of occupancy information in control systems: control strategies based on user-defined schedules, and occupancy detection and monitoring. In the former category, occupancy information is manually included by users, and HVAC systems act according to user-defined schedules. This category is further classified into three subcategories based on their flexibility to receive occupancy schedules: manual, programmable, and scheduled thermostats. These control strategies will be discussed in Section 3. The control systems in the latter category are integrated with the occupancy detection and monitoring networks to automatically capture occupancy information without the need for occupants' interventions. These controllers are further classified into reactive and predictive control. Reactive approaches act based on real-time occupancy information in the monitored building. The performance of these strategies is mainly dependent on occupancy detection and types of sensor networks implemented to infer occupancy. In addition to using real-time information, predictive approaches also take advantage of occupancy models to provide insight into future occupancy states. Such strategies are also called proactive, as they can be prepared in advance before future events happen. As well as occupancy detection systems, their performance is also dependent on occupancy prediction models. These strategies are divided into rule-based, and optimal control categories, which will be discussed in Section 5.

3. HVAC operation based on user-defined occupancy schedules

The integration of occupancy information with control systems differs depending on building types. In commercial buildings, occupants usually lack access to thermostat control for changing the setting [25]. It is usually the responsibility of facility managers to define setback or setpoint schedules in commercial buildings [11]. Fixed occupancy profiles are often defined by facility managers based on the type of buildings and its functionality. In this study, this type of control that is based on fixed pre-defined occupancy schedules is called scheduled control. The shortcoming of this control approach is that the static schedules can be different from the actual ones in many cases. The discrepancy between these schedules can cause unnecessary conditioning during unoccupied hours and over ventilate during partial occupancy.

In contrast, occupants in residential buildings can control their indoor environment by directly interacting with thermostats, opening or closing windows, and changing their clothing. Using manual and programmable thermostats, occupants can define a setback temperature according to their occupancy patterns and need. However, due to the interactive nature of these kinds of thermostats, they do not necessarily lead to energy saving. As demonstrated in Ref. [13], using manual and programmable thermostats can even negatively impact the energy performance as compared with always-on thermostats. According to several field evaluations covering more than 700 homes in Ref. [26], employing programmable thermostats results in no significant energy saving or even can increase energy usage depending on occupants' behavior. In some other studies, a slight improvement in energy saving from programmable thermostats was reported. For example, an average of 6% and 3.6% were reported in Refs. [27,28]. In addition to the poor energy saving ability of such thermostats, the mismatch between pre-defined schedules and the real daily occupancy patterns can also cause thermal discomfort especially upon arrival [14].

Fig. 3 shows the popularity of thermostat types among US

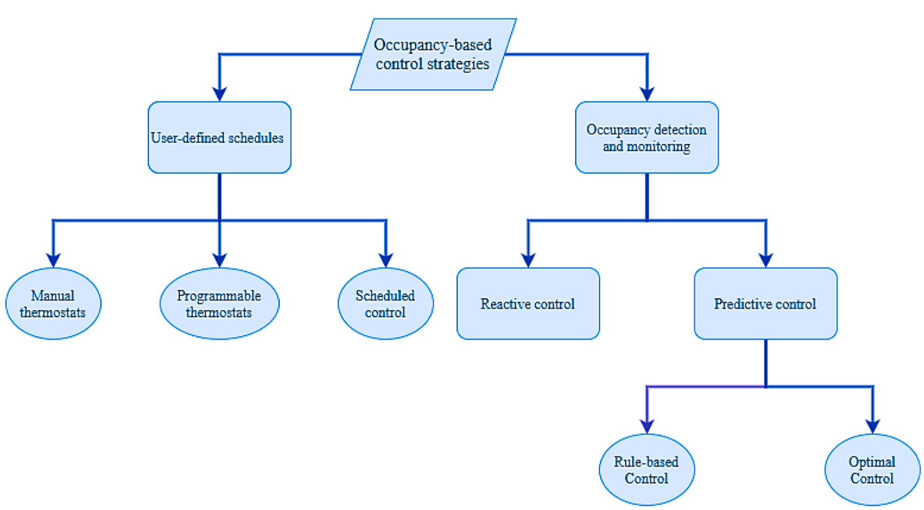

Fig. 2. Classification of occupancy-based HVAC control systems based on types of control strategies and the integration of occupancy information in systems.

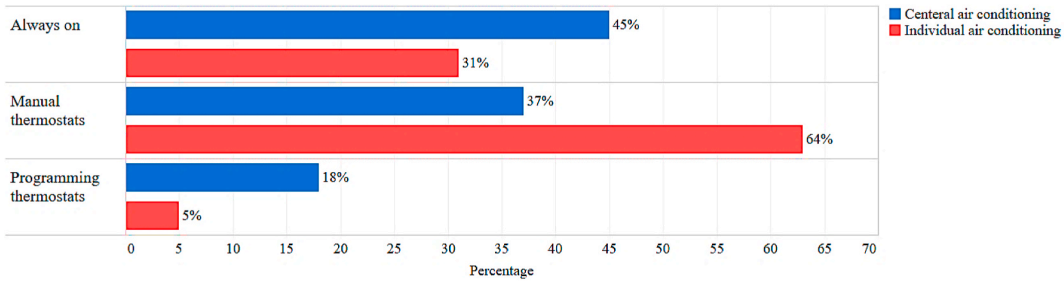

Fig. 3. The proportion of U.S. households using different types of thermostats with central or individual air conditioning system [29].

households in 2015 [29]. It can be observed that programmable thermostats were the least popular and accounted for approximately 5% and 20% of households with individual and central air conditioning units, respectively. In households with individual units, manual thermostats were the most popular type at 64% of households, while the most preferred approach for people with central units was to keep the thermostat unchanged.

With the advent of IoT devices in smart buildings, the remote-control of HVAC systems have gained a great popularity. Koehler et al. [30] conducted a field evaluation and a survey to evaluate the performance of remote controllers. In this study, they developed an eco-feedback system on occupants' smartphones. The system was employed by 10 participants over a three-month period. The participants were provided with a control interface through Android applications so that they could control the thermostat from any location. To provide occupants with a guideline to help them with saving more energy, this application sent them frequent real-time feedback about their energy consumption patterns and possible energy saving strategies. The application compared daily energy consumption patterns and demonstrated the effects of their behavior on energy consumption. They defined two performance criteria: "UnnecessaryHeating" and "LostComfort". These two indicators were utilized in the literature using different terminologies. In this study, all the indicators with the same concept are called "WasteTime" and "MissTime" based on the definitions in Refs. [31,32]. Throughout this paper, WasteTime and MissTime are respectively defined as the average of unoccupied hours when the indoor temperature deviates from the setback, and the average of occupied hours when indoor temperature deviates from the desired setpoint. According to the results, an average of 72.5% of the overall testing period, setpoint and setback temperature were correctly set by occupants. It was indicated that this remote-control system on average ended up with almost 5 h of WasteTime, and 73 min of MissTime for occupants. Forgetting to set the temperature to the recommended setback accounted for 96% of the overall WasteTime.

4. Reactive control

The main shortcoming of the control strategies using user-defined occupancy schedules is linked with manual interventions required from occupants. This issue made programmable thermostats useless in many cases, and as a consequence, Energy Star suspended its certification on programmable thermostats in 2009 [33]. The following findings were the main reasons preventing them from being widely recommended:

- Complexity for some users to effectively program it.
- Uncertainties in occupants' plans that make a discrepancy between actual and programmed schedules.
- Unwillingness of occupants to put effort into interacting with the thermostats.

In order to solve the main problem of user-defined schedules, i.e. manual interactions required by users, reactive control systems started to increasingly gain attention. These systems minimize manual interventions while improving performance [34]. As the name suggests, reactive control automatically reacts to real-time occupancy information received from occupancy detection and monitoring systems to dynamically change the temperature setpoint. In addition, they can make use of occupancy levels (i.e. counts) to adjust ventilation rates. Researchers have implemented a variety of different occupancy detection instruments such as passive infrared (PIR) sensors, CO_2 sensors, electricity meters, door reed switches, chair movement sensors, Wi-Fi, cameras, and Bluetooth devices depending on the type of building and privacy issues [7,35–39]. However, providing details about these methods is out of the scope of this review study. Interested readers in occupancy detection technologies are referred to the related review articles summarized in Table 1.

A summary of the reactive control algorithms reviewed in this paper can be found in Table 2. Among these studies, some researchers employed reactive control in buildings while keeping the investment cost low by avoiding large-scale retrofits such as new rewiring systems. To this aim, Agarwal et al. [38] proposed a reactive control strategy based on low-cost magnetic door reed switches and PIR sensors in office buildings. This reactive control responded to occupancy states achieved from a combination of these two types of sensors. In their study, setpoint and setback temperatures were selected as 22.9 °C and 26.1 °C, respectively. Using EnergyPlus to simulate office buildings, they reported that this reactive control reduced energy consumption by 15%, compared with scheduled control as the baseline. Although the occupancy detection system required a low-cost infrastructure, it was prone to providing lower accuracy than more complex systems. As occupancy detection performance is the most essential factor in reactive controllers, decreasing accuracy can cause thermal discomfort and higher energy consumption [38]. However, in this study, the performance of occupancy detection was not evaluated to demonstrate the effectiveness of the system. Balaji et al. [36] used the existing WiFi networks to identify occupants and their locations for reactive control. This network provided an accuracy of 86%, without a need for any additional investment in infrastructure. They showed that integrating the occupancy detection algorithm with HVAC control systems could result in 17.8% electricity saving. It was also reported that no considerable thermal discomfort was caused using this proposed system. It was because of using a highly conservative temperature setback during unoccupied hours to guarantee thermal comfort upon arrival. However, using highly conservative setbacks limits the system energy saving ability.

Stopps and Touchie [41] conducted a field experiment to monitor HVAC runtime, controlled by programmable and smart thermostats. The experiment was conducted using field data gathered from 56 thermostats in two different apartment buildings. To achieve a fair comparison between the thermostats, each day during the monitoring period was randomly associated with controllers. In addition, a random forest algorithm was trained using weather data to provide an estimation of baseline run time in those days with smart thermostats running. The results showed that using smart thermostats reduced HVAC runtime by an average of 17%. However, the direct relationship considered between HVAC run time and energy consumption can be mentioned as a

Table 2
Summarization of occupancy-based control strategies proposed in the literature.

Ref.	Building type	Occupancy detection	Control				Performance evaluation		
			Type	V[1]	H[2]	C[3]	Method	Performance	Baseline
[40]	Residential	PIR	Reactive control	–	✓	✓	Field evaluation	Up to 9% energy saving on regular days and up to 30% during long vacancy periods.	Manual
[36]	Office	Wi-Fi network	Reactive control	✓	✓	✓	Field evaluation	17.8% Energy saving No thermal discomfort	Scheduled
[38]	Office	Door reed switches PIR	Reactive control	–	–	✓	Simulation EnergyPlus	15% energy saving	Scheduled
[41]	Residential	–	Reactive control	–	✓	✓	Field evaluation	17% decrease in the runtime of HVAC	Programmable
[42]	Residential	PIR	Reactive control	–	✓	–	Field evaluation	14.4% energy saving	Whole building control
[43]	Office	–	Reactive control	–	–	✓	Simulation EnergyPlus	Up to 28.3% energy saving	Scheduled
[44]	Residential	Survey	Reactive control	–	✓	✓	Simulation EnergyPlus	20% energy saving Payback period of one year	Always-on Programmable
[45]	Residential	–	Reactive control	–	✓	✓	Simulation DOE2	Up to 38.7% decrease in energy consumption 34.7% reduction in peak demand	Always-on
[46]	Office	–	RBC[4] using occupancy probability	–	✓	✓	Simulation EnergyPlus	Up to 50% electricity saving Up to 66 million fossil fuel saving 0.9–3.7 million metric tons CO2 reduction 168-658 million dollars saving in energy cost	Always-on Programmable
[14]	Residential	GPS Cellular network Wi-Fi	RBC using occupancy probability	–	✓	✓	Simulation EnergyPlus	28% energy saving 48 min MissTime	Programmable Reactive Perfect prediction
[47]	Office	Motion sensors	RBC using occupancy probability	–	–	✓	Field evaluation	7–52% energy saving.	Scheduled
[31]	Residential	RFID tags Motion sensors	RBC using conditioning rate	–	✓	–	Field evaluation	No energy saving compared to baseline energy consumption. Up to 92% MissTime reduction	Programmable
[48]	Residential	GPS	RBC using preconditioning time				Field evaluation	7% energy saving.	Manual Programmable
[30]	Residential	GPS	RBC using preconditioning time	–	✓	–	Field evaluation	MissTime of 0.95 h WasteTime of 0.94 h	Manual GPS-thermostat PreHeat
[49]	Office	Cellular network Wi-Fi	RBC Preconditioning time	–	✓	–	Field evaluation	26% energy saving compared	Always on Reactive
[50]	Office	Thermal sensors PIR	RBC using preconditioning time	✓	✓	✓	Simulation EnergyPlus	Up to 25% energy saving Maximum RMSE of 0.415 °C in temperature violation	Scheduled Reactive Setpoint control without ventilation
[51]	Conference hall	Acoustics Lighting PIR CO2 Temperature Humidity	RBC using preconditioning time	–	–	✓	Simulation EnergyPlus	Up to 30% saving	Scheduled Meeting schedules Reactive
[52]	Office	Cameras	RBC using preconditioning time	✓	✓	✓	Simulation EnergyPlus	42% less energy consumption	Scheduled Reactive Setpoint control without ventilation
[53]	Office	Cameras	RBC using preconditioning time	✓	✓	✓	Field evaluation Simulation	26% energy saving for field evaluation and up to 30% based on yearly energy simulation	Scheduled Reactive Setpoint control without ventilation Perfect prediction
[54]	Office	PIR Ultrasonic sensors	RBC using preconditioning time	–	✓	✓	Simulation EnergyPlus	Up to 28% energy saving Up to 40% improvement in thermal comfort	Reactive
[32]	Residential	Energy meters	RBC using preconditioning time	–	✓	✓	–	0.42 kWh energy saving per day 44.28 min decrease in mismatch time	Programmable
[55]	Residential	Applications on smartphones	RBC using preconditioning time	–	✓	–	Simulation RC	Up to 26.2% energy saving 28.2 h and 132.1 h for rule-based and reactive thermostats respectively.	Always on Reactive
[56]	Office	Bluetooth tags	Optimal control	–	✓	✓	Simulation EnergyPlus	2% energy saving 50% decrease in thermal discomfort	Scheduled
[57]	Office	–	Optimal control (MPC)	–	✓	✓	Simulation RC	Negligible energy saving for including occupancy prediction in MPC	MPC without occupancy information
[58]	Office	–	Optimal control (MPC)	–	✓	✓	Simulation RC	Negligible energy saving for including occupancy prediction in MPC	MPC without occupancy prediction
[59]	Residential	Light sensors	Optimal control (MPC)	–	✓	–	Simulation RC	32.80% decrease in temperature violation	MPC without occupancy prediction

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Table 2 (*continued*)

Ref.	Building type	Occupancy detection	Control				Performance evaluation		
			Type	V[1]	H[2]	C[3]	Method	Performance	Baseline
[60]	Office	–	Optimal control (MPC)	–	✓	✓	Simulation ThermalSim	Robustness to errors	MPC without PEC
[61]	Residential	–	Optimal control (MPC)	–	–	✓	Simulation RC	8% energy saving	Conventional MPC
[62]	Residential	Applications on smartphones Surveys	Optimal control (MPC)	–	✓	✓	Simulation EnergyPlus	Up to 13.3% energy saving.	Always on Rule-based Reactive
[63]	Residential	–	Optimal control	–	–	–	–	MissTime: Up to 40% reduction Conditioned time: 15% decrease	Programmable

[1] Ventilation.
[2] Cooling.
[3] Heating.
[4] Rule-based control.

limitation of this study. According to the field evaluation performed by Pritoni et al. [40], implementing HVAC run time as a performance criterion can cause overvaluation of the performance. They monitored 2500 rooms in three university residence halls before and after retrofitting them with smart thermostats. Before the retrofit, all rooms were equipped with manual thermostats, which were selected as the baseline. Smart thermostats, installed after the retrofit, utilized real-time occupancy information from PIR sensors to learn appropriate setback temperatures that can be recovered in an acceptable period of time. It was reported that due to heat flows from corridors and neighboring rooms, room temperature rarely reached the defined setback despite having long unoccupied hours with HVAC systems turned off. In other words, although the run time was significantly reduced in one vacant zone, an extra energy load was induced to the HVAC system because of the interzonal heat flows between occupied and unoccupied zones. As a result, consideration of HVAC run time as an energy indicator can cause overestimation of the performance.

A limitation of previously reviewed studies is that they mostly focused on whole-building control strategies. Indeed, occupancy patterns often vary across different rooms in buildings and the operation of HVAC systems can be adjusted to these zonal patterns. As highlighted by Kim and Oldham [64], using zoned temperature and humidity control in different hotel rooms can improve occupants' thermal comfort. Yang and Becerik-Gerber [43] demonstrated that considering a unique optimal schedule for each individual zone led to 5% more energy saving, compared with employing a shared optimal profile in the whole building. Sookoor et al. [42] developed a zoned reactive HVAC control strategy, called RoomZoner, and compared its performance with that of a whole-building control approach as the benchmark. RoomZoner was designed based on the concept of micro-zoning that was utilized by Rose et al. [65]. In this algorithm, the airflow from HVAC systems to each zone was dynamically changed based on the current temperature and occupancy states in each room. In order to keep the initial cost as low as possible, they developed a low-cost occupancy inferring system using PIR motion sensors installed in each zone. They assessed RoomZoner performance based on a 42-day field evaluation. It was demonstrated that using this zonal control resulted in a 14.4% reduction in energy consumption.

In the reviewed previous work, the proposed approaches were evaluated in terms of energy saving and thermal comfort, neglecting other performance indicators such as economic and peak-shifting criteria. To fill this gap, Krarti [45] evaluated the peak-shifting ability of zonal reactive thermostats in residential buildings. They reported that these thermostats decreased peak demand and energy consumption by up to 34.7% and 38.7%, respectively compared with an always-on thermostat. Wang et al. [44] conducted a financial analysis to evaluate the economic merits of reactive control. Always-on and programmable thermostats were considered as baselines. They used American Time Use Survey [66] to construct a probability function to involve occupancy patterns in the development of the control strategy. To construct occupancy profiles, they used random numbers between 0 and 1, which were then compared with the probability of occupancy in each time-interval. They showed that the reactive strategy resulted in an energy saving of 20% and a payback period of less than one year.

5. Predictive control

As discussed in the previous section, reactive control strategies are able to overcome the main shortcoming of the control strategies using user-defined occupancy schedules. However, reactive control can cause thermal discomfort during transitions from setback to setpoint temperature upon occupants' arrival. The lag time associated with the HVAC systems to return to the desired setpoint temperature is the main reason for this limitation [67].

To deal with this issue, the control system can take advantage of occupancy prediction models to create proactive control rather than being reactive. Proactive controllers forecast future occupancy patterns and accordingly, precondition buildings before occupancy. However, the performance of these control strategies is highly dependent on the model prediction performance. Indeed, predicting future occupancy in a building is a challenging task as occupant behavior is highly stochastic in nature [47]. Furthermore, it is also challenging to effectively integrate the occupancy models in HVAC control in order to make a trade-off between energy saving and thermal comfort. The predictive control methods and occupancy models developed in the literature are respectively summarized in Table 2 and Table 3.

5.1. Occupancy prediction models

Because of the complexities and importance of occupancy prediction, some researchers focused on developing occupancy prediction models without investigating the integration of the models with control systems. Occupancy models are established based on databases gathered during occupancy monitoring periods. Depending on available data, occupancy models can predict binomial states of future occupancy, estimate occupancy levels, or predict occupancy patterns for each individual occupant.

5.1.1. Occupancy state/level prediction

Occupancy states are usually presented by 0 and 1, respectively denoting vacant and occupied hours, and used to regulate the setback and setpoint temperature. In order to develop models to predict occupancy states, relatively simple monitoring sensors, such as motion detectors, would suffice to provide an acceptable level of accuracy, while for occupancy levels, more advanced infrastructure such as camera networks is often required. Occupancy levels are helpful for controlling ventilation rates, as ventilation rates are adjusted based on the number of occupants in the monitored space.

Table 3
Summarization of occupancy models used in the reviewed papers.

Ref.	Building	Model	Features	Occupancy Level	Performance
[52]	Office	Markov model	Time of day	✓	Duration JSD Occupancy flow
[54]	Office	Hypothetical model	–	–	Accuracy False negative/positive rates
[68]	Office	SVM Random forest Decision tree kNN	Holiday Time of day Day of week Weekends Season	–	Accuracy F-score
[69]	Office	kNN SVM Linear regression M5-Rules REPTree Gaussian processes Baggigng	Day of week Month Occupancy duration Arrival time Departure time Time of day Temperature Wind speed Cloudiness Precipitation Snowfall	✓	MAE
[70]	Office	KNN-DTW Random forest SVM PreHeat [31]	Time of day Day of week Weekends Season	–	F-score
[71]	Residential	HMM kNN SVM	Zonal occupancy states Time of day Occupancy duration	✓	F-score
[32]	Residential	Proportional model	Time of day	–	Accuracy Matthews Correlation Coefficient
[63]	Residential	Proportional model	Time of day Departure time Arrival time	–	–
[50, 53]	Office	Blended Markov model	Time of day	✓	Accuracy
[72]	Residential	PreHeat [31] Proportional model Hybrid model proposed in [73]	Time of day Location	–	Accuracy
[74]	Office	Markov model Semi-Markov model	Season Day of week Time of day State transition	✓	NRMSE
[51]	Conference hall	Semi Markov Model	Acoustic level Lighting level CO2 Concentration Temperature Relative Humidity	–	–
[75]	Office	Genetic programming	Day of week Time of day Occupancy duration	✓	Accuracy
[76]	Office	Markov model	Arrival time Departure time Occupancy duration State transition	✓	NRMSE K-L
[77]	Office	Markov model	Identity Occupancy duration Activity type	✓	Accuracy
[78]	Exhibition hall	LSTM ARIMA RNN Holt-winter	Time of day	✓	RMSE MAE MAPE
[79]	Commercial	GRU	Location Activity type	✓	RMSE MAE MSE
[80]	Research laboratory	LSTM	CO2 concentration	✓	Accuracy RMSE
[62]	Residential	Proportional model Perfect prediction	Time of day Day of week	–	Accuracy
[55]	Residential	Perfect prediction	–	–	–
[56]	Office	Proportional model	Time of day Day of week	–	–
[73]	Residential				

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Table 3 (*continued*)

Ref.	Building	Model	Features	Occupancy Level	Performance
[81]	Residential	Proportional model Drive time Logistic regression Random forest kNN Markov model HMM LSTM	Time of day Day of week Time of day Weekends	–	Accuracy Computational time
[82]	Office	Decision tree HMM	Time of day CO2 concentration Appliance energy consumption Lighting level	✓	Accuracy
[46]	Office	Proportional model	Time of day	–	–
[14]	Residential	Proportional model	Time of day	–	Accuracy
[48]	Residential	Drive time	Location	–	–
[30]	Residential	Hybrid of destination prediction and proportional model.	Location Time of day	–	Accuracy
[49]	Office	Hybrid of route classification and a time-aided order-k Markov predictor	Location Time of day	–	Accuracy
[57, 58]	Office	Perfect prediction	–	–	–
[59]	Residential	k-means clustering	Time of day Day of week	–	–
[60]	Office	Proportional model	–	–	Accuracy
[61]	Residential	Revised Logistic regression	Time of day Weekends	–	MAE
[47]	Office	kNN k-means clustering	Arrival time Departure time Vacancy duration	–	Accuracy
[31]	Residential	PreHeat	Time of day Weekends	–	Accuracy

Chen et al. [76] proposed an inhomogeneous Markov chain model to predict occupancy levels in office buildings based on their preliminary results [83]. Five attributes were considered in developing this model: mean of occupancy level, first arrival time, last departure time, occupied duration, and occupancy transitions. To assess the performance of the developed model, normalized root mean square deviation and Kullback-Leibler (K-L) were employed. They compared the performance of the proposed model with that of an agent-based algorithm proposed by Liao et al. [84,85] and showed the superiority of their proposed Markov models. Adamopoulou et al. [74] developed a model using spatial-temporal features to capture relationships between occupancy patterns in different rooms. They grouped highly correlated rooms into different zones and deployed a unique Markov model for each defined zone. Transition matrices were constructed to provide the probability of interzone occupants' transitions. These matrices were then used in occupancy models to capture spatial relationships. They employed these matrices as well as season, time of day, and day of week as features to develop the model. Depth-image cameras with 95% accuracy were implemented to collect occupancy data in an office and a kitchen while in a rest area, PIR and acoustic sensors were used. A limitation of these reviewed studies is linked with the fundamental assumption considered in Markov chain models. To be more specific, in the Markov models, it is assumed that future states are only dependent on the current state. Using this assumption might neglect some important information existing in the past time intervals for predicting occupancy states.

In order to deal with this issue, Kim et al. [78] established a long short-term memory (LSTM) network, which was able to memorize important information from past events. They used this model to predict occupancy levels in a large exhibition hall and compared its performance with that of an auto regressive integrated moving average (ARIMA), holt-winter, and recurrent neural networks (RNN). They collected data from the exhibition hall in 15-min time intervals using image sensors. Root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were utilized as evaluation criteria to assess the performance of the deep learning algorithms. According to the results, LSTM model provided the best performance among the implemented machine learning models. However, there is a shortcoming associated with using cameras in data collection, as implementing cameras in buildings could cause privacy issues for occupants.

To protect occupant privacy, some researchers have implemented other alternatives, such as environmental features, in developing occupancy models. Ryu et al. [82] developed a decision tree for occupancy detection using indoor and outdoor CO2 concentration, lighting, and appliance energy consumption. They applied the results of occupancy detection to develop a hidden Markov model (HMM) algorithm to predict future occupancy states and levels in office buildings. According to the results, occupancy prediction using environmental features had an accuracy of more than 90%. Elkhoukhi et al. [80] deployed an LSTM algorithm to predict short-term occupancy levels using historical CO2 concentration data. First, they evaluated the correlation between CO2 concentration and the occupant number. In the next step, they trained an LSTM model to predict future CO2 concentrations. Based on the steady-state equation proposed in Ref. [86], they estimated the number of occupants as a function of CO2 concentration in a research laboratory. The results showed that this LSTM algorithm provided accuracy and RMSE of 70% and 2.93, respectively. Although these research studies addressed privacy issues with a high level of accuracy for occupancy prediction, they did not evaluate the impact of using these alternatives on the model performance. There is a need for comparing these proposed models with common approaches to demonstrate whether using environmental features can have any impact on the model prediction performance.

There have been a variety of occupancy models developed by researchers, which highlights the necessity of evaluating and comparing the models using the same dataset to reveal their strengths and limitations. For this purpose, Kleiminger et al. [72] compared the performance of PreHeat, a hybrid model, and a proportional model which were respectively proposed in Refs. [14,31,73]. They applied these models to a dataset collected using GPS, Wi-Fi connections, and cellular networks through smartphones, described in Ref. [87]. The results demonstrated that the proportional method outperformed other algorithms with a median accuracy of 85%. Using the upper bounds of human mobility prediction performance defined in Ref. [88], they also estimated an upper bound accuracy of almost 90% for using more complex methods. Huchuk et al. [81] compared the performance of logistic regression, kNN, LSTM, random forest, Markov models, and HMM in terms of computational time and accuracy. Time of day, weekends/weekdays, and previous occupancy states were utilized as features to train the models. The results showed that the random forest algorithm provided the highest accuracy for occupancy prediction among the selected machine learning techniques, while logistic regression provided the best computational cost. Caleb et al. [68] applied SVM, random forest, decision trees, and k-NN, to an occupancy dataset with a resolution of 10 min to develop occupancy models. They included seasons, holidays, time of day, weekends, and day of week features in developing the models. The results showed that for schedules with a high occupancy rate (i.e. the frequency of being occupied), SVM outperformed other algorithms, while for lower occupancy rates, all models provided a similar performance. Sangogboye et al. [70] assumed that no single occupancy model can perform the best for all cases. Hence, they established the PROMPT algorithm that consisted of four occupancy algorithms, namely PreHeat, SVM, kNN-DTW, and random forest, developed based on previous work [31,89]. F-score performance of each model was compared in every prediction case, and the best algorithm was selected for the prediction task. It was shown that PROMPT increased F-score by up to 2.3% when compared with each individual model. In these studies, the impact of the data collection period, dataset resolution, the window size, and types of features used to develop the models were neglected. As the performance of models could depend on these factors, analyzing their sensitivity to these parameters can be important while comparing the models.

The impact of training set duration and dataset resolution on the performance of occupancy prediction models were evaluated by Salimi and Hammad [90] through a sensitivity analysis. They employed an inhomogeneous Markov chain model which was proposed in their previous work [77] and selected the coefficient of determination and normalized root mean square error (NRMSE) as the performance evaluation metrics. They showed that a sudden improvement in the accuracy was achieved by changing the period of the training dataset from one to two months, while for longer periods, the impact on accuracy was relatively smaller. In addition, the best time resolutions for the two occupancy zones investigated in this study were 5- and 10-min intervals. However, the dataset used was limited to monitoring occupancy levels in a single office building. More research is needed using wider datasets to achieve more reliable results.

5.1.2. Prediction of individuals' occupancy patterns

Some researchers developed models to predict individuals' occupancy patterns rather than predicting occupancy levels in an entire zone. These predicted patterns can be, then, aggregated to construct occupancy level profiles. Occupancy models developed based on individuals' behavior might result in more accurate predictions, because they employ occupant identities as an extra feature [21]. However, using identities can cause privacy issues for occupants.

Salimi and Hammad [77] aimed to develop an adaptive occupancy prediction model in office buildings, utilizing identities, occupancy duration, and activity types (e.g. dining or working states) to train a Markov model. Occupancy information was gathered using Bluetooth tags, associated with each occupant. In this study, different prediction horizons were utilized based on two applications of occupancy prediction: HVAC and lighting control. In terms of HVAC control, due to the lag time associated with preheating, a 30-min prediction horizon was considered, while for lighting, a short-term prediction, i.e. 5-min, was utilized. The results showed that prediction accuracy significantly decreased from 86% to 68% when the prediction horizon increased from 5 to 30 min. A limitation of this study is linked with the occupancy detection system; the system did not collect any occupancy information regarding visitors to the office. Therefore, if one person occupied the office temporarily, the system failed to detect the occupancy presence and could not meet thermal comfort conditions. Additionally, they limited the prediction horizon to only one lag time, i.e. 30 min. As discussed in Section 5.2, the lag time varied from 30 min to 3 h, and considering a wider range of preconditioning horizons would be more valuable when evaluating an occupancy model.

Shao et al. [71] developed an episode-generating HMM for occupancy prediction based on temporal relationships in occupancy patterns. An episode was defined as an ordered sequence of different zones visited by an occupant, such as kitchens, bedrooms, and corridors. The episode prediction algorithm was similar to life pattern mining proposed in Ref. [91]. They predicted future events according to the most frequent episodes, and the time of start and end of the last event. The results showed that the proposed model improved the F-score performance of occupancy prediction, compared with that of kNN and SVM models. However, they limited the proposed model to sequential visited spaces inside the building, such as different rooms. In other words, they neglected the relationship between these indoor spaces and outdoor locations visited by each occupant. Hence, there is a need for evaluating the possible improvements that can be achieved by defining an episode as an ordered sequence of visited indoor zones and outdoor locations in occupancy models.

Instead of predicting occupancy patterns, Das and Kjærgaard [79] focused on predicting the next specific locations of each occupant using a gated recurrent unit (GRU) algorithm. The locations were determined using video cameras by recording occupants' coordinates. To make the prediction more accurate, they added *sitting* and *moving* labels to each record in the dataset. MSE, MAE, and RMSE were selected as the performance evaluation criteria. They demonstrated that the GRU model predicted future locations with an RMSE of 4.79 cm. Although predicting the next locations of each individual can be helpful for predicting future occupancy states, the performance of this method for future pattern prediction was not evaluated.

Yu [75] proposed a novel model using a genetic programming algorithm for predicting occupancy patterns of individuals in single-person offices. The model was trained based on the following attributes: day of week (except for weekends), time of day, duration of occupancy in the last state, and the period from the last arrival time to the office. According to the results, the algorithm provided up to 83% accuracy for predicting occupancy states. However, no comparison between the proposed method and commonly used machine learning and statistical models in the literature were made. As the prediction performance significantly depends on occupancy profiles in buildings, without providing a direct comparison between occupancy models applied to the same dataset, the effectiveness of the proposed model cannot be well evaluated.

In contrast to the previously reviewed studies that used a few features, Gjoresk et al. [69] developed an occupancy prediction algorithm based on a relatively wide range of features including day of week, month, difference between total and expected working hours per month, historical arrival time, historical departure time, morning temperature, wind speed, cloudiness, daily precipitation quantity, and snowfall. A database collected from historical occupancy patterns of seven employees and weather data in 2 years were utilized to establish prediction algorithms. Naïve approach as a baseline model as well as kNN, SVM, Linear regression, M5-Rules, REPTree, Gaussian processes, and bagging algorithms were implemented for this regression problem. The proposed algorithm decreased MAE value by up to 50% and 32% for arrival and departure time predictions, respectively, compared with the baseline. However, although a relatively large number of features were utilized in the development of this algorithm, the importance of these features in predicting individual patterns was not clarified. To be more specific, a feature selection method was lacking in this study to determine the most effective features in developing occupancy models.

5.2. Rule-based control

In rule-based (RB) control, a pre-defined set of rules are applied to predicted future occupancy to provide energy saving and thermal comfort. In the literature, these rules were mainly defined as a function of preconditioning time, conditioning rate, or occupancy probability. Preconditioning time, also called the lag time of HVAC systems or preheating/cooling time, is defined as the time it takes to precondition a building to reach the setpoint temperature from a setback. Conditioning rate is defined as the rate of temperature change per hour during preconditioning periods. The previous research items are categorized based on the types of rules and are discussed in the following subsections.

5.2.1. RB control using preconditioning time and conservative setback

The majority of earlier work defined the rules in RB control as a function of future occupancy states and estimated preconditioning time. In these strategies, first, an approximate preconditioning time is estimated based on previous operations of HVAC systems. Then, it is used as the prediction horizon of the occupancy model. If the building is predicted to become occupied during this period, the controller turns the HVAC system on to bring back the setpoint before occupants' arrival.

Researchers considered various ranges for setback during unoccupied hours. As the depth of setback can considerably impact energy saving and occupants' comfort, the reviewed articles on RB control are classified into conservative and deep setback categories. The conservative setback is defined as a temperature deviation from the setpoint by 3 °C. Larger deviations are classified as a deep setback.

Lee et al. [49] deployed an RB control strategy using a hybrid occupancy prediction model based on occupants' locations received from cellular towers and Wi-Fi connections. This hybrid model used two different methods depending on transition time (i.e. the time it took for occupants to reach the target place from their current location). In cases when the transition time was larger than preconditioning time, a route classification algorithm was deployed. For short transitions, a time-aided order-k Markov predictor was applied to historical occupancy data to predict future destinations and associated arrival time. Using historical data, preconditioning time was estimated as 21.82 min with 1.98 min error for an average temperature difference of 2.5 °C. In order to evaluate the performance, they measured energy consumption and air temperature in target zones. The results showed that the proposed strategy decreased energy consumption by 26%, compared with always-on thermostats and was able to predict 70% of transitions with an error of less than 10 min. However, the method failed to learn unregular occupancy patterns with an overall accuracy of less than 60%.

Dong and Andrews [51] applied RB HVAC control to a conference hall. First, they developed an occupancy pattern recognition method based on gathered data from 6 types of sensors: acoustics, lighting, motion detectors, CO2 concentration, temperature, and relative humidity. The most frequent patterns and their subsets were selected as candidates to determine patterns with the strongest correlation with occupant behavior. In all control strategies, night and day setback temperatures were defined at 30 °C and 27 °C, respectively with a setpoint of 24 °C. The results showed that RB control resulted in up to 30% energy saving. As well as setpoint temperature control used in this study, OBSERVE control algorithm proposed by Erickson et al. [52] took both ventilation and temperature control into account using an RB control. The number of occupants from 8 different zones including offices, laboratories, and conference rooms was gathered using a network of 7 cameras installed in each corridor for a period of five days. In this study, a Markov chain model was used to predict occupancy. To evaluate the occupancy model performance, duration of occupancy states and the rate of people entering and exiting different zones were compared with the ground truth data. Jensen Shannon divergence (JSD) indicator was also used to compare the distributions of predicted results and ground truth during the testing period. The ventilation rates were adjusted based on the occupancy levels in each zone using the relationships suggested in ASHRAE Standard 62.1 [92]. The allowed temperature was in the range of 21.1–23.9 °C and 25.5–27.8 °C for heating and cooling seasons, respectively. Based on three virtual test environments simulated in EnergyPlus, it was demonstrated that this control system can save 42% annual energy, compared with scheduled control.

However, most of the mentioned works limited their study to evaluating energy saving performance and provided no analysis regarding thermal comfort of occupants. As the main aim of predictive control is to ensure a thermally comfortable indoor environment for occupants, it is essential to consider this criterion when evaluating predictive control systems. Some earlier work considered both energy saving and thermal comfort when evaluating the performance of control systems. Beltran et al. [50] proposed a control strategy for ventilation and temperature regulation, named ThermoSense. ThermoSense employed a network of thermal and PIR sensors and implemented a blended Markov chain model [52], to predict future occupancy states with a prediction horizon of 1 h. The results demonstrated that ThermoSense decreased the annual energy consumption by 24.8%. However, it was shown that implementing a reactive control instead of ThermoSense provided higher energy saving of 29.6%. The amount of energy consumed for preconditioning the building before arrival time was the main reason for the lower energy performance of ThermoSence. However, due to this preconditioning period, ThermoSence provided lower temperature deviation from the setpoint with a maximum RMSE of 0.415 °C, while reactive thermostat resulted in a maximum RMSE of 1.23 °C. A similar algorithm, named POEM, was proposed by Erickson et al. [53]. The main distinction of POEM algorithm with ThermoSense was using a network of cameras to provide more accurate occupancy detection. The camera network provided an estimation of occupancy levels to regulate temperature schedules and minimize ventilation rates while meeting the ASHRAE standards [92]. The results showed that POEM reduced energy consumption by 26%. Moreover, it was demonstrated that there was no significant difference between the performance of POEM and reactive control algorithms in terms of energy saving; however, the reactive controller caused thermal discomfort upon occupants' arrival.

5.2.2. RB control using preconditioning time and deep setback

A limitation of the research items reviewed in the previous section is linked with the conservative temperature range considered in the control systems. This conservative range of setback temperature, although is essential in reactive control to minimize the discomfort upon arrival, can be widened in predictive control to save more energy in long unoccupied periods. It is because of the ability of the system to predict future occupancy and precondition the zone before the arrival time. Therefore, some researchers have studied a wider range of temperature in the control strategies.

Koehler et al. [30] developed an RB control algorithm, called TherML. This algorithm employed a hybrid occupancy prediction model based on contextual information from individual occupants. More specifically, the occupancy prediction was dependent on whether the occupant was driving or not. If the monitored occupant was driving, a methodology, similar to that implemented in Refs. [93,94], was used, in which a sequence of previously visited locations by occupants as well as time of day were implemented to predict future destinations. Otherwise, the system made predictions using a proportional model by calculating the frequency of historical occupancy states in 5-min time intervals. The average preconditioning time to change temperature from 15.5 °C to personal desired temperature (an average of 20.6 °C over all participants) was estimated as 59 min based on a data collection over 5 weeks. They compared the performance of TherML with that of GPS-thermostat [48], PreHeat algorithm [31], and a manual remote controller described in Section 3. It was demonstrated that TherML outperformed other methods in terms of accuracy and energy saving, providing an average accuracy of 92.1%, which was 1.5% higher than that of PreHeat algorithm. The average MissTime and WasteTime for TherML were respectively estimated as 0.95 and 0.94 h, which were slightly lower than those related to PreHeat algorithm. A sensitivity analysis was also performed to show the impact of traveling distance on the accuracy of TherML. For long distances, 14,000 m, TherML could provide up to 7% higher accuracy than PreHeat, while for short distances such as 200 m, only 1% improvement was achieved using TherML. Implementing the simple proportional occupancy model can be mentioned as one of the limitations of this hybrid model. More advanced techniques such as machine learning models could be implemented to find more hidden patterns in occupancy profiles to boost the accuracy of occupancy prediction.

Gluck et al. [54] evaluated the impact of occupancy prediction errors and depth of setback temperature on the performance of RB control. To this end, they proposed a hypothetical occupancy model with 25%, 15%, and 5% errors in accuracy. Their hypothetical model was based on real data collected from 235 rooms in an office building with PIR and ultrasonic sensors. Three different ranges for setback temperature were considered in this study; 1) low-bound setback with a maximum 2 °C deviation from setpoint, 2) medium-bound with a maximum 6 °C deviation, and 3) large-bound with a maximum 10 °C deviation as the deepest bound. A reactive thermostat based on the low-bound setback was utilized as the baseline. According to the results, using a medium-bound and large-bound setback saved up to 26% and 40% energy, respectively compared to reactive thermostats. It was also reported that a 10% reduction in prediction errors resulted in up to almost 9% and 16% improvement in energy saving and MissTime, respectively. Although they considered a deep setback in the high-bound and medium-bound temperature ranges, only a fixed approximate preconditioning time of 1 h was considered in this study.

Nägele et al. [55] compared the performance of manual, programmable, reactive, and RB thermostats in terms of energy saving and thermal comfort. They also assessed the impact of including weather prediction, obtained from meteorological weather stations, on the performance of reactive and predictive control. They collected occupancy data through smartphone applications over a 14-month period. The preconditioning time was estimated as 1 h. They estimated energy consumption of the building through a Resistance-Capacitance (RC) model and demonstrated that the highest energy saving was achieved using reactive control at an average of 26.2%, which was followed by RB control at 23.7%. On the other hand, predictive controllers provided the lowest MissTime of 28.2 h, which was 103.9 h lower than that of reactive control. A limitation of this study is linked with the utilized occupancy prediction model. More specifically, they implemented perfect occupancy prediction and neglected the impact of errors on the control system performance. Therefore, the results for the RB controller is overestimated, providing an ideal upper bound for the RB control. As well as utilizing perfect prediction, occupancy models can be also implemented to give an insight into predictive control performance in real-world applications.

Iyengar et al. [32] focused on improving currently installed programmable thermostats without a need of additional infrastructure. They called these revised thermostats iProgram. iProgram predicted future occupancy based on energy consumption patterns in residential buildings without the need of a training dataset, as it is not available in many homes with programmable thermostats. They evaluated the performance of the proposed occupancy detection algorithm using accuracy and Matthews correlation coefficient. As for controller performance, MissTime, WasteTime, mismatch time (sum of WasteTime and MissTime) were assessed by simulating 100 homes as virtual test cases. It was demonstrated that iProgram resulted in 0.42 kWh average energy saving per day. Furthermore, the mismatch time decreased by an average of 42 min having a median deviation of almost 30 min. However, the proposed occupancy detection method using energy consumption patterns was limited to predicting occupancy during the day and failed to predict occupancy during the nighttime when people are sleeping.

5.2.3. RB control using conditioning rate and occupancy probability

In the earlier work concerning RB control, researchers considered an average preconditioning time as the prediction horizon to make control decisions for initiating the preconditioning process. However, this static time cannot consider the actual difference between dynamic room temperature and the desired setpoint. As a consequence, when room temperature reaches a setback after a long vacant period, it clearly takes more time than the average to precondition the building before occupants' arrival, which increases the MissTime. Similarly, after a short vacancy, it can cause energy waste due to over preconditioning the zone. Hence, some researchers have defined the preconditioning time by multiplying the conditioning rate and the difference between actual room temperature and setpoint. This definition is more helpful when a wider range for temperature is allowed in control algorithms. Besides, some researchers have employed occupancy probability in control systems rather than using deterministic occupancy models. In these cases, RB control systems determine the depth of setback as a function of occupancy prediction confidence. For example, when the probability of occupancy remains negligible in the following hours, a deeper setback is defined to save more energy. In contrast, when the probability of presence is relatively high, a conservative setback is set to ensure occupants' comfort.

Nikdel et al. [46] studied the benefits of using RB control in office buildings from a national point of view. They evaluated the influence of such systems on the amount of fossil fuel consumption, greenhouse gas emission, and energy cost, compared with always-on and programmable thermostats. They defined setpoint temperature as a linear function of the presence probability. Based on this relationship, the temperature was allowed to change between 15.6 and 21.1 °C in the winter and 23.9 and 29.4 °C in the summer. The results showed that up to 50% and 87% reduction in electricity and natural gas consumption was respectively obtained using this occupancy-based HVAC operation, compared with always-on control. With all small offices in the US having this type of control, the saving of fossil fuel, CO_2 emission, and cost at the national level were estimated as 15–66 million GJ, up to 3.7 million metric tons, and 658 million dollars, respectively. However, the impact of RB control on the thermal comfort conditions was neglected in this study. As improving cost or energy saving are often obtained at the expense of occupants' thermal comfort, the control system should be also evaluated in term of providing thermal comfort for occupants.

Using a two-level probabilistic occupancy model, Peng et al. [47] defined an RB HVAC control strategy for use in office buildings. At the first level, a k-means clustering algorithm was applied to a real occupancy dataset, collected using motion sensors, to cluster similar data records. In the second level, a k-NN algorithm was utilized to predict occupants' first arrival time and the duration of occupied hours in office buildings. Arrival time, last departure time, and maximum unoccupied duration were utilized as features for developing occupancy models. They defined the setback temperature as a function of the probability of presence obtained from the occupancy model. The setback temperature could increase from the comfort temperature to 35 °C in cooling seasons depending on the occupancy probability. In this study, a field evaluation was performed in an office building with a meeting room, and single- and multi-person offices. Energy meters were utilized to evaluate the amount of energy consumed by chillers. The results achieved from this experiment demonstrated 7%–52% energy saving in comparison with scheduled cooling systems. However, in this study, although a novel two-level occupancy prediction algorithm was proposed, no comparison between this algorithm and conventional one-level predictions was provided to show the strengths of the proposed model.

Lu et al. [14] proposed a smart thermostat to automatically adjust zone temperature to occupancy states in buildings. The proposed smart thermostat employed three strategies to save energy while keeping an acceptable thermal comfort level. They included turning off the HVAC system after residents left home or slept, preheating the home before their arrival, and employing a deep setback temperature during confidently vacant hours. They used a hidden Markov model (HMM) to infer three different possible occupancy modes at home; 1) active, 2) away, and 3) sleep modes. Future arrival time was estimated using the historical arrival times recorded by the occupancy detection system. Three features were used in the occupancy model; 1) time of day, 2) total number of true signals received from occupancy sensors, and 3) signals received from door sensors. The results showed that this approach led to almost 28% energy saving, compared to conventional thermostats.

Scott et al. [31] developed an RB control, called PreHeat, for heating five homes in the UK and US. They collected occupancy information using radio-frequency identification (RFID) tags associated with residences' keys and motion detectors installed in homes. Based on this data, they created a partial occupancy vector that consisted of occupancy information from midnight until the current time step. They used this vector as a primary attribute for developing occupancy prediction in 15-min intervals. They reported that occupant behavior in the considered homes was highly dependent on weekends or weekdays, and as a result, they used this parameter as the second feature. They used a kNN algorithm to calculate the probability of presence, based on the mean of 5 nearest historical occupancy states. PreHeat employed occupancy models and an empirical preconditioning rate based on the historical data. They utilized a room-based control for 2 homes in the UK and whole-home control for 3 homes in the US. They measured gas consumption for each residential unit to evaluate the energy performance of controllers. The results demonstrated that PreHeat decreased MissTime by up to 92% without the need for human interventions. However, PreHeat did not provide improvements in energy saving compared with programmable thermostats.

As well as using historical occupancy patterns to predict future occupancy in a target zone, some researchers have employed information about occupants' routines even when they are not in the monitored building. Gupta et al. [48] proposed a thermostat, called GPS-Therm based on real traveling data collected from four households in the US. Occupants' locations were utilized to estimate the time it took for the nearest occupant to reach home. The estimated traveling time was then employed to schedule a setback profile to save energy. The setback was defined as a function of traveling time so that the HVAC system has enough time to preheat the building before the arrival. Implementing this heating strategy resulted in 7% energy saving in the considered households. However, as the setback temperature was defined as a function of traveling time, in cases with short traveling time, a too shallow setback is defined using this method. Therefore, in these cases, the GPS-Therm leads to no substantial energy saving compared with always-on thermostats. Krumm and Brush [73] developed a proportional occupancy model and compared its performance with that of GPS-Therm in terms of occupancy prediction accuracy. They developed their model based on real data collected from 11 households using time of day and day of week as input features. It was demonstrated that the proportional model performed much better than the drive-time algorithm. The reason was that, occupants spent most of their time near their homes, and as a result, the traveling time was often short. They reported a slight improvement in the performance of occupancy prediction when they combined both methods.

5.3. Optimal control

In contrast to rule-based control, in which a set of rules are implemented, in optimal control, optimization algorithms are employed to make optimal sequences of decisions. In most studies conducted in this field, optimal controllers were employed to make an optimal trade-off between minimizing energy consumption and maximizing thermal comfort. Model predictive control (MPC) has been the most utilized occupancy-based optimal control strategy in the literature. Interested readers can find more information about MPC operation in HVAC control applications in Ref. [19].

Despite many papers published on MPC-related topics, there are a limited number of papers that implemented occupancy prediction in MPC. Oldewurtel et al. [57] evaluated the impact of using occupancy prediction in MPC in terms of energy saving. To this end, they compared the performance of an MPC using instant information from occupancy sensors, as the baseline, with that of an MPC that took advantage of perfect occupancy prediction for HVAC and lighting control. In this study, the temperature setpoint was constrained in the range of 5–40 °C in the optimization problem during vacant hours. This wide temperature range was assumed to give an upper bound of energy saving that can be achieved from this control system. Based on the assumptions, they concluded that the amount of energy saving achieved by using complex occupancy predictions led to a relatively low improvement in the system performance and might not compensate for its complexity. In a similar work by Goyal et al. [58], the performance of a reactive control and that of an MPC using 24-hr perfect occupancy prediction were compared in terms of energy saving. In this study, the range of setback temperature in all cases during unoccupied periods was considered from 21.1 °C to 24.4 °C, which was close to the range of 21.9 °C–23.6 °C, considered during occupied hours. They showed that all three proposed methods resulted in a considerable amount of energy saving (almost 50%). However, despite the high complexity of MPC-based algorithms, these methods did not lead to significantly higher performance. Goyal et al. [95] also verified the conclusions made in Ref. [58] by conducting an experimental study on a single zone office as a testbed. However, it should be noted that in none of these studies the impact of MPC on occupants' comfort was evaluated. As one of the key purposes of using predictive control is to improve thermal comfort, considering energy-efficiency as the sole indicator can lead to underestimation of the system performance.

As well as minimizing energy consumption of the system, Salimi and Hammad [56] utilized a multi-objective genetic algorithm to minimize MissTime. In their study, occupancy profiles were predicted by applying a Markov model to historical occupancy data gathered from an individual office. They utilized EnergyPlus to estimate the performance of the proposed algorithm and demonstrated that this optimal approach enhanced thermal comfort by 50% and decreased the energy consumption by 2%, compared to a scheduled control. However, MissTime fails to consider the difference between the actual and desired room temperature in the optimization problem. To deal with this limitation, Shi et al. [61] proposed a cost function, similar to that implemented by Killian and Kozek [59], to be minimized in the optimization algorithm of MPC. The cost function consisted of thermal discomfort and energy consumption terms. The former term was defined by multiplying the presence probability, achieved from occupancy models, and a thermal discomfort factor, defined as the difference between the actual room and the desired room temperature. In this optimization problem, setpoint and setback temperatures were respectively constrained in the ranges of 18–28 °C and 20–24 °C. The results indicated that using occupancy prediction in MPC improved energy saving by up to 8%, compared with the traditional MPC, and maintained an acceptable level of thermal comfort. Turley et al. [62] evaluated the performance of occupancy-based MPC and compared it with that of reactive control. The ground truth occupancy data was gathered using applications installed on the users' phones and using regular surveys filled by occupants. Prediction and control horizons for MPC were selected as 24 h and 1 h, respectively. They employed a particle swarm optimization algorithm to find the temperature that optimized predicted mean vote (PMV) and energy use in a weighted optimization algorithm. The results showed that MPC reduced energy consumption by up to 13.3%. They also reported that MPC with perfect occupancy prediction saved almost 3% more energy, compared to MPC with occupancy prediction models.

Killian et al. [59] compared the performance of MPC with and without integration to occupancy prediction models in terms of temperature violation from setpoint in residential buildings. They applied a k-means clustering algorithm to an occupancy dataset, collected using lighting sensors, to develop an occupancy prediction model. They showed that an MPC with occupancy prediction reduced the temperature violation by up to 32.80%. Gao and Whitehouse [63] developed an optimal control based on modifying programmable thermostats. They called the system “self-programmed thermostats”, that was able to construct a temperature schedule based on historical occupancy data. Future occupancy patterns were constructed based on maximum departure time and minimum arrival time in the last one-month occupancy patterns. They constructed an optimization algorithm to minimize HVAC run time as an indicator of energy saving. Their preliminary results showed that using self-programmable thermostats rather than standard programmable ones decreased HVAC run time by 15%. It also decreased MissTime by 12%–40% depending on occupancy patterns.

6. Discussion and recommendations for future research

Based on this comprehensive literature review, the research gaps in the field of occupancy-based HVAC control are discussed in this section. To this aim, the reviewed papers are summarized and explored from the following different viewpoints: performance assessment methodologies for occupancy models and control strategies, the features used in developing occupancy models, types of occupancy models and control systems, and testbeds used for model evaluation.

6.1. Performance indicators for evaluating control systems

Fig. 4 demonstrates the frequency of different performance criteria used to assess occupancy-based control systems. It can be seen that energy saving was the most popular performance indicator in previous studies. However, as discussed in Section 5.3, using energy saving as the only indicator can result in undervaluation of predictive control performance, especially when compared with the performance of reactive control. This is because reactive control often decreases energy consumption at the expense of thermal comfort, while predictive control improves comfort by preconditioning the building. This preconditioning can cause more energy consumption, and if only energy saving is

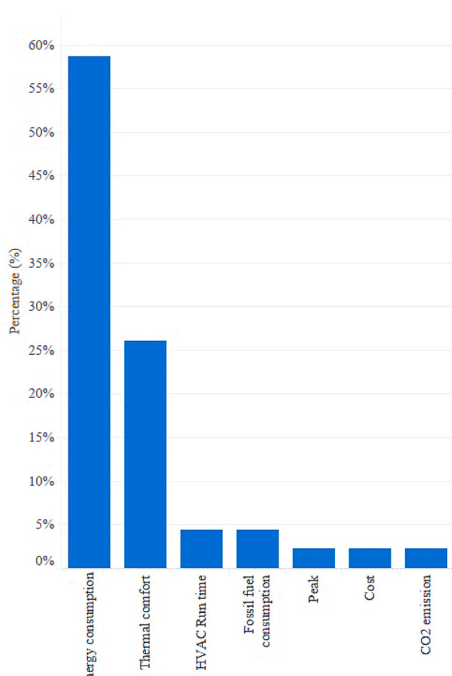

Fig. 4. The frequency of different performance criteria utilized to assess the merits of occupancy-based control strategies in the reviewed studies.

concerned, reactive control can outperform predictive control by neglecting their benefits in providing thermal comfort. Therefore, it is strongly recommended not to ignore thermal comfort conditions while evaluating the performance of predictive control strategies.

It can be also observed that HVAC runtime has been rarely utilized by researchers to assess the merits of the control strategies. This is consistent with the results achieved by Pritoni et al. [40], reviewed in Section 4. Briefly, they demonstrated that there is not always a relationship between HVAC run time and energy saving, and employing HVAC run time as performance merit can lead to overestimation of system performance. Therefore, using energy saving rather than HVAC run time is more recommended to provide more reliable results.

As demonstrated in Fig. 4, the financial merit of control systems has been one of the least-used criteria in evaluating control systems in the earlier studies. However, this is an essential factor for encouraging building owners to replace the old control systems in buildings with more intelligent ones. To be more specific, the main barrier for many owners in retrofitting the buildings with intelligent control is the initial costs; therefore, evaluating the economic benefits, estimated through financial analysis, can be a great incentive for them. Similarly, the majority of earlier work have neglected peak-shifting performance, despite its importance in demand response management. In some areas with cold climates, utility companies encounter serious challenges to provide electricity for customers during on-peak periods in winter. The focus in such areas is to find a solution to shift on-peak demand to the off-peak periods via encouraging costumers to manage peak demands or using energy storage [96]. However, the occupancy-based control systems proposed in the literature aimed to keep the temperature at setback during vacant hours and return the thermal condition as soon as occupancy states were changed. It naturally can bring about a sudden change in energy demand profiles and, consequently, are prone to cause peak energy use. However, as researchers have rarely investigated the control systems in terms of peak demand, these aspects have not been clarified yet. In addition to these factors, the environmental impacts of occupancy-based HVAC control have been mostly neglected by researchers and there is not enough information to show their performance from environmental dimensions.

Overall, the performance of occupancy-based HVAC control systems from economic, energy, and environmental points of view have not been well investigated in previous studies. Because of the importance of these aspects, it is recommended to take these factors into account when proposing and evaluating control algorithms in this field.

6.2. Features used to develop occupancy models

The frequency of features implemented to develop occupancy models is represented in Fig. 5. Time of day was the most frequent feature at more than 25%, that is followed by day of week, that accounts for almost 12% of all the utilized features. It is clear that features such as time of day, day of week, weekends and seasons are most likely to affect occupancy prediction performance, as we can find obvious correlations between them and occupancy patterns. For example, people mostly work during the day and sleep at night or schedule their routines based on day of week. However, it is still a question that which features are the most effective ones and how many features will provide the best results. It is shown that almost 25 different features have been employed in earlier works to develop occupancy models. Considering this variety of features, a wise selection of attributes can be of great importance as it can improve the accuracy of the prediction, provide a better understanding of the underlying process and enhance the computational speed [97,98]. Too many or too few features can, respectively, result in overfitting or underfitting problems [99]. Additionally, as mentioned in Ref. [100], finding the most relevant features in developing an optimal model can minimize the cost of purchasing too many sensors. However, despite the importance of feature engineering in developing data-driven models, there is still a question that what number and what types of

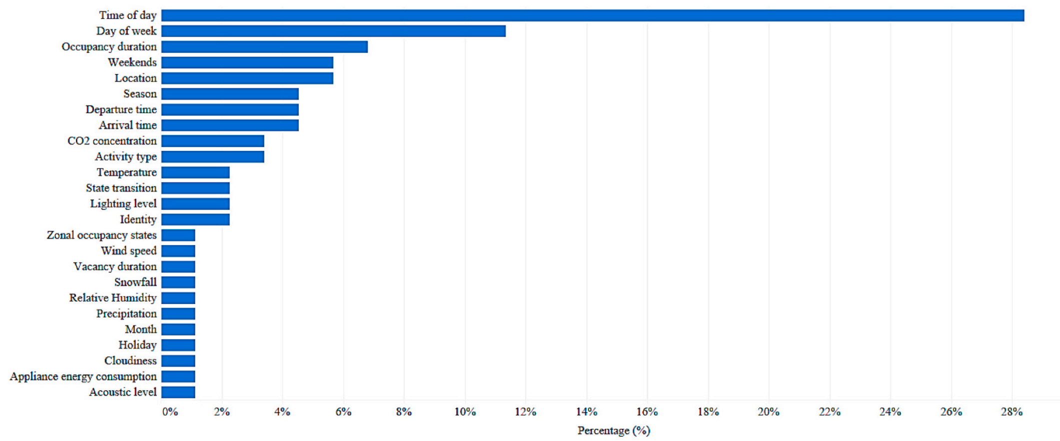

Fig. 5. Frequency of different features used for developing occupancy models in the reviewed papers.

attributes should be selected for future occupancy prediction. In other words, feature engineering studies in the field of occupancy prediction lacks in the literature. Hence, investigating the optimal features is recommended as future work to provide a guideline for researchers to select the most appropriate features.

6.3. Types of control strategies and evaluation methods

Fig. 6 demonstrates the distribution of earlier works based on types of control strategies and evaluation methods (i.e. simulation or field evaluation). As can be seen, rule-based control was the most used control strategy in earlier research work, accounting for almost half of all the studies. It was followed by reactive and optimal control at 26%. It is observed that all the studies on optimal control were simulation-based studies, and no researchers have applied them to actual testbeds. In contrast, half of the studies on reactive control were evaluated using real case studies. One of the reasons can be linked with the fact that while optimal control strategies are still under development, reactive and rule-based controls are commercially available for use in buildings. In fact, many commercial buildings already utilize reactive strategies to control HVAC and lighting systems, which makes field evaluation more possible. In addition, optimal control often requires higher computational power than the currently available power in building management systems. These factors have made the experimental evaluation of optimal strategies more challenging. Hence, there is a need to deal with this challenging task and investigate such systems when applied to real-world applications.

As mentioned in Section 5.3, MPC was the most-utilized approach for occupancy-based optimal control in the literature. Despite its promising performance, there are some barriers preventing them from being widely utilized in the building sector, such as their poor potential of generalization for use in different buildings and the intensive expertise required to develop MPC models [101]. In the last decade, reinforcement learning (RL) has attracted a great deal of attention as a powerful alternative to MPC in HVAC control systems. RL algorithms are data-driven approaches that can be utilized in HVAC control without a need for the development and calibration of building models [102]. RL has been utilized in many different building-related applications such as the control of lighting systems [103], cogeneration systems [104], domestic water heaters [105], energy storage [106], and HVAC systems [107]. However, there is still a need for investigating the effectiveness of RL algorithms for occupancy-based HVAC control. It is recommended to evaluate and compare the performance of RL-based HVAC control with that of MPC-based algorithms to reveal the strengths and limitations of each approach in this field.

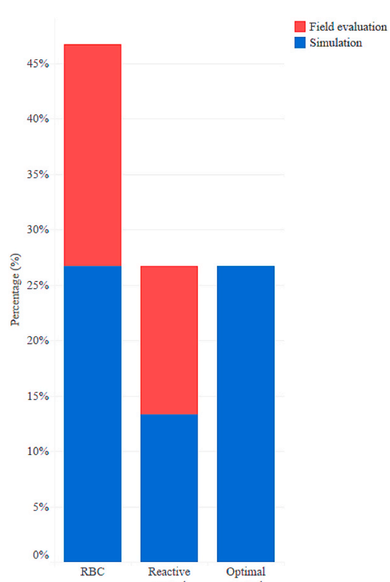

Fig. 6. Distribution of the papers based on control type and evaluation methods.

6.4. Building types

Fig. 7 depicts the proportion of different building types used as testbeds in the reviewed papers. It can be seen that office buildings accounted for approximately half of the previous research studies. These offices were mostly occupied by researchers in educational institutions. The reason is that such buildings are more accessible for researchers to conduct experiments and collect the required data. In contrast,

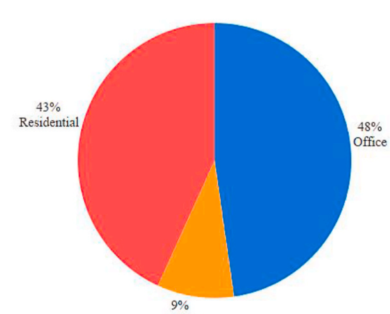

Fig. 7. The distribution of testbeds used to evaluate occupancy-based control systems in the reviewed papers.

gathering data in other types of commercial buildings can cause more privacy issues and have been less studied by researchers. It can be observed that other commercial buildings such as exhibition halls, conference halls, and hotels account for 9% of the previous studies, and there is less information about the effectiveness of occupancy-centric HVAC control in these applications. Therefore, investigating different testbeds rather than research offices and residential buildings are recommended to provide an insight into using these control strategies in various case studies.

6.5. Occupancy prediction models

The frequency of using different occupancy models is demonstrated in Fig. 8. The most used occupancy models were Markov and proportional models which accounted for almost 28% of all the occupancy models. These models are not complex to be implemented and provided an acceptable level of accuracy in most of the cases. These models are followed by kNN that accounted for around 8% of the models. However, there has been relatively less effort put into developing more complex models such as deep learning algorithms. More specifically, deep learning algorithms, namely, LSTM, GRU, and RNN account for less than 8% of the developed models. Hence, it is recommended to make attempts into applying more complex models to occupancy prediction in order to capture further hidden patterns in occupancy datasets and improving the performance of the models.

6.6. Performance indicators for occupancy models

Different performance metrics utilized for evaluating occupancy models in the reviewed papers are shown in Fig. 9. Accuracy was by far the most utilized indicator, at around 45% of all metrics. However, accuracy might be misleading when used as the primary indicator to show the effectiveness of an occupancy model [32]. In some cases, when occupancy/vacancy rates are high (i.e. people stay home or are outdoors most of the time), occupancy models might select the most frequent state in the dataset as the future occupancy prediction results for all future time steps. In this way, the model can provide an acceptable level of accuracy, while the results would not be practically useful for HVAC control. Besides, as mentioned in Ref. [60], the impact of occupancy prediction errors on HVAC control depends on its nature and timing. However, the commonly used performance indicators address none of these factors. Hence, there is a need for research studies to compare and evaluate different performance indicators to show their limitations when applied to occupancy models in HVAC control.

7. Conclusion

This paper reviews the state-of-the-art occupancy-based HVAC control systems proposed in the literature for residential and commercial buildings. To this aim, previously published papers are classified into two main categories according to the integration of occupancy information with control systems. Then, the papers are further classified based on the control strategies applied to occupancy information. The research items in each category are explored in detail, and the methodologies are investigated from different viewpoints. It is pointed out that the HVAC control systems based on user-defined occupancy schedules provide poor performance in terms of energy saving and thermal comfort in many cases. Therefore, there has been an increasing interest in using occupancy detection and monitoring systems to minimize occupants' interventions. Reactive control is considered as a successful approach to minimize the interactions; however, employing this type of control can cause thermal comfort issues for occupants upon arrival owing to the lag time of HVAC systems. Predictive control strategies were proposed in the literature as a solution to this issue by enhancing thermal comfort of occupants. However, it was reported that in many cases, using predictive control results in lower energy performance than reactive control due to preconditioning buildings before occupant arrival.

This thorough literature review shed light on the limitations of different methodologies. These limitations are summarized according to different dimensions, including feature utilization in developing occupancy models, types of occupancy models, types of buildings used as testbeds, performance metrics used to evaluate control systems and occupancy models, and types of control systems integrated with occupancy models. It is indicated that the majority of occupancy-based control systems were studied with respect to energy efficiency and thermal comfort, and consequently, their effectiveness from other viewpoints such as financial merits, demand-response management, and greenhouse gas emissions was not well evaluated in the literature. Additionally, despite many studies on developing occupancy models, a limited number of research items implemented more advanced algorithms, such as deep learning methods, to capture more hidden patterns in occupancy profiles. Furthermore, it is shown that 91% of the previous studies focused on occupancy-based control systems in office or residential buildings. Consequently, limited information regarding their performance in other types of buildings, such as conference halls, schools, and shopping centers, can be found in the literature. Based on the research gaps inspected in this field, the following objectives are recommended for future research work:

- Evaluating occupancy-based HVAC control in terms of peak shifting, cost saving, and carbon dioxide emission.

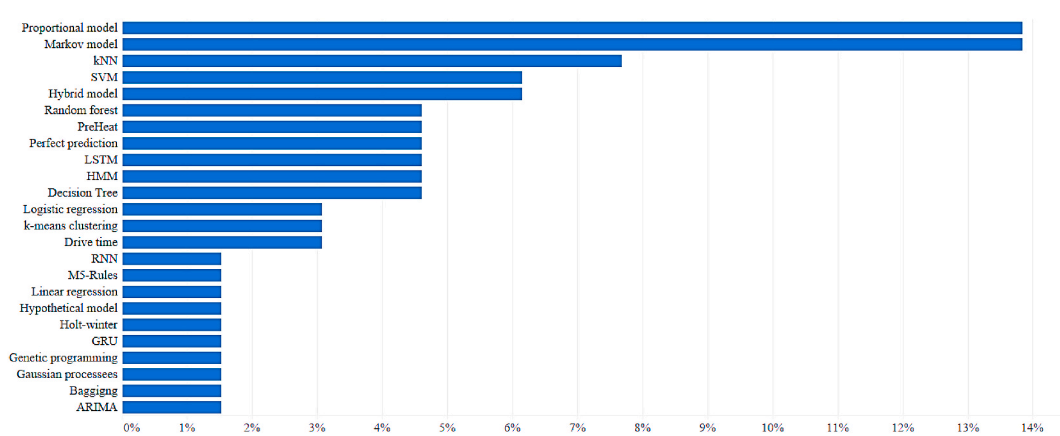

Fig. 8. Frequency of various occupancy models used in the literature.

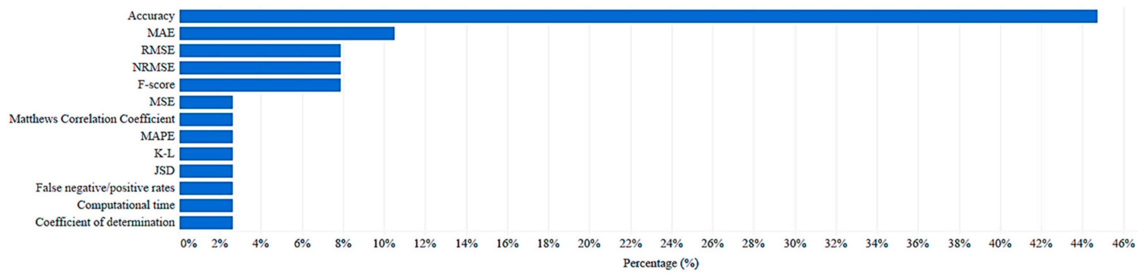

Fig. 9. Performance criteria used for evaluation of occupancy models.

- Identifying optimal features with the highest impact on the performance of occupancy models.
- Implementing more advanced techniques, such as deep learning methods, to find hidden patterns in occupancy profiles.
- Conducting field evaluation studies to assess the performance of optimal occupancy-based control.
- Developing reinforcement learning algorithms for occupancy-based HVAC control systems as an alternative to MPC and comparing their performance.
- Employing different testbeds rather than research offices and residential buildings in evaluating occupancy-based control systems.

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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