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Building energy simulation and its application for building performance optimization: A review of methods, tools, and case studies

Yiqun Pan [a,*], Mingya Zhu [a], Yan Lv [b], Yikun Yang [a], Yumin Liang [a], Ruxin Yin [a], Yiting Yang [a], Xiaoyu Jia [a], Xi Wang [a], Fei Zeng [a], Seng Huang [c], Danlin Hou [d], Lei Xu [e], Rongxin Yin [f], Xiaolei Yuan [g]

[a] *School of Mechanical Engineering, Tongji University, Shanghai, China*
[b] *GD Midea Heating & Ventilating Equipment Co., Ltd., Foshan, Guangdong, China*
[c] *Oak Ridge National Laboratory, Oak Ridge, TN, USA*
[d] *Department of civil engineering, University of Victoria, Vic, Canada*
[e] *School of Civil Engineering, Georgia Institute of Technology, Atlanta, USA*
[f] *Grid Integration Group, Lawrence Berkeley National Laboratory, Berkeley, CA, USA*
[g] *Department of Mechanical Engineering, Aalto University, Espoo, Finland*

A R T I C L E I N F O

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A B S T R A C T

As one of the most important and advanced technology for carbon-mitigation in the building sector, building performance simulation (BPS) has played an increasingly important role with the powerful support of building energy modelling (BEM) technology for energy-efficient designs, operations, and retrofitting of buildings. Owing to its deep integration of multi-disciplinary approaches, the researchers, as well as tool developers and practitioners, are facing opportunities and challenges during the application of BEM at multiple scales and stages, e.g., building/system/community levels and planning/design/operation stages. By reviewing recent studies, this paper aims to provide a clear picture of how BEM performs in solving different research questions on varied scales of building phase and spatial resolution, with a focus on the objectives and frameworks, modelling methods and tools, applicability and transferability. To guide future applications of BEM for performance-driven building energy management, we classified the current research trends and future research opportunities into five topics that span through different stages and levels: (1) Simulation for performance-driven design for new building and retrofit design, (2) Model-based operational performance optimization, (3) Integrated simulation using data measurements for digital twin, (4) Building simulation supporting urban energy planning, and (5) Modelling of building-to-grid interaction for demand response. Additionally, future research recommendations are discussed, covering potential applications of BEM through integration with occupancy and behaviour modelling, integration with machine learning, quantification of model uncertainties, and linking to building monitoring systems.

1. Introduction

Nowadays, carbon neutrality is a common goal for many countries in the world as the promising response to global climate change with the ever-increasing energy demand and carbon emissions. The building sector is key to the achievement of carbon peaking and carbon neutrality commitment as it accounts for about 40% of global energy-related carbon emissions [1]. The energy use of Chinese building sector presently accounts for 20% of total energy use in China, one of the world's largest emitters [2]. Moreover, the energy use of building sector in China still has the potential to form a significantly increasing portion of total global emissions by 2050 in the absence of strong policies or effective energy saving technologies to reduce these emissions. Rapid and continuing growth in the building sector could imperil the Chinese government's commitment for CO_2 emissions to peak around 2030 and to neutrality around 2060.

As one of the most important and advanced technology for carbon-mitigation in the building sector, building energy modelling (BEM) has increasingly become practical and supportive method for energy-efficient designs [3], operations [4], and retrofitting of buildings [5], with the aim of energy performance improvement and carbon emission reduction.

Scientific models can be generally classified in two ways: (1) diagnostic or prognostic models, and (2) physical (forward) or data-driven (in-

* Corresponding author.
E-mail address: yiqunpan@tongji.edu.cn (Y. Pan).

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Table 1
Questions to be solved by application of BEM on varied scales of building phase and spatial resolution.

Relevant sections	Phase	Spatial resolution	Key questions to solve
2	Design	Buildings	Performance-driven design
3	Operation	Buildings	Model-based operational performance optimization
4	Operation	Buildings	Integrated simulation using data measurements for digital twin
5	Operation	District/urban	Urban models using building simulation methods
6	Operation	Buildings/District/urban	Building-to-grid interaction for demand response

verse) models. The common BEM models can be recognized as prognostic physical models due that they predict the behaviour of a complex system given system properties, conditions and a set of well-defined laws, such as energy balance, mass balance, conductivity, heat transfer, etc. [6]. Different from data-driven models that describe a system with few adjustable inputs, the physical models are usually over-parameterised and require more inputs, while in that they can model the system behaviour with previously unobserved conditions.

Fuelled by the rapid development of various data sensing, modelling and visualizing technologies, BEM has attracted increasingly attention for application researches for optimizing energy efficiency on multiple scales, such as different stages during the whole building lifecycle [7], and different spatial scales (e.g. system level, building level, district or community level, and building sector level) [8]. During the application of BEM on different scale, the researchers, as well as tool developers [9], and practitioners are still facing huge challenges and confusions, owing to highly complex integration of the possibly involved multi-disciplinary approaches [10].

Under this circumstance, this paper attempts to provide a clear picture on the state-of-the-art progress and potential advancement of BEM, being a strong and effective guide/reference for the current and future researchers in the field of BEM and its application.

With this aim, our study totally collected 157 publications, which were screened for the relevance to the review objective based on the criteria: (1) the study focused on the application of building energy/performance simulation for different stages, e.g. building design and operation, or on different scales, e.g. building/district/urban levels; (2) the study contained the case/pilot related to modelling methods of building energy/performance simulation; (3) the study is not just a purely case study of the commonly-used modelling method; (4) the study was published after 2011. After reviewing these publications, we preliminarily classified the existing literature into the following five application questions that are probably solved by the comprehensive integration of BEM on varied scales of building phase and spatial resolution, as listed in Table 1.

As for the building design phase, the BEM technologies are extensively used to optimize the design strategies for low-carbon and net-zero buildings, namely performance-driven design. As for the building operation phase, the physics-based energy model can be used to simulate the operational performance and optimize the control strategies of building energy systems. With the development of computer science, the availability of measured energy use and indoor environment data have promoted the integration of traditional physics-based BEM and advanced digital twin technologies, making the building information modelling a helpful solution to prediction and fault diagnosis of building energy systems. In addition to the operation of individual buildings, the application of BEM has been extended to the district and urban scales. Urban building energy modelling can be used to analyse the operational performance of urban energy system, promoting the utilization of renewable energy resources for urban sustainable development. Besides, another critical application of BEM is to enhance the energy resilience of buildings by integrating the simulation of building energy system and local grid to balance the energy production and demand at urban scale.

Fig. 1 shows the distribution of the 157 studies across various application scenarios. From the figure, it is apparent that the literatures related to each scenario are relatively evenly distributed, with a slightly

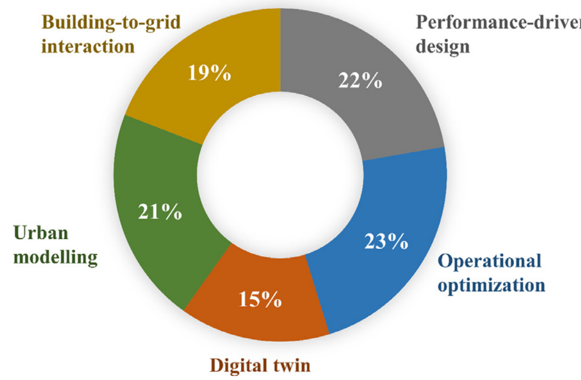

Fig. 1. Distribution of the selected studies across various application scenarios.

higher proportion on performance-driven design and operational optimization, as well as the lower proportion on digital twin. The yearly trends of the studies on the five application scenarios in Fig. 2 have implied that the scenarios of digital twin, urban modelling, and building-to-grid interaction get increasingly attention in the recent several years. This review also classifies the selected literatures into two types: review, and research papers. Fig. 3 illustrates the sub-categories of the selected studies for each application scenario. It is obvious that the majority of existed studies in the field of BEM are classified as research paper, such as on research framework, simulation methods, case study, etc.

Even though there have been massive BEM application studies over the past decade, the majority papers have paid more attention to propose/utilize a specific modelling framework /methodology for specific case buildings. With the generation of considerable interest in advanced application, such as digital twin and urban modelling, the BEM area is undergoing a revolution in terms of extrapolating simulation and modelling methodology to the wider scales and levels. In this context, we believe that outlining the past-present focuses of the BEM application studies is one of the most important issues to be addressed for facing the upcoming challenges from varying simulation demand in various scales of energy performance modelling.

This review could be a good start that aims to enhance the integration of BEM application in the future researches on improving building/urban energy efficiency, also assist other related researchers to understand the state-of-the-art of BEM application studies easily. Our objectives are to:

- Categorize relevant BEM application literature into five application scenarios related to various building stages and research scales.
- Perform detailed summary of framework, methodology, key cases and research gap for each application scenario.
- Provide recommendations on future perspectives and possible challenges in the field of BEM.

This review paper has the structure as follows. Sections 2–6 elaborate the review of literatures on the five application scenarios in the order of (1) Performance-driven design; (2) Building operational optimization; (3) Digital twin; (4) Urban modelling; and (5) Building-to-grid interaction. Section 7 discusses our perspectives on future directions and

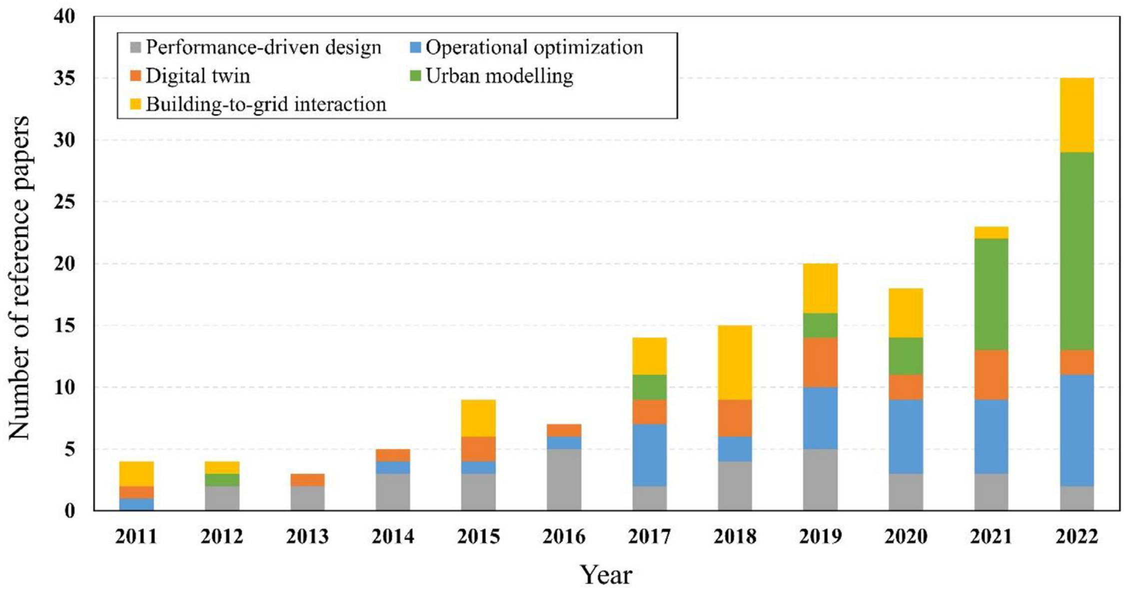

Fig. 2. Yearly trends of literatures for various application scenarios.

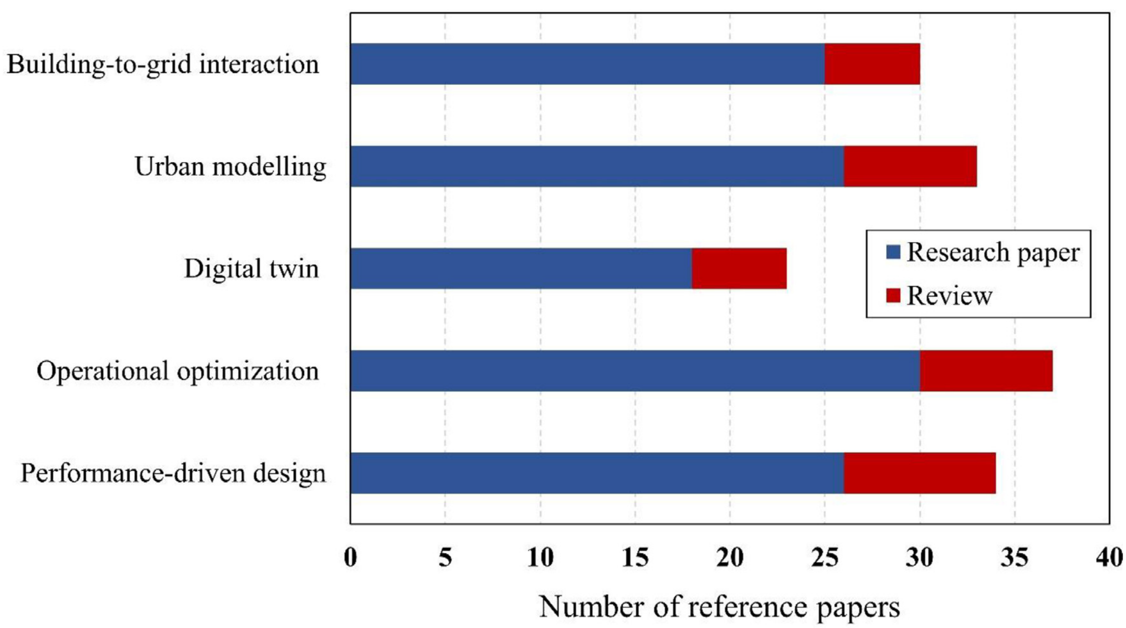

Fig. 3. Sub-categories of literatures on various application scenarios.

potential challenges of BEM research and development. Section 8 concludes this review paper.

2. Performance-driven design

2.1. Goals of performance-driven design

During the building design process, engineers strive to reconcile qualitative and quantitative approaches to meet the requirements related to a building's performance [11,12]. Green building standards and guidelines have been implemented in many countries [13], which establish performance evaluation criteria to guide and optimize building design and to promote the evolvement of the performance-driven design. The building performance-driven design can help to strengthen the connections between various stakeholders, such as building decision-makers, designers, and users, as well as the multiple stages of building design, building evaluation, and building decision-making, in order to improve efficiency and enable significant improvements in building performance. Through building performance-driven design, the conditions and results of building design are intuitively linked to facilitate the control of building design results, thus promoting the scientific, accurate and efficient development of building design.

The workflow of performance-driven design is illustrated in Fig. 4, mainly consisting of three parts [6,14]: (1) preliminary design schemes, including parametric setting and system selection; (2) building modelling and performance simulation, containing modelling and analysis of various aspects of building performance (e.g., energy analysis, environmental analysis); (3) optimization, mainly using multi-objective

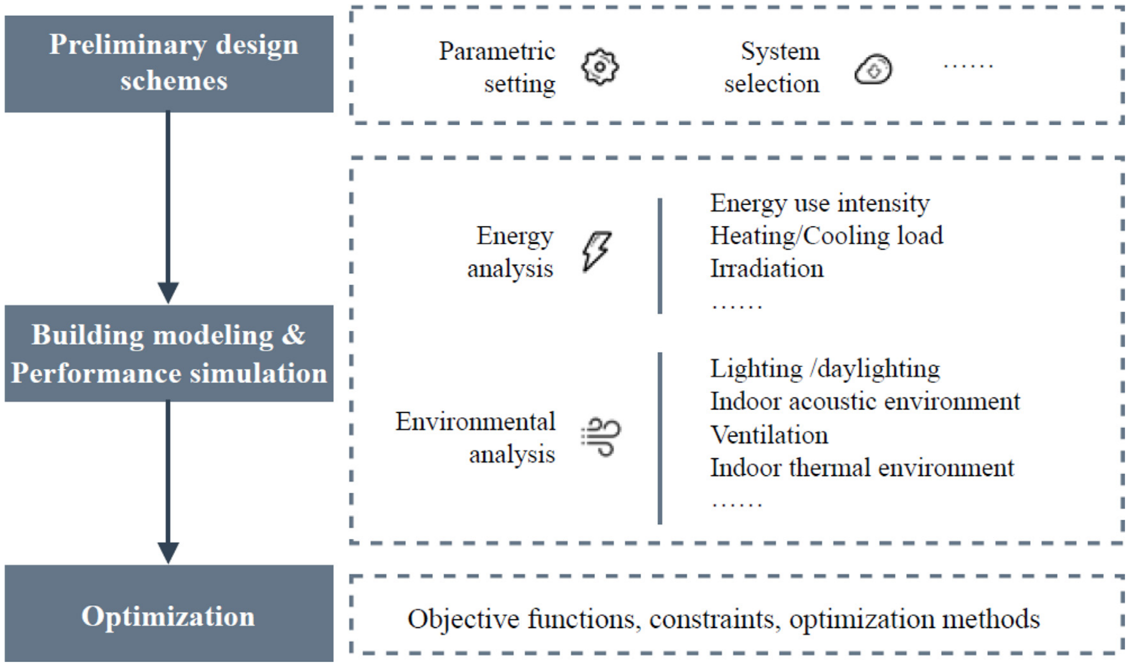

Fig. 4. A common workflow of performance-driven design.

functions to improve the building performance. The following sections present a literature review on performance-driven building design from the perspective of approaches and applications.

2.2. Approaches of performance-driven design

2.2.1. Methods for preliminary design

In the preliminary design stage, the primary purpose is to obtain a reasonable initial design scheme. From the perspective of target building types, performance-driven design can be divided into new building-orientated and building retrofit-orientated, each with its applicable methods.

For new building-orientated design, due to the lack of available data, it is necessary to select a reference, which is the prototype design method. According to the source of the prototype, it can also be divided into standard prototype and database prototype. The standard prototype method is based on standards formulated for a specific kind of buildings (e.g., offices, hotels, dwellings, schools, and hospitals). Some international standards have been embedded in simulation software as templates. The database prototype method can be thought to be the reverse application of building prototyping. Each geographical region can contain one or more typical prototypical buildings representing the limited building types within that region [15]. Building prototyping is a method to obtain statistically representative prototypes to identify the effect of different technology packages and offer guidance for design optimization [16]. On the contrary, the database prototype method is to select a template scheme that meets the requirements in the database composed of these prototypes [17].

For building retrofit-orientated design, it can be summarized as a self-reference method, which can be interpreted from two aspects: (1) as the building retrofit aims at the existing buildings, the modelling data is determined and measurable rather than referring to other prototypes; (2) the performance of the before-retrofit building is considered as a baseline for evaluating the performance of retrofit technologies. Building retrofit technologies can be categorized into four groups: heating and cooling demand reduction, energy-efficient equipment and low energy technologies, renewable energy technologies and electrical system retrofits, and human factors, from which the preliminary design schemes can be selected [18].

2.2.2. Methods for performance simulation

In the design stage, a variety of building performances are considered for different design needs, which can be divided into two groups: energy performance (e.g., energy use intensity [19], heating/cooling load [20,21]) and environmental performance (e.g., lighting [22], indoor acoustic environment [23], ventilation [24], indoor thermal environment [25]). In this section, we summarize the simulation methods for different aspects of building performance in detail.

2.2.2.1. Methods for building energy performance. Energy modelling for heating and cooling load estimation and energy use prediction is essential to achieve the goal of energy saving and emission reduction of buildings. As summarized in Table 2, the methods of energy modelling generally fall into three computational categories: (1) simplified evaluation method, (2) detailed physical method, and (3) statistical and regression method, and the first two belong to the forward modelling approach while the third is the inverse modelling approach [20]. The simplified evaluation method assumes a steady-state feature of building thermal systems to quickly predict energy use and study trends so that the inputs are more straightforward and the calculation is faster than detailed physical simulation [21]. The detailed physical method is based on analytical relationships amongst various building components (e.g., envelope, HVAC system, plants, terminal equipment) through physics theories and numerous formulas. With the development of programming technology, simulation programs (e.g., EnergyPlus, DOE2, TRNSYS) embedded with these physical models have been developed rapidly into visualization tools with graphical user interfaces (GUI) [22,26]. The statistical and regression method focuses on correlations between condition parametric setting and system structure, and historical energy data. Because of the dependence on historical energy data, this method only applies to the building retrofit-orientated design. The models established in the statistical and regression method are powerfully mathematical with excellent accuracy but poor physical interpretation [19].

2.2.2.2. Methods for indoor environmental performance. In addition to energy performance in the macro aspect, detailed environmental performances are in need for occupant health and comfort. Simulation methods for three group environmental performances are summarized in Table 3, as well as the applicability and typical simulation tools.

Table 2
Summary of three different methods for building energy performance simulation.

Method	Order	Advantage	Limitation	Typical method/Tool
Simplified evaluation method	Forward	Simple inputs Fast calculation	Limited applicability	Degree-day method Bin method
Detailed physical method	Forward	Visualization tools Good physical interpretation	Complex inputs	EnergyPlus DOE2 TRNSYS
Statistical and regression method	Inverse	Accurate prediction Fast calculation	Only for existing buildings Poor physical interpretation	Multiple linear regression Artificial neural network Support vector machine

Table 3
Summary of simulation methods for environmental performances.

Environmental performance	Simulation method	Applicability	Typical simulation tools
Lighting & Daylighting	1. Direct calculations 2. View-dependent algorithms 3. Scene-dependent algorithms	1. Artificial lighting 3. Image generation 3. Lighting calculations	Radiance, Ecotect, Honeybee, DElight
Indoor acoustic environment	1. Wave-based method 2. Geometrical acoustics method 3. Hybrid method	1. Inhomogeneous media 2. Engineering applications 3. Combine the above two	Odeon, Epidaure, Raynoise
Ventilation and indoor thermal environment	1. CFD method 2. Multi-zone method 3. Zonal method	1. Complex air distribution 2. Rough and quick simulation 3. Based on prior estimation	Fluent, Airpack, CONTAM, COMIS

For lighting/daylighting performance, the lighting simulation algorithms can be classified into direct calculations, view-dependent algorithms, and scene-dependent algorithms [27]. Direct calculations currently are used for artificial lighting, following local standards. The view-dependent algorithms represented by ray tracing are available for forward and backward ray tracing so that they are applicable for image generation. Compared with this, the scene-dependent algorithms represented by radiosity are used mainly for lighting calculations due to more rigorous and complex formulas.

For indoor acoustic environment, the acoustic prediction methods include the wave-based method, and geometrical acoustics method. The wave-based method can solve the problem of sound propagation in inhomogeneous media in the complex environment such as sports halls [24]. The geometrical acoustics method is widely used in engineering applications because of its applicability for complex building geometry and high computation demand. The hybrid method combines the strengths of different methods to achieve more accurate results with less computational cost.

For ventilation and indoor thermal environment, the physical modelling methods for indoor environment fall into three categories: computational fluid dynamics (CFD) method, zonal method, and multi-zone method [20]. The CFD method can solve complex air distributions and visualize the quantitative results by integrating fluid mechanics, thermodynamics, numerical analysis, and computer science [28]. To avoid high computational costs, the multi-zone method is a good choice for quick airflow and contaminant distribution simulation. It assumes uniform air distribution in each zone that is represented simply with one node and form a fluid network with doors, windows, and other openings. With the same assumption as the multi-zone method, the zonal method divides a zone into several sub-zones. It establishes mass and energy conservation equations to obtain more detailed air parameter distributions than the multi-zone method with less computing time than the CFD method [25].

2.2.3. Performance optimization methods

For optimal design, optimization is usually necessary for performance-driven design in recent studies [29]. In the building design, the various performance requirements lead to numerous optimization problems, often expressed as multi-objective nonlinear problems [30]. In the common workflow of performance optimization, the program usually couples with the simulation process in each iteration to form a loop [31], as shown in Fig. 5. The optimization program consists of three necessary items: objective functions, constraints, and optimization methods.

Numerous optimization methods have been developed to deal with various types of problems. The mostly-used to building performance optimization can be classified into direct search, gradient-based, meta-heuristic, and hybrid methods [14]. Direct search methods are suitable for discrete variables without the need for derivative information. Hasan et al. applied the brute-force search (namely exhaustive search) method to achieve the minimization of the life cycle cost of a detached house by optimizing two discrete variables (*u*-value of the windows and type of heat recovery) [32]. With fast convergence, gradient-based methods are sensitive to multi-modal functions and discontinuities in the cost function [14]. Vakiloroaya et al. solved the minimization of energy consumption and the optimal set-points of air-cooled central cooling plant systems through a developed gradient projection algorithm [33]. Meta-heuristic methods do not depend too much on the organizational structure information of the algorithm and can be widely used in function combination optimization and function calculation. The non-dominated sorting genetic algorithm-II (NSGA-II) is one of the most popular multi-objective meta-heuristic methods [34]. Bre and Fachinotti adopted NSGA-II in their study and achieved more than 80% improvement both in energy efficiency and thermal comfort in dwellings [35]. The hybrid methods usually combine multiple approaches to enhance the strengths and limit the weaknesses. Combining the global features of the particle swarm optimization (PSO) with the powerful convergence ability of the Hooke-Jeeves (HJ) algorithm, the hybrid PSO-HJ method performed great effectiveness and robustness for the optimized complex fenestration system solutions [36].

2.3. Application and case summary

According to the common workflow, building performance-driven design consists of three major parts: (1) preliminary design, (2) simulation for energy and environmental performance, and (3) optimization. The representative studies are summarized in Table 4. In the following subsections, the application scenarios of performance-driven design are discussed in detail.

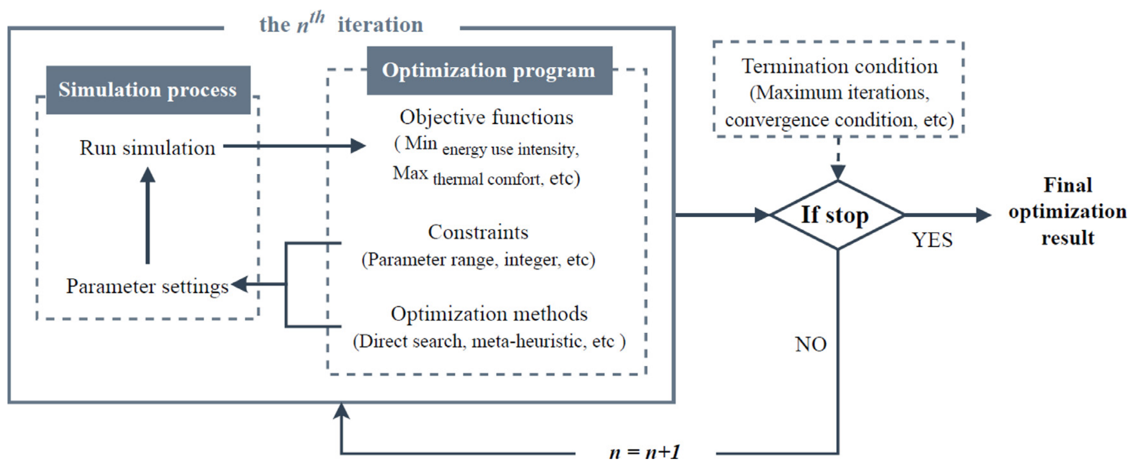

Fig. 5. The optimization loop coupling with simulation process.

Table 4
Review on the applications of performance-driven design.

Ref.	Building types	Simulation tool	Applications: Energy-related	Environmental analysis: Thermal	Daylighting	Air quality	Optimization objectives
[37]	Office	Rhinoceros; Grasshopper; Honeybee			●		UDI, sDA, ASE
[38]	Residential	DesignBuilder; EnergyPlus	●				Energy consumption, CO2 emissions
[39]	Hospital	CFD				●	Average air age
[40]	Office	TRNSYS; IBE-e	●				Energy consumption
[41]	Education	Sketchup; Radiance			●		DA, UDI
[42]	Education	DesignBuilder; eQUEST; EnergyPlus		●		●	CO2 concentration, Indoor air temperature
[43]	Education	Radiance; EnergyPlus		●	●		Daylighting scores, Heating loads and cooling loads
[44]	Office & Education	EnergyPlus	●	●			Energy use, Non-comfortable hours, Exergy destructions
[45]	Office	Rhinoceros; DIVA			●		UDI

Notations: UDI= useful daylight illuminance, sDA= spatial daylight autonomy, ASE = annual solar exposure, DA= daylight autonomy.

2.3.1. *Preliminary design*

The first step in developing a performance-driven building design is preliminary design. As discussed in the previous section, parameter setting and model development are generally based on typical prototype or on-site measured data. Loche et al. [37]. developed the parametric study using a representation of a "typical" mixed-mode office room model as a base case. They used the plug-in Grasshopper to model the case. The results demonstrated that balconies could be an efficient shading device and daylight diffuser with proper dimensions. As an example of design decisions in the early design phase of residential buildings in Turkey, Gercek and Durmuş Arsan [38] assessed the impact of climate change on building energy and environmental performance characteristics and synthesized the correlation between building energy and environmental performance criteria and design parameters. Based on a large general hospital project, Yao et al. [39] made the field test on the indoor air quality of hospital buildings and established the geometric model according to the test data. They employed the CFD software to carry out the numerical simulation and study the effects of three different air distributions.

2.3.2. *Simulation for energy and environmental performance*

Currently, performance simulation is mainly focused on energy and environmental analysis. Li et al. [40] proposed a performance-based design method based on overall energy consumption and progress for the nearly zero-energy building. The design process of the actual case was analyzed, and the optimal solution for the near-zero energy building was derived by taking into account the cooling and heating sources, the environment, and renewable energy.Nocera et al. [41] focused on assessing the existing lighting conditions of a historical building to define suitable retrofit solutions for daylighting systems, and the approach was adopted to assess daylight availability in a representative classroom in an educational heritage building in Syracuse (Italy). Tam et al. [42] monitored indoor air temperature, and CO_2 concentration in multiple lecture halls in Toronto, and one classroom was chosen as a representative case study for retrofitting. And the evaluations were conducted using building performance simulation (BPS) to investigate the causes of discomfort in the classroom and to identify methods for regulating temperature and CO_2 concentration.

2.3.3. *Optimization*

Setting different optimization objectives based on performance requirements to arrive at the optimal building design solution is an important performance-driven design process. Futrell et al. [43] used a hybrid GPS Hooke Jeeves/PSO algorithm in combination with the Epsilon Constraint Method for optimizing building envelope design to find a Pareto-efficient solution for the thermal and lighting performance optimization objectives. García Kerdan et al. [44] presented an exergy-based multi-objective optimization tool for assessing the impact of various retrofitting measures, to determine the optimal retrofitting measures while minimizing energy use, exergy destructions, and thermal discomfort. Two UK archetype case studies (an office and a primary school) were used to test the feasibility of the proposed framework. Lu et al. [45] investigated the improvements in daylight efficiency of office buildings by optimizing curved facades. The results of the typical office building demonstrated that the optimized curved facade can significantly improve the daylight efficiency.

Through modelling, simulation, and optimization, performance-driven building design facilitates the development of design solutions for buildings that satisfy performance requirements. Currently, building performance focuses mainly on enhancing indoor air quality and energy efficiency. The studies mentioned above demonstrate that performance-driven design may greatly improve building indoor environmental performance, emphasizing its importance in accomplishing building performance-related objectives. Consequently, practitioners can optimize building performance in this manner during the design stage.

Actually, the building design during the scheme phase is closely related to the building's performance in usage and operation. Performance-driven design is function-driven, particularly as some building design parameters (e.g., window-to-wall ratios, envelope heat transfer coefficients, etc.) have a direct impact on daylighting, ventilation, and thermal comfort, therefore incorporating performance variables at the scheme stage can make a difference in the performance of the building design. Furthermore, since building design is a complex process with many factors to consider, performance-driven building design will assist to restore the systematic features to the design process and enhance efficiency, leading to substantial improvements in building performance. Technically, the more mature performance-based building design methodologies currently evaluate building performance with simulation techniques. Its computer-automated design optimization process enables a large number of design alternatives to be generated and analysed in a short period of time to identify the best performing designs. However, the technical knowledge necessary for design optimization in this manner is extensive, and the time and effort required by the user (e.g., the architect) to set up and operate the design optimization process may be an important concern for future study.

3. Model-based operational performance optimization

3.1. Goals of model-based operational performance optimization

Operational optimization focuses on optimizing the operational settings of a given system to achieve the desired objective functions [46,47]. When it comes to the building systems, those objective functions include reducing building energy costs [48], emissions [49], building energy efficiency [50] while maintaining occupant comfort [51]. Since those objectives are conflicting, building operational optimization can be challenging. To make things worse, the building operational optimization also needs to handle complicated building systems, which tend to be highly non-linear and stochastic. The system model has been proved as a useful tool in addressing those difficulties.

3.2. Approaches for optimizing operational performance

The common workflow of building simulation for operation is shown in Fig. 6. Firstly, real-time operation data and geometry data are collected from building energy management systems, building information modelling (BIM), respectively. Secondly, pre-processing and data analysis are conducted to identify the building operation pattern, which is used to establish the system models of the building and the HVAC system. Then the building and HVAC systems are simulated to validate the effectiveness of optimal control strategies. With the objective function, the optimal settings of decision variables that minimize the system energy consumption and/or optimize indoor environmental conditions are obtained by optimization algorithms. Thirdly, the optimal operational settings of chillers, pumps, and cooling towers will be determined. The following subsections discuss these steps in depth.

3.2.1. Data acquisition and analysis

The efficacy of the model depends on the quality and reliability of the inputs [52,53]. With the development of modern infrastructure and technologies, e.g., smart technologies and the Internet of Things (IoT), massive building operational data can be obtained from building energy management systems. The collected operational data include temperature, humidity, flow rate, pressure, power of the equipment, on-off states of equipment and so on. Also, the outside temperature and humidity were collected in some studies to determine the impact of disturbances in weather conditions [54]. These data can be used to identify building operational patterns, e.g. occupancy and lighting schedules [55]. In the last few years, the collecting and processing of occupancy data have become emerging issues since they can affect, either directly or indirectly, the operation of buildings. The sensors to collect occupancy data can be built-in temperature sensors in smartphones of the building occupants [56] or the occupancy recognition system based on real-time video [57].

Besides the operational data for building services systems, the other data required for simulation or calibration are building envelope parameters (e.g., U-values of wall and windows, absorptivity of walls and G-value of windows). These data are needed to describe the building features when solar thermal systems, heat pumps and heat recovery technologies are used as active building technologies. The pre-processing phase plays a significant role in the success of the optimization to avoid the risk of over-simplification or delaying the optimization process [14]. There are several typical pre-processing steps, e.g., data cleaning, normalization [53], and sensitivity analysis [58].

To learn the operation patterns of HVAC systems and the resulting impacts on energy efficiency, data mining (DM) techniques are recommended to develop data-driven models that reflect interactions between state variables and operation efficiency. Motif and discord detection, clustering and association rule mining are three main types of unsupervised data mining technologies for knowledge discovery in the building field [59]. For example, DM was used to compute the variable importance in terms of the optimal control reward [60] and displacing groups of occupants with similar occupancy patterns to the same thermal zone [61].

3.2.2. Modelling approaches

A detailed whole building dynamic energy model to simulate the overall building performance needs to consider various building specifications and characteristics, including internal loads and schedules and technical energy system specifications. Due to the functional characteristics of modular and flexible construction and step-by-step calculation, simulation tools e.g., EnergyPlus [58], TRNSYS [62], DeST [63], and Modelica [64] are broadly used to depict building performance. The accuracy in using these simulation programs depends on the ability of the user to input parameters that result in a good model of actual building energy use. Thus, it is necessary that the parameters of the model be fitted to the actual physical system, which is called model calibration. In general, the measured data and weather data might be used to calibrate or validate the models. For example, Huang et al. tuned the coefficients of the chiller performance curve, the chilled water temperature, etc. to minimize the difference between the measured and simulated power of the chiller using the actual temperatures of the condenser and chilled water entering the chillers [65]. Capozzoli et al. implemented an optimized HVAC operation schedule based on a model calibrated with the actual weather data and the building energy consumption [61].

Regarding the techniques used in the optimization, the genetic algorithm (GA) was commonly used [66–68]. Both Functional Mock-up Interface (FMI) and Building Control Virtual Testbed (BCVTB, LBNL) have been widely used to exchange the I/O and data when MATLAB and EnergyPlus are co-simulated [69,70]. For example, Wang et al. used EnergyPlus software to determine electricity, heating, and cooling demands, and MATLAB software to investigate the impacts of key cycle parameters on thermodynamic and economic performance and to model the optimal design of the CCHP system. After that, an artificial neuron

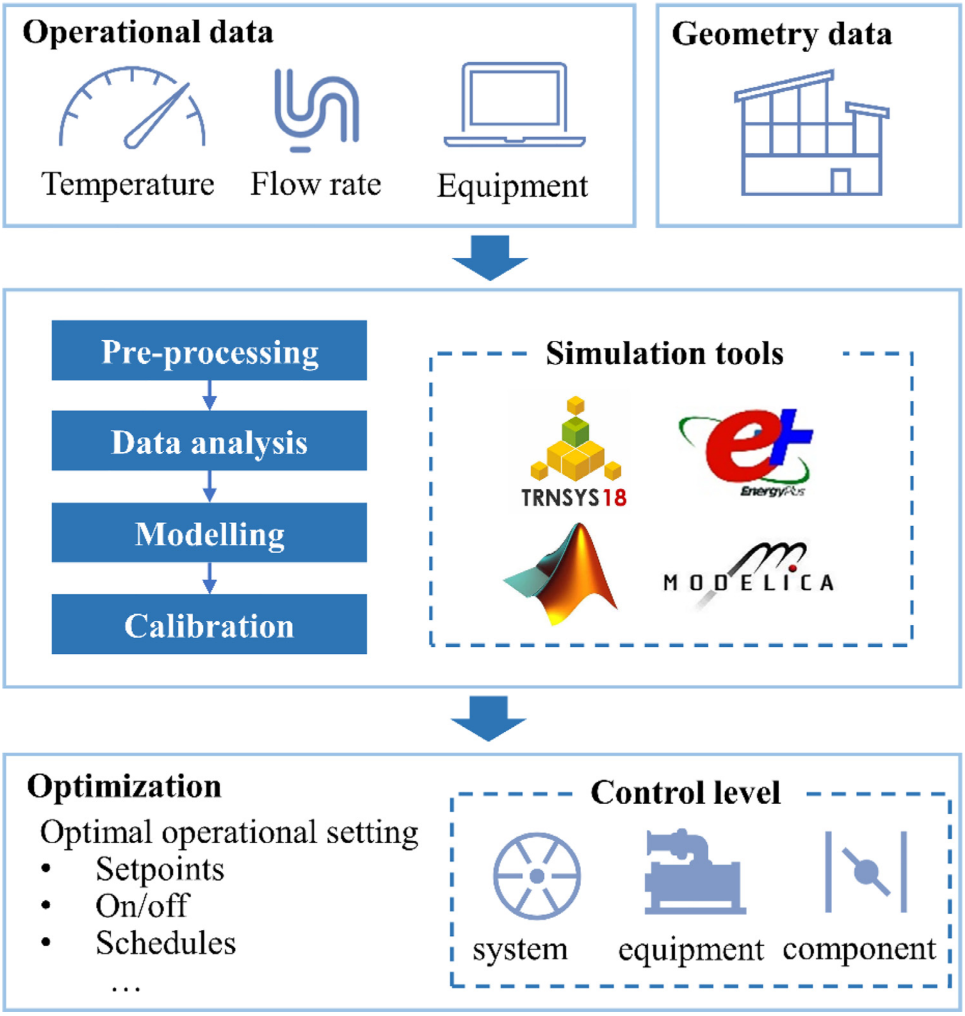

Fig. 6. A common workflow of model-based operational performance optimization.

network (ANN) black-box model was trained to replace it with the original model by EnergyPlus to make the GA optimization possible and faster [63]. Gomez-Romero et al. created a grey-box model to optimize HVAC operation in non-residential buildings, which relied on the existing corpus of expert knowledge to model thermal behaviour by using differential equations encoding the physical principles of mass, energy and momentum transfer, and they apply statistical models to tune model outputs based on historical and live data [71]. Souayfane et al. adopted weather-clustering technique and coupling TRNSYS and GenOpt to determine the optimal cooling operation of a single-zone office building conditioned by an air-source heat pump. The optimal cooling control operation strategy found for each representative day is then applied for all days of the same cluster [72].

3.2.3. *Operational optimization strategies*

In the existing literature, control of HVAC systems typically involves optimizing on-off status, operating modes and setpoints (e.g., thermostat setpoints, HVAC supply airflow rate, supply air temperature, pressure setpoints) to minimize energy consumption or operating costs for the overall system while thermal comfort is satisfied. For example, Garnier et al. considered five non-predictive strategies to optimize the operation of all the HVAC subsystems in a real non-residential building located in Perpignan (south of France), including four basic scheduling techniques modelled using the EnergyPlus software and pre-heating or pre-cooling during off-peak periods [68]. Papadopoulos et al. fine-tuned the HVAC cooling and heating setpoints using the simulated-based multi-objective framework on typical large office buildings in seven different climate zones in the US [73]. In terms of equipment, Fan et al. studied the local control including staging control, speed control, isolation valve control, and bypass valve control. Supervisory control strategies were also taken into account, including cooling mode control sequences, a chilled water supply temperature reset control, chilled water loop differential pressure reset control, and a condenser water supply temperature reset control [64].

3.3. *Applications and case studies*

By reviewing current studies, building simulation for operational optimization is mainly applied for three different levels to identify the optimal operational settings: (1) system, (2) equipment, and (3) components. Table 5 summarizes the findings of several representative studies, along with their frameworks, approaches, and applications. The following subsections discuss the three application levels of HVAC systems in detail.

3.3.1. *System-level optimization*

There are many studies about system-level optimization. For the models used to evaluate the energy impact of proposed changes in the control scheme before implementation, the processes are mainly pure simulation and generated offline. For instance, Vering et al. used process intensification to consider the heat pump system design and operation simultaneously. After the design is optimized in an annual dynamic

Table 5
Review on the applications of building simulation for operation.

Ref.	Type of buildings	Tools	Application (Case study)			Optimization Strategy
			System	Equipment	Component	
[74]	non-residential building	Modelica	●			· The compressor speed PID-controller parameters, K_P and T_I were optimized.
[75]	educational building	DesignBuilder	●			· Heating and cooling setting temperature of air conditioning were selected as decision-making parameters.
[63]	hotel	DeST	●			· The output schemes of the solar CCHP under climate change were tackled.
[57]	mosque	EnergyPlus	●			· The HVAC setpoint schedule is modified subject to the thermal-comfort threshold based on the temperature response as well as the occupancy prediction.
[76]	educational building	R		●		· Identification for flow rates of chilled water and condensing water, the supplied chilled water temperature, and the cooling tower fan speed.
[62]	metro station	TRNSYS		●		· The chiller loading was optimized by adjusting the set points of the chilled water outlet temperature.
[77]	commercial building	IES-VE		●		· The supply temperature of the AHU and the airflow of VAV are optimized independently.
[78]	–	EnergyPlus, CONTAM, and Matlab			●	· Optimal trajectories of damper angles and fan pressure were determined.
[79]	–	Matlab			●	· The pressure drops of AHU's filters due to clogging were predict.
[80]	data center	TRNSYS			●	· The operation mode (mechanical cooling, partial, free cooling, and free cooling) that can satisfy the cooling requirement and give the best performance was selected.
[81]	office building	EnergyPlus			●	· Window and ventilation supply air fans were controlled in mixed-mode buildings.

building performance simulation, the system controller is optimized in the second stage using a GA with the same dynamic simulation models [79]. Wu et al. developed a random forest-nondominated sorting genetic algorithm- III (RF-NSGA-III) hybrid intelligent method that can predict and optimize multi-dimensional performance. The result indicated that the optimization of air conditioning setting parameters reduced the life cycle air conditioning energy consumption by 54% [80]. Wang et al. optimized and analyzed the output of the hybrid solar combined cooling, heating, and power system by establishing the operation optimization model. The influence exerted by climate change on the energy load and solar output was identified with the aid of PRECIS and DeST [67]. The collection of operational data remains a challenge due to the complexity and dynamic nature of real building systems and equipment, which leads to a discrepancy between the modelled HVAC system and the actual system. Some studies used hybrid modelling techniques to extract valuable information for the development of modelling with limited measured data. For example, to better simulate the operation energy consumption of each equipment in the HVAC system, Du et al. use the mathematical models of chiller and pump established and combine TRNSYS to establish actual building equipment modules [87].

Additionally, occupant behaviour has been identified as a major factor contributing to the discrepancy between simulation predictions and real energy use [88]. To optimize HVAC control, the actual occupant information and comprehensive context-aware information of the target building are required, occupant characteristics are then identified and input into the control network to make appropriate decisions. For example, Aftab et al. deployed and evaluated an automatic HVAC control system for providing automatic HVAC control in the large public indoor space of a mosque, featuring real-time occupancy recognition and simulation-guided model predictive control. The real-time HVAC control is guided by an onboard EnergyPlus simulator and ported on the Raspberry Pi embedded system platform [58].

3.3.2. Equipment-level optimization

Moreover, many researches were reported on optimizing equipment operation. The models of this part are mainly implemented in the actual building or involved hardware-in-the-loop. Due to the existence of measurement uncertainties and ever-changing operating conditions, optimal switching points of equipment staging often deviate significantly from predefined thresholds. To deal with these uncertainties, stochastic approach is used broadly. In addition, machine learning and advanced data analytics are used to extract valuable information of the equipment. For instance, Fan et al. proposed a gradual pattern mining method for discovering usage patterns and knowledge from building operational data as a generic approach and applied this method for chiller and cooling tower control optimization [81]. Qiu et al. proposed a model-free optimized chiller loading method based on Q-learning to optimize chiller operation. The central chiller of an office building in Shanghai is selected as a case system, and the energy-saving performance of this method is studied through simulation [66]. Zhuang et al. developed a stochastic decision-making scheme to evaluate the risks of chillers' operation and to optimize chillers' sequencing strategy. The central cooling system concerned in this study is a complex primary-secondary chilled water system and the virtual simulation was constructed using TRNSYS [82].

3.3.3. Component-level optimization

Less researches about optimization of HVAC components (e.g., thermostat, air damper, valves, filters, evaporator coil, condenser coil, etc.) have been done so far to the best knowledge of the authors. There are several studies about the optimization of dampers, filters, pipes, and pumps. The application of optimization in actual components is challenged by the difficulty in handling uncertainties in the implementation of actual systems and indirect calculations. To address the above challenges, researchers model the uncertainties as random but bounded noise or obtain the input data from BIM or other sources directly. Li et al. present a tube-based MPC strategy for multi-zone demand-control ventilation systems, and the optimal trajectories of damper angles and fan pressure were determined to minimize energy consumption [83]. To identify the clog behaviors in HVAC filters, Alimohammadi et al. drive a grey-box model from the pressure drop signal [84]. Cheung et al. evaluated different piping and pump designs and optimal control algorithms to suggest an optimized design of free cooling systems in data centers, using a steady-state model of a realistic data center cooling system and compared five different data center cooling systems [85].

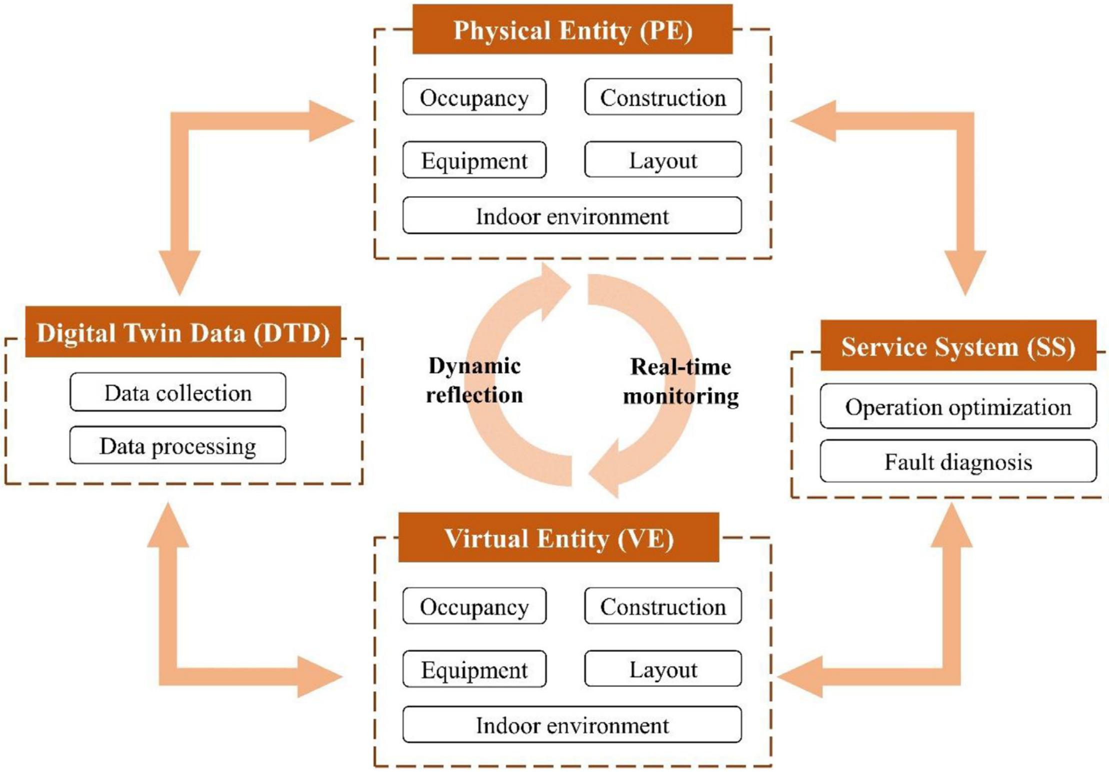

Fig. 7. Concept of digital twins.

May-Ostendorp et al. examined optimizing control sequences based on MPC for window operation in mixed-mode buildings. The optimal solution outperforms by controlling ventilation supply air fans and windows [86].

4. Integrated simulation using data measurements for digital twin

4.1. Digital twin and simulation

The whole life cycle of buildings is inseparable from the exchange of information [82]. In the past two decades, researchers often use known and static building information to build virtual models, such as building information modelling (BIM) and building energy modelling (BEM), to optimize the design, construction, or operation of buildings [83]. However, due to the lack of real-time information input, it makes the virtual models hard to reflect the changes of the actual buildings over time, which limits the use of the models [84]. The emergence of Internet of Things (IoT) and advance metering infrastructure (AMI) enable the real-time interaction between virtual models and actual buildings and the timeliness and rationality of operation decision and fault diagnosis.

With the rapid development of sensing technology, the concept of the digital twin (DT) comes to life through the integration of virtual building models and real-time data from advanced measurement technologies. Building digital twin is the method that builds accurate digital virtual entities of physical entities in real time, and uses data analysis and integration to control, simulate, verify and predict the whole life cycle process of physical buildings, so as to realize intelligent decision-making and optimization [85]. According to the concept in Fig. 7, most of the studies focused on the following 2 key aspects in DTs [85]:

(1) Data interaction: with the help of IoT and data analysis techniques, the raw data (including measured data from sensors, static design information from drawings and equipment nameplates) is collected, cleaned, filtered, and transmitted to create and modify the virtual building. Then through the dynamic monitoring and simulation by the virtual model, the future parameter changes of the actual building can be inferred and fed back, so as to assist the decision-making during the building construction phase and operation phase.
(2) Building simulation and modeling: comprehensive perception of building physical system is the premise of the implementation of DT. In order to realize the efficient interaction between virtual and physical entities at different phases, it is necessary to use different types of data and modeling methods to accurately describe the conditions of the buildings. DT has shown promising potential for wide future uses though it is still in its infancy. To facilitate the understanding of the concept of DT, following the order of building main life phases (construction, and operation phases), this part summarizes the different data and different modelling methods used DTs.

4.2. Data interaction in digital twin

Correct and useful data is the basis of DT applications in intelligent buildings [86]. This part mainly describes the methods and types used in data collection and the possible uses of corresponding models, not including data cleaning or filtering methods.

In the construction phase, the information to be collected mainly includes the following 5 types: workers, materials/structures, machines, methods, and environment [87]. Amongst them, the methods (the technologies adopted in the construction, the method of engineering test, and related regulations) are static data, which do not require real-time monitoring by sensors. The main types of data being collected during the construction are summarized in the following Table 6.

In the operation phase, the information to be collected mostly incorporate 4 types: energy consumption, occupancy, device conditions, building structures, and indoor environment. The main types of data being collected and corresponding sensors during the operation phase are summarized in the following Table 7.

Table 6
Overview of dynamic data collection on the construction site.

Ref	Type	Concrete type	Sensors	Use
[88]	Environment	Natural environment and operating environment of the construction site	3D-scanning, virtual reality (VR)	Deployment
[89]	Materials/ Structures	The conditions of incomplete building entities and construction materials (degree of completion, crack, deformation, temperature, et al.)	3D-scanning, VR, velocity sensors, acceleration sensors, seismic sensors, temperature sensors, optic fibre sensors, et al.	Quality and process management
[90]	Workers	Locations, behaviour and conditions of workers	Radio frequency identification (RFID)	Safety management and schedules deployment
[91]	Machines	Performance and efficiency of all kinds of mechanical equipment used)	Slewing sensors, cable length sensors, boom angle sensors, et al.	Facilities and devices management

Table 7
Overview of the use of sensors in operation.

Ref	Type	Data	Sensors	Use
[92]	Energy	· Energy consumption of lighting, device, and HVAC system	· IoT, smart meter	· Energy management and monitoring
[93]	Occupancy	· Occupancy ratio and occupant behaviour	· IoT, Wi-Fi, Bluetooth low energy (BLE), AR	· Energy-saving behaviour and strategies
[94]	Devices	· Operation data of devices	· Temperature sensors, liquid sensors, pressure sensors, et al.	· Fault diagnosis, operation monitoring
[95]	Structures	· Building envelope status and deformation	· 3D laser scanning	· Structural damage monitoring and restoration
[96]	Indoor Environment	· Indoor temperature, humidity, metabolic ratio	· IoT, temperature, and humidity Sensors	· Thermal comfort evaluation and improvement
[97]	Indoor Environment	· O_2, CO_2, and harmful gases	· Gas sensors	· Hazards identification, evacuation planning

4.3. Simulation and modelling in digital twins

4.3.1. Simulation and modelling in design and construction phase

In the early stage of building construction, simulations are widely applied to help schedule and optimize the construction process. Based on the information of construction site, the construction simulation establishes the model in 4 main parts: geometry, physics, rules, and behaviours, as shown in Fig. 8 [89].

a) Geometric part refers to the basic information such as the appearance, size, and model of the unfinished buildings, components and equipment. The establishment of a high-fidelity geometric model can truly reflect the geometric characteristics of the implementation process.
b) Physical part refers to the material parameters and mechanical properties of components and devices during the construction process. To describe and monitor the changes, the physical model is often established by finite element analysis software such as Midas and ANSYS [98].
c) Rule part refers to the national standards and regulations. It needs to model and parameterize the corresponding standards or specifications to ensure the mechanical performance parameters of the components and the operating status of the equipment during the hoisting process within limits.
d) Behaviour part refers to the corresponding changes in material parameters, mechanical properties, and progress during the hoisting process in response to the decision changes and system instructions.

4.3.2. Simulations and modelling in operation phase

Fig. 9 shows the workflow of digital twins in buildings operation phase. For the current energy simulation physics-based methods, the models often ignore the specific geometric shape and volume, and only input the abstraction of the shape. It cannot simulate the parameters in different indoor positions. In CFD simulation, the models pay more attention to the parameters related to fluid dynamics such as air speed and temperature, but ignore the energy consumption. The BEM is a good foundation for energy simulation and air distribution simulation, because it can include all the parameters required for the above simulation and coupling the various types of simulation to make the resulting virtual model more closely fit the actual building.

Usually based on BIM in DTs, the virtual buildings can provide not only geometry information but also physical parameters, such as envelope materials, indoor thermal properties, occupant behaviour, and HVAC system. The DT model can not only include the CFD model and the BEM model, but also with the Virtual Reality (VR) to improve the interactive relationship between architecture and occupancy. Comparing to separate traditional simulation methods, this method generally leads to more interactive and more useful simulation.

4.3.3. Applications of AI algorithms

Virtual models combined with artificial intelligence algorithms can be applied to a greater extent. For example, BIM model can combine machine learning algorithms and optimization methods to more accurately describe the relationship between energy consumption and physical parameters, so as to improve building energy utilization efficiency [99]. Pour et al. uses the combination of Unity, BIM and machine learning to automatically update the three-dimensional view of the construction site and monitor the working progress in real time [100]. Ma et al. combined DTs with artificial neural network to predict indoor thermal comfort under the influence of energy-saving strategies [101].

4.4. Applications and case studies

The life cycle of a building includes design, construction, operation, maintenance and destruction. According to the current study, simulation in DTs is commonly applied in the construction and operational phases. In the construction process, DT is mainly used for the deploy-

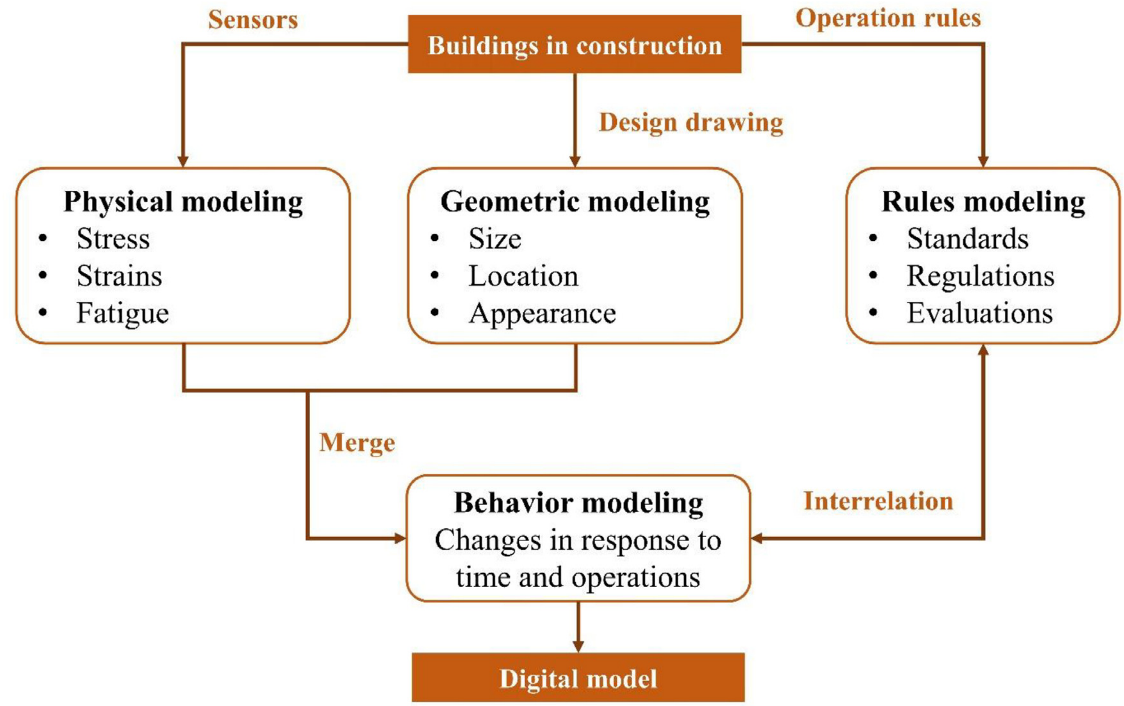

Fig. 8. Simulations during the construction process.

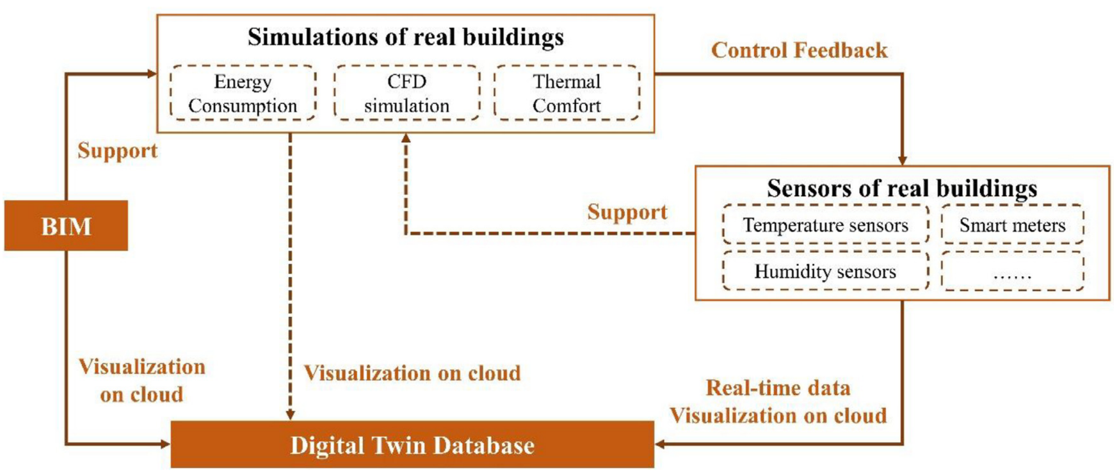

Fig. 9. The workflow of digital twins in buildings operation phase.

ment and compliance check of materials, worker' safety management and forecast, progress monitoring and control. With the help of DTs, the information exchange can be greatly improved, the construction efficiency can be strengthened, and the potential risks in the construction can be reduced. In the process of operation, DTs improves the energy saving of the building and indoor thermal environment, and also plays a key role in monitoring the possible damage to the building structure and equipment fault.

The main applications and methods deployed during the building lifecycle process are listed in the following Table 8. By reviewing current research and use about building digital twin, it is easy to find that DT is not yet fully used in area of buildings on a large scale. True digital twin buildings are far from being created. Most studies have been limited to digital description of part of buildings (parts of parameters or space), but most of the results show that the introduction of DTs has a positive impact on buildings without considering budget. In fact, DT is built on timely building-related data in high quality and quantity, and requires high intensity and timely transmission of data flow between physical and virtual entities. Therefore, to ensure the correct implementation of DTs, the requirements for data collection, precision and stability of sensor, the capacity of data storage device and the speed of data transmission are too high to reach in the short time. But DTs still provide a promising direction for the future of building system.

5. Urban models using building simulation methods

5.1. Goals of urban building energy modelling

Rapid urbanization brings increased attention to the role of the city in energy system planning for its ability to integrate large-scale district heating/cooling networks and renewable energy utilization toward the sustainable development of society [102]. Thus, implementing the BEM on urban scale has shown more and more benefits, promoting the concept of urban building energy modelling (UBEM) [103]. Different from

Table 8
Applications of integrated simulation of DTs in the buildings.

Ref.	Data type Environment	People	Materials	Devices	Energy	Simulation Structure	Energy	Environment	Applications Construction	Operation
[85]			●		●		●	● (in)		●
[86]		●						● (in)		●
[88]	●							● (out)	●	
[89]			●			●			●	
[90]		●						● (out)	●	
[92]					●		●			●
[93]		●			●		●			●
[94]				●	●		●			●
[95]			●			●				●
[96]	●	●			●		●	● (in)		●
[97]	●							● (in)		●
[100]	●		●	●				● (out)	●	
[101]	●				●		●	● (in)		●

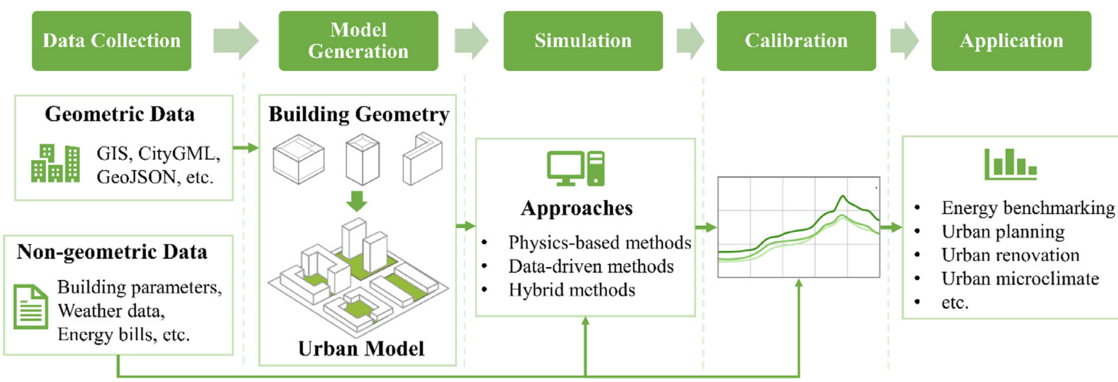

Fig. 10. A common workflow of urban building energy modelling.

modelling an individual building, UBEM studies the energy performance of a block, a city, or even the whole country, supporting the urban energy efficiency and management [104]. Due to the spatial complexity, UBEM often requires more resources and effort to achieve reliable results [105]. In recent years, a variety of studies have covered this field from different perspectives, contributing to both the approaches and applications of UBEM.

5.2. Approaches of urban building energy modelling

Following the idea of applying individual building energy simulation to building stock at the urban level, the workflow of UBEM commonly consists of five steps as shown in Fig. 10, including data collection, model generation, simulation, calibration, and application [106].

As the basis of the entire workflow, collection and pre-processing of UBEM-relevant data are necessary. The information required to build urban models can be classified into geometric and non-geometric data. Geometric data such as the data extracted from the geographic information system (GIS), which are crucial to describe the spatial and geometrical features of urban buildings [107]. Urban geometric data can also be derived from geographical coordinates and vectors in files like city geography markup language (CityGML) [108] or geographic JavaScript object notation (GeoJSON) [109]. Besides, Wang et al. innovatively proposed a systematic method to develop 3D urban models, which combines the building footprint from OpenStreetMap, building height measured by the vertical edges and the window-wall ratio calculated from buildings' elevation images with Artificial Intelligence [110].

The other data required for simulation or calibration are categorized into non-geometric ones. Energy-related parameters (e.g., U-values of envelopes, thermal systems efficiency, operation schedules, and occupancy behaviors) are needed to describe the building features such as the input IDF files for EnergyPlus [107]. Another important input for UBEM is the weather data, which may either be used in the form of a typical meteorological year (TMY) or synthetically generated to involve the urban microclimate (e.g., urban heat island effects and local wind patterns) [111] or the long-term climate change [112]. Additionally, the measured energy bills of building stock are sometimes required for training algorithms in data-driven methods or calibrating urban models.

According to the different data inputs, approaches of UBEM can be fundamentally divided into three categories: (1) physics-based methods, which explicitly simulate the energy consumption by building geometric data and thermal features; (2) data-driven methods, which apply data mining or machine learning algorithms to reflect the energy profiles; (3) hybrid methods, which combine the elements from both physics-based and data-driven methods. Table 9 summarizes the characteristics of three different approaches and the relevant studies are further reviewed in the following sections.

5.2.1. Physics-based methods

The conventional physics-based methods employ first-principle for simulating the thermal dynamic of each building, and then add the results up to generate the urban energy profiles. As an evidence-based approach, physics-based methods have the advantage to describe the clear connection between the urban building features and the energy performance. For instance, Prataviera et al. developed an open-source tool for city-scale simulation based on the electrical analogy, in which way the building thermal process was modelled with resistance-capacitance networks [113]. The model accurately predicted the urban energy demand in both a small neighbourhood and a large district. Since the physics-based method requires a lot of technical data to describe buildings in detail, it presents an inherent limitation when applied on urban scale. To reduce the computing burden for simulation in UBEM, prototypical models are built to simplify the input of building geometries and other parameters with prototypical models. Abolhassani et al. further

Table 9
Summary of three different approaches used in UBEM.

Approaches	Data inputs	Strengths	Limitations	Applications	Refs.
Physics-based methods	· Building geometry · Building parameters · Weather data	· Describe the clear thermal dynamic of buildings · Can be applied without measured energy data	· Require detailed building physical data · Large computing burden on urban scale	· Mainly applied to neighborhoods or districts · analyse the energy use in different scenarios · System planning and operational optimization	[109,113–116]
Data-driven methods	· Measured energy data · Weather data	· Capture the temporal courses of energy data · Do not require detailed building technical information	· Require a large amount of energy data · Unable to reveal the physical process · Limited spatial and temporal granularity	· Can be applied to neighborhoods, districts, cities, or countries · Predict energy profiles once physical data are limited	[107,117,118]
Hybrid methods	· Simplified building data · Energy use data · Weather data	· Leverage the strengths of physics-based and data-driven methods	· Require robust modelling design and pre-simulation process	· Can be applied to neighborhoods, districts, or cities	[119–122]

developed the traditional physics-based methods by automatically selecting the building archetypes from open-source data [114]. The selected archetypes, along with other energy-related parameters were fed into EnergyPlus for UBEM of downtown Montreal building stock, where the method performed well calibrated by the measured energy data.

However, using building archetypes for simplification in UBEM may reduce the results' accuracy. To figure out the loss, Johari et al. evaluated the urban modelling performance in both complex and simplified levels of building details, of which results showed a very small difference (around 6%) [115]. Compared to the complex models, the simplified models overestimated the energy performance in IDA Indoor Climate and Energy (IDA ICE) and underestimated that in EnergyPlus. Moreover, by conducting the uncertainty and sensitivity analysis, the most influential parameters (e.g., the floor area, set-point temperature, external walls U-values, and thermal system type) explaining the urban energy use can be determined to guide the model simplification [116]. Prataviera et al. coupled the physics-based method with uncertainty and sensitivity analysis and applied the procedure to a district of more than 600 buildings in Milan [109]. Compared to the deterministic archetype-based method, the overestimation of residences' peak load was reduced from 80% to 25% by selecting the most sensitive input parameters.

5.2.2. Data-driven methods

Data-driven methods employ statistical theories to mine the patterns of historically measured energy data, so as to build the urban energy model. The development of intelligent metering devices in recent years has widely achieved the digitalization of building energy systems, allowing the energy data to become more available and promoting the application of data-driven methods [123].

With the different functions for various research targets, data-driven methods can be classified into regression-based, probability-based, and clustering-based ones. Regression-based methods are found to be mainly used for predicting energy consumption. Kontokosta and Tull used data-driven methods to predict the energy performance of 1.1 million buildings in New York City with linear regression, random forest, and support vector regression algorithms trained by energy use data from 23,000 buildings [117]. The results showed that the linear regression model performed best for the entire city, while support vector regression provided the lowest mean absolute error for energy use prediction on a smaller scale. Probability-based methods can be applied to deriving the missing information on urban scale based on the prior empirical data. Na and Wang developed a probability-based data-driven model with the input energy data from 2062 heating substations in Beijing [118]. The model was calibrated by Bayesian inference and Markov chain Monte Carlo simulation and was successfully applied to studying the urban-scale energy benchmarks of space heating in Beijing. Clustering-based methods are able to characterize the spatial and temporal pattern of urban energy use. Afaifia et al. combined the GIS data, regression analysis, and hierarchical clustering to model and analyse the energy consumption profiles of residential buildings in all provinces of Algeria from 1995 to 2018 [107].

5.2.3. Hybrid methods

Given the limitations of physics-based and data-driven methods, increasing studies try to combine the two methods to leverage their respective strengths and produce more comprehensive simulation results in UBEM [119]. For instance, Li and Yao used the Urban Modelling Interface (UMI) tool for generating physical models and then applied ten machine learning algorithms to the pre-simulated energy use data for predicting the heating/cooling energy use intensity in Chongqing, China [120]. The results showed that the Gaussian radial basis function kernel support vector regression performs the best on urban scale. Liang et al. proposed a surrogate modelling approach by applying the K-nearest-neighbours algorithm to a pre-simulated building thermal load database [121]. The hybrid methods provide more accurate estimates of energy performance in building stock lacking exact information than physics-based methods, retain the physical description of each building, and overcome the gaps of data missing in pure data-driven methods.

5.3. Applications and case summary

By reviewing current studies, UBEM is mainly applied for four different purposes: (1) energy benchmarking, to compare energy use amongst peers; (2) urban planning, to provide optimal strategies for urban form and energy systems; (3) urban renovation, to support energy retrofit decisions for city policymakers; (4) urban microclimate, to analyse the impact of urban microclimate on energy performance. Table 10 summarizes the findings of representative case studies, along with their spatial scales, approaches, and applications. The following sections discuss the four application scenarios of UBEM in depth.

5.3.1. Energy benchmarking

As an overall evaluation of the energy profiles of a city or country over different periods, energy benchmarking is a basic application of UBEM. Lien et al. presented a physics-based method to predict the energy consumption of the Norwegian building stock. They found an expected decrease in final energy use between −2 and −12 TWh towards 2050, corresponding to a −3% to −14% reduction of that in 2020 [124]. Mohammadiziazi et al. built the urban model for commercial building stock in Pittsburgh, Pennsylvania by identifying twenty archetypes with eight commercial use types [125]. The simulation results showed an average annual energy use intensity between 74 and 1302 kWh/m^2 for different use types, which provided the government with scientific support to promote building energy efficiency.

Table 10
Summary of the applications of UBEM.

Ref.	Spatial Scale			Approaches			Applications				Objectives
	Country	City	Block	Physics-based	Data-driven	Hybrid	benchmarking	planning	renovation	microclimate	
[112]	●				●		●				· Proposed UBEM framework can estimate the energy baseline of building stocks considering the impacts of technology deployment.
[124]	●			●			●				· Integrated building stock modelling, hourly energy demand profiles, and energy system modelling provide the building sector with a long-term prediction of both annual and hourly energy use for different energy carriers.
[125]		●		●			●				· Developed archetype library and imaging techniques to retrieve envelope properties provide a holistic UBEM structure for commercial buildings.
[126]			●	●				●			· The shading effect of neighbouring buildings on target buildings was calculated by parametric method to examine the influence of shading on energy use.
[127]		●	●			●		●			· A GIS-based community-level UBEM was used to identify the most influential planning factors on the energy use of urban residential sectors (i.e., the floor area ratio and building coverage ratio).
[128]			●	●					●		· CityBES was used to model and assess energy conservation measures for the renovation of a low-income district in Venice, addressing the challenges of a large number of historical buildings and insufficient space in the area.
[129]		●				●			●		· An approach based on large building stock energy modelling was developed to assess the energy footprint and potential savings of railway buildings.
[130]		●		●					●		· An archetype approach was used to obtain the building data needed to run UMI to evaluate the effectiveness of community energy retrofit policies.
[131]			●	●						●	· This study investigated how the UBEM performance for high-density residences in the tropical climate is affected by weather datasets, involving the TMY data, suburban ground-measured data, and microclimate datasets
[132]			●	●						●	· A validated CFD model was coupled with UBEM to quantify the effect of urban surface compositions on urban microclimate and building energy demand.
[133]	●			●					●		· Developed UBEM for the Kingdom of Saudi Arabia can assess the impact of energy efficiency or demand-side management programs for residential sectors.

Notations: UBEM = Urban Building Energy Modelling; GIS = Geographic Information System; UMI = Urban Modelling Interface; TMY = Typical Meteorological Year; CFD = Computational Fluid Dynamics.

5.3.2. Urban planning

Since urban typology has a significant influence on the energy performance, policymakers can employ UBEM to gain an effective understanding of the energy use in different urban forms and also the advice for urban energy system planning. Liu et al. studied the impact of shading from nearby buildings on thermal energy demands of different community forms, where 93 114 cases were simulated by Grasshopper and EnergyPlus for seven cities in four climate zones in China [126]. Take the community in Lanzhou as an example, the cooling load can be overestimated by 45%, and the heating load underestimated by 21% due to shading from surrounding buildings, emphasizing the importance of reasonable community planning. Yu et al. combined the UBEM and sensitivity analysis to prioritize eight key factors on the energy performance of urban planning [127]. Results of 1963 residential communities in Shanghai revealed that the floor area ratio and building coverage ratio were the most sensitive parameters for energy consumption, technically supporting the urban designer to achieve energy-efficient planning.

5.3.3. Urban renovation

Urban renovation is a strategic process to improve the poorly developed areas of a city with energy conservation as one of the purposes. The energy-saving or carbon-reducing potential for various retrofit measures (e.g., enhanced lighting, thermal insulation, and upgrades of energy systems) on urban scale can be estimated by UBEM. Teso et al. used City Buildings, Energy, and Sustainability (CityBES) to model and evaluate energy conservation measures for renovating a low-income district in Venice [128]. By four common retrofit measures, the energy-saving potential at the district level reached 67%, along with the annual carbon emission reduction of 1.1 $MtCO_2$. Barone et al. assessed the energy performance and saving potential of the Italian railway building stock with a hybrid method [129]. Various energy-saving strategies were simulated, and a comprehensive analysis showed that the most effective measure was enhancing lighting systems which saved the primary energy up to 26% with a very low payback time of about 1 year. Buckley et al. ran the UBEM using UMI to evaluate the performance of energy-saving measures for an area with 9000 residential buildings in Dublin, Ireland [130]. By quantifying the most cost-effective mix of envelope retrofit and onsite energy production, renovation of this case was expected to achieve a 60% reduction in greenhouse gas emissions by 2030, of which the conclusion can contribute to the European Union Green Deal plans for a carbon neutral economy by 2050.

5.3.4. Urban microclimate

The urban typology and activities usually create a local climate different from the surrounding environment, namely the urban microclimate (e.g., the urban heat island effect and the local wind pattern disturbed by buildings). Xu et al. developed the on-site measured microclimate data and used them for UBEM of a residential neighbourhood at Everton Park in Singapore, where the results showed that the least mean bias error was 6% using microclimate data but was 12% using TMY data [131]. The conclusion indicates that the urban microclimate indeed influences energy performance. To better understand the effects, Brozovsky et al. combined the UBEM and the CFD modelling to quantify the impact of different urban surfaces on the microclimate and energy demand of office buildings in Trondheim, Norway [132]. The results of scenario analysis demonstrated a clear benefit from urban greening as it reduced the cooling energy demand by 28.5% than without vegetation. The findings also help the planners to improve urban climate resilience in response to climate change.

By reviewing the current applications, it is found that the UBEM has been increasingly used to simulate the energy profile of large building stock considering their diversity in geometry, construction, and uses, as well as their interaction to achieve targeted research objectives. In the context of the low-carbon transition of the building sector, the energy resilience achieved by technologies of demand response in energy communities has paved the way to flexibility for the building operators and the energy grid. Thus, although the potential of UBEM used for energy planning and building decarbonization has been clearly and widely studied, it is still suggested to incorporate new technologies and the UBEM to create a mature environment for energy community modelling that can help the stakeholders implement more advanced energy-efficient and environmental-friendly solutions.

6. Modelling of building-to-grid interaction for demand response

6.1. Goals of building to grid (B2G) modelling

With the increasing penetration of on-site renewable energy resources such as PV panels and wind turbines, buildings can deploy those resources to offset their onsite grid electricity and even sell excess produced electricity back to the grid as prosumers [134]. However, renewable energy, such as solar and wind, are inherently intermittent and uncontrollable. And with its high penetration, it's urgent to improve the buildings' electricity demand flexibility [135,136].Different from traditional building performance simulation, the simulation of building-to-grid (B2G) needs to couple with renewable energy generation and utility grid [134]. In recent years, many scholars have covered this field from different perspectives, contributing to both the approaches and applications of simulation for B2G.

6.2. Approaches of building to grid (B2G) modelling

As mentioned above, the simulation for B2G includes not only the parts of traditional BPS, but also the renewable energy system, energy storage system, the unity grid, and more. This section will summarize the simulation methods of these subsystems, as shown in Fig. 11.

6.2.1. Renewable energy system

Currently, the common renewable energy resources used for building power generation is solar PV and wind [137,138]. And usually, the modelling of a renewable energy system is to predict its power generation for sizing, optimization, and control. The methods are divided into two categories:

The first method is the simplified method. Simplified method means that the model is established according to the principle of power generation, using weather parameters combined with the performance parameters of PV panel and wind turbine [139]. Fan et al. used the simplified model to calculate the PV and wind turbine power output, which include the weather parameters (like solar irradiance, wind velocity and air density) and performance parameters of the device (like overall efficiency, angle, area, capacity and so on) [140]. Similarly, Arabzadeh et al. also adopted a simplified method to forecast the power generation, and the difference is only the difficulty and form of the model and the input parameters [141]. Undoubtedly, this method is simple and does not require a large amount of historical data [142], but the prediction accuracy is dependent on the numerical weather prediction and the parameters provided by device manufacturers [143].

The second is the data-driven method. With the development of computer technology, many scholars have introduced data-driven methods in the renewable energy system. Many data-driven prediction models have been investigated for power generation. VanDeventer et al. proposed a genetic algorithm-based support vector machine (GASVM) model for short-term PV power forecasting [144]. Marquez and Coimbra developed and validate the solar irradiance forecasting through ANN model [145]. Chen et al. adopted a radial basis function network to forecast 24 h ahead of PV power generation [146]. Wang et al. proposed a hybrid method based on wavelet transform, deep convolutional neural network and ensemble technique for probabilistic wind power forecasting [147]. The input data of these models often contains the meteorological data or the historical power data. Compared with a simplified method, this method may achieve higher accuracy [148], but it needs extensive historical data.

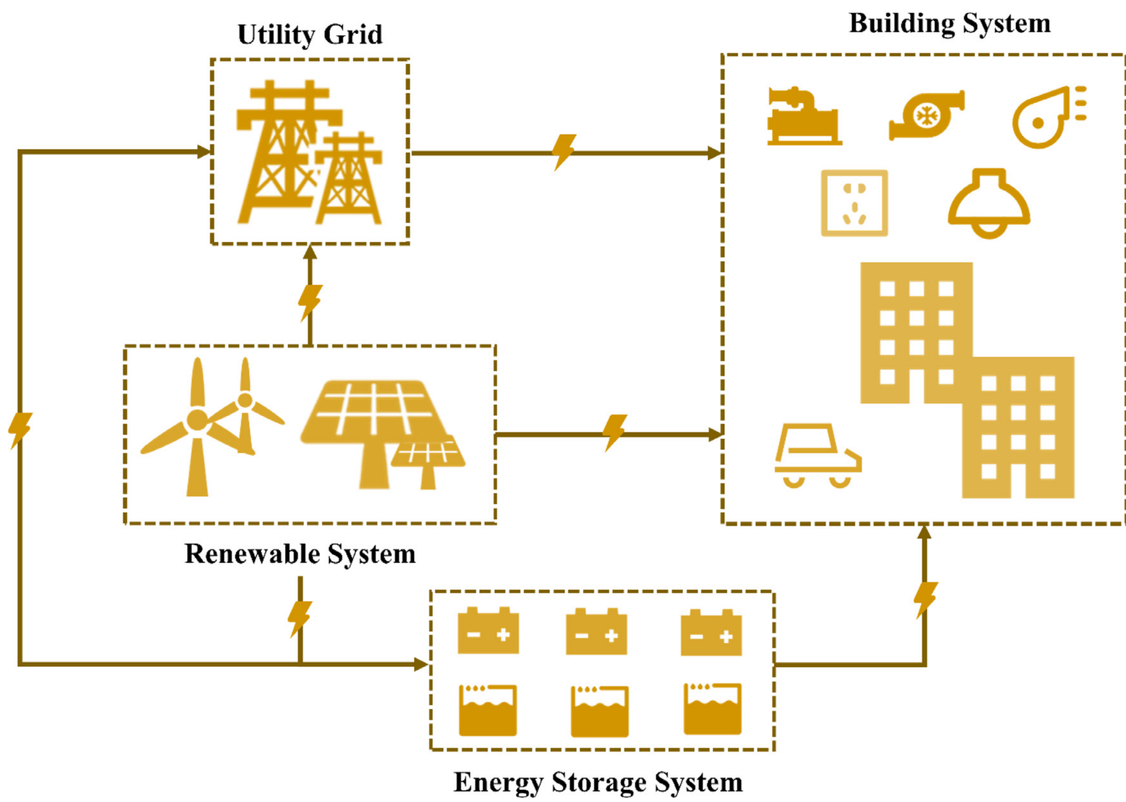

Fig. 11. A simple system composition of B2G.

6.2.2. Energy storage system

In the gird-interactive buildings, there are usually two types of energy storage systems, one is electrical storage system, the other is thermal storage system. Both of them can improve the flexibility of building energy consumption by storing and releasing energy.

The most common electrical storage system in buildings is battery. There are many kinds of battery systems, but the chemical battery is the commonest coupled with renewable energy generation systems [136]. However, in the view of simulation for B2G, we focus more on the energy storage changes than its internal chemical process. Therefore, Chabaud et al. establish the mathematical model of the system based on the energy balance: by the power in and out of the battery to establish the state of charge (SOC), and at the same time consider its conversion loss between the electrical and chemical energy [142]. Besides, due to the limitation of the charging rate in different states of the battery, they usually use this as a limitation of the model. Thermal storage tank usually is used as thermal energy storage device, and the medium is water or ice. Like the battery system, we pay more attention to the conservation of heat in and out when building the thermal storage model. Although a series of simplifications have been made for the energy storage system in studies, and the focus is more on the change of its energy value, this simplification is reasonable because the purpose of this field is to make buildings have lower energy consumption and more comfortable environment

6.2.3. Utility grid

Because of the instability of renewable power generation, the demand-supply mismatch can also be solved by the grid. Therefore, in many studies of B2G, the utility grid takes on the role of the merchant, which means the buildings can buy or sell electricity from it. So many scholars are concerned more with the price and the amount of electricity [149], and they built the model on energy balance with other subsystems like the battery and building load [150]. At the same time, the grid-interactive buildings emphasize their grid-friendliness, which usually means reducing the fluctuation between grid and buildings to mitigate the grid stress in ensuring power balance, and the energy exchange between buildings and grid is usually used as an evaluation index [142].

6.2.4. Building system

There are many contents in building systems which consume energy, such as HVAC, electrical appliances, lighting, and in residential buildings, and kitchen utensils. Besides, with a rapid growth market for electric vehicles (EVs), many scholars have incorporated EVs into the building system, and their electrical demand should also be taken into account. And in the building system energy simulation, there are three main ways:

(1) White-box method

The first way is white-box method, which refers to the use of heat and mass equations to build building energy models. And many software products such as EnergyPlus, Dymola, TRNSYS, DOE-2, can solve these equations conveniently. Wang and Wang adopted this method to obtain the heating and cooling load [151], and Ran et al. used this method to calculate the HVAC energy consumption [152]. The advantage of the white box model is its strong explanatory power, but it often takes a lot of time to input all the detailed building parameters.

(2) Black-box method

The second way is black-box method, and it often means using the historical data to build the model. Therefore, it does not need the building's physical information. And based on the data, the complex relationship between the input and output can be found mathematically. Gao et al. developed a simplified cooling load prediction by calibrating the reference day's load profile according to the weather parameters [153]. Besides, many machine learning algorithms are introduced to build the energy model [154]. Compared with the white-box model, the black-box model is simpler in the development process, but it needs a lot of historical data.

(3) Grey-box method

Table 11
Summary of the approaches for different system used in B2G.

Systems	Approaches	Strengths	Limitations
Renewable energy system	Physical-based	· Simple · Can be applied without measured data	· The accuracy depends on the data given by the manufacturer;
	Data-driven	· No need to consider complex physical processes;	· Require a large amount of data;
Battery system	Energy balance	· Easy to establish	· Ignore the internal changes
Utility grid	Energy balance	· Easy to establish	–
Building system	White-box method	· Describe the clear thermal dynamic of buildings · Can be applied without measured energy data	· Required detailed information of the buildings
	Black-box method	· Do not need the physical information of the buildings	· Require a large amount of data; · Unable to reveal the physical process;
	Grey-box method	· Leverage the strengths of white-box and black-box methods	· Require robust modelling design

What's more, the third way is the grey-box model. This method is between the white-box model and the black-box model, and uses a simplified physical model and easily accessible data to simulate energy demand. The most commonly used grey-box method is resistance–capacitance (RC) model. Bay et al. adopted 3-resistance-2-capacitance (3R2C) model to perform the thermal performance of the target buildings [155], and Dong et al. adopted 2-resistance-1-capacitance (2R1C) model to establish it [156]. The grey-box model makes a certain choice between the white-box and the black-box model, so when the other two models need insufficient information, the grey-box model may be a better choice.

Table 11 is a summary of the approaches for different system used in B2G.

6.3. Applications of building to grid (B2G) modelling

By reviewing current studies as shown in Table 12, in the view of the whole life cycle of the building, B2G modelling is mainly adopted in the design and operation stage. And the main purpose of these studies is to make the buildings more grid-friendly and cut down the operation cost.

6.3.1. Design

During the design stage, many scholars focus on the combination of parameters to make the building more grid-friendly, including the sizing factor of the energy storage system, the capacity of the renewable generation system and so on. In addition, due to the interactive and complex energy systems and better performance of net zero energy building (NZEB), which need comprehensive evaluation, some studies pay more attention to the design of NZEBs. Sun et al. adopted a non-linear heuristic glow-worm swarm optimization (GSO)-based optimization to identify all possible local optimums for designs, and compared with the default NZEB settings, the optimization settings performed better grid-independence and lower cost [157]. Zhang et al. compared the impacts of 24 influential parameters in over/under voltage, grid dependence and energy loss and identified the key parameters affecting NZEB grid interactions by global sensitivity analysis [158]. Salvador et al. proposed a sizing methodology to minimize the energy impact of buildings equipped with energy storage and generation systems on the electricity grid, and apply it to a single storey house and an industrial building [159]. The simulation results show that, compared with the standard size, the right size leads to a better energy impact. In general, if B2G is fully considered in the design stage, the optimal parameter combination of all building components can be determined to achieve lower cost and create a more comfortable environment

6.3.2. Operation

In the operation stage, several studies focus on the control strategy to reduce the impact on the utility grid and the operation cost.

For different types of single buildings, they are equipped with different systems. And it can be categorized into two types: (1) Commercial building: Razmara et al. designed a real-time optimization framework based on Model Predictive Control (MPC) to control the power flow of a commercial building equipped with renewable energy and energy storage system for demand response (DR) and demand flexibility (DF) programs, which significantly reduce the maximum load ramp-rate of the electric grid [149]. Li et al. proposed an operation strategy to schedule the overall power flow in real time based on a dynamic programming algorithm, in order to minimize the net present value in a typical year, and evaluate the strategy in an office building in Beijing, China [160]; (2) Residential building: Arabzadeh et al. integrated the data-driven predictive demand response control for residential buildings with heat pump and on-site energy generation and discussed the impact of heat demand predictive error on the performance of control [141]. Pallonetto et al. compared two DR algorithms (rule-based and predictive-based approach) under the same DR price scheme in a typical residential building in Ireland [161]. And the simulation results showed that the predictive-based algorithm did better in electricity end-use expenditure, utility generation cost and carbon emissions. Goudarzi et al. studied on a five-story residential building, which energy scheduling performed *via* GA, to maximize its profit, and the results show that for a typical day, the profit was about 11.53 $/day [162].

However, in multiple buildings, because of the inherent differences in building usage and system configuration, the buildings often show various sufficiency of renewable energy at same moments. In order to achieve a win-win situation within the buildings and minimize the energy impact on the grid, many scholars proposed methods to control at the building group level. Fan et al. proposed a new collaborative control to realize the renewable energy sharing amongst 3 NZEBs, and compared it with the traditional control in operation cost and grid friendliness [140]. Pinto et al. explored two multi-agent methods (a centralised controller and a decentralized controller) in the energy management of four buildings equipped with thermal energy storage and PV panels [150]. Zhang et al. introduced several metrics to quantify building-to-grid DR flexibility from heat pump aggregations and proposed specific control algorithms for the aggregations [163]. And the results indicated that payback behaviour vary widely depending on the type of residential buildings. Wang et al. introduced a rule-based carbon responsive control framework to respond the grid's carbon emission signals in real time, and performed simulation study on a residential community in Basalt, Colorado, United States [164]. And the simulation results showed that the control can reduce home's annual carbon emission up to 20.5%. Hurtado et al. proposed a dual agent-based method to optimize the interoperation of the smart grid–building energy management system framework and tested it through virtual multi-zone buildings [165]. And it was shown that it can improve the voltage profile of the feeder while maintaining acceptable comfort. In all, studying the B2G operation strat-

Table 12
Review of the applications of B2G.

Ref.	Type of buildings		Scale		Stage		Findings
	Commercial	Residential	Single building	Multi-buildings	Design	Operation	
[157]	●		●		●		· The developed heuristic multiple objectives algorithm based on the GSO to refine the optimization of the grid-interactive (NZEB) design and it performed well.
[158]			●				· For NZEB, in the aspects of overvoltage, grid dependence, and energy loss, the key parameters optimization can rapidly improve the considered performance.
[159]			●		●		· With the design optimization strategy by fussy algorithm, the power purchased from the grid is reduced while the produced energy is partially self-consumed.
[149]	●		●			●	· The proposed optimization and control framework of the B2G system can prevent duck-curve problems.
[160]	●		●			●	· Electricity price is the most sensitive parameter to the system's economy through sensitivity analysis, and compared with other strategies, the proposed strategy has greater flexibility and more economical.
[161]		●	●			●	· Compared with rule-based approach, the predictive-based method was better in electricity expenditure, utility energy cost and carbon emission.
[162]		●	●			●	· The optimal schedule obtained from this study can maximize the building profit.
[163]		●		●		●	· The payback behaviour of heating units following a demand response vary with different types of dwellings: in high thermal inertia dwellings it can be negligible while in dwelling with low it can reach 10%–50%.
[164]		●		●		●	· The carbon responsive controllers can reduce the homes' annual carbon emissions by 6.0% to 20.5%.
[165]	●	●		●		●	· By an agent-based approach and Particle Swarm Optimization, an integrated simulation show that the operation of the building can be dynamically changed to support the voltage control of the local power grid.

Notations: NZEB = net zero energy building; GSO = glow-worm swarm optimization; B2G = building-to-grid.

egy in multiple buildings can not only reduce the operation cost through the cooperation between different buildings, but also reduce the pressure on the utility grid.

7. Future perspectives and challenges

Researchers also pointed out the future perspectives and the questions to be solved in the field of building energy modelling (BEM) based on the limits of their theoretical or case study results. We summarize them into following five research orientations which are corresponding to Chapter 2~6 in this paper:

(1) Performance-driven design.

The future perspectives and challenges of performance-driven design remain in the generation, simulation, and optimization. The generation challenges are about how to encode the design logic, which is the core idea of the concept of "generative design". In the process of generative design, designers should become the developers of the algorithms that can adjust the design parameters automatically to meet the different demands of clients. Similarly, the performance-driven methods, really shifted from the conventional architectural design, can focus on the concept generation logic rather than the result of it. The current algorithms handle metric variables easily but lack variation in geometric forms. It is delicate to expand the design space while maintaining rationality. In practice, architects usually parameterize the massing concept and the façade texture. The extreme freeform as cellular automata lack architectural interpretation. Apart from the building shell, the inner space topology also affects the energy/ventilation performance, which is rarely studied.

Although bestowed with the increasing computing power, the simulation may still be time-consuming in each iteration, especially for CFD. Improving the physical model and the equation solver is challenging. However, one can make it scalable with proper space-time resolution to suit the design problem or use the surrogate model, such as the instant CFD feedback from the neural network. Another challenge is the interoperability between the design document and the simulation model, especially in geometry. For example, the freeform envelope of modern architecture requires tessellation for energy simulation, and robust meshing for CFD is a must for automated iteration.

The optimization steers the design process to the final decision. Future research should be orientated towards improving the efficiency of search techniques and approximation methods. With presumptive design inputs, further effort is required to target the sensitive variables and quantify the uncertainties of the result. In practice, the integrated modelling platform such as Rhinoceros may collect the results and guide the model generation, which also challenges the architects to be versatile at programming and algorithms.

(2) Model-based operational performance optimization.

Simulation for optimization is an important step to accomplish energy saving, carbon emission reduction and thermal comfort during the operation of buildings. Nowadays, the methodology of building operational optimization usually refers to model predictive control (MPC), where the simulation results of the models are the key points that affect the optimal performance of MPC. In many recent studies, researchers pointed out that the efficiency and effectiveness of model simulation should be further improved in the future work, which means that the performance of building simulation for optimization can be improved from two aspects: the computation speed of simulation and the accuracy of simulation results.

For computation speed, there is a requirement that must be met in engineering practice: the time consumed for one-step optimization should be less than the time step applicable for real-time control. In many application scenarios, the minimum time granularity for analysis will reach 10 min. After removing the time from calculation to convergence required by the optimization algorithm, the simulation time left for the model will be even less than 10 min. It means that the time cost by computation should also be considered as a constraint of the optimization algorithm applied for operational control.

On the other hand, the model should not be too simple to reduce too much accuracy if only pursuing the computation speed. The similarity between the model/predictive results and the reality will directly affect the effectiveness of MPC. Therefore, how to strike a balance between the computation speed and accuracy of the model in MPC has become a hot topic that many scholars and engineers are devoting themselves to.

(3) Integrated simulation using data measurements for digital twin.

Digital twins are usually considered the inevitable result of the evolution of BIM concepts combined with the integrated information between digital and physical buildings. Although on the technical level DT is feasible, the inadequate development of the following aspects the cost still limits its vigorous development. From another perspective, these challenges can also be understood as the future development direction of research related to the integrated simulation for DT.

The methodology to keep the integrity and accuracy of data is required. Enough data with high quality is very important to the integrated simulation for DT. To obtain such data, a large number of different types of sensors of high quality will be used in the whole life cycle of buildings, bringing a large economic burden. The maintenance and overhaul of sensors also cost a lot. The necessary development trend in the future is to reduce the cost of sensors and improve the accuracy of sensors.

The performance of timely simulations and feedback is another aspect to be considered for the integrated simulation for DT. Current simulation is typically based on historical data instead of real-time data, and also costs much time to finish. The time lag caused by historical input data and the calculation process usually leads to irrelevance between virtual models and real-time building conditions. So, fast and online look-ahead simulations should be developed to ensure an accurate description of the real-time physical parameters change.

In addition, the applicable scale range of the methodology of simulation should also be extended with the expansion of the use of DT. At present, DT is mostly used in single buildings or specific systems, and few researchers study its application on an urban scale. On the urban scale, data in more types and quantities are needed to ensure that the virtual city can describe the real city correctly. For instance, DT on an urban scale needs to interface with various energy data sources and monitor the flow of residents. DT on the urban scale can play a significant role in achieving smart cities and making future city policies.

(4) Building simulation supporting urban energy planning.

The approaches and applications of UBEM indicate that building archetype modelling plays a crucial role in predicting urban energy profiles. However, it is still possible to improve the accuracy of building archetypes by uncertainty analysis and model calibration. As a consequence, the following summarizes the main research gaps to be solved in UBEM.

In modelling building archetypes, uncertainty analysis can be used to assign a probability distribution to uncertain parameters (e.g., indoor air temperature and infiltration rate). Future UBEM studies can delve into this and determine the building parameter values in a statistically accurate way. Moreover, regarding the uncertainty associated with simplified archetypes, the reliability of the UBEM is closely related to the calibration of models. Through the calibration process, various inputs to the model are fine-tuned so that the predicted values of the outputs can be close to those obtained experimentally.

The influence of occupant behaviour on building energy consumption is one of the most studied topics recently. Different occupants-related models are developed, achieving realistic modelling of human activities with existing deterministic and stochastic models on the building level. However, models accounting for the urban-level occupants' behaviour have rarely been considered. As a solution, integrating UBEM with urban mobility models, which essentially describe human activities in both space and time, is likely to improve the model's accuracy.

The analysis of the energy generation infrastructure (especially the recyclable energy) is also an important topic for the studies on modelling the energy performance of urban building stock. For example, building-integrated technologies such as photovoltaic systems are particularly important to be included in UBEM. At the design stage of a photovoltaic system, the solar potential analysis such as identifying roof features and urban-level data on available installed area is meaningful, which can aid energy system modelling. Therefore, it would be helpful in future studies to integrate the UBEM with urban energy system models (e.g., local energy utilities and energy distribution systems).

(5) Modelling of building-to-grid interaction for demand response.

With the continuous advancement of building energy conservation and carbon reduction, how to better understand and handle the interaction between buildings with the grid has received extensive attention. Through the investigation of the literature in this field, we believe that the following problems still need to be solved urgently.

The future modelling method should take full advantage of the flexibility of the built environment. Most of the current research is relatively simple for the model of building systems, and the flexibility of the built environment is underutilized. Besides, due to the rapid changes in grid prices and photovoltaic power generation conditions, the building energy consumption simulation need to keep up with them. Thus, how to make full use of building flexibility and reflect it in grid interaction is a big challenge.

The large-scale model and control will be required for the simulation. Currently, as in our literature review above, most studies in B2G focus on the single building or multiple buildings, and few studies address larger scales. However, looking at the larger urban scale, how to effectively control and cooperate between different types of buildings, between different micro-grids is still unknown.

The new B2G modelling method should fill the missing of the impact of occupancy. As we all know, occupancy has a great impact on building energy consumption, and many studies focus on it. However, in the modelling of B2G, few scholars took occupancy into account, which also leads to the lack of the occupancy influence on the thermal comfort and energy consumption in this field. Therefore, how the occupancy affects the optimization of the B2G operation is still not addressed.

8. Conclusions

The literature reviewed in this paper describes the scope and state of building performance simulation and its application in multiple scenarios during the life cycle of buildings. In general, this review summarized and sorted out the relevant principles/methods/tools that are most suitable for engineers and researchers, as well as some case studies that are of academic or practical interests. In particular, this review was presented as five individual parts according to the objectives of building performance simulation in application: performance-driven design, model-based operational performance optimization, integrated simulation using data measurements for digital twin, building simulation supporting urban energy planning, and modelling of building-to-grid interaction for demand response.

The current observations on the research activities in this paper indicate that solutions through building performance simulation including automated building design, establishment of building energy model, model predictive control for optimization, digital twins and demand response are continuously emerging. For the construction industry, these developments can lead to an overall improvement in building performance, such as emission reduction of CO_2 related to buildings, using or living experience in buildings with high quality, or productivity increase of building design and maintenance personnel. This also shows that building performance simulation will play a key role in the future development of the architectural industry.

Building performance simulation is really a big theme. It is obviously unrealistic to complete a detailed introduction of all aspects covered in only one review paper. Therefore, in this paper, we mainly introduce the research direction and the status of BEM that most researchers concerned in the past decade. In addition, we also concluded various kinds of questions to be solved in the future in such research directions that are still in the initial stage of development as the future prospects of relevant fields based on the literature review. In sum, the future perspectives and challenges of building performance simulation can be summarized as the following four aspects: acquiring high quality data by new hardware or software technologies, fast and effective algorithm for modelling and optimization, improvement of intelligence during the workflow in building design and operation, modelling method on a large scale such as urban simulation. In different application scenarios of BEM, the theoretical or engineering problems due to the above challenges will be encountered more or less. The future goal of academic researchers and engineers in industry is to find or further optimize the solutions to such problems.

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.

CRediT authorship contribution statement

Yiqun Pan: Conceptualization, Writing – review & editing, Supervision. **Mingya Zhu:** Data curation, Methodology, Writing – original draft, Visualization, Investigation, Writing – review & editing. **Yan Lv:** Data curation, Methodology, Writing – original draft. **Yikun Yang:** Data curation, Methodology, Writing – original draft. **Yumin Liang:** Data curation, Methodology, Writing – original draft, Visualization, Investigation, Writing – review & editing. **Ruxin Yin:** Data curation, Methodology, Writing – original draft. **Yiting Yang:** Data curation, Methodology, Writing – original draft. **Xiaoyu Jia:** Data curation, Methodology, Writing – original draft. **Xi Wang:** Data curation, Methodology, Writing – original draft. **Fei Zeng:** Data curation, Methodology, Writing – original draft. **Seng Huang:** Writing – review & editing. **Danlin Hou:** Writing – review & editing. **Lei Xu:** Writing – review & editing. **Rongxin Yin:** Writing – review & editing. **Xiaolei Yuan:** Writing – review & editing.

Data availability

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

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