Renewable and Sustainable Energy Reviews 183 (2023) 113496

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Review Article

Energy modelling and control of building heating and cooling systems with data-driven and hybrid models—A review

Yasaman Balali [a,*], Adrian Chong [b], Andrew Busch [a], Steven O'Keefe [a]

[a] Griffith School of Engineering and Built Environment, Griffith University, Nathan Campus, Brisbane, 4111, QLD, Australia

[b] Department of the Built Environment, National University of Singapore, 4 Architecture Drive, 117566, Singapore

ARTICLE INFO

Keywords:
Building thermal performance regulation
HVAC control
Machine learning
Modelling techniques
Model predictive control
Reinforcement learning

ABSTRACT

Implementing an efficient control strategy for heating, ventilation, and air conditioning (HVAC) systems can lead to improvements in both energy efficiency and thermal performance in buildings. As HVAC systems and buildings are complicated dynamic systems, the effectiveness of both data-driven and model-based control methods has been widely investigated by researchers. However, the main challenges that impede the practical application of model-based methods in real buildings are their reliance on the precision of control-oriented models and the dependence of data-based systems on the quantity and quality of input–output data. The objectives of this study are: (1) To present an overview of the prevalent thermal modelling strategies used as control-oriented models or virtual environments in model-based and data-based control methods, addressing the main requirements of thermal models; (2) the state-of-the-art of MPC and RL control techniques; (3) the data requirements for thermal models. The findings emphasise the need for unified guidelines to validate and verify the proposed control methods, ensuring their practical implementation in real buildings. Moreover, the inclusion of occupancy forecasts in models presents challenges due to the intricate nature of accurately predicting human behaviour, occupancy patterns, and their effects on thermal dynamics. Balancing thermal comfort and energy efficiency in HVAC systems with a supervisory controller remains a difficult task, but combining data-driven and physics-based models can help overcome challenges. Further research is needed to compare the effectiveness of MPC and RL approaches, and accurately measuring the impact of human behaviour and occupancy remains a significant obstacle.

1. Introduction

Heating, ventilation, and air conditioning (HVAC) systems used in commercial buildings are designed to provide comfortable indoor conditions for the occupants. This is done via the regulation of multiple indoor control variables, while considering energy efficiency simultaneously. Buildings thermal satisfaction depends on both environmental and occupancy factors [1]. Examples of the former are indoor temperature, humidity [2], thermal radiation, and airflow patterns [3,4]. The latter refers to behaviour, clothing level, and the number of occupants. Consequently, indoor air quality, occupant comfort, and systems parameters are used in the calculation of temperature set points [5]. Furthermore, thermal comfort standards such as the American society of heating, refrigerating and air conditioning engineers (ASHRAE) summarise the requirements for adjusting set points of control variables [5], while their values might be kept constant to reduce the complexity of control problems. In parallel, minimisation of energy usage is important. HVAC systems, mainly their compressors and air handling units (AHU), contribute to more than half of the energy consumption in commercial buildings [6–8]. Heat transfer from internal and external loads caused by environmental factors affects HVAC energy usage [4,9]. For instance, outdoor temperature and solar radiation cause heat losses or gains related to the opaqueness/transparency of windows and slab floor of the building structure [10]. These loads influence the HVAC dynamics indirectly as external disturbances [11].

Efficient control of HVAC systems can lead to effective indoor air regulation [12,13], reducing building energy demands and improving occupants' comfort levels [14]. Different factors, such as outdoor weather conditions, building geometry, seasonal variation in indoor thermal variables, thermal properties of materials, and occupancy, complicate the deployment of accurate thermal energy models [15,16]. As a result, approximations and estimations are considered in the deployment of models to reduce the model complexity [17]. The existing implemented control techniques in the building management system (BMS) for supervisory control of building HVAC system are mainly

* Corresponding author.
E-mail address: yasaman.balali@griffithuni.edu.au (Y. Balali).

https://doi.org/10.1016/j.rser.2023.113496
Received 15 March 2023; Received in revised form 7 June 2023; Accepted 22 June 2023
Available online 5 July 2023

Nomenclature

Abbreviations

AHU	Air Handling Unit
ANN	Artificial Neural Network
ASHRAE	American Society of Heating, Refrigerating, and Air Conditioning Engineers
BDQ	Branching Duelling Q-network
BEM	Building Energy Modelling
BMS	Building Management System
C	Capacitance
CO_2	Carbon Dioxide
CFD	Computational Fluid Dynamic
CNN	Convolutional Neural Network
CRI	Contribution of Indoor Climate
DDPG	Deep Deterministic Policy Gradient
DDQN	Double Deep Q-Network
DNN	Deep Neural Network
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
FMI	Functional Mock-up Interface
FMU	Functional Mock-up Unit
HVAC	Heating, Ventilation, and Air Conditioning
MPC	Model Predictive Control
MRE	Mean Relative Error
NARX	Nonlinear Autoregressive Network with Exogenous Inputs
PID	Proportional Integral Derivative
PIR	Passive Infrared
PPO	Proximal Policy Optimisation
R	Resistance
RBC	Rule-Based Controller
RC	Resistance-Capacitance
RL	Reinforcement Learning
RT	Regression Tree
SVM	Support Vector Machine
TDNN	Time Delay Neural Network
VAV	Variable Air Volume
XML	Extensible Mark-up Language

traditional controllers such as rule-based controllers (RBC) [18,19] following control rules of set point boundaries without applying any optimisation algorithms.

Model predictive control (MPC) is a dominant alternative control scheme implemented for supervisory control of building HVAC systems. The key requirements of MPC are desired models of a complex nonlinear system as a representation of a real system, prediction of disturbances, and an optimisation algorithm [20,21] (for theoretical explanations see [22]). Difficulties in modelling both accurate and efficient dynamic models, uncertain system parameters, and multiple operational constraints are the challenges that needs to be overcome in MPC solutions. Another theoretical effort involved in model identification is the calibration of parameters to improve the prediction results [23]. Despite the theoretical and experimental explorations on MPC formulation confirming its potential, there are still limitations including difficulties in the identification of minimum required data, generalisation of standards for validation and verification, understanding essential level of detail for model development, and model calibration. Lower dependency of the control strategy performance on the accuracy of system parameters and dynamic behaviour is a benefit as exact parameters estimation is difficult [24]. In learning-based control methods like reinforcement learning (RL), optimal control policies are learned without explicit dynamic models [25–27]. The existence of sensing infrastructure in buildings, involving sensors and actuators [9, 28] facilitates the monitoring of thermal variables and the regulation of their set points [29,30]. Accordingly, without detailed mathematical models and with simulated or real data, learning control agents can be trained [26,31]. Therefore, both MPC and RL strategies have been investigated and proven with potential for supervisory control in this topic with their limitations.

1.1. Previous reviews on building thermal energy modelling and control

Model development is integral to both mentioned advanced control methods, even a more generalised model is applied for learning-based methods. Different modelling methods for building thermal energy modelling and HVAC systems are addressed by [32–35], while [32] stressed the shortcomings and potentials of models in a more comparative way. Basic theories and frameworks of energy modelling with data-driven strategies for predicting and classifying building energy usage are reviewed in [36]. They indicated that developed data-driven models should not be limited to energy consumption and HVAC load predictions, but should also evaluate indoor air quality and occupancy-related factors. A paper by [18] has provided a comparison of data-driven methods based on the lifetime adaptability, safety, complexity of objectives, and numerical scalability. Recent improvements in eight frequently selected data-driven techniques for building energy consumption modelling and prediction are highlighted in [37] listing selected input variables for modelling. They recommend further study on combining data-driven methods with physical models to evaluate feasible improvements and the influence of including accurate occupancy behaviour, number, and activity data on building energy studies. The theory of grey-box modelling for building thermal energy is explained in [38], pointing to a lack of comprehensible guidelines on theoretical model order selection and essential theoretical assumptions based on the applications, unified software for model creation, and more precise guidelines on grey-box models applications. Furthermore, the role of model calibration, which defines the tuning of numerical/physical parameters/variables of the model to reduce the mismatch between the real values and observed ones, for the simulation outcomes is covered in [23]. This paper pointed out the common input–output variables and parameters of the model that are selected for calibration in building simulation models.

After the selection and development of the model, the model is used as a test-bed for control systems. The principles of learning control systems are explained in [39], discussing the required information and differences in the theoretical computations. More recently, a review of building control strategies is provided in [40] concluding that appropriate control solutions can deal with uncertainties, are adaptive, and include optimisation techniques. In terms of the MPC framework for building control, the authors in [41] looked into possible opportunities and potentials. MPC for commercial buildings is reviewed in [42,43]. To make MPC a financially feasible control method for non-domestic buildings, there is a pressing need for research on automating the creation and updating of predictive models, and testing it on full-scale buildings to demonstrate its viability [43]. To improve the effectiveness of MPC in building control, future research should focus on comparing optimisation algorithms and parameters, as well as exploring the sensitivity of timestep and horizon to minimise uncertainties, particularly related to climate forecast accuracy [42]. An in-depth summary of MPC formulation is presented in [19], including both theoretical and practical features that should be considered in real applications. Hardware and communication barriers of the MPC framework are studied in [44]. Analyses of MPC by answering ten common concerns in MPC implementation for buildings control studies are carried out in [45].

Difficulties in MPC modelling and parameterisation and the absence of commercial tools to formulate MPC are the underlined issues limiting MPC adoption as the supervisory controller for real buildings. The authors in [21] identified a lack of quantitative comparison between nominated modelling methods for MPC strategies, guidelines on minimum performance requirements of control-oriented models, and study on minimum data requirements based on model objectives. A level of details framework is defined to compare the data requirements for a different levels of building modelling stages. A review of district heating and cooling was presented in [46], and the theory and application of HVAC systems with MPC models were reviewed in [47]. Combining the model based on the artificial neural network (ANN) with MPC control for HVAC systems is carried out in [48]. The paper stresses the importance of setting reductions in the operating cost of HVAC systems as an objective rather than energy consumption minimisation. It also showed that enhancements in measurements of occupant activities and behaviour lower the level of uncertainty related to occupancy data. The overall methodologies for occupancy prediction are highlighted in [49,50], stating the importance of occupant behaviour modelling for building energy modelling and HVAC control [50]. The highlighted challenges are obtaining accurate valid data, the inclusion of physical occupancy routines with historical data and contextual information, lack of larger spatial resolutions for evaluations, and deficiency in the real case study implementations [49]. The use of MPC for occupancy behaviour is outlined in [51,52], highlighting the application of occupant behaviour modelling in building energy modelling and HVAC controls.

A review of deep reinforcement learning (DRL) application in building energy management including HVAC system is presented in [26,53,54]. In comparison with model-free DRL methods, model-based ones are founded more practical solutions, as abundant training data is available from the modelled environment [26]. Moreover, they mentioned low data resolution and the difficulties faces for multiple objective situations are the current difficulties limiting DRL applications. Evaluating the potential of RL algorithms in comparison with other control methods in experiments is suggested as future research direction in Ref. [53]. They also noted that the effectiveness of RL strategies during abnormal weather conditions has not been well-studied. The computer science related challenges of RL methods are covered in [54] for building energy control applications. Data sample efficiency is the prerequisite of model-based RL approaches, while further theoretical analyse is suggested to find minimum required data [54,55]. Different RL algorithms and modelling techniques that are tested for demand response consisting building energy and HVAC control are presented in [56], suggesting study of multi-agent systems to a greater extent. Control occupant comfort with RL algorithms is conducted in [57]. The need for inclusion of occupancy patterns/feedback and study of model-based RL controllers are some of the mentioned gaps. Building energy and HVAC system become a complex problem for system performance level analyses. There is a need for multi-agent DRL systems in these situations. The possible aspects, barriers, and applications of DRL in for multi-agent scenarios are explained in [58]. They presented ideal solutions for non-stationary problems caused by interaction of multiple agents, incomplete observable information of interacting environment accessible for agents, agents training, and application of DRL in continuous domain.

1.2. Statement of contribution

Motivated by recent surveys on the topic, consideration of multiple objectives integrating multiple control variables has increasingly become the research focus, as there are multiple interacting systems variables for multi-zones building HVAC system situations. Dealing with multiple objectives by applying advanced control strategies instead of conventional reactive RBC methods, specially for these complex nonlinear dynamical systems, is still difficult and not competitive in terms of simplicity. Despite the existence of numerous studies on thermal energy modelling and control strategies buildings, most studies focused to provide comprehensive overview of them separately. However, a study integrating them with the aim of providing the overview of requirements for thermal energy performance is missing. This manuscript aims to fill the existing gap in the literature by integrating thermal energy modelling and control strategies to provide a comprehensive overview of the requirements for thermal energy performance in buildings. Specifically, the contribution of this study includes:

(1) **Discussion of thermal modelling strategies:** The manuscript discuss different thermal modelling strategies employed for prediction and control of building heating and cooling research problem, highlighting how they meet the primary requirements of thermal models for effective control methods;

(2) **Overview of advancements in Model Predictive Control (MPC) and Reinforcement Learning (RL):** The study provides an overview of the latest advancements in MPC and RL control techniques, emphasising their potential for addressing the challenges of multiple objectives and complex nonlinear dynamical systems in building HVAC control;

(3) **Comparative analysis of data requirements for thermal models:** The manuscript conducts a comparative analysis of the data requirements as variables and/or parameters of thermal models, aiding researchers and practitioners in selecting appropriate data-driven approaches for building thermal energy modelling.

To achieve these objectives, the up to date research simulations and experiments are reviewed to notify the potential of different applied methodologies, possible research directions, and practicable industrial considerations. The paper is structured as follows. Section 2, provides the research methodology of this paper. Section 3 gives an overview about idea of building control for thermal energy modelling. Section 4 describes the state-of-the-art thermal modelling approaches compatible with control strategies representing the system model. In Section 5, the integration of thermal energy models with MPC and RL controllers as leading methods is discussed. Then, Section 6 comparatively point to data requirements as variables and/or parameters of the thermal models. Section 7 presents noteworthy findings and outlines potential research avenues. Lastly, Section 8 concludes the paper.

2. Methodology

The critical review was employed to present an impartial and comprehensives overview of available literature on thermal energy modelling, supervisory level control, and data requirements in model development used for building energy performance. Through a continual process of review, a set of related keywords was identified and used to conduct a literature search. Multiple keywords and phrases were combined with “OR” and “AND” to maximise the coverage of the search results. The keywords were initially categorised based on “Thermal energy modelling strategies in building-HVAC problems”, “Supervisory control methods for control-oriented building energy models”, and “Data requirements for model developments”. Additional generic keywords, including indoor air quality, HVAC system control, Indoor thermal variables prediction, were incorporated into the search list for each category to expand the search terms. Subsequently, more specific terms related to each category (such as RC models and specific machine learning algorithms, MPC, and RL) were added to the search list to enhance the comprehensiveness of the search. Further improvements to the search criteria were carried out by eliminating any unrelated or extraneous topics (battery energy modelling, thermal energy storage systems modellings, local control level of HVAC system parts).

IEEE Xplore, Google scholar, Griffith University library, and Scopus were the main databases used to find top peer-reviewed journals, technical engineering reports, and books in English. To determine the focus of this review paper, the authors examined the most current peer-reviewed literature. The review process was ongoing throughout the entire manuscript preparation phase.

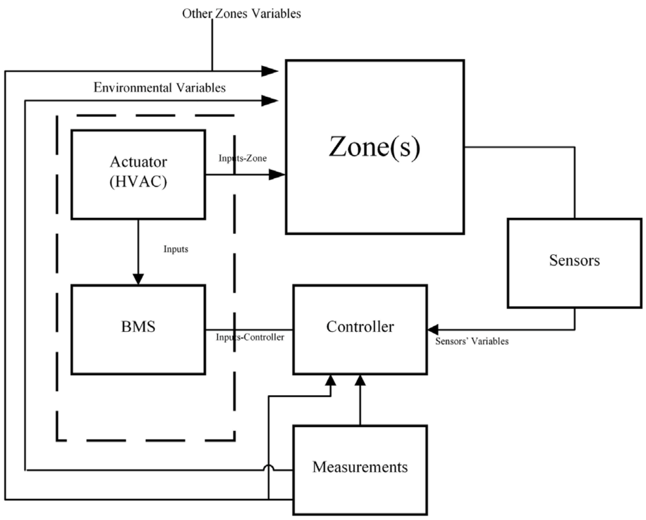

Fig. 1. Control framework of building indoor thermal energy modelling at supervisory control level.

3. Building modelling control problem

Dynamic behaviour of buildings [17] and non-linearity of HVAC systems creates challenges in the development of controllers [59] for the thermal energy of these systems. The operation of a zone in a real building is represented in Fig. 1.

The building zone is affected by disturbances related to outside weather conditions, which are time-varying and there is uncertainty in their prediction. It is also subject to HVAC actuators, responsible for adjusting the devices in the HVAC to regulate the variables of its components. Environmental variables including temperature, humidity, occupancy, and lighting data also contribute to the thermal energy of building zones. There is an influence of the thermal energy of neighbouring zones on a single zone as well. The HVAC system is the main system in building zones that affect indoor thermal performance as it is responsible to regulate indoor variables like temperature and humidity related to thermal energy. As the physical characteristics of the systems (e.g. HVAC systems) used for indoor thermal regulations are different based on their type, universal control models cannot be proposed [18, 60]. Control of the HVAC system requires system identification [20] as its dynamic behaviour is represented by differential equations. Bilinear interactions of variables, including temperature rates, airflow rates, and heat transfer during the temperature adjustments confirm non-linearity in HVAC models [61,62]. The control of the HVAC system can be divided into local and supervisory levels, which are connected via communication protocols. The former refers to the control of HVAC system elements and building internal dynamics [63]. The latter is an additional control layer that aims to supervise and manage the HVAC system and other influencing factors such as weather data, occupancy data, and HVAC operating schedule. Although conventional proportional integral derivative (PID) and RBC are unappealing control algorithms for high-level prediction accuracy [11,64,65], indoor thermal energy is still controlled by RBC techniques at the supervisory level and PID ones at the local level in most buildings [66]. Moreover, there is a time response delay in PID control systems compared to strategies with adaptive and predictive control potential [67]. RBC techniques also lack continuous adaptation with condition changes [18]. These limitations highlight the need for intensive research into the development of advanced control strategies specially for the supervisory control level. The designed control system can be model-free or model-based. In the model-free method, the control laws of the implemented controller are defined based on the behaviour of the collected input–output data from the plant with an online estimation of unknown parameters [68]. However, a little information about the system or a generic model of the system might be used for offline training or tuning of the controller. Model-free controller is different from black-box identification (see [69]). In the model-based method, the dynamic models of the plant are used to design the controller [68]. Based on the controller predictions for the future behaviour of variables, the required actuation will be sent to the corresponding system components. The main features that need to be considered in the development of control-oriented building indoor thermal energy models are summarised in Table 1.

There is no exact model of the system and all of the models are uncertain. However, depending on the models objective(s), they can be useful for implementing the controller. The main thermal modelling methods that can be used for the control of indoor thermal energy are provided in the next section.

4. Modelling strategies for buildings

White-box/physics-based, black-box/data-driven-based, and grey-box/hybrid-based models are used to develop building energy and thermal models [72]. An overview of these models, with their main comparative features in Figs. 2, 3, and 4, is delivered below.

(1) White-box models: The thermal modelling of buildings can be developed based on the physical properties of the materials in the buildings by using thermal dynamic equations or resistance-capacitance (RC) modelling [73]. However, physics-based models require detailed knowledge about the physical properties of buildings and HVAC systems [74–76], including geometry, building materials, and heat conduction. The inaccessibility of this information makes these approaches less practical solutions.

(2) Black-box models: Mathematical relationships between input and output variables can be developed by considering system performance measuring data requirements beside accuracy and complexity level [32]. The real-time data for training the model consists of time series components, such as seasonal data and set points of variables [74]. It also considers the periodic behaviours of the building components. The accuracy of this strategy depends on the availability of sufficient data [32,77].

(3) Grey-box models: In these models, a combination of white-box and black-box models [78] are used when there is insufficient measured data and physical information of the system physical characteristics [32]. Although less information about physical systems is needed, parameter estimations for the models can be based on stochastic differential equations derived from dynamical information of the system and system identification. If the formation of the thermal model of the whole building is the objective and the complexity of building systems is high, these models are not suitable [79]. Model order reduction is an ideal solution for reducing the complexity of the models [80].

Co-simulation of software for building modellings: In cases where an individual software tool lacks libraries for simulating the whole building and HVAC system or different applications have been used for simulations, co-simulation of software is a solution [81]. This refers to the integration of simulated sub-models to exchange/run simulations in different software simultaneously [82]. A comparative survey on software limitations is presented in [81]. The models can be computed parallel and/or distributed in the co-simulation server [83]. The installation of all coupling software is required when a virtual server (as an interface) is used for the integration, while the simulation models are running individually in their software [84]. An example interface for co-simulation is a functional mock-up interface (FMI) that runs by the functional mock-up unit (FMU) [83,85]. The FMI contains an extensible mark-up language (XML) model description file of variables [86]. Model exchange co-simulation interfaces have an individual solver, as a simulated model can be exported to an FMU format and imported to a host platform, including the other models [84].

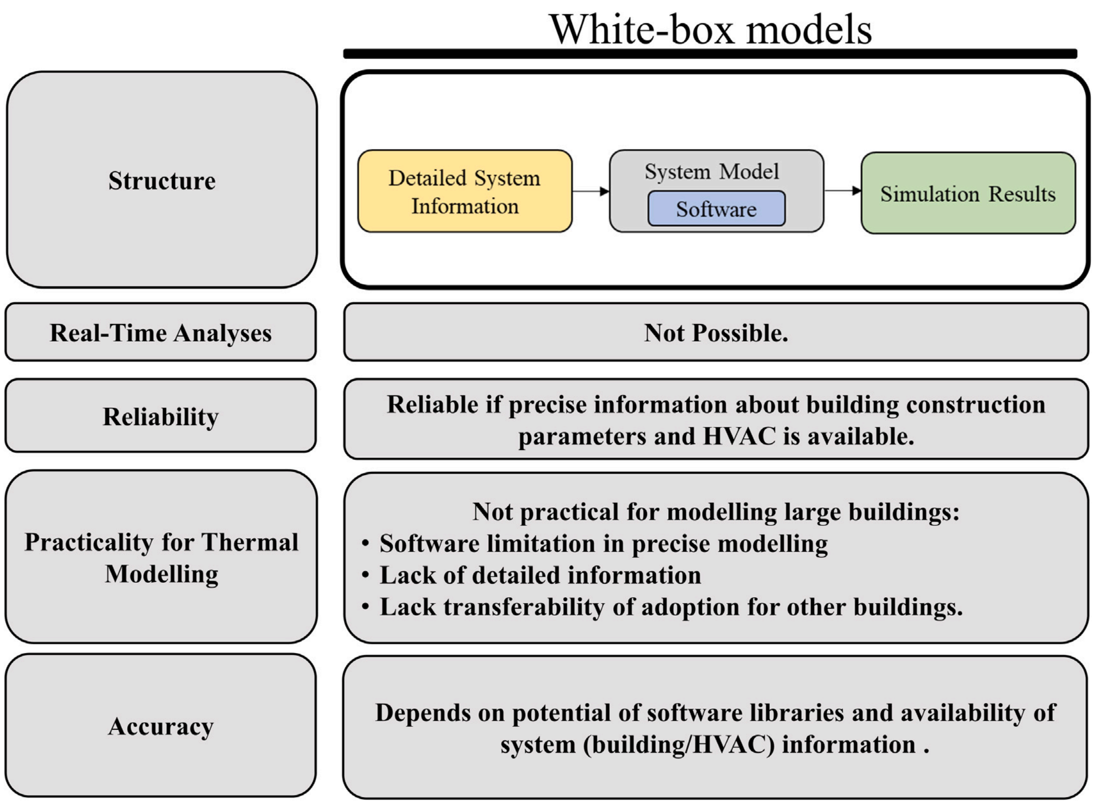

Fig. 2. Main features for white-box models (Reliability and Accuracy-system information [32], Practicality-detailed information [18], Practicality-transferability [19].).

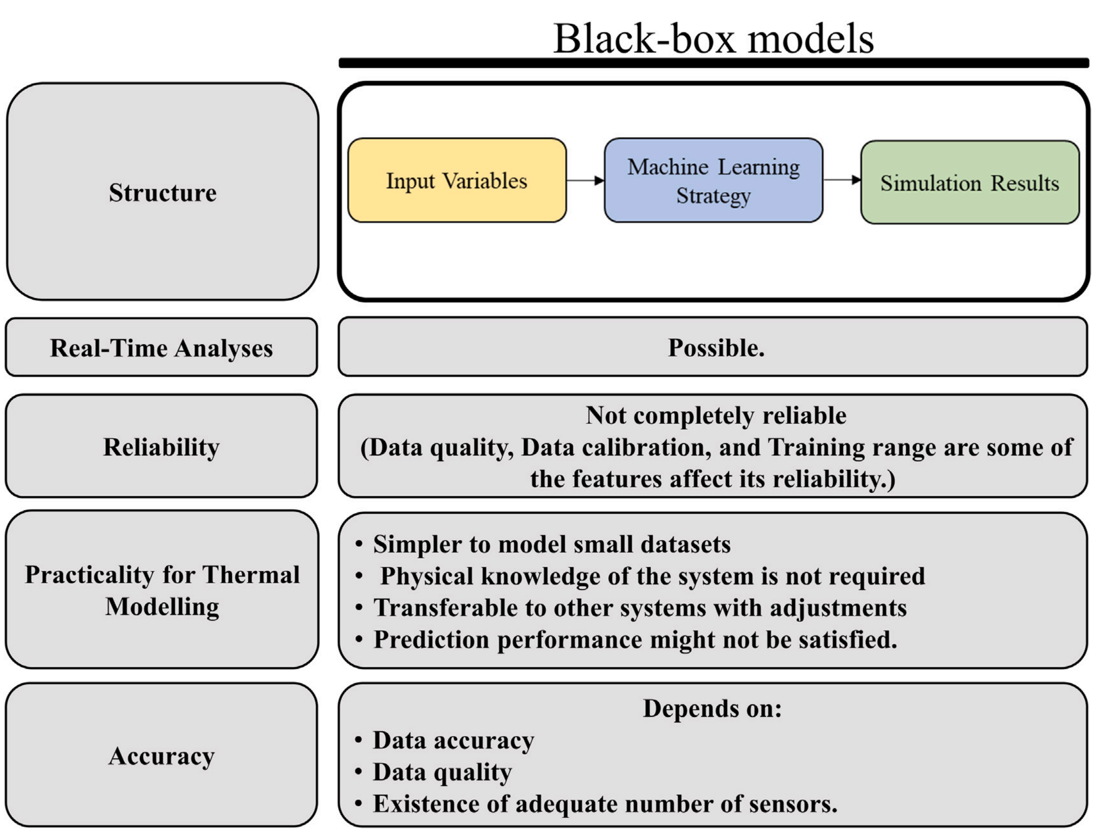

Fig. 3. Main features for black-box models (Reliability, Accuracy, Practicality-Prediction performance [32], Practicality-Simpler to model small datasets and Physical knowledge [18], Practicality-transferability [19].).

Table 1
Main features for the development of control-oriented building indoor thermal energy models.

Data	Model	Validation
Variables selection: • Reduce model complexity by selecting input variables [32]. • Consider extra variables may not improve controller predictions [32]. • Include adequate data for each climate condition [32].	**Model complexity:** • Consider model complexity reduction for controllers [32]. • Evaluate model complexity and controller performance.	**Model Validation:**. • For building envelope, mechanical equipment and energy generation equipment conduct [70], • Comparative tests • Analytical verification • Empirical validation
Location and number of Sensors: • Evaluate the effect of sensor location on measurement accuracy [71]. • Consider the effect of sensors numbers on model accuracy [71].	**Effect of Input–output arrays:** • Examine the influence of multiple variables on the model performance [32].	
Quality of measured data: • Consider data quality depends on sensor accuracy. • Calibrate inaccurate data [18].	**Number of Zones to model** • Investigate model compatibility for multiple zones.	**Control system validation:** • Validate control performance versus model accuracy. • Assess predictions accuracy over a lengthy horizon [32].
Sampling periods: • Recognise variable sampling periods may differ [18].		
Size of training data: • Minimise training time by selecting adequate training data. • Consider impact of training data size on model accuracy.		

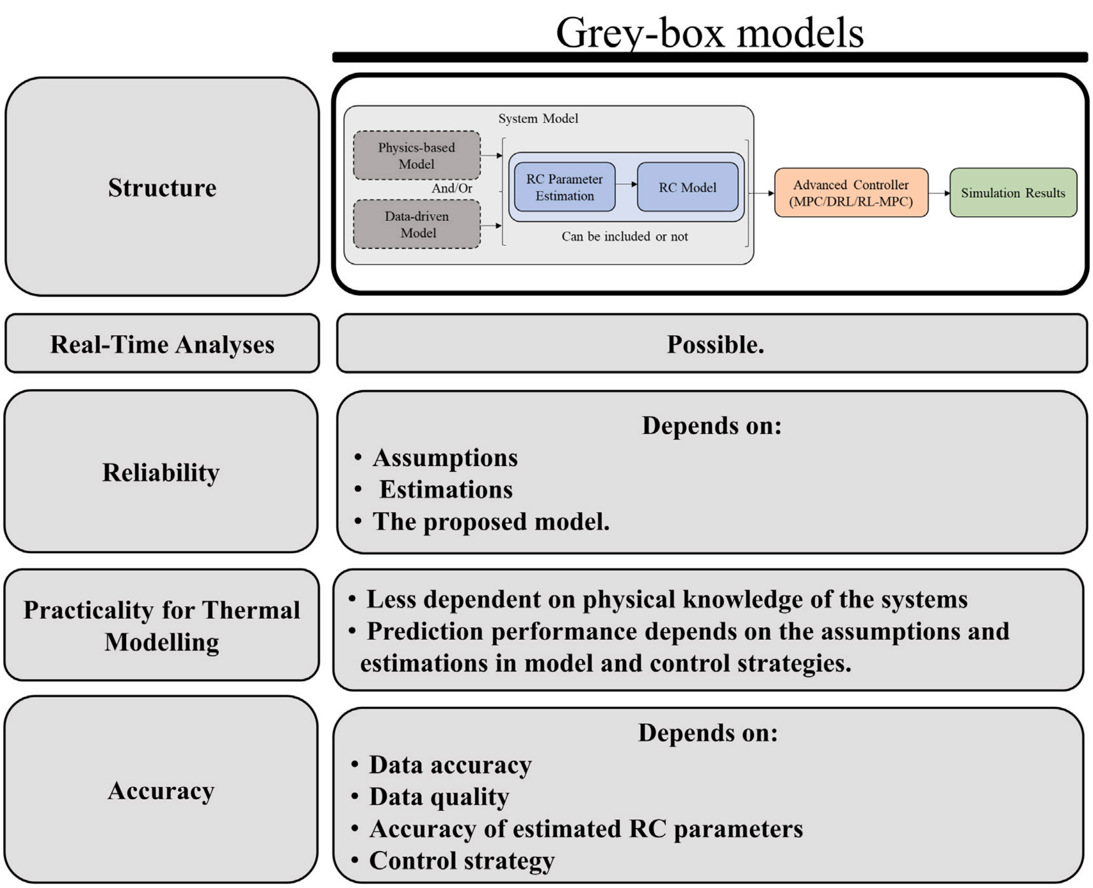

Fig. 4. Main features for grey-box models (Reliability, Accuracy, Practicality [32], Accuracy-RC [19].).

4.1. Computational fluid dynamic thermal modelling strategy

Computational fluid dynamic (CFD) simulations are white-box models. These models are derived from coupled Navier–Stokes equations [80], which are partial differential equations of viscous fluid substances motion, and energy balance equations. They are mainly used for air movement and distribution simulations in the building zones. In order to efficiently use natural ventilation from airflow through the building, a building geometry, façade, and floor plan are required to be optimised with thermal efficiency methods such as energy and CFD [87]. Based on the simulation results, an appropriate U-Value is selected for the building façade (windows, walls, and roofs). However, adopting a high-resolution CFD model for large datasets leads to a long computing simulation time [88], which reduces its adoption for building thermal modelling as the primary selection [89]. Especially when the simulated data in the CFD application has nonlinear and transient behaviour, limited simulations are insufficient to predict parameter patterns [90]. Although the CFD simulation strategy can be used to model indoor air quality, energy usage [91], and pollution distribution [92], it lacks the real-time monitoring functionality and exact information on air quality outcomes [93]. The use of ANN and the contribution of indoor climate (CRI) methods with CFD could solve this issue [94]. As a result, CFD incorporated with a linear ventilation model based on an ANN was created to forecast indoor air quality, and CFD combined with a linear temperature model based on CRI was used for indoor thermal performance analyses [94]. Air change rates per hour and supply air temperatures were taken as input layers for an ANN model and CRI models respectively in [94], with the conversion of high-resolution data to a low dimensional model to predict carbon dioxide (CO_2) concentration in an indoor environment. As occupants and equipment in the zone contribute to the CO_2 concentration level, CO_2 measurements can be used to evaluate the accuracy of heat gain calculations related to these internal loads [95]. They concluded that the error of the proposed models separately was under 10 percent, while the relationship between the models was not considered. A division of the database into smaller regions for CFD simulation can reduce the inaccuracy occurring in data dimension reduction, in particular for large-scale building analyses [96].

CFD simulation can be also used for the deployment of sensor locations for thermal energy analyses in buildings. The location of installed sensors in systems or buildings is an influential factor in the result of the measured data, which needs to be decided based on the measurements of the variables [97]. For instance, CFD and building energy simulations were conducted [98] to find out indoor temperature distribution for variable air volume (VAV) control (local control level). They concluded that installing an indoor temperature sensor near a return air inlet or locations with a high number of occupants and equipment (where the temperature is higher) increases the supply airflow rate [98]. In contrast, placing the indoor temperature sensor closer to the supply air diffuser (where the air temperature is lower) decreases the supply airflow rate [98]. Another study [99] implemented a low-dimensional linear ventilation model based on ANN for simulating a CFD low-resolution dataset, the HVAC control strategy has the potential to forecast indoor air quality with the use of data from air velocity meters and CO_2 sensors [99]. The optimised location of sensors was close to the outlet region of the examined area. Furthermore, the sensors with the same functionality, which were installed in parallel or the same stream directions, predicted similar results [99]. However, their investigation was limited to a small indoor environment. In order to identify the number of required sensors and their optimised locations, a Fuzzy C-Mean unsupervised clustering algorithm can be used to classify the sample data into different groups of clustering datasets [71]. As a result, the centre of each cluster can be used to distribute the corresponding sensor type effectively [71]. This method was adopted in [71] to find an optimal solution for sensor deployment in a control model, while the CFD model and a low-dimensional linear ventilation model based on ANN were simulated for indoor pollution control of the HVAC. Moreover, it is important to place thermostats close to occupied zones for both thermal comfort and ventilation. Conducting CFD simulations based on sensor installation may not always be the simplest approach, as the cost of indoor environmental sensors is reasonable and experimental tests may also provide appropriate solutions. Unless the main objective of the study requires CFD simulation analyses, The complexity of the CFD model and the high computational cost of these simulations make them inappropriate solutions for building controls.

4.2. Black-box/data-driven models for thermal modelling

Different data-driven (machine and deep learning) techniques are employed to develop energy models for building and predict the indoor/outdoor thermal energy variables, which impact building energy consumption and performance. Building energy models with data-driven models are developed through training, validating, and testing the dataset of input/output variables. Various classifications of data-driven methods are explained for building energy predictions [100] and modelling [37]. Based on the modelling objectives and data features (e.g type, quantity, and accuracy) the capable techniques can be applied, as a standardised protocol meeting the objectives of dissimilar problems is missing [37]. There is still a lack of guidelines for data-driven method selection based on the case study [100]. Also, their potential for control-oriented models including MPC is rarely studied [100].

Based on review study [37], ANN and support vector machine (SVM) techniques are expensively implemented for building energy predictions, most noticeably in cases where a single method was used. Regardless of accurate prediction fulfilment with SVM, parameter calibration is challenging [37]. ANN methods are capable to be used for combined methods including ensemble models and improved ones (integrating both a single model and optimisation techniques). As energy modelling of buildings involves different data types, the adaptability of these models with the combination of data types makes these approaches an alternative solution for building energy problems. Furthermore, they can be used for both supervised (for classification and regression) and unsupervised (for clustering) learning [101]. Non-linear ANN modelling can deal with complex prediction models considering uncertainties, non-linearity, and different forecasting horizons. ANN approaches are modelled by receiving the input variables information, processing the information based on a mathematical calculation, and transmitting the calculated values as output variables [102]. An ANN model consists of input, hidden, and output layers with interrelated neurons, which create a nonlinear machine learning model [103–105]. A zero value for a weight between two neurons/nodes cancels the interaction between these nodes [106]. Furthermore, the initial values of weights and biases for the neural network are randomly selected, which can have a significant deviation from optimised values [106]. As a result, with the use of optimisation algorithms, a higher accuracy rate in the prediction of variables, optimal values for weights/biases, and an adequate number of hidden layers can be identified [106]. The interconnection of input and output layers can be distinguished by the corresponding data related to each layer [107]. The distribution of the input datasets is an unrelated factor in determining interconnections between input variables [108]. The hidden layer can be divided into multi-layers, while an over-fitting modelling error can occur in the dataset [104]. Datasets of variables including training and validation real-time data are adopted to test the potential of the proposed ANN-based model in prediction accuracy [102]. The combination of ANN with computational processing elements, and adaptive neuro-fuzzy inference systems can be used for the information modelling of systems [109]. Data from a simulated HVAC system in TRNSYS software and sensor measurements were collected in [110] to propose an auto-associative neural network in MATLAB software for the data validation and fault diagnosis of the HVAC system in a small building. The input data dimension is increased through a nonlinear mapping algorithm to simplify the analyses [110]. Transferred data then creates a lower number of output units to be used as inputs for a de-mapping layer, which remaps the compressed data to its actual dimension for the output layer [110]. HVAC mathematical specifications are not included in data-driven strategies for sensor data validation and fault detection [110]. An evaluation of roof heat flux based on the ANN model using a heat flux sensor, which was located inside the cell consisting of a constant temperature zone and zone temperature measurements is conducted in [111]. They concluded that the value of heat flux decreases with increases in ambient temperature, while a higher solar irradiance and internal surface temperature resulted in a greater values for heat flux [111]. A nonlinear autoregressive network with exogenous inputs (NARX) model was developed in MATLAB software [112] for the real-time indoor temperature prediction of a library building in Murdoch University in Australia, without inclusion of occupancy patterns. NARX neural network methodology can predict future patterns of real-time parameters using the previously collected data [113]. Relevant affecting features on indoor temperatures, including a number of input parameters, size of the training data and NARX network, the effect of seasonal weather conditions, and prediction accuracy over a time are the main factors to be considered [112]. As ANN models are trained and tested based on the specific dataset, they are not completely transferable for another set of dataset [37].

Deep learning techniques are developed based on neural networks with more flexibility in data types, while they are less applied for building energy modelling and predictions [114]. Applications of deep learning in building energy performance, HVAC system, thermal comfort, and occupancy are discussed in [101]. It is highlighted that deep learning is mostly applied for occupancy (sensing and tracking, pattern recognition, behaviour prediction, and quantitative prediction) and then thermal comfort evaluation (temperature forecasting, thermal comfort management, and thermal comfort with energy demand). The HVAC system studies with deep learning are mainly focused on minimisation of energy demand with real-time occupancy detection including their rate and activities through image/video data [115]. In another study [116], different machine learning forecasting techniques, including deep neural network (DNN), SVM, and ANN, are employed for energy consumption prediction in a real case study building. ANN techniques with reasonable complexity and lower mean relative error (MRE) had higher performance, even if the predictions with DNN were close to other methods. In [117], the potential of deep-learning models for building heating and cooling energy demand prediction is studied. For their test data, deep learning had higher prediction accuracy than simple ANN technique. However, they concluded that the feasibility of these methods for energy prediction needs to be tested on more case studies.

4.3. Resistance-capacitance modelling

In the RC approach, thermal circuits model the heat transfer dynamics of systems [118]. Thermal resistance (R) and capacitance (C) are the parameters of the model with physical meaning [119–121]. The estimated values of R and C parameters are inserted into the model [122]. This is obtained via physics-based modelling [123] (when all building property information is available) or data-driven strategies [124] such as least-square regression [125,126] (its barriers [127]) or system identification [128–130]. A combination of dynamics characteristics of the system and real-time measured data [131] are needed when the physics-based model is not selected. R represents the thermal resistance of building materials (e.g. walls, floors, and ceilings) that separate zones with different temperatures on each of their sides [122]. C represents the capacity of each zone or material regarding thermal energy storage. Windows and glass materials are modelled with only thermal resistance due to the low level of heat storage for these building components [80]. In a single-zone model, the RC network model is based on the floor plan of each zone to estimate the zone temperature using mathematical equations by considering the thermal heat from the HVAC system, solar radiation, internal heat sources [121], and external structure [75]. The single-zone model is repeated to develop the multiple-zone model, and example studies are [132–134]. An RC network model for a multi-zone building requires separate models considering different parameters and conditions in each zone, based on its floor plan [121], while model order reduction is vital for simplification [124,135–137]. The main steps for RC modelling and estimation of its parameters are represented in Fig. 5.

The model is not completely transferable to another system [73], but the model structures are similar [138]. The equations that explain the physics of the zones are easier to use in MPC formulation compared to other models [19]. Although the amount of data required by this model is lower than that of data-driven models [139], the impact of data quality is still more important than the precision of RC analogy in the modelling [140]. The estimated values of the parameters change by retrofitting structural materials in zones [141].

5. Building energy and HVAC system control

5.1. MPC approach for building control

MPC is an optimisation-based control strategy that uses the model of the system and tries to approximate the infinite time optimal control problem with a sequence of the finite prediction horizons [19]. It requires the dynamic modelling of a system to predict the states of the set variables in the model [142] over a specific prediction time horizon, while optimising the performance of the model [143]. An MPC model is a combination of state, control, and disturbance variables. States hold the current status of selected variables to be connected to the control variables, and the disturbances are the external variables influencing the status of the state variables [144]. These disturbances can be controllable or uncontrollable variables.

An integration of disturbances in MPC modelling, which controls and eliminates the mismatches between the actual values of the variables and the recorded values due to inaccuracy or insufficiency of variables measurements, reduces uncertainties in the proposed MPC model [143]. Knowledge of disturbances or uncertain variables as well as mathematical descriptions/probability distributions of these parameters are required [145]. The fault signals among the recorded values, which can be caused by failures of the sensors and/or actuators, failures of the operating HVAC system, or an unpredictable alternation in the internal and/or external variables, can be detected and solved by optimisation controlling approaches [146]. The estimated values of both prediction and control horizons as well as sampling time influence the computation time of the model and its potential to control the disturbances, which can be adjusted based on the prediction time intervals of the disturbances [143]. The inclusion of disturbances, which can be humidity ratio, solar irradiation, occupancy rate, ambient temperature, and wind speed [80], can increase prediction accuracy in the developed controlling approach [143]. The other possible factors influencing uncertain disturbances can be slab floor area and sensible heat gains ascribed to the thermal loads of occupants/lights/electrical equipment, as well as infiltration/ventilation [147]. The main solar radiation variables are direct and/or diffusive solar radiation on walls and windows [80].

Sensible and latent heat transfers corresponding to cooling and dehumidifying coils can be included in MPC thermal modelling with humidity evaluations, as the temperature and humidity variables depend on inlet cooling and dehumidifying coil conditions [148]. An adequate time prediction for identifying disturbances increases the accuracy of the control model in thermal and energy consumption prediction, so 24 h was selected in the MPC thermal model [148]. Limitations in the accessibility of measurement data from the required variables, including the time-varying uncertainties, dynamic parameters, and disturbances, lead to accuracy reduction in the prediction of controlling variables [149]. The optimisation approaches are developed based on the predicted disturbances, and the building modelling responses are based on the control rules built in the optimisation method [150]. As all the states defined in the MPC model have physical definitions in the building, the simulated model is both accurate and reliable [151]. The model is developed based on the control rules that were calculated at the beginning of the simulated time-steps for the states measured values, and the variables subsequent values are consecutively predicted in each time-step [150]. The differences between the set and actual values of the variables should be minimised using the selected optimisation method [76].

5.1.1. Centralised and decentralised MPC method

A centralised MPC has high computational costs compared to decentralised control strategy, while it offers higher performance [152,153]. A failure in a centralised MPC controller impacts the control performance of the whole building [154]. Parallelisation and subdivision of an optimisation model can reduce the computational costs in

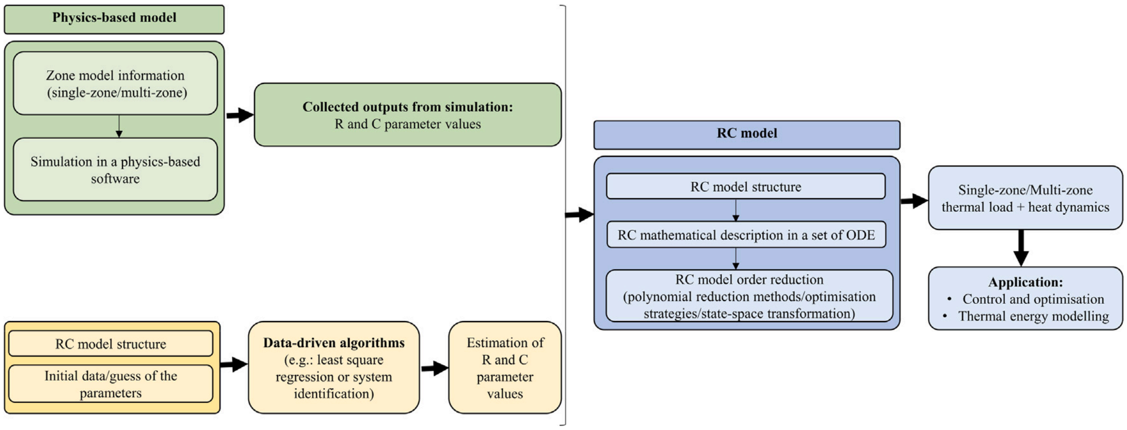

Fig. 5. Steps for RC model development.
Source: Created from [38].

MPC strategies [155]. Compared to centralised MPC algorithms, the reduction of computational complexity in distributed MPC systems is due to the modelling of an individual MPC for each zone as a subsystem in a building that requires the inclusion of interrelated parameters between interacting zones [154]. In cases that the system is uncertain, the robust nonlinear-MPC strategy can solve parametric optimisation problems by using initial states of inputs to calculate the optimal values of the variables [156]. The development of a decentralised control strategy for building zones, and including thermal interactions among zones, is more efficient in regards to fault isolation of a zone and mitigating its impact on the performance of other zones, compared to centralised approaches [157]. Moreover, simpler computational and communicational analyses are required for the decentralised control model of the HVAC system [158].

5.1.2. MPC application for building control

A distributed adaptive temperature regulation control method for HVAC systems, considering heat transmission among connected zones, implemented in MATLAB combined with EnergyPlus building modelling software, is proposed in [24]. The performance of the developed control system is evaluated based on the weather conditions of each month over a year [24]. Zone temperature is directly impacted by temperatures related to supply air, surfaces included in each building zone, outside weather conditions, and open surfaces of connecting zones that transfer heat [24,159]. In addition, the existence of occupants and equipment creates internal heat gains, while outside weather heat gains, which influence zone temperatures, are considered in the calculation [24]. However, adaptive control approaches that are feasible strategies for systems with linear parameters lack high accuracy for nonlinear systems such as HVAC systems [142].

An autonomous hierarchical control system has been developed in [160] for an HVAC system with central AHU and VAV units in zones that use a closed-loop MPC controller to control the temperature in six rooms. The autonomous hierarchical controller has been introduced to simplify the computational requirements rather than adopt the MPC approach individually by combining open-loop and closed-loop MPC-based control methods [160]. Moreover, it is considered that chilled water temperature related to coils impacts supply air temperature, while the supply air temperature constantly varies [160]. MPC control model for a single-zone commercial building using an RC thermal model for temperature prediction was proposed, while EnergyPlus was used to simulate cooling and dehumidifying coils [148]. Due to the potential of EnergyPlus software to upload custom weather data, adding unmixed air to the simulation leads to complete control of the temperature and humidity ratio [161].

A high-resolution MPC controller, which includes each zones temperature, specifications, and control commands, requires high computational calculations, especially for multi-zone buildings [162]. A multi-zone hierarchical MPC-based controller that combined two-controller levels for a multi-zone building with 33 zones in the University of Florida was developed considering different weather conditions and humidity in the controlling model [162]. Compared to their previous work [148], this approach considered solar irradiation and outdoor air temperature in addition to other inputs. Linear approximation and one-time calibration of the developed model cause inaccuracy in the building prediction models, as buildings are dynamic and time-dependent [163]. A combination of the MPC model with an adaptive model that re-calibrates the building model frequently and a robust control strategy to reduce uncertainties can increase the prediction accuracy of building thermal models [163]. An MPC thermal model that adapted the EnergyPlus software and bi-linear RC modelling resulted in higher accuracy than the MPC combined with modified random forest algorithms [122]. The datasets are divided based on features to manage their interactions in the same testing framework [122]. In contrast to a decision tree algorithm, which is a hierarchical tree of partitioning the relationship between independent and dependent variables, a random forest algorithm is a classification/regression predictive strategy with higher prediction precision for larger datasets [164].

The NARX ANN approach was used and implemented in MATLAB in [165], as an alternative solution to physics-based strategies for predicting time-dependent variables in modelling with the potential of updating building changes in the MPC model. A non-linearity of the NARX ANN machine learning method was solved based on hybrid optimisation, integrating both global and gradient-based optimiser [165]. The MPC method was used to modify optimisation algorithms at control intervals to solve control errors [165]. A time delay neural network (TDNN) algorithm includes a real-time status of input variables and their previous statuses, with the potential to store delayed information regarding inputs [166]. The MPC system simulated in MATLAB is proposed in [64] using TDNN and regression tree (RT) as machine learning approaches. The simulation results from the MPC were high dimensional databases with multiple outcome time series variables, which required regression-based machine learning strategies to approximate the behaviour of the control system, reduced the data storage size, and simplify its complexity [64]. The implemented RT had a lower performance efficiency than the PID and TDNN, while the TDNN-based strategy combined with the MPC with minor loss in the performance of the MPC was a practical and simplified solution [64].

5.2. Reinforcement learning for building control

RL is a model-based/model-free deep learning control strategy for building control problems. The structure of RL methods, as shown in

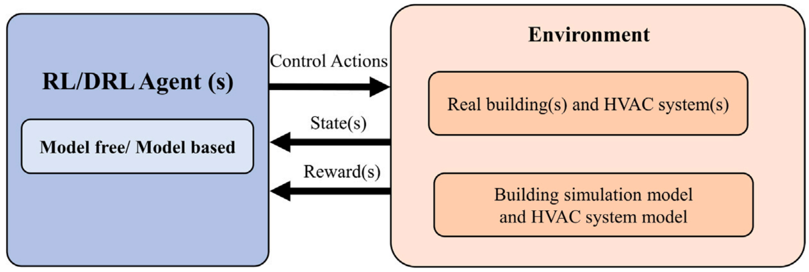

Fig. 6. RL/DRL framework application to building controls.

Fig. 6, consists of an agent and environment that interact with each other in discrete time-steps. In RL/DRL, the agent, which is composed of a neural network model, takes in the states that represent the conditions of variables in the environment, and then determines the necessary actions that must be executed within the environment [167].

In cases that the behaviour of the environment is known, the employed RL is model-based. However, even if RL controllers are stated as model-free without requiring dynamic knowledge of systems [168], the calibrated energy models are usually used for offline training of RL agents. Even though the RL control algorithm can be adopted for continuous real-time values of states, the computational cost for the large state space, caused by the feature values, is high compared to a DRL algorithm [169]. In the DRL control strategy, the dynamic thermal model can obtain efficient and accurate control policies, which are determined based on the trial and error of building information, for the model's agent [26]. As a result, the trained DRL agent is inserted into the control system to test the proposed model, which reduces the uncertainties in the values of parameters [26]. As DRL control systems are modelled by using real-time data-driven information, mathematical modelling of the system is not required [26]. Moreover, the learning process among state observations, reward function inserted into the agent, and the action continues until the control policy reaches the defined convergence level [170]. For instance, in the HVAC modelling, the data related to the thermal state of parameters is inserted into the model and then based on the identified control policy, the control action is activated in the thermal model to modify the set points of the systems [170]. As a result, based on the recorded state (for example, the indoor temperature), a reward or penalty is assigned to the agent [11]. An action is then sent to the model to regulate the set point of the variable [11].

Multi-agent control models are possible solutions with RL/DRL methods, enabling the interaction of multiple agents from different building systems, which are interrelated for the decision-making of the variables [171]. In contrast to single-agent RL strategies that one agent is used for the whole model, in the multi-agent RL method separate agents are defined for each subsystem, while the optimal control policy is learned based on the interaction of agents [172]. Moreover, in cases that the number of agents is high, a distributed controller for multi-agent RL approaches outweighs the centralised controller, due to the exponential growth in learning tasks of the proposed model and simplification of describing new agents [173]. However, the numerical scalability of many agents is difficult, as the agent should consider the behaviour of other integrated agents [58]. The information about the whole environment can be noisy in multi-agent cases [58]. Also, the implementation of multi-agent models for larger case studies requires consideration of computation cost minimisation for training, over-fitting possibilities, and the capability of RL models for continuous action spaces [58].

An RL control method integrated with edge-cloud for the demand response of small and medium-sized commercial buildings is developed in [174] by assuming similar fixed outdoor temperature and humidity variables during demand response events. A thermal modelling approach is proposed [170], in which the states of the DRL model are received from the HVAC system and building thermal model simulation in TRNSYS. A model-based DRL method for an HVAC system was proposed in [175], which combined EnergyPlus software and a DRL algorithm. The HVAC system was modelled by combining EnergyPlus software, used to model building energy modelling (BEM) in offline mode, and the DRL algorithm, which takes the calibrated BEM data from EnergyPlus software to train the RL agents for developing the DRL control model and deploying the trained agent to the building automation system for real-time analysis [175]. The quality of the calibrated data based on the bayesian regularisation algorithm could not meet the requirements for multiple output BEM [175]. It was suggested to add system operational changes into future DRL-based models [175]. In HVAC control modelling with the DRL algorithm for a multi-zone building, an individual neural network was modelled in Phyton for approximation of Q-values in the Q-learning (model-free RL algorithm) method, which is related to the control actions of each zone in the simulated building [169]. As a result, higher efficiency in the feasibility of the model was achieved with the large state space of actions [169]. Integration of a model-free control strategy with low computational costs and a model-based control strategy with high accuracy to develop a hybrid control model can be investigated in future building control systems [176]. As in model-free RL, the optimal policies in the controller are identified without any knowledge about the dynamics of the building [27]. However, the agent needs to be pre-trained offline in a virtual environment of the system model (could be a physics-based model) to enhance the control performance of the model and reduce its computing time [25]. Table 2 provides some additional DRL studies on HVAC control and thermal comfort applications.

5.3. Reinforced-MPC for building control

The control strategy implemented, based on the RL strategy, solely requires a large dataset of variables and lacks the possibility of including constraints of the system [156]. In cases that long prediction horizons are required, the number of input and state variables for MPC optimisation increases, which adds difficulty in the optimisation of infinite discontinued horizons [182]. The model with both RL and MPC had the potential of continuous learning and consideration of uncertainty in zones [182]. The merge of the RL strategy with learning methods such as MPC leads to distinguishing the behaviour of the systems that cannot be obtained from the collected data and eliminating the requirements of redesigning the whole control system with alternations in control tasks [156]. In the combination of RL and MPC, MPC can act as a function approximator, in which the actions are imposed on the model explicitly during the prediction horizons [182]. This strategy is named 'differentiable MPC' and implemented in [183]. The other method of merging MPC and RL is forcing the action explicitly in the first control step, with the use of the controller model, and taking value function for the remaining prediction horizon, while the action is forced implicitly [182]. The 'differentiable MPC' has the potential to optimise model parameters end-to-end [183].

Table 2
DRL studies on HVAC control and thermal comfort.

RL method	Reference	Computing method	Note
Double-deep-Q-network (DDQN) Multi-agent	[172]	Simulation	• Transfer learning and domain knowledge are used for numerical scalability. Instead of re-training many agents for similar systems (e.g a subset of AHU and chiller set points) in the same building, the knowledge of optimal policy obtained by training multiple agents of the subset is transferred to similar subsets in the same building.
Proximal policy optimisation (PPO) Deep deterministic policy gradient (DDPG)	[177]	Simulation-Experiment	• PPO and DDPG were compared for performance validation of the models. • The influences of different weather conditions, simulation days, and temperature penalty were considered in experiment.
Branching Duelling Q-network (BDQ)	[178]	Simulation-Experiment	• Gaussian process-based Bayesian optimisation is applied calibrate model for mismatches between simulation and real case study.
Deep Q-network (DQN)	[179]	Simulation	• Performance compared with RBC method and a case that airflow direction is fixed.
DQN	[180]	Simulation	• Gassian process regression for thermal comfort prediction. • DQN for control. • Performance compared with RBC.
DDPG including actor-critic networks	[181]	Simulation-Real data	• The proposed model is compared with DQN, RBC, and fixed methods to verify the control performance.

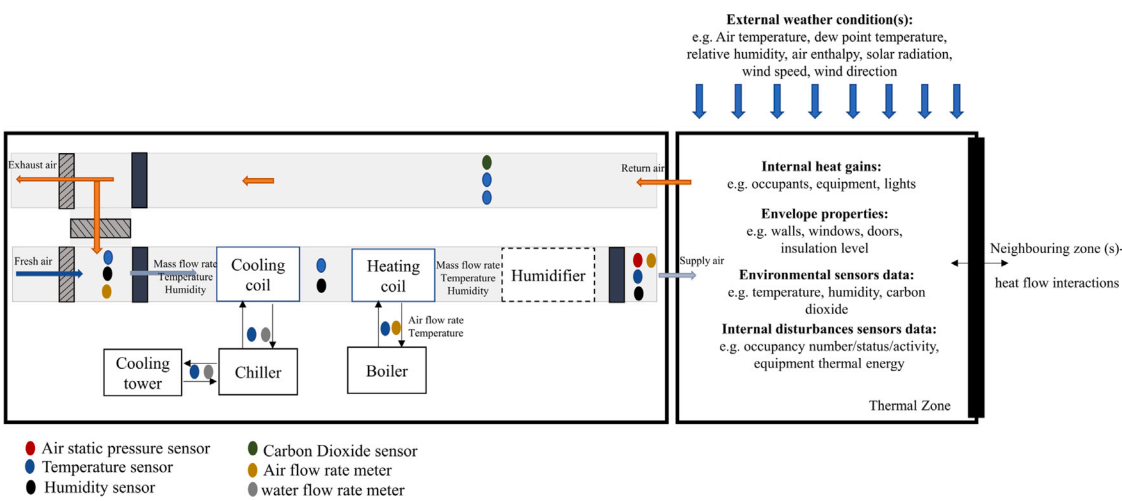

Fig. 7. Schematic of a thermal zone with a typical HVAC system.

6. Data requirements for building thermal modelling

One of the important steps in building thermal modelling is the selection of the minimum required data for model identification. This data minimisation depends on the modelling method and its objective(s). Fig. 7 represents a schematic representation of a single thermal zone with a typical HVAC system including the commonly selected variables.

(1) White-box models: Detailed information of the system is required. The model is implemented by heat and mass transfer and energy balance equations derived based on physical knowledge of the system describing the dynamical behaviour of systems. Based on the purpose of the model, all the parameters and variables, which are needed to derive the ordinary differential equations of the model, are required data. In the building zone(s) model as an example, all the building geometry, construction, and thermal properties data are required to simulate the model of the system. A detailed HVAC system modelling is added in cases that the HVAC operation optimisation is involved.

(2) Black-box models: Time-series collected sensor data are trained, validated, and tested as inputs of the data-driven techniques. Based on the objective of the study whether it is limited to load predictions, thermal comfort or system performance, the required data is identified. In the building zone model as an example, the data related to weather conditions, indoor thermal comfort conditions, occupancy (consisting of real-data, estimated data, and status), and HVAC set-point and operating condition can be used for modelling. As the data is collected in time-series, any time-related information, such as the timestamp of recorded data, previous data points, and period of data collection, is used for modelling. The main focus of the studies regarding data is related to modelling requisites including the amount of data and processing of data. However, the identification of the minimum necessary data type for meeting more complex objectives aiming at a building thermal model/HVAC system control is still missing.

Based on a study, which reviewed the frequency of input variables selected for ANN and RL control strategies modelled for thermal comfort and indoor air quality of buildings, the main variables computed to the model were indoor/outdoor temperatures, volume flow rates, and relative humidity, as opposed to building design variables [184]. Air velocity, surface temperatures, mean radiant temperatures, and building design variables were mentioned as influencing variables on indoor air temperature and air quality [184]. However, the unavailability of measured/monitored values of these variables limited the researchers in adding these variables into their models [184]. For instance, in the selection of input variables for the RL methodology, surface temperature and air density were not considered in any of the reviewed articles by researchers in Ref. [184]. As a result, the elimination of variables related to a building design was mostly due to the complexity of measuring their values in contrast with the values of indoor/outdoor temperature and humidity ratios, which are simply measurable with sensors. The other reason can be the applied control strategy. For example, with MPC methods the variables that their measurement is not accurate or is missed might be included as controllable or uncontrollable disturbances, which is the limitation of other methods. As occupancy data is mostly uncertain, especially occupancy behaviour and exact measurement of occupants number, occupancy data is not included in many studies. Unless the objective of the study is the occupancy prediction, then the occupancy data is available.

(3) Grey-box models: As mentioned previously, the grey-box models are mostly developed with RC models. The RC models are commonly transferred to the state-space model of the system to create a mathematical model of the system. In these models, the parameters and variables of the models should be differentiated before the identification of required data. For example, R and C values are the parameters of the model and mostly as the real-time data of these parameters is not available, constant/time-varying estimated values are employed to the models. When dealing with the complexity of a model caused by the absence or difficulty in obtaining accurate measurements for model parameters and variables, employing a reduced order model becomes a viable alternative. The variables and parameters that are impossible to obtain are merged together to simplify the model and address the challenge presented by the unavailability or difficulty in acquiring specific data.

6.1. Occupancy data

Occupancy data of the building zones influence the energy consumption of HVAC systems [185] and its sizing [186–188]. Occupants are internal disturbances influencing both indoor temperature and humidity, which are correlated with HVAC operation. As a result, consideration of occupancy as an internal load in thermal energy modelling [189–191] for indoor temperature regulation as well as HVAC operation mode can optimise the HVAC energy performance [192]. This variable also helps in the estimation of occupancy thermal satisfaction [193]. For instance, some studies consider human body temperature and clothing level when controlling indoor air quality to obtain a higher level of thermal satisfaction [194,195]. In this case, the relationship between human skin temperature and ambient thermal conditions can be evaluated.

The study of occupant impacts can be limited to assumptions based on working schedules and standards of the buildings or actual data. Although occupant number, behaviour, and their corresponding internal heat gain are uncertain variables in indoor thermal models [131], their imprecise estimation effect the control model accuracy [196–199]. For instance, the main occupancy schedule of the building was identified to evaluate thermal discomfort levels by considering the average indoor air temperatures and humidity ratios of the building's spaces in [200]. It was highlighted that including a higher level of occupant behaviour measurements in analyses could increase the model's accuracy to reduce thermal discomfort, as occupant activities are a remaining uncertainty for energy models [200]. A humidity ratio below a certain level had a more negative impact on thermal satisfaction than indoor temperature [200].

An MPC model based on RC modelling of the zones was studied [131] by including occupancy impact based on estimating internal heat gains. The inclusion of electricity consumption of lighting and equipment as well as CO_2 measurements in a zone, which do not follow similar patterns because of the changes in occupant number, could more precisely estimate internal heat gain [131]. For the implementation of DRL for building thermal energy control with insertion of occupancy number, the building control dynamics in Modelica was required as a virtual environment for agent training [178]. One limitation of their work [178] was occupancy number, which was included based on manual measurement. Machine learning technologies have the potential to model occupant behaviour from previous data to optimise the energy usage of smart buildings [201,202]. An example of the neural network strategy for a single occupant space is [203] with a training dataset collected through manual counting. There are different sensor technologies for occupancy counting and detection, including indoor air quality sensors (temperature, relative humidity, and CO_2 concentration [48]), motion sensors, vision sensors [185,204–206], and Bluetooth low energy sensors [207]. Non-dispersive infrared sensors can monitor CO_2 concentrations, while the accuracy of the results depends on temperature, relative humidity, and pressure variables [208]. Table 3 provides the main features of three commonly used sensing technologies for occupancy detection, followed by studies as examples.

6.2. HVAC system data requirements

The provision of a comfortable indoor thermal environment for occupants is one of the objectives of the HVAC system in commercial buildings. This includes control of indoor temperature and humidity to satisfy the indoor thermal condition and air quality to modify air contaminant level (e.g. CO_2 from occupants and equipment). Different types of HVAC systems are used in commercial buildings. A commercial HVAC system is composed of several types of equipment including but not limited to an AHU including main components for controlling the supply air parameters, a chiller supplying chilled water to the AHU system [243], and a cooling tower.

AHU in HVAC systems is responsible for supplying heated/cooled air to zones [48] with the use of components such as supply fans, dampers, and heating/cooling coils [244]. Water flows inside the cooling/heating coils of the HVAC system to regulate the temperature of the mixed air, passing through the coils, via an exchange of heat between the air and water flow inside the coils [245]. The fan in the AHU is responsible for flowing the air to building zones via ducts [245]. The temperature of supply air is an output variable of AHU to be included in a control model developed for cooling mode operation of an HVAC system, while return temperature and air mass flow rate of return air are the input variables entering the AHU [246]. The calculated supply air temperature in the designed control systems should be similar to the one provided by the AHU of an HVAC system [247]. The outside air can be mixed with the returned air from zones based on the position of dampers [248], while the exhaust air is discarded from the air circulation of the HVAC system [249].

Each equipment in the HVAC system has an independent local controller with possible communication with other interacting equipment. The required data to model and control each sub-system of the HVAC system varies based on the type of sub-system. In supervisory level control where the outside weather condition data and zone data are taken into account, the data from the HVAC system might be limited to supply air temperatures and supply airflow rates, which are directly influencing the indoor zone temperature. However, it is imperative to consider the interaction of HVAC systems parts for HVAC system performance investigations [250]. The minimum HVAC system data (input variables and parameters of the model) which is required for supervisory level control based on thermal model selection is still missed in the literature.

7. Discussion

7.1. Modelling techniques

The selection of modelling method depends on the available information about the investigated building. It is also important to consider the strengths and weaknesses of each model to select the most appropriate one based on the objective requirements. Based on the reviewed literature, there is significant attention on data-driven models due to availability of sensors data measurements and research growth in machine learning algorithms. However, limitations such as data insufficiency, dependency of prediction performance on data quality and sensors accuracy, lack of reliability due to in-dependency from physical dynamic behaviour, leads to selection of other methods. Based on the findings of this review, the white-box models are more suitable

Table 3
Benefits and drawbacks of sensing technologies for occupancy estimation in buildings.

Sensing method	Strengths and weaknesses	Research studies
CO_2 Sensors	**Benefits:** • Mostly available in buildings [209,210]. • Occupancy can be estimated approximately [206]. **Drawbacks:** • Failure to measure sudden occupancy changes [211,212]. • Sensitive to environmental conditions [190,210]. • Estimations are based on indirect measurements which can affect accuracy [213]. • CO_2 emission per occupant can vary [214]. • High occupancy rates can increase the error in occupancy detection [215]. • Requires detailed physical information of the zone [216].	• Occupancy number estimation using CO_2 concentration, zone temperature , and fresh air inflow signals via system identification and deconvolution problem solving phases was employed in [217]. • The prediction accuracy of the occupancy detection with environmental signals data (including CO_2 measurements) implementing statistical learning models was evaluated in [218]. • Estimation with stochastic differential equations was proposed in [209], without the effect of opening/closing doors. • An insertion of environmental signals, such as the air change rates between the zone and neighbouring zones, infiltration rate, and exterior CO_2 level, into the detection algorithm (e.g. based on mass balance equations [219,220]) can increase its precision [221].
Passive infrared (PIR) Sensors	**Benefits:** • Its implementation is easy and can be cost effective [222] if only a few sensors are required (for example, studies limited to single occupant zones). • Low power usage [212]. • Low computational cost, as the collected data is in a binary format [214]. **Drawbacks:** • Limited to presence detection [225,227]. • Failure to detect stationary status of occupant [228,229]. • Failure to distinguish multi-/single-occupancy [222].	• People counting with a limited number of PIR sensors was developed in [223], however, the study was conducted in small office spaces. **Sensor location:** • PIR sensors, as an example of motion sensors was mounted under work desks to detect occupancy presence behind the desk in [186] and on the users' desk in [224], as a direct 'line of sight' is needed to detect movements [213,225,226].
Camera	**Benefits:** • Occupancy number can be identified [205]. **Drawbacks:** • A 'line of sight' is needed [213]. • Optimal location for sensor installation needs investigation [213]. • Poor lighting condition can negatively affect the results [235]. • It has a high computational cost for image-/video-based models [212].	**Detection methods:** • A convolutional neural network (CNN) was used for occupancy counting, with head detection strategy [230,231] or low-resolution camera images for occupancy privacy [232,233]. • CNN was adopted for fast and accurate head detection to count occupants number [234]. • YoLo deep neural network for occupancy counting was modelled in [228]. **Sensor location:** • Deep learning strategy was developed and the ceiling was suggested for camera installation, and its angle and position were important factors in the reduction of under-counting probabilities [236]. • The installation of cameras in the entrance of rooms collects overhead views, while occupancy measurements are based on the occupants' direction of motion [215] (for overhead occupancy detection see [237–242]). • The installation of cameras in the interior makes the detection more complicated due to the existence of many objects in the zones [215].

solutions in cases where the detailed system information is available and prediction accuracy is less important (as they lack real-time prediction). Moreover, white-box models were selected in cases for parameter estimations of grey-box models and RL/DRL offline training step. Grey-box models and their integration with data-driven methods is identified as the future research direction especially when multiple variables are aimed to be predicted. This possible the selection of the most suitable method based on the data type for each objective. For instance, in cases that data type is images (occupancy forecasting with cameras), deep learning data-driven method is the promising solution. While RC model might be selected for zone temperature prediction, as it is developed based on heat balanced equations.

The process of variable prediction with predictive building models is represented in Fig. 8, consisting of input variables, building predictive model, building model calibration, and output variables. The model calibration step adjust the numerical/physical model parameters to reduce the mismatch between real-data and predicted data.

7.2. Supervisory control methods

The prominent findings from MPC approach application in building HVAC controls problems are:

• It is important to identify the level of detailed information is required in model developments for MPC strategy based on the research objectives [19].

• MPC is a suitable approach for supervisory control in building HVAC control applications with the potential of integrating with local controllers in buildings [45].

• An unique model formulation is needed for each building HVAC control [25], as control performance of MPC is influenced by model prediction accuracy [21].

A schematic representation of a typical MPC framework in building control application is provided in Fig. 9. The main step in MPC development is the formulation of building predictive model. This process can be time consuming and requires expert knowledge of MPC implementation. Identification of minimum data requirements varies based on the models objectives. Disturbances have direct influence on building predictive models and high level of uncertainty in disturbances negatively impacts the model accuracy. MPC uses optimisation to make control decisions for a planning horizon, repeating the process indefinitely and handling constraints effectively [148].

Based on the review, it can be inferred that RL-based building control is an active area of research, with ongoing efforts to refine and optimise these methods for practical use. The implementation of RL-based building control methods is hindered by several challenges, including the time-consuming and data-intensive training process, and the need to ensure the security and safety of building controls [27]. There is a lack of comparative case studies on RL and MPC, to compare the control performance of these methods in real experimental research. Building control problems mainly consists of multiple objectives requiring multiple agents for RL/DRL controllers. The process of managing multiple agents presents greater challenges than managing a single agent due to factors like agent heterogeneity, defining collective goals, scalability, and the need to address nonstationarity [58]. Careful tuning of numerous hyperparameters is required to achieve good performance in DRL algorithms, in addition to the pre-training of the

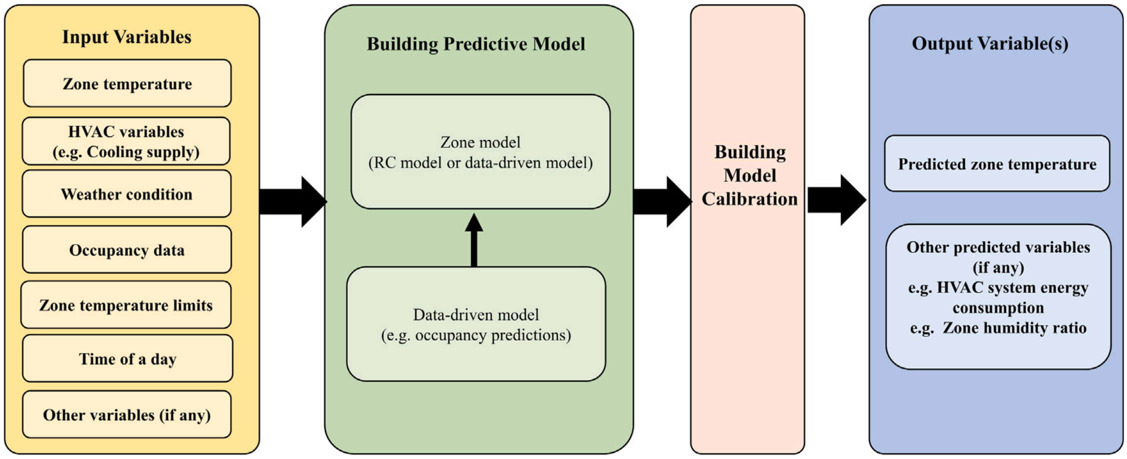

Fig. 8. Variable prediction structure with building predictive modelling.

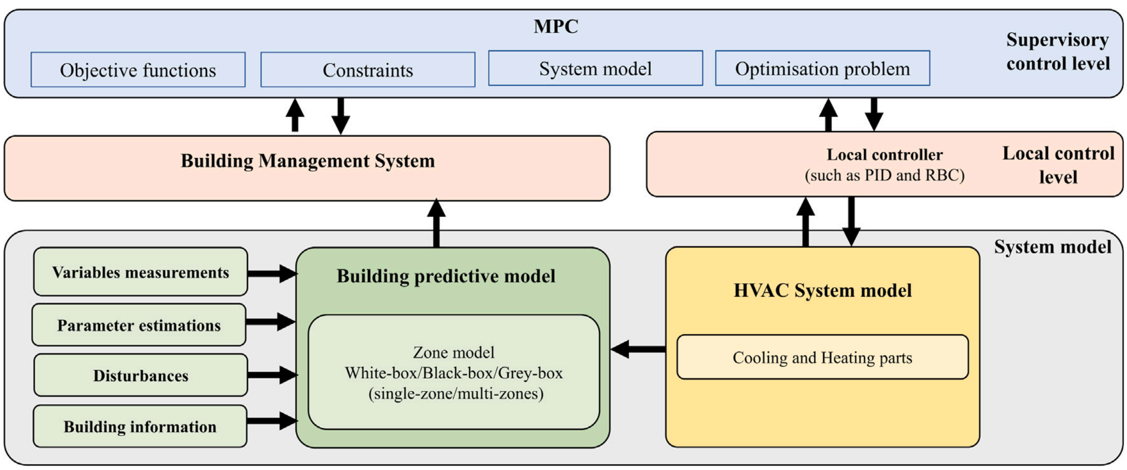

Fig. 9. MPC framework application to building HVAC controls.

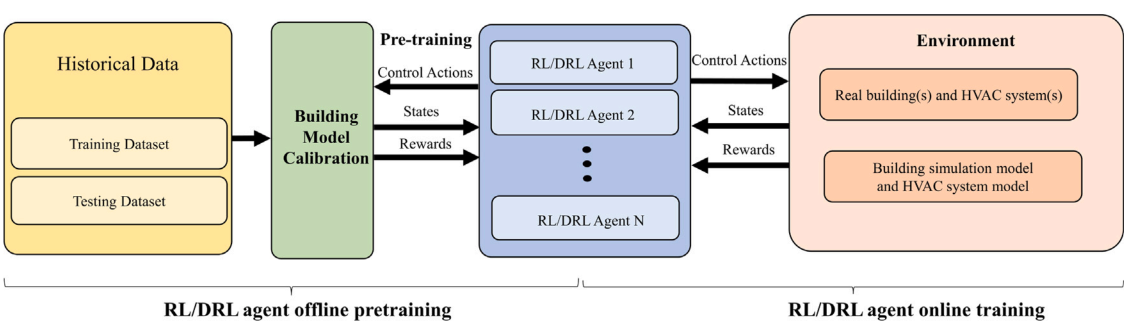

Fig. 10. RL/DRL framework with offline and online process to building controls.
Source: Idea adopted from [178].

control agent [25]. The combination of MPC and RL have not yet been widely adopted in practical applications.

A possible RL/DRL framework with RL/DRL framework with offline and online process to building controls is presented in Fig. 10, including building HVAC system modelling, model calibration, RL/DRL training, and deployment of the control actions to the real system [251] . In the pre-training step, a calibrated model of the energy system is utilised to train a DRL control agent during a specific training period and find out unknown calibration parameters [251]. The re-calibration of building model might be conducted during online training with the updated data [178].

7.3. Data requirements

Different modelling techniques for building HVAC problems have varying data requirements. Empirical models typically are built upon limited data, such as basic building information and historical energy consumption data. A comparative representation of required data for the three main modelling techniques reviewed in this manuscript is provided in Fig. 11. Simplified models demand more detailed data, including building geometry, thermal properties, and HVAC system specifications, along with some sensor data for calibration and validation. Whole-building energy simulation models have extensive data

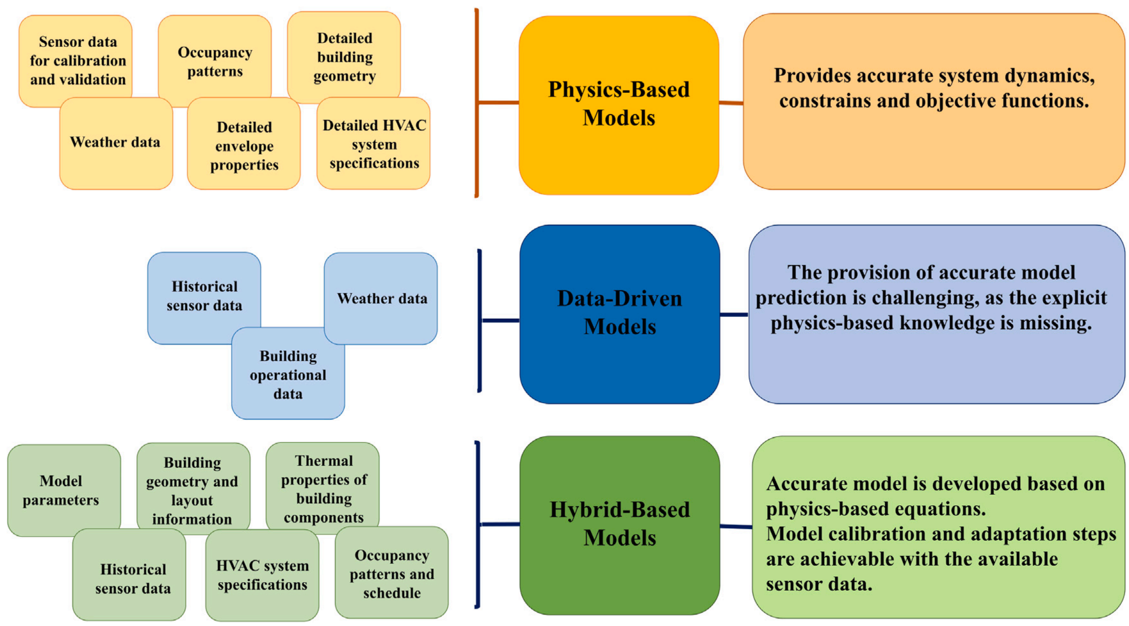

Fig. 11. Comparative representation of data requirements for energy modelling techniques.

requirements, including detailed building geometry, envelope properties, HVAC system specifications, occupancy patterns, weather data, and sensor data for calibration and validation. CFD models need even more extensive data, including intricate building geometry details, thermal properties, HVAC system specifications, occupancy patterns, weather data, and sensor data for calibration and validation. In contrast, grey Box models require data such as building geometry and layout information, thermal properties of building components, HVAC system specifications, occupancy patterns and schedules, weather data, and historical sensor data for calibration and validation. Data-driven models rely heavily on historical sensor data, weather data, and building operational data for training and learning the relationships and patterns in the data. The data requirements for data-driven models include substantial amounts of high-quality data from various sources to ensure accurate modelling. The choice of modelling technique depends on the available data, modelling goals, and the desired level of accuracy and complexity in capturing the building's thermal behaviour.

The choice between MPC and RL for supervisory control depends on the modelling strategy employed. In the case of physics-based models, MPC is a natural fit. The accurate system dynamics and constraints provided by the physics-based models allow MPC to solve optimisation problems and determine optimal control actions based on predictions. RL, although feasible, faces challenges due to the need for extensive data [252] and may serve as a means of refining control policies learned from the physics-based models. However, physics-based models mostly lack real-time predictions. In contrast, grey Box models strike a balance between accuracy and flexibility, making them suitable for both MPC and RL. MPC utilises the model's predictions to optimise control decisions, while RL can be employed to explore alternative strategies and refine control actions. With data-driven models, MPC can be challenging due to the absence of explicit physics-based models. However, if a reliable data-driven model is available, MPC can leverage its predictions for control optimisation. RL, on the other hand, is well-suited for data-driven models, allowing for adaptive and optimised control based on the available data. Ultimately, the choice between MPC and RL in supervisory control depends on the specific modelling strategy employed and the trade-offs between interpretability, computational requirements, and model adaptability.

All reviewed modelling techniques are built upon the input data as the fundamental source, which can profoundly affect the accuracy of modelling and forecasting [37]. The level of detail and sampling frequency of time-series data are critical characteristics to consider, as they can have a substantial impact on the outcome of model predictions [37]. As a result, it is crucial to identify the variables that have a significant impact on the predicted variables, evaluate the precision of measurements, and determine the necessary time intervals for each variable. Occupancy related data (such as behaviour and number) has noticeable influence on the indoor thermal variable and building energy usage. However, lack of precise data, data measuring difficulties, high level of uncertainty in data accuracy and incomplete data are some of the common challenges faced when collecting and utilising occupancy-related data in building energy management. To overcome the challenges of collecting and using occupancy-related data for building energy management, several strategies can be implemented. Firstly, incorporating non-intrusive sensor technology like occupancy sensors, temperature sensors, and CO_2 sensors can aid in precise data collection. Secondly, utilising data analytic techniques, including machine learning algorithms, can uncover meaningful insights and patterns in the data that can inform energy management decisions. Finally, involving building occupants in the data collection process can enhance data accuracy and completeness by gaining valuable feedback on their behaviour patterns and how they use the building. Having a standard framework that specifies the necessary level of detail for data and sensor accuracy can be highly advantageous. This can ensure that the data collected is reliable and can be used with confidence to make informed building energy management decisions.

8. Conclusion

In conclusion, although building energy management systems exist for most of the buildings, developing an efficient and a practical supervisory controller reducing the thermal comfort dissatisfaction, while considering energy efficiency of HVAC systems is still a concern to focus on. The research has focused on control-oriented models for supervisory control, emphasising the dominant thermal energy modelling techniques in building HVAC systems. The integration of data-driven models with grey-box/physics-based models has been identified as a promising approach to overcome challenges associated with sensor measurements and dynamic system modelling.

Furthermore, the paper has discussed the increasing interest in model-free or less model-dependent control strategies, particularly RL, to address the complexity and non-linear dynamics of building HVAC systems. However, the competitiveness of these approaches, including RL, is still limited compared to model-based advanced controllers like MPC. The comparison between MPC and RL for building HVAC systems reveals distinct strengths and limitations. MPC is a model-based control strategy that optimises control actions using a mathematical model of the system. It offers precise control, handles complex dynamics, and considers multiple objectives and constraints. On the other hand, RL is an approach that learns control policies through trial-and-error interactions with the environment. RL adapts well to non-linear dynamics and system changes, but requires significant data and computational resources. To leverage the benefits of both approaches, researchers are exploring the integration of RL within an MPC framework to enhance adaptability and robustness.

The choice between grey-box, physics-based, or black-box models depends on the specific requirements and characteristics of the building HVAC system and the control objectives at hand. Relying solely on data-driven models for thermal energy modelling in buildings may be limited by their lack of interpretability, extrapolation capabilities, dependence on data quality and availability, and the need for a more comprehensive understanding of underlying physical mechanisms, making hybrid models that combine data-driven and physics-based approaches a more robust and reliable choice. Hybrid models are recommended for thermal energy modelling in buildings due to their flexibility, accuracy, and ability to capture complex interactions, providing more robust and adaptable predictions. Physics-based models are mainly selected when a detailed understanding of the underlying physical processes is necessary, for example, at building construction stage. Also, in case of availability, they are used for model parameter estimation or training.

To advance the field and promote more energy-efficient building HVAC systems, several research gaps have been identified. First, the impact of sensor measurement accuracy on model calibration requirements needs further exploration. Second, the level of detail required for considering occupancy activity and behaviour should be determined based on research objectives. Third, there is a need for more generalised frameworks for prediction and control horizons, tailored to specific research objectives. Finally, the development of a unified metric for performance verification and validation of simulated models would simplify comparisons across different studies.

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.

Data availability

No data was used for the research described in the article.

References

[1] Kim J, Schiavon S, Brager G. Personal comfort models–A new paradigm in thermal comfort for occupant-centric environmental control. Build Environ 2018;132:114–24.
[2] Thongkhome P, Dejdumrong N. A neural network based modeling of closed room thermal comfort environmental prediction for sensor hub. In: 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON). IEEE; 2020, p. 55–8.
[3] American society of heating, refrigerating and air-conditioning engineers Inc.: Atlanta, GA, USA; 2009.
[4] Verbeke S, Audenaert A. Thermal inertia in buildings: A review of impacts across climate and building use. Renew Sustain Energy Rev 2018;82:2300–18.
[5] Ghahramani A, Jazizadeh F, Becerik-Gerber B. A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points. Energy Build 2014;85:536–48.
[6] Harish V, Kumar A. A review on modeling and simulation of building energy systems. Renew Sustain Energy Rev 2016;56:1272–92.
[7] Belussi L, Barozzi B, Bellazzi A, Danza L, Devitofrancesco A, Fanciulli C, Ghellere M, Guazzi G, Meroni I, Salamone F. A review of performance of zero energy buildings and energy efficiency solutions. J Build Eng 2019;25:100772.
[8] Bagnasco A, Massucco S, Saviozzi M, Silvestro F, Vinci A. Design and validation of a detailed building thermal model considering occupancy and temperature sensors. In: 2018 IEEE 4th International Forum on Research and Technology for Society and Industry. RTSI, IEEE; 2018, p. 1–6.
[9] Molina-Solana M, Ros M, Ruiz MD, Gómez-Romero J, Martín-Bautista MJ. Data science for building energy management: A review. Renew Sustain Energy Rev 2017;70:598–609.
[10] Homod RZ, Sahari KSM, Almurib HA, Nagi FH. Double cooling coil model for non-linear HVAC system using RLF method. Energy Build 2011;43(9):2043–54.
[11] Azuatalam D, Lee W-L, de Nijs F, Liebman A. Reinforcement learning for whole-building HVAC control and demand response. Energy and AI 2020;2:100020.
[12] Zhang S, Cheng Y, Fang Z, Huan C, Lin Z. Optimization of room air temperature in stratum-ventilated rooms for both thermal comfort and energy saving. Appl Energy 2017;204:420–31.
[13] Tham K, Ullah M. Building energy performance and thermal comfort in Singapore. ASHRAE Trans 1993;99(pt 1):308–21, ScholarBank@NUS Repository.
[14] Mason K, Grijalva S. A review of reinforcement learning for autonomous building energy management. Comput Electr Eng 2019;78:300–12.
[15] Yu L, Xie W, Xie D, Zou Y, Zhang D, Sun Z, Zhang L, Zhang Y, Jiang T. Deep reinforcement learning for smart home energy management. IEEE Internet Things J 2019;7(4):2751–62.
[16] Zafra RG, Mayo J, Villareal PJM, De Padua VMN, Castillo MHT, Sundo MB, Madlangbayan MS. Structural and thermal performance assessment of shipping container as post-disaster housing in tropical climates. Civil Eng J 2021;7.
[17] Liu Y, Yu N, Wang W, Guan X, Xu Z, Dong B, Liu T. Coordinating the operations of smart buildings in smart grids. Appl Energy 2018;228:2510–25.
[18] Maddalena ET, Lian Y, Jones CN. Data-driven methods for building control—A review and promising future directions. Control Eng Pract 2020;95:104211.
[19] Drgoa J, Arroyo J, Figueroa IC, Blum D, Arendt K, Kim D, Ollé EP, Oravec J, Wetter M, Vrabie DL. All you need to know about model predictive control for buildings. Annu Rev Control 2020.
[20] Schubnel B, Carrillo RE, Alet P-J, Hutter A. A hybrid learning method for system identification and optimal control. IEEE Trans Neural Netw Learn Syst 2020;32(9):4096–110.
[21] Zhan S, Chong A. Data requirements and performance evaluation of model predictive control in buildings: A modeling perspective. Renew Sustain Energy Rev 2021;142:110835.
[22] Borrelli F, Bemporad A, Morari M. Predictive Control for Linear and Hybrid Systems. Cambridge University Press; 2017.
[23] Chong A, Gu Y, Jia H. Calibrating building energy simulation models: A review of the basics to guide future work. Energy Build 2021;253:111533.
[24] Lymperopoulos G, Ioannou P. Building temperature regulation in a multi-zone HVAC system using distributed adaptive control. Energy Build 2020;215:109825.
[25] Brandi S, Fiorentini M, Capozzoli A. Comparison of online and offline deep reinforcement learning with model predictive control for thermal energy management. Autom Constr 2022;135:104128.
[26] Yu L, Qin S, Zhang M, Shen C, Jiang T, Guan X. A review of deep reinforcement learning for smart building energy management. IEEE Internet Things J 2021.
[27] Wang Z, Hong T. Reinforcement learning for building controls: The opportunities and challenges. Appl Energy 2020;269:115036.
[28] Martirano L, Parise G, Greco G, Manganelli M, Massarella F, Cianfrini M, Parise L, di Laura Frattura P, Habib E. Aggregation of users in a residential/commercial building managed by a building energy management system (BEMS). IEEE Trans Ind Appl 2018;55(1):26–34.
[29] Hannan MA, Faisal M, Ker PJ, Mun LH, Parvin K, Mahlia TMI, Blaabjerg F. A review of internet of energy based building energy management systems: Issues and recommendations. Ieee Access 2018;6:38997–9014.
[30] McGlinn K, Yuce B, Wicaksono H, Howell S, Rezgui Y. Usability evaluation of a web-based tool for supporting holistic building energy management. Autom Constr 2017;84:154–65.
[31] Huang J-W, Gao J-W. How could data integrate with control? A review on data-based control strategy. Int J Dyn Control 2020;8(4):1189–99.
[32] Afroz Z, Shafiullah G, Urmee T, Higgins G. Modeling techniques used in building HVAC control systems: A review. Renew Sustain Energy Rev 2018;83:64–84.
[33] Afram A, Janabi-Sharifi F. Review of modeling methods for HVAC systems. Appl Therm Eng 2014;67(1–2):507–19.
[34] Homod RZ. Review on the HVAC system modeling types and the shortcomings of their application. J Energy 2013;2013.
[35] Harish V, Kumar A. A review on modeling and simulation of building energy systems. Renew Sustain Energy Rev 2016;56:1272–92.
[36] Wei Y, Zhang X, Shi Y, Xia L, Pan S, Wu J, Han M, Zhao X. A review of data-driven approaches for prediction and classification of building energy consumption. Renew Sustain Energy Rev 2018;82:1027–47.

[37] Bourdeau M, qiang Zhai X, Nefzaoui E, Guo X, Chatellier P. Modeling and forecasting building energy consumption: A review of data-driven techniques. Sustainable Cities Soc 2019;48:101533.

[38] Li Y, O'Neill Z, Zhang L, Chen J, Im P, DeGraw J. Grey-box modeling and application for building energy simulations-A critical review. Renew Sustain Energy Rev 2021;146:111174.

[39] Fu K-S. Learning control systems–Review and outlook. IEEE Trans Automat Control 1970;15(2):210–21.

[40] Royapoor M, Antony A, Roskilly T. A review of building climate and plant controls, and a survey of industry perspectives. Energy Build 2018;158:453–65.

[41] Serale G, Fiorentini M, Capozzoli A, Bernardini D, Bemporad A. Model predictive control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. Energies 2018;11(3):631.

[42] Hilliard T, Kavgic M, Swan L. Model predictive control for commercial buildings: trends and opportunities. Adv Build Energy Res 2016;10(2):172–90.

[43] Rockett P, Hathway EA. Model-predictive control for non-domestic buildings: a critical review and prospects. Build Res Inform 2017;45(5):556–71.

[44] Zong Y, Su W, Wang J, Rodek JK, Jiang C, Christensen MH, You S, Zhou Y, Mu S. Model predictive control for smart buildings to provide the demand side flexibility in the multi-carrier energy context: Current status, pros and cons, feasibility and barriers. Energy Procedia 2019;158:3026–31.

[45] Killian M, Kozek M. Ten questions concerning model predictive control for energy efficient buildings. Build Environ 2016;105:403–12.

[46] Werner S. International review of district heating and cooling. Energy 2017;137:617–31.

[47] Afram A, Janabi-Sharifi F. Theory and applications of HVAC control systems–A review of model predictive control (MPC). Build Environ 2014;72:343–55.

[48] Afram A, Janabi-Sharifi F, Fung AS, Raahemifar K. Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: A state of the art review and case study of a residential HVAC system. Energy Build 2017;141:96–113.

[49] Jin Y, Yan D, Chong A, Dong B, An J. Building occupancy forecasting: A systematical and critical review. Energy Build 2021;251:111345.

[50] Zhao L, Li Y, Liang R, Wang P. A state of art review on methodologies of occupancy estimating in buildings from 2011 to 2021. Electronics 2022;11(19):3173.

[51] Mirakhorli A, Dong B. Occupancy behavior based model predictive control for building indoor climate—A critical review. Energy Build 2016;129:499–513.

[52] Dong B, Liu Y, Fontenot H, Ouf M, Osman M, Chong A, Qin S, Salim F, Xue H, Yan D, et al. Occupant behavior modeling methods for resilient building design, operation and policy at urban scale: A review. Appl Energy 2021;293:116856.

[53] Mason K, Grijalva S. A review of reinforcement learning for autonomous building energy management. Comput Electr Eng 2019;78:300–12.

[54] Weinberg D, Wang Q, Timoudas TO, Fischione C. A review of reinforcement learning for controlling building energy systems from a computer science perspective. Sustainable Cities Soc 2022;104351.

[55] Shaqour A, Hagishima A. Systematic review on deep reinforcement learning-based energy management for different building types. Energies 2022;15(22):8663.

[56] Vázquez-Canteli JR, Nagy Z. Reinforcement learning for demand response: A review of algorithms and modeling techniques. Appl Energy 2019;235:1072–89.

[57] Han M, May R, Zhang X, Wang X, Pan S, Yan D, Jin Y, Xu L. A review of reinforcement learning methodologies for controlling occupant comfort in buildings. Sustainable Cities Soc 2019;51:101748.

[58] Nguyen TT, Nguyen ND, Nahavandi S. Deep reinforcement learning for multiagent systems: A review of challenges, solutions, and applications. IEEE Trans Cybern 2020;50(9):3826–39.

[59] Jones WP. Air Conditioning Engineering. Routledge; 2007.

[60] Gao G, Li J, Wen Y. DeepComfort: Energy-efficient thermal comfort control in buildings via reinforcement learning. IEEE Internet Things J 2020.

[61] Zeng T, Barooah D. An adaptive MPC scheme for energy-efficient control of building HVAC systems. ASME J Eng Sustain Build Cities 2021;1–12.

[62] Mantovani G, Ferrarini L. Temperature control of a commercial building with model predictive control techniques. IEEE Trans Ind Electron 2014;62(4):2651–60.

[63] Belic F, Hocenski Z, Sliskovic D. HVAC control methods-a review. In: 2015 19th International Conference on System Theory, Control and Computing. ICSTCC, IEEE; 2015, p. 679–86.

[64] Drgoa J, Picard D, Kvasnica M, Helsen L. Approximate model predictive building control via machine learning. Appl Energy 2018;218:199–216.

[65] Salsbury TI. A survey of control technologies in the building automation industry. IFAC Proc Vol 2005;38(1):90–100.

[66] Mechri HE, Capozzoli A, Corrado V. USE of the ANOVA approach for sensitive building energy design. Appl Energy 2010;87(10):3073–83.

[67] Shaikh PH, Nor NBM, Nallagownden P, Elamvazuthi I, Ibrahim T. Intelligent multi-objective control and management for smart energy efficient buildings. Int J Electr Power Energy Syst 2016;74:403–9.

[68] Lovera M. Control-Oriented Modelling and Identification: Theory and Practice, vol. 80. IET; 2015.

[69] Fliess M. Model-free control and intelligent PID controllers: towards a possible trivialization of nonlinear control? IFAC Proc Vol 2009;42(10):1531–50.

[70] Judkoff R, Neymark J. Model validation and testing: The methodological foundation of ASHRAE Standard 140. Tech. Rep., National Renewable Energy Lab.(NREL), Golden, CO (United States); 2006.

[71] Cao S-J, Ding J, Ren C. Sensor deployment strategy using cluster analysis of fuzzy C-means algorithm: towards online control of indoor environment's safety and health. Sustainable Cities Soc 2020;102190.

[72] Delcroix B, Le Ny J, Bernier M, Azam M, Qu B, Venne J-S. Autoregressive neural networks with exogenous variables for indoor temperature prediction in buildings. In: Building Simulation. Springer; 2021, p. 1–14.

[73] Zhang X, Pipattanasomporn M, Chen T, Rahman S. An IoT-based thermal model learning framework for smart buildings. IEEE Internet Things J 2019;7(1):518–27.

[74] Kathirgamanathan A, De Rosa M, Mangina E, Finn DP. Data-driven predictive control for unlocking building energy flexibility: A review. Renew Sustain Energy Rev 2021;135:110120.

[75] Gao S, Sui M, Zhang C, Wang M, Yan Q. Thermal model identification of commercial building based on genetic algorithm. In: 2019 Chinese Automation Congress. CAC, IEEE; 2019, p. 550–4.

[76] Santoro BF, Rincón D, da Silva VC, Mendoza DF. Nonlinear model predictive control of a climatization system using rigorous nonlinear model. Comput Chem Eng 2019;125:365–79.

[77] Lu Q, Lee S. Image-based technologies for constructing as-is building information models for existing buildings. J Comput Civ Eng 2017;31(4). http://dx.doi.org/10.1061/(asce)cp.1943-5487.0000652.

[78] Dang H-A, Delinchant B, Wurtz F. Toward building energy management: Electric analog modeling for thermal behavior simulation. In: 2016 IEEE International Conference on Sustainable Energy Technologies. ICSET, IEEE; 2016, p. 246–50.

[79] Privara S, Cigler J, Váňa Z, Oldewurtel F, Sagerschnig C, Žáčeková E. Building modeling as a crucial part for building predictive control. Energy Build 2013;56:8–22.

[80] Atam E, Helsen L. Control-oriented thermal modeling of multizone buildings: methods and issues: intelligent control of a building system. IEEE Control Syst Mag 2016;36(3):86–111.

[81] Atam E. Current software barriers to advanced model-based control design for energy-efficient buildings. Renew Sustain Energy Rev 2017;73:1031–40.

[82] Cucca G, Ianakiev A. Assessment and optimisation of energy consumption in building communities using an innovative co-simulation tool. J Build Eng 2020;32:101681.

[83] Schiera DS, Barbierato L, Lanzini A, Borchiellini R, Pons E, Bompard E, Patti E, Macii E, Bottaccioli L. A distributed multi-model platform to co-simulate multi-energy systems in smart buildings. IEEE Trans Ind Appl 2021.

[84] Yuan R, Fletcher T, Ahmedov A, Kalantzis N, Pezouvanis A, Dutta N, Watson A, Ebrahimi K. Modelling and co-simulation of hybrid vehicles: A thermal management perspective. Appl Therm Eng 2020;115883.

[85] Hatledal LI, Chu Y, Styve A, Zhang H. Vico: An entity-component-system based co-simulation framework. Simul Model Pract Theory 2021;108:102243.

[86] Perabo F, Park D, Zadeh MK, Smogeli Ø, Jamt L. Digital twin modelling of ship power and propulsion systems: Application of the open simulation platform (osp). In: 2020 IEEE 29th International Symposium on Industrial Electronics. ISIE, IEEE; 2020, p. 1265–70.

[87] Sha H, Qi D. A review of high-rise ventilation for energy efficiency and safety. Sustainable Cities Soc 2020;54:101971.

[88] Liu W, You R, Zhang J, Chen Q. Development of a fast fluid dynamics-based adjoint method for the inverse design of indoor environments. J Build Perform Simul 2017;10(3):326–43.

[89] Morozova N, Trias F, Capdevila R, Pérez-Segarra CD, Oliva A. On the feasibility of affordable high-fidelity CFD simulations for indoor environment design and control. Build Environ 2020;184:107144.

[90] Cao S-J, Ren C. Ventilation control strategy using low-dimensional linear ventilation models and artificial neural network. Build Environ 2018;144:316–33.

[91] Zhang T, Liu Y, Rao Y, Li X, Zhao Q. Optimal design of building environment with hybrid genetic algorithm, artificial neural network, multivariate regression analysis and fuzzy logic controller. Build Environ 2020;175:106810.

[92] Zhang T, Li X, Zhao Q, Rao Y. Control of a novel synthetical index for the local indoor air quality by the artificial neural network and genetic algorithm. Sustainable Cities Soc 2019;51:101714.

[93] Ren C, Cao S-J. Implementation and visualization of artificial intelligent ventilation control system using fast prediction models and limited monitoring data. Sustainable Cities Soc 2020;52:101860.

[94] Ren C, Cao S-J. Development and application of linear ventilation and temperature models for indoor environmental prediction and HVAC systems control. Sustainable Cities Soc 2019;51:101673.

[95] Zeng T, Barooah P. Identification of network dynamics and disturbance for a multizone building. IEEE Trans Control Syst Technol 2020;28(5):2061–8.

[96] Ren J, Cao S-J. Development of self-adaptive low-dimension ventilation models using OpenFOAM: Towards the application of AI based on CFD data. Build Environ 2020;171:106671.

[97] Rinaldi S, Flammini A, Pasetti M, Tagliabue L, Ciribini A, Zanoni S. Metrological issues in the integration of heterogeneous lot devices for energy efficiency in cognitive buildings. In: 2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). IEEE; 2018, p. 1–6.
[98] Du Z, Xu P, Jin X, Liu Q. Temperature sensor placement optimization for VAV control using CFD–BES co-simulation strategy. Build Environ 2015;85:104–13.
[99] Ren J, Cao S-J. Incorporating online monitoring data into fast prediction models towards the development of artificial intelligent ventilation systems. Sustainable Cities Soc 2019;47:101498.
[100] Sun Y, Haghighat F, Fung BC. A review of the-state-of-the-art in data-driven approaches for building energy prediction. Energy Build 2020;221:110022.
[101] Tien PW, Wei S, Darkwa J, Wood C, Calautit JK. Machine learning and deep learning methods for enhancing building energy efficiency and indoor environmental quality–a review. Energy AI 2022;100198.
[102] Satrio P, Mahlia TMI, Giannetti N, Saito K. Optimization of HVAC system energy consumption in a building using artificial neural network and multi-objective genetic algorithm. Sustain Energy Technol Assess 2019;35:48–57.
[103] Amasyali K, El-Gohary NM. A review of data-driven building energy consumption prediction studies. Renew Sustain Energy Rev 2018;81:1192–205.
[104] Ghofrani A, Nazemi SD, Jafari MA. HVAC load synchronization in smart building communities. Sustainable Cities Soc 2019;51:101741.
[105] Luo M, Xie J, Yan Y, Ke Z, Yu P, Wang Z, Zhang J. Comparing machine learning algorithms in predicting thermal sensation using ASHRAE comfort database II. Energy Build 2020;210:109776.
[106] Han H, Xu L, Cui X, Fan Y. Novel chiller fault diagnosis using deep neural network (DNN) with simulated annealing (SA). Int J Refrig 2021;121:269–78.
[107] Deng Z, Chen Q. Artificial neural network models using thermal sensations and occupants' behavior for predicting thermal comfort. Energy Build 2018;174:587–602.
[108] Ngo N-T. Early predicting cooling loads for energy-efficient design in office buildings by machine learning. Energy Build 2019;182:264–73.
[109] Lu Q, Lee S, Chen L. Image-driven fuzzy-based system to construct as-is IFC BIM objects. Autom Constr 2018;92:68–87. http://dx.doi.org/10.1016/j.autcon.2018.03.034.
[110] Elnour M, Meskin N, Al-Naemi M. Sensor data validation and fault diagnosis using auto-associative neural network for HVAC systems. J Build Eng 2020;27:100935.
[111] Ledesma S, Hernández-Pérez I, Belman-Flores JM, Alfaro-Ayala JA, Xamán J, Fallavollita P. Using artificial intelligence to analyze the thermal behavior of building roofs. J Energy Eng 2020;146(4). http://dx.doi.org/10.1061/(asce)ey.1943-7897.0000677.
[112] Afroz Z, Urmee T, Shafiullah G, Higgins G. Real-time prediction model for indoor temperature in a commercial building. Appl Energy 2018;231:29–53.
[113] Afroz Z, Shafiullah G, Urmee T, Higgins G. Prediction of indoor temperature in an institutional building. Energy Procedia 2017;142:1860–6.
[114] Amasyali K, El-Gohary NM. A review of data-driven building energy consumption prediction studies. Renew Sustain Energy Rev 2018;81:1192–205.
[115] Tien PW, Wei S, Calautit JK, Darkwa J, Wood C. Occupancy heat gain detection and prediction using deep learning approach for reducing building energy demand. J. Sustain. Dev. Energy Water Environ. Syst. 2021;9(3):1–31.
[116] Amber K, Ahmad R, Aslam M, Kousar A, Usman M, Khan MS. Intelligent techniques for forecasting electricity consumption of buildings. Energy 2018;157:886–93.
[117] Singaravel S, Suykens J, Geyer P. Deep-learning neural-network architectures and methods: Using component-based models in building-design energy prediction. Adv Eng Inform 2018;38:81–90.
[118] Doddi H, Talukdar S, Deka D, Salapaka M. Data-driven identification of a thermal network in multi-zone building. In: 2018 IEEE Conference on Decision and Control. CDC, IEEE; 2018, p. 7302–7.
[119] Kramer R, Van Schijndel J, Schellen H. Simplified thermal and hygric building models: A literature review. Front Archit Res 2012;1(4):318–25.
[120] Li A, Sun Y, Xu X. Development of a simplified resistance and capacitance (RC)-network model for pipe-embedded concrete radiant floors. Energy Build 2017;150:353–75.
[121] Guo Z, Coffman AR, Munk J, Im P, Barooah P. Identification of aggregate building thermal dynamic model and unmeasured internal heat load from data. In: 2019 IEEE 58th Conference on Decision and Control. CDC, IEEE; 2019, p. 2958–63.
[122] Smarra F, Jain A, De Rubeis T, Ambrosini D, D'Innocenzo A, Mangharam R. Data-driven model predictive control using random forests for building energy optimization and climate control. Appl Energy 2018;226:1252–72.
[123] Wani M, Hafiz F, Swain A, Ukil A. Estimating thermal parameters of a commercial building: A meta-heuristic approach. Energy Build 2021;231:110537.
[124] Ogunsola OT, Song L. Review and evaluation of using RC thermal modeling of cooling load prediction for HVAC system control purpose. In: ASME International Mechanical Engineering Congress and Exposition, vol. 45233. American Society of Mechanical Engineers; 2012, p. 735–43.
[125] Dewson T, Day B, Irving A. Least squares parameter estimation of a reduced order thermal model of an experimental building. Build Environ 1993;28(2):127–37.
[126] Zhang D, Xia X, Cai N. A dynamic simplified model of radiant ceiling cooling integrated with underfloor ventilation system. Appl Therm Eng 2016;106:415–22.
[127] Chen T, Athienitis A. Investigation of practical issues in building thermal parameter estimation. Build Environ 2003;38(8):1027–38.
[128] Unbehauen H, Rao G. A review of identification in continuous-time systems. Annu Rev Control 1998;22:145–71.
[129] Nelles O. Nonlinear dynamic system identification. In: Nonlinear System Identification. Springer; 2001, p. 547–77.
[130] Kim D, Cai J, Braun JE, Ariyur KB. System identification for building thermal systems under the presence of unmeasured disturbances in closed loop operation: Theoretical analysis and application. Energy Build 2018;167:359–69.
[131] Zhan S, Lei Y, Jin Y, Yan D, Chong A. Impact of occupant related data on identification and model predictive control for buildings. Appl Energy 2022;323:119580.
[132] Goyal S, Barooah P. A method for model-reduction of non-linear thermal dynamics of multi-zone buildings. Energy Build 2012;47:332–40.
[133] Deng K, Barooah P, Mehta PG, Meyn SP. Building thermal model reduction via aggregation of states. In: Proceedings of the 2010 American Control Conference. IEEE; 2010, p. 5118–23.
[134] Giretti A, Vaccarini M, Casals M, Macarulla M, Fuertes A, Jones R. Reduced-order modeling for energy performance contracting. Energy Build 2018;167:216–30.
[135] Antoulas AC, Sorensen DC, Gugercin S. A survey of model reduction methods for large-scale systems. Tech. Rep., 2000.
[136] Rabenstein R. Application of model reduction techniques to building energy simulation. Sol Energy 1994;53(3):289–99.
[137] Kim D, Braun JE. A general approach for generating reduced-order models for large multi-zone buildings. J Build Perform Simul 2015;8(6):435–48.
[138] Reynders G, Diriken J, Saelens D. Quality of grey-box models and identified parameters as function of the accuracy of input and observation signals. Energy Build 2014;82:263–74.
[139] Arendt K, Jradi M, Shaker HR, Veje C. Comparative analysis of white-, gray- and black-box models for thermal simulation of indoor environment: Teaching building case study. In: Proceedings of the 2018 Building Performance Modeling Conference and SimBuild Co-Organized By ASHRAE and IBPSA-USA, Chicago, IL, USA. 2018, p. 26–8.
[140] Verhelst C. Model predictive control of ground coupled heat pump systems in office buildings (modelgebaseerde regeling van grondgekoppelde warmtepompsystemen in kantoorgebouwen). 2012.
[141] Deb C, Schlueter A. Review of data-driven energy modelling techniques for building retrofit. Renew Sustain Energy Rev 2021;144:110990.
[142] Chi R, Lv Y, Huang B. Distributed iterative learning temperature control for multi-zone HVAC system. J Franklin Inst B 2020;357(2):810–31.
[143] Yao Y, Shekhar DK. State of the art review on model predictive control (MPC) in heating ventilation and air-conditioning (HVAC) field. Build Environ 2021;107952.
[144] Fang J, Ma R, Deng Y. Identification of the optimal control strategies for the energy-efficient ventilation under the model predictive control. Sustainable Cities Soc 2020;53:101908.
[145] Yu L, Sun Y, Xu Z, Shen C, Yue D, Jiang T, Guan X. Multi-agent deep reinforcement learning for HVAC control in commercial buildings. IEEE Trans Smart Grid 2020;12(1):407–19.
[146] Tian W, Han X, Zuo W, Wang Q, Fu Y, Jin M. An optimization platform based on coupled indoor environment and HVAC simulation and its application in optimal thermostat placement. Energy Build 2019;199:342–51.
[147] Homod RZ, Gaeid KS, Dawood SM, Hatami A, Sahari KS. Evaluation of energy-saving potential for optimal time response of HVAC control system in smart buildings. Appl Energy 2020;271:115255.
[148] Raman NS, Devaprasad K, Chen B, Ingley HA, Barooah P. MPC for energy efficient HVAC control with humidity and latent heat considerations. 2019, arXiv preprint arXiv:1903.04652.
[149] Li Y, Tong Z. Development of real-time adaptive model-free extremum seeking control for CFD-simulated indoor thermal environment. Sustainable Cities Soc 2021;103166.
[150] Saletti C, Gambarotta A, Morini M. Development, analysis and application of a predictive controller to a small-scale district heating system. Appl Therm Eng 2020;165:114558.
[151] Drgoa J, Picard D, Helsen L. Cloud-based implementation of white-box model predictive control for a GEOTABS office building: A field test demonstration. J Process Control 2020;88:63–77.
[152] Lefebure N, Khosravi M, Badyn MH, Bünning F, Lygeros J, Jones C, Smith RS. Distributed model predictive control of buildings and energy hubs. Energy Build 2022;259:111806.
[153] Christofides PD, Scattolini R, de la Pena DM, Liu J. Distributed model predictive control: A tutorial review and future research directions. Comput Chem Eng 2013;51:21–41.
[154] Eini R, Abdelwahed S. Distributed model predictive control based on goal coordination for multi-zone building temperature control. In: 2019 IEEE Green Technologies Conference (GreenTech). IEEE; 2019, p. 1–6.

[155] Schreiber T, Netsch C, Eschweiler S, Wang T, Storek T, Baranski M, Müller D. Application of data-driven methods for energy system modelling demonstrated on an adaptive cooling supply system. Energy 2021;230:120894.
[156] Karg B, Lucia S. Reinforced approximate robust nonlinear model predictive control. In: 2021 23rd International Conference on Process Control. PC, IEEE; 2021, p. 149–56.
[157] Lymperopoulos G, Ioannou P. Distributed adaptive control of multi-zone HVAC systems. In: 2019 27th Mediterranean Conference on Control and Automation. MED, IEEE; 2019, p. 553–8.
[158] Zhang X, Shi W, Yan B, Malkawi A, Li N. Decentralized and distributed temperature control via HVAC systems in energy efficient buildings. 2017, arXiv preprint arXiv:1702.03308.
[159] Elnour M, Meskin N. Multi-zone HVAC control system design using feedback linearization. In: 2017 5th International Conference on Control, Instrumentation, and Automation. ICCIA, IEEE; 2017, p. 249–54.
[160] Mei J, Xia X. Multi-zone building temperature control and energy efficiency using autonomous hierarchical control strategy. In: 2018 IEEE 14th International Conference on Control and Automation. ICCA, IEEE; 2017, p. 884–9.
[161] Raman NS, Devaprasad K, Chen B, Ingley HA, Barooah P. Model predictive control for energy-efficient HVAC operation with humidity and latent heat considerations. Appl Energy 2020;279:115765.
[162] Srivaths Raman N, Umashankar Chaturvedi R, Guo Z, Barooah P. MPC-based hierarchical control of a multi-zone commercial HVAC system. 2021, arXiv E-Prints, arXiv:2102.02914.
[163] Yang S, Wan MP, Chen W, Ng BF, Zhai D. An adaptive robust model predictive control for indoor climate optimization and uncertainties handling in buildings. Build Environ 2019;163:106326.
[164] Vellei M, Herrera M, Fosas D, Natarajan S. The influence of relative humidity on adaptive thermal comfort. Build Environ 2017;124:171–85.
[165] Yang S, Wan MP, Chen W, Ng BF, Dubey S. Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization. Appl Energy 2020;271:115147.
[166] Li X, Han Z, Zhao T, Zhang J, Xue D. Modeling for indoor temperature prediction based on time-delay and elman neural network in air conditioning system. J Build Eng 2021;33:101854.
[167] Sutton RS, Barto AG. Reinforcement Learning: An Introduction. MIT Press; 2018.
[168] Zhou Y, Zheng S. Machine-learning based hybrid demand-side controller for high-rise office buildings with high energy flexibilities. Appl Energy 2020;262:114416.
[169] Wei T, Wang Y, Zhu Q. Deep reinforcement learning for building HVAC control. In: Proceedings of the 54th Annual Design Automation Conference 2017. 2017, p. 1–6.
[170] Gao G, Li J, Wen Y. Energy-efficient thermal comfort control in smart buildings via deep reinforcement learning. 2019, arXiv preprint arXiv:1901.04693.
[171] Han M, May R, Zhang X, Wang X, Pan S, Yan D, Jin Y, Xu L. A review of reinforcement learning methodologies for controlling occupant comfort in buildings. Sustainable Cities Soc 2019;51:101748.
[172] Nagarathinam S, Menon V, Vasan A, Sivasubramaniam A. MARCO-multi-agent reinforcement learning based control of building hvac systems. In: Proceedings of the Eleventh ACM International Conference on Future Energy Systems. 2020, p. 57–67.
[173] Da Silva FL, Glatt R, Costa AHR. MOO-MDP: an object-oriented representation for cooperative multiagent reinforcement learning. IEEE Trans Cybern 2017;49(2):567–79.
[174] Zhang X, Biagioni D, Cai M, Graf P, Rahman S. An edge-cloud integrated solution for buildings demand response using reinforcement learning. IEEE Trans Smart Grid 2020;12(1):420–31.
[175] Zhang Z, Chong A, Pan Y, Zhang C, Lam KP. Whole building energy model for HVAC optimal control: A practical framework based on deep reinforcement learning. Energy Build 2019;199:472–90.
[176] Nagy A, Kazmi H, Cheaib F, Driesen J. Deep reinforcement learning for optimal control of space heating. 2018, arXiv preprint arXiv:1805.03777.
[177] Hanumaiah V, Genc S. Distributed multi-agent deep reinforcement learning framework for whole-building hvac control. 2021, arXiv preprint arXiv:2110.13450.
[178] Lei Y, Zhan S, Ono E, Peng Y, Zhang Z, Hasama T, Chong A. A practical deep reinforcement learning framework for multivariate occupant-centric control in buildings. Appl Energy 2022;324:119742.
[179] Sakuma Y, Nishi H. Airflow direction control of air conditioners using deep reinforcement learning. In: 2020 SICE International Symposium on Control Systems (SICE ISCS). IEEE; 2020, p. 61–8.
[180] Yoon YR, Moon HJ. Performance based thermal comfort control (PTCC) using deep reinforcement learning for space cooling. Energy Build 2019;203:109420.
[181] Du Y, Zandi H, Kotevska O, Kurte K, Munk J, Amasyali K, Mckee E, Li F. Intelligent multi-zone residential HVAC control strategy based on deep reinforcement learning. Appl Energy 2021;281:116117.
[182] Arroyo J, Manna C, Spiessens F, Helsen L. Reinforced model predictive control (RL-MPC) for building energy management. Appl Energy 2022;309:118346.
[183] Chen B, Cai Z, Bergés M. Gnu-rl: A practical and scalable reinforcement learning solution for building hvac control using a differentiable mpc policy. Front Built Environ 2020;6:562239.
[184] Ma N, Aviv D, Guo H, Braham WW. Measuring the right factors: A review of variables and models for thermal comfort and indoor air quality. Renew Sustain Energy Rev 2021;135:110436.
[185] Peng Y, Rysanek A, Nagy Z, Schlüter A. Occupancy learning-based demand-driven cooling control for office spaces. Build Environ 2017;122:145–60.
[186] Khan DS, Kolarik J, Hviid CA, Weitzmann P. Method for long-term mapping of occupancy patterns in open-plan and single office spaces by using passive-infrared (PIR) sensors mounted below desks. Energy Build 2021;230:110534.
[187] Sun Y, Gu L, Wu CJ, Augenbroe G. Exploring HVAC system sizing under uncertainty. Energy Build 2014;81:243–52.
[188] D'Oca S, Hong T, Langevin J. The human dimensions of energy use in buildings: A review. Renew Sustain Energy Rev 2018;81:731–42.
[189] Azar E, Menassa CC. A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings. Energy Build 2012;55:841–53.
[190] Yang J, Santamouris M, Lee SE. Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings. Energy Build 2016;121:344–9.
[191] Dodier RH, Henze GP, Tiller DK, Guo X. Building occupancy detection through sensor belief networks. Energy Build 2006;38(9):1033–43.
[192] Xue Y, Zhao K, Qian Y, Ge J. Improved operating strategy for air-conditioning systems based on the indoor occupancy rate. J Build Eng 2020;29:101196.
[193] Choi J-H, Yeom D. Study of data-driven thermal sensation prediction model as a function of local body skin temperatures in a built environment. Build Environ 2017;121:130–47.
[194] Trofimova P, Cheshmehzangi A, Deng W, Hancock C. Post-occupancy evaluation of indoor air quality and thermal performance in a zero carbon building. Sustainability 2021;13(2):667.
[195] Jung W, Jazizadeh F. Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions. Appl Energy 2019;239:1471–508.
[196] Abuimara T, O'Brien W, Gunay B, Carrizo JS. How assumptions about occupants can misinform building design. ASHRAE J 2020;62(1):14–8.
[197] Menezes AC, Cripps A, Bouchlaghem D, Buswell R. Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. Appl Energy 2012;97:355–64.
[198] O'Brien W, Abdelalim A, Gunay HB. Development of an office tenant electricity use model and its application for right-sizing HVAC equipment. J Build Perform Simul 2019;12(1):37–55.
[199] Salimi S, Hammad A. Critical review and research roadmap of office building energy management based on occupancy monitoring. Energy Build 2019;182:214–41.
[200] Niemann P, Schmitz G. Impacts of occupancy on energy demand and thermal comfort for a large-sized administration building. Build Environ 2020;182:107027.
[201] Mariano-Hernández D, Hernández-Callejo L, Zorita-Lamadrid A, Duque-Pérez O, Santos García F. A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis. J Build Eng 2021;33. http://dx.doi.org/10.1016/j.jobe.2020.101692.
[202] Ebadat A, Bottegal G, Varagnolo D, Wahlberg B, Johansson KH. Estimation of building occupancy levels through environmental signals deconvolution. In: Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings. 2013, p. 1–8.
[203] Javed A, Larijani H, Ahmadinia A, Gibson D. Smart random neural network controller for HVAC using cloud computing technology. IEEE Trans Ind Inf 2016;13(1):351–60.
[204] Dong B, Prakash V, Feng F, O'Neill Z. A review of smart building sensing system for better indoor environment control. Energy Build 2019;199:29–46.
[205] Ahmad J, Larijani H, Emmanuel R, Mannion M, Javed A. Occupancy detection in non-residential buildings–a survey and novel privacy preserved occupancy monitoring solution. Appl Comput Inform 2020.
[206] Chen Z, Jiang C, Xie L. Building occupancy estimation and detection: A review. Energy Build 2018;169:260–70.
[207] Salimi S, Liu Z, Hammad A. Occupancy prediction model for open-plan offices using real-time location system and inhomogeneous Markov chain. Build Environ 2019;152:1–16.
[208] Mylonas A, Kazanci OB, Andersen RK, Olesen BW. Capabilities and limitations of wireless CO2, temperature and relative humidity sensors. Build Environ 2019;154:362–74.
[209] Wolf S, Calì D, Krogstie J, Madsen H. Carbon dioxide-based occupancy estimation using stochastic differential equations. Appl Energy 2019;236:32–41.
[210] Rueda L, Agbossou K, Cardenas A, Henao N, Kelouwani S. A comprehensive review of approaches to building occupancy detection. Build Environ 2020;180:106966.
[211] Ekwevugbe T, Brown N, Pakka V, Fan D. Improved occupancy monitoring in non-domestic buildings. Sustainable Cities Soc 2017;30:97–107.
[212] Zou H, Zhou Y, Yang J, Spanos CJ. Device-free occupancy detection and crowd counting in smart buildings with WiFi-enabled IoT. Energy Build 2018;174:309–22.

[213] Trivedi D, Badarla V. Occupancy detection systems for indoor environments: A survey of approaches and methods. Indoor Built Environ 2020;29(8):1053–69.
[214] Azimi S, O'Brien W. Fit-for-purpose: Measuring occupancy to support commercial building operations: A review. Build Environ 2022;108767.
[215] Sun K, Zhao Q, Zou J. A review of building occupancy measurement systems. Energy Build 2020;216:109965.
[216] Pedersen TH, Nielsen KU, Petersen S. Method for room occupancy detection based on trajectory of indoor climate sensor data. Build Environ 2017;115:147–56.
[217] Ebadat A, Bottegal G, Varagnolo D, Wahlberg B, Johansson KH. Regularized deconvolution-based approaches for estimating room occupancies. IEEE Trans Autom Sci Eng 2015;12(4):1157–68.
[218] Candanedo LM, Feldheim V. Accurate occupancy detection of an office room from light, temperature, humidity and CO2 measurements using statistical learning models. Energy Build 2016;112:28–39.
[219] Wang S, Jin X. CO2-based occupancy detection for on-line outdoor air flow control. Indoor Built Environ 1998;7(3):165–81.
[220] Jiang C, Masood MK, Soh YC, Li H. Indoor occupancy estimation from carbon dioxide concentration. Energy Build 2016;131:132–41.
[221] Calì D, Matthes P, Huchtemann K, Streblow R, Müller D. CO2 based occupancy detection algorithm: Experimental analysis and validation for office and residential buildings. Build Environ 2015;86:39–49.
[222] Ding Y, Han S, Tian Z, Yao J, Chen W, Zhang Q. Review on occupancy detection and prediction in building simulation. In: Building Simulation. Springer; 2021, p. 1–24.
[223] Wahl F, Milenkovic M, Amft O. A distributed PIR-based approach for estimating people count in office environments. In: 2012 IEEE 15th International Conference on Computational Science and Engineering. IEEE; 2012, p. 640–7.
[224] Shetty SS, Chinh HD, Gupta M, Panda SK. User presence estimation in multi-occupancy rooms using plug-load meters and PIR sensors. In: GLOBECOM 2017-2017 IEEE Global Communications Conference. IEEE; 2017, p. 1–6.
[225] Guo X, Tiller D, Henze G, Waters C. The performance of occupancy-based lighting control systems: A review. Lighting Res Technol 2010;42(4):415–31.
[226] Soltani MM, Motamedi A, Hammad A. Enhancing cluster-based RFID tag localization using artificial neural networks and virtual reference tags. Autom Constr 2015;54:93–105.
[227] Delaney DT, O'Hare GM, Ruzzelli AG. Evaluation of energy-efficiency in lighting systems using sensor networks. In: Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings. 2009, p. 61–6.
[228] Mutis I, Ambekar A, Joshi V. Real-time space occupancy sensing and human motion analysis using deep learning for indoor air quality control. Autom Constr 2020;116:103237.
[229] Wu L, Wang Y. A low-power electric-mechanical driving approach for true occupancy detection using a shuttered passive infrared sensor. IEEE Sens J 2018;19(1):47–57.
[230] Zou J, Zhao Q, Yang W, Wang F. Occupancy detection in the office by analyzing surveillance videos and its application to building energy conservation. Energy Build 2017;152:385–98.
[231] Conti F, Pullini A, Benini L. Brain-inspired classroom occupancy monitoring on a low-power mobile platform. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2014, p. 610–5.
[232] Kraft M, Aszkowski P, Pieczyński D, Fularz M. Low-cost thermal camera-based counting occupancy meter facilitating energy saving in smart buildings. Energies 2021;14(15):4542.
[233] Callemein T, Van Beeck K, Goedemé T. Anyone here? Smart embedded low-resolution omnidirectional video sensor to measure room occupancy. In: 2019 18th IEEE International Conference on Machine Learning and Applications. ICMLA, IEEE; 2019, p. 1993–2000.
[234] Meng Y-b, Li T-y, Liu G-h, Xu S-j, Ji T. Real-time dynamic estimation of occupancy load and an air-conditioning predictive control method based on image information fusion. Build Environ 2020;173:106741.
[235] Naylor S, Gillott M, Lau T. A review of occupant-centric building control strategies to reduce building energy use. Renew Sustain Energy Rev 2018;96:1–10.
[236] Choi H, Um CY, Kang K, Kim H, Kim T. Application of vision-based occupancy counting method using deep learning and performance analysis. Energy Build 2021;252:111389.
[237] Ahmed I, Ahmad A, Piccialli F, Sangaiah AK, Jeon G. A robust features-based person tracker for overhead views in industrial environment. IEEE Internet Things J 2017;5(3):1598–605.
[238] García J, Gardel A, Bravo I, Lázaro JL, Martínez M, Rodríguez D. Directional people counter based on head tracking. IEEE Trans Ind Electron 2012;60(9):3991–4000.
[239] Sun K, Zhao Q, Zhang Z, Hu X. Indoor occupancy measurement by the fusion of motion detection and static estimation. Energy Build 2022;254:111593.
[240] Cho SI. Vision-based people counter using CNN-based event classification. IEEE Trans Instrum Meas 2019;69(8):5308–15.
[241] Ahmed I, Adnan A. A robust algorithm for detecting people in overhead views. Cluster Comput 2018;21(1):633–54.
[242] Petersen S, Pedersen TH, Nielsen KU, Knudsen MD. Establishing an image-based ground truth for validation of sensor data-based room occupancy detection. Energy Build 2016;130:787–93.
[243] Yang Y, Srinivasan S, Hu G, Spanos CJ. Distributed control of multizone HVAC systems considering indoor air quality. IEEE Trans Control Syst Technol 2021.
[244] Shahnazari H, Mhaskar P, House JM, Salsbury TI. Heating, ventilation and air conditioning systems: Fault detection and isolation and safe parking. Comput Chem Eng 2018;108:139–51.
[245] Png E, Srinivasan S, Bekiroglu K, Chaoyang J, Su R, Poolla K. An internet of things upgrade for smart and scalable heating, ventilation and air-conditioning control in commercial buildings. Appl Energy 2019;239:408–24.
[246] Afram A, Fung AS, Janabi-Sharifi F, Raahemifar K. Development and performance comparison of low-order black-box models for a residential HVAC system. J Build Eng 2018;15:137–55.
[247] Ioannou P, Lymperopoulos G. Distributed adaptive control of a multi-zone hvac system. 2020, US Patent App. 16/797, 218.
[248] Yu L, Xie D, Huang C, Jiang T, Zou Y. Energy optimization of HVAC systems in commercial buildings considering indoor air quality management. IEEE Trans Smart Grid 2018;10(5):5103–13.
[249] Altayeva A, Omarov B, Im Cho Y. Towards smart city platform intelligence: PI decoupling math model for temperature and humidity control. In: 2018 IEEE International Conference on Big Data and Smart Computing (BigComp). IEEE; 2018, p. 693–6.
[250] Satyavada H, Baldi S. An integrated control-oriented modelling for HVAC performance benchmarking. J Build Eng 2016;6:262–73.
[251] Zhang Z, Lam KP. Practical implementation and evaluation of deep reinforcement learning control for a radiant heating system. In: Proceedings of the 5th Conference on Systems for Built Environments. 2018, p. 148–57.
[252] Nagy Z, Henze G, Dey S, Arroyo J, Helsen L, Zhang X, Chen B, Amasyali K, Kurte K, Zamzam A, et al. Ten questions concerning reinforcement learning for building energy management. Build Environ 2023;110435.