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Advanced controls on energy reliability, flexibility and occupant-centric control for smart and energy-efficient buildings

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ABSTRACT

Advanced controls have attracted increasing interests due to the high requirement on smart and energy-efficient (SEE) buildings and decarbonization in the building industry with optimal tradeoff strategies between energy consumption and thermal comfort of built environment. However, a state-of-the-art review is lacking on advanced controls for SEE buildings, especially considering advanced building energy systems, machine learning based advanced controls, and advanced occupant-centric controls (OCC). This study presents a comprehensive review on the latest advancement of advanced controls for SEE buildings, which covers recent research on data collection through smart metering and sensors, big data and building automation, energy digitization, and building energy simulation. Machine learning based advanced controls are comprehensively reviewed, including supervised, unsupervised and reinforcement learning, together with their roles and underlying mechanisms. In addition, advanced controls for energy security, reliability, robustness, flexibility, and resilience are further reviewed for energy-efficient and low-carbon buildings, with respect to fault detection and diagnosis, fire alarming and building energy safety, and climate change adaptation. Moreover, this study explores the advanced OCC systems and their applications in SEE buildings. Last but not the least, this study emphasizes the challenges and future prospects of the trade-off between complexity and predictive/control performance, AI-based controllers and climate change adaptation, OCC in thermal comfort and energy saving for the SEE buildings. This study offers valuable insights into the latest research progress concerning the underlying mechanisms, algorithms and applications of advanced controls for SEE buildings, paving the path for sustainable and low-carbon transition in building sectors.

1. Introduction

The global building sector accounts for approximately one-third of the world's final energy consumption and carbon emissions, leading to the crucial role of building industry in mitigating the global climate change [1–3]. In the next 30–40 years, both developed and developing

Abbreviations: ABM, agent-based modeling; AI, artificial intelligence; AMLFN-AD, adaptive multi-level fusion network attack detection framework; ANN, artificial neural network; AR, augmented reality; BASs, building automation systems; BIM, building information modeling; CNN, convolutional neural network; DL, deep learning; DT, digital twin; FDD, fault detection and diagnosis; FDS, fire dynamic simulator; GIS, geographic information system; HVAC, heating, ventilation, and air conditioning; HDCMARL, hybrid deep clustering of multi-agent reinforcement learning; IoMT, internet of medical things; IoT, internet of things; KPIs, key performance indicators; ML, machine learning; MPC, model predictive control; OCC, occupant-centered control; PCA, principal component analysis; PID, proportional-integral-derivative; PV/T, photovoltaic/thermal; RBC, rule-based control; RL, reinforcement learning; RLC, reinforcement learning control; SEE, smart and energy-efficient; SL, supervised learning; SBIPV, smart building integrated photovoltaic; SVM, support vector machine; UNSL, unsupervised learning.

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countries will face the challenge of decarbonizing their existing building stocks [4,5]. As a result, energy efficiency and decarbonization in buildings have become one of the most critical concerns for sustainable development, attracting an increasing number of researchers to engage in related research activities [6–8]. In response to the urgent need to decrease energy consumption and mitigate climate change, there is an increasing demand for sustainable building solutions to minimize environmental impacts and ensure energy security [9–11]. With the integration of advanced technologies (e.g., smart sensors, big data analytics, and machine learning (ML) algorithms), smart and energy-efficient (SEE) buildings have been identified as a potential solution to address these challenges to optimize energy performance, improve occupant comfort and health, and enhance building resilience [12,13]. Compared to the conventional intelligent buildings, SEE buildings specifically refer to buildings that not only incorporate intelligent features but also prioritize energy efficiency and sustainability.

In recent years, SEE buildings have become increasingly popular, which leverage integrated technologies developed using existing and advanced control techniques, such as Internet of Things (IoT) sensors, artificial intelligence (AI), and augmented reality (AR) [14–16]. Advanced controls are crucial for improving energy efficiency in buildings while maintaining occupant comfort and safety. Compared to traditional controls that typically rely on fixed setpoints and predefined rules, advanced controls offer flexibility, adaptability, data-driven decision making, and system integration. In addition, advanced controls differ from traditional controls in terms of control logic. Advanced control incorporates dynamic and adaptive strategies that utilize real-time data and are optimized using advanced algorithms, which enables personalized adjustments, proactive decision-making and continuous optimization [17] to achieve higher levels of energy efficiency and occupant comfort in SEE buildings [18,19]. Advanced controls play a key role in enabling SEE buildings to achieve these goals by providing the intelligence and automation for energy management in buildings [20,21].

Recently, there has been increasing interests in advanced energy management strategies using ML methods, such as supervised learning (SL), reinforcement learning (RL), unsupervised learning (UNSL), and semi-supervised learning [22,23]. ML applications mainly include operations, optimization, control, scheduling, and management [24–26]. Zhou [27] comprehensively reviewed the applications of AI in carbon neutral and community energy management from the view of energy supply and storage, regional demand, and energy management. The results indicated that, in building energy management systems, SL works well on classification and regression problems, while UNSL and RL is mainly used for clustering optimal scheduling. For sustainable energy supply systems, such as solar and wind energy systems, ML algorithms are mainly applied to solar irradiance prediction, wind resource prediction, photovoltaic power prediction, smart control, as well as fault detection and diagnosis (FDD).

SEE buildings and related research have drawn significant attention in academic. In recent years, researchers have conducted comprehensive review analyses of smart buildings from different perspectives. Table 1 summarizes these existing review studies on this topic.

In general, these existing reviews on smart buildings focus on specific technologies (e.g., IoT, AI, 5G, BIM, and GIS). Some of them demonstrates the significance of advanced control systems in smart buildings, as they optimize energy performance and enhance operational flexibility. However, existing literature in the field of SEE building exhibits several research gaps: firstly, there is a lack of comprehensive up-to-date reviews focusing on advanced building energy systems, in terms of three components (i.e., smart metering and sensors, big data and building automation, energy digitalization and building energy simulation). Secondly, reviews on underlying mechanisms, fundamental roles, and advanced algorithms of advanced controls for SEE buildings, have not been conducted, although these aspects determine the possibility to achieve building automation based on the big data. More importantly,

Table 1
Summary of review literature related to smart buildings.

Authors	Time	Topic	Main viewpoints/ findings
Alfalouji et al. [28]	April 2023	A taxonomic review: co-simulation for buildings and smart energy systems	This paper provides a systematic analysis of the technology, standards, tools, and applications of collaborative simulation in the fields of building and smart energy systems. The literature on collaborative simulation in this field was reviewed and categorized using a taxonomy approach.
Rodríguez-Gracia et al.[15]	April 2023	Review: AI techniques in green/smart buildings	This survey investigates the correlation and benefits of integrating AI technology in green and smart buildings. Using Web of Science and Scopus databases through a comprehensive review on the publishing productivity, most influential articles, and relevant participants in this field through bibliometric analysis.
Khan et al. [29]	December 2022	Review: critical fire event library for buildings and safety framework	This paper establishes a smart firefighting action framework based on significant fire incidents or consequences. The main reasons for casualties among firefighters in building fires are reviewed. By generating a database of key and precursor fire events, it guides future designs for intelligent firefighting and building fire safety. This framework can predict significant fire incidents in a sub-real-time manner.
Liu et al. [30]	January 2023,	Review: data-driven smart building-integrated photovoltaic systems	This paper comprehensively summarizes recent literature on data-driven smart building integrated photovoltaic (SBIPV) from four aspects: data perception, data analysis, data-driven prediction, and data-driven optimization.
Xia et al. [31]	September 2022	Review: GIS (geographic information system) and BIM (building information modeling) integration as the city digital twin (DT) technologies for sustainable smart city design	This paper summarizes the ontology-based data integration approaches for GIS and BIM integration in smart cities. This paper mainly uses the keyword analysis, co-occurrence analysis, and co-citation and coupling analysis using CiteSpace to achieve the viewpoint.
Pinto et al. [25]	February 2022	A critical review: algorithms, and	This study provides a comprehensive overview on the application of

(continued on next page)

Table 1 (*continued*)

Authors	Time	Topic	Main viewpoints/ findings
		applications for smart buildings	transfer learning in smart buildings through categorizing 77 articles into 4 major application areas. In addition, this paper emphasizes the utilization of deep learning (DL) in transfer learning applications and discusses the solutions to integrate transfer learning into the ecosystem of smart buildings.
Dwivedi et al. [32]	April 2022	A systematic review: potential of Internet of Medical Things (IoMT) applications in building a smart healthcare system	This paper identifies the role of the IoT applications in improving the healthcare system, and analyzes the research status on the benefits of IoT for patients and healthcare systems. It also briefly introduces the challenges of IoT and the challenges faced in developing intelligent healthcare systems.
Huseien and Shah [12]	January 2022	Review: 5G technology for smart energy management and smart buildings in Singapore	This paper discusses the international trends of applying 5G technology to smart buildings and extensively reviews the support on 5G technology from the Singapore government.
Aguilar et al. [13]	November 2021	A systematic review: the use of AI in energy self-management for smart buildings	This paper systematically reviews existing studies that implement AI to energy management systems in smart buildings. It groups these studies into specific tasks that autonomous management systems require, such as monitoring, analysis, and decision-making, to achieve goals in the environment.
Malagnino et al. [16]	August 2021	Review: BIM and IoT integration for smart and sustainable environments	This paper reviews existing research on technological solutions of BIM and IoT to enhance the sustainability and intelligence of the built environment. It analyzed the literature published from 2015 to 2020.
Stopps et al. [33]	January 2021	A critical review: occupant-centric smart HVAC controls in residential buildings	This paper critically reviews the latest research on simulation and field experiments, which are not entirely consistent with existing commercial intelligent home control technologies centered on residents. This paper compares and criticizes the demographic, location, building system, implementation goals, and experimental methods of the research to understand the areas that need to be focused on in simulation and field experiments.
Dakheel et al. [34]	October 2020	Review: smart buildings features and key performance indicators	This study aims to review the intelligence in the building environment, highlighting the key features, functions, and technologies of intelligent buildings, as well as discussing the challenges that may arise in implementing intelligent retrofitting applications. The paper reviews existing key performance indicators (KPIs) that measure the performance of intelligent buildings and their success in achieving goals.
Panteli et al. [35]	August 2020	A critical review: BIM applications in smart buildings from design to commissioning and beyond	This study introduces the main progress when developing building integrated models for smart buildings, with a focus on integrating the IoT into building intelligence operations. The latest developments are also discussed considering interoperability issues related to data sharing among various BIM-related applications.
Dong et al. [36]	September 2019	Review: smart building sensing system for better indoor environment control	This paper comprehensively reviews how indoor sensors impact the management of building environments from the aspect of energy efficiency, thermal comfort, visual comfort, and indoor air quality.
Jia et al. [37]	May 2019	Review: adopting IoT for the development of smart buildings	This paper reviews IoT concepts and investigates the most advanced projects on the adoption of the IoT to smart buildings in both academia and industry.

the occupant-centric control (OCC) should be thoroughly reviewed as they represents a transformative approach to building management, integrating perceptions of indoor environmental quality, occupant presence, and occupant interaction with the building, which can be used to optimize the operational efficiency of building energy systems and occupant comfort [38]. In addition, there is a dearth of information on advanced controls regarding energy security, reliability, robustness, flexibility, and resilience in SEE buildings. Lastly, the latest developments, challenges, and opportunities in advanced controls within this domain remain unclear, and there is a lack of clear theoretical guidance for researchers.

To cover the aforementioned gaps, the objective of this paper is to comprehensively review advanced controls for SEE buildings and to specifically demonstrate the importance and advantages of OCC. To do so, advanced building energy systems are firstly summarized in terms of smart metering and sensor technology for data collection, big data analysis system and building automation system based on advanced control strategies [39], as well as data digitalization and building simulation system. Next, ML-based advanced control strategies are reviewed in terms of ML algorithms and their application. Then, to highlight the impact of occupancy behavior and occupants' preference on the control performance, existing studies on OCC are summarized. Lastly, challenges and future perspectives are discussed for upcoming studies. Therefore, the primary contribution of this paper lies in providing a well-structured overview of the advancement and widespread adoption of advanced controls (especially for OCC) in SEE buildings, as well as offering valuable insights into future research directions.

2. Methodology

The overall framework of this paper is presented in Fig. 1. It includes advanced building energy systems, ML based advanced controls, advanced OCC and also considering the current status, technical challenges and future prospects. Firstly, the advanced building energy systems are reviewed, in terms of data collection with smart metering and sensors, big data and building automation, energy digitalization and building energy simulation. Afterwards, ML algorithms and advanced controls are provided, including SL, UNSL, and RL, and different types of controls for energy-saving and low-carbon buildings, fault detection and diagnosis, fire alarming and building energy safety. Advanced OCCs in buildings are summarized. In addition, challenges and future perspectives are also provided, including trade-off between complexity and predictive/control performance, AI-based controllers and climate-adaptive controls in SEE buildings, OCC in thermal comfort and energy saving with smart controls in buildings.

To conduct the state-of-the-art review on advanced controls for SEE buildings, a comprehensive and targeted approach was employed. The review aimed to identify the latest advancements and trends in the field, focusing on the key themes of 'smart building', 'energy-efficient building', 'intelligent control', 'machine learning', and 'occupant-centric control'. The reputable academic databases such as ScienceDirect, and other relevant databases were searched to identify recent journal articles, conference papers, and technical reports.

The search was primarily focused on retrieving articles published between the years 2013 and 2023 to ensure the inclusion of the most recent developments in the field, which was conducted using the title, abstract, and keywords in the selected databases and platforms. Firstly, the titles and abstracts of the retrieved articles were meticulously evaluated to assess their relevance to the research topic. Articles that did not align with the key themes or were not recent were excluded at this stage. Then, the full texts of the remaining articles were critically analyzed to determine their suitability for inclusion in the state-of-the-art review. Articles that showcased the latest advancements, novel approaches, and substantial contributions to the field of advanced controls for SEE buildings were selected. From the selected articles, the relevant information on research objectives, key findings and future directions was carefully extracted. The extracted data are then synthesized to provide a well-structured and comprehensive overview of the current state-of-the-art in the field of advanced control of SEE buildings. This review aims to highlight recent advances, emerging trends, and noteworthy contributions from researchers in the field.

3. Advanced building energy systems

This section presents a comprehensive summary of studies focusing on advanced building energy systems, specifically examining the areas of smart metering and sensor technologies, big data and building automation, and energy digitalization and building energy simulation. Each aspect encompasses an overview of relevant studies, encompassing the existing challenges, corresponding solutions, and discussions on potential implementation strategies.

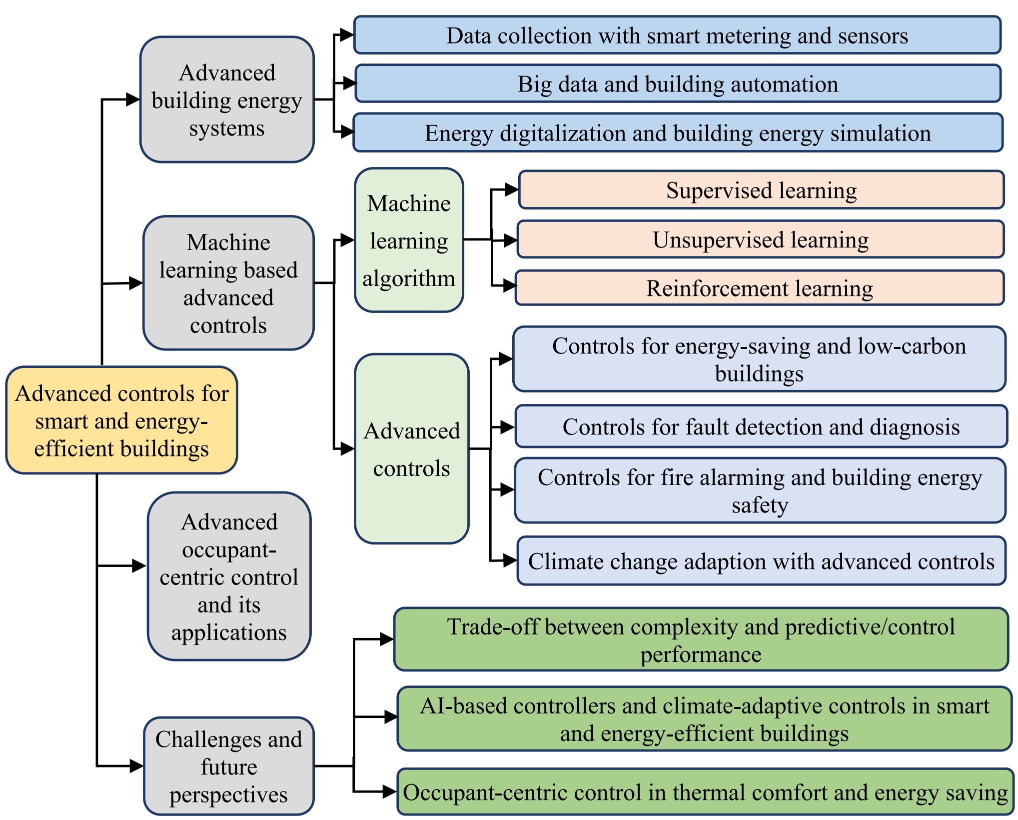

Fig. 1. A holistic overview on advanced controls for SEE buildings.

3.1. Data collection with smart metering and sensors

Whereby providing detailed and accurate data about energy consumption patterns and building performance for more targeted and effective energy management strategies, smart metering and sensor technology have been increasingly applied to improve energy efficiency of building energy systems in recent years [40,41]. As a result, the implementation of smart metering and sensor technology may contribute significant energy savings and cost reductions for building owners and operators [42,43]. Thus, it is expected that future building energy systems will become more intelligent by installing various smart IoT devices, building automation systems, distributed energy equipment, electrical measurement devices, and smart meters. Furthermore, buildings are now being connected to external systems such as weather information and electricity markets to enhance the potential intelligence of building energy systems that operate more efficiently and provide a safer and more comfortable living environment for occupants [16,44]. Based on the on-board data collected from IoT devices, data-driven approaches are becoming increasingly popular in the field of building energy management, which integrates on-board data into statistical modeling techniques. The data-driven approaches mainly serve as "controllers" for building system control [45], such as in MPC, and the tool to characterize building energy performance [46,47].

However, the heterogeneous data collected from the numerous data collection devices and sources may seriously affect the actual operation of the data collection platform. It may also cause compatibility issues and data silos [35]. For instance, the format and temporal granularity of data could be distinct among different external systems. The large number of measurement may impede the input of the data collection platform [48]. Thus, how to deal with or aggregate the massive heterogeneous data would be a challenging topic. One potential solution is to develop standardized and open protocols for different types of sensors and intelligent meters and to develop a common data model to ensure that the collected data can be easily shared and integrated across different systems. Furthermore, to aggregate the heterogeneous data, Antti et al. [49] developed a modern building data acquisition and auxiliary control platform for smart energy applications, as shown in Fig. 2. This platform allows various stakeholders to monitor and utilize various distributed energy sources. The platform includes an edge-based data collector for collecting, filtering, and buffering data, as well as for fast control operations, and an IoT back-end platform for energy management visualization and slow response. This platform offers the ability to support the heterogeneity of data sources, high capacity and time resolution of data, ML-based energy and power quality analysis. By providing these features, the platform enables comprehensive and dependable data collection, and it facilitates the more intricate integration of smart buildings in microgrids.

Extracting informative features from massive data would be another challenge when adopting smart metering and sensor technologies. One example could be given in the field of building energy system renovation, traditional renovation decisions heavily rely on expert knowledge and manual collection of building characteristics, which may require significant time and resources [50] [51]. To address this challenge, ML methods have been widely applied in the analysis of building energy system renovation. However, how to automatically collect building feature data became a problem to be solved [52,53]. To overcome this problem, Paul et al. [54] proposed a data-driven method for identifying building features from a raw smart meter data set to enable large-scale analysis of energy-efficient building renovation, as shown in Fig. 3. This method utilizes energy features, which condenses the electricity consumption of each building into an information-rich chart. By employing a support vector regression model, the proposed method extracts the shape of each signature and clusters them to automatically collect building feature data. This method can significantly improve the existing set of techniques that extract qualitative building features by solely utilizing smart meter data. As a result, it can enable large-scale and precise analysis of building renovations, making it a valuable tool for building management. However, the generalizability of the proposed solution to other applications remains to be demonstrated.

Moreover, the use of smart metering and sensor technologies in advanced building energy systems can present issues of data privacy and security, such as the network attacks [55,56]. For instance, although monitoring human activity could provide valuable insights into the connection between energy consumption and occupant behavior [57], the collection of occupancy-related information, such as occupancy status and occupancy counts, may result in disclosing privacy information. Such measures might cause apprehensions regarding the real-time tracking of human activity, e.g., work, study, and social activities. One direct solution to protect this private information is to eliminate it from the dataset [58]. However, this solution may destroy the information

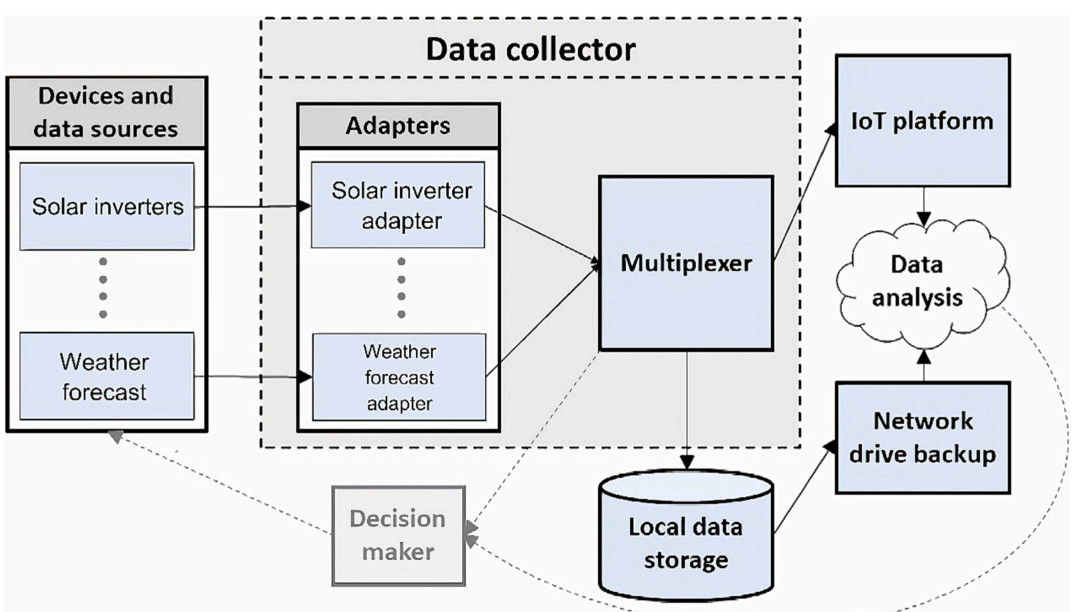

Fig. 2. Data acquisition and complementary control platform structure diagram [49].

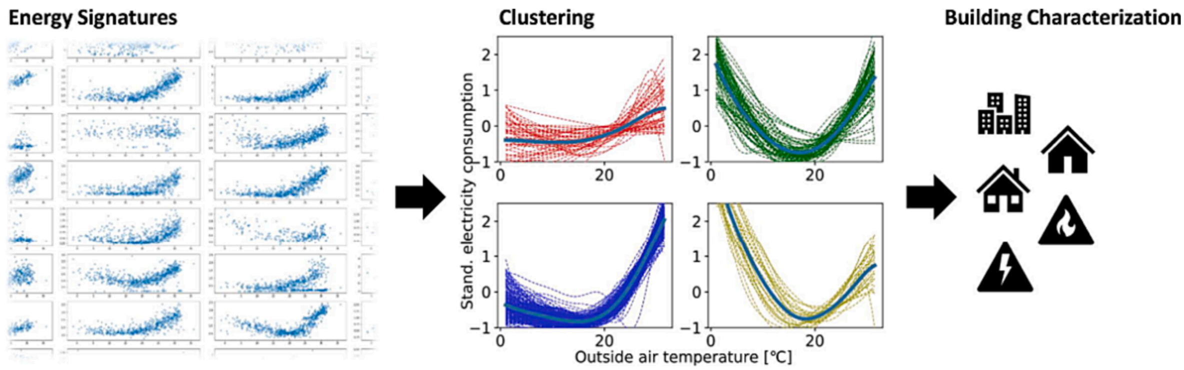

Fig. 3. Smart meter data based on UNSL of energy features to identify heating systems and building types [54].

quality of the collected data. Besides, it is necessary to develop strong data security protocols and policies to ensure that users' sensitive information is protected or encrypted. Data encryption methods, such as homomorphic encryption method [59], could be considered. Additionally, fuzzy information such as heat maps, low-resolution images, and low-quality videos can be employed to implement monitoring measures and tackle these challenges. However, the applicability of these data protection methods still have not been proofed in the building engineering domain.

3.2. Big data and building automation

With the emergence of smart metering and sensor technology, massive data have been collected and analyzed to optimize building energy use and reduce energy waste. A plenty of researchers have explored various techniques to analyze the large amount of data to optimize building energy use, such as using ML to predict energy usage and identify patterns in data. Furthermore, big data analytics have also been applied to identify faults in building systems for secure and reliable operation [60,61].

Besides, building automation systems (BASs) could record thousands of real-time measurement and control signals, with data volume continuously increasing over the building lifecycle [62]. However, in practice, the data sources for existing buildings are generally collected through separate systems, resulting in low data utilization rates and making it difficult to achieve more accurate and detailed measurement data requirements for analyzing and controlling energy systems [49]. In addition, due to the advancements in information, computing the control technologies, BASs provide a valuable network-based digital platform for automatically managing complex building systems, including HVAC, and lighting [63,64]. Currently, BASs are widely utilized in large residential and office buildings to control the electrical devices, enabling the automatic management and control of these devices. A prominent example is the BAS solutions offered by Siemens, which can be reportedly increase the energy efficiency of HVAC system in commercial buildings by up to 30% [65].

Integrated BASs refer to integrated systems that could both remotely monitor energy consumption of end-users in real-time and optimize functionality. To achieve this goal, Marinakis et al. [66] proposed a building energy-saving automation integration system tailored to user requirements and building characteristics. The proposed system, combined with optional installation and operation of sensors and instrumentation automation systems, can effectively enhance the interactivity of BASs, representing a significant advancement in the simulation and optimization of building industry energy consumption. As green buildings continue to gain importance in improving energy efficiency [67], BASs have become increasingly important in effectively reducing unpredictability in resident behavior and poor energy management. Qiang et al. [68] critically reviewed BASs used in green buildings for energy and comfort management. Their research findings suggest that there is still insufficient research on building automation systems in the field of green buildings, with a focus primarily on improving energy efficiency and resident comfort. Comprehensive integration of BASs and green buildings face four challenges: uncertainty, long-term prediction and control, sustainability goals supported by building automation systems, and privacy and security concerns.

With the increasing interconnectivity among appliances and sensors, smart building systems are becoming vulnerable to network attacks [69]. These vulnerabilities are often targeted by attackers, leading to disruptions in the normal operation of building automation systems and serious infringement on user' rights. While there are several network security technologies proposed for addressing these issues, few are designed specifically for smart building systems. To tackle this challenge, Yuan et al. [70] proposed an Adaptive Multi-Level Fusion Network Attack Detection framework (AMLFN-AD) to detect network attacks on smart building systems, as depicted in Fig. 4. The first level employs efficient and simple decision trees to quickly identify attacks from normal samples. The second level uses a hybrid model selection method to adaptively select basic classifiers from a model pool containing multiple candidate classifiers. Additionally, oversampling and undersampling techniques are combined to mitigate data imbalance issues. A series of experiments were conducted on three datasets to compare with other methods, and the results demonstrate that AMLFN-AD can achieve excellent performance.

3.3. Energy digitalization and building energy simulation

Currently, many urban building energy models rely on DT models as the primary input for energy simulation. A city-level DT is a precise virtual representation of urban objects that can be paired with a dynamic predictive model of their energy performance, but cities without DT datasets face limitations in energy assessments. To address this issue, HosseiniHaghighi et al. [71] proposed a workflow to enhance and integrate building datasets for urban building energy modeling, as depicted in Fig. 5. The workflow focuses on GIS data processing, utilizing multi-level spatial data integration and refinement to address inconsistencies in building databases and establish a unified housing dataset. The developed workflow enables programmatic 3D urban modeling and automatic conversion to semantic CityGML format, resulting in a DT of the study area in an open data model.

As a significant contributor to urban energy consumption, buildings can play a crucial role in providing regulatory flexibility to energy systems through active management of energy demands [72,73]. However, sharing indoor temperature and occupancy information with external energy management systems can pose privacy risks for occupants and limit building energy flexibility. Except privacy protection methods summarized in Section 3.2, a privacy protection could be achieved by adding noise to the building's state data. For instance, Song et al. [74] utilized the model-free advantages of the data-driven component and the building energy flexibility range obtained from the DT to manage

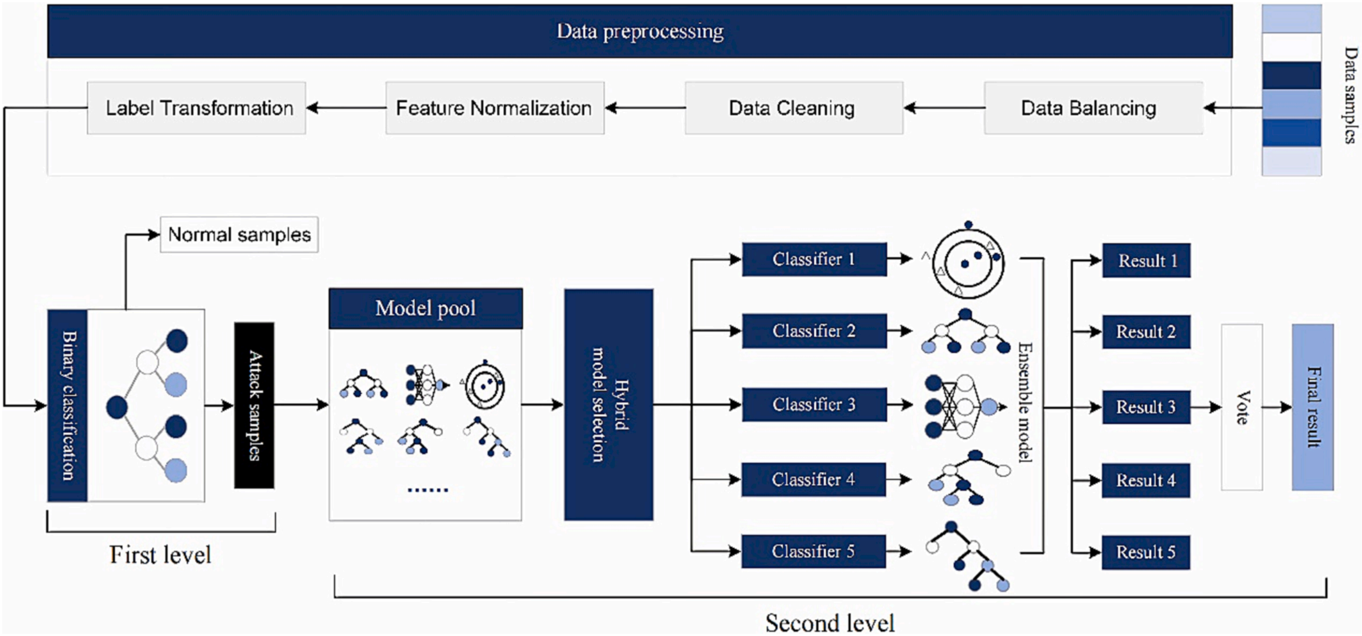

Fig. 4. Adaptive multi-level integrated converged network attack detection framework [70].

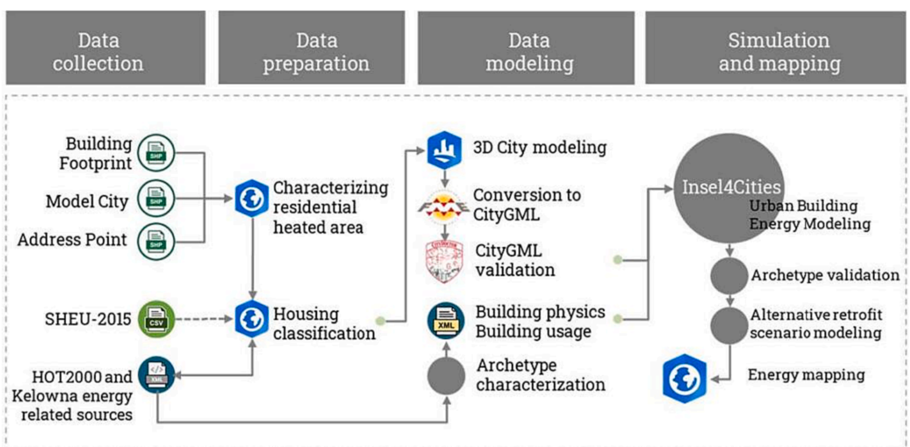

Fig. 5. Workflow of energy data preparation, modeling, simulation and mapping for urban buildings [71].

thermal parameter errors and state noise in building energy flexibility scheduling. The schematic diagram of flexible scheduling framework can be seen in Fig. 6. In this framework, the deduction results, constantly updated through the dispatch process, are utilized as the data-driven component to establish a dependable boundary for the regulatory range of the building energy flexibility in the dispatch formulation. The determination of this boundary remains unaffected by the building thermal dynamic mechanism model and thermal parameters. Consequently, it effectively addresses the influence of parameter inaccuracies and state disturbances in the mechanism model on the dispatch performance. By doing so, the proposed scheduling strategy can achieve parameter fault tolerance and privacy protection, significantly enhancing building energy flexibility.

Despite significant progress in energy digitization and building energy simulation, there are still challenges that need to be addressed. One major challenge is the lack of standardized data and models. Building energy simulation heavily relies on accurate data and models, and the lack of standardization can lead to inconsistent results. In addition, there is a need to explore the synergy between energy digitization and building energy simulation to maximize their potential benefits. For example, energy digitization can provide real-time data for improving the accuracy of building energy simulation.

4. Machine learning (ML) based advanced controls

4.1. Machine learning (ML) algorithms

In general, there are two main basic types of control systems, which are closed-loop and open-loop controls, as shown in Fig. 7. The closed-loop control is also called extrinsic control or ‘active’ control, permitting interventions from users, which adopts an external decision-making system to return feedback signals. This mechanism will raise both the initial cost and complexity level [75]. In contrast, the open-loop control, also known as the intrinsic control, ‘direct’ and ‘passive’ control depends on internal self-adjustment, which forbids users’ involvement and any external input but demands low startup cost. Compared to closed-loop systems, open-loop systems allow more flexibility in calibration. In brief, in contrast to open-loop systems, the installation of sensors in closed-loop systems must be carefully calibrated [76]. Pre-known outcomes of control inputs are supported by open-loop control. However, it

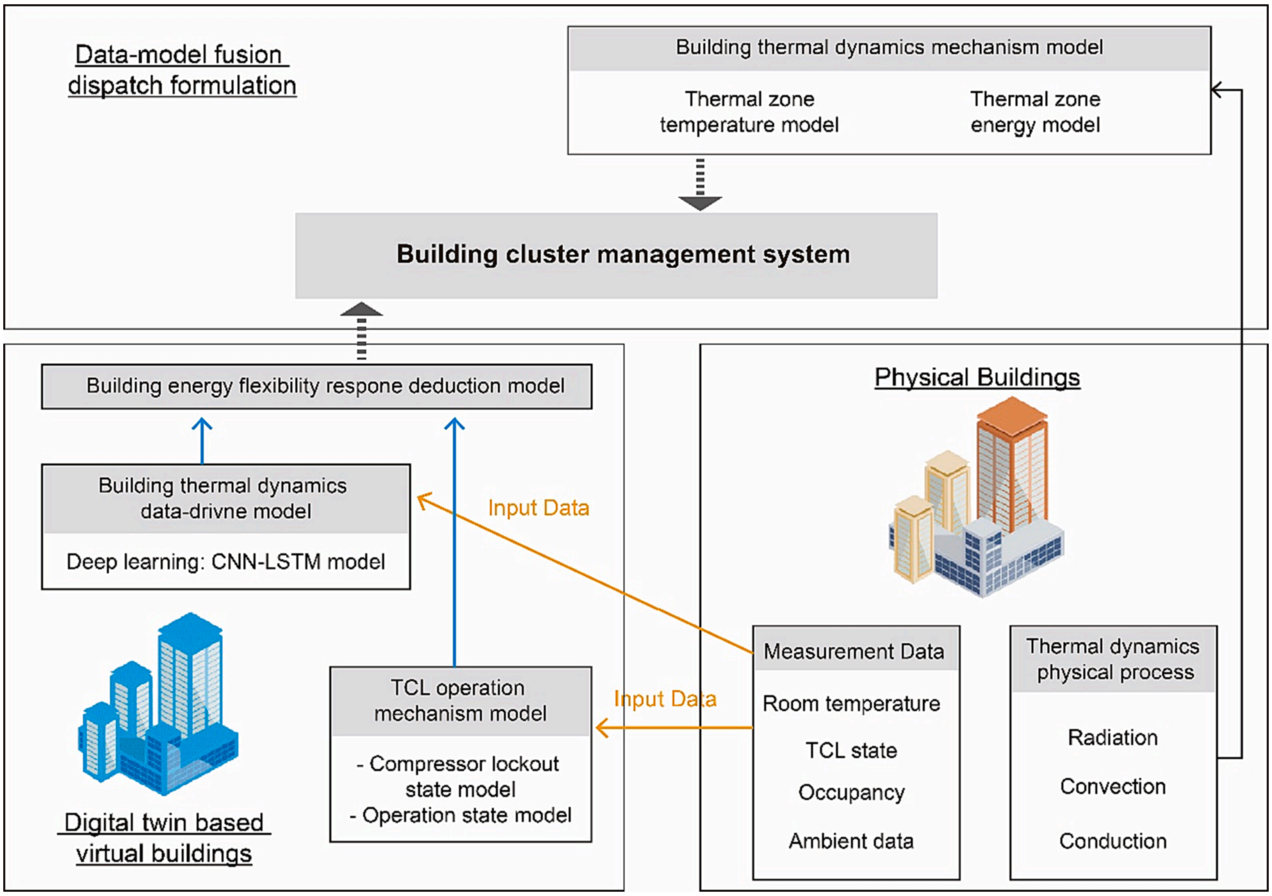

Fig. 6. Flexible scheduling framework for building energy based on DT (modified from [74]).

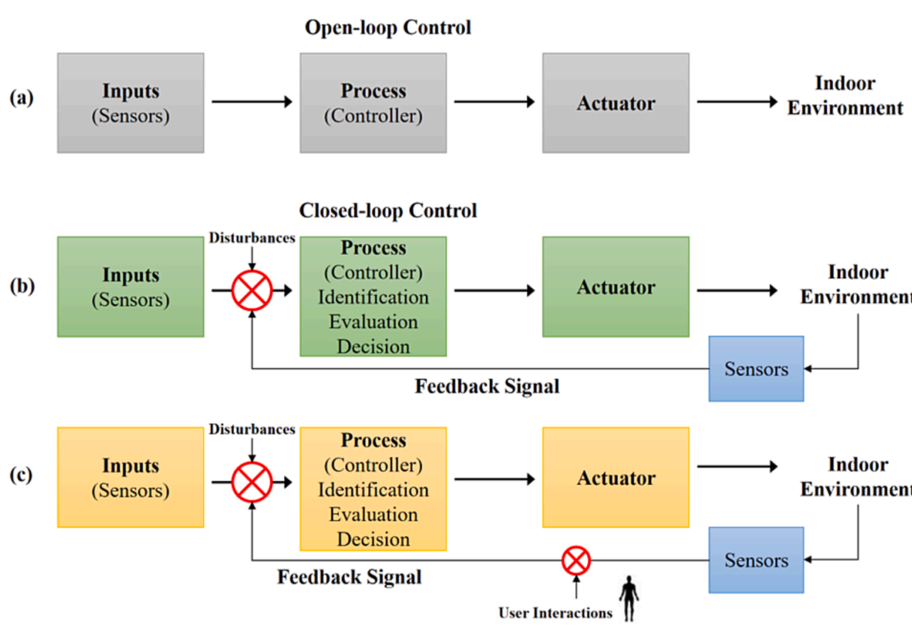

Fig. 7. Diagrams of open-loop and closed-loop control algorithms (modified from [75]).

is impossible to assess the responses and corrections for any internal and/or external disruptions in open-loop control. The closed-loop control system addresses this limitation of open-loop by continuously comparing the responses with desired outcomes and adjusting the control process to narrow the deviation gap [77]. From another perspective, the common ML algorithms that used in smart buildings can be mainly divided into three categories, namely, SL, UNSL and RL, as shown in Fig. 8. Additionally, SL, UNSL, and RL are also used for controlling building environments through HVAC systems [78], aiming to maintain both the thermal comfort level of occupants and the building energy

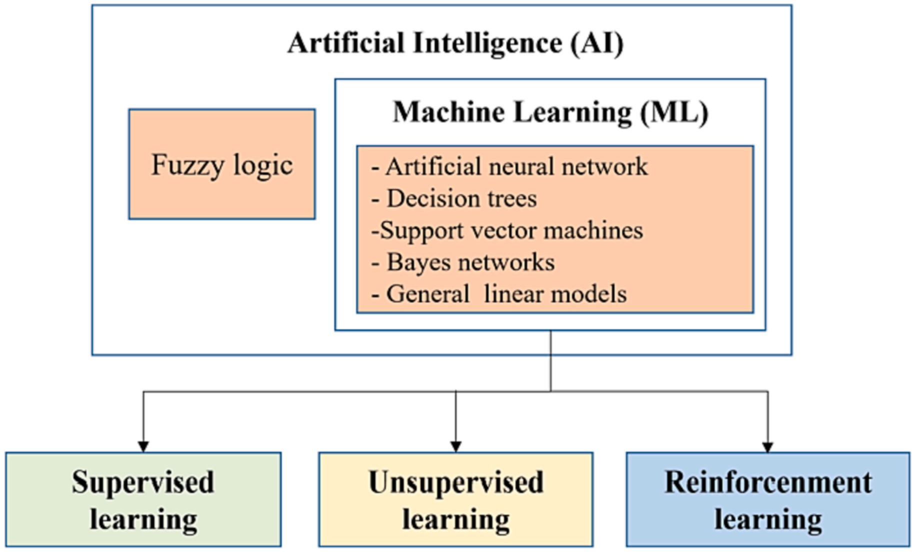

Fig. 8. Three main types of ML algorithms (modified from [80]).

efficiency [79]. A systematic summary and analysis of these three contents will be presented in the following sections, respectively.

4.1.1. Supervised learning (SL)

ML models fundamentally function as black-box models [81], which require no physical information of the system for modeling. The black-box model is different from the grey-box [45,47,82] and white-box [83] models, where physical knowledge plays a vital role in model construction. In other words, ML models only explore and characterize the statistical correlations between input data and corresponding output targets, such as building energy performance based on given input data [84].

In general, both SL and UNSL methods work well for observing and predicting, but are less effective in adjustment, management, and interaction [85]. The usage of labeled data or observations clearly distinguishes between SL and UNSL methods, i.e., SL uses labeled input and output data, while UNSL algorithm does not use labeled input and output data [86]. Specifically, the SL algorithm involves observations i = 1, 2 …, n and a collection of associated response parameters (i.e., labeled data). Meanwhile, SL is goal-oriented and aims to 'supervise' algorithms in making predictions or categorizing based on the labeled input and output data [87]. On the contrary, no associated response variables are needed in UNSL, since it only seeks to explore and characterize the unrevealed correlation or relationship between the

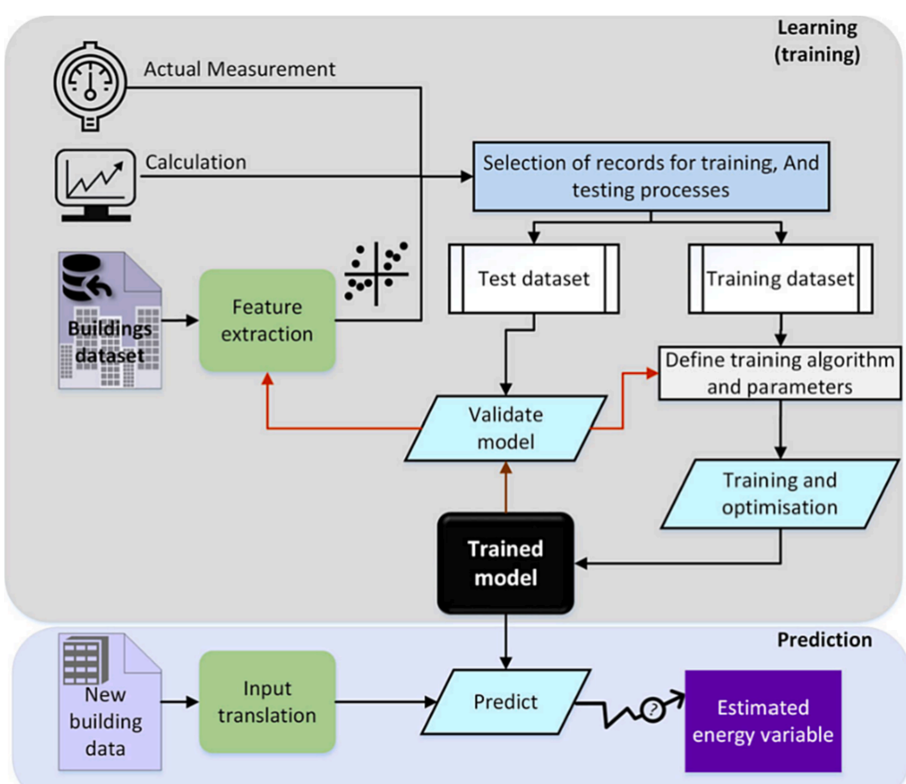

Fig. 9. Diagram of SL in buildings [84].

observations within an exploratory fashion [87]. Therefore, in SL, labeled historical data is required to characterize and extrapolate the potential correlation between inputs and outputs. The trained SL models are applicable to new datasets for predictive applications. Fig. 9 illustrates the general schematic diagram of SL in buildings, in which the recorded dataset was divided into training and test datasets to facilitate the training of the control model.

It should be noted that the three aforementioned types of control approaches are not mutually exclusive. For example, Yu et al. [88] presented a technique that combines both SL and UNSL techniques to extract interpretable control rules, and its workflow can be seen in Fig. 10. Specifically, unsupervised clustering is used to identify dominant patterns of recurring control, while supervised classification modeling is applied to determine the optimal strategy for regulating daily temperature. This approach has shown the promising potential to remarkably shrink energy consumption and corresponding energy costs.

4.1.2. Unsupervised learning (UNSL)

UNSL, on the other hand, offers an exploratory path to identify the hidden patterns in massive amounts of input data [89]. UNSL, commonly referred to unsupervised classification, is widely used to cluster unlabeled data ‘based on hidden patterns and similarities underlying features’ [84]. In supervised learning, the model has prior knowledge that circle and triangle points are different (i.e., labeled data), and the goal is to understand how to separate the data space between these two types of data points. On the other hand, in UNSL, the model has no foreknowledge of the data (i.e., unlabeled data), and the model is required to comprehend how to divide the observed points into distinct clusters, with maximized similarity of data points within each cluster and with two clusters that are as different from one another as possible [90].

The natural advantage of UNSL is beneficial for discovering unknown information incorporated in the data. For example, UNSL can cluster buildings with the same or similar statistical characteristics more precisely, instead of categorizing buildings mainly based on the building usage types in the conventional approach. ‘Clustering is the most common general unsupervised approach applied to building performance data’ [87]. In addition to clustering, there are additional four main types of UNSL: novelty detection, motif and discord detection, rule extraction, and visual analytics [87]. In practical applications, owing to the lack of anomaly labels, unsupervised anomaly detection is more feasible for smart controlling via on-site building operational data, compared to supervised ones, since UNSL does not need anomaly labels [91,92]. UNSL has demonstrated considerable benefits in the data-driven modeling of building operational data, particularly in exploratory data analysis and knowledge mining applications [93].

Xu et al. [94] developed a unsupervised anomaly detection framework based on DL, which incorporated both recurrent neural networks and quantile regression. Moreover, the framework is applicable to identify the building with unusual energy usage profile. Gunay et al. [95] presented a unsupervised ML clustering method for anomaly detection, which is capable of synthesizing building automatic operation data into distinct operational patterns. By visualizing these patterns, this method can facilitate fault detection and interpretation. In addition, by coupling both UNSL and RL, Homod et al. [96] proposed a hybrid deep clustering technique for multi-agent RL (HDCMARL), as shown in Fig. 11. In this study, the fundamental idea underlying the HDCMARL design is to construct a hybrid structure consisting of two-dimensional layers, enabling effective handling of extensive amounts of multi-agent action data and a large action space. The primary obstacle lies in appropriately adjusting the hybrid parameters, including neural network weights and physical parameters, leveraging the knowledge extracted from the collection of multi-agent actions. These hybrid parameters are fine-tuned to align with the cluster centers of the multi-

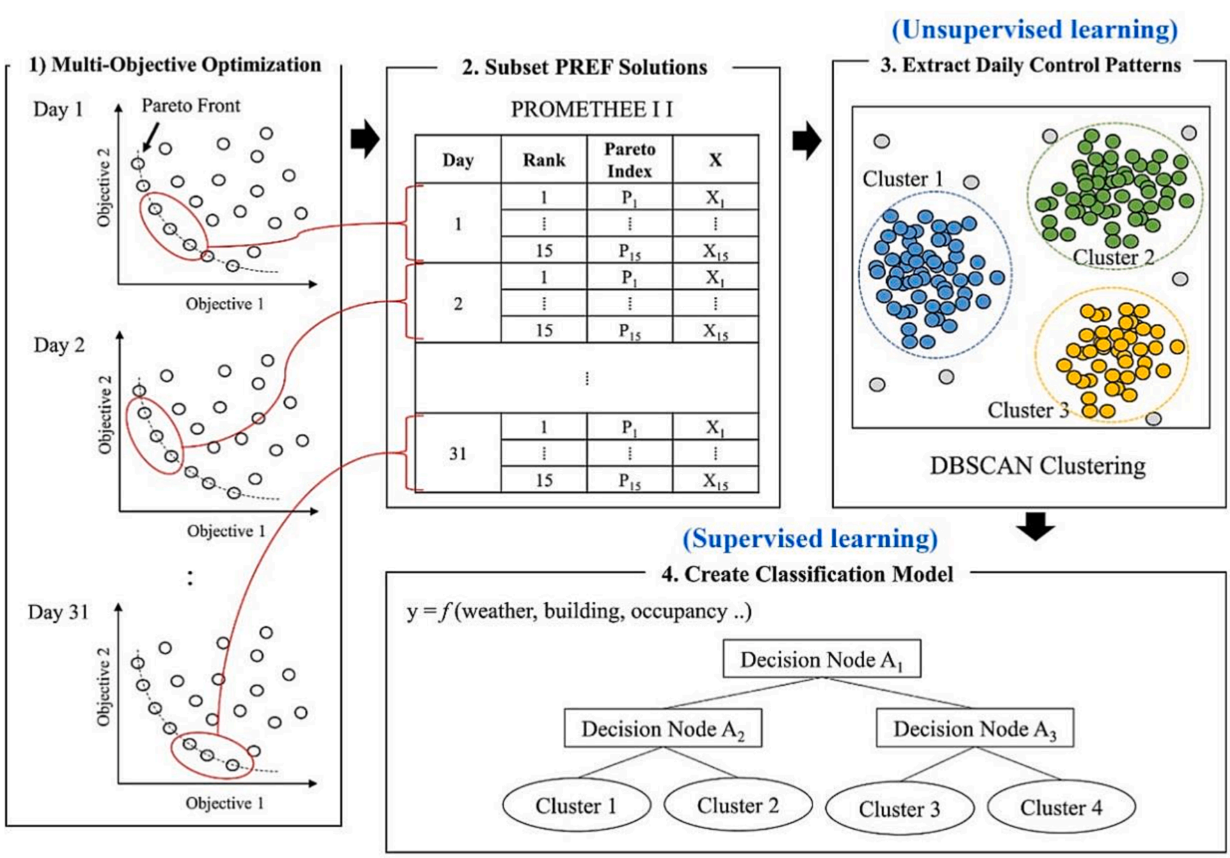

Fig. 10. The workflow of combing UNSL and SL approaches (modified from [88]).

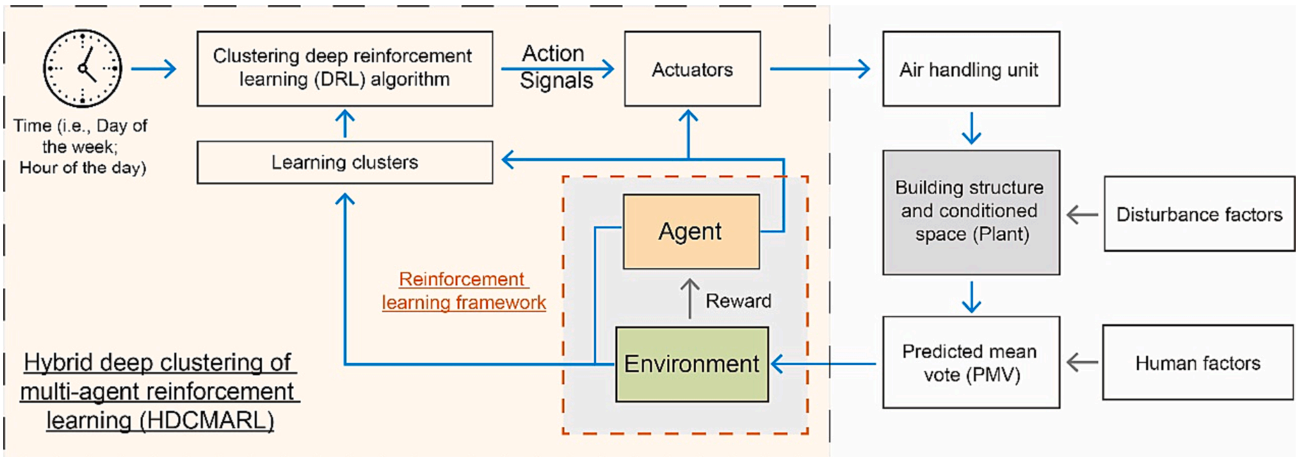

Fig. 11. The framework OF HDCMARL for controlling HVAC systems in smart buildings (modified from [96]).

agent action data generated by the RL algorithm. HDCMAL is designed for scenarios with an extremely large state-action space, where conventional RL methods typically perform poorly. By leveraging the advantages of hybrid deep clustering, providing a greater capacity to understand large spaces and process massive amounts of data, the outcomes of this study revealed that, treating the results of commonly used proportional–integral–derivative controller (PID) controller as a reference, HDCMARL can achieve a 32% cutting in consumed energy and a 21% enhancement in thermal comfort.

4.1.3. Reinforcement learning (RL)

As mentioned above, both SL and UNSL methods are suitable for observation and prediction, but less effective in adjustment, management, and interaction [85]. On the contrary, RL is a suitable method for latter applications [97]. The RL method has been widely used for system control since 1990s [98], which is a goal-orientated algorithm that engages in real-time decision-making while interacting with the environment [99]. Similar to UNSL, historically labeled data is not required for RL training, but a specific purposed environment has to be established for the agent of RL [85]. Inspired by psychology, RL investigates how artificial 'agents' might operate in an 'environment' to reach a particular goal. The 'environment' represents the dynamic system, which is characterized by states in discrete time steps [100]. Fig. 12 illustrates the key concepts and processes of RL. In brief, the RL algorithm, so-called (RL) 'agent', learns from the consequences of its activities (i.e., rewards or penalties from the 'environment'), interacting in discrete time steps (i.e., t or $t+1$) [101]. In other words, by executing an action at t, the 'agent' updates to a new state at $t+1$ [100].

Based on the feedback from the 'environment' this updating process, such as 'environmental' benefits or punishments, 'the agent gradually learns to take actions with beneficial outcomes' [85] and aims to maximize the lumped rewards over time. RL has great potential to apply in complex, real-world scenarios [102], since RL can 'learn through trial-and-error search by interacting with the environment' [78]. The general data-driven controlling process is visualized in Fig. 13.

Yang et al. [78] demonstrated the applicability of RL control in a real-world building equipped with a hybrid Photovoltaic/Thermal (PV/T) and geothermal heat pump system. The case study revealed that reinforcement learning control (RLC) can achieve enhanced performance compared to rule-based control (RBC), such as increasing the demand satisfaction for heating from 97% to 100% of the time. Meanwhile, the RLC system incrementally produced cumulative net power from the PV/T panels with progressively increased percentages, from 5.73% to 11.47%, over three consecutive years of operation. Moreover, the natural advantages of RLC are confirmed in this work, including low demands in prior knowledge and remarkable self-adaptation capabilities for variations in environment and inputs. Liu et al. [103] also developed a multi-step prediction-orientated deep RL algorithm, named MSP-DRL method for effectively managing the model-free HVAC system. The MSP-DRL method is demonstrated to over-perform other control rules,

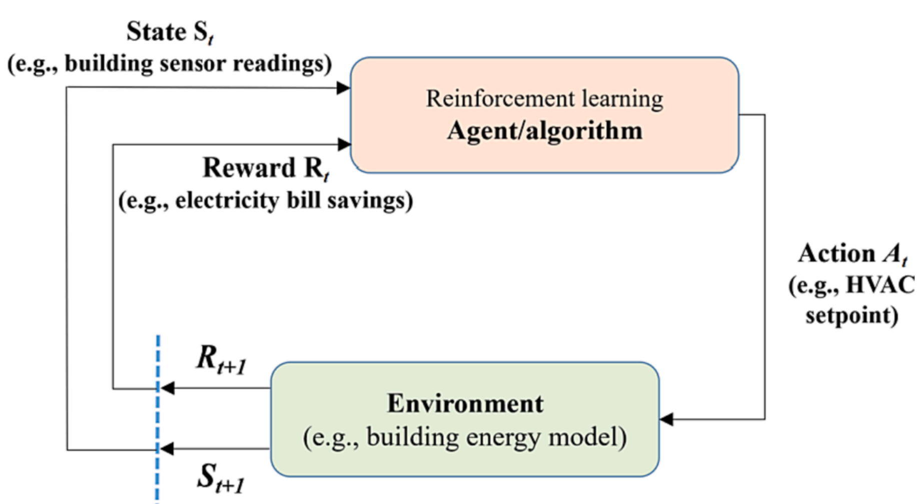

Fig. 12. A diagram of interactions between the agent and the environment in RL (modified from [85,89]).

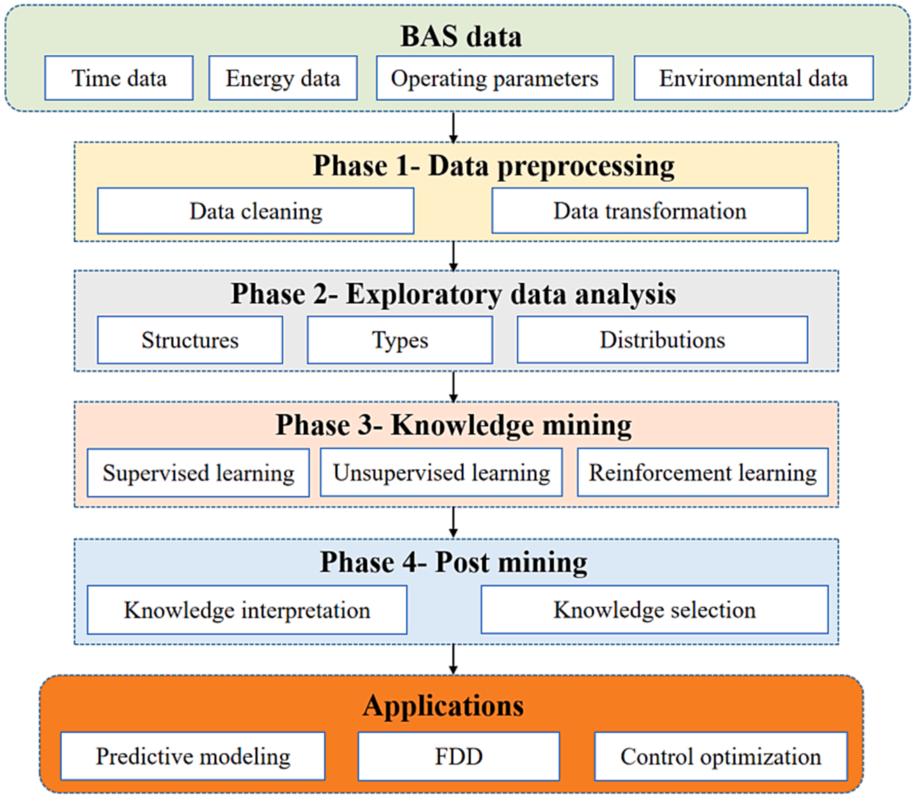

Fig. 13. The general workflow of analyzing and applying building operational data (modified from [93]).

maintenance of indoor thermal comfort, with benefits such as a 12.79% decrease in power consumption costs, compared with commonly used on/off rule. Du et al. [104] also proposed a data-driven approach that uses deep RL to optimize the performance of HVAC systems for multiple objectives, which predominately targets minimizing energy consumption while ensuring occupant' comfort simultaneously.

Qin et al. [105] proposed a novel control approach for distributed RL. Fig. 14 illustrates the structure of the multi-agent-based distributed RL algorithm. The control method combines multi-agent DRL with an iterative sequential action selection algorithm. This integration allows a controller to effectively model the electrical energy demands within a district building energy system. In this study, they tested this approach in campus buildings to minimize energy consumption while maintaining thermal comfort across nine regional buildings. This innovative control system includes sharing parameters and optimizing coordination between regional buildings, which goes beyond the standard RL techniques used for a single building. Furthermore, this study demonstrated that the distributed RL method outperformed traditional control methods such as RBC and model predictive control (MPC).

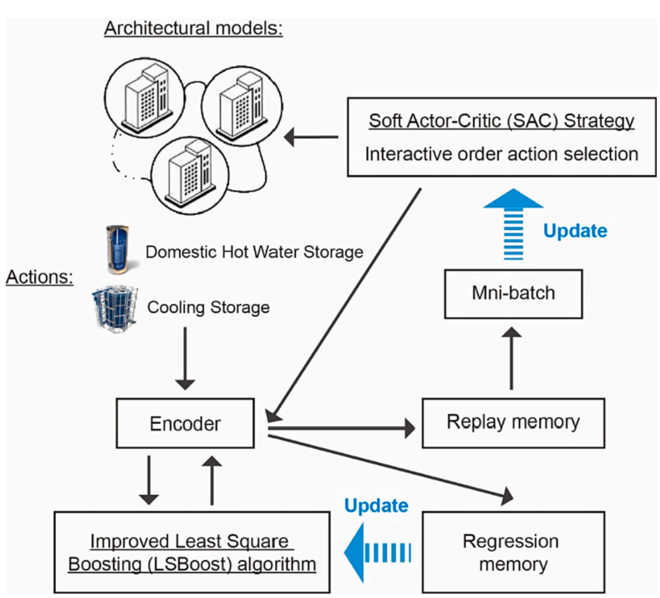

Fig. 14. Diagram of distributed RL algorithm based on multi-agent (modified from [105]).

4.2. *Advanced control applications*

4.2.1. *Controls for energy-saving and low-carbon buildings*

As building energy systems become more complex and integrated, advanced control methods for energy efficiency and low-carbon buildings become increasingly important. Energy management systems in current buildings often lack flexibility and adaptability for optimization of energy systems [106]. To improve the flexibility and efficiency of building energy systems, control strategy upgrades and hardware architecture improvements are often employed. While many studies have been conducted on the control of heating and cooling systems in buildings, implementing advanced control strategies remains a challenging task due to the distributed nature of building energy systems and the heterogeneity basic components. Despite the theoretical analysis of proposed control schemes, there is a lack of comprehensive, real-world demonstrations of their implementation and cost-effectiveness [107]. Furthermore, even when real-world testing is carried out, specific data collection and control implementation details are often limited to certain building types [108]. Against this backdrop and motivation, Bird et al. [109] developed a cloud-based monitoring platform for optimizing HVAC systems in commercial buildings. This platform includes a universal MPC framework for building HVAC systems, which can be applied to all modern building management systems at minimal upfront and ongoing costs (as low as 6.39 USD/month). The MPC scheme calculates the optimal temperature setpoints for each AHU to minimize overall costs or carbon usage while ensuring occupants' thermal comfort.

Numerous studies have demonstrated that advanced control strategies, including MPC, can achieve a balance between energy efficiency, thermal comfort, and indoor air quality, providing demand flexibility, minimizing peak load requirements, and maximizing renewable energy utilization in buildings, such as via using BIPV (Building-integrated photovoltaics) system [110]. In a recent study, Wei and Calautit [111] investigated the potential of combining price-responsive MPC with low-temperature heating systems and passive structural thermal storage, as well as integrating PV systems, as illustrated in Fig. 15. The study also examined different design and operational conditions, such as different heat gains, occupancy patterns, and internal heat gains, setpoint strategies, and operating temperatures for the low-temperature heating system, and evaluated the system performance under future climate conditions. The authors assessed the performance of passive building energy storage technologies under future climate conditions (2030, 2050, and 2080) and found that higher utilization of low-cost energy and lower heating energy use can be achieved under future climate conditions. These findings have significant implications for achieving sustainability in the built environment and reducing the carbon footprint of buildings.

In practice, the mismatch between heating supply and demand in building energy systems has restricted the efficient operation of district heating systems. Based on advanced automation and information technology, Liu et al. [112] proposed a dynamic integration control method for buildings and heat exchange stations (HES). This study verified the proposed method through a case study in Qingdao, China, as shown in Fig. 16. Through integration control, the calculated matching value of heating supply and actual heating demand for buildings ranged from 85.46% to 96.90%, accounting for over 90% of the entire centralized heating system. Four years of operation data showed that this integration control method achieved energy saving rates ranging from 12.75% to 31.08%, electricity saving rates ranging from 5.23% to 24.62%, and reduced CO_2, SO_2, and NO_x emissions by 3803 tons, 35 tons, and 10 tons, respectively. The facts also demonstrated that by adopting this method, almost all buildings were heated to the required indoor temperature, completely eliminating the imbalance between heating supply and demand.

Although the potential benefits of advanced control are enormous, there are also significant challenges that need to be addressed. For example, advanced control techniques may be complex and require specialized knowledge and skills for design, installation, and effective operation. Building owners, operators, and designers may lack awareness and understanding. Furthermore, different manufacturers may have different communication protocols and interfaces, making it difficult to integrate systems from different manufacturers. This can result in interoperability issues and reduce the effectiveness of advanced control systems. It is essential to address these challenges in the future to realize the potential of advanced control in achieving energy-efficient and low-carbon buildings [113,114].

4.2.2. Controls for fault detection and diagnosis

As a subfield of control engineering, a FDD process that identifies fault occurrences and pinpoints the fault causes is vital for the safe and reliable operation of systems/devices. In buildings, FDD is widely used for identifying anomalies of equipment in HVAC systems, such as boilers, chillers, pumps, fans, and valves, etc. Besides, it could also be applied to lightings, elevators and any other equipment in buildings.

The applications of AI and ML algorithms on FDD for building systems have been comprehensively summarized in existing studies. For instance, Shi and O'Brien [115] mentioned that black-box models (e.g., artificial neural network (ANN), support vector machine (SVM), and principal component analysis (PCA), etc.), have drawn increasing attention on feature generation for FDD of building systems since 2010. Mirnaghi and Haghighat [116] classified commonly used FDD methods for HVAC systems into three categories: model-based methods, data-driven methods, and knowledge-based methods. Further, data-driven methods could be separated into qualitative methods and quantitative methods. Among them, qualitative-based methods include expert systems, fuzzy logic, pattern recognition, and frequency analysis. On the other hands, data-driven quantitative-based methods include statistical methods and ML algorithms (such as neural networks). Zhao et al. [117] introduced commonly used AI-based FDD techniques for building energy systems, including classification-based methods, regression-based methods, and UNSL-based methods. Through comparing strengths and shortcomings of AI-based FDD technologies, they pointed out that these AI-based methods are limited by reliability and robustness. Chen et al. [118] reviewed the general procedure of data-driven FDD, which mainly include data collection, data cleaning, data preprocessing, baseline establishment, and FDD. Furthermore, Mariano-Hernández et al. [119] found that FDD is usually considered in non-residential buildings.

AI-based FDD, especially supervised learning-based FDD, heavily relies on data measured from sensors, while sensor failure could be a major equipment failure. There are mainly four types of sensor faults [120]: drifting, bias, complete failure, and precision degradation. Sensor failure may harm the control performance of controllers designed based on the residual difference between measured value and set-point. Thus, identifying misplaced sensors or locating sensor failures would be an effective way to recognize potential energy saving directions [121]. Furthermore, faults occurred during equipment operation process could be classified into system level and component level [122]. For instance, for an air conditioning system, insufficient refrigerant maybe a system level failure, while fan failure is a component level failure. As failure varies among devices/systems, verification of the robustness and generalizability of AI-based FDD techniques become a challenging research direction.

UNSL-based FDD is also considered by some researchers to enhance building energy efficiency [123]. Fan et al. [92] developed an

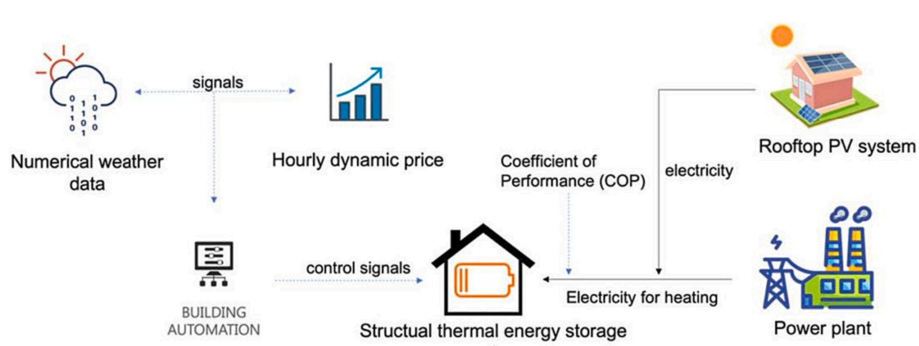

Fig. 15. Predictive control framework diagram for a low-temperature heating system with passive thermal storage and PV system [111].

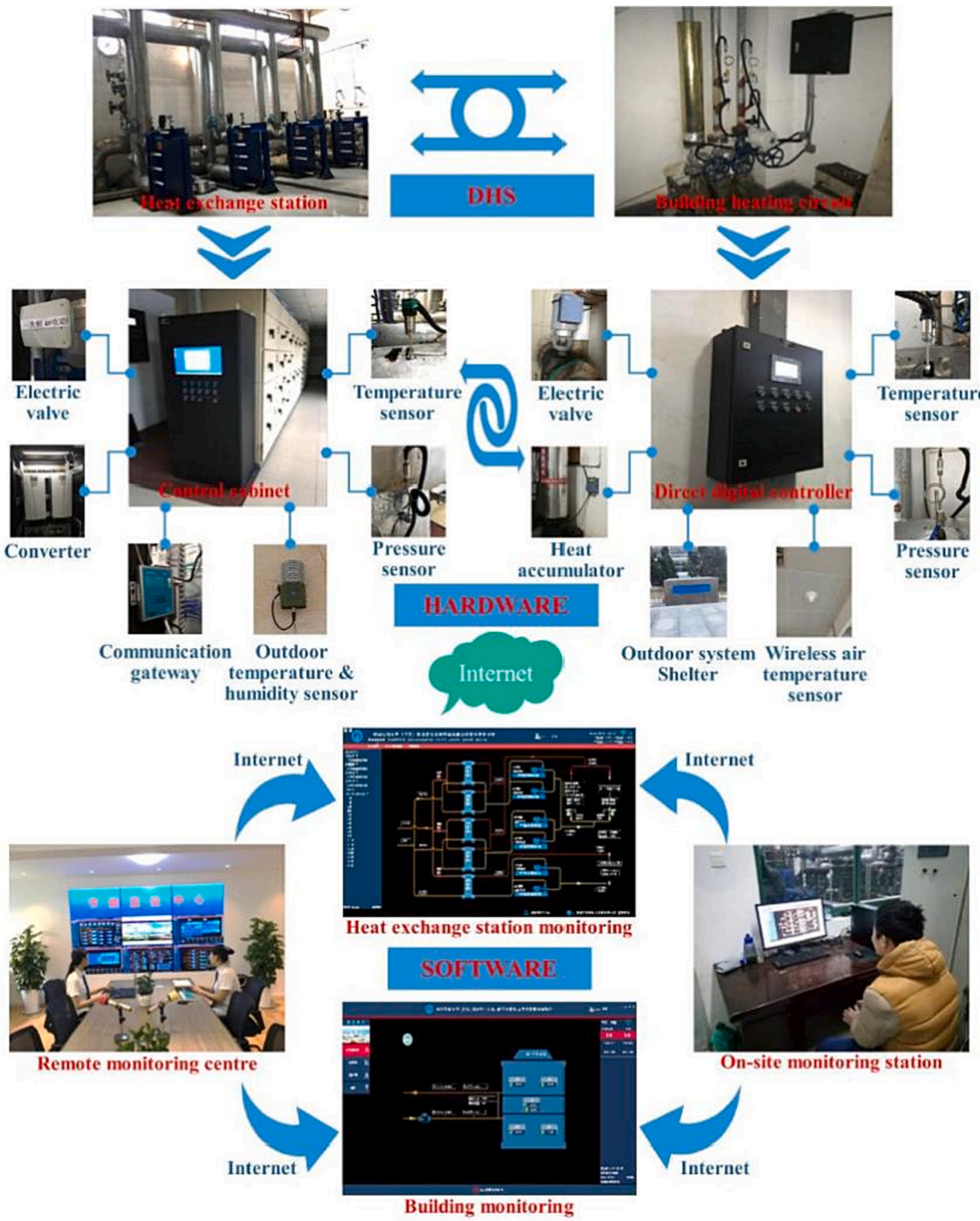

Fig.16. The configuration of the integrated control platform [112].

autoencoder-based UNSL method for anomaly detection based on building energy data. In addition, this study also examined and compared the performances of the proposed technique on different autoencoder types and training schemes. Autoencoder is an algorithm for UNSL, composed by encoder and decoder (Fig. 17). To compress input data, the encoder extracts characteristics from the input data without any support from label information [90].

Du et al. [124] presented a data-driven technique for enhancing operative building energy efficiency through fault detection and diagnosis, which combines dual neural networks and the subtractive clustering method. The use of the subtractive clustering method in this technique empowers its ability to diagnose previously unknown faults, such as sensor faults in buildings. Guo et al. [125] presented a fault diagnosis technique by optimizing the back propagation neural network. This technique was applied to control the variable refrigerant flow air conditioning system in a heating scenario, which achieved the best fault diagnosis correct ratio of 96.40%.

While building data is valuable, excessive and irrelevant data dimensions may cause overfitting and excessive computational loads if not used appropriately. Recently, DTs have emerged as a promising concept for smart building FDD. Xie et al. [126] used building HVAC systems' FDD process as an example and applied symbolic AI techniques to identify specific sensory dimensions related to building faults through the symbolic representation of labeled time series data. They developed a DT data platform that labels real-time data with fault labels, as depicted in Fig. 18. By identifying the informative subsystems for

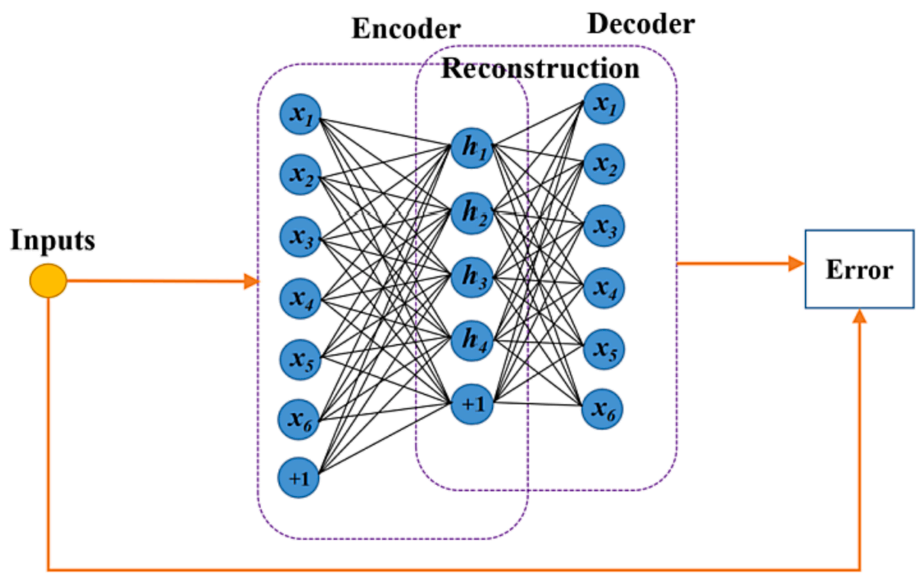

Fig. 17. The structure diagram of Autoencoder network (modified from [90]).

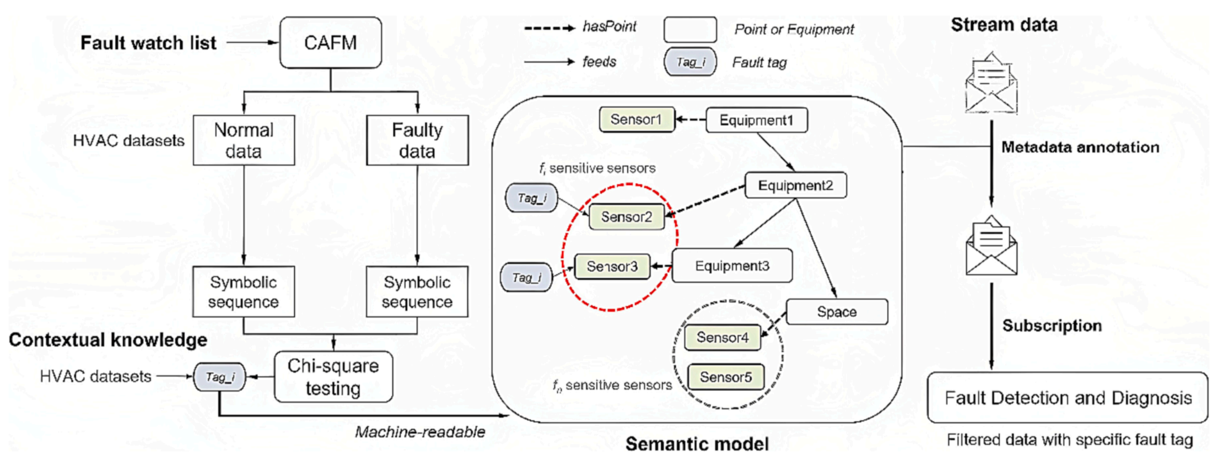

Fig. 18. Diagram of the FDD process of the building HVAC system (modified from [126]).

arbitrary faults and assigning appropriate knowledge tags to relevant sensors within each subsystem, the ad-hoc temporal knowledge is retained. This enables the customization of data pipelines to drive FDD processes. Auxiliary fault label annotation on the data stream enables additional low-latency, high-bandwidth real-time data streams to be automatically extracted with designated fault labels for FDD functionality. This provides data for dynamic asset management functionality using DTs. The divide-and-conquer strategy applied here helps to achieve real-time capabilities and reduce the computational burden of providing intelligent functionality.

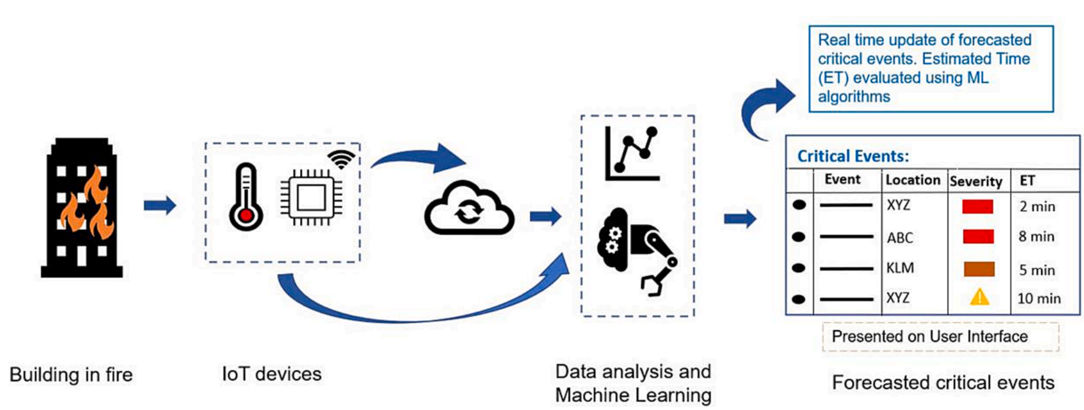

Fig. 19. Prediction process for the key events [29].

4.2.3. Controls for fire alarming and building energy safety

Effective building safety diagnosis relies on professionals who can organize and transform data into actionable frameworks. The use of IoT, BIM, and fire simulation tools generates real-time data that can be analyzed with AI and ML technology to provide quick decision support information for emergency responders [127,128]. Computer vision technology and natural language processing based on DL algorithms can provide real-time feedback on building conditions to the command and control center [129]. Fig. 19 illustrates a framework that uses a key event library to predict events through sensor data and ML algorithms [29]. Predicting key events can be achieved through data-driven methods, using AI and ML techniques to match real-time data streams with large-scale databases. Sensors continuously collect relevant data such as temperature and heat generation, which can be processed by IoT devices or read on cloud-based servers. AI engines enable automation of firefighting processes by providing advanced information about the fire scene and facilitating the use of DTs. This study creates an intelligent fire DT for the building by creating an event library and predicting events using AI engines.

To enhance fire safety management in dense buildings, advanced computational modeling concepts like BIM, fire dynamic simulator (FDS), and agent-based modeling (ABM) have been used for simulating fire safety performance [130,64]. However, these methods face challenges such as data interoperability and technical limitations of currently available BIM software, making it difficult to simulate fire-driven fluid flow and personnel evacuation processes simultaneously. Sun and Turkan [131] developed a BIM-based simulation framework to address these challenges, implementing FDS and ABM for improved accuracy of fire simulation results, as shown in Fig. 20. The proposed framework can minimize casualties and property damage, as well as optimize building fire protection design and explore factors that affect personnel evacuation efficiency.

In recent years, researchers have proposed various ML algorithms to establish complex relationships between sensor data and fire events for real-time fire prediction [132,133]. For example, RNN-based AI algorithms have been used to identify fire scene information and predict critical fire events in the future [134], while convolutional neural networks (CNN) algorithms are better suited for supporting firefighting commanders' on-site decision-making [135]. Despite these advances, the current application of AI in fire engineering is still relatively immature. However, it is expected that future AI algorithms will become more sophisticated and capable of predicting complex fire scenarios in a super-real-time manner and revealing deep information from large databases. With the development of building IoT and DTs, it is envisioned that mature AI-driven fire prediction engines will be installed in every building to identify and predict fire scenarios and support intelligent firefighting.

4.2.4. Climate change adaption with advanced controls

SEE buildings can play a key role in mitigating the impact of climate change. By implementing advanced controls and technologies, these buildings can be designed to adapt to changing environmental conditions while minimizing energy consumption. To achieve the goal of automatically adjusting HVAC systems based on environmental conditions, efficient HVAC control systems are crucial. However, most existing methods require accurate knowledge of system parameters and/or sufficient historical data and may not perform well in situations where dynamic parameter changes occur due to human activity, material degradation and wear, or weather conditions. To address these issues, Lymperopoulos and Ioannou [136] proposed a distributed adaptive control scheme for HVAC systems in multiple climate regions, shown in Fig. 21. This scheme regulates zone temperatures effectively by applying online learning and assuming information exchange between adjacent zones. Unlike other methods, this scheme does not require accurate knowledge of system parameters and utilizes real-time parameter estimators to estimate unknown parameters and update controller parameters accordingly. Similarly, Ghahramani et al. [137] proposed an adaptive hybrid metaheuristic algorithm using ML, while Radhakrishnan et al. [138] proposed learning-based adaptive methods. The combination of adaptive control and learning technologies, along with distributed control, eliminates the need for precise and up-to-date information on system parameters and has high practical significance for HVAC systems.

Numerous studies have indicated that improving building intelligence can help mitigate the impact of climate change by optimizing energy management through the use of IoT, sensors, and data analysis. However, implementing distributed sensor systems is complex and requires accurate positioning to optimize building systems. To address this, Tsao et al. [139] proposed a continuous approximation approach to determine the required number and location of sensors and the intelligence level of each sensor while maximizing the total network cost reduction. The building energy system includes renewable energy generation systems, energy storage systems, the grid, and intelligent sensors, which are connected through IoT and Wi-Fi, as shown in Fig. 22(a). The sensor system (Fig. 22(b)) collects information and transmits it to application services through gateways and network servers, which then analyze and make decisions for other applications. The proposed model can be a useful tool for building managers to determine the type/level of

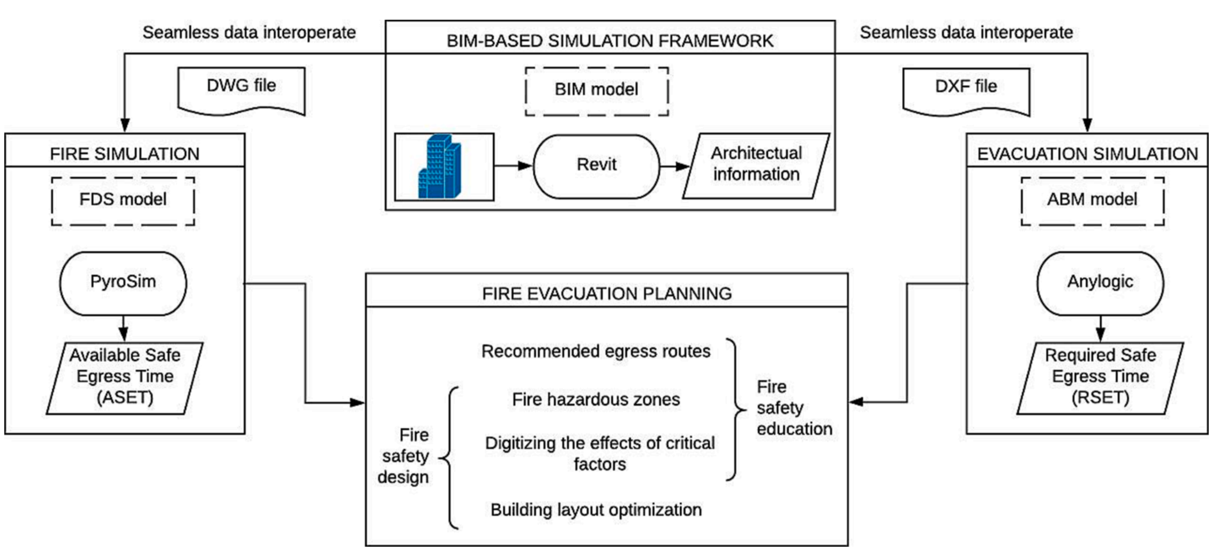

Fig. 20. The BIM-based simulation framework [131].

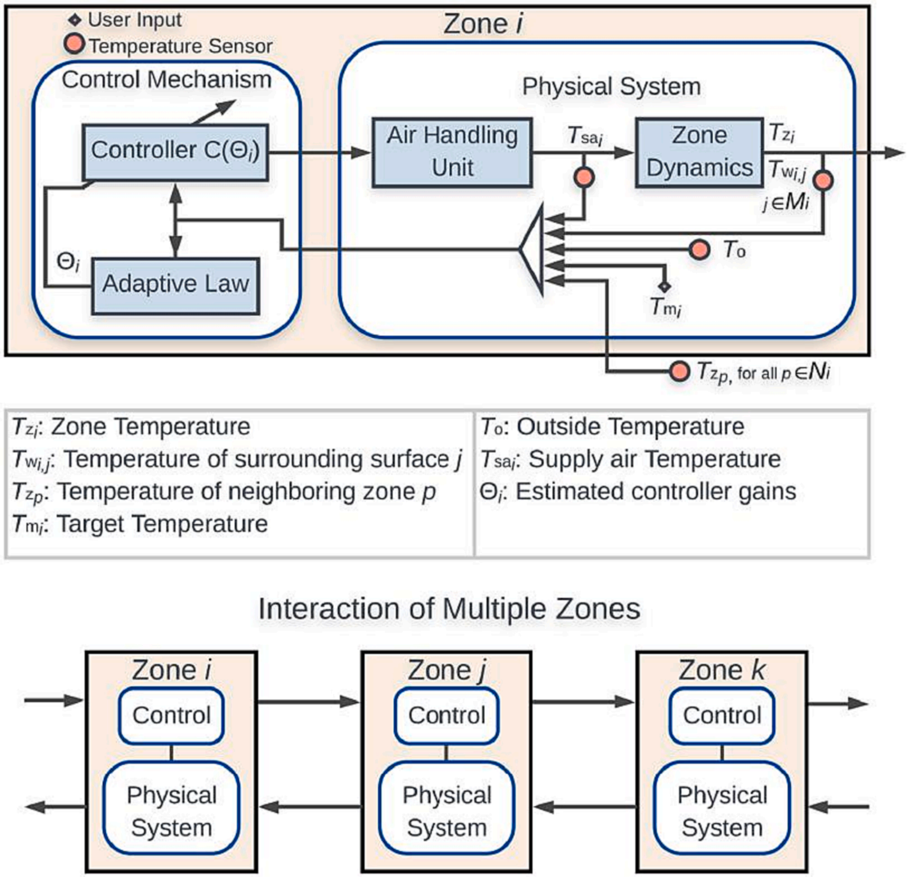

Fig. 21. The distributed adaptive control scheme for HVAC systems [136].

sensors and the number of sensors while maximizing the total cost reduction of the building energy system.

Advanced control for SEE buildings provides a promising solution to make buildings adaptable to climate change and reduce energy consumption. However, the implementation of advanced control brings various problems and challenges that need to be addressed, including high costs, lack of awareness, and lack of consensus on the best implementation methods. In addition, effective integration with existing building energy systems is also one of the major challenges faced in implementing smart control systems to make buildings adaptable to climate change, which involves developing interfaces and protocols that can communicate with various building energy systems.

5. Advanced occupant-centric control (OCC) and its applications

OCC refers to control mechanisms that control system/device operations and internal building conditions based on occupants' preferences [33,140]. Because occupants' energy usage habits/pattern determines the actual energy consumption of a building, the OCC for demand-side management works effectively on energy conservation and energy flexibility, while maintaining the indoor environment within occupants' comfort requirement [141,142]. Sensors and technologies for collecting occupancy-related data, such as occupant presence/number, occupants' location, occupants' activity and energy behaviors, occupants' physiological parameters related to thermal comfort, etc., are summarized in Ref. [143–145]. Moreover, in Ref. [145], existing research on OCCs was summarized in terms of reactive response to occupancy, control to individual occupant preference, control based on the prediction of future occupancy/behaviors, and control to individual behaviors/activities. Predicting occupant-related context enables the HVAC system to preemptively condition a thermal comfort space while achieving energy saving. However, the complex prediction models would require more computational cost. Thus, balancing the complexity of a prediction model against its contribution to energy saving would be a critical point for the application of AI-based occupant prediction models to OCC.

Advanced OCC in buildings are increasingly utilizing ML techniques, such as DL and RL, to reach optimization in multi-objectives, such as thermal comfort enhancement and building energy reduction. For instance, a controller of OCC for building lighting systems is proposed by Park et al. [146]. In this study, based on the experiment data in five offices for eight weeks, it was demonstrated that the proposed occupant-centric lighting controller, called LightLearn, can adjust its control parameters by customized set-points determination for its operation, which is fundamentally based on the learning of occupants' behaviors and interior environment dynamics. According to the survey findings, participants reported that overall lighting has been slightly enhanced by LightLearn, compared to the previous lighting situation. Yang et al. [147] conducted a preliminary investigation on how stratum ventilation systems can adapt to dynamic occupancy using OCC. The multi-objectives were reducing energy consumption, improving occupants' thermal comfort, and maintaining indoor air quality. This study employed a DL-based computer vision method to monitor real-time occupant information, and the data on the number of occupants are used to adjust the OCC control in stratum ventilation. Based on experiments conducted in a controlled climate chamber, initial findings showed promising outcomes compared to the conventional control strategy, including a 43%–73% improvement in thermal comfort and a 2.3%–8.1% energy saving while ensuring acceptable indoor air quality. Fig. 23 shows a framework for building performance metrics that can be employed in OCC, and Fig. 24 illustrates a diagram of a RL-based OCC framework.

Supervised ML technologies have been integrated into OCC through

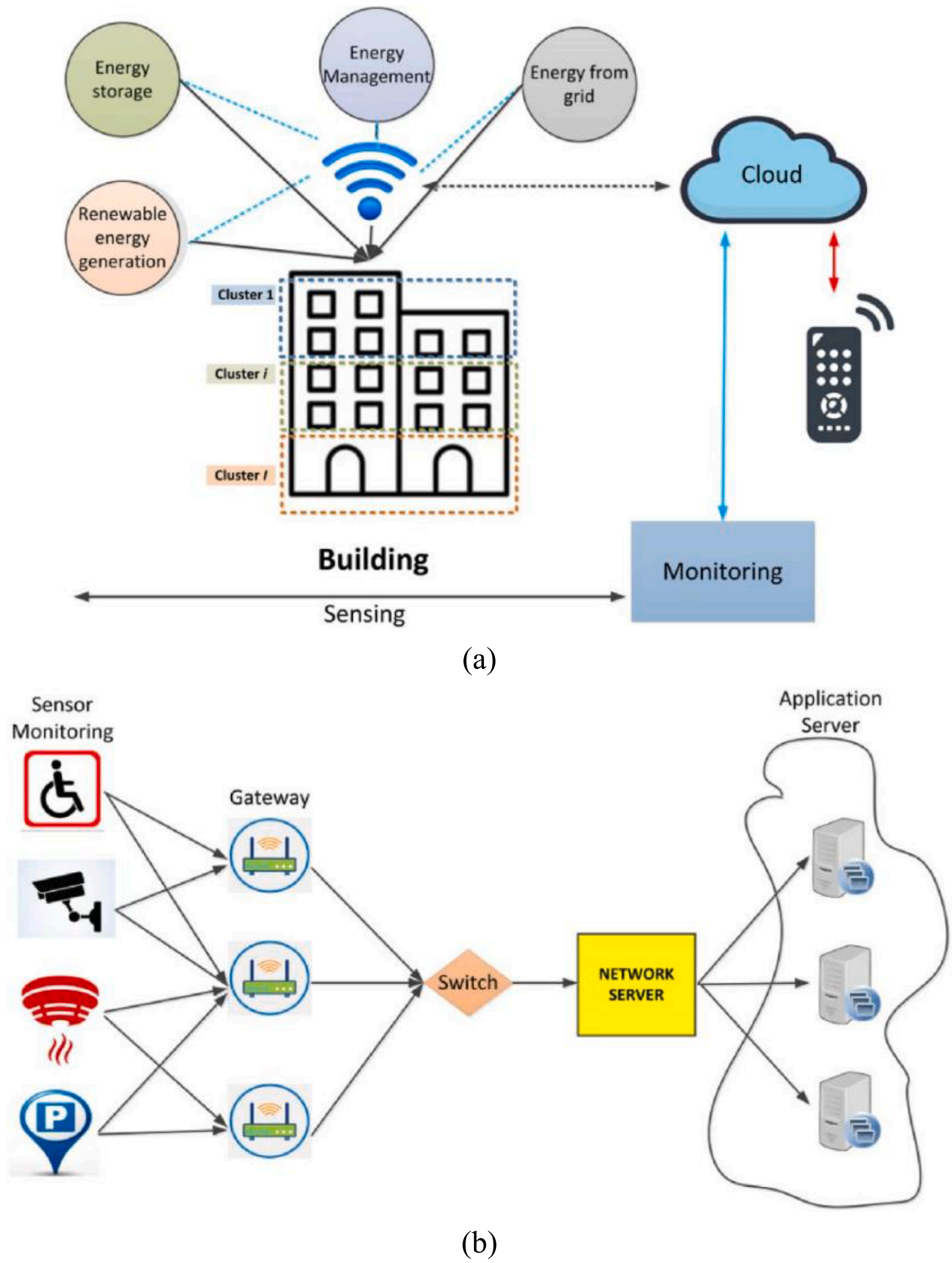

Fig. 22. (a) Intelligent building system; (b) Sensor network structure [139].

predicting occupants' presence/behavior. For instance, Yayla et al. [149] proposed a HVAC control mechanism that schedules set-point based on hourly predicted occupancy counts from an ANN model. Through comparing with a traditional control strategy that sets set-point temperature based on real-time measured occupancy-related data, the AI-based OCC achieves over 10% energy saving while providing a more thermal comfort indoor environment in a shopping mall, located in Istanbul, Turkey. Taheri and Razban [150] developed ML models to predict CO_2 concentration of a campus classroom, and then, adjusted the ventilation rate of the HVAC system based on the predictive result. The novel control strategy reduced the energy consumption of fans in a HVAC system by 51.4%, while ensuring the required ventilation by the ASHRAE standard. Based on DL and RL algorithms, Jung et al. [151] developed an OCC system for managing buildings' real-time indoor temperature, named Real-COMFORT. This OCC system enables optimizing both the thermal comfort of individual occupants and building energy consumption. Specifically, in this system, occupants' activities are automatically recognized by CNN-based model to satisfy the dynamic and customized demands in OCC. The development of this system incorporates data from a climate chamber experiment, including indoor environment, occupant, and energy consumption data. This study showed that, with the same building energy consumption, the proposed system can mitigate 10.9% of thermal discomfort experienced by occupants engaged in dynamic activities, thereby improving indoor thermal comfort.

Besides, unsupervised algorithms, such as Explicit Duration Hidden Markov Model (EDHMM), show the ability to detect occupant presence and provide a basis for occupant-centric load management [152]. Furthermore, using RL for OCC has been proved to be effective on minimizing energy consumption while ensuring occupants' comfort

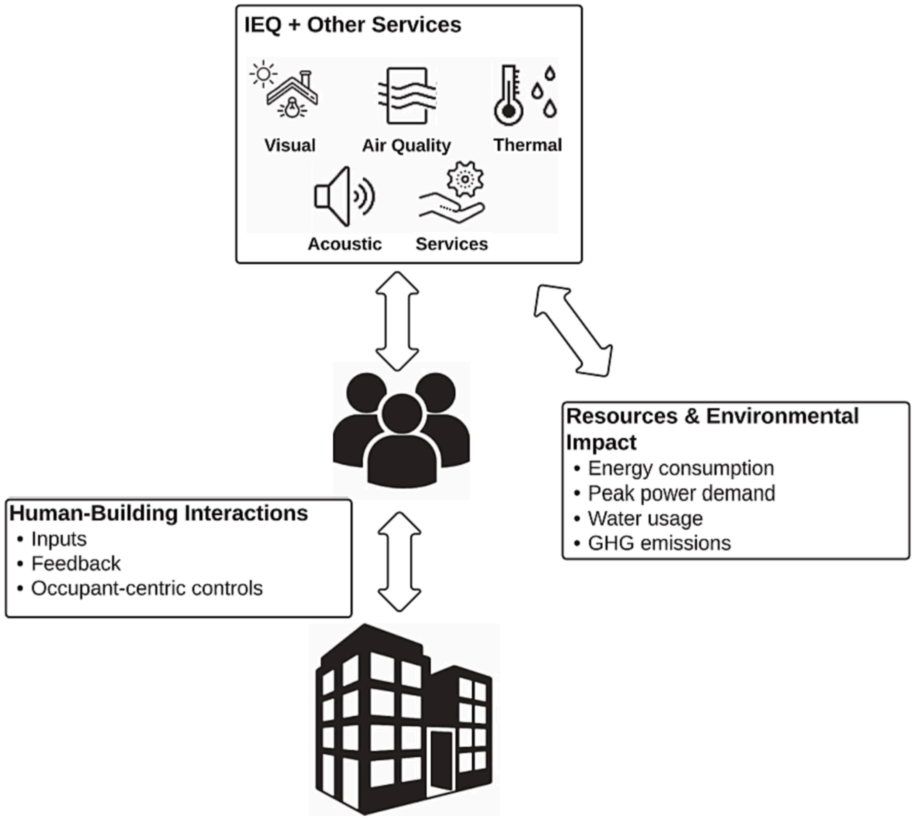

Fig. 23. A diagram of metrics for occupant-centric building performance [148].

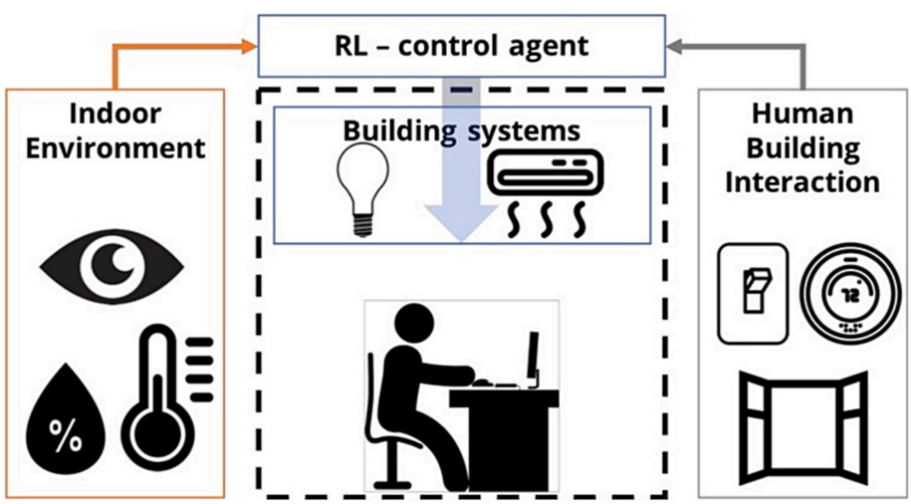

Fig. 24. A diagram of the RL based OCC framework [2].

[153]. Compared with other OCC strategies, e.g., rule-based control [154] or MPC strategies, RL shows the advantages of considering the stochastic occupants' behavior with no requirement of predictive models. To adapt to the schematic occupancy profile when scheduling space heating, Heidari and Khovalyg [155] proposed a control framework, namely DeepValve, based on RL. The proposed controller could be quickly applied to new control spaces to save energy while maintaining thermal comfort. Lei et al. [156] offered a multivariate OCC system, based on DRL that takes into account individual thermal comfort and occupancy status. The objective of this control system is to enhance the learning efficiency of HVAC system control. This study validated the control performance of the proposed controller in a real office, and the results showed a 13.9% reduction in building cooling load while simultaneously improving the total thermal acceptability by 11%. Heidari et al. [157] presented a model-free RL based control framework aimed at optimizing several conflicting objectives of heat pump water heating systems in buildings, including water hygiene, occupants' comfort, and energy saving. This OCC framework focuses on understanding stochastic occupants' behavior to effectively optimize the said objectives. In this study, a stochastic hot water usage model, powered by offline training, is introduced to mimic the hot water use behavior of tenants. Based on a case study of a residential home in Switzerland, this study demonstrated that the RL-based OCC framework successfully met both occupants' hot water demand and maintain comfort, while

achieving a remarkable 23.8% reduction in energy consumption, by a deeper understanding of occupants' behavior and its integration into the control framework. More studies on RL for OCC could be found in Ref. [156,158,159].

6. Challenges and future perspectives

6.1. Trade-off between complexity and predictive/control performance

As illustrated in Section 5, predictive-based OCC shows improved control performance than other types of OCCs [145]. The control performance of predictive-based OCC highly depends on the predictive accuracy. For AI-based building/occupancy models, plenty of studies have focused on improving their predictive accuracy through implementing supervised ML algorithms with more complex structure in recent years. For instance, DL algorithms have been widely used to predict energy consumption [160,161] and integrate into MPC to control devices in buildings [162]. Deep RL has been implemented to strength the control performance of traditional RL algorithms [163,164].

However, the increased complexity of predictive or control algorithms would result in more computational cost, including both computational time and computational power. A longer computational time may harm the effectiveness of predictive results or control strategies. For instance, if a MPC is established to control a HVAC system by sending an optimal control signal every 5 min but the predictive process takes more than 5 min, the temporal mismatch between the control process and prediction process will impose challenges on the practicability feasibility. Besides, a higher requirement on computational power indicates more investment on computing resources. Therefore, although more complex predictive or control algorithms may lead to better predictive accuracy or control performance, balancing the complexity and predictive/performance remains an interesting and vital research direction.

6.2. AI-based controllers and climate-adaptive controls in SEE buildings

Existing studies on smart control in buildings show diverse methodologies and research targets. For instance, for a MPC, various of predictive models could be selected. A proposed control framework could be implemented to different types of buildings, such as commercial buildings, educational buildings, and residential buildings. The implementation scale would vary in terms of spatial (e.g., zone level, building level, district level, and national level) and temporal (e.g., minute, hour, year, and decades).

Therefore, a verified predictive model or control strategy in a specific case study could not ensure its generalizability on other cases. There are existing studies on evaluating and enhancing the robustness of ML algorithms [165–167]. The generalizability of ML models and preprocessing methods have been investigated in Ref. [168]. However, the study on robustness and generalizability of AI-based control strategies is still lacking. Because of this research gap, suggestions on selecting proper AI technologies for distinct study cases could not be consistent.

Research on adapting to climate change through intelligent control in SEE buildings is a rapidly developing field that has the potential to significantly impact reducing CO_2 emissions and mitigating the effects of climate change [21,169,170]. However, there are still many research challenges that need to be addressed to fully realize the potential of advanced controls in SEE buildings. One key challenge is developing smart control systems that are effective across various building types and climate zones. Building characteristics, occupant behavior, and local climate conditions all affect the effectiveness of smart control systems [36,171,172]. Therefore, future research should focus on developing smart control solutions that are tailored to different building types and regions and can adapt to changing conditions over time. Developing cost-effective climate adaptation solutions is another major challenge as it requires identifying affordable solutions that can easily be integrated into existing buildings. Future research should explore using data analysis and ML to optimize smart control systems for cost-effectiveness. ML algorithms can identify patterns and trends in data from building sensors, meters, and other sources that can be used to optimize energy usage and reduce costs [173].

6.3. OCC in thermal comfort and energy saving

OCC in SEE buildings aims to achieve the dual objectives of thermal comfort and energy efficiency. However, this approach encounters several challenges that must be addressed for its effective implementation. In this section, a critical analysis of the challenges faced by OCC was presented and the future research directions to advance this field was proposed to drive the development of OCC in SEE buildings.

One of the major challenges in smart buildings is the diversity of occupant behaviors and preferences, which poses challenges to achieving thermal comfort and energy-saving goals. Each occupant has different requirements for thermal comfort, activity patterns, and sensitivity to temperature. Moreover, occupants have varied priorities regarding thermal comfort and energy-saving. This complexity makes it difficult to develop control strategies that cater to the needs of each individual while balancing energy-saving requirements [174,175]. Therefore, OCC strategies need to be flexible enough to accommodate individual preferences while ensuring overall efficiency [144]. Future research should focus on developing adaptive control algorithms that personalize indoor environments based on individual preferences and behavior patterns, while considering thermal comfort and energy-saving goals. Additionally, integrating advanced sensing technologies (e.g., IoT-based sensors, wearable devices, and occupant tracking systems [176]) along with ML algorithms, can help capture and analyze occupant behavior data, leading to a better understanding and prediction of occupant behavior and improved accuracy of control strategies.

Providing occupants with real-time feedback on energy consumption and the impact of their behaviors is crucial for promoting energy-saving behaviors and enhancing thermal comfort [177]. However, achieving this goal is not without challenges. In practice, occupants may have limited awareness of their energy consumption and the impact of their behaviors. Effective feedback mechanisms can increase occupants' awareness of the relationship between their behaviors and energy consumption, thereby motivating energy-saving behaviors. Future research should explore user-friendly interfaces, energy dashboards, and occupant feedback mechanisms to effectively communicate energy consumption and energy-saving-related information, empowering occupants to make informed decisions and better manage and adjust their behaviors [178]. Additionally, leveraging data visualization techniques, combined with occupant education programs and awareness campaigns, can enhance occupants' awareness and engagement in energy-saving practices.

Seamless integration of OCC systems with other smart building systems and automation platforms is essential to achieving thermal comfort and energy-saving goals [68,179]. However, this integration may face technical and operational challenges. Incompatibility between different systems and challenges in information exchange may lead to conflicts between thermal comfort and energy-saving goals. Future research should focus on developing standardized protocols and communication frameworks to facilitate interoperability among different building systems. Additionally, exploring comprehensive approaches to building systems integration, where different subsystems can collectively optimize thermal comfort and energy-saving goals, can help address conflicts and improve overall performance.

In summary, OCC in SEE buildings presents a promising approach for achieving thermal comfort and energy efficiency goals. By addressing the challenges posed by diverse occupant behaviors, limited occupant awareness, integration issues, and the need for adaptive control strategies, researchers can advance the field. Future research endeavors should focus on developing personalized control strategies, improving occupant feedback mechanisms, enhancing integration techniques, and leveraging advanced sensing technologies. By doing so, OCC can effectively contribute to the realization of thermal comfort and energy-saving objectives in SEE buildings.

7. Conclusions

In this study, a state-of-the-art review was conducted on advanced controls for SEE buildings. Data collection with smart meters and sensors, big data and building automation, energy digitalization and building energy simulation are reviewed for advanced energy systems. Advanced ML algorithms that can be equipped in advanced controls are reviewed, and their roles and underlying mechanisms of advanced controls are provided in SEE buildings. Advanced controls for energy security, reliability, robustness, flexibility, and resilience are reviewed for SEE buildings, with respect to fault detection and diagnosis, fire alarming and building energy safety and climate change adaptation. Moreover, this study explores the advanced OCC systems and their applications in the SEE buildings. Last but not the least, this paper highlights the current challenges and future potential, thereby establishing a foundation for reaching sustainability and facilitating a low-carbon transition within the domain of the building sectors.. Main conclusions are summarized below:

1) The use of smart metering and sensor technologies in advanced building energy systems can provide more detailed and accurate data on energy consumption patterns and building performance. However, the use of these technologies raises concerns about data privacy and security. Building automation systems can automatically manage complex building systems and record real-time measurement and control signals, but the low data utilization and independent data sources of existing buildings remain a challenge. Remote control technology can monitor end-user energy consumption in real-time and optimize functionality, and a DT-based building energy flexibility data-model fusion scheduling strategy can achieve parameter fault tolerance and privacy protection.
2) ML algorithms for advanced control of SEE buildings with fundamental differences between SL, UNSL, and RL algorithms. SL and UNSL are mainly used for observation and prediction, while RL is suitable for adjustment, management, and interaction. Furthermore, RL is a goal-oriented algorithm that participates in real-time decision-making with dynamic interaction with the environment. Advanced control technologies play crucial roles in reducing energy consumption while enabling buildings adaptive to climate change. Various FDD methods have been investigated and analyzed for building systems, with data-driven methods being more commonly used. AI and ML algorithms have been widely applied to FDD in building systems. However, the reliability and robustness of these AI-based methods are still limited. DTs can reduce the computational load with intelligent functions.
3) A plenty of ML algorithms have been integrated into OCC to predict the presence and behavior of occupants, while minimizing energy consumption and ensuring their comfort. The results show that OCC can achieve a balance between energy efficiency, thermal comfort, and indoor air quality, while providing energy flexibility to maintain the indoor environment within occupants' comfort requirement.
4) Challenges and future prospects of advanced controls for SEE buildings mainly include balancing the prediction complexity and computational cost, the robustness and scalability of AI-based control strategies, climate adaptive controls, and OCC in thermal comfort and energy saving.

Overall, this study provides a comprehensive understanding of the current state-of-the-art advanced controls for SEE buildings. Advanced control has significant potential to improve energy efficiency, security, and resilience of buildings, but the various technical, organizational, and social factors involved in its implementation should be carefully considered. By addressing these challenges and issues, building owners and operators can achieve significant energy savings and cost reductions while also contributing to reducing carbon emissions in the building industry. Future studies are suggested to focus on developing tailored smart control solutions that can adapt to changing conditions over time and integrate with climate models to predict future environmental changes. In addition, researchers should explore the use of data analysis and ML to optimize the cost-effectiveness of smart control systems and to assess their environmental and economic impacts throughout their life cycle. Finally, there are social and behavioral challenges that need to be addressed, such as the design of user-centered intelligent control systems and the development of strategies to promote energy-efficient behavior among building occupants.

Declaration of Competing Interest

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

Data availability

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

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