Renewable and Sustainable Energy Reviews 142 (2021) 110835

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

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

Data requirements and performance evaluation of model predictive control in buildings: A modeling perspective

Sicheng Zhan, Adrian Chong *

Department of Building, School of Design and Environment, National University of Singapore, 4 Architecture Drive, Singapore, 117566, Singapore

ARTICLE INFO

Keywords:
Model predictive control
Control-oriented model
Data requirements
Level of detail
Performance evaluation
Model identification

ABSTRACT

Model predictive control (MPC) has shown great potential in improving building performance and saving energy. However, after over 20 years of research, it is yet to be adopted by the industry. The difficulty of obtaining a sufficient control-oriented model is one major factor that hinders the application. In particular, what data is required to build the model and what control performance can be expected with a certain model remain unclear. This study attempts to uncover the underlying reasons and guide future research to tackle the challenges. It starts by clarifying a finer categorization of past studies with respect to both modeling methods and modeling purposes. An extended Level of Detail (LoD) framework is proposed to quantify the data usage in each study. Accordingly, meta-analyses are conducted to compare the data requirements of different modeling categories. The criteria and approaches for model performance evaluation are summarized and classified into validation and verification methods, followed by a discussion about the relationship between the model and control performance. The critical review provides new perspectives on the data requirements and performance evaluation of control-oriented models. Ultimately, the paper concludes with five directions for future research to bridge the gaps between data requirements, model performance, and control performance.

1. Introduction

1.1. MPC and control-oriented models

Buildings take up 30–40% of global greenhouse gas emission and energy consumption [1], among which up to 85% is consumed in the operation phase [2]. Building system control is a challenging task because of the varying system dynamics and disturbances. At present, PID control are mostly used in practice, yielding the unsatisfactory performance if not well-tuned and the absence of multi-objective supervisory control [3]. These suggest the great energy-saving potential of implementing advanced optimal control schemes.

Model Predictive Control (MPC) was first applied for industrial process control [4] and has been tested in buildings since the 1990s [5,6]. It is capable of adapting different system dynamics and disturbances, improving the thermal comfort conditions and energy performance simultaneously. The benefits are more prominent when the control task goes beyond setpoint tracking, such as occupancy-based control [7] or Demand Response (DR) applications [8]. However, not many actual implementation cases are spotted over the years, which can be attributed to the relatively high requirements on modeling, expertise, data, hardware, usability, and costs [9,10]. Reducing the modeling effort and enhancing the model reliability are still essential problems to tackle.

Fig. 1 displays the typical framework of MPC. Three main processes are involved in obtaining the control decision: disturbance forecast, control-oriented model, and optimization. While all the three processes are essential, the control-oriented model has been acknowledged as the cornerstone of MPC [11,12]. Disturbance forecast provides the boundary condition for the control-oriented model over the prediction horizon, such as ambient conditions [13], occupant presence [14], and energy prices [15]. Under the boundary condition, the control-oriented model predicts the building's thermal response and energy performance with different control decisions. Based on the model, optimization is applied to identify the optimal control decision. According to the modeling purposes and methods, building metadata and/or time series training data may be needed for model identification. The optimization problem is defined by the objective function and the constraints, which are recently categorized in Ref. [16]. Different optimization algorithms may be selected depending on the problem formulation and the model

* Corresponding author.
E-mail address: adrian.chong@nus.edu.sg (A. Chong).

https://doi.org/10.1016/j.rser.2021.110835
Received 26 July 2020; Received in revised form 24 January 2021; Accepted 15 February 2021
Available online 5 March 2021
1364-0321/

derivability [17]. To facilitate the optimization, a desirable model is expected to have a simplified structure and high accuracy, requiring less calibration and computational cost and maintaining certain physical significance [18].

1.2. Past reviews and research gaps

To procure a satisfactory model is one of the main barriers to implementing MPC in buildings. As reported in Henze [19], building and calibrating the models account for 70% of the total effort. In fact, it is not just modeling that is hard, but assessing the difficulty in advance as well [11]. Due to the importance and difficulty of this process, extensive research has been trying to tackle the challenge. Many review studies in the past few years have discussed relevant issues. Fundamentally, the modeling methods are usually categorized into physical-based (white-box), data-driven (black-box) and hybrid (gray-box) models [9,11,20]. In addition to that, Li & Wen [12] covered the mechanism of different building thermal response models, as well as models of energy storage and generation systems. Afram & Janabi-Sharifi [21] summarized the specific modeling techniques used in each of the three categories and introduced the general process from model creation to evaluation. Mirakhorli & Dong [7] outlined the optimization techniques used corresponding to different modeling methods. Hilliard et al. [17] categorized the modeling methods by different spatial scales and listed the inputs and outputs of representative studies. Atam & Helsen [22] reviewed and compared different modeling methods, specifically for Ground Source Heat Pumps (GSHP). Afram et al. [23] reviewed the data collection and handling issues specifically for the Artificial Neural Networks (ANN) models. Rockett & Hathway [24] talked about the effect of model update, occupancy uncertainty, and data handling on the model and control performance from a practical point of view. Afroz et al. [20] defined the physical processes in the physical models of different sub-systems, classified the sub-categories of black-box models (also covered in Ref. [8]), and elaborated the pros and cons of the three fundamental categories. The comparison is conducted with respect to prediction accuracy, generalization capability, training data requirement, and complexity. Serale et al. [25] separated the white-box models into detailed simulation models and reduced-order models, and also differentiated the models as building, HVAC systems, and building with HVAC systems. Fontenot & Dong [16] specified the main challenges in modeling as the high complexity of thermal models, and the uncertainties in disturbances. Pallonetto et al. [26] also distinguished the detailed and simplified white box, and thoroughly discussed the features and calibration issues of detailed simulation models.

There are three major gaps in the existing review studies. First, despite the model's well-known crucial role, a holistic review on model performance evaluation and its relationship with the control performance is missing. Model performance refers to the authenticity of control-oriented models, which is usually evaluated by the prediction accuracy. In the meantime, it is also deemed to be necessary that the models represent the building dynamics for better extrapolation capabilities [27]. Control performance is reflected in the control results, such as energy consumption, thermal comfort, and the like. Model and control performance were shown closely related [28], but no quantitative relationship has been established.

Besides, the comparison of modeling methods is conducted mainly across the three fundamental categories. However, variations exist within the same category in terms of, for instance, data usage and prediction performance. For example, while black-box models are generally considered to be more accurate, different modeling techniques could result in up to 100% difference in prediction accuracy [29]. Also, gray-box models are declared to require less building metadata than white-box models and less training data than black-box models. Yet, depending on different modeling purposes and model fidelity, gray-box models can use extensive metadata [30] or training data [31].

Moreover, current discussions among different modeling methods are conceptual and qualitative. The lack of quantitative investigation leaves the modeling challenges unresolved. Hence, this study aims to promote the application of MPC in buildings by shedding some light on the modeling-related issues, specifically, two research questions:

- **What is the necessary and desirable data to build a satisfactory control-oriented model?** With the increasing deployment of building information modeling (BIM) and building management systems (BMS), much more data is being generated over the building life cycle, exerting a big challenge on data management and utilization [32]. For MPC, among the numerous potentially useful data, what is really needed to build a satisfactory model remains an open question. Therefore, a framework to quantify the data usage in different studies is needed to enable future studies and improve the generalization capability.
- **What is the minimum performance requirement of a control-oriented model?** Root Mean Square Error (RMSE) is a typical metric that quantifies models' prediction error, which has been shown insufficient to inform the control performance [33]. Meanwhile, there are other approaches and metrics for model evaluation. On the other hand, only few studies have focused on how the model performance would affect the control performance [33,34]. Thus, future research towards this direction could benefit from a systematic review and a deeper understanding of the model and controller performance evaluation.

1.3. Scope and structure

This paper gives a critical review on studies related to the control-oriented models used for MPC in buildings, mainly from the perspective of data requirements and performance evaluation. Section 2 presents a new model categorization regarding modeling purposes and

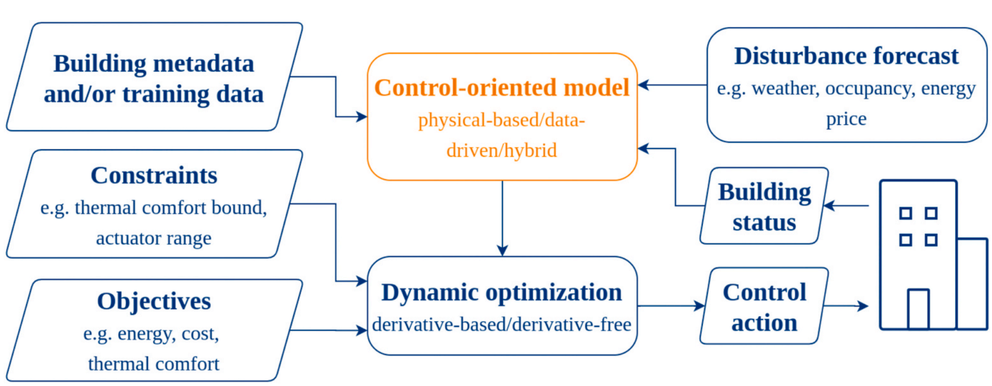

Fig. 1. Typical MPC framework, control-oriented model as the cornerstone.

modeling methods. Section 3 proposes a novel Level of Detail (LoD) framework to quantify the data usage in model identification and conducts meta-analyses about the data requirements of different model categories. Then, existing methods and conclusions of model and controller performance evaluation are reviewed in section 4. Section 5 discusses the major findings in this review and future research directions. Finally, the study is concluded in section 6.

2. Model categorization

Past studies are first categorized according to the model types to facilitate further analysis on data requirements and performance evaluation. In addition to the widely-accepted modeling method categorization of white/gray/black-box, another dimension of modeling purposes is added to differentiate what the model predicts as load prediction/thermal response/system performance. In this section, representative studies are selected in each category to clarify the definitions and variations.

2.1. Modeling methods

The mechanisms and technical details of different modeling methods have been covered in several review papers [12,16,20]. These studies classified model types based on the physical/hybrid/data-driven model structures. Meanwhile, it is important to note the distinctions regarding the data requirements. Table 1 summarizes the extended definitions of white/gray/black-box models and their corresponding properties.

2.1.1. White-box models

White-box models, also known as physics-based models, are based on equations that describe the fundamental heat and mass balance, where the parameters are decided by domain knowledge, system specifications, and actual measurements. In some cases, this category refers to those well-established building simulation software that requires substantial metadata such as Energyplus [35,36]. As opposed to other models that are built explicitly for control [37], those models are not ideal for forming standard optimization problems. However, with the presence of derivative-free optimization methods such as Genetic Algorithm (GA) [38] and Particle Swarm Optimization (PSO) [39], and tools like JModelica [40], these programs are also applicable for MPC and therefore are considered in this study.

Still based on building metadata, simplified white-box models are developed to be more suitable for optimization. There are three kinds of approaches: physical inference, model reduction, and simulation-assisted identification. OptiControl is the most famous project using physical inference, where a thermal network model was built for an office building, and the parameters were decided according to the specifications [41]. Due to the nonlinear nature of the resulting model, it was linearized at each time step, and Sequential Linear Programming was applied for control optimization [13]. This process of model construction and parameter inference is not intuitive, so automation tools have been built [42,43].

Model reduction is applied to reduce the complexity or the number of states of the full-order models so that the computational cost is reduced with the expense of accuracy loss. This is a critical step to make the optimization problem tractable, especially when it comes to multi-zone complex buildings [44]. Typical methods include Linear Approximation [45], Balanced Truncation [46], Singular Decomposition [47], and Proper Generalized Decomposition [48]. To maintain the physical structure in the reduced model, aggregation method [49] and iterative trimming [50] were proposed. Considering the trade-off between model complexity and accuracy, the minimum model complexity should be preserved [34,51].

Simulation-assisted identification uses high-fidelity models to generate data for simplified model identification [52,53]. It is important to note the difference between these simulation-assisted identification studies and simulation studies that use a high-fidelity model as a virtual testbed to test the proposed gray or black-box model. The difference is on the assumption that whether the detailed model is available in real applications, in other words, what information is initially used to obtain the controller model. In this sense, while the thermal network model structure, also known as the resistor-capacitor (RC) or lumped parameter model, is more famous as a gray-box approach [54], it should be considered a white-box if the parameters are determined by building metadata.

2.1.2. Gray-box models

Gray-box models are typically based on the thermal network (RC) model structure, using time series training data to identify the parameters [37]. There is no consensus on the optimal model complexity, i.e. the number of R and C used to represent the building. While lower-order models may not be able to catch the thermal dynamics, higher-order model may reduce the parameter identifiability and lead to overfitting problems [33]. Therefore, the model complexity is usually decided on a case-by-case basis and varies a lot. For instance, a 4R2C model was used to simplify the whole campus [55], yet a 6R2C model was applied to represent a single room [56]. Note that the RC models were transformed into a State Space Model (SSM) form in many studies [57–59]. Compared with the SSM identified by Subspace State Space System Identification (4SID) [60], they are still gray-box models as the parameters have their physical meaning.

Algorithms used for parameter identification include Maximum Likelihood Estimation (MLE) [10], Least Squares [61,62], Interior Point [56], GA [63], PSO [64], Non-Linear Programming (NLP) [65], agent-based [66], and MPC Relevant Identification (MRI) [67]. Complementarily, properly define the initial guesses and bounds for the parameters can improve the identification results [33]. The time series data used for identification can be classified into real operation data and designed excitation data. Excitation experiments apply designed input signals such as Pseudo-Random Binary Sequence (PRBS) [68] and step function [69]. Having the opportunity to explore a wider range and decompose the coupled thermal effects, the experiments do not guarantee the thermal comfort and therefore is costly and intrusive. For real operation data, MRI was shown to be able to compensate for the poor quality or excitation [27].

2.1.3. Black-box models

The model structures used for black-box modeling are more diversified than the previous two categories, including linear regression [70], decision tree regression [71], SSM [72], Autoregressive Exogenous

Table 1
Characteristics of the three modeling methods.

Modeling methods	Definitions		Properties	
	Model structure	*Data requirements*	*Calibration/identification effort*[a]	*Optimization cost*
White-box	physics/simplified physics	building metadata	high	low - high[b]
Gray-box	simplified physics	metadata & time series data	medium	low
Black-box	machine learning, statistical, etc.	time series data	low	low - high[b]

[a] Qualitative need of expert knowledge and human interference when calibrating/identifying the models.
[b] Depending on model structure. Optimization cost is low when derivative-based is applicable.

(ARX) type models [73,74], Support Vector Machine (SVM) [75], Artificial Neural Networks (ANN) [76], and ensemble models [77,78]. Model complexity selection is required for models such as SSM [29], ARX [79] and ANN [80]. Similar to the gray-box models, too complex model could lead to overfitting [81]. Without the physical implication, black-box models generally have worse extensibility (extrapolation capability) [82]. Therefore, the training data is expected to cover the seasonal variation [20].

Though black-box models are claimed to be more suitable for large scale systems [52], control-oriented modeling for multi-zone complex buildings is still a challenge, regardless of the modeling methods [37]. Simply aggregating single-zone models to form a centralized model would lead to too many states and an intractable optimization problem [64]. On the other hand, decentralized models that neglect the thermal interaction between adjacent zones cannot guarantee the performance [83]. Thus, distributed MPC was proposed to take advantage of decoupled optimization while considering the thermal interaction [84]. Meanwhile, depending on the building's thermal characteristics, no significant difference was found between centralized and decentralized methods [85], or even a single zone approximation achieved similar performance [83].

2.2. Modeling purposes

Even within each of the three kinds of modeling methods, significant variations exist in the data requirements and performance evaluation. Therefore, the control-oriented models are further categorized by their purposes according to the predicted and controlled variables. Essentially, the three modeling purposes are differentiated by the underlying assumptions (Table 2).

2.2.1. Load prediction

In load prediction models, only the electricity or thermal load during the prediction horizon is predicted, assuming that ideal HVAC systems track temperature setpoints well. Load prediction models are mainly used for Demand Side Management (DSM) applications involving grid interaction [86] or thermal storage systems [55]. Cole et al. [87] built an Energyplus model and generated training data with perturbation to fit a quadratic model for power prediction. Ogunsola et al. [88] applied an RC model without the indoor temperature node based on the idealistic assumption. Time series models were used more often in this context [89,90]. Many grid-interactive studies emphasized the optimization and coordination between different sub-systems [26] and neglected the uncertainty in load prediction. Perfectly known load profiles with [91] or without [92] randomization are used for simulation, or even imitated in an experiment using a load bank of resistors [93].

2.2.2. Thermal response

Thermal response models consider the thermal response of buildings to incorporate thermal comfort in the optimization problem. The assumption of static or ideal HVAC system performance is still held. In these studies, the indoor thermal condition is predicted, given certain disturbances and control inputs. The trade-off between thermal comfort and energy consumption can be dealt with by a) including comfort violation in the optimization objectives [78] or b) applying thermal comfort constraints [94]. Ma et al. [73] demonstrated significant improvement in both energy performance and temperature setpoint tracking. West et al. [95] showed less energy consumption while maintaining a similar level of Predicted Percentage of Dissatisfied (PPD). More conservatively, Chen et al. [77] provided better thermal comfort by using more energy than a well-tuned Rule-Based Control (RBC). It is worth noting that while load prediction models are solely applicable for DSM studies, plenty of thermal response models were also used in DSM studies [10,70,96]. When necessary, the thermal comfort can be prioritized over fulfilling Demand Response (DR) requests [68].

2.2.3. System performance

In addition to the building thermal response, this category added detailed HVAC system performance models, bringing the benefit of further optimizing the system operating conditions. For example, Kusiak et al. [76] saved around 20% by avoiding unnecessary cooling and reheating, Coninck & Helsen [97] improved system performance by first using the system with higher efficiency, and Drgoňa et al. [98] achieved more than 50% energy saving by recirculating as much as possible hot water within the Thermally Activated Building System (TABS). Recently, Cupeiro Figueroa et al. [99] demonstrated the extra energy saving of having a nonlinear Coefficient of Performance (COP) model and a dynamic borefield model, compared with simpler static models. As more data and system dynamics are involved in this category, integrated modeling methods are sometimes used. In Ref. [69], 4SID was applied to identify the zone thermal response model, while semi-physical models were built for sub-systems' performance. By contrast, Coninck & Helsen [97] used an RC model for the thermal dynamics of an office and linear regression to fit the COP equation.

2.3. Categorization

113 studies about MPC in buildings during the past ten years were reviewed and categorized by their modeling purposes and methods (Table 3). 33 (27.9%) of the studies are actual experiments, which are also distinguished from the simulation-based studies in the table and Fig. 2. Five papers that used integrated models are assigned to two categories and counted twice, resulting in 118 models. Based on the categorization results, several observations can be summarized:

- Regarding modeling methods, white-box models have the largest population of 45, followed by gray-box (40) and then black-box (33). While the hybrid modeling method is considered promising with combined benefits of the other two, it is not adopted more frequently. Interestingly, considering only the experimental studies, the ranking becomes black-box (14), gray-box (12), and white-box (7). Black-box models being more welcome in actual experiments may be attributed to the extra domain knowledge requirements of the other two. The significantly lower percentage of experiments in white-box models affirms this. In general, none of the three methods shows the dominance in past studies.
- Among the three modeling purposes, thermal response accounts for the largest number of studies. This is because providing thermal comfort to occupants is one main function of the built environment, and therefore the thermal response is not negligible when optimizing control. On the other hand, HVAC system models are more data-intensive and make the optimization problems nonlinear and non-convex. Another potential reason is that this review mainly focuses on building-level modeling and control. Readers interested in more

Table 2
Characteristics of the three modeling purposes.

Modeling methods	Definitions		Properties	
	Predicted variables	*Assumptions*	*Data requirements*	*Applications*
Load prediction	electricity/thermal load	ideal temperature setpoint tracking	low	demand response, microgrid, etc.
Thermal response	building thermal response	static/ideal HVAC system performance	medium	microgrid, building level control, etc.
System performance	building load & thermal response	None	high	building/system level control

Table 3
Categorization of 113 papers according to model methods and model purposes.

Modeling purposes	Modeling methods		
	White-box	*Gray-box*	*Black-box*
Load prediction	[53,87,91–93,104]	[63,82,88], [55][a]	[86,89], [90,105][a]
Thermal response	,[13–15,34,38–40,42,44,46,47,49,50,52,96, 106–116], [94,117–121][a]	,,,,,,,,,,,[27,28,30,33,43,56–58,64,65,67,83,85,122–131], [10,59,61,62,95,97,132,133][a]	[68–71,77,79,81,84,134–138], [72,74, 78,80,139–141][a]
System performance	[99,142–146], [98][a]	[31,147], [66,69][a]	,,,,,,[29,76,148–151], [55,73,97,132, 152] [a]

[a] Demonstrated with actual experiments.

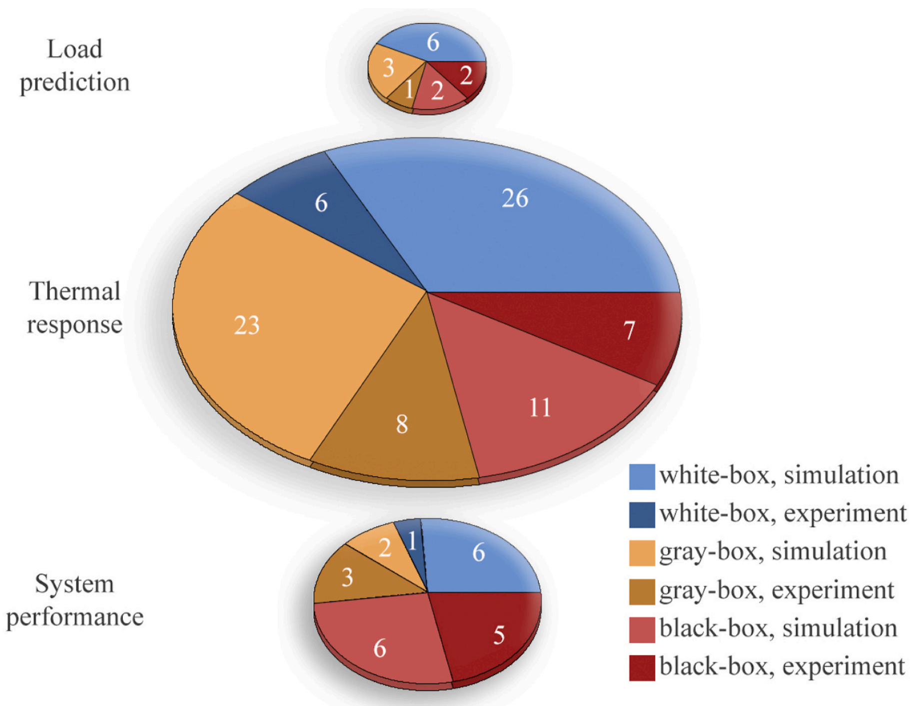

Fig. 2. Proportion of each category in the reviewed studies.

details about grid-level or system-level models are referred to these two review papers [16,100].

- The geographical distribution of these studies is displayed in Fig. 3, where the color overlays represent the main climate zones [101], triangles are simulation studies, and circles are experimental studies. Most (83.9%) studies are located in the temperate, especially cool temperate zones. Compared with the large population in North America and Europe, there might be great potential to exploit in the large area with a similar climate in Asia. One desired building characteristic for MPC, especially for load shifting applications, is higher thermal mass [102]. Therefore, the smaller number of studies in the tropical area is possibly due to the relatively lighter envelop. However, performance improvement is still achievable [30], and integrating renewable energy may bring better opportunities [103].
- Regarding the modeling and control scales, the proportions of the number of controlled zones are displayed in pie charts (Fig. 4). In total, 34.7% (41) studies are demonstrated in single zones, while only 16.9% (20) are full-scale applications. The lack of large-scale cases, regardless of simulation/experiment, agrees with Rockett & Hathway [24]. However, the ratio of full-scale demonstration increases to 35.5% considering only experiments, whereas 70.8% simulation studies used less than five zones.

3. Data requirements

Depending on the modeling methods and purposes, as well as building systems, different data or information is used to build the model. Data availability and resolution are critical for model calibration, for either white-box methods [153] or data-driven methods [154]. Meanwhile, data management and utilization have become a challenge with the increasingly available data over the building life cycles [32, 155]. Hence, a framework based on extended Level of Detail (LoD) is proposed to quantify and categorize data (including building metadata and time series data) used for modeling in past studies.

3.1. Definition of extended Level of detail

In the context of Building Information Models (BIM), Level of Detail (LoD), or Level of Development, defines and illustrates inputs and information requirements of the different levels for building elements. This clear articulation allows model authors to define what their models can be relied on for, and allows downstream users to clearly understand the usability and the limitations of models they are receiving [156]. The original theme of LoD aligns with the need for control-oriented models to clarify the required data and to further imply the performances. However, as illustrated in the left part of Fig. 5, the original LoD definition and some extension studies [157,158] all focused on the design and construction phases, considering the static characteristics of

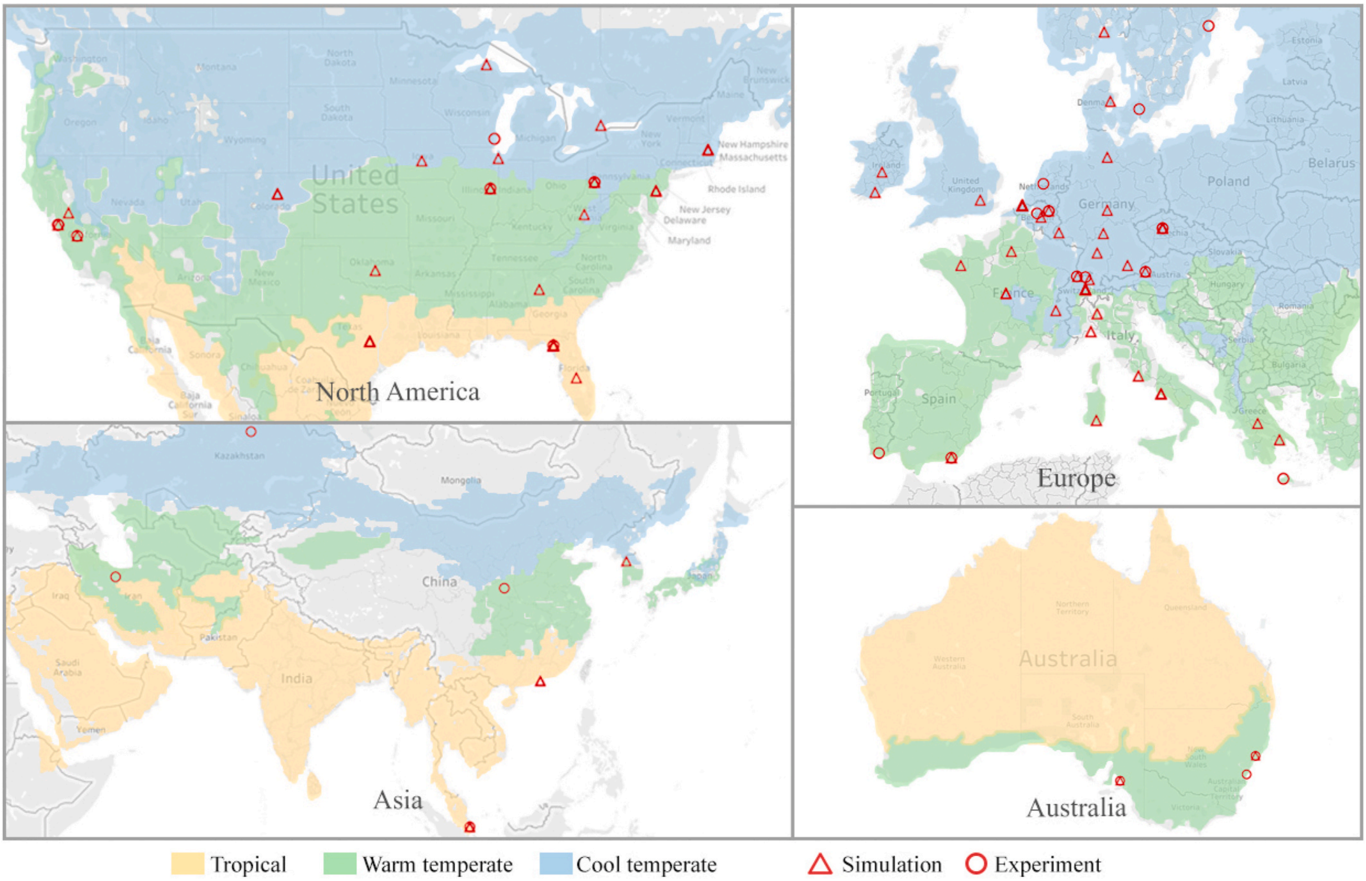

Fig. 3. Geographical distribution of the reviewed simulation and experiment studies. Color overlays reflect three main climate zones.

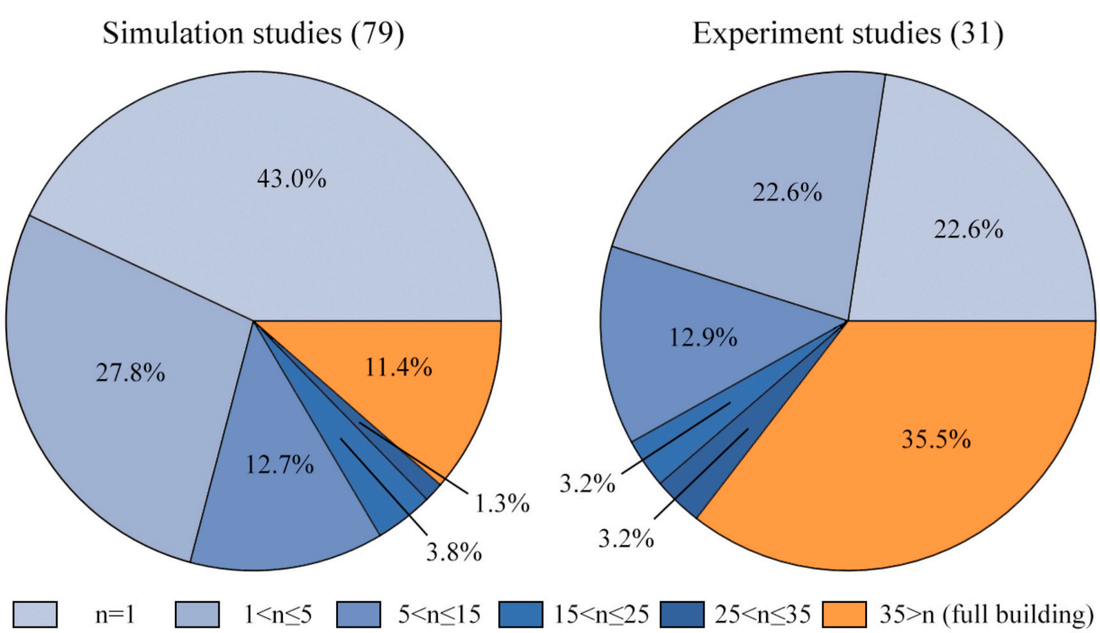

Fig. 4. Proportion of the number of controlled zones (n) in the reviewed studies. Full building applications are counted as >35.

building elements. Becerik-Gerber et al. [159] noted the increasing need for identifying non-geometric data requirements to apply BIM for facility management but overlooked the considerable variation in time series data.

This paper extends the original definition to take in time series sensor data used for MPC. The extended LoD inherits the original form of using three-digit numbers to describe certain levels, yet endowing every digit with an actual interpretation: time validity, measurement granularity, and temporal resolution. Fig. 6 displays the definitions and interpretations of each digit. The sankey flows denote possible

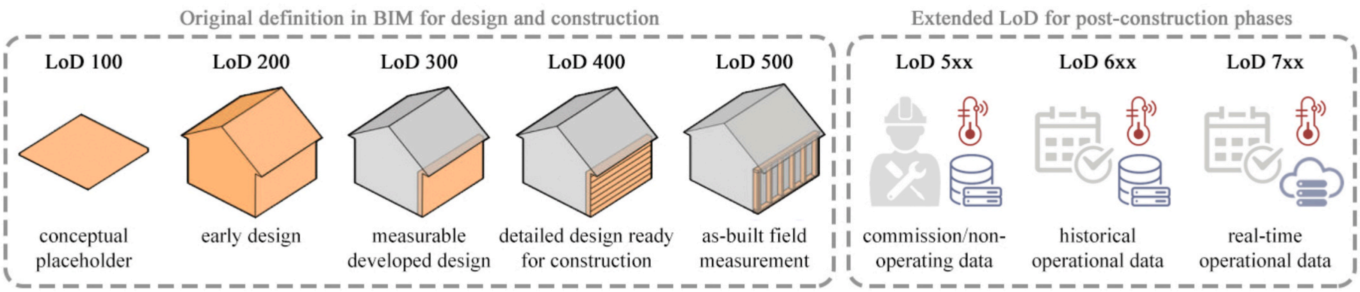

Fig. 5. The original LoD definition in BIM and the extended definition for time series sensor data.

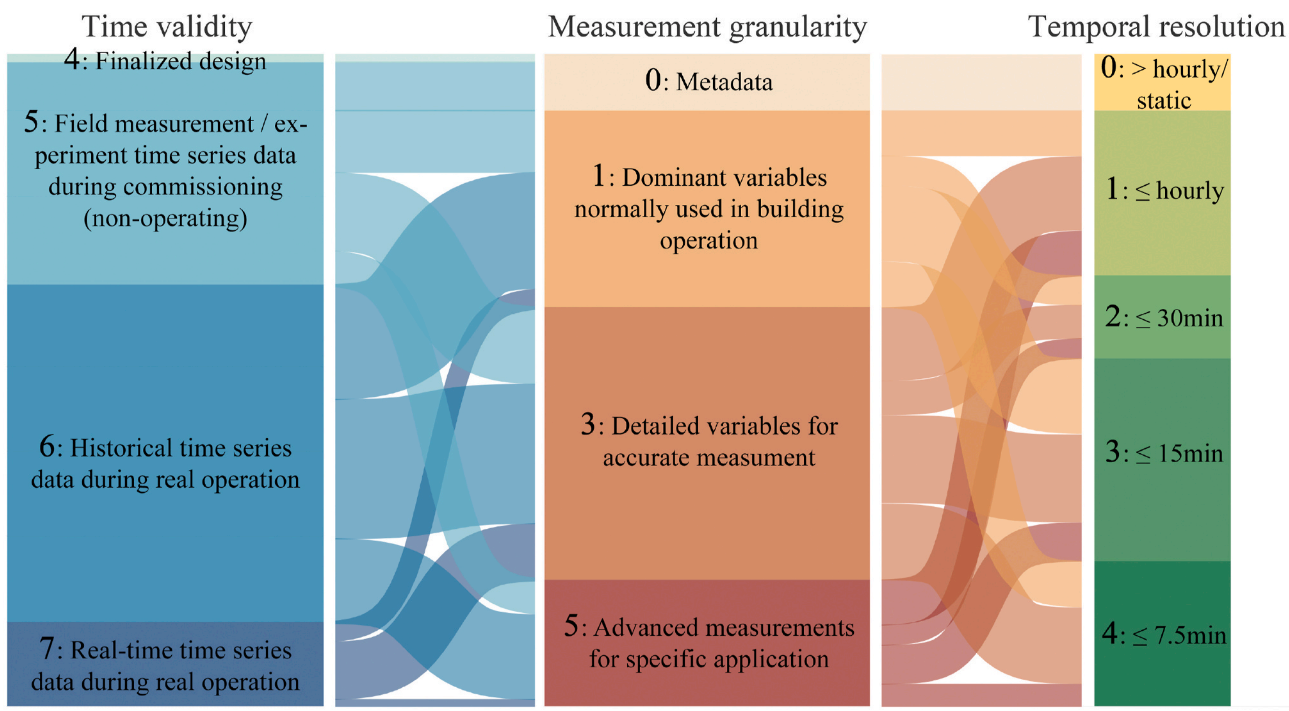

Fig. 6. Definition of the extended Level of Detail (LoD). The sankey flows represent the LoD levels appearing in the literature. The widths of Sankey flows and the heights of bars reflect the usage frequency of each possible level.

combinations of the three digits. Meanwhile, the usage frequencies of each LoD in the reviewed papers are reflected in the widths of sankey flows and the heights of bars. In general, larger LoD implies a higher cost of data acquisition. Apart from the sensor and operating costs, data storage, exchange, processing, and computing all introduce additional costs [160].

3.1.1. Time validity

The first digit represents the time validity of data, i.e., how up-to-date the data is. LoD 400 is simply adopted from BIM for building metadata as detailed and accurate design information, ready for construction. As an example, Kwak et al. [107] used design drawings to build an Energyplus model. Level 5 involves field measurement, including as-built metadata [14] and time series data from designed experiments [139]. The measurement is typically conducted during building commissioning or other non-operating periods to avoid intruding on occupants [73]. Since verification of metadata is usually carried out, the white-box models are considered using level 5 unless explicitly pointed out. Although LOD 400 is rarely mentioned, evolving from that improves the compatibility with BIM definition. Level 6 refers to historical data collected during real operation, which is commonly used for gray-box [33] and black-box [152] model identification. Level 7 stands for real-time operation data, requiring data exchange modules in the system architecture [30]. For clarification, while real-time data is normally used when implementing control, level 7 is meant to distinguish models that are regularly updated [95,140]. Compared with level 5, time series data at level 6 and 7 are fully exposed to uncertainties and closer to real operation.

3.1.2. Measurement granularity

The second digit means the measurement granularity. Again, level 0 is stuck to the BIM definition for building metadata. For time series data, level 1 includes the principal variables that are usually measured for building operation, level 3 contains the detailed measurements to describe the object more accurately, and level 5 is the advanced measurements taken for specific purposes, subject to customized change. As illustrated in Table 4, The four basic levels of LoD refer to different specific variables for the six data categories: energy consumption, indoor condition, internal disturbance, external disturbance, system condition, and envelop condition. The categories are inspired by the one proposed by Mahdavi & Taheri [161] and modified to fit the data requirements of control-oriented models.

- **Energy consumption (EN)** of the entire building is usually measured for billing purpose, which forms level 1. Different energy sources, such as electricity and gas, are separated if applicable [74].

Table 4
Detailed definition of measurement granularity for the 6 data categories.

Level	*0*	*1*	*3*	*5*[a]
Energy consumption	N/A	Total consumption by energy sources	Separated consumption by usage type	Separated consumption by sub-components
Indoor condition	N/A	Indoor air temperature	Variables affecting thermal comfort	Thermal comfort/sensation feedback
System condition	System specifications	On/off operating mode, thermostat setpoints	Temperature and flow rate variables	Static pressures
Envelop condition	Geometric and thermal properties	N/A	Surface or core temperature	N/A
Internal disturbance	Assumed operating schedules/profiles	N/A	Estimated operating profile	Additional occupant sensors
External disturbance	N/A	Weather data of the city/region	On-site weather station/sensors	Solar heat gain on different orientations

[a] Level 5 here is illustrated with typical examples. Actual variables might be subject to customized change in specific studies.

For level 3 detailed measurements, the energy consumption is splitted into different end use, such as heating [84], cooling [82], lighting [14], and plug [107]. As advanced measurements, the energy consumption is further disaggregated by sub-components, such as boilers [97], heat pumps [61], pumps [68], and fans [149].

- **Indoor condition (IC)** means indoor thermal comfort conditions in most cases and is usually represented by indoor air temperature [33,57,58]. For detailed measurements, other factors affecting thermal comfort are involved, including mean radiant temperature [117], humidity [80], and operative temperature [77]. At level 5, special measurements are taken to investigate specific problems. For example, occupant thermal comfort feedback is collected for an occupant-oriented MPC [144], and illuminance is considered for optimal control of blind position [52].
- **Internal disturbances (ID)** are the sources of internal heat gain: occupants, equipment, and lights. The metadata in this category refers to the assumed operating on/off schedules [55] or ratio based profiles [59]. The information can be based on standard or expert knowledge. There is no level 1 because they are not necessary for normal building operations. As level 3, the profiles are estimated based on electricity [97] or temperature [73] trends. CO_2 concentration is the most used advanced measuring method [122,132]. Passive infrared (PIR) sensors and people counters are also used [152]. Internal radiative and convective heat gain are used in many simulation studies [33,58], but is hardly measurable in real operation unless using load emulators [30,76].
- **External disturbances (ED)** are the climate conditions that cause external heat gain. While the dry-bulb temperature and solar irradiance are used much more frequently than other variables like wind speed [77] and ground temperature [10], they are not differentiated in different levels given their similar availability with the existence of weather stations. Level 1 refers to the publicly available weather data of the city or the region [74,94]. On-site weather stations are used to accurately measure the buildings' ambient condition [69,97,107], therefore defined as level 3. The Typical Meteorological Year (TMY) used in most simulation studies [33,58] are also considered accurate measurements since the buildings are assumed to be under these typical conditions. At level 5, solar heat gain on different orientation serves as an example [43,106].
- **System conditions (SC)** describe how the HVAC systems are operated. Level 0 as static information requires information such as capacity and COP [39]. Note that sometimes COP is assumed to be constant just to estimate energy consumption [65], which is not considered to require level 0 SC information. Level 1 is usually available in building operation, including the on/off operating mode [140] and thermostat setpoints [55]. Detailed measurements cover the flow rates and temperatures on the water side [62] and the air side [73]. These points are often used to estimate thermal loads when the power meters are not in place [30,124]. Valve [81], damper [150] and blind [129] positions are also categorized into level 3 as they imply the heat flow. As an advanced measurement example, supply air static pressure was taken for system performance estimation [76].
- **Envelop condition (EC)** only has level 0 static characteristics and level 3 detailed measurements. Level 0 may involve geometric properties like areas and volumes [30], and/or thermal properties like U-value and Solar Heat Gain Coefficient (SHGC) [50]. Information like the number of rooms can be easily observed and therefore is not explicitly accounted for. For level 3, surface and/or core temperatures of the envelops are measured. These variables are usually found in buildings with radiant systems such as TABS or Concrete Core Activation (CCA).

3.1.3. Temporal resolution

Larger numbers as the third digit indicate higher temporal resolution of the time series data. Level 0 includes the static building characteristics and time series data with the interval larger than an hour. Time interval of less than or equal to an hour but larger than 30 min falls into level 1. Similarly, less than or equal to 30 min but larger than 15 min belongs to level 2, and so forth. Thereby, level n corresponds to 2^{n-1} to 2^n data points per hour.

3.2. Data requirements of different models

The data usage of the 118 models is categorized and quantified according to the extended LoD framework. The average LoD of the six categories is also calculated for each study to enable the quantitative comparison between different model types. Since the resulting data is unpaired and non-Gaussian distributed, the Mann-Whitney U tests are applied. Representative studies are selected for presentation in Tables 5–7. The selection is done by stratified sampling from each of the nine model types.

3.2.1. Comparing modeling purposes

It is expected to see the most data used in system performance models (Table 7), followed by thermal response models (Table 6), and then load prediction models (Table 5). It is obvious that load prediction models require the least. While the difference between thermal response and system performance models may not be visually detected from Tables 6 and 7, the Mann-Whitney U test on the average LoD gets 0.016 p-value, indicating a significant difference. The medians are 626 for system performance models and 528 for thermal response models. The general data requirements of the three modeling methods are respectively summarized:

- With the assumption on indoor condition, load prediction models requires no IC data. They predict the total or thermal loads (level 1 or 3 measurement granularity) based on past values [89,92,93] or the disturbances [55,86,88]. Most studies assumed constant room

Table 5
Data usage of load prediction models.

Modeling methods	Reference	Building type	Primary HVAC system	Data category					
				EN	*IC*	*ID*	*ED*	*SC*	*EC*
White-box	[87]	Residential	Ideal			500			500
	[92]	Residential	Ideal	611					
	[93]	Grid		613					
Gray-box	[55]	University	Chiller	631		500	611	611	
	[88]	Office	Ideal	631		651	631		
Black-box	[86]	Residential	Ideal	613			613		
	[89]	Grid		611					

Table 6
Data usage of thermal response models.

Modeling methods	Reference	Building type	Primary HVAC system	Data category					
				EN	*IC*	*ID*	*ED*	*SC*	*EC*
White-box[a]	[14]	Office	TABS						500
	[94]	Office	TABS			500			500
	[96]	Residential	Heat pump					500	500
	[107]	Office	VAV			500		500	400
	[111]	Grid				500			500
Gray-box	[30]	Office	FCU		734	754	754	734	500
	[43]	University	VAV	633	613	653	633	633	400
	[59]	Office	TABS		612	500	612	632	632
	[61]	Residential	Hybrid	554	514	554	534	534	
	[67]	University	Radiant		612		632	632	
	[83]	Residential	Radiant	733	713	753	733		
	[85]	Residential	Ideal	631	611		631		500
	[95]	Office	VAV	734	734	734	734	734	
	[125]	Office	TABS		511	551	551	531	531
	[126]	Lab	Ideal	534	514		534		534
	[28]	Office	VAV		612	652	632	632	632
	[131]	Lab	Hybrid	531	511	551	551		531
	[133]	Lab	Radiant		612		632	632	
Black-box	[71]	Residential	GSHP	653	613		633	613	
	[72]	University	Radiant		611		631	631	
	[77]	Office	Hybrid	631	511		531	511	
	[79]	University	TABS	653	613	500	613		
	[84]	Office	Ideal	633	613	500			
	[135]	Office	Radiant	735	715		735	735	
	[140]	Lab	VRF		513	633	513	513	

[a] 13 white-box thermal response models are selected by stratified sampling, where the data usages are mostly similar. Therefore, only 5 are displayed here to be concise.

Table 7
Data usage of system performance models.

Modeling methods	Reference	Building type	Primary HVAC system	Data category					
				EN	*IC*	*ID*	*ED*	*SC*	*EC*
White-box	[98]	Office	TABS			500		500	500
	[143]	Residential	Radiant			500		500	500
	[144]	Office	Hybrid		651			500	500
Gray-box	[31]	Office	FCU	653	613	653	633	633	633
	[147]	Office	Radiant		614	634	614	634	634
Black-box	[55]	University	Chiller	631			611	631	
	[73]	Lab	VAV	553	513	633	513	533	
	[76]	Lab	VAV	631	611	651	631	651	
	[149]	Office	TABS	651	631	651	631	651	631
	[151]	Office	Radiant	652	612	652	652	632	632

temperature setpoints [86,89]. If not, the setpoint is used as a model input [55].

- To model the building's thermal response, IC and EC data are added for model identification. Almost all selected gray and black-box thermal response models used room temperature, except some [30,95] required both temperature and humidity. Envelop surface [28] or core [59] temperatures are sometimes required. Besides, more SC data of level 3 measurement granularity is needed as the controlled inputs. These points are indispensable if no energy consumption data is used.
- For the system performance models, the most noticeable change is the increased use of component-level energy consumption. The supply air static pressure is also measured [76,149]. These higher-granularity measurements help obtain information about the dynamic system performance. It is unforeseen that system performance models generally acquire more ID data than thermal response

models to estimate internal heat gains (p-value 0.047). This could be a side benefit of deploying more sophisticated sensing systems.

3.2.2. Comparing modeling methods

It can be seen that white-box models mostly use just building metadata of LoD 400 and 500. One exception is Zhao et al. [144] embedded historical occupant thermal comfort feedback to predict thermal comfort. Most gray-box models need information such as the building layout, which is not counted as using metadata. Some used metadata to provide initial guesses [43] or value bounds [83] for parameter identification. The usage of metadata was shown crucial for some identification algorithms, especially in cases like MRI, when the optimization problem is non-convex [59]. It is worth noting that metadata, particularly the operation profile, was also used in black-box models [79,84]. As another example, Li et al. [151] used the system specification to obtain the heat pump performance and other temperature measurements to model other sub-systems.

Gray and black-box models use a similar amount of time series data. The statistical test gives 0.232 p-value, showing no significant difference. In fact, gray-box models have slightly higher median average LoD (617 over 606). This observation disagrees with the conclusion in Ref. [20] that gray-box models require less data. It is still arguable that the difference lies in the training data length. The length is not quantified in this review because many studies did not report. However, training data length varying from one day to one year is found in both modeling methods.

3.2.3. Other comparisons

Although the modeling methods greatly impact the usage of metadata, when it comes to time series data, the usage of level 5, 6, and 7 is almost evenly distributed in different model types. Faster system dynamics requires higher temporal resolution. For example, the average resolution level of Fan Coil Unit (FCU) models is 3.75, while the average of TABS models is 2.11. To summarize, among the three dimensions of LoD, time validity is partially influenced by the modeling methods, measurement granularity is affected by the modeling purpose, and temporal resolution is typically decided by the system dynamics.

4. Performance evaluation

A control-oriented model with acceptable prediction capability is the prerequisite to achieve good control. Potential model mismatch could lead to control performance degradation. Therefore, it is crucial to obtain a structured perception of model performance evaluation and its impact on control. With the intention to quantify the relationship, two gaps are noticed: a) the absence of a standard or comparable approach for model performance evaluation, and b) the paucity of research remarking the relationship. This section gives an overview on these two issues.

4.1. Model evaluation

The approaches to evaluate the credibility of a computerized model can be categorized into validation and verification [162]. Validation substantiates that a model, within its domain of applicability, possesses a satisfactory range of accuracy. Verification substantiates that a model represents the conceptual model within specified limits of accuracy.

4.1.1. Validation metrics

Most studies evaluate the model through validation. A number of them adopted a qualitative approach to plot the model outputs with the test data and show a good tracking [62,72,73]. To quantify the error over a period, Mean Bias Error (MBE, Equation (1)) is a basic metric. However, it is rarely used because positive and negative errors cancel each other when summing up and may distort the results. Therefore, Mean Absolute Error (MAE, Equation (2)), Mean Squared Error (MSE, Equation (3)), and Root Mean Squared Error (RMSE, Equation (4)) are normally used [50,86,123]. Concerning about the variation of error, Maximum Absolute Error (MaxAE, Equation (5)) and Standard Deviation of Absolute Error (StdAE, Equation (6)) were also used [29,124]. These metrics are useful to avoid the potential thermal comfort violation caused by the model mismatch [97,139]. There is no consensus on the acceptable error, but many studies tried to contain the errors within $\pm 1^{\circ}C$.

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right) \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\left(\hat{y}_i - y_i\right)\right| \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{4}$$

$$MaxAE = max_{i\in[1,n]}\left|\left(\hat{y}_i - y_i\right)\right| \tag{5}$$

$$StdAE = \sqrt{\frac{1}{n-1}\sum_{n}^{i=1}\left(\left|\left(\hat{y}_i - y_i\right)\right| - MAE\right)^2} \tag{6}$$

To diminish the effect of absolute value scales when comparing different models, the error metrics are normalized to obtain percentages. Mean Absolute Percentage Error (MAPE, Equation (7)) and Coefficient of Variation (RMSE) (CV(RMSE), Equation (8), also known as Normalized RMSE) are commonly used [76,132]. Replacing the average of the measured value in the denominator of equation (8) with the range of predicted values yields standardized RMSE [43]. However, comparing models with these normalized percentages still requires some caution. For instance, consider model A that predicts room temperature around 26°C with 1°C RMSE and model B that gives similar RMSE around 20°C, the lower CV(RMSE) of model A does not make it more accurate. Alternatively, R squared (R2, Equation (9), sometimes referred to as the goodness of fit), estimating the ratio of explained variance in the prediction, is frequently used as well [77,95].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\left(\hat{y}_i - y_i\right)}{y_i}\right| \tag{7}$$

$$CV(RMSE) = \frac{1}{\bar{y}}\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{9}$$

Usually, closed-loop, or one-step ahead, prediction is validated. As a stricter approach, open-loop prediction was validated on occasion to examine the model performance over the horizon [44]. For example, multi-step RMSE (MS-RMSE, Equation (10)) was applied [27]. In equations (1)–(10), $\hat{y}$ is the model output, y is the test data, $\bar{y}$ is the average of test data, p is the prediction horizon, n is the length of test data, i and k refer to the time step.

$$MS-RMSE = \sqrt{\frac{1}{p(n-p)}\sum_{i=1}^{n-p}\sum_{k=1}^{p}\left(\hat{y}_{i+k|i} - y_{i+k}\right)^2} \tag{10}$$

One consideration is the dataset used for validation. The mostly applied in practice is the historical data over a period of time. It can be obtained either from the real operation or using a high-fidelity simulation model. Otherwise, using real-time data, Finck et al. [90] validated the model outputs against measurements during the control experiment. Several datasets were designed for the purpose of better examining the models' prediction capability. Kim et al. [130] suggested validating the model in a cross-validation manner if significant disturbances present in operations. Li et al. [82] tested the extensibility (extrapolating capability) by designing scenarios when the boundary conditions exceed the range of the training dataset. Several studies made datasets with step signals to check impulse responses between input-output pairs [27,163]. These designed datasets are usually generated using a high-fidelity simulation model. It was noted in the field of hydrology that the uncertainty in measured data should be carefully contained to effectively validate the models [164], which was rarely concerned by building control studies.

4.1.2. Verification and identifiability

It has been recognized that a desired control-oriented model should not only predict with small error but also represent the actual building systems [27]. In line with this, a desired [58] or minimum [34] model complexity is needed by different building systems. Verification can also be done by physically interpreting the model outputs or parameters. In the frequency domain, model responses to different input stimuli were compared. The zone thermal reaction to heat input at different frequencies was examined [34], and "error with respect to input" was defined to quantify the performance [163]. Privara et al. [52] examined the whiteness of residuals using a cumulative periodogram, confirming that the system dynamics was properly modeled, and the residuals were caused by noises. For parameter inspection of gray box models, the identified RC values were compared with the physical meaning [58, 125]. Significance index and correlation index were introduced to evaluate how the parameters affect the model performance [66]. A model is expected to be less sensitive to parameter perturbation [37] and have less correlated parameters [66].

As a model becomes more complex and has more degree of freedom, identifiability comes to be an issue [126,153]. If a model is over-parameterized, i.e., has too many parameters to identify, parameter estimation, model evaluation, and further application could be more difficult [56,165,166]. It has been shown that the parameter values can be varied a lot without significantly changing the validation results [83,151]. The parameter identifiability can be decomposed into structural and output identifiability [123]. To correctly identify the models instead of overfitting the training data, an appropriate model structure is the most important factor [167]. Therefore, model selection methods were applied for both white-box [168], gray-box [43,127] and ANN models [80]. Further, Privara et al. [57] applied different model selection criteria for probabilistic and deterministic identification algorithms.

4.2. Relating to control performance

4.2.1. Control performance evaluation

MPC in buildings aims at energy saving, thermal comfort improvement, peak load reduction, system efficiency improvement, etc. The effectiveness can be demonstrated through simulation or experiment. A realistic simulation-based demonstration framework requires a control-oriented model and a high-fidelity simulation model. The simulation model serves as a virtual testbed, to which the control action based on the controller model is applied [25]. Tools and desired features of simulation models are reviewed in Ref. [169]. Typical tools include Building Controls Virtual Test Bed (BCVTB) [170], TRNSYS (type 15,17, 56,155) [171], and Modelica [172]. However, a number of simulation-based studies deployed an idealistic framework by using the same model for optimization and simulation. 72.0% (85) of the categorized papers are demonstrated by simulation, out of which 41.2% (35) are idealized. Assuming that the controller model is perfectly representing the building overlooks the influence of the model performance on the control performance. Studies using white-box methods, such as model reduction, typically tend to be idealized. Yet, without comparing to experimental data or higher fidelity models, the effectiveness of model reduction methods was claimed to be questionable [44].

Unlike simulation-based demonstration, where different control strategies can be compared under the same boundary conditions, the comparison is not as straightforward in actual experiments. The most used approach is normalizing the control results, usually energy consumption, by degree days [62,97] or outdoor temperatures [173]. Alternatively, some studies showed that different strategies are applied under similar averages [59] or profiles [98] of outdoor temperature.

Baseline selection is another concern when evaluating the control performance. The most convenient way is to compare with the default control in the building. However, it was argued that the default settings in BMS are possibly poor-tuned, disputing the improvement of control performance [24]. It was noted that the saving potential brought by MPC could also be achieved by fine-tuning the rule-based controller (RBC) [152]. Accordingly, the RBC was pre-tuned to consolidate the control comparison [95,106]. Moreover, MPC with simpler configurations were used to show the superiority of robust MPC [123], non-linear MPC [117], and system performance MPC [99]. The upper performance bound of MPC was quantified by using the perfect model and disturbance prediction [13]. Additionally, different combinations of HVAC systems and control algorithms were considered as integrated baselines [149].

4.2.2. Affecting factors

The performance of MPC varied among different situations from worse than baselines to over 100% better. Apart from the model performance, the wide range is also affected by factors including building characteristics [102], ambient conditions [94], operation constraints [39], disturbances [122], and etc. These factors function in a combined and complicated way. For example, the impact of internal disturbance was moderated during the heating season, as compared with the cooling season [31]. Consequently, extracting the relationship between model and control performance involves explicitly designed experiments, which is rare in the past years.

Several studies showed that model mismatch could result in more energy consumption [119,132] and/or discomfort [97,139]. To quantify, 10% error led to 5% more energy cost and 100% more comfort violation [28]. On the other hand, a more accurate model, in terms of RMSE, did not necessarily lead to better control performance [33]. The prediction horizon matters as well. Zong et al. [10] found the energy cost decreased and then increased as the prediction horizon increased, which might be relevant to the open-loop prediction accuracy. Regarding the model structure and characteristics, a multi-zone model achieved better thermal comfort than a simplified single-zone model with a similar amount of energy [83], a certain number of states was found necessary to capture the thermal dynamics [34], and a non-convex model caused multiple local optima in the optimization, some of which deteriorated the control [174].

5. Discussion

Through the categorizations and discussions in the last three sections, several research gaps are spotted. This section summarizes the review with five directions for future study, three of which regarding the data requirements and the other two about the performance evaluation. These topics interrelate and should be studied together systematically.

5.1. What are the minimum data requirements to build a control-oriented model?

The answer to this question is subject to modeling purposes, modeling methods, and building systems (section 3.2). While the variation between different modeling purposes or building systems is clear, the border, in terms of data requirements, between modeling methods is not. Due to the lack of description, the usage of building metadata is mostly referred to as LoD 500. However, LoD 400 can be useful to build either white-box [175] or gray-box [43] models. On the other hand, the usage of time series data is typically omitted in white-box studies, although it is involved in both manual and automated calibration [176]. Better describing the data usage would help justify the modeling effort and correspondingly the scalability of the proposed methods. Therefore, future research would benefit from explicitly quantifying the data requirements.

Another important question to answer is whether extra excitation or regular update is necessary for model identification. As shown in Fig. 6, LoD 6xx is mostly needed, but both 5xx and 7xx are also used in many studies. It was argued that the operation data generated by normal operations led to poor identification, so the data must fulfill specific requirements [163]. There are pretty mature methodologies to generate excitation signals [177], but these experiments are usually not compatible with normal operations. On the other hand, unoccupied experiments are not exposed to the uncertainties brought by occupants and other internal disturbances [8]. As a potential solution, the excitation could be partially conducted within the comfort range during daily operations [147]. As for LoD 7xx, regularly-updated models are found to be desired in several cases [22,56]. The problem is the increased cost for data exchange and computation. Also, it is practically impossible to provide full excitation and regular update simultaneously.

The proposed LoD covers the variations in time validity, measurement granularity, and temporal resolution. Besides, there are other factors found in the literature. The length of training data is not counted in the current framework since no pattern is observed. However, it may change the cost of data acquisition, especially for LoD 5xx and 7xx. Hence, it will be added as an attribute in the future plan of reforming the LoD in an object-oriented way. The spatial resolution of indoor conditions also makes a difference when modeling large scale buildings. Reference room temperature [78] and average room temperature [97] were used in different studies. These choices are made mainly to reduce model complexity. Considering the room temperature is usually available with the thermostats, the spatial resolution is not specified in the framework. The data quality or sensor accuracy is another factor that might affect the modeling procedure. Yet, it is hard to estimate and rarely declared. Thus, unbiased measurements are assumed.

5.2. How to balance the trade-off between model complexity and data requirements?

When building a control-oriented model, fewer assumptions and better prediction capability are desired [20], calling for more states and higher complexity. For example, adding a state for wall temperature improved the performance [10]. On the other hand, higher-order models require more data to identify [58]. Insufficient training data could result in issues of identifiability (section 4.1.2). Inadequately informative data could also deteriorate model performance [178]. Therefore, it is essential to find a balanced point between model complexity and data requirements. The prediction error of a numerical model can be generally attributed to aleatoric uncertainty and epistemic uncertainty [179]. The epistemic uncertainty can be further decomposed into structural and parameter uncertainties, which paves the way to balance the trade-off [180]. illustrated an abstracted relationship between model uncertainty and complexity for HVAC simulation models. Inspired by the idea, the qualitative relationship between model complexity, potential prediction error, and data availability is depicted in Fig. 7.

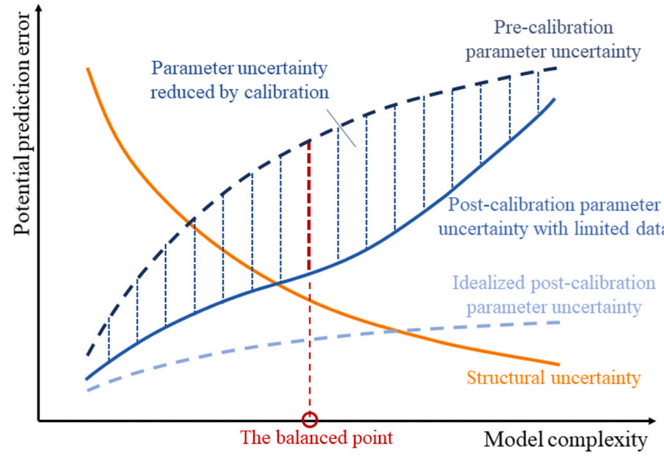

Fig. 7. Qualitative relationship between model complexity, potential prediction error, and data availability.

As the model complexity increases, the model describes the physical process more precisely, reducing the structural uncertainty (orange line). On the contrary, the dark blue dash line represents the parameter uncertainty, which increases with the number of parameters in the model. With the building metadata and time series data, calibration (including calibration for white-box models and parameter identification for data-driven models) is conducted to bring down the parameter uncertainty. The cyan dash line refers to an idealized situation, where all data requirements can be fulfilled, and the parameter uncertainty can be mostly removed. The remaining part could be caused by aleatoric uncertainties. More complex models require more data for calibration and benefit more from the calibration. In such an idealized situation, the most complex model may be favored.

In reality, however, building systems are hardly data-rich [181]. The limited amount of available data results in the solid blue line in between. Given a specific level of data availability, if the model complexity is too high or too low, the data would be overfitted or underfitted [33]. Consequently, the parameter uncertainty reduced by the calibration, marked by the vertical dash lines, will increase and then decrease as the complexity increases. Thereby, the balanced point is where the improvement brought by the calibration reaches its maximum, highlighted in red. This point corresponds to the best performance that can be achieved with the data. As more data is available, a more complex model could be supported, and the balanced point could be shifted to the right, yielding better prediction capability and smaller potential error. More research is needed to quantify this relationship.

Pragmatically, transferability is a barrier to the commercial application of MPC in buildings [182]. The configuration effort remains high every time when it comes to a new building. With the LoD framework and the quantified relationship, the upper bound of model and control performance of a building can be estimated based on its data availability. Along this line, an automated modeling framework could promote the scalability and potential of MPC.

5.3. What is the significance or potential benefits of higher measurement granularity for the role of occupants?

Occupant behavior is one of the major uncertainty sources in building energy assessment [183]. Therefore, more accurate measurements and estimations are desired. Compared with other data categories, great variations exist in the advanced measurements of internal disturbances. CO_2 and PIR sensors were used in past MPC studies [122, 152]. However, the reliability of both methods was questioned [184, 185]. Meanwhile, there are other advanced techniques available such as

WiFi and camera [186]. Regarding the trade-off between measurement cost, accuracy, and resolution [187], how to properly estimate the internal disturbances is to be investigated.

Apart from generating internal heat gains, occupants also affect building operations in an active way [188]. For example, people may change the thermostat setpoints or blind positions based on their thermal or visual comfort preference. The occurrence and influence of these behaviors are hard to predict. How to interact with occupants and their preferences remains an open question for optimal control methods [155]. In the existing literature, the indoor conditions are mostly measured at lower granularity levels. The consideration and measurements of occupant thermal comfort and sensation are to be integrated into MPC [189]. Involving occupants is not just about providing more satisfactory indoor conditions but also about reevaluating the energy-saving potential in certain situations. Many studies saved energy by approaching the upper or lower bound of the acceptable temperature range [30,106], which may change if the goal is improving thermal comfort instead of minimizing setpoint violation. The effect of integrating occupant thermal comfort on energy saving could be positive and negative [190].

5.4. How to properly evaluate the performance of a control-oriented model?

It is essential to estimate the prediction capability of a model accurately. Following the idea of parsimonious modeling, the simplest "good-enough" model is wanted. While applying model selection methods could lead to the simplest, the key is to find the criteria for "good-enough". To identify the right optimal control decision via optimization, the control-oriented models should be able to predict the system response given different control actions. Since the range of control actions to explore could be broader than normal operation, conducting validation over a period of normal operation may underestimate the potential error. Misleading prediction further causes degradation in control performance. Hence, a robust and comprehensive evaluation approach is needed, where domain knowledge may be essentially involved [191]. Validating on a designed dataset and integrating verification are the two possible paths.

Meanwhile, how a model should be evaluated also affects the data requirements. For instance, the additional verification requires building metadata and/or time series data at LoD 5xx. In the case of fast-changing system dynamics, regularly evaluating a model needs data at LoD 7xx. From a practical standpoint, standardized evaluation approaches and generalizable metrics are desired, at least for a particular type of building and HVAC system.

5.5. What is the relationship between the model and control performance?

While better prediction generally leads to better control, the exact quantified relationship is to be identified. The minimum requirement on the model performance that can guarantee a satisfactory control is crucial for the commercial application of MPC. On the other hand, as illustrated in Fig. 7, the model mismatch can never be completely removed. As the model complexity gets higher, the additional modeling efforts and data requirements will increase, but the improvement in control performance may become marginal. Being able to quantify the cost and benefits would help decide when to stop the effort and go with the near-optimal solutions. Methods like offset-free MPC [34] and robust adaptive MPC [129] can contain a low level of prediction error.

Due to the various factors involved in the MPC framework, the relationship can only be studied through carefully designed experiments. A testing framework is needed to anchor other influential factors and evaluate the model and control performance in a standardized way. A robust and unified comparison framework for different configurations is also the path of moving MPC from research to industry [192]. BOPTEST is a newly-developed platform that could be useful [193]. Besides, to ensure the control performance in practice, more real-world longer-term demonstrations are needed beyond Prove-of-Concept [3]. While existing research mainly focused on heating and cooling dominated periods, more attention should be paid on the transition season.

6. Conclusion

This paper addresses two critical issues relating to the control-oriented models for MPC in buildings: what data is required, and how a model should be evaluated. Over a hundred studies in the past ten years are reviewed and categorized according to not just the modeling methods but the purposes as well. The data usage of each study is quantified and compared among the finer categories, using a newly proposed extended Level of Detail (LoD) framework. After that, the model evaluation criteria and approaches are summarized and thoroughly discussed. Based on the critical review, five directions for future research are introduced, pinpointing the gaps between data requirements, model performance, and control performance.

The paper serves both practitioners and researchers. For practitioners who want to apply MPC in their buildings, section 2 and 3 are useful to look up what data is needed for their purposes, or vice versa, which method to adopt based on their data availability. Section 4 guides how to evaluate their model and what to expect with the model. For researchers, the advice on data requirements and performance evaluation makes future studies more generalizable. Ultimately, bridging the identified gaps is essential to promoting the actual application of MPC in buildings.

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.

References

[1] Abergel T, Dean B, Dulac J. Towards a zero-emission, efficient, and resilient buildings and construction sector: global status report. Paris, France: UN Environment and International Energy Agency; 2017.
[2] Anderson JE, Wulfhorst G, Lang W. Energy analysis of the built environmentâ€"a review and outlook. Renew Sustain Energy Rev 2015;44:149–58. https://doi.org/10.1016/j.rser.2014.12.027.
[3] 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. https://doi.org/10.1016/j.enbuild.2017.10.022.
[4] Lee JH. Model predictive control: review of the three decades of development. Int J Contr Autom Syst 2011;9(3):415. https://doi.org/10.1007/s12555-011-0300-6.
[5] Braun JE. Reducing energy costs and peak electrical demand through optimal control of building thermal storage. Build Eng 1990;96(2):876–88.
[6] Henze GP, Dodier RH, Krarti M. Development of a predictive optimal controller for thermal energy storage systems. HVAC R Res 1997;3(3):233–64. https://doi.org/10.1080/10789669.1997.10391376.
[7] Mirakhorli A, Dong B. Occupancy behavior based model predictive control for building indoor climateâ€"a critical review. Energy Build 2016;129:499–513. https://doi.org/10.1016/j.enbuild.2016.07.036.
[8] Maddalena ET, Lian Y, Jones CN. Data-driven methods for building controlâ€"a review and promising future directions. Contr Eng Pract 2020;95:104211. https://doi.org/10.1016/j.conengprac.2019.104211.
[9] Benndorf GA, Wystrcil D, Réhault N. Energy performance optimization in buildings: a review on semantic interoperability, fault detection, and predictive control. Appl Phys Rev 2018;5(4):041501. https://doi.org/10.1063/1.5053110.
[10] Zong Y, Böning GM, Santos RM, You S, Hu J, Han X. Challenges of implementing economic model predictive control strategy for buildings interacting with smart energy systems. Appl Therm Eng 2017;114:1476–86. https://doi.org/10.1016/j.applthermaleng.2016.11.141.
[11] Killian M, Kozek M. Ten questions concerning model predictive control for energy efficient buildings. Build Environ 2016;105:403–12. https://doi.org/10.1016/j.buildenv.2016.05.034.
[12] Li X, Wen J. Review of building energy modeling for control and operation. Renew Sustain Energy Rev 2014;37:517–37. https://doi.org/10.1016/j.rser.2014.05.056.
[13] Oldewurtel F, Parisio A, Jones CN, Gyalistras D, Gwerder M, Stauch V, Lehmann B, Morari M. Use of model predictive control and weather forecasts for energy efficient building climate control. Energy Build 2012;45:15–27. https://doi.org/10.1016/j.enbuild.2011.09.022.

[14] Oldewurtel F, Sturzenegger D, Morari M. Importance of occupancy information for building climate control. Appl Energy 2013;101:521–32. https://doi.org/10.1016/j.apenergy.2012.06.014.

[15] Oldewurtel F, Ulbig A, Parisio A, Andersson G, Morari M. Reducing peak electricity demand in building climate control using real-time pricing and model predictive control. In: 49th IEEE conference on decision and control (CDC). IEEE; 2010. p. 1927–32. https://doi.org/10.1109/CDC.2010.5717458.

[16] Fontenot H, Dong B. Modeling and control of building-integrated microgrids for optimal energy management–a review. Appl Energy 2019;254:113689. https://doi.org/10.1016/j.apenergy.2019.113689.

[17] Hilliard T, Kavgic M, Swan L. Model predictive control for commercial buildings: trends and opportunities. Adv Build Energy Res 2016;10(2):172–90. https://doi.org/10.1080/17512549.2015.1079240.

[18] Wang S, Ma Z. Supervisory and optimal control of building hvac systems: a review. HVAC R Res 2008;14(1):3–32. https://doi.org/10.1080/10789669.2008.10390991.

[19] Henze GP. Model predictive control for buildings: a quantum leap? J Build Perform Simulat 2013;6:157–8. https://doi.org/10.1080/19401493.2013.778519.

[20] 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. https://doi.org/10.1016/j.rser.2017.10.044.

[21] 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. https://doi.org/10.1016/j.buildenv.2013.11.016.

[22] Atam E, Helsen L. Ground-coupled heat pumps: Part 1–literature review and research challenges in modeling and optimal control. Renew Sustain Energy Rev 2016;54:1653–67. https://doi.org/10.1016/j.rser.2015.10.007.

[23] 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. https://doi.org/10.1016/j.enbuild.2017.02.012.

[24] Rockett P, Hathway EA. Model-predictive control for non-domestic buildings: a critical review and prospects. Build Res Inf 2017;45(5):556–71. https://doi.org/10.1080/09613218.2016.1139885.

[25] 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. https://doi.org/10.3390/en11030631.

[26] Pallonetto F, De Rosa M, D'Ettorre F, Finn DP. On the assessment and control optimisation of demand response programs in residential buildings. Renew Sustain Energy Rev 2020;127:109861. https://doi.org/10.1016/j.rser.2020.109861.

[27] Žáčeková E, Váňa Z, Cigler J. Towards the real-life implementation of mpc for an office building: identification issues. Appl Energy 2014;135:53–62. https://doi.org/10.1016/j.apenergy.2014.08.004.

[28] Bengea S, Adetola V, Kang K, Liba MJ, Vrabie D, Bitmead R, Narayanan S. Parameter estimation of a building system model and impact of estimation error on closed-loop performance. In: 2011 50th IEEE conference on decision and control and European control conference. IEEE; 2011. p. 5137–43. https://doi.org/10.1109/CDC.2011.6161302.

[29] Afram A, Janabi-Sharifi F. Black-box modeling of residential hvac system and comparison of gray-box and black-box modeling methods. Energy Build 2015;94:121–49. https://doi.org/10.1016/j.enbuild.2015.02.045.

[30] 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. https://doi.org/10.1016/j.buildenv.2019.106326.

[31] Dong B, Lam KP. A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting. Build Simulat 2014;7(1):89–106. https://doi.org/10.1007/s12273-013-0142-7.

[32] Tang S, Shelden DR, Eastman CM, Pishdad-Bozorgi P, Gao X. A review of building information modeling (bim) and the internet of things (iot) devices integration: present status and future trends. Autom ConStruct 2019;101:127–39. https://doi.org/10.1016/j.autcon.2019.01.020.

[33] Blum D, Arendt K, Rivalin L, Piette M, Wetter M, Veje C. Practical factors of envelope model setup and their effects on the performance of model predictive control for building heating, ventilating, and air conditioning systems. Appl Energy 2019;236:410–25. https://doi.org/10.1016/j.apenergy.2018.11.093.

[34] Picard D, Drgoňa J, Kvasnica M, Helsen L. Impact of the controller model complexity on model predictive control performance for buildings. Energy Build 2017;152:739–51. https://doi.org/10.1016/j.enbuild.2017.07.027.

[35] Harish V, Kumar A. A review on modeling and simulation of building energy systems. Renew Sustain Energy Rev 2016;56:1272–92. https://doi.org/10.1016/j.rser.2015.12.040.

[36] American Society of Heating. Refrigerating and air-conditioning engineers (ASHRAE), 2017 ASHRAEÂ® handbook - fundamentals. SI Edition. Atlanta, GA: ASHRAE; 2017.

[37] Atam E, Helsen L. Control-oriented thermal modeling of multizone buildings: methods and issues: intelligent control of a building system. IEEE Contr Syst Mag 2016;36(3):86–111. https://doi.org/10.1109/MCS.2016.2535913.

[38] Ascione F, Bianco N, De Stasio C, Mauro GM, Vanoli GP. Simulation-based model predictive control by the multi-objective optimization of building energy performance and thermal comfort. Energy Build 2016;111:131–44. https://doi.org/10.1016/j.enbuild.2015.11.033.

[39] Li X, Malkawi A. Multi-objective optimization for thermal mass model predictive control in small and medium size commercial buildings under summer weather conditions. Energy 2016;112:1194–206. https://doi.org/10.1016/j.energy.2016.07.021.

[40] Jorissen F, Boydens W, Helsen L. Taco, an automated toolchain for model predictive control of building systems: implementation and verification. J Build Perform Simulat 2019;12(2):180–92. https://doi.org/10.1080/19401493.2018.1498537.

[41] Gwerder M, Gyalistras D, Sagerschnig C, Smith R, Sturzenegger D. Final report: use of weather and occupancy forecasts for optimal building climate controlâ€"part ii: demonstration (opticontrol-ii). Zug, Switzerland: Automatic Control Laboratory, ETH Zurich; 2013. p. 156.

[42] Sturzenegger D, Gyalistras D, Semeraro V, Morari M, Smith RS. Brcm matlab toolbox: model generation for model predictive building control. In: 2014 american control conference. IEEE; 2014. p. 1063–9. https://doi.org/10.1109/ACC.2014.6858967.

[43] Andriamamonjy A, Klein R, Saelens D. Automated grey box model implementation using bim and modelica. Energy Build 2019;188:209–25. https://doi.org/10.1016/j.enbuild.2019.01.046.

[44] Kim D, Braun JE. A general approach for generating reduced-order models for large multi-zone buildings. J Build Perform Simulat 2015;8(6):435–48. https://doi.org/10.1080/19401493.2014.977952.

[45] Picard D, Jorissen F, Helsen L. Methodology for obtaining linear state space building energy simulation models. In: Proceedings of the 11th international Modelica conference, Versailles, France, september 21-23, 2015. Linköping University Electronic Press; 2015. p. 51–8. https://doi.org/10.3384/ecp1511851.

[46] Robillart M, Schalbart P, Chaplais F, Peuportier B. Model reduction and model predictive control of energy-efficient buildings for electrical heating load shifting. J Process Contr 2019;74:23–34. https://doi.org/10.1016/j.jprocont.2018.03.007.

[47] Touretzky CR, Baldea M. Nonlinear model reduction and model predictive control of residential buildings with energy recovery. J Process Contr 2014;24(6):723–39. https://doi.org/10.1016/j.jprocont.2013.09.022.

[48] Berger J, Mendes N, Guernouti S, Woloszyn M, Chinesta F. Review of reduced order models for heat and moisture transfer in building physics with emphasis in pgd approaches. Arch Comput Methods Eng 2017;24(3):655–67. https://doi.org/10.1007/s11831-016-9184-1.

[49] Deng K, Goyal S, Barooah P, Mehta PG. Structure-preserving model reduction of nonlinear building thermal models. Automatica 2014;50(4):1188–95. https://doi.org/10.1016/j.automatica.2014.02.009.

[50] De Rosa M, Brennenstuhl M, Andrade Cabrera C, Eicker U, Finn DP. An iterative methodology for model complexity reduction in residential building simulation. Energies 2019;12(12):2448. https://doi.org/10.3390/en12122448.

[51] Andrade-Cabrera C, De Rosa M, Kathirgamanathan A, Kapetanakis D-S, Finn D. A study on the trade-off between energy forecasting accuracy and computational complexity in lumped parameter building energy models. In: The 10th Canada conference of international building performance simulation association (eSim 2018), Montreal, Canada, 9-10 may 2018, IBPSA; 2018.

[52] 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. https://doi.org/10.1016/j.enbuild.2012.10.024.

[53] Cole WJ, Hale ET, Edgar TF. Building energy model reduction for model predictive control using openstudio. In: 2013 American control conference. IEEE; 2013. p. 449–54. https://doi.org/10.1109/ACC.2013.6579878.

[54] Foucquier A, Robert S, Suard F, Stéphan L, Jay A. State of the art in building modelling and energy performances prediction: a review. Renew Sustain Energy Rev 2013;23:272–88. https://doi.org/10.1016/j.rser.2013.03.004.

[55] Ma Y, Borrelli F, Hencey B, Coffey B, Bengea S, Haves P. Model predictive control for the operation of building cooling systems. IEEE Trans Contr Syst Technol 2011;20(3):796–803. https://doi.org/10.1109/TCST.2011.2124461.

[56] Berthou T, Stabat P, Salvazet R, Marchio D. Development and validation of a gray box model to predict thermal behavior of occupied office buildings. Energy Build 2014;74:91–100. https://doi.org/10.1016/j.enbuild.2014.01.038.

[57] Privara S, Váňa Z, Žáčeková E, Cigler J. Building modeling: selection of the most appropriate model for predictive control. Energy Build 2012;55:341–50. https://doi.org/10.1016/j.enbuild.2012.08.040.

[58] 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. https://doi.org/10.1016/j.enbuild.2014.07.025.

[59] Váňa Z, Cigler J, Široký J, Žáčeková E, Ferkl L. Model-based energy efficient control applied to an office building. J Process Contr 2014;24(6):790–7. https://doi.org/10.1016/j.jprocont.2014.01.016.

[60] Van Overschee P, De Moor B. Subspace identification for linear systems: theory—implementation—applications. Springer Science & Business Media; 2012.

[61] Fiorentini M, Wall J, Ma Z, Braslavsky JH, Cooper P. Hybrid model predictive control of a residential hvac system with on-site thermal energy generation and storage. Appl Energy 2017;187:465–79. https://doi.org/10.1016/j.apenergy.2016.11.041.

[62] Široký J, Oldewurtel F, Cigler J, Prívara S. Experimental analysis of model predictive control for an energy efficient building heating system. Appl Energy 2011;88(9):3079–87. https://doi.org/10.1016/j.apenergy.2011.03.009.

[63] Xue X, Wang S, Sun Y, Xiao F. An interactive building power demand management strategy for facilitating smart grid optimization. Appl Energy 2014;116:297–310. https://doi.org/10.1016/j.apenergy.2013.11.064.

[64] O'Dwyer E, De Tommasi L, Kouramas K, Cychowski M, Lightbody G. Modelling and disturbance estimation for model predictive control in building heating

systems. Energy Build 2016;130:532–45. https://doi.org/10.1016/j.enbuild.2016.08.077.
[65] Antonov S, Helsen L. Robustness analysis of a hybrid ground coupled heat pump system with model predictive control. J Process Contr 2016;47:191–200. https://doi.org/10.1016/j.jprocont.2016.08.009.
[66] Joe J, Karava P. Agent-based system identification for control-oriented building models. J Build Perform Simulat 2017;10(2):183–204. https://doi.org/10.1080/19401493.2016.1212272.
[67] Žáčeková E, Privara S, Váňa Z. Model predictive control relevant identification using partial least squares for building modeling. In: 2011 Australian control conference. IEEE; 2011. p. 422–7.
[68] Bianchini G, Casini M, Vicino A, Zarrilli D. Demand-response in building heating systems: a model predictive control approach. Appl Energy 2016;168:159–70. https://doi.org/10.1016/j.apenergy.2016.01.088.
[69] Asad HS, Yuen RKK, Huang G. Multiplexed real-time optimization of hvac systems with enhanced control stability. Appl Energy 2017;187:640–51. https://doi.org/10.1016/j.apenergy.2016.11.081.
[70] Mirakhorli A, Dong B. Market and behavior driven predictive energy management for residential buildings. Sustain Cities Soc 2018;38:723–35. https://doi.org/10.1016/j.scs.2018.01.030.
[71] Pallonetto F, De Rosa M, Milano F, Finn DP. Demand response algorithms for smart-grid ready residential buildings using machine learning models. Appl Energy 2019;239:1265–82. doi:j.apenergy.2019.02.020.
[72] Privara S, Širokỳ J, Ferkl L, Cigler J. Model predictive control of a building heating system: the first experience. Energy Build 2011;43(2–3):564–72. https://doi.org/10.1016/j.enbuild.2010.10.022.
[73] Ma Y, Matuško J, Borrelli F. Stochastic model predictive control for building hvac systems: complexity and conservatism. IEEE Trans Contr Syst Technol 2014;23(1):101–16. https://doi.org/10.1109/TCST.2014.2313736.
[74] Erfani A, Rajabi-Ghahnaviyeh A, Boroushaki M. Design and construction of a non-linear model predictive controller for building's cooling system. Build Environ 2018;133:237–45. https://doi.org/10.1016/j.buildenv.2018.02.022.
[75] Massana J, Pous C, Burgas L, Melendez J, Colomer J. Short-term load forecasting for non-residential buildings contrasting artificial occupancy attributes. Energy Build 2016;130:519–31. https://doi.org/10.1016/j.enbuild.2016.08.081.
[76] Kusiak A, Xu G, Zhang Z. Minimization of energy consumption in hvac systems with data-driven models and an interior-point method. Energy Convers Manag 2014;85:146–53. https://doi.org/10.1016/j.enconman.2014.05.053.
[77] Chen J, Augenbroe G, Song X. Lighted-weighted model predictive control for hybrid ventilation operation based on clusters of neural network models. Autom ConStruct 2018;89:250–65. https://doi.org/10.1016/j.autcon.2018.02.014.
[78] Killian M, Kozek M. Implementation of cooperative fuzzy model predictive control for an energy-efficient office building. Energy Build 2018;158:1404–16. https://doi.org/10.1016/j.enbuild.2017.11.021.
[79] Killian M, Mayer B, Kozek M. Effective fuzzy black-box modeling for building heating dynamics. Energy Build 2015;96:175–86. https://doi.org/10.1016/j.enbuild.2015.02.057.
[80] Ferreira P, Ruano A, Silva S, Conceicao E. Neural networks based predictive control for thermal comfort and energy savings in public buildings. Energy Build 2012;55:238–51. https://doi.org/10.1016/j.enbuild.2012.08.002.
[81] Huang H, Chen L, Hu E. A neural network-based multi-zone modelling approach for predictive control system design in commercial buildings. Energy Build 2015;97:86–97. https://doi.org/10.1016/j.enbuild.2015.03.045.
[82] Li X, Wen J, Bai E-W. Developing a whole building cooling energy forecasting model for on-line operation optimization using proactive system identification. Appl Energy 2016;164:69–88. https://doi.org/10.1016/j.apenergy.2015.12.002.
[83] Arroyo J, Spiessens F, Helsen L. Identification of multi-zone grey-box building models for use in model predictive control. J Build Perform Simulat 2020;13(4):472–86. https://doi.org/10.1080/19401493.2020.1770861.
[84] Moroşan P-D, Bourdais R, Dumur D, Buisson J. Building temperature regulation using a distributed model predictive control. Energy Build 2010;42(9):1445–52. https://doi.org/10.1016/j.enbuild.2010.03.014.
[85] Pedersen TH, Hedegaard RE, Knudsen MD, Petersen S. Comparison of centralized and decentralized model predictive control in a building retrofit scenario. Energy Procedia 2017;122:979–84. https://doi.org/10.1016/j.egypro.2017.07.456.
[86] Bartolucci L, Cordiner S, Mulone V, Santarelli M. Hybrid renewable energy systems: influence of short term forecasting on model predictive control performance. Energy 2019;172:997–1004. https://doi.org/10.1016/j.energy.2019.01.104.
[87] Cole WJ, Powell KM, Hale ET, Edgar TF. Reduced-order residential home modeling for model predictive control. Energy Build 2014;74:69–77. https://doi.org/10.1016/j.enbuild.2014.01.033.
[88] Ogunsola OT, Song L, Wang G. Development and validation of a time-series model for real-time thermal load estimation. Energy Build 2014;76:440–9. https://doi.org/10.1016/j.enbuild.2014.02.075.
[89] Jin M, Feng W, Liu P, Marnay C, Spanos C. Mod-dr: microgrid optimal dispatch with demand response. Appl Energy 2017;187:758–76. https://doi.org/10.1016/j.apenergy.2016.11.093.
[90] Finck C, Li R, Zeiler W. Optimal control of demand flexibility under real-time pricing for heating systems in buildings: a real-life demonstration. Appl Energy 2020;263:114671. https://doi.org/10.1016/j.apenergy.2020.114671.
[91] Zhang Y, Zhang T, Wang R, Liu Y, Guo B. Optimal operation of a smart residential microgrid based on model predictive control by considering uncertainties and storage impacts. Sol Energy 2015;122:1052–65. https://doi.org/10.1016/j.solener.2015.10.027.
[92] Dagdougui H, Minciardi R, Ouammi A, Robba M, Sacile R. Modeling and optimization of a hybrid system for the energy supply of a â green building. Energy Convers Manag 2012;64:351–63. https://doi.org/10.1016/j.enconman.2012.05.017.
[93] Parisio A, Rikos E, Glielmo L. Stochastic model predictive control for economic/environmental operation management of microgrids: an experimental case study. J Process Contr 2016;43:24–37. https://doi.org/10.1016/j.jprocont.2016.04.008.
[94] Sturzenegger D, Gyalistras D, Morari M, Smith RS. Model predictive climate control of a swiss office building: implementation, results, and cost–benefit analysis. IEEE Trans Contr Syst Technol 2015;24(1):1–12. https://doi.org/10.1109/TCST.2015.2415411.
[95] West SR, Ward JK, Wall J. Trial results from a model predictive control and optimisation system for commercial building hvac. Energy Build 2014;72:271–9. https://doi.org/10.1016/j.enbuild.2013.12.037.
[96] Bruni G, Cordiner S, Mulone V, Sinisi V, Spagnolo F. Energy management in a domestic microgrid by means of model predictive controllers. Energy 2016;108:119–31. https://doi.org/10.1016/j.energy.2015.08.004.
[97] De Coninck R, Helsen L. Practical implementation and evaluation of model predictive control for an office building in brussels. Energy Build 2016;111:290–8. https://doi.org/10.1016/j.enbuild.2015.11.014.
[98] Drgoňa 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 Contr 2020;88:63–77. https://doi.org/10.1016/j.jprocont.2020.02.007.
[99] Cupeiro Figueroa I, Picard D, Helsen L. Short-term modeling of hybrid geothermal systems for model predictive control. Energy Build 2020;215(0378-7788):109884. https://doi.org/10.1016/j.enbuild.2020.109884.
[100] Afram A, Janabi-Sharifi F. Review of modeling methods for hvac systems. Appl Therm Eng 2014;67(1–2):507–19. https://doi.org/10.1016/j.applthermaleng.2014.03.055.
[101] Support to renewable energy directive. 2010. https://esdac.jrc.ec.europa.eu/projects/RenewableEnergy/.
[102] Kavgic M, Hilliard T, Swan L. Opportunities for implementation of mpc in commercial buildings. Energy Procedia 2015;78:2148–53. https://doi.org/10.1016/j.egypro.2015.11.300.
[103] Wanjiru EM, Sichilalu SM, Xia X. Model predictive control of heat pump water heater-instantaneous shower powered with integrated renewable-grid energy systems. Appl Energy 2017;204:1333–46. https://doi.org/10.1016/j.apenergy.2017.05.033.
[104] Petrollese M, Valverde L, Cocco D, Cau G, Guerra J. Real-time integration of optimal generation scheduling with mpc for the energy management of a renewable hydrogen-based microgrid. Appl Energy 2016;166:96–106. https://doi.org/10.1016/j.apenergy.2016.01.014.
[105] Parisio A, Rikos E, Glielmo L. A model predictive control approach to microgrid operation optimization. IEEE Trans Contr Syst Technol 2014;22(5):1813–27. https://doi.org/10.1109/TCST.2013.2295737.
[106] Drgoňa J, Picard D, Kvasnica M, Helsen L. Approximate model predictive building control via machine learning. Appl Energy 2018;218:199–216. https://doi.org/10.1016/j.apenergy.2018.02.156.
[107] Kwak Y, Huh J-H, Jang C. Development of a model predictive control framework through real-time building energy management system data. Appl Energy 2015;155:1–13. https://doi.org/10.1016/j.apenergy.2015.05.096.
[108] Domahidi A, Ullmann F, Morari M, Jones CN. Learning decision rules for energy efficient building control. J Process Contr 2014;24(6):763–72. https://doi.org/10.1016/j.jprocont.2014.01.006.
[109] Gondhalekar R, Oldewurtel F, Jones CN. Least-restrictive robust periodic model predictive control applied to room temperature regulation. Automatica 2013;49(9):2760–6. https://doi.org/10.1016/j.automatica.2013.05.009.
[110] Favoino F, Fiorito F, Cannavale A, Ranzi G, Overend M. Optimal control and performance of photovoltachromic switchable glazing for building integration in temperate climates. Appl Energy 2016;178:943–61. https://doi.org/10.1016/j.apenergy.2016.06.107.
[111] Korkas CD, Baldi S, Michailidis I, Kosmatopoulos EB. Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. Appl Energy 2016;163:93–104. https://doi.org/10.1016/j.apenergy.2015.10.140.
[112] Wetter M, Bonvini M, Nouidui TS. Equation-based languages–a new paradigm for building energy modeling, simulation and optimization. Energy Build 2016;117:290–300. https://doi.org/10.1016/j.enbuild.2015.10.017.
[113] Goyal S, Barooah P. A method for model-reduction of non-linear thermal dynamics of multi-zone buildings. Energy Build 2012;47:332–40. https://doi.org/10.1016/j.enbuild.2011.12.005.
[114] Long Y, Liu S, Xie L, Johansson KH. A scenario-based distributed stochastic mpc for building temperature regulation. In: 2014 IEEE international conference on automation science and engineering (CASE). IEEE; 2014. p. 1091–6. https://doi.org/10.1109/CoASE.2014.6899461.
[115] Hu J, Karava P. Model predictive control strategies for buildings with mixed-mode cooling. Build Environ 2014;71:233–44. https://doi.org/10.1016/j.buildenv.2013.09.005.
[116] Scherer HF, Pasamontes M, Guzmán JL, Álvarez J, Camponogara E, Normey-Rico J. Efficient building energy management using distributed model predictive control. J Process Contr 2014;24(6):740–9. https://doi.org/10.1016/j.jprocont.2013.09.024.
[117] Castilla M, Álvarez J, Normey-Rico J, Rodríguez F. Thermal comfort control using a non-linear mpc strategy: a real case of study in a bioclimatic building. J Process Contr 2014;24(6):703–13. https://doi.org/10.1016/j.jprocont.2013.08.009.

[118] Zhang Z, Lam KP. An implementation framework of model predictive control for hvac systems: a case study of energyplus model-based predictive control. In: 2017 ASHRAE annual conference; 2017.
[119] Baldi S, Michailidis I, Ravanis C, Kosmatopoulos EB. Model-based and model-free "plug-and-play" building energy efficient control. Appl Energy 2015;154:829–41. https://doi.org/10.1016/j.apenergy.2015.05.081.
[120] 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. https://doi.org/10.1016/j.apenergy.2018.07.089.
[121] Yang S, Wan MP, Ng BF, Dubey S, Henze GP, Rai SK, Baskaran K. Experimental study of a model predictive control system for active chilled beam (acb) air-conditioning system. Energy Build 2019;203:109451. https://doi.org/10.1016/j.enbuild.2019.109451.
[122] Maasoumy M, Razmara M, Shahbakhti M, Vincentelli AS. Handling model uncertainty in model predictive control for energy efficient buildings. Energy Build 2014;77:377–92. https://doi.org/10.1016/j.enbuild.2014.03.057.
[123] Agbi C. Scalable and robust designs of model-based control strategies for energy-efficient buildings. Ph.D. thesis. Carnegie Mellon University; 2014.
[124] Pčolka M, Žáčeková E, Robinett R, Čelikovský S, Šebek M. Bridging the gap between the linear and nonlinear predictive control: adaptations for efficient building climate control. Contr Eng Pract 2016;53:124–38. https://doi.org/10.1016/j.conengprac.2016.01.007.
[125] Sourbron M, Verhelst C, Helsen L. Building models for model predictive control of office buildings with concrete core activation. J Build Perform Simul 2013;6(3):175–98. https://doi.org/10.1080/19401493.2012.680497.
[126] Brastein OM, Perera DWU, Pfeifer C, Skeie N-O. Parameter estimation for grey-box models of building thermal behaviour. Energy Build 2018;169:58–68. https://doi.org/10.1016/j.enbuild.2018.03.057.
[127] De Coninck R, Magnusson F, Åkesson J, Helsen L. Toolbox for development and validation of grey-box building models for forecasting and control. J Build Perform Simul 2016;9(3):288–303. https://doi.org/10.1080/19401493.2015.1046933.
[128] Platt G, Li J, Li R, Poulton G, James G, Wall J. Adaptive hvac zone modeling for sustainable buildings. Energy Build 2010;42(4):412–21. https://doi.org/10.1016/j.enbuild.2009.10.009.
[129] Tanaskovic M, Sturzenegger D, Smith R, Morari M. Robust adaptive model predictive building climate control. IFAC-PapersOnLine 2017;50(1):1871–6. https://doi.org/10.1016/j.ifacol.2017.08.257.
[130] Kim D, Cai J, Ariyur KB, Braun JE. System identification for building thermal systems under the presence of unmeasured disturbances in closed loop operation: lumped disturbance modeling approach. Build Environ 2016;107:169–80. https://doi.org/10.1016/j.buildenv.2016.07.007.
[131] Hu J, Karava P. A state-space modeling approach and multi-level optimization algorithm for predictive control of multi-zone buildings with mixed-mode cooling. Build Environ 2014;80:259–73. https://doi.org/10.1016/j.buildenv.2014.05.003.
[132] Huang H, Chen L, Hu E. A new model predictive control scheme for energy and cost savings in commercial buildings: an airport terminal building case study. Build Environ 2015;89:203–16. https://doi.org/10.1016/j.buildenv.2015.01.037.
[133] Khakimova A, Kusatayeva A, Shamshimova A, Sharipova D, Bemporad A, Familiant Y, Shintemirov A, Ten V, Rubagotti M. Optimal energy management of a small-size building via hybrid model predictive control. Energy Build 2017;140:1–8. https://doi.org/10.1016/j.enbuild.2017.01.045.
[134] Ma J, Qin J, Salsbury T, Xu P. Demand reduction in building energy systems based on economic model predictive control. Chem Eng Sci 2012;67(1):92–100. https://doi.org/10.1016/j.ces.2011.07.052.
[135] Lautenschlager B, Lichtenberg G. Data-driven iterative learning for model predictive control of heating systems. IFAC-PapersOnLine 2016;49(13):175–80. https://doi.org/10.1016/j.ifacol.2016.07.947.
[136] Le K, Bourdais R, Guéguen H. From hybrid model predictive control to logical control for shading system: a support vector machine approach. Energy Build 2014;84:352–9. https://doi.org/10.1016/j.enbuild.2014.07.084.
[137] Chen Y, Tong Z, Zheng Y, Samuelson H, Norford L. Transfer learning with deep neural networks for model predictive control of hvac and natural ventilation in smart buildings. J Clean Prod 2020;254:119866. https://doi.org/10.1016/j.jclepro.2019.119866.
[138] Bianchini G, Casini M, Pepe D, Vicino A, Zanvettor GG. An integrated model predictive control approach for optimal hvac and energy storage operation in large-scale buildings. Appl Energy 2019;240:327–40. https://doi.org/10.1016/j.apenergy.2019.01.187.
[139] Ma J, Qin SJ, Salsbury T. Application of economic mpc to the energy and demand minimization of a commercial building. J Process Contr 2014;24(8):1282–91. https://doi.org/10.1016/j.jprocont.2014.06.011.
[140] Aswani A, Master N, Taneja J, Culler D, Tomlin C. Reducing transient and steady state electricity consumption in hvac using learning-based model-predictive control. Proc IEEE 2012;100(1):240–53. https://doi.org/10.1109/JPROC.2011.2161242.
[141] Lindelöf D, Afshari H, Alisafaee M, Biswas J, Caban M, Mocellin X, Viaene J. Field tests of an adaptive, model-predictive heating controller for residential buildings. Energy Build 2015;99:292–302. https://doi.org/10.1016/j.enbuild.2015.04.029.
[142] Corbin CD, Henze GP, May-Ostendorp P. A model predictive control optimization environment for real-time commercial building application. J Build Perform Simulat 2013;6(3):159–74. https://doi.org/10.1080/19401493.2011.648343.
[143] Ascione F, Bianco N, De Stasio C, Mauro GM, Vanoli GP. A new comprehensive approach for cost-optimal building design integrated with the multi-objective model predictive control of hvac systems. Sustain Cities Soc 2017;31:136–50. https://doi.org/10.1016/j.scs.2017.02.010.
[144] Zhao J, Lam KP, Ydstie BE, Loftness V. Occupant-oriented mixed-mode energyplus predictive control simulation. Energy Build 2016;117:362–71. https://doi.org/10.1016/j.enbuild.2015.09.027.
[145] Lehmann B, Gyalistras D, Gwerder M, Wirth K, Carl S. Intermediate complexity model for model predictive control of integrated room automation. Energy Build 2013;58:250–62. https://doi.org/10.1016/j.enbuild.2012.12.007.
[146] Liu X, Paritosh P, Awalgaonkar NM, Bilionis I, Karava P. Model predictive control under forecast uncertainty for optimal operation of buildings with integrated solar systems. Sol Energy 2018;171:953–70. https://doi.org/10.1016/j.solener.2018.06.038.
[147] Joe J, Karava P, Hou X, Xiao Y, Hu J. A distributed approach to model-predictive control of radiant comfort delivery systems in office spaces with localized thermal environments. Energy Build 2018;175:173–88. https://doi.org/10.1016/j.enbuild.2018.06.068.
[148] Zakula T, Armstrong PR, Norford L. Modeling environment for model predictive control of buildings. Energy Build 2014;85:549–59. https://doi.org/10.1016/j.enbuild.2014.09.039.
[149] Zakula T, Armstrong P, Norford L. Advanced cooling technology with thermally activated building surfaces and model predictive control. Energy Build 2015;86:640–50. https://doi.org/10.1016/j.enbuild.2014.10.054.
[150] Liang W, Quinte R, Jia X, Sun J-Q. Mpc control for improving energy efficiency of a building air handler for multi-zone vavs. Build Environ 2015;92:256–68. https://doi.org/10.1016/j.buildenv.2015.04.033.
[151] Li S, Joe J, Hu J, Karava P. System identification and model-predictive control of office buildings with integrated photovoltaic-thermal collectors, radiant floor heating and active thermal storage. Sol Energy 2015;113:139–57. https://doi.org/10.1016/j.solener.2014.11.024.
[152] Bengea SC, Kelman AD, Borrelli F, Taylor R, Narayanan S. Implementation of model predictive control for an hvac system in a mid-size commercial building. HVAC R Res 2014;20(1):121–35. https://doi.org/10.1080/10789669.2013.834781.
[153] Chong A, Menberg K. Guidelines for the bayesian calibration of building energy models. Energy Build 2018;174:527–47. https://doi.org/10.1016/j.enbuild.2018.06.028. publication/pdf/chong-2018527.pdf.
[154] Amasyali K, El-Gohary NM. A review of data-driven building energy consumption prediction studies. Renew Sustain Energy Rev 2018;81:1192–205. https://doi.org/10.1016/j.rser.2017.04.095.
[155] Shaikh PH, Nor NBM, Nallagownden P, Elamvazuthi I, Ibrahim T. A review on optimized control systems for building energy and comfort management of smart sustainable buildings. Renew Sustain Energy Rev 2014;34:409–29. https://doi.org/10.1016/j.rser.2014.03.027.
[156] Level of development specification for building information models. 2019. https://bimforum.org/resources/Documents/BIMForum_LOD_2019_reprint.pdf.
[157] Biljecki F, Ledoux H, Stoter J. An improved lod specification for 3d building models. Comput Environ Urban Syst 2016;59:25–37. https://doi.org/10.1016/j.compenvurbsys.2016.04.005.
[158] Abualdenien J, Borrmann A. A meta-model approach for formal specification and consistent management of multi-lod building models. Adv Eng Inf 2019;40:135–53. https://doi.org/10.1016/j.aei.2019.04.003.
[159] Becerik-Gerber B, Jazizadeh F, Li N, Calis G. Application areas and data requirements for bim-enabled facilities management. J Construct Eng Manag 2012;138(3):431–42. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000433.
[160] Abdelrahman MM, Zhan S, Chong A. A three-tier architecture visual-programming platform for building-lifecycle data management. In: 2020 proceedings of the symposium on simulation for architecture and urban design, SimAUD; 2020. p. 445–52.
[161] Mahdavi A, Taheri M. An ontology for building monitoring. J Build Perform Simulat 2017;10(5–6):499–508. https://doi.org/10.1080/19401493.2016.1243730.
[162] Schlesinger S. Terminology for model credibility. Simulation 1979;32(3):103–4.
[163] Lin Y, Middelkoop T, Barooah P. Issues in identification of control-oriented thermal models of zones in multi-zone buildings. In: 2012 IEEE 51st IEEE conference on decision and control (CDC). IEEE; 2012. p. 6932–7. https://doi.org/10.1109/CDC.2012.6425958.
[164] Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 2007;50(3):885–900.
[165] Paudel R, Jawitz JW. Does increased model complexity improve description of phosphorus dynamics in a large treatment wetland? Ecol Eng 2012;42:283–94. https://doi.org/10.1016/j.ecoleng.2012.02.014.
[166] Perrin C, Michel C, Andréassian V. Does a large number of parameters enhance model performance? comparative assessment of common catchment model structures on 429 catchments. J Hydrol 2001;242(3–4):275–301.
[167] Gan TY, Dlamini EM, Biftu GF. Effects of model complexity and structure, data quality, and objective functions on hydrologic modeling. J Hydrol 1997;192(1–4):81–103. https://doi.org/10.1016/S0022-1694(96)03114-9.
[168] Tian W. A review of sensitivity analysis methods in building energy analysis. Renew Sustain Energy Rev 2013;20:411–9. https://doi.org/10.1016/j.rser.2012.12.014.
[169] Atam E. Current software barriers to advanced model-based control design for energy-efficient buildings. Renew Sustain Energy Rev 2017;73:1031–40. https://doi.org/10.1016/j.rser.2017.02.015.
[170] Wetter M, Haves P, Coffey B. Building controls virtual test bed. Tech. rep. Lawrence Berkeley National Laboratory; 2008.

[171] S. Klein, W. Beckman, J. Mitchell, J. Duffie, N. Duffie, T. Freeman, J. Mitchell, J. Braun, B. Evans, J. Kummer, et al., Trnsys 17: a transient system simulation program. solar energy laboratory, Madison, Madison, USA: University of Wisconsin.

[172] Wetter M, Zuo W, Nouidui TS, Pang X. Modelica buildings library. J Build Perform Simulat 2014;7(4):253–70. https://doi.org/10.1080/19401493.2013.765506.

[173] Chen B, Cai Z, Bergés M. Gnu-rl: a precocial reinforcement learning solution for building hvac control using a differentiable mpc policy. In: Proceedings of the 6th ACM international conference on systems for energy-efficient buildings, cities, and transportation; 2019. p. 316–25. https://doi.org/10.1145/3360322.3360849.

[174] Kelman A, Ma Y, Borrelli F. Analysis of local optima in predictive control for energy efficient buildings. J Build Perform Simulat 2013;6(3):236–55. https://doi.org/10.1080/19401493.2012.671959.

[175] Chong A, Xu W, Chao S, Ngo N-T. Continuous-time bayesian calibration of energy models using bim and energy data. Energy Build 2019;194:177–90. https://doi.org/10.1016/j.enbuild.2019.04.017.

[176] Coakley D, Raftery P, Keane M. A review of methods to match building energy simulation models to measured data. Renew Sustain Energy Rev 2014;37:123–41. https://doi.org/10.1016/j.rser.2014.05.007.

[177] Zhu Y. Multivariable system identification for process control. Elsevier; 2001.

[178] Chong A, Augenbroe G, Yan D. Occupancy data at different spatial resolutions: building energy performance and model calibration. Appl Energy 2021;286:116492. https://doi.org/10.1016/j.apenergy.2021.116492.

[179] Der Kiureghian A, Ditlevsen O. Aleatory or epistemic? does it matter? Struct Saf 2009;31(2):105–12. https://doi.org/10.1016/j.strusafe.2008.06.020.

[180] Trčka M, Hensen JL. Overview of hvac system simulation. Autom ConStruct 2010;19(2):93–9. https://doi.org/10.1016/j.autcon.2009.11.019.

[181] T. Dixon, S. Bright, P. Mallaburn, K. B. Janda, C. Bottrill, R. Layberry, Learning from the “data poor”: energy management in understudied organizations, J Property Invest Finance:10.1108/JPIF-03-2014-0018.

[182] Schmidt M, Åhlund C. Smart buildings as cyber-physical systems: data-driven predictive control strategies for energy efficiency. Renew Sustain Energy Rev 2018;90:742–56. https://doi.org/10.1016/j.rser.2018.04.013.

[183] Tian W, Heo Y, De Wilde P, Li Z, Yan D, Park CS, Feng X, Augenbroe G. A review of uncertainty analysis in building energy assessment. Renew Sustain Energy Rev 2018;93:285–301. https://doi.org/10.1016/j.rser.2018.05.029.

[184] Fisk WJ. A pilot study of the accuracy of co2 sensors in commercial buildings. Tech. rep. Lawrence Berkeley National Laboratory; 2008.

[185] Jin Y, Yan D, Sun H. Lighting system control in office building using occupancy prediction based on historical occupied ratio. EES (Ecotoxicol Environ Saf) 2019;238(1):012009. https://doi.org/10.1088/1755-1315/238/1/012009.

[186] Chen Z, Jiang C, Xie L. Building occupancy estimation and detection: a review. Energy Build 2018;169:260–70. https://doi.org/10.1016/j.enbuild.2018.03.084.

[187] Melfi R, Rosenblum B, Nordman B, Christensen K. Measuring building occupancy using existing network infrastructure. In: 2011 international green computing conference and workshops. IEEE; 2011. p. 1–8. https://doi.org/10.1109/IGCC.2011.6008560.

[188] Hu S, Yan D, Azar E, Guo F. A systematic review of occupant behavior in building energy policy. Build Environ 2020:106807doi. https://doi.org/10.1016/j.buildenv.2020.106807.

[189] Park JY, Nagy Z. Comprehensive analysis of the relationship between thermal comfort and building control research-a data-driven literature review. Renew Sustain Energy Rev 2018;82:2664–79. https://doi.org/10.1016/j.rser.2017.09.102.

[190] Jung W, Jazizadeh F. Energy saving potentials of integrating personal thermal comfort models for control of building systems: comprehensive quantification through combinatorial consideration of influential parameters. Appl Energy 2020;268:114882. https://doi.org/10.1016/j.apenergy.2020.114882.

[191] Arnold JG, Moriasi DN, Gassman PW, Abbaspour KC, White MJ, Srinivasan R, Santhi C, Harmel R, Van Griensven A, Van Liew MW, et al. Swat: model use, calibration, and validation. Trans ASABE 2012;55(4):1491–508. https://doi.org/10.13031/2013.42256.

[192] Drgoňa J, Arroyo J, Cupeiro Figueroa I, Blum D, Arendt K, Kim D, Ollé EP, Oravec J, Wetter M, Vrabie DL, Helsen L. All you need to know about model predictive control for buildings. Annu Rev Contr 2020;50(1367-5788):190–232. https://doi.org/10.1016/j.arcontrol.2020.09.001.

[193] Blum D, Jorissen F, Huang S, Arroyo J, Benne K, Li Y, Gavan V, Rivalin L, Helsen L, Vrabie D, et al. Prototyping the boptest framework for simulation-based testing of advanced control strategies in buildings. In: Proceedings of the international building performance simulation association, international building performance association (IBPSA); 2019.