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A comprehensive review of predictive control strategies in heating, ventilation, and air-conditioning (HVAC): Model-free VS model

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ABSTRACT

Predictive control offers significant advantages in nonlinear control, high thermal inertia, and dynamic control. This article uses a Systematic Reviews and Meta-Analyses methodology to review 245 studies on predictive control in HVAC systems over the past 12 years, focusing on Model Predictive Control (MPC) and Model-Free Predictive Control (MFPC). In cooling systems, MPC is widely applied to energy efficiency management, continuous operation and maintenance, and overall system optimization in multi-zone residences. Its advantage is its ability to respond to system dynamics and precisely control key components such as cooling towers, condensers, evaporators, and pumps. Research focuses on simplifying models, reducing computational complexity, and enhancing real-time performance. In contrast, MFPC saves energy in equipment components and overall operation through intelligent valves, agent control programs, and other methods. Research focuses on developing new reinforcement learning algorithms to improve control efficiency and reliability. MPC research in heating systems focuses on hydraulic and thermal balance in central heating systems and expands to managing renewable energy hybrid systems. The research aims to dynamically adjust to meet user thermal comfort requirements while reducing energy consumption and improving efficiency. Key technologies include modeling techniques, distributed MPC, cross-regional integrated control, and efficient renewable energy integration strategies. MFPC precisely controls heating system water supply temperature, heat pump energy efficiency, and heating terminals through model-free algorithms like deep reinforcement learning and multivariable extremum seeking control. In integrated HVAC systems, MPC research focuses on managing multi-energy systems through hierarchical decomposition and multi-layer strategies, seamless renewable energy integration and optimization, and developing multi-objective optimization and decision support tools. MFPC research includes automatic grading strategies for integrated controllers, online optimization balancing methods, multi-agent methods, and developing intelligent model-free adaptive control strategies. However, MFPC integration in practical applications still needs strengthening. This review guides researchers in selecting the best predictive control mode for various HVAC system applications.

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List of abbreviations:	
A2C	Advantage Actor-Critic
A3C	Asynchronous Advantage Actor-Critic
AFT-CAO	Automated Fine-Tuning Cognitive Adaptive Optimization
AHU	Air Handling Units
AI	Artificial Intelligence
AMPC	Adaptive-Model Predictive Control
ASHP	Air-source heat pump
B2DN	Buildings-to-Distribution-Network
BEMS	Building Energy Management System
BO	Bayesian optimization
BOC	Building Optimization and Control System
C-SMPC	Chance-constrained stochastic model predictive control
CTES	Ice-cold thermal energy storage
DCC-AB	Distributed cooperative control-based online air balancing
DCS	District cooling system
DCV	Demand-controlled ventilation
DDIP	Dual dynamic integer programming
DDPG	Deep Deterministic Policy Gradient
DEO	Differential Evolution Optimization
DMPC	Distributed-Model Predictive Control
DQN	Deep Q-network
DR	Demand Response
DRL	Deep Reinforcement Learning
EMPC	Economic-Model Predictive Control
ESC	Extremum Seeking Control
ESS	Energy Storage System
FH	Floor heating
FMMPC	Fuzzy model-based multivariable predictive functional control
GA	Genetic algorithm
HMPC	Hybrid model predictive control
HVAC	Heating, Ventilation, and Air-conditioning
ICA	Inner control algorithm
ICT	Information and Communications Technology
IEQ	Indoor Environmental Quality
IPOPT	Non-linear programming problem solver
IPSO	Improved particle swarm optimization
IRA	Integrated Room Automation
LLNFMs	Local linear neuro-fuzzy models
LS-MDP	Linear Solvable Markov decision process
LSTM	Long Short-Term Memory
MC	Monte Carlo
MDP	Markov Decision Process
MFC	Model-free control
MFPC	Model-free predictive control
MILP	Mixed integer linear programming
MIMO	Multiple input and multiple outputs
MOBO	Measured Occupancy Based Optimal
MPC	Model predictive control
NR	Newton-Raphson
OF-MPC	Offset-free Model Predictive Controller
PAB	Parameter-adaptive building
PCAO	Parameterized Cognitive Adaptive Optimization
PID	Proportional integral derivative
PMV	Predicted Mean Vote
PPD	Predicted Per-centage Dissatisfied
PV	Photovoltaic
QCQP	Quadratically constrained quadratic programming
RC	Rules Control
RE	Rule extraction
RL	Reinforcement Learning
RM-MPC	Recursive Modelling Model Predictive Controllers
RMPC	Robust model predictive control
RNN	Artificial Neural Network
RTUs	Roof air conditioning units
SBMPC	Stochastic scenario-based Model Predictive Control
SV-MFPC	Smart-valve-assisted model-free predictive control
TABS	Thermo-Active Building Systems
TCL	Thermostatically controllable loads
TD	Temporal Difference

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List of abbreviations:	
TES	Thermal energy storage
VAV	Variable Air Volume
VCC	Vapor Compression Cycles

1. Introduction

Due to the improvement of living standards and the increase of industrialization, urbanization and population size, the energy consumption of buildings increases exponentially. Currently, buildings account for nearly 40 % of the world's total energy consumption and 40 % of its total direct and indirect carbon dioxide emissions [1]. In this case, improving the energy efficiency of buildings reduces not only the energy cost of buildings but also carbon emissions. The primary energy consumption of most types of buildings is the HVAC system. Improving the HVAC system's energy efficiency has become the key to raising the energy efficiency of the entire building.

In HVAC systems, "control" refers to the process of monitoring, adjusting, and managing key system parameters to ensure stable operation according to the specified environmental requirements. The purpose of control is to sense current environmental conditions and automatically adjust heating, ventilation, and air conditioning equipment based on predetermined targets to meet user demands for indoor comfort and air quality. Reasonable and scientific collaborative control is a powerful tool for achieving energy savings and reducing carbon emissions in energy-intensive HVAC systems. Numerous studies demonstrated that advanced HVAC control can significantly reduce energy consumption and greenhouse gas emissions, with an average energy savings of 13 %–28 % [2].

For BEMS, which is popular among researchers today, it is essentially a type of integrated energy system. With the global trend towards clean energy development, modern comprehensive energy systems are developing in the direction of decentralized development and integration of renewable energy sources. Decentralized development enhances the overall complexity of the energy system, and the introduction of renewable energy sources increases the volatility at the source end of the energy system; therefore, BEMS has the need for more refined management, and needs to intervene in a more powerful energy management and control method. The current part of the traditional control cannot meet the refined control requirements of the energy system, the need to use some of the more advanced control methods to achieve the transformation of the energy system. In addition, the control strategy plays an essential role in indoor environmental quality, such as thermal comfort and indoor air quality.

Currently, the control methods used in HVAC systems mainly include Bang-Bang control, proportional integral derivative (PID) control, Adaptive control, Optimal control, Model predictive control (MPC), Nonlinear control and Robust control, and soft control as Neural network, Fuzzy logic, Genetic algorithm, and other intelligent methods [3,4]. Since the 1970s, many researchers have investigated the control strategies of buildings and HVAC systems, although they have made many efforts to improve the performance of HVAC systems, reduce energy consumption, and maintain user comfort. However, effectively addressing the large-scale and nonlinear nature of HVAC systems remains a critical and urgent issue, including the system's pure lag time, high thermal inertia, response to uncertain interference factors, such as dynamic load and frequent weather changes, the adjustment of controllable variables at their set points and related discrete, nonlinear and highly constrained optimization problems [5]. Due to the problems of underdeveloped intelligent technology and insufficient computer computing power, the control mainly used simple rule control or fixed control strategies, such as on/off and PID controllers in classical control technology. Because of its simple design and low computational complexity, it has been widely applied to control HVAC systems. However, detailed physical modeling is cumbersome and complex, and the simplified RC model cannot fully capture the long-term dynamic characteristics of large buildings. The traditional control design method of PID and RC is prone to more problems, so more advanced control methods are required to achieve more significant energy savings while ensuring the user's thermal comfort level [6,7].

In recent years, the advancement of Information and Communication Technology (ICT), the decrease in hardware costs, and the improvement of data accessibility have made it possible to collect and store many high-quality building-related data, allowing researchers to develop more accurate and robust intelligent control methods. Introducing a predictive model has further improved the control efficiency of artificial intelligence-based control methods (AI). It plays a vital role in nonlinear regulation, long time delay, high thermal inertia, dynamic regulation, and high anti-interference [7].

The emerging predictive control methods can be divided into two categories, namely model predictive control and model-free predictive control, under which various control methods have also been derived. Compared to the model-based control method, the model-free method can directly obtain the control strategy without establishing the mathematical model of the building HVAC system. Model-free supervisory control mainly includes control methods using expert systems and reinforcement learning (RL). The control method relying on an expert system has a simple structure and strong stability characteristics, but its parameter setting is primarily determined by the engineer's previous engineering experience rather than the optimization algorithm. Hence, the dynamic adjustment ability of the control method utilizing an expert system is weak [8]. Reinforcement learning (RL) focuses on designing a learning agent to modify its behavior according to environmental rewards to achieve a predefined goal (for example, getting the most rewards). The action taken by the agent depends on the agent's accumulated experience rather than prior knowledge. There has been extensive research on applying RL to model-free control in the building and HVAC fields [9].

Model predictive control has been extensively studied in HVAC systems. MPC is an advanced form of advanced control strategy for process control, with the basic principle of satisfying constraints. It comprises a model, an optimizer solver, and a predictive range for generating a process's control trajectory [10]. MPC can save energy and improve control performance, accuracy, stability, and anti-interference ability. They are usually employed where control measures are stringent. The potential application of MPC in buildings is not limited to the classic HVAC system. Natural expansion can include lighting systems and various power generation and storage technology combinations, including wind and solar energy, cogeneration, batteries, ice storage, or fuel cells. The optimal control of such a complex system must consider the future demand for heating, cooling, and electricity for a particular building, local electricity production from renewable energy sources, and variable prices for electricity and other primary energy sources [11]. MPC has a lengthy and relatively mature development history compared to model-free predictive control. It has a long tradition in the process industry, such as refineries and chemical plants, and has indisputable architectural potential. However, due to the specific aspects of the building environment, its practical application will present numerous challenges [12,13].

At present, many researchers have reviewed the predictive control of HVAC systems and their related contents, which can be mainly divided into the following aspects.

(1) Using the MPC as the primary research point, these papers summarize the related contents of various predictive control in an HVAC system. Many researchers, such as Maher et al. [8], Najafabadi et al. [14], Salimi et al. [15], and Afroz et al. [16] reviewed the data-driven model, occupancy model supervision, and various new modeling techniques.
(2) Reviewing predictive control for HVAC systems under certain application scenarios. Many researchers, such as Yu et al. [3], Yuan et al. [17], Tarragona et al. [10] and Ref [9,18] reviewed the underground space subway station, swimming pool building, commercial and residential HVAC power system with active energy storage system and the most advanced ventilation system, HVAC system based on thermal comfort profile, and HVAC system smart grid relying on reinforcement learning.
(3) Taking the building energy system as the primary research object and applying the predictive control method. Many researchers, such as Zhan et al. [19], Saloux et al. [20], Arroyo et al. [21], Arteconi et al. [22] and Ref [4,11,12,23–28] analyzed the domestic occupant-centric controls (OCC) technology, hybrid ventilation buildings, sensors for building control, all MPCs applied in buildings, control strategies of various buildings, and application of reinforcement learning to build control.
(4) Some reviews focus on the comprehensive introduction of various HVAC system control modes. Many researchers, such as Herrero et al. [29], Price et al. [30] and Shi et al. [31] and Ref [5–7,32–35] studied many system control strategies, for example, zoning HVAC control, various energy-saving control strategies, artificial intelligence control technology, learning-based comfort, reinforcement learning based, and other types of HVAC control under the background of zero energy consumption building are reviewed, respectively.

Evaluation of the above reviews: (1) Most of the reviews are a systematic review of HVAC in specific applications, i.e., a single application, while the predictive control of the building as a whole focus more on the study of the overall energy consumption of the building and less on the HVAC system alone. The above content systematically shows the characteristics and advantages of the predictive control method of the HVAC system, and reflects the mainstream research trends and prospects. However, it rarely analyzes the respective characteristics of the two predictive control methods, the model-based and the model-free methods, in different HVAC system (cooling system, heating system, and composite system) application scenarios. (2) Most current reviews on HVAC systems do not emphasize predictive control methods to introduce as comprehensively as possible various energy-saving control strategies. Besides, the content of current reviews only focuses on the predictive control method and does not elaborate on applying various predictive control methods to different types of HVAC systems. They also fail to introduce the model-free method and compare to the model predictive control.

In conclusion, the above reviews fail to systematically classify the application of model-free predictive control and model predictive control in various types of HVAC systems to highlight their respective characteristics and application circumstances. This study provides a systematic review of the research conducted over the past 12 years, elucidates the basic concepts of the application of two kinds of predictive control methods in an HVAC system, divides various system forms, summarizes the main characteristics of each predictive control method under different system forms, and refines the combination of system form and control mode. Finally, a comparative analysis highlights the benefits and drawbacks of each predictive control and the application instances. It provides researchers in related professional fields with guidance for selecting appropriate predictive control methods for future HVAC system application scenarios.

This paper's chapters are organized as follows. Section 2 provides a brief overview of the distribution of papers under each control method. Section 3 is dedicated to explaining the basic concepts and principles of the two control methods. Section 4 delves into the practical applications of these control methods in various HVAC systems, demonstrating the controllers' effectiveness through detailed analyses of different system types. Section 5 analyzes and discusses the characteristics of two control strategies and their respective future development directions. Finally, the conclusion is drawn in Section 6.

2. Methodology

2.1. Methodology for paper review

The review covers English articles from January 1, 2011, to April 30, 2024. To clearly show the characteristics and development trends of model-free predictive control and model-based predictive control, this study focuses on the last twelve years. This period saw the rise of methods like reinforcement learning, which spurred new developments in model-free predictive control. The review procedure follows PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), including identification, screening, eligibility check, and inclusion [36], shown as follows.

1. Articles in the fields of energy and engineering are mainly published by Elsevier, Springer, Taylor & Francis, SAGE, Wiley, and MDPI. To focus on SCI papers, these six publishers were chosen as the search engines. "Predictive Control of HVAC" was used as the keyword.
2. Research records were screened by titles, keywords, and abstracts. Those highly related to "MPC of HVAC" and "Model-free predictive control of HVAC" were kept.
3. The screened records were further assessed for eligibility. To exclude paper with relatively low content quality or those not aligning with the research topic. For example, papers outside the classification scope of HVAC systems or with weak HVAC system content.
4. Eligible articles were further analyzed for content quality using databases like Scopus or Web of Science. This phase excluded papers outside the scope of HVAC system categorization (see Fig. 1).

2.2. *Classification of predictive control mode*

Based on the screened prediction control papers, the HVAC systems control methods are classified according to their primary application purposes as follows: Cooling system: Conventional household and small cooling system, Large central air conditioning system, New refrigeration system, or other methods. Heating system: Conventional heating system, Heating terminal related control, New heating system and new control mode, and other approaches. At the same time, Integrated HVAC systems are subdivided into the following types according to the application: Conventional integrated HVAC system, Building Energy Management Systems, Composite renewable energy systems, Regional energy and centralized systems, Ventilation is dominant in the entire HVAC system, Special space (personal space, vehicle). As shown in Fig. 2 describes the HVAC system forms according to three main categories: cooling system, heating system, and integrated system, where the MPC literature is rich, so in order to analyze the characteristics of the

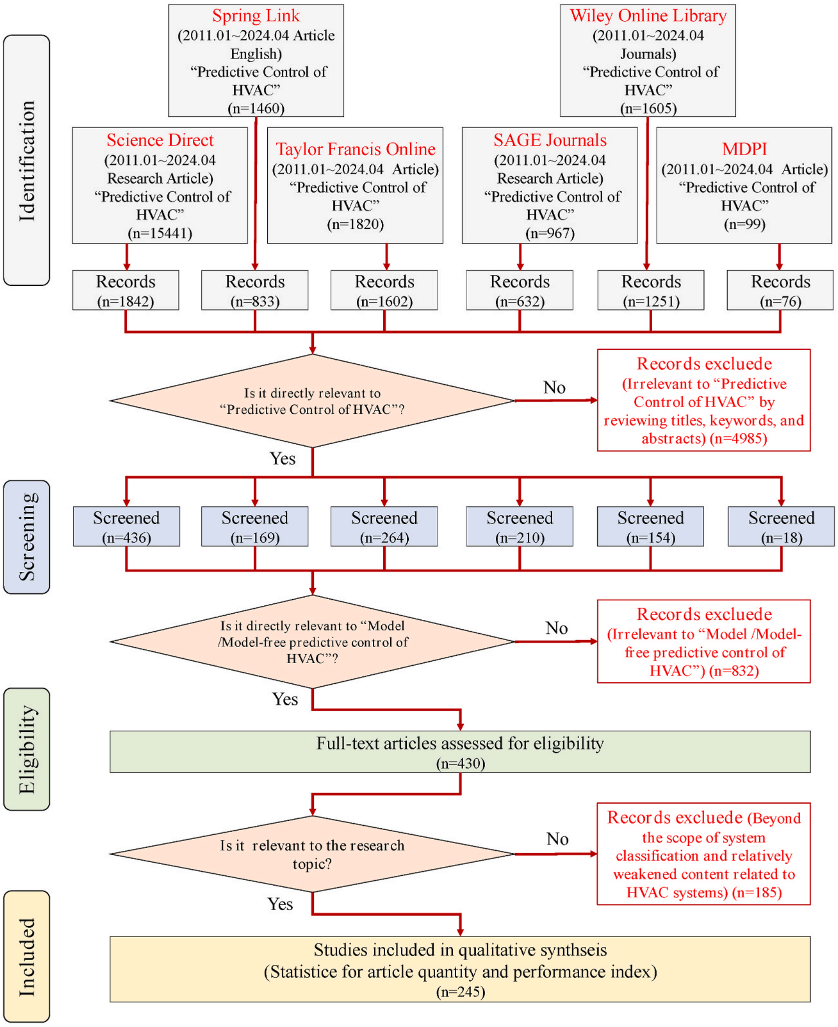


Fig. 1. Methodology of predictive control for HVAC systems review.

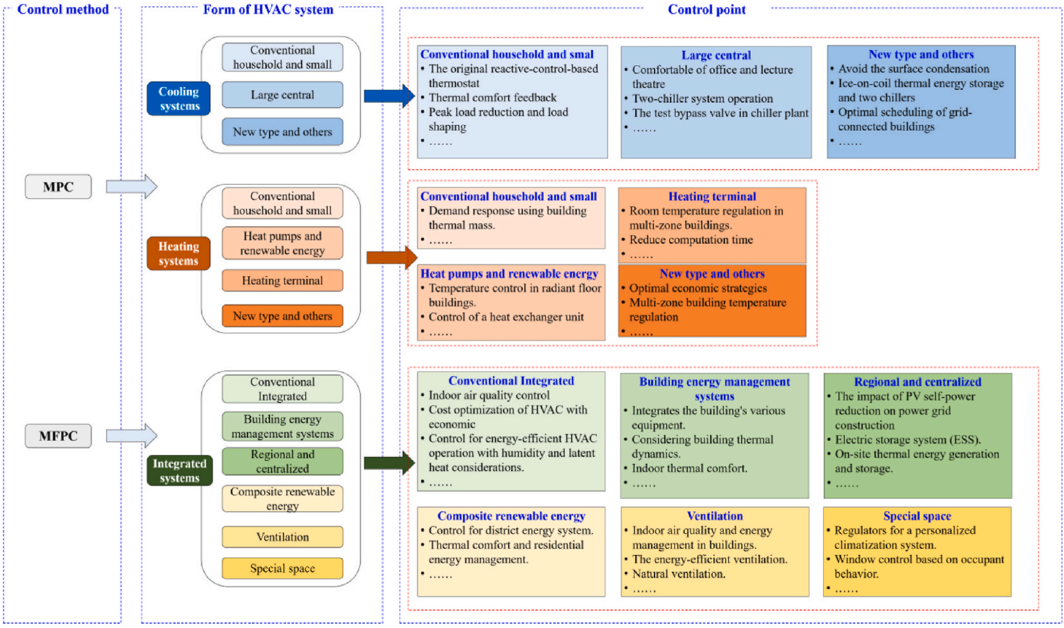


Fig. 2. Classification of predictive control in HVAC system.

different systems corresponding to the control mode, they are categorized in more detail. After completing the classification, the application of model predictive control and model-free predictive control in different systems will be presented, describing the control points and control methods of various systems, and finally summarizing their characteristics and outlook, taking the form of HVAC systems as a starting point.

Typically, Reinforcement Learning (RL) is the most common method for model-free predictive control. Model-free control primarily consists of reinforcement learning and expert systems. Expert systems function as a classification tree that necessitates a massive database and depends on human experience. Due to these limitations, current research on expert systems is relatively limited, while exploration of the model-free approach centers mainly on reinforcement learning. In order to obtain higher accuracy, many researchers [9,17,37–69]also improve the reinforcement learning method for the applicable system form or combine it with other algorithms, such as Deep Q-network (DQN), Deep Deterministic Policy Gradient (DDPG), Z-learning, and others. The Extremum Seeking Control (ESC), Distributed cooperative control-based online air balancing (DCC-AB), Adaptive hybrid metaheuristic algorithm, Automated Fine-Tuning CAO (AFT-CAO), and others are additional model-free control methods applied to HVAC systems (Fig. 3). Fig. 4 illustrates the main trends of model-free control research from January 2011 to April 2024. A total of about 50 papers are identified in this review. The preliminary conclusion is that the research and increasing model-free control in HVAC systems started in 2017. The number of articles published has risen sharply, especially since 2020, and peaked in 2020 and 2021. Reinforcement Learning

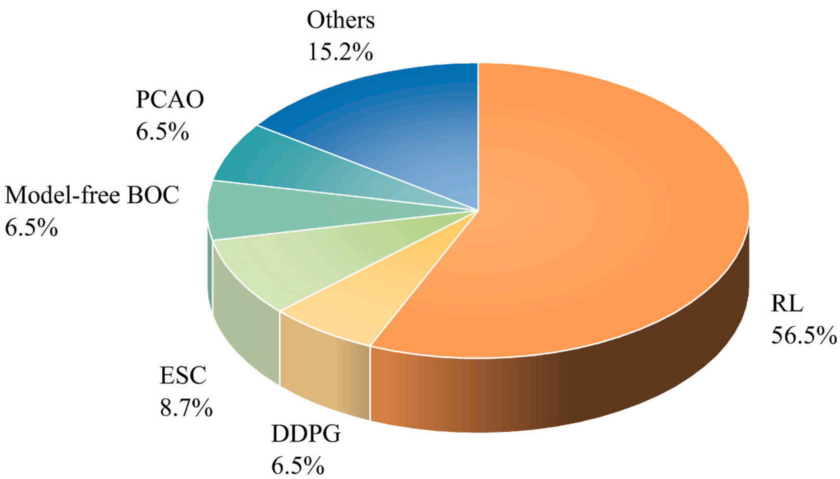


Fig. 3. The proportion of different model-free control methods in HVAC systems.

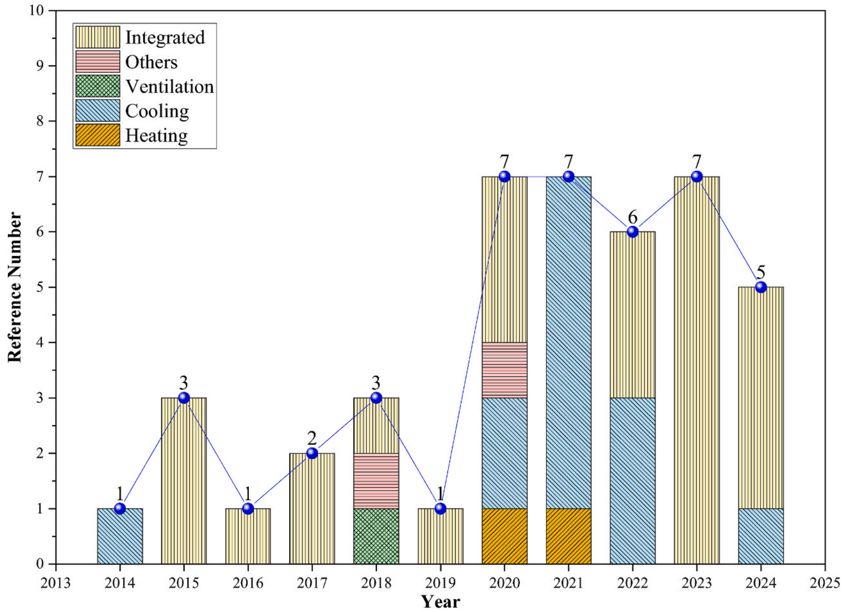


Fig. 4. Distribution of references in model-free predictive control.

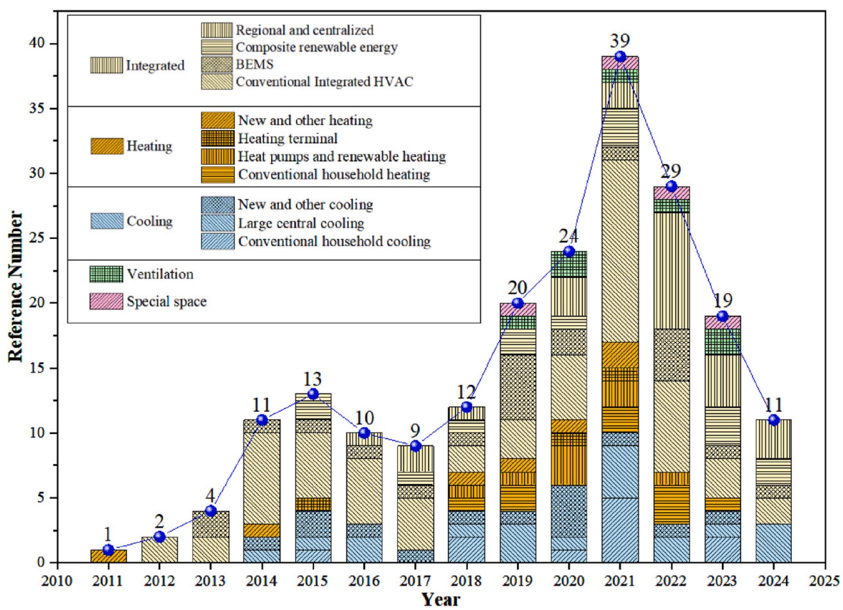


Fig. 5. Distribution of references in predictive model control.

accounted for 56.5 % of the total number of model-free control studies, followed by Extreme Seeking Control (8.7 %) and Deterministic Policy Gradient (6.5 %), model-free BOC methodology (6.5 %), and Parameterized Cognitive Adaptive Optimization (PCAO) (6.5 %). In contrast, the number of other studies with model-free controls is relatively low and proportional.

The application of MPC is intricately linked with the form of the HVAC system [13]. Thus, the relationship between the form of the system and the implementation of MPC is crucial. The forms and control points of various HVAC systems result in differing system models, constraints, and objective functions, as illustrated in the accompanying table in the attached materials.

Fig. 5 depicts the main trends of model control research from January 2011 to April 2024, with about 200 papers identified in this review. It indicates that most model control research focuses on the operation control of traditional HVAC systems, accounting for 44.9 % of the field. Second is the integrated MPC system for building energy consumption regulation, such as the Energy Management System, accounting for 15.4 %, followed by the most popular combination of renewable energy systems and HVAC systems in recent years, accounting for 11.1 %. From the perspective of the annual number trend of the published papers, the number of papers on applying MPC in HVAC systems has increased gradually since 2014 and will continue to rise until 2021. Since the annual number of published documents cannot be counted in 2024, it can be inferred that the number of published documents will increase further.

3. Description of predictive control in HVAC systems

3.1. Description of model predictive control

3.1.1. Predictive control method (Modeling)

The application of MPC in HVAC systems has been extensively studied. The primary characteristics of this control mode are.

(1) MPC can achieve optimal control effects if it fully understands the system.
(2) MPC is excellent for achieving optimal control in systems with high-quality historical data.
(3) Implementing MPC requires a highly accurate system or device model.
(4) MPC generally supports MIMO (multiple input multiple output) systems, which helps find and build system parameters related to input and output.
(5) MPC requires better processors and larger memory due to the need for online optimization and storage of many variables.

MPC control scheme can minimize the cost and solve the uncertainty caused by interference factors within the defined range. The general MPC can be expressed by Eq. (1) through (5):

$$\min \sum_{k=0}^{N_p-1} a(x(k), u(k), r(k)) \textit{ Objective Function} \tag{1}$$

Subjected to,

$$x_0 = x \textit{ Initial State} \tag{2}$$

$$x(k+1) = f(k)x(k) + g(k)u(k) + h(k)r(k) \textit{ Update State Variable} \tag{3}$$

$$a(k) = O(x(k), u(k), r(k), c(k)) \textit{ Output Variables} \tag{4}$$

$$(x(k), u(k), r(k)) \leq 0 \textit{ Constraints} \tag{5}$$

where k is the sampling time, N_P is the prediction range, $x (k)$ is the system state, $u (k)$ is the control input, $r (k)$ is the vector of the system interference factor, and $a (k)$ is the system output on the system. State vectors, control inputs, and disturbances are constrained. In each time step, the MPC scheme determines the control by solving an open-loop optimization problem for the defined prediction and control range, as depicted in Fig. 6.

Proper modeling of the system and components is the basis for controlling the dynamic process in an HVAC system using MPC. The HVAC modeling process involves high thermal inertia, real lag time, uncertain interference factors, and other physical characteristics, resulting in a dynamic, nonlinear, high-order system model. When developing an HVAC system model, it is crucial to determine the model sequence and parameter identification. This ensures the control algorithm can handle interference, constraints, uncertainty, time-varying dynamics, slow processes, and a wide range of operating conditions. HVAC system models can be categorized into three types: white box, black box, and grey box models. To help readers locate the model type used in the text quickly, this paper categorizes the reference documents corresponding to the models as white box [70–104], black box [83,105–123], and grey box [87,124–159].

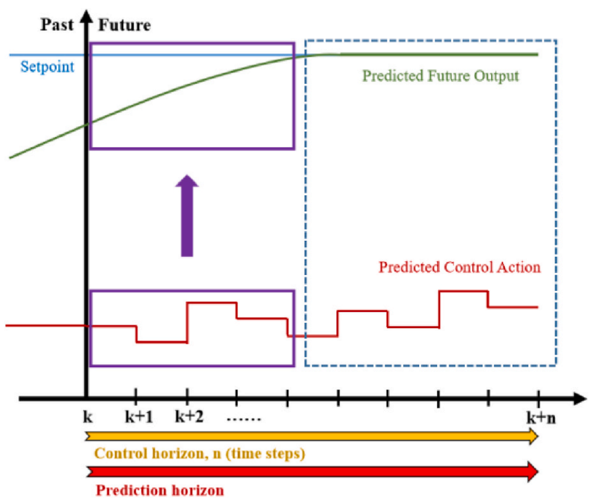


Fig. 6. Schematic diagram of MPC principle.

The reader is referred to the descriptions in the relevant literature for more specific information.

1 White box model (Physics-based model)

The white box model describes the HVAC system's physical characteristics and derives equations based on the physical process, including momentum, energy, heat, and mass balance [13]. This model is typically used during the design phase to predict and analyze HVAC system performance through simulation. Physical models for various HVAC components include the chiller, cooling tower, Air Handling Unit (AHU), mixing box, partition box, heating/cooling coil, humidifier, fan, pump, pipe, sensor, damper, and valve. Despite software advancements, the modeling process remains manual and burdensome. For complex systems, the generated model often includes hundreds or even thousands of parameters. Numerous potential sources of model inaccuracy make the parameter-setting process highly challenging. Conversely, with accurate parameters, the white box model yields highly reliable results due to its adherence to the system's physical properties. Furthermore, a detailed HVAC model can yield more precise control effects.

2 Black box model (Data-driven model)

The black box model, commonly used in HVAC system modeling, relies on system performance data collected from real-world practice [160]. This approach involves developing input and output variables through mathematical techniques like statistical regression and artificial neural networks [13]. Data-driven methods in HVAC system modeling have been extensively explored in various studies. This paradigm is suitable for systems with sufficient training data. Common data-driven models in HVAC systems include state space, geometric, case-based reasoning, stochastic, instantaneous, frequency domain, fuzzy logic, and statistical models. Unlike other approaches, the black box model learns system dynamics solely from measured data, without relying on physical assumptions. The primary advantage of black box methods is their ability to reduce development costs, as they do not require knowledge of the underlying physics and can accept any signal as an input or output. However, the black box model requires more training data than the grey box model. Moreover, the absence of explicit physical processes introduces randomness and unreliability, leading to inaccurate predictions. Furthermore, any proposed model must be verified through practical implementation in a real system.

3 Grey box model (Hybrid model)

The grey box model incorporates both knowledge of the system's physical processes and input-output data, leveraging the advantages of both approaches. While the physical model allows for generalization, the black box model offers higher accuracy. However, certain physical processes in HVAC systems may not be precisely defined by thermodynamic equations and may lack sufficient training data. In such cases, the grey box or hybrid model proves to be effective [160]. This technique is particularly advantageous for control applications, especially when the model is represented in a suitable form such as transfer function or state space. The inclusion of hard-coded model equations allows the grey box model to maintain reliability beyond the calibration range compared to the black box model. Moreover, the equations in the grey box model can be readily adapted to meet the requirements of the MPC solver. Additionally, the grey box model can be easily transferred to similar systems, facilitating its use in various contexts. Unlike many data-driven models, grey box models typically perform better with larger datasets. However, careful attention must be paid to selecting training data in grey box modeling.

3.1.2. *Optimizing functions and goals*

The following types of optimization function objectives are usually applied to HVAC system models: 1. Economic objectives (power

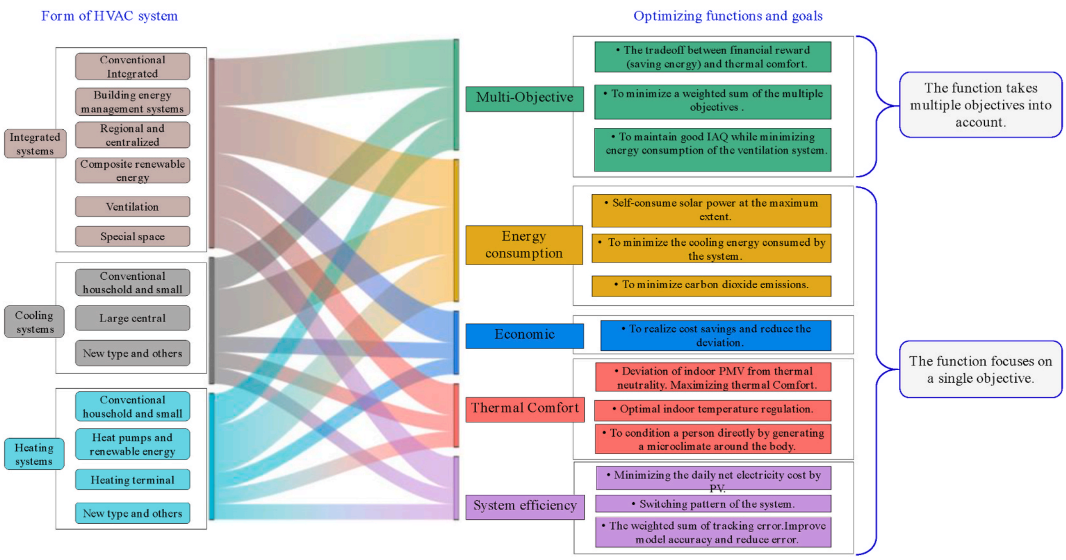


Fig. 7. Summary of optimizing functions and goals in MPC for HVAC.

consumption and energy cost); 2. thermal comfort objectives (PPD and PMV); 3. control target (room temperature tracking error, temperature or flow set point, and others.). In addition, based on system optimization technology, it can also be divided into single-objective and multi-objective optimization, with thermal comfort and economic objectives generally requiring multi-objective optimization. The scalar objective of the general multi-objective problem can be described as follows:

$$Y(N_L, N_M, N_U) = \sum_{k=N_L}^{N_u} a(k)[g(t+k|t) - h(t+k)]^2 + \sum_{k=1}^{N_u} \varphi(k)[\Delta u(t+k-1)]^2 \tag{6}$$

where g is the output prediction, h is the reference signal, and the control work is ΔU, N_L and N_M are the minimum and maximum prediction ranges, and Nu is the control range; t is the time step.

The HVAC system maximizes residents' thermal comfort and indoor environmental quality (IEQ). Additionally, minimizing energy use in buildings does not necessarily minimize related operating costs. For example, when energy prices fluctuate significantly, it can be beneficial to transfer loads and store heat energy during cheaper periods for later use when costs are higher. Heat energy can be stored in buffer heat storage tanks, geothermal fields, or within the building's thermal inertia. To minimize carbon emissions, users can set this goal to reduce the carbon footprint of HVAC systems. Unlike economic objectives, the cost factor is replaced by the emission factor of the energy used. When using only conventional fossil energy, minimizing greenhouse gases and energy consumption are equivalent (Fig. 7).

3.1.3. Constraints

MPC can handle multiple constraints on state, input, or output variables. Constraints are generally divided into hard and soft constraints. The classification of constraints in different system forms is summarized in Appendix.

Hard constraint: there is no compromise, i.e., it is mandatory. An example of this constraint is the state update equation given by the equality constraint, which must be satisfied every time in the entire prediction range.

$$\underline{u} \leq u_k \leq \overline{u} \tag{7}$$

Soft constraint: it provides a certain degree of flexibility for the operation restriction, and the penalty generated in the objective function can be partially violated. Typically, variables are relaxed, added to the objective function, and punished.

$$\underline{y}_k - s_k \leq y_k \leq \overline{y}_k + s_k \tag{8}$$

Another type of constraint includes time-varying constraints, varying with time compared to constant constraints.

$$\Delta u_k = u_k - u_{k-1} \tag{9}$$

$$\underline{\Delta u} \leq \Delta u_k \leq \overline{\Delta u} \tag{10}$$

3.1.4. Prediction horizons and sampling time

The prediction horizon of MPC refers to the future control intervals the controller predicts when optimizing control variables, significantly influencing performance. The control horizon refers to the control variables optimized at the control input, always limited between 1 and the prediction horizon, and their values are less than the prediction horizon. Selecting the horizon length is essential for practical MPC implementation. The added value of multiple free control actions is limited because the prediction model's accuracy

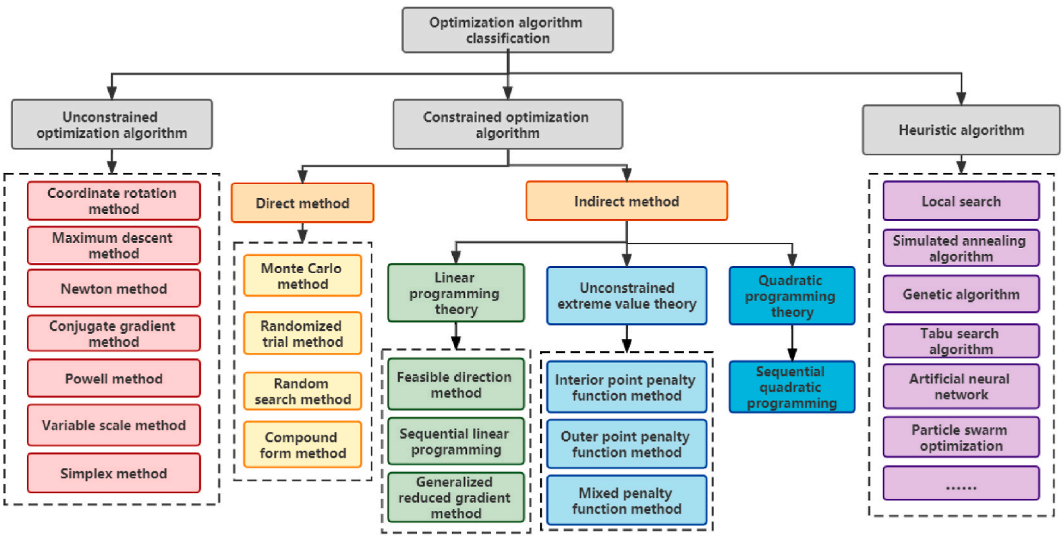


Fig. 8. Classification of optimization methods for MPC.

decreases as the horizon reduces. The time step, control domain, and prediction domain selection are affected by the time constant and the dynamic behavior of the controlled process. Compared to other industrial processes, the building heat and mass transfer process requires increased control time step [8,12].

Due to the faster dynamic response of HVAC systems, they require a shorter control time step. On the one hand, if a small prediction range is adopted, the controller's calculation is reduced. They can affect its reliability by ignoring the influence of a part of the system dynamics. If the prediction horizon is too large compared to the control time step, it increases calculation time without significantly improving performance. Additionally, because the optimal solution is based on a fixed and uncertain disturbance prediction, too large a prediction horizon affects reliability, thus impacting the solution's optimality [13].

3.1.5. Optimization methods

Appropriate optimization algorithm plays a vital role in implementing HVAC system with MPC. MPC method contains the link of rolling optimization. Generally, the optimization problem of the HVAC system must be solved using mixed integer linear programming (MILP), quadratic programming (SQP), and other related equations. Recently, many optimization algorithms have emerged in optimization problems. In order to make it easier for researchers to explore the types of optimization algorithms used in various HVAC systems, they are categorized into three groups in Fig. 8 in this paper.

1) Unconstrained optimization algorithm. The unconstrained optimization problem is the most fundamental of all optimization problems. It does not limit the range of independent variables, so it is unnecessary to consider the feasibility of independent variables. It usually appears as a background or comparison object in the research of HVAC systems in recent years.
2) Constrained optimization algorithm. The optimization algorithms for constrained optimization problems are generally developed using mature unconstrained optimization algorithms, linear programming, and quadratic programming optimization algorithms. This algorithmic component is essential to MPC. Therefore, one of the above algorithms is usually used in the research of designing the MPC method.
3) Heuristic algorithm. As the research highlights optimization algorithms in the future, many HVAC system research contents of composite optimization algorithms have also appeared. The intelligent algorithm can obtain a better computational optimization effect when the system's complexity is high, and the nonlinear characteristics are apparent. Hence, applying hybrid intelligent algorithms has gradually emerged in various HVAC systems, and their application will continue to expand.

3.2. Description of model-free predictive control

In some cases, model-free predictive control can be implemented without an HVAC system operation database or reliable data for model learning. The typical characteristics of model-free predictive control for HVAC systems are.

(1) It can achieve predictive control without large, high-quality historical data.
(2) It eliminates the need for complex model building, saving time, energy, and manual calibration effort.
(3) It reduces the workload of engineers for supervision and manual adjustments.
(4) Previous analysis shows that integrating other methods can improve the RL algorithm for various system forms. For example, using expert knowledge to guide the dynamic action space can improve the RL-based controller's robustness, stability, and learning speed.
(5) For complex systems, it can be combined with historical data for rapid calculation, reducing time and cost.

The model-free method uses an agent to perform trial and error in a specific environment, collecting control response data. Then, techniques are employed to achieve optimal control (Fig. 9). The trial-and-error approach uses an agent to interact with the site in an environment without historical data to obtain a reward. This process achieves optimal control through maximum expected accumulated rewards, without needing a control model.

Based on this concept, HVAC systems have many model-free control methods, with Reinforcement Learning and trial and error being the most widely used. The trial-and-error method must be coordinated with reinforcement learning. Through continuous testing, agents can learn the optimal control strategy and maximize future rewards. In addition, there are some other model-free control methods, for example, Extreme Seeking Control (ESC), Distributed Cooperative Control based Online Air Balancing (DCC-AB) [46], An online learning algorithm (Adaptive hybrid metric algorithm) [53], Automated Fine-Tuning CAO (AFT-CAO) [49], and others

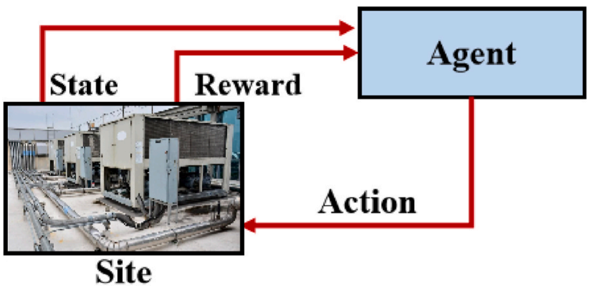


Fig. 9. Schematic of the trial-and-error control method.

Table 1
Common model-free control methods.

Model-free control methods	Total control logic	Characteristic
Reinforcement learning (RL)	The trial-and-error control method should be coordinated with reinforcement learning. The agent should learn the optimal control strategy through continuous tests and obtain the maximum value of future reward from the environment to achieve the effect of predictive control	The derived methods are rich and varied and apply to most types of systems, which can give full play to the advantages of model-free trial and error control
The Extremum Seeking Control (ESC)	ESC can be considered a dynamic version of gradient search, in which the online estimation of gradient information is realized by using pairs of dither-demodulation signals and proper filtering.	The optimum search process is made nearly invariant to process variation, external disturbance, and measurement noise of other frequencies. These merits make ESC a more robust and faster converging scheme for real-time optimization
Distributed cooperative control-based online air balancing (DCC-AB)	It is mainly used in the ventilation duct system. Inspired by the application of distributed cooperative control (DCC) in network communication, DCC is introduced into the HVAC system to solve the air balance problem.	An online method that eliminates the need for centralized supervision and control and does not require prior knowledge of system topology and pipeline parameters.
An online learning algorithm (adaptive hybrid metaheuristic algorithm	An adaptive hybrid meta-heuristic that uses real-time data stores it in an automated system, then finds the best-set point and controls the set point accordingly. A control policy uses an intelligent selection of daily setting points as the basis for its control.	It can perform synchronous control of various systems, with high control precision and the overall increase of system energy saving rate.
Automated Fine-Tuning CAO (AFT-CAO)	A model-free online control optimization scheme, parametric cognitive adaptive optimization, is introduced for designing a model-free "plug-and-play" Building Optimization and Control (BOC) system.	Automatic tuning of the system, initial deployment of the controller, and continuous application of the trimmer can be provided without human intervention or simulation models.

(Table 1).

Reinforcement learning, the most popular model-free method, is based on Markov Decision Process (MDP), providing a formal description for sequential decision problems. The process involves five elements, which can be expressed as a state space S, an action space A, transition probabilities $P : S \times A \times S'$, and a reward function $R : S \times A$. Then, a policy π maps state to actions as π: $S \rightarrow A$ and the value function $V^{\pi}(s)$ is the expected reward when the agent starts in state s and follows policy π:

$$V^{\pi}(s) = \sum_{a} \pi(s,a) \sum_{s'} P^{a}_{ss'} \left[R^{a}_{ss'} + \gamma V^{\pi}(s) \right] \tag{11}$$

where $R^{a}_{ss'}$ sometimes denoted by $r(s,a)$ is the reward for taking action $a = \pi(s_k)$ and transitioning from the current state s to the next state s', and $\gamma \in [0,1]$ is a discount factor for future rewards. Agents using $\gamma=1$ will place more weight on long-term rewards, while for $\gamma=0$ greater value is assigned to those states that cause high immediate rewards. In general model-free approaches, the agent learns values associated with each *(s, a)* pair without explicitly computing transition probabilities or expected rewards.

Q- Learning is most commonly used in model-free reinforcement learning. In Q-learning, the Q value is updated by the Bellman equation:

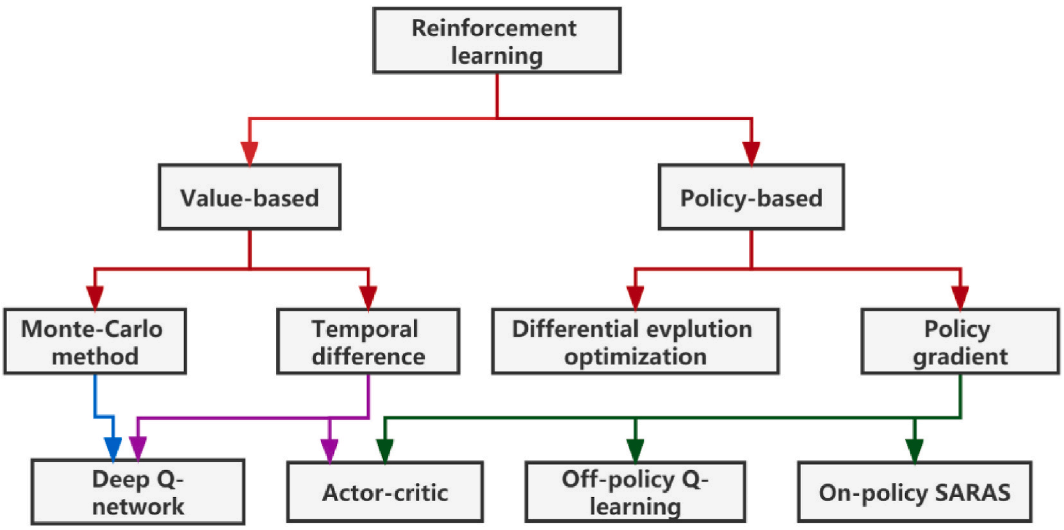


Fig. 10. Reinforcement learning techniques employed in model-free control.

$$Q(s,a) \leftarrow (1-\alpha) * Q(s,a) + \alpha * (r(s,a) + \gamma * \max_{a'} Q(s', a')) \tag{12}$$

Learning rate α indicates sensitivity to new experience, and discount factor γ determines the weight between direct and future rewards. During the training process, choose random actions with decreasing probability. In this technique, called electronic greed, the experience of the environment is increased over time, and the performance is improved over time.

Reinforcement learning methods are divided into value-based and policy-based methods. Value-based methods include Monte Carlo (MC) and Temporal Difference (TD).

The MC method process is the trial-and-error control approach described above. The TD method uses bootstrapping to learn after sampling when a complete process cannot be obtained. The Actor-Critic method is used when agents learn new skills. This method is further divided into Advantage Actor-Critic (A2C) and Asynchronous Advantage Actor-Critic (A3C). Policy-based methods include Differential Evolution Optimization (DEO) and Policy Gradient. DEO is used for situations where the control function is non-differentiable, controlling the strategy gradient. The policy gradient method can execute the "state–action–reward–state–action" strategy through agents with learning abilities. If the agent does not learn skills, it performs out-of-policy Q-learning after receiving information.

Many improved methods have been derived from basic reinforcement learning (Fig. 10). Several common derivative reinforcement learning methods include:

Deep Q-network (DQN): Tabular Q-learning is unsuitable for large random state spaces due to the "Curse of Dimensionality" so DQN was proposed.

Deep Deterministic Policy Gradient (DDPG) is a hybrid of policy-based and value-based algorithms, following the actor-critic architecture for continuous action spaces.

Z-learning in LS-MDP: Linear Solvable Markov Decision Process (LS-MDP) is a variant of traditional MDP. The simplified LS-MDP problem suits the z-learning method, improving Q-learning. Z-learning updates the value function in the current state, relying on samples that provide state connection information rather than averaging all possible future states as in LS-MDP. Z-learning samples are passively collected from the discretized underlying distribution. The specific divergence form of the optimal strategy is then updated to accelerate calculation.

4. Application of predictive control in HVAC systems

4.1. Application of MPC in HVAC systems

This section will discuss the implementation of MPC within the HVAC field. The discussion will expand to cover the cooling system, heating system, and integrated system in turn. This paper outlines the research contents and features of MPC in various types of systems, including the objective function, constraints, optimization methods and other contents.

4.1.1. Cooling systems

(1) Conventional household and small cooling system

In a cooling system, applying model predictive control is on-off primarily control of the household air-conditioning system or its use to related controllers. The control purpose is to ensure the quality of the indoor environment and the regulation ability provided by the HVAC system can be utilized to the maximum extent. At the same time, demand response can be employed to reduce the power grid load and system energy consumption. Wang et al. [124] proposed a hierarchical optimal control strategy consisting of a regulation bidding controller and a power use following controller. They optimized the power use baseline and regulation capacity and controlled HVAC systems to provide qualified frequency regulation service. Kang et al. [107] developed an artificial neural network (ANN) based

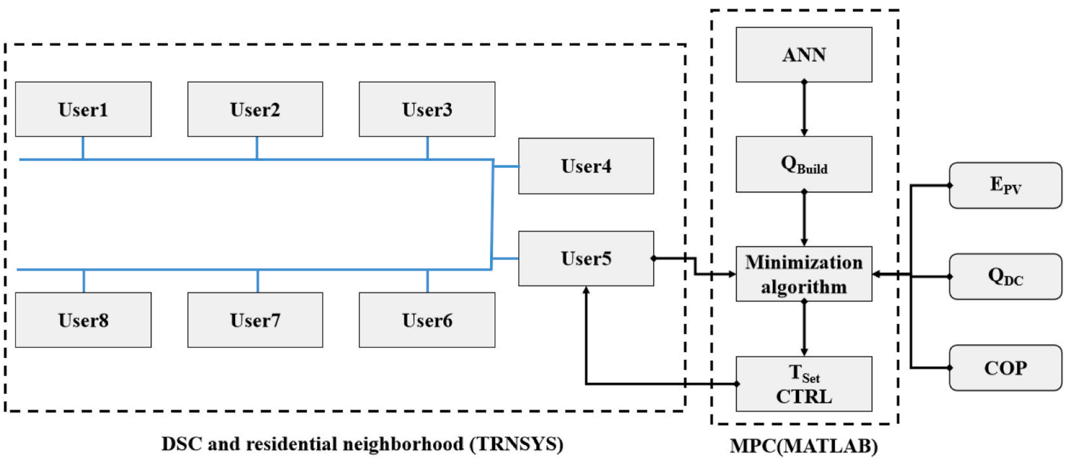


Fig. 11. Block diagram of the simulation environment.

real-time predictive control and optimization algorithm for a chiller-based cooling system (Fig. 11).

Christopher Winstead et al. [161] presented a computationally inexpensive, dynamic, and retrofit-deployable control strategy to effect peak load reduction and load shaping. Pang et al. [71] verified the correct operation of an open-source MPC tool chain developed for radiant slab systems and demonstrated its efficacy in a test facility. Feng et al. [162] developed a simplified dynamic model of the radiant slab system for implementation in real-time MPC. The parameters are continuously tuned through recursive estimation and update approaches, making the MPC insensitive to prediction errors and achieving the optimal superheat response.

For domestic or small-scale cooling systems, research trends have focused on exploring improved MPC techniques, incorporating real-time data, considering thermal comfort, optimizing energy efficiency, and investigating new control strategies for specific cooling system components. Due to the shortcomings of linear MPC, researchers (Yang et al. [105], Wang et al. [70], Tesfay et al. [126] and Ref [163–165]) from the establishment of nonlinear building models, research and development of time-varying MPC, adaptive MPC and other methods to improve the application of MPC in cooling systems, whether it is the control of the evaporator or condenser valves or the system as a whole start-stop control, the matching problem of the new MPC method with the control point will be a major problem for future research (Fig. 12).

Addressing the challenge of regulating multiple rooms within a single refrigeration system, researchers (Pandey et al. [106], Coccia et al. [108], Chen et al. [125], and Ref [75,163–168]) investigated the application of MPC in residential split air conditioners, variable load air-water heat pumps, ceiling radiant cooling systems, variable capacity cooling (VCC) systems, and other cooling systems, The above cooling systems undoubtedly require higher degrees of control than traditional domestic air-conditioning systems, highlighting the advantages of using the MPC methodology, and its application in the above cooling systems to simplify the dynamic modeling and study of the MPC tool will be a future trend of research.

(2) Large central air conditioning system

The central air conditioning system with a large application area has a more complex system form than a small or household refrigeration system. Hence, the adopted MPC methods are primarily presented in a composite way, with a combination of distributed or centralized MPC. Asad et al. [169] proposed a distributed RtOpt scheme for typical centralized HVAC systems. The system was divided into three sub-systems: the cooling distribution, the cooling generation, and the heat rejection sub-systems. Optimal control and energy consumption of the system are achieved by distributed control (Fig. 13).

Yang et al. [170] proposed an approximate MPC that mimics the dynamic behaviors of MPC using the recurrent neural network with a structure of a nonlinear autoregressive network with exogenous inputs. Terzi et al. [109] suggested a learning-based model of predictive control (MPC) for the cooling system of a large business and commercial center. Nasruddin et al. [110] examined a university building with radiant cooling and VAV systems. A multi-objective optimization method combining neural networks has successfully defined optimal building operations. Zhuang et al. [127] introduced a new modeling method for a medium-sized commercial building. An MPC strategy with a feed-forward control structure is developed to increase the supply of chilled water temperature. The step response and PSD methods are used respectively for system modeling under these two categories of variables. Lara et al. [128] offered the application of an offset-free model predictive controller (OF-MPC) for an energy-efficient operation of the central chiller plant. Lara et al. [73] introduced two modeling approaches of the return water temperature of a central chiller plant using data from the actual operation of a building, weather disturbances, and the temperature of a reference thermal zone. They integrated the building's actual measurements with a room simulator model. Borja-Conde et al. [171] and Chen et al. [172] proposed predictive

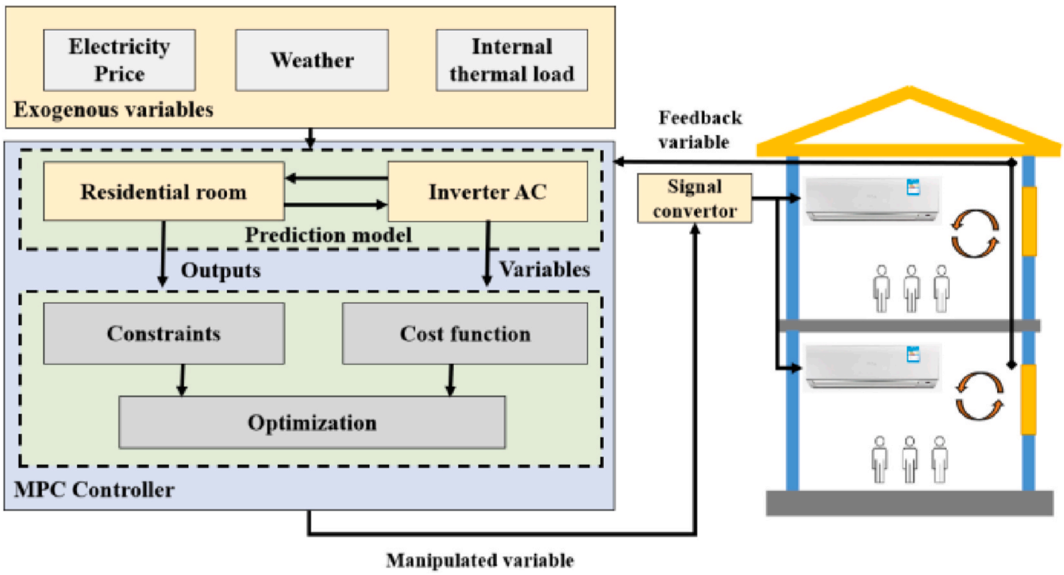


Fig. 12. ML-based MPC with an instantaneous linearization (IL) scheme.

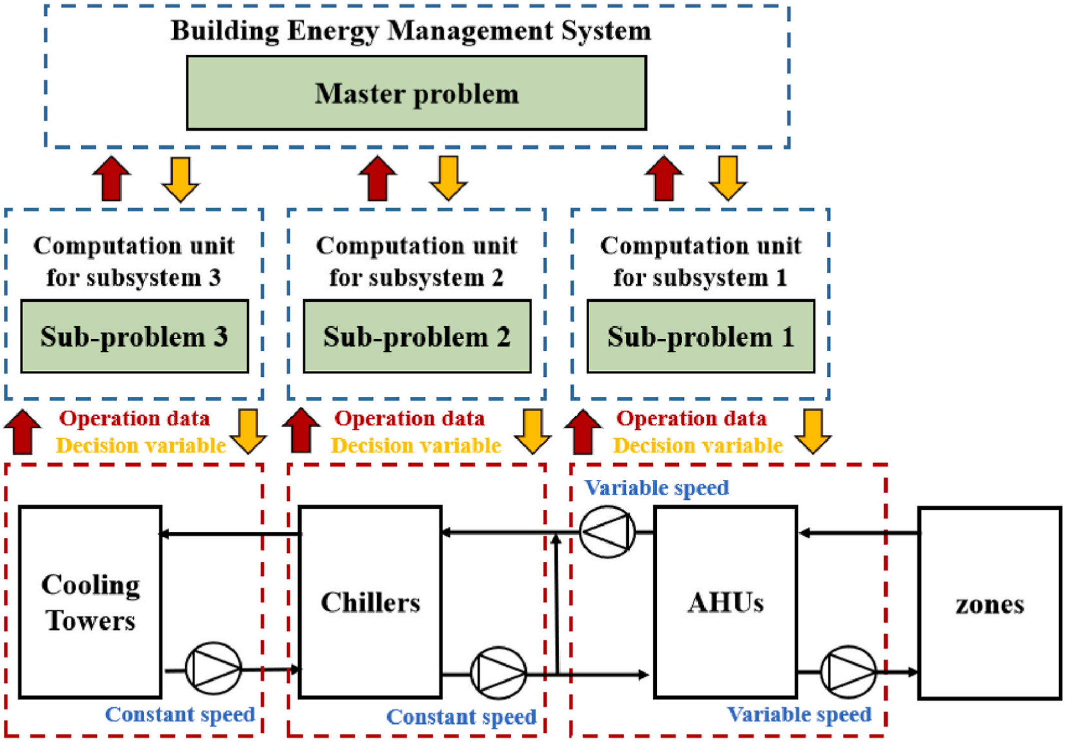


Fig. 13. Structure of decentralized real-time optimal control of HVAC system.

control approach to manage the operation of chiller units. Cho, Seongkwon et al. [173] proposes a transfer learning (TL)-based control-oriented model development framework and applied it to existing buildings.

In the study of control strategies for chilled water systems, predictive control has shown significant characteristics and advantages. Zhu et al. [174]accurately identified the refrigerant loop dynamics using an LPV model structure and ensured the stability of chilled water temperature through model predictive control. Zhang et al. [175]proposed an MIQP optimal control strategy using a refrigeration system model described by the thermal balance process, optimizing system performance. Yuan et al. [176]developed a new MPC method based on a data-calibrated distribution model, effectively adjusting valves and pumps to eliminate hydraulic imbalance and significantly reduce energy consumption. Park et al. [177]combined AI retraining technology to predict air handler supply temperatures, achieving energy-efficient control of data center cooling systems. Kang et al. [178]developed real-time predictive control and optimization algorithms based on ANN, significantly improving cooling efficiency in actual buildings. Additionally, the work of Zhao et al. [179]and Deng et al. [180]demonstrated the application value of simplified models and integrated learning in control strategies, further optimizing the energy efficiency and operational stability of chilled water systems.

The above studies provide valuable insights into solving complex optimization problems in centralized or large HVAC cooling systems. Decomposing the centralized air conditioning system into multiple subsystems and introducing distributed methods can well solve the energy distribution problem of the system; introducing a variety of new modeling methods such as neural networks enriches the MPC strategy. In addition, machine learning techniques can be integrated to improve control and optimization, and innovative modeling methods such as neural networks can be developed to improve the performance and energy efficiency of large central air conditioning systems.

(3) New refrigeration system and other refrigeration methods

In addition to the traditional refrigeration system, some refrigeration-capable systems or equipment can be used on special occasions, for example, Chiller-air handling units, roof air conditioning units (RTUs), packaged air conditioners, and others. Wang et al. [74] built a complete Chiller-air handling units (Chiller-AHU) model and proposed a nonlinear MPC strategy for the system. Lee et al. [111] validated the feasibility of an MPC strategy for a commercial building in response to occupancy variations and time-variant electricity prices. Kim et al. [181] introduced an MPC algorithm that can be used for real applications and evaluated the energy savings potential of optimally supervising multiple RTU economizer operations. Pertzborn [130] employed the MPC to generate an optimal schedule for operating a cooling plant consisting of ice-on-coil thermal energy storage and two chillers with different maximum capacities.

Future research on novel cooling systems will further advance the development of nonlinear MPC strategies. Many researches (Joe et al. [129], Woo et al. [182]) have provided new ideas for MPC applications by cutting from alternative perspectives, such as proposing virtual heat storage by combining the building's own thermal inertia, preventing condensation on the building surface by MPC, and etc. These research contents show the advantages of MPC outside the traditional objective function. Refrigerated containers (Sørensen et al. [77]), industrial refrigeration systems (Nadales et al. [183]), cold and ice energy storage (CTES) (Beghi et al. [78]) and other refrigeration equipment, MPC can reduce energy consumption while ensuring proper operation. In addition, multi-device and system coordination optimization (Kim et al. [131]), advanced algorithms such as mixed-integer MPC (Luchini et al. [184]), economic performance optimization of novel cooling systems (Zhao et al. [76]), dynamic simplified substitution modeling, and data-driven modeling will become hot spots of research in the future, which will play an important role in improving system modeling and control strategies of novel cooling systems (Fig. 14).

4.1.2. Heating systems

(1) Conventional heating system

Corresponding to the cooling system. Many heating system research objects about heat pumps, radiation heating, and others exist. Wang et al. [79] proposed an MPC approach to optimize the operation of a transcritical CO_2 air source heat pump (ASHP) water heater. Pippia et al. [132] combined a stochastic scenario-based MPC (SBMPC) controller with a nonlinear Modelica model that can provide a more detailed building description and capture the dynamics of the building more accurately than linear models (Fig. 15). Kuboth et al. [80] investigated the potential of model-predictive heat pump control in detached houses regarding electric energy consumption, thermal comfort, and photovoltaic energy self-consumption.

The above research (Hu et al. [133], Finck et al. [185], Ma, Liangdong et al. [186] and Ref [187,188]) shows the advantages of MPC in the application of household or small-scale heating systems with decentralized heating characteristics, in which the research of household heat pump system is more popular, MPC heat pump control in independent houses has a better application effect in terms of energy consumption, thermal comfort and other aspects, and the system is smaller to make up for some of the shortcomings of MPC computationally high cost; The role of building thermal inertia is better reflected in heating, and it is also very useful to study the combination of nonlinear building modeling and MPC; in addition, low-inertia heating by MPC can be used to study the simultaneous optimization of the operation of indoor environments in different areas of the household heating system.

(2) Heat pumps and renewable energy-related heating systems

Due to renewable energy development, many renewable energy and air heat pump systems have appeared in the heating system, and many researchers have conducted composite research on them. Rastegarpour et al. [189] designed a reduced-order, linear, adaptive time-varying predictive model of the heat pump COP. Mor et al. [112] developed and validated an original methodology for the Flexibility Function estimation to evaluate the delivered energy flexibility of several Automated Demand Response services applied on various heat pump systems under actual operations. Tarragona et al. [81] proposed the MPC strategy for an air-to-water heat pump-based hybrid heating system with PV panels, TES, and grid connection. Joan Tarragona et al. [81] evaluated the economic impact of a novel MPC strategy that employed an inner control algorithm (ICA) to decrease the cost of electricity reduction in 17 different climate zones. The studied system was composed of an air-to-water heat pump (HP), photovoltaic (PV) panels, and a water TES tank (Fig. 16).

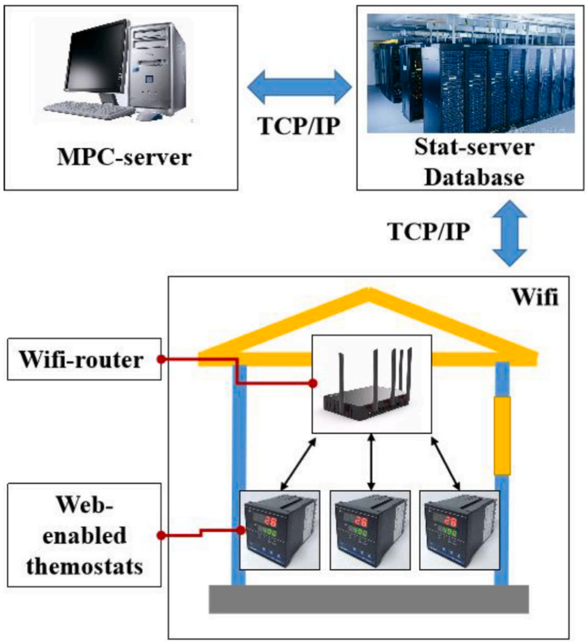


Fig. 14. A conceptual schematic of a control architecture for implementing MPC for small or medium-sized buildings.

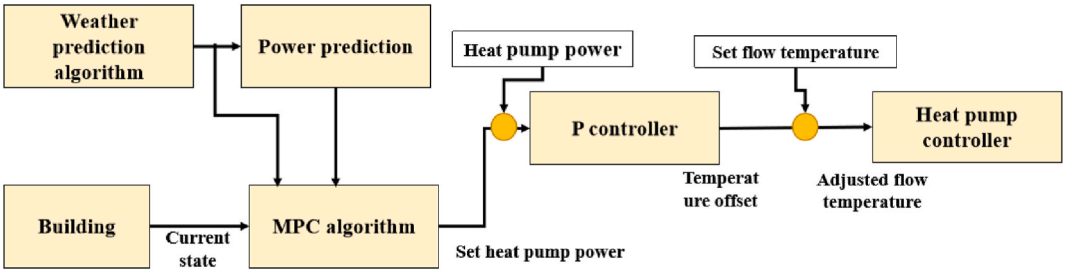


Fig. 15. A stochastic scenario-based MPC (SBMPC) controller.

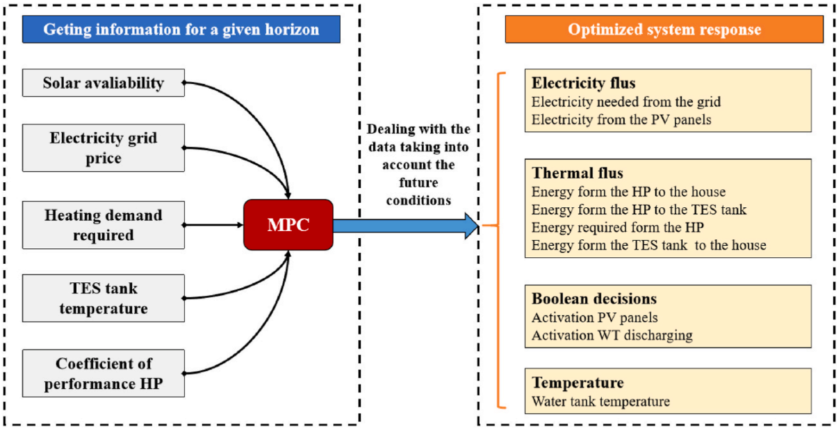


Fig. 16. Energy fluxes managed by the MPC controller.

Optimization of heat pump systems using MPC technology to consider the operation of systems under different operating conditions and system configurations should be one of the important directions to be studied in the future. Introduction of renewable energy sources to develop MPC strategies for multi-energy integration, such as solar thermal systems or photovoltaic electric heat pumps, to improve overall system performance and achieve energy savings, where the MPC strategy should consider the use of energy storage devices (e.g., storage heaters or batteries) to optimize energy use. In addition, solar thermal heating from renewable energy systems requires the development of MPC strategies for different heating climate zones to optimize energy consumption and reduce electricity costs, including changes in weather conditions, solar radiation, and heating demand in different regions. (Fig. 17). (Ref [83,190–193],

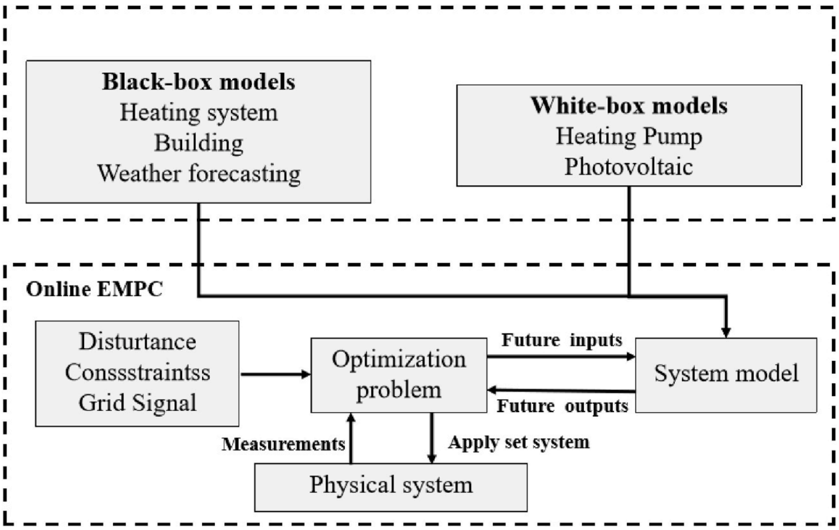


Fig. 17. Methodological diagram of economic MPC in heating system.

Morovat et al. [194] and Coninck et al. [195])

(3) Heating terminal-related control

The heating terminal is an essential part of the heating system. Many researchers have also applied the MPC method in various terminals to explore, maximize the thermal comfort requirements, and ensure each room's hydraulic and thermal balance in the secondary network or user's single building. Li et al. [84] presented an MPC approach for room temperature regulation in multi-zone buildings. A hybrid optimization algorithm was proposed, consisting of the improved particle swarm optimization (IPSO) algorithm and Newton-Raphson (NR) method in online optimization of MPC for a single zone building. Rogers et al. [85] suggested a Recursive Modelling Model Predictive Controllers RM-MPC control scheme that can be retrofitted to existing homes economically. Löhr et al. [196] offered an approach to replacing the mixed-integer program with a simpler quadratic program utilizing learning techniques for MPC. Then the control performance for different approaches was investigated for a domestic heating system.

On the heating terminal side, the study of MPC-controlled radiant heating systems is popular and needs to be considered factors such as occupancy patterns, thermal comfort requirements and energy efficiency; For multi-zone buildings to further explore the MPC method of regulating room temperature by controlling the end in multi-zone buildings.

(4) New heating system and new control mode

MPC is also applied to many new heating systems, and numerous researchers have proposed new heating control modes. Narayanan et al. [197] focused on investigating the adaptability of a white-box model MPC using a generic objective function for increasing renewable energy fraction and self-consumption in a decentralized integrated renewable energy system. Chen et al. [134] examined the indoor convective heat transfer process, short-wave radiant heat transfer among interior envelope surfaces, long-wave solar radiation, and the complicated heat transfer model of the capillary mat radiant floors. Zhang et al. [86] proposed a practical control framework (named BEM-DRL) using deep reinforcement learning for building energy model (BEM), which is used for the control of HVAC systems. Hedegaard et al. [87] reported on a simulation-based study investigating whether there is a significant impact on the performance of MPC schemes when substituting these weather measurements with data from meteorological weather services. Lillian et al. [198] introduced an MPC structure with decoupled MPCs for building heating control using weather forecasts and occupancy information. A Fuzzy MPC was presented to optimize user comfort on a high level. Frison et al. [88] examined the suitability of deep neural networks for approximating optimal economic MPC strategies for this task. Moro et al. [113] addressed the case of multi-zone building temperature regulation, where the available electrical power is less than the sum of the maximum powers of local heaters. A distributed MPC (DMPC) algorithm using Dantzig-Wolfe decomposition was proposed, considering also the thermal coupling between adjacent zones.

Among the novel heating systems or heating models, centralized, decentralized, and distributed MPC algorithms for building heating control can be explored in the future for decentralized versus centralized heating systems. This includes considering thermal coupling between different zones and developing efficient algorithms to optimize comfort and energy consumption in multi-zone buildings. Many novel systems require completely new models, so in order to implement the MPC strategy more accurately, advanced heat transfer models applicable to novel systems can be developed that take into consideration various factors affecting heat transfer, such as convective heat transfer, radiative heat transfer, and solar radiation, and incorporate complex dynamics based on the existing models to improve the accuracy of control of the heating system. Similar to the other heating systems described in the previous section, the study of deep neural networks and other approximation techniques to develop optimal and economical MPC strategies for novel heating systems remains a key research focus, resulting in the most cost-effective control solutions for novel heating models.

4.1.3. Integrated system, ventilation system, and others

(1) Conventional integrated HVAC system

This part mainly includes using MPC to improve the system operation mode of the whole or partial components of the traditional HVAC system. Razban [199] constructed a dynamic indoor CO_2 model to forecast CO_2 concentrations across various forecasting horizons. A control strategy capable of modeling and detecting dynamic patterns of CO2 level was utilized to modulate the ventilation rate in real-time and reduce energy consumption. Santoro et al. [135] proposed a nonlinear economic model of predictive control (eMPC) using a budget constraint. Lu et al. [200] presented a framework for exploiting reference models in Bayesian optimization (BO). The approach was motivated by an MPC tuning application for central HVAC plants. Liu et al. [201] introduced a novel HVAC energy management scheme to schedule the thermostat setpoints of HVAC optimally and to provide recommendations on occupants' optimal hourly clothing decisions through a predicted mean vote model.

Fontenot et al. [90] developed a novel framework for Buildings-to-Distribution-Network (B2DN) integration. The proposed B2DN framework implemented a receding horizon by solving a quadratically constrained quadratic programming (QCQP) problem with MPC. Chen et al. [202] investigated the accelerated distributed MPC strategy for HVAC systems with local and global power input constraints. Raman et al. [115] suggested an MPC controller for an HVAC system in which humidity and latent heat are incorporated principally and constructed low-order data-driven models of a cooling and dehumidifying coil that can be used in the MPC formulation. Jan et al. [116] presented a range control MPC formulation for Vapor Compression Cycles (VCC). Köhler et al. [203] introduced an economic MPC framework that applies to nonlinear time-varying problems and online changing operating conditions. Bursill et al. [138] tested an approach to MPC using rule extraction (RE) that can be easily implemented in building controllers to override sub-optimal control. Toub et al. [139] offered a real-time MPC framework to minimize the energy consumption and operational cost of building an HVAC system with integrated MicroCSP. Lee et al. [204] presented a novel self-tuned HVAC controller that improves occupant thermal satisfaction, energy efficiency. Joe et al. [140] introduced a smart building operation strategy for hydronic radiant floor systems based on MPC. Dullinger et al. [141] proposed a hierarchical MIMO MPC framework for energy-, wear-, and comfort-optimized operation of HVAC. Verhelst et al. [205] illustrated an economic performance evaluation methodology to examine the performance of HVAC controllers under the influence of persistent degradation faults. Schwingshackl et al. [92] presented work that deals with the multi-input, multi-output (MIMO) control of HVAC systems. The applied control strategy includes a linear MPC and a local linear neuro-fuzzy model (LLNFMs). Ascione et al. [93] introduced a new comprehensive approach to support the cost-optimal design of the building envelope's thermal characteristics and HVAC systems in the presence of a simulation-based MPC for heating and cooling operations. Aftab et al. [206] presented an automatic HVAC control system featuring real-time occupancy recognition, dynamic occupancy prediction, and simulation-guided MPC implemented in a low-cost embedded system. Zhao et al. [207] offered an occupant-oriented mixed-mode Energy Plus predictive control system to optimize HVAC energy consumption while meeting the individual thermal comfort preference. Schwingshackl et al. [143] proposed an MPC strategy based on a network of local linear models to deal with the multi-input-multi-output (MIMO) control of an air handling unit (AHU) in an industrial HVAC system. Perez et al. [208] focused on the combination of air-conditioning use with the operation of time-shift able appliances. A centralized MPC scheme minimizes peak air-conditioning energy use by altering the thermostat setpoints in individual homes. Ascione et al. [94] suggested a simulation-based MPC procedure to achieve the multi-objective optimization of the HVAC system control strategy, with a 24-h day-ahead planning horizon (Fig. 18).

Razmara et al. [144] derived and formulated exergy destruction as a function of the physical parameters of the building. Liang et al. [118] developed a system-level dynamical model and MPC design for HVAC systems. Huang et al. [209] presented a hybrid model predictive control (HMPC) scheme, minimizing the energy and cost of running HVAC systems in commercial buildings. Goyal et al. [210] presented an experimental evaluation of two occupancy-based control strategies for HVAC systems in commercial buildings. The control algorithms are MOBS (Measured Occupancy Based Setback) and MOBO (Measured Occupancy Based Optimal). West et al. [146] suggested optimizing commercial HVAC systems' operation using MPC. Touretzky et al. [95] developed a novel approach for controlling buildings with thermal energy storage (TES) using a scheduling and control perspective. The centralized E-MPC for the economic-oriented control and energy management of buildings was transformed into a hierarchy of coordinated controllers. Mendoza-Serrano et al. [119] discussed the effect of TES in reducing operating costs related to HVAC systems for building temperature control and concluded that savings strongly depend upon the information level provided to the EMPC algorithm. Ma et al. [211] presented an industrial application of an economic MPC strategy to optimize setpoints in HVAC systems for load shifting and cost minimization. Castilla et al. [212] proposed the actual application inside the building of a hierarchical control architecture, which optimizes a non-linear model predictive control approach to control thermal comfort and a split-range controller in the lower layer to maintain energy efficiency. Oldewurtel et al. [147] investigated the potential of using occupancy information to achieve a more energy-efficient building climate control. An MPC controller is used as a benchmark. Avci et al. [148] proposed a reasonable cost and energy-efficient model predictive HVAC load control (MPC) strategy for buildings facing dynamic real-time electricity pricing. Oldewurtel et al. [96] examined how MPC and weather predictions can increase energy efficiency in Integrated Room Automation (IRA) and presented a newly developed SMPC strategy for building climate control. Castilla et al. [97] focused on demonstrating the practical applicability of a hierarchical control system using only one cost function involving thermal comfort and energy savings.

The integrated HVAC system combines multiple systems and can accomplish various functions like cooling, heating, ventilation, and power control. Its control points are similar to those of the decomposed independent system, and it only requires integration with

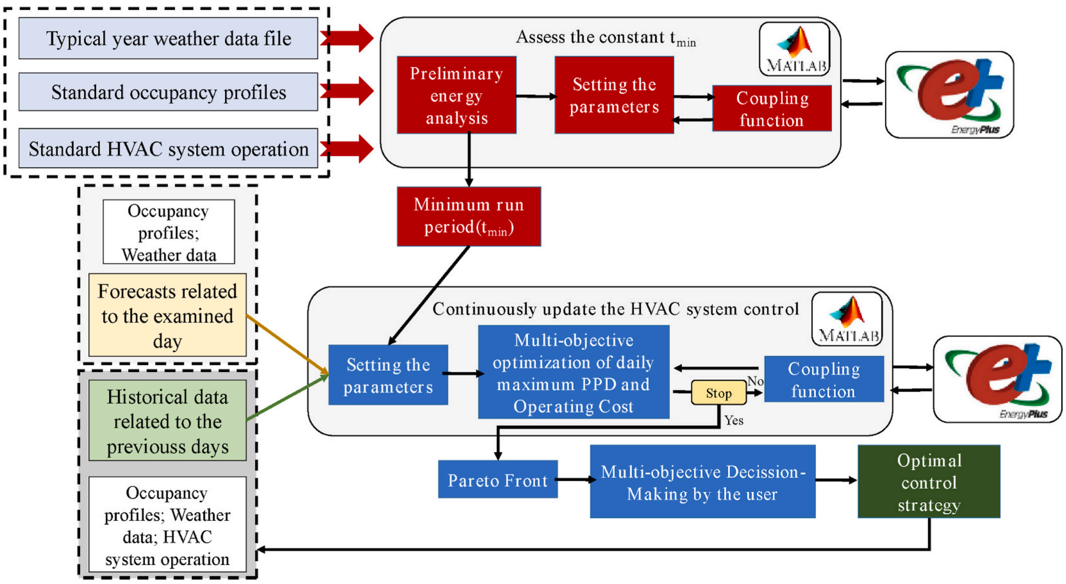


Fig. 18. MPC framework with multi-objective optimization of HVAC system.

the corresponding control points.

Similarities between systems lie in the fact that most research begins with the system controller and employs MPC to enhance operation. Aside from conventional chillers, heat pumps, and refrigeration equipment, applications have also been made to building loads, power demand, real-time tariffs, operating mode switching, and system fire efficiency.

The distinction from a singular system lies in the enhanced and intricate functionality of the system, which poses greater difficulty in resolution. Consequently, many researchers and scholars have explored numerous novel algorithms that are applied to MPC including (Turhan et al. [114], Mtibaa et al. [213], Ma et al. [213] and Ref [91,117,137,142,145,189,214–229]): Thermal comfort-driven control algorithms (PTC-DC), a model predictive control system based on genetic algorithms, a real-time control framework for managing a building's thermal environment using encoder-decoder recurrent neural networks, an algorithm for managing residential HVAC systems using the proper Orthogonal Decomposition (POD) method, and so on. Their research addresses numerous shortcomings of traditional MPC, and further research is necessary to enhance these algorithms in the future.

With the increasing complexity of the system, the development of more applicable new MPC methods is the research trend, when the integrated system is complex and involves the control of multiple subsystems within the system, in addition to the idea of distributed MPC, the combination of common methods in the model-free such as reinforcement learning and MPC is also a very good research idea (Huchuk et al. [89]), and can utilize the advantages of each method to complement each other as a whole in the same system (Fig. 19).

(2) Building energy management systems

HVAC system accounts for a large proportion of the overall energy consumption of buildings. As a result, when studying the application of MPC in building energy management systems, many scholars usually pay special attention to an HVAC system to reduce the overall energy consumption of buildings, ensure thermal comfort, and increase energy efficiency. Nagpal et al. [149] presented a generic and comprehensive BEMS framework for SSBs. The overall mixed-integer linear programming (MILP) problem was solved through MPC (Fig. 20).

Jin et al. [230] proposed a hierarchical energy management method for the UC to optimally schedule the UC's energy usage and control the buildings' HVAC. Drgonaa et al. [98] reported a successful cloud-based implementation and remote operation of white-box MPC in a hybrid GEOTABS office building. Sangi et al. [99] developed an exergy-based control strategy for building energy systems and investigated its real-world applicability. MPC for building energy systems using the exergy principles was established, and Programming (MILP) was employed to develop the controller.

Many scholars (Ryzhov et al. [100], Péan et al. [231], Gonzato et al. [232] and Ref [101,120–122,150,233–241]) begin with analyzing the building as a whole and utilize the integrated energy management system to investigate diverse control methods and the alteration of operation modes of energy-consuming equipment. This approach helps maintain indoor comfort while reducing the overall energy consumption of the building. The research involves examining the total electricity usage of the building, implementing load shifting and demand response techniques, regulating indoor environmental control, and coordinating the pricing of various equipment in the building.

Control points typically include indoor temperature control points, energy supply control points (e.g., control of photovoltaic systems, grid power purchases, and energy storage systems), load management control points (e.g., control of equipment such as lighting, appliances, pumps, etc.), and window and shading control points (regulation of the degree of opening and closing of windows and shading devices to control indoor light and heat gain and loss). BEMS necessitates increased coordination, partially due to the limitations of the MPC model. Consequently, research must overcome the following challenges: optimizing data integration between the building model and multiple system models, developing multi-objective optimization and decision support tools, cross-systems integration, and collaborative control design within the building, incorporating more advanced intelligent sensing and monitoring technologies, and introducing currently popular renewable energy sources while self-sufficiently managing the design. Some literature findings indicate the benefits of model-free control in specific scenarios as an alternative to MPC. Section 4.2 will include an extended

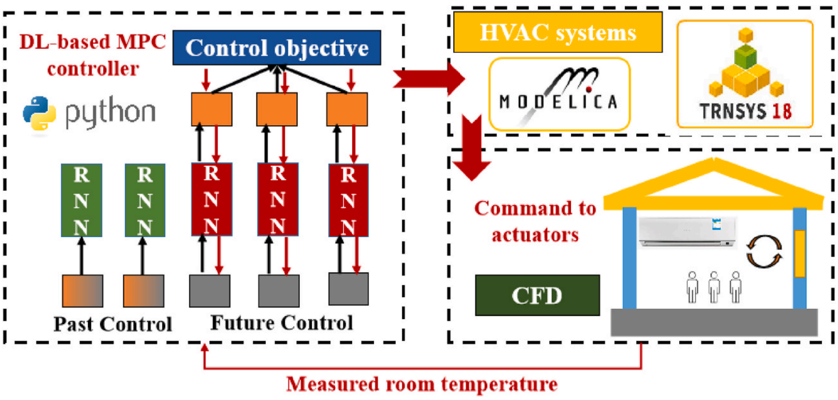


Fig. 19. Deep Learning based MPC framework.

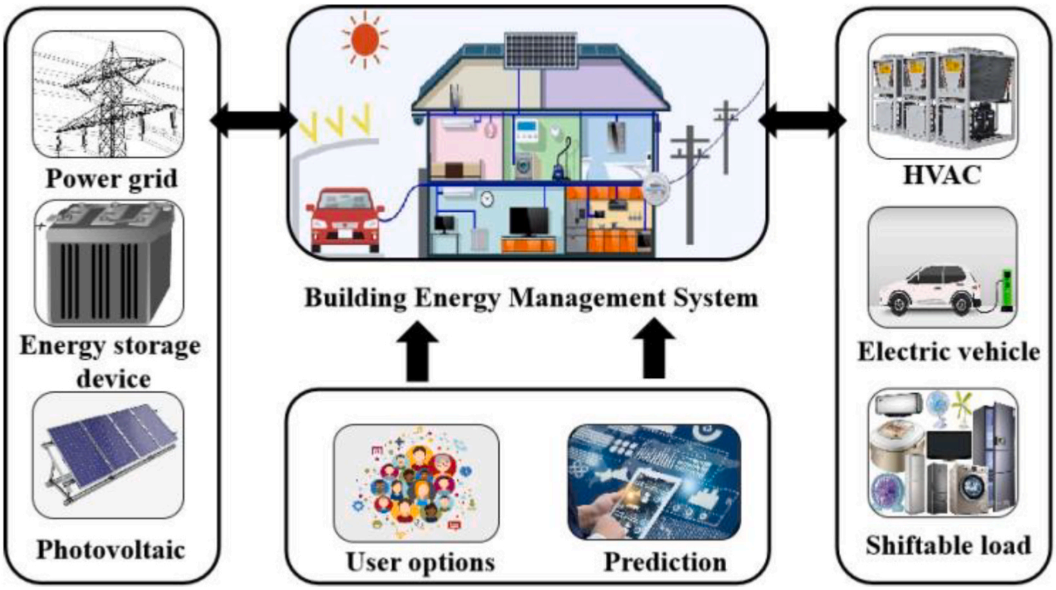


Fig. 20. The framework of multiple building energy management system.

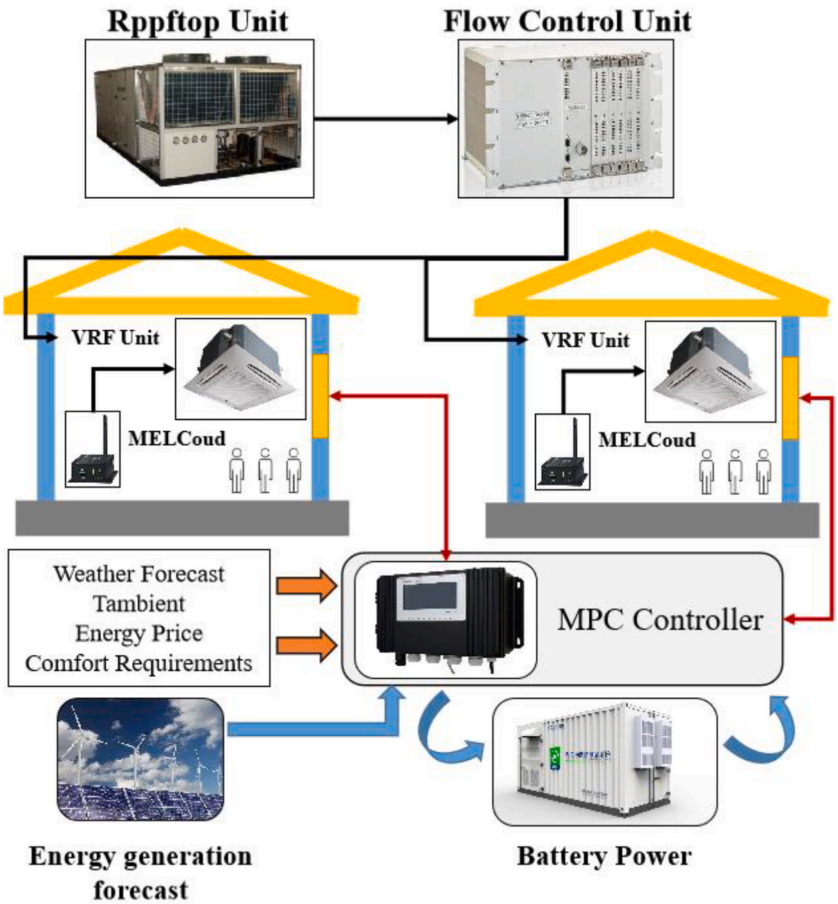


Fig. 21. Schematic diagram of building thermal environment control with MPC.

analysis of the model-free approach.

(3) Composite renewable energy systems

Introducing many renewable energy sources has promoted the development of consumption reduction and energy conservation of HVAC systems. The MPC method has played an excellent role in combining photovoltaic, photothermal, biomass, air energy, and others. Rehman et al. [151,242] investigated the impact of PV self-consumption curtailment on Building to Grid (B2G) operations and the MPC used in the Energy Storage System (ESS) and HVAC system. Wanga et al. [152] presented a scheme based on a chance-constrained stochastic model predictive control (c-SMPC) to optimally schedule HVAC and electric storage system (ESS) coordinately to enable the highly efficient utilization of solar power and economical energy conservation in the building. Reddy et al. [243] presented a new control method to optimize energy flows of a micro-scale concentrated solar power (MicroCSP) system to minimize electrical energy consumption. Biyik et al. [244] established an optimal control framework (MPC) to coordinate HVAC, battery energy storage, and renewable generation in buildings (Fig. 21).

Bianchini et al. [153] discussed the problem of the cost-optimal operation of smart buildings. The proposed solution relied on a specialized MPC strategy to optimally manage the HVAC system and storage devices. Razmara et al. [245] designed a real-time optimization framework using MPC to control the power flow from the grid, solar Photovoltaic (PV) panels, and ESS to a commercial building with HVAC systems. Fiorentini et al. [154] described the development, implementation, and experimental investigation of a Hybrid Model Predictive Control (HMPC) strategy to control solar-assisted HVAC systems with on-site thermal energy generation and storage. Bruni et al. [246] demonstrated a control strategy for managing a microgrid power system. Godina et al. [247] presented an alternative MPC strategy to stimulate the efficient use of home heating energy.

In addition to the above research, there are many researchers (Bianchini et al. [153], Razmara et al. [245], Fiorentini et al. [154] and Ref [246–252]) who have conducted extensive studies on linking renewable energy systems with HVAC systems. The integration of renewable energy technologies and MPC is one of the most popular and interesting research topics in the future. As discussed in the preceding section on heating systems, MPC plays an integral part in HVAC power systems that utilize renewable energy sources. MPC can optimize energy flow in energy storage systems (ESS) in buildings, HVAC system operation, and micro-concentrated solar power systems to improve energy efficiency. The HMPC strategy applied to energy flow control requires further refinement and exploration. Furthermore, there has been extensive research on integrating photovoltaic and wind microgrid systems with MPC, demonstrating the use of control strategies in managing microgrid power systems and promoting efficient household heating energy utilization.

(4) Regional energy systems and centralized systems

Investigating regional energy and centralized HVAC systems has derived many centralized and distributed MPC methods. MPC also plays a vital role in coordinating and controlling users, buildings, energy, and system equipment. Zhao et al. [155] proposed a forecasted load-and-time delay-based predictive control district energy system model. Yang et al. [72] suggested the MPC system for coordinated control of multiple building services. The core of the proposed MPC system was the integrated building model capturing the dynamics of multiple building services. Seal et al. [156] proposed a centralized model of predictive control (MPC) for zone-based comfort and energy management in a residential building, relying on a photovoltaic (PV) solar system, a stationary home battery unit, and a heat pump (HP). Lymperopoulos et al. [253] considered buildings with several climate zones and proposed a distributed adaptive control scheme for a multi-zone HVAC system. Kumar et al. [102] presented a stochastic MPC framework for an HVAC central plant and used the framework to rigorously assess the benefits of stochastic MPC over deterministic MPC in terms of economic

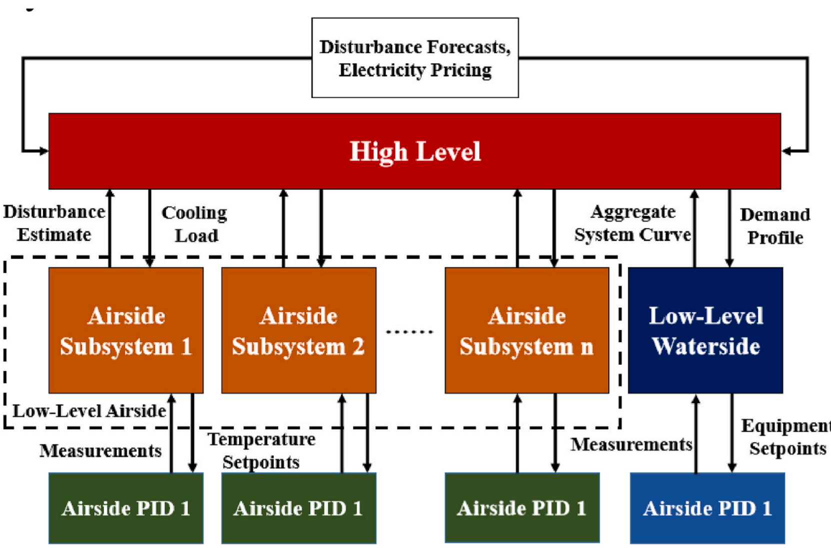


Fig. 22. Regional-level system control hierarchy diagram.

performance and constraint violations.Radhakrishnan et al. [103] offered a novel approach to ensure energy-efficient operations for HVAC systems in commercial buildings. A Central Scheduler gathers token requests from all Zone Modules and allocates tokens to minimize the chiller's and fans' energy consumption.

The study demonstrates that the MPC system effectively optimizes multiple targets in buildings equipped with numerous HVAC controllers. The coordinated system controls users, buildings, energy sources, and equipment, significantly contributing to regional and centralized system efficiency. Developments in centralized and distributed MPC methods have enhanced the system's capabilities. District energy systems or centralized systems often incorporate several energy sources, including solar, wind, geothermal, and municipal power grids. Energy sources experience random fluctuations in generation and consumption, resulting in a mismatch between supply and demand. By utilizing hierarchical decomposition and hybrid multilayered MPC (Rawlings et al. [254], Hilliard et al. [255], Afram et al. [157] and Ref [256–273]), multiple energy points can be effectively managed and coordinated to achieve efficient energy utilization (Fig. 22). MPC must predict and account for the stochastic nature of every energy source in an integrated energy system to achieve rational matching and scheduling of energy sources. This helps to optimize energy scheduling and storage strategies, improve system stability and reliability. By forecasting energy supply and demand, load demand, and other crucial factors, MPC can develop optimal scheduling strategies and increase energy utilization efficiency.

(5) Ventilation is the dominant HVAC system

MPC has also been widely used in HVAC systems, mainly based on ventilation. Ventilation systems are also more focused on regulating indoor air quality than heating and cooling systems (Li et al. [274]), with some researchers developing prediction models to predict indoor pollutant concentrations based on time-varying outdoor concentrations and indoor emissions (Ganesh et al. [104]), based on physical building models. The control points typically comprise indoor air supply, indoor air velocity, ventilation energy efficiency ratio, and the switch between natural and mechanical ventilation. An optimal cost function design, which effectively balances occupant comfort, indoor air quality, and energy consumption, has been determined (Zhang et al. [275]). Additionally, there are researchers who have integrated innovative MPC techniques with ventilation systems, including implementing robust MPC strategies for multi-zone demand-controlled ventilation (DCV) systems (Fang et al. [158]).

Additional parameters to consider in future studies regarding MPC are the indoor standards of carbon dioxide, ozone, and formaldehyde concentration equivalents (Chen, Elence Xinzhu et al. [276], Chen, Yibo et al. [277]). These parameters can be added to the MPC to improve the constraint and objective functions. To enhance the performance and energy efficiency of ventilation systems to adapt to changing occupancy patterns, weather conditions, and indoor air quality requirements, explore adaptive and self-learning MPC technologies. Integrating advanced sensor technologies, including indoor occupancy sensors, CO2 sensors, and pollutant sensors, to obtain real-time data for MPC control and optimizing ventilation systems. Researching energy-efficient ventilation strategies that employ building thermal inertia, which reduces the need for immediate ventilation after a drop in outdoor temperature. The approach involves calculating the delay time for each room to determine optimal ventilation based on predicted temperature changes. The ventilation is then controlled through mechanical, natural, and hybrid systems using the MPC approach to maximize energy savings while maintaining indoor comfort. Exploring human-centered control methods: The study examines designing and controlling ventilation systems using MPC, while considering passenger preferences, comfort, and behavior. The ventilation system is integrated with other building systems to optimize energy use and achieve synergistic control through MPC, comprehensively considering interactions between different systems.

(6) Special space: personal space, vehicle environment

At present, some HVAC systems are suitable for special occasions. Through the application of MPC, the local and indoor environments in the enclosed spaces of various vehicles are adjusted. Liu et al. [278] proposed a control strategy to reduce the risk of COVID-19 infection and save energy for the air conditioning (AC) and ventilation systems. The cooperative control strategy for the AC system has a better all-around performance than the MPC with complete or without ventilation. Chen et al. [159,279] investigated three primary control schemes: spontaneous occupant control, informed occupant control, and fully automatic control. It is recommended to adopt the fully automatic natural ventilation control system to achieve maximum energy-saving potential or allow occupant autonomy for natural ventilation controls to achieve a lower initial installation and maintenance cost budget.

The research on applying predictive control through special systems yields new characteristics. One notable example is using MPC in enclosed spaces of vehicles (such as cars, trains, and other modes of transportation [280,281]). This approach demonstrates distinct advantages for optimizing local conditions in such confined spaces. Future research trends involve optimizing MPC control algorithms while considering energy efficiency, passenger comfort, and cost-effectiveness of special ventilation and air-conditioning systems. This involves exploring spontaneous occupant control, informed occupant control, and fully automated control to give passengers autonomous natural ventilation regulation to reduce initial installation and maintenance costs.

4.2. Application of MFPC in HVAC systems

This section focuses on MFPC. It will introduce the three parts of the cooling system, heating system, and integrated system, and describe the content and characteristics of the study of MFPC in various system forms. This includes the control points, model-free methods, and control objectives.

4.2.1. Cooling systems

Some researchers optimize the cooling system for specific equipment components using model-free control technology. The main features of this type of model-free control application are to achieve the overall energy-saving effect of the system by controlling the valves of the chiller, condensers, fans, and pumps in the vapor compression refrigeration system. Lee et al. [37] developed the smart-valve-assisted model-free predictive control (SV-MFPC). Smart valves (hardware) and an agent control program (software) were employed, and A2C and policy gradient were chosen among different RL methods to perform predictive control. Koeln et al. [38] proposed an alternative system architecture, utilizing a receiver and an additional electronic expansion valve to control condenser sub-cooling independently. Qiu et al. [39] suggested a model-free optimal control method relying on reinforcement learning to control the building's cooling water system. The proposed method uses Q-learning. Hence, if the researcher intends to improve the overall operation effect of a system by enhancing its components, the above model-free method is recommended. Yu et al. [282] proposed a model-free control strategy based on the deep reinforcement learning (DRL) without the requirement of accurate system model and uncertainty distribution.

In addition to optimizing the control mode of cooling system components, applying model-free control to the overall operation optimization is also very popular. Du et al. [40] applied the deep deterministic policy gradient (DDPG) to generate an optimal control strategy for a multi-zone residential HVAC system to minimize energy consumption cost while maintaining the users' comfort. Chi et al. [41] focused on improving the cooperation between the IT system and cooling system to increase the energy efficiency of data centers, and a hybrid AC-DDPG cooperative framework is designed in this study using multi-agent DRL methods. Biemann et al. [42] conducted experiments to evaluate four actor-critic algorithms in a simulated data center. All applied algorithms can reduce energy consumption by at least 10 % through simultaneously keeping the hourly average temperature in the desired range. Yuan et al. [283] utilized the RL algorithm to the operation optimization of the air-conditioning system and proposed an innovative RL-based model-free control strategy combining rule-based and RL-based control algorithms and a complete application process. Qiu et al. [284] combined RL technology with expert knowledge to propose a hybrid model-free chilled water temperature reset method, significantly enhancing the robustness and learning speed of RL control. The above research contents all consider the overall operation optimization control of the cooling system as the breakthrough point. In addition, the adopted model-free methods are reinforcement learning and its derivative methods, supplemented using actor critical algorithms and deep deterministic strategy gradient (DDPG) to increase the system's operation control mode and reduce system energy consumption or operation cost.

There are some studies on the cooling system as the main body, optimizing the system from other aspects through model-free control. Schreiber et al. [43] investigated the potential of two different RL algorithms (Deep Q-Networks DQN and Deep Deterministic Policy Gradient DDPG) for load shifting in a cooling supply system. The two various algorithms control the operating parameters of a central compression chiller for a price signal. The applicability of Q-Learning and the data processing accuracy affect the system control.

Model-Free Predictive Control (MFPC) optimizes the energy efficiency and operation of the system without relying on a model. This feature improves the complexity and uncertainty of the cooling system, which includes researching various cooling components and exploring ways to optimize the overall operation of the system. Reinforcement learning and related techniques are currently dominant in the context of cooling systems. Additionally, numerous resources have emerged, including various derivatives of DDPG [60].

The control points in a model-free cooling system share similarities with those in MPC. Typically, there are three main categories: equipment input and output parameters, including temperatures at the condenser's inlet and outlet, and the evaporator's working pressure. Additionally, equipment working status parameters are monitored, like the valve opening degree and the pump working frequency. Finally, environmental parameters like indoor and outdoor temperature and humidity are measured. The selection of control points primarily relies on the system's operating principle and performance standards. For instance, adjusting the condenser's inlet and outlet temperatures using reinforcement learning approaches have an immediate impact on the cooling capacity of the cooling system. Similarly, modifying the opening degree of several valves with the DDPG technique can alter the water flow rate, thus impacting the cooling system's energy transfer efficiency. The main objective of most cooling system control points is to achieve

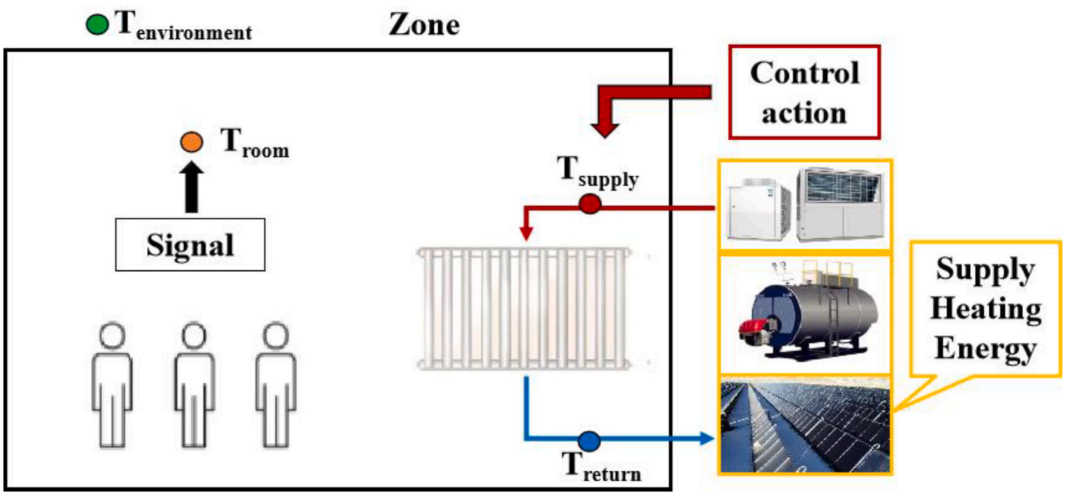


Fig. 23. Illustration of the model-free control flow for the heating system application.

energy savings by adjusting equipment parameters to optimize system operation, resulting in reduced energy consumption and improved performance.

There remain unresolved issues in the field, with both model-free and modeled approaches capable of handling system nonlinearity and uncertainty. However, it should be noted that the control accuracy of the model-free method is relatively low, for example, the cooling system will be affected by a variety of factors such as ambient temperature, humidity, etc., and the change of these factors may lead to changes in the dynamic performance of the system, and the coupling of multiple models can effectively correlate a variety of factors, and the model-free method of Multi-agent can also achieve this. However, issues with intelligence training can impact the effectiveness of the control strategy. Future research should investigate new reinforcement learning algorithms to more effectively handle system nonlinearities and uncertainties, improve data processing accuracy to better train agent, increase the efficiency and reliability of model-free predictive control algorithms for effective control with limited time and computational resources, and examine Multi-agent reinforcement learning algorithms for cooling system control applications.

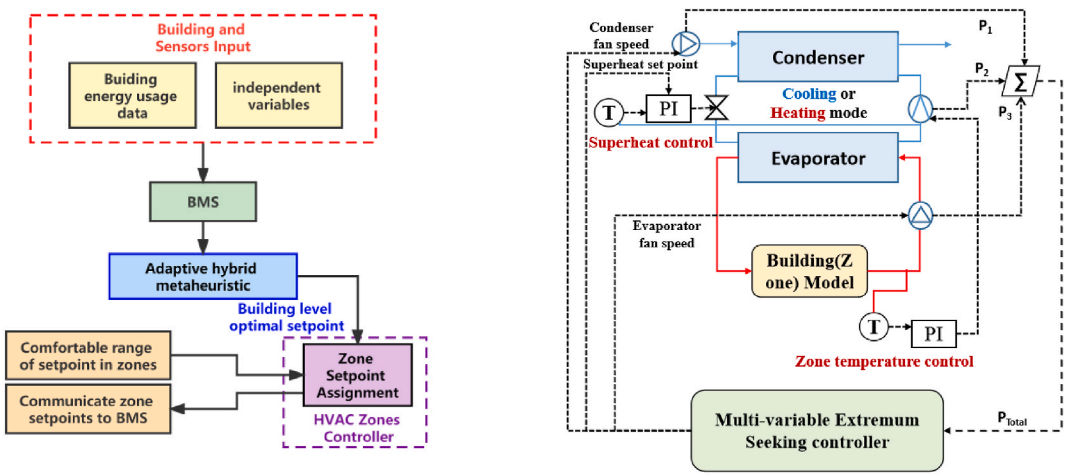
4.2.2. *Heating systems*

In the HVAC system based on heating and hot water supply, some researchers use the model-free control method to modify the system operation to reduce energy consumption, improve energy efficiency, and maintain indoor thermal comfort. Coraci et al. [44] investigated a model-free algorithm belonging to the Deep Reinforcement Learning (DRL) class to control the supply water temperature of radiant terminal units in a heating system serving an office building (Fig. 23). Wang et al. [45] suggested a novel control strategy for model-free real-time optimization of energy efficiency for the cascade heat pump using the Multivariable Extremum Seeking control.

Similar to the cooling system, the model-free approach for heating systems involves Deep Reinforcement Learning (DRL) for the real-time optimization of control strategies to increase the energy efficiency of cascaded heat pumps. Control points include the operating state of the boiler or heat pump, the setpoints for the supply and return water temperatures, flow rates, and controlling auxiliary heat sources, circulating pumps, valves, and terminal equipment. As the heating system is used in a more specialized environment, the thermal comfort requirements are higher than those of the cooling system. Current research on the model-free approach to studying the heating end is limited. In the future, the model-free application of a Multi-agent approach can be explored in different buildings or rooms. This can be done under a method of collaborative control to synchronize and meet the thermal comfort requirements of multiple rooms. This approach can further solve complex modeling problems, high computational costs, and unstable communication signals compared to distributed MPC.

4.2.3. *Integrated system, ventilation system, and others*

More research has been conducted on the overall comprehensive application of HVAC systems, including refrigeration, heating, and ventilation functions. Most researchers consider the controller of the HVAC system as the starting point and improve the operation state utilizing on-off. Dong et al. [51] presented a model-free control and automatic staging strategy for operating a variable refrigerant flow system with multiple outdoor units, which maximized energy efficiency in real-time and handled the outdoor-unit operation during load changes. Wang et al. [52] introduced a model-free actor-critic Reinforcement Learning (RL) controller with Long-Short-Term Memory (LSTM) networks (Fig. 24 a). Ghahramani et al. [53] presented an online learning algorithm (Adaptive Hybrid Metaheuristic Algorithm) to search and learn the setpoints for the optimal control of an HVAC system. The control policy uses real-time data (gas/electricity consumption, weather, and occupancy) to set optimal setpoints at thermal zones' thermostats. Michailidis et al. [54] considered an alternative Plug-*n*-Play control approach to Building Optimization and Control (BOC) system design, providing automated fine-tuning of the BOC system: no human intervention or a simulation model is required for the initial



(a) Reinforcement learning (RL) (b) Extremum seeking control (ESC)

Fig. 24. Flowchart of model-free control application.

deployment of the controller. Ruelens et al. [55] proposed an auto-encoder and a popular model-free batch reinforcement learning technique (Q-iteration). Dong et al. [56] suggested multi-input Extremum Seeking Control (ESC) scheme for the heating and cooling operation of the air-source heat pump (ASHP). The compressor's total power consumption, the condenser fan, and the evaporator fan are measured as input to the ESC, while the ESC controls the evaporator fan speed, the condenser fan speed, and the suction superheat setpoint (Fig. 24 b).

Many scholars investigate the building as a unit and use the integrated energy management system as the breakthrough point to search the building's overall power consumption and load transfer through model-free control. Hassan et al. [47] presented a data-driven learning method for controlling TCL (thermostatically controllable loads) ensemble using the MDP (Markov Decision Process) and Z-learning approaches. Canteli et al. [285] introduced a new simulation environment by merging CitySim, a building energy simulator, and TensorFlow, a powerful machine learning library. Amasyal et al. [48] proposed a scalable hierarchical model-free transactional control approach incorporating elements of virtual battery, game theory, and model-free control (MFC) mechanisms. The results showed that the proposed approach achieves peak load reduction and profit maximization for the distribution system operator and reduces costs for end users while maintaining their comfort (Fig. 25). Michailidis et al. [49] applied a novel, decentralized, agent-based, model-free BOC methodology (L4GPCAO) to a modern non-residential building equipped with controllable HVAC systems and renewable energy sources utilizing the existing Building Management System (BES). Baldi et al. [50] introduced Parametrized Cognitive Adaptive Optimization (PCAO) can be used to design model-based and model-free plug-and-play'' Building Optimization and Control (BOC) systems with minimal human effort (Fig. 26).

For applying model-free control in the ventilation system, Cui et al. [46] proposed a new online air balancing method, the DCC-AB method, to balance the airflow in a ventilation duct system. The ultimate goal is to achieve optimal wind regulation balance. This method is a good choice if researchers need to find a design process requirement suitable for large-scale ventilation systems.

In addition, some scholars applied a model-free control algorithm to control building thermal performance (door and window control) and combined it with an HVAC system to further control the indoor temperature to ensure an excellent thermal comfort environment. Han et al. [57] offered a novel reinforcement learning (RL) method for advanced window opening and closing control. An RNN-LSTM predictive model was used for predicting the indoor temperature given environmental variables and was verified by a test set. Chen et al. [58] introduced a reinforcement learning control strategy that makes optimal control decisions for HVAC and window systems (Fig. 27) .

The researchers employed model-free control to investigate overall power consumption and load shifting across buildings, as well as model-free control and automatic grading strategies for variable refrigerant flow systems featuring multiple outdoor units. (Farhad et al. [59], Xi et al. [63], Liu et al. [61] and Ref [62,64–69,286–289]). Furthermore, they developed a model-free, online learning algorithm capable of generating optimal setpoints from real-time data. The control points employed include thermostatic controllers, controllable loads (TCLs), demand response (DR), energy usage regulation, condensers, evaporator fan speeds, and inhalation overheating. These points are all utilized to schedule the flow of energy between the power grid and energy storage devices, and to develop charging and discharging strategies for battery energy storage systems. The main control point for the ventilation system is the regulation of airflow in its ducts, achieved through methods such as DCC-AB to maintain the optimal airflow balance. Additionally, model-free control points involve the regulation of doors and windows, combined with room air conditioning, for the greatest energy savings. Future research trends for integrated systems, ventilation systems, and special systems include exploring multi-agent approaches, optimizing model-free control algorithms, optimizing energy consumption and load balancing, and developing intelligent model-free and adaptive control strategies to enhance energy efficiency and user comfort.

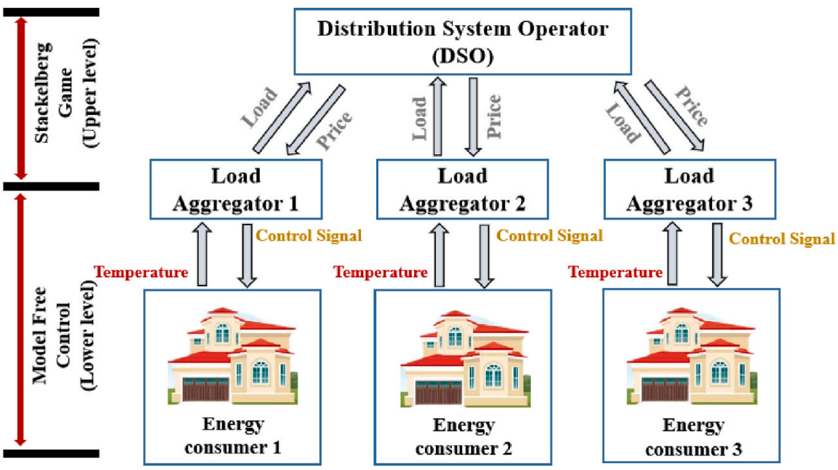


Fig. 25. Flowchart of model-free control with DSO.

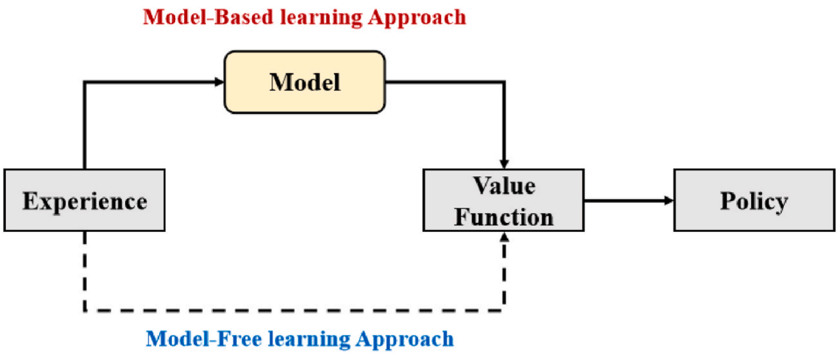


Fig. 26. Model-free and model-based learning approaches.

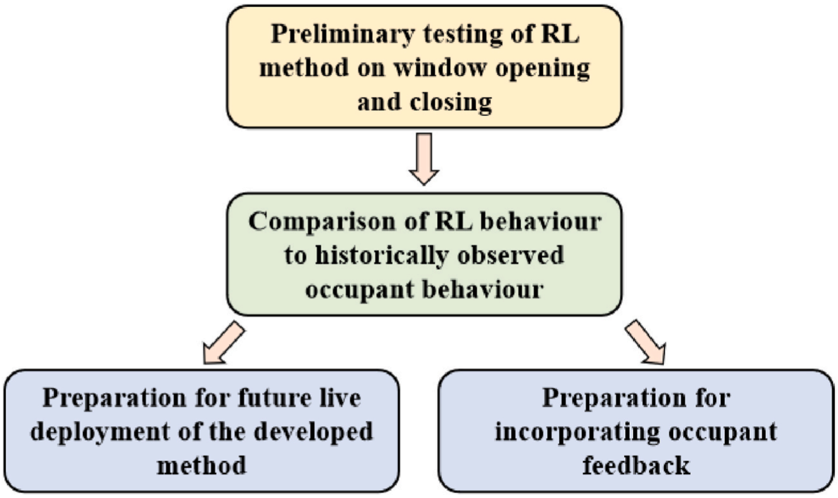


Fig. 27. Door and window closure and HVAC system control flowchart.

4.3. *Comparative analysis and summary of MPC and MFPC*

4.3.1. *Cooling systems*

MPC in cooling systems involves controlling multi-zone residential systems, continuous schedule-based operations, and overall household building optimization. MPC is applied to critical control points, focusing on cooling towers, condensers, evaporators, and pumps. It aims to reduce energy consumption and improve efficiency through load forecasting and system requirements. Specifically, the performance of cooling towers is strongly influenced by meteorological parameters. MPC predicts cooling tower performance and provides feedback to the refrigerator to control condenser equipment. The refrigeration unit's control points are largely influenced by room temperature, which depends on the building's load demand. Due to the building's heat storage and time delay characteristics, MPC can plan the refrigeration machine's cooling capacity. Pump control points adjust the flow rate and pressure of chilled or condenser water. MPC optimizes pump operation based on system requirements and adjusts water temperatures to improve refrigeration efficiency. The main features of predictive control in chilled water systems include accurately identifying system dynamics and optimizing control strategies. It has shown excellent results in controlling both conventional and large data center chilled water systems, ensuring stable operation while significantly improving energy efficiency (Table 2).

The emergence of regional and novel cooling systems has increased system complexity. Simplifying models to reduce computational complexity and improve real-time performance has become a research focus. To address these challenges, researchers analyze from the following perspectives.

1. Adopting Distributed MPC quickly connects different regions, supporting multi-region cooperation and overall system optimization.
2. Exploring multi-scale modeling methods to build refrigeration system models and control systems for different time scales, better meeting various application needs.
3. Introducing reinforcement learning methods to achieve lower computational costs and higher local control accuracy, suitable for household refrigeration systems optimization, enabling MPC to better respond to dynamic changes.

Table 2
Control and optimization objectives cooling system.

Control type	System	Control and optimization objectives
MPC	**Conventional household and small cooling system**	**Multi-Objective:** ● Daily cooling cost, PPDmax, PPDmean, DHshrae. ● The goal of MPC is to choose the water valve position so that a weighted combination of comfort violation and energy usage is minimized over a prediction horizon *N*. **Single-Objective Energy consumption:** ● Searches the optimal cooling power set-points for the FCU in the prediction horizon using an objective function. ● The MPC controller has the goal of determining a binary control output (ON/OFF). ● Reducing the electricity taken from the grid by a multi-energy system. **Single-Objective Thermal Comfort:** ● Minimizing the error between the predicted mean air temperature and the reference temperature. **Single-Objective System efficiency:** ● Achieving optimal energy efficiency in air conditioning systems with high prediction accuracy. ● AI-based MPC determined the optimal charging and discharging rates of the TES system. ● Optimizes the cooling supply of inverter ACs. ● Guarantee the response speed. ● Set the cooling tower's condenser water outlet temperature and the chiller' s chilled water outlet temperature as the system control variables. ● To determine a sequence of control moves so that the predicted response moves to the set point in an optimal manner.
	Large central air conditioning system	**Multi-Objective:** ● To minimize cooling energy consumption and deviation of indoor PMV from thermal neutrality. ● Annual building energy consumption and PPD are chosen to be the first and second objective functions, respectively. **Single-Objective Energy consumption:** ● The real-time optimal control of the HVAC system can be formulated to minimize the total power of the systems. **Single-Objective System efficiency:** ● To regulate the switching pattern of the chillers in order to provide cooled water to the users. ● To minimize the opening level of the bypass valve. ● The steady-state targets required to solve the constrained optimal control problem.
	New refrigeration system and other refrigeration methods	**Multi-Objective:** ● The optimization problem is to minimize a weighted sum of the multiple objectives of energy consumption, peak power and comfort violations with some weight. **Single-Objective Energy consumption:** ● By coordinating the power consumption from the fan, pump, and chiller, MPC leads to the minimum total power consumption while maintaining the same room temperature. ● Coordinating the operation of many HVAC units to reduce the electricity cost while limiting the peak aggregate power demand. ● Minimizing carbon dioxide emissions and energy consumption of system. **Single-Objective Thermal Comfort:** ● Harnessing the spatial differentiation of the thermal environment to satisfy the different temperature preferences of the individuals. **Single-Objective System efficiency:** ● Determining a trajectory of all RTU stages for a relatively short prediction horizon. ● To minimize power consumption and wear of the compressors, and to provide the desired cooling capacity.
MFPC	/	**Multi-Objective:** ● Minimizing energy consumption cost while maintaining the users' comfort. **Single-Objective Energy consumption:** ● Obtaining the best energy-saving effect. ● Load shifting in a cooling supply system. **Single-Objective System efficiency:** ● To optimize cooling towers, cooling water pumps, and chillers. ● Predict flow rates and exert control. ● To find the optimal subcooling. ● To offer an alternative to the buildings whose accurate system performance models are not accessible due to the lack of data or sensors. ● Overcome the high-dimensional state and action space problems of the data center energy optimization.

Utilizing MFPC technology, specific cooling system components like smart valves and agent control programs can be optimized to achieve overall energy conservation. MFPC is also used in operational optimization, adopting methods like Deep Deterministic Policy Gradient to reduce energy costs while maintaining user comfort. These model-free methods rely on reinforcement learning and its derivatives, reducing energy consumption or costs by enhancing operational control modes. The selection and optimization of control points are crucial. For example, adjusting the condenser's inlet and outlet temperatures directly affects cooling system performance. More research focuses on applying new reinforcement learning algorithms in cooling systems, combining multi-agent strategies to

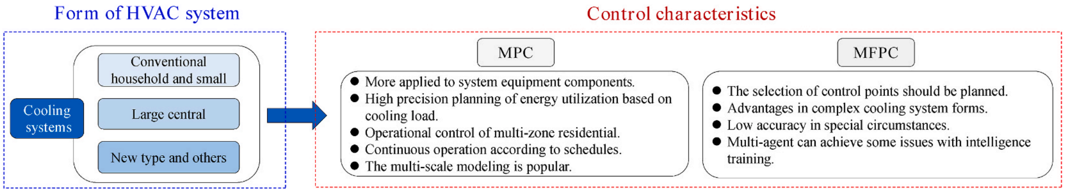


Fig. 28. Main characteristics of cooling system under two control strategies.

improve data processing accuracy and agent training, enhancing the efficiency and reliability of model-free predictive control (Fig. 28).

4.3.2. Heating systems

MPC is widely used in heating systems to address complex hydraulic and thermal balance issues in central heating systems and renewable energy composite systems. Its main objectives are reducing energy consumption, improving energy efficiency, and maintaining indoor thermal comfort. Control strategies typically consider heating temperature, auxiliary heat source operation, stable indoor temperature, and energy consumption. Compared to cooling systems, heating systems focus more on utilizing different user terminals (secondary network side of central heating) as the subject of control research. MPC has become important by dynamically adjusting temperature set points to meet user comfort requirements (Table 3).

As heating systems integrate more with renewable energy, research focuses on constructing accurate dynamic models for hydrothermal balance, ensuring supply-demand balance, reducing energy consumption, and addressing renewable energy volatility. To tackle these challenges, researchers conduct in-depth analyses from the following perspectives.

1. Developing advanced modeling techniques to describe the dynamic characteristics of buildings and heating systems, integrating data-driven methods with machine learning. These techniques leverage historical data, sensor information, and predictive modeling to enhance control precision and achieve hydraulic and thermal balance.

Table 3
Control and optimization objectives heating system.

Control type	System	Control and optimization objectives
MPC	**Conventional heating system**	**Multi-Objective:** ● Considering the constraints that control room temperature in the building while minimizing energy costs and discomfort. **Single-Objective Energy consumption:** ● The total energy used over the optimization horizon; the total indirect CO_2 emissions over the optimization horizon; the total SPOT price over the optimization horizon. **Single-Objective Thermal Comfort:** ● Maintaining a constant indoor temperature through predictive control of the boiler. **Single-Objective System efficiency:** ● Finding the optimal flow rate of the building thermal inlet. ● To maximize the system COP of the ASHP water heater.
	Heat pumps and renewable energy-related heating systems	**Multi-Objective:** ● Minimizing the overall electrical power consumption of the heat pump compressor and second to track the requested inlet water temperature profile for the radiant-floor building. ● To minimize the total energy cost of the heating, including the cost of backup heater and the fan applied to the system in order to drive air from TES to room at on-peak hours. **Single-Objective Energy consumption:** ● To minimize the electricity cost at the user level. ● Costs of export of electricity and the costs of electricity consumption, minimizes the total costs of energy usage
	Heating terminal-related control	**Single-Objective Thermal Comfort:** ● Optimal indoor temperature regulation is achieved by adjusting the radiators of the central heating system. ● Achieving the optimal temperature control. **Single-Objective System efficiency:** ● The weighted sum of tracking error and control effort.
	New heating system and new control mode	**Multi-Objective:** ● To reduce the Mullion system heating demand and maintain an acceptable overall thermal comfort quality. ● To minimize the total operational cost while maintaining room temperatures within a predefined comfort interval. ● FMPC ensures user comfort and MI-MPC minimizes energy cost. ● The economic nonlinear MPC problem that minimizes the cost of the used energy while ensuring that the provided water temperature is sufficiently high to be able to satisfy the building heating demand.
MFPC	/	● High precision indoor temperature control. ● Power minimization and COP maximization.

2. As the number of users increases, the computational cost of MPC rises significantly. To meet real-time optimization demands, addressing computational complexity in large-scale heating systems becomes a challenge. Researchers propose strategies like subsystem partitioning, communication protocols, and exploring Distributed, Decentralized, and Centralized MPC to optimize system flexibility and adaptability. This allows adaptation to different heat sources, conditions, seasonal variations, and user needs.
3. Exploring strategies for integrated control of cross-regional and building heating systems to optimize energy efficiency and system performance.
4. Combining clean heating trends with renewable energy and low-carbon technologies to develop a more efficient and eco-friendlier MPC framework. This framework addresses fluctuations from renewable energy, enabling efficient integration and utilization within MPC control.

Researchers explore model-free algorithms based on deep reinforcement learning and multivariable extreme optimization control to achieve precise control of water supply temperature and cascade heat pump efficiency in heating systems. These model-free methods involve multiple control points like boilers, heat pumps, and water supply and return temperatures, focusing on the collaborative management of auxiliary heat sources, circulating pumps, and other equipment. Research also focuses on exploring multi-agent model-free methods in building or room temperature control to meet thermal comfort needs of multiple spaces and address issues like modeling complexity, high computational cost, and unstable communication. Additionally, there is currently little research on model-free methods for heating terminals (Fig. 29).

4.3.3. Integrated system, ventilation system, and others

The main research areas in MPC include strategies for BEMS, addressing challenges in renewable energy systems, managing multiple energy points within integrated energy systems, pairing MPC with ventilation systems, and implementing MPC in special spatial systems. Scholars are currently focusing on the following key points (Table 4).

1. Research on complex HVAC systems focuses on using MPC to improve operational modes, including automatic adjustment, reducing energy consumption, optimizing thermostat settings, and exploring multi-objective cost functions. Additionally, combining MPC with advanced technologies like Bayesian optimization, economic performance evaluation, and reinforcement learning addresses system complexity and enhances control accuracy.
2. Building Energy Management Systems are crucial for reducing overall building energy consumption, ensuring thermal comfort, and improving energy efficiency. Scholars focus on optimizing hierarchical management methods for energy use, using exergy principles to establish an MPC framework. These studies involve control points like indoor temperature, energy supply, load management, and window shading, emphasizing coordination, data integration, and multi-objective optimization tools.
3. In renewable energy-based HVAC systems, MPC optimizes energy flows in building energy storage and micro solar power generation systems. Integrating MPC with renewable energy is a research hotspot, facilitating seamless integration and optimization of various sources. Exploring the synergy between demand response programs and MPC, and studying two-way energy exchange between renewable systems and the grid, can enhance grid stability and energy sharing.
4. In district energy or centralized HVAC systems, centralized and distributed MPC methods are widespread. Studies show MPC applications in various scenarios, such as predictive control for district energy systems, coordinated control of building services, and distributed adaptive control of multi-zone HVAC systems. MPC effectively manages multiple energy sources through hierarchical decomposition and hybrid strategies, achieving efficient energy use. Additionally, MPC can predict and manage the randomness of energy sources, optimizing energy scheduling and storage to enhance stability and reliability. Researchers are exploring the modeling and optimization of multi-energy systems, considering human behavior and equipment operation to address energy randomness and uncertainty.
5. Ventilation systems focus on regulating indoor air quality. Researchers predict indoor pollutant concentrations using physical building models to optimize control points. MPC technology integration optimizes multi-zone demand-controlled ventilation. Important research directions include adaptive and self-learning MPC techniques, integrating advanced sensors, energy-saving ventilation strategies using building thermal inertia, and human-centered control methods. In special situations, such as enclosed vehicle spaces or personalized space conditioning, MPC optimizes local conditions to enhance comfort and save energy.

Researchers in MFPC focus on integrating various HVAC system controllers, improving operation through model-free control and automatic grading strategies. In building energy management systems, they manage power consumption and load shifting with model-free control. Ventilation systems and building thermal performance involve online optimization for air balancing and window control.

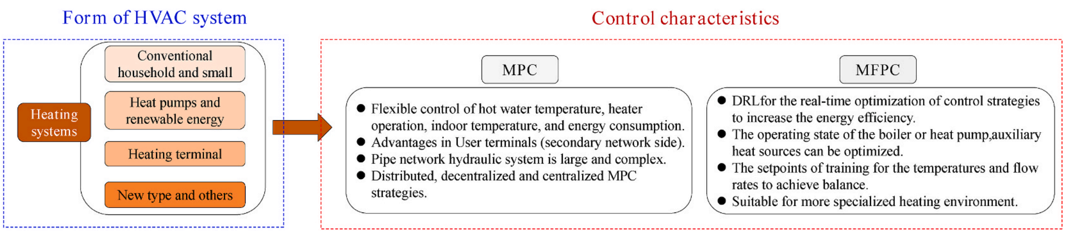


Fig. 29. Main characteristics of heating system under two control strategies.

Table 4
Control and optimization objectives integrated system.

Control type	System	Control and optimization objectives
MPC	**Conventional integrated HVAC system**	**Multi-Objective:** ● Minimizing the electricity cost and the occupant thermal discomfort under uncertainty. ● Optimize the operating cost for space heating (OC) and the thermal comfort, quantified by the predicted percentage of dissatisfied (PPD). ● Reduce energy consumption and save operation cost by EMPC. **Single-Objective Energy consumption:** ● To minimize the system power consumption by both minimizing the system cooling supply and maximizing the system operation efficiency. ● Reduce the energy consumption of air handling units (AHU) by applying optimal control. ● To minimize the electrical energy consumption of the building HVAC system equipped with the MicroCSP. **Single-Objective Economic:** ● Reducing the operating costs based on the local Time-of-Use (ToU) utility structure. ● To minimize the HVAC energy cost of the building considering a time-of-use electricity rate structure. ● Minimizes the electricity related costs, the thermal demand introduced from the airside components to the waterside. ● Load shifting and cost savings. **Single-Objective Thermal Comfort:** ● Minimize thermal discomfort and running time. ● The control goal is to minimize this closed-loop average cost and achieve constraint satisfaction. ● Minimize the peak load for the neighborhood by leveraging the physical differences and individual preferences between houses. **Single-Objective System efficiency:** ● A time-varying model predictive control (TV-MPC) controller was used to optimally select the AIS mode. ● The objective of the MPC controller is to track the temperature Set points without violating the constraints. ● A new design strategy is used to calculate the sub-optimal solution to reduce the computational workload. ● Maximize the efficiency of equipment operation and ensure the feasibility of operation. ● Better control capability and lower system latency to achieve optimal switching of control modes. ● Make up for the shortage of linear control, obtain more accurate control effect, improve control performance. ● Multi parametric model predictive control (mpMPC): improved energy usage with an acceptable relaxation in thermal comfort. ● Solving a dynamic scheduling problem in the slow time scale.
	Building energy management systems	**Multi-Objective:** ● Trade-off between electricity expenses and thermal comfort. ● To maintain optimal energy consumption of the AC while enhancing occupants' comfort. ● Minimizing energy use and thermal discomfort for the building. ● To minimize the exergy destruction of the energy system. At the same time, the hot and cold forward flow temperatures of the energy system should be within a certain temperature interval. ● To minimize the energy consumption while maintaining a thermally comfortable environment for occupants. ● To manipulate the building inputs such that required comfort criteria are kept within the range while the total amount of used energy is minimized. ● A trade-off between energy savings and user welfare. **Single-Objective Energy consumption:** ● Minimizing the energy consumption cost of the building for entire time horizon. ● The energy consumption for a room heating/cooling, ventilation air heating and Propulsion. ● To minimize energy use, while maintaining a temperature of 23 °C in the building during occupied hours. ● Minimizing the peak airflow would dramatically reduce fan energy consumption. **Single-Objective Economic:** ● Reduce the peak-valley load difference and minimize the operating cost of the UC. ● Minimizing operational costs. ● Minimizing comfort boundary violations, peaks in power demand and total electricity costs. **Single-Objective Thermal Comfort:** ● The new agent can consistently better manage the indoor temperature, this agent is not computationally costly to implement. ● The minimum optimal horizon required, related to the thermal inertia of the building, change the internal temperature in cases of comfort band change or temperature setbacks. ● Minimizing comfort boundary violations, peaks. **Single-Objective System efficiency:** ● The demand-side control utilizing thermal inventory is to minimize the HVAC operating cost for the planning horizon.

(*continued on next page*)

Table 4 (*continued*)

Control type	System	Control and optimization objectives
	Composite renewable energy systems	**Multi-Objective:** ● The optimizer decreases the exergy destruction in the building while increasing the exergy recovered in the ORC, along with meeting comfort and system constraints. ● Minimizing energy costs, while maintaining the optimal environmental comfort in the house. **Single-Objective Energy consumption:** ● To exploit the thermal dependency of building zones, and to find the optimal thermostat setpoints and BES power commands to reduce peak load demand in the building. **Single-Objective Economic:** ● The system hopes to operate under off-grid conditions and minimize interactions with the grid. ● To increase the PV self-consumption in such a way that the daily net electricity cost has to be minimized. **Single-Objective System efficiency:** ● Maximizing the passive operation of HVAC in a novel low-energy building design. ● To increase the amount of useful heat and reduce PV overheating.
	Regional energy systems and centralized systems	**Multi-Objective:** ● To minimize the electricity costs given by a time variable electricity price while ensuring the OTS. ● The MPC scheme calculates the optimal temperature setpoint required for each Air-Handling Unit (AHU) to minimize its overall cost or carbon usage, while ensuring thermal comfort of occupants. ● To meet the working condition within the global limit on supply air mass rate, reduce the operating cost of HVAC, and maintain a comfortable temperature for occupants. **Single-Objective Energy consumption:** ● The optimization objective to be the weighted sum of heating, cooling and fan energy consumption. ● To shift the heating and cooling load of a house to off-peak hours. **Single-Objective Economic:** ● To minimize the expected total forecast cost of the system and satisfy the constraints under all scenarios over the prediction horizon. **Single-Objective Thermal Comfort:** ● Effectively regulate zone temperature by applying on-line learning and assuming exchange of information between neighboring zones. **Single-Objective System efficiency:** ● The energy generation, the storage devices, and the controllable loads are managed simultaneously to improve the performance of the microgrids without losing thermal comfort. ● Optimizing the operation of the hall' s HVAC system for enhanced energy use and indoor environment quality, as well as for providing occupancy profile recommendations to aid the facilities' managers in handling their operation.
	Ventilation is the dominant HVAC system	**Multi-Objective:** ● To maintain indoor air temperature and CO2 concentration within the predefined comfort range while optimizing energy efficiency by controlling automated windows in a naturally ventilated room in winter. ● The main objective is to maintain good IAQ for each zone while minimizing energy consumption of the ventilation system. ● To identify the optimal air exchange rate at each time step, that minimizes the energy consumption of the DVS and maintains the indoor pollutant concentrations at their respective desired set points. ● The best energy saving performance and occupant satisfaction.
	Special space: personal space, vehicle environment	● To condition a person directly by generating a microclimate around the body through the use of local conditioning actuators considering the respective individual' s preference. ● To control the compressor power and fan speed and achieve the precise control of cabin temperature and energy saving. ● To balance both the short-term and long-term thermal comfort and energy consumption by simulating on a multiple-step time horizon.
MFPC	/	**Multi-Objective:** ● DRL can adapt to diverse changes in the system it controls on both the demand and the supply side. ● Achieve peak load reduction and profit maximization for distribution system operators while maintaining user comfort and reducing costs. ● Reduce energy consumption, save power and improve control efficiency through dynamic self-regulation. **Single-Objective Energy consumption:** ● Efficiently adjust the building energy system to reduce energy consumption without affecting thermal comfort. **Single-Objective Economic:** ● More use of natural ventilation. **Single-Objective Thermal Comfort:** ● Meet the requirements of indoor thermal comfort and improve indoor air quality. **Single-Objective System efficiency:** ● Balance the air flow in a ventilation duct system. ● To achieve the DRL control strategy transfer. ● Derive the optimal policy for the DR aggregator to control TCLs. ● Maximizes energy efficiency in real time and handles the outdoor-unit operation during load changes. ● Improve the energy saving rate of air source heat pump system.

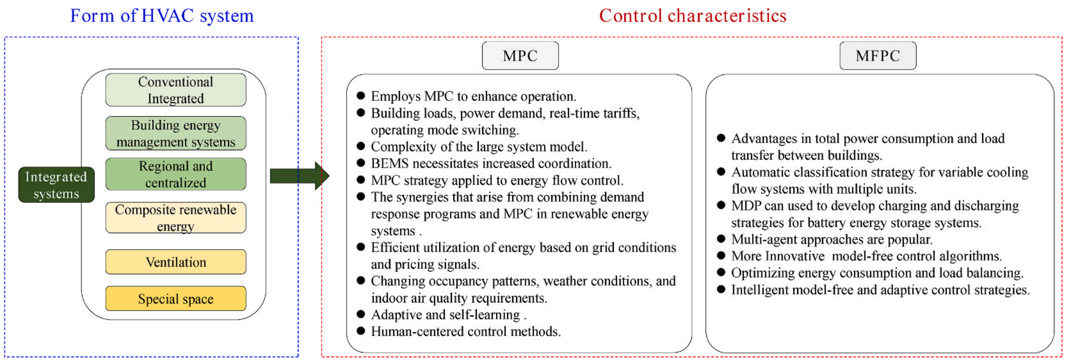


Fig. 30. Main characteristics of Integrated system, ventilation system, and other.

Table 5
Characteristics of predictive control in the HVAC system.

Control mode	Historical data requirement	Computational speed	Calculation time	Labor effort	Degree of recombination with other controls
Model-free	High demand	Fast computation speed	Short computation time	Less	High
Model	Low demand	Computation speed decreases as model complexity increases	Computation time increases as model complexity increases	Less	High
Control mode	**Control effect**	**Historical data requirement**	**The variety of applicable system forms**	**Computing hardware requirements**	**The cost of calculation**
Model-free	★★	★★★	★★	★★★	★
Model	★★★	★	★★★	★★	★★★

Research priorities include multi-agent methods, optimizing model-free control algorithms, and developing model-free adaptive control strategies (Fig. 30).

4.3.4. Model-free VS model

This paper has identified the characteristics of both model-free and model-based controls in various HVAC systems. This section summarizes the content and refines the main features of the two methods. The following table compares and analyzes their main characteristics (Table 5).

Generally, for HVAC systems lacking sufficient data or certain equipment, the model-free control method is better than MPC due to its online self-learning mechanism with lower data and model requirements. If the system has a high-precision model, rich historical data, online learning capabilities, low complexity, low computational cost, and high hardware configuration, MPC is recommended.

Although MPC has shown maturity and advantages in many applications, its use in HVAC system control still faces challenges. Sensor errors and equipment failures add uncertainty to the control process. For model-free approaches, some research has been practically verified, demonstrating MFPC's advantages, but most studies still lack real-world integration. Any model-free predictive control system requires sufficient learning time to make optimal decisions in different environments. This requirement poses challenges in practical implementation, which can be addressed by building more simulation platforms. These platforms can accelerate the convergence of control algorithms, improve learning accuracy, reduce data collection and sensor errors during training, and expand the interpretability of model-free control strategies.

5. Discussion and prospects

5.1. MPC

Future research should explore the advantages of MPC in the HVAC system and continue to improve and enrich the relevant research content. MPC has superior performance in accurate regional temperature tracking and energy efficiency improvement in an HVAC system. When the point is the controller of indoor air conditioning, researchers can simplify the system with linearization characteristics by using MPC combined with some data-driven models. Using MPC can reach good results, which is insensitive to prediction errors and achieves the best overheating response. In addition, some MPC control strategies can also be used in part of the HVAC system, such as chilled water supply cycle, air-cooled units, and other systems with active cooling capacity, to solve the multi-objective optimization problem. The accuracy of the control model can be further improved by adding more random variables, such as occupancy rate and power consumption. Adding more variables can improve the model's accuracy. Currently, online optimization algorithms based on indoor occupancy rate prediction or other interference factors have been applied to building control systems with wireless sensors, so they can be combined with the MPC model to ensure good MPC performance in an HVAC system in the presence of a variety of dynamic and irregular environmental factors. The research on the identification of many system models is slightly insufficient. In the future, exploring the appropriate model reduction method is possible when the model is complex and the calculation is cumbersome. It can also fully exploit the advantages of MPC and incorporate more training data and more complex models into the MPC of buildings. The robustness and ability of model predictive control will be further improved.

In terms of the physical model, the use of a pure physical white box model corresponding to MPC may not meet the system's real-time requirements due to its particularity. Therefore, it is more meaningful to use the grey box model to establish the MPC development system and study its model accuracy and optimization time. In the future, introducing more black box models or grey box models can further improve the efficiency of system modeling and make up for the high cost of MPC calculation in overly complex systems to a certain extent.

In terms of constraints, the current research on any HVAC system is linear to achieve the boundary limit of system operation, which appears in the form of convex quadratic constraints. In addition, as more derived MPC methods are applied to HVAC systems, other constraint methods must be further explored, such as the chance constraint method used in the SMPC method, to limit the behavior of system dynamics and input variables in the sense of probability.

Regarding optimization functions and objectives, most researchers expressed the minimization of energy consumption in HVAC systems as an objective function that ignores thermal comfort. However, the research considering thermal comfort and the energy consumption is more meaningful, so optimizing the objective function has higher requirements. In addition, if the requirements for energy conservation and carbon reduction are low, it is a good choice to use tracking error to express the objective function. Most of the content involved in the HVAC system has typical nonlinear characteristics. The nonlinear objective function is more complex and increases the calculation time of the optimization algorithm. The objective function of the optimization algorithm plays a vital role in finding the appropriate solution to a given problem and properly defined constraints. The correct expression in the problem ensures less computational work, so researchers should accurately describe the target problem and choose the appropriate optimization algorithm. In the past, linear and quadratic programming techniques were widely used to solve optimization objectives, but various nonlinear techniques such as genetic algorithm, PSO, MILP, and others are widely employed to solve multi-objective objectives. Although different kinds of nonlinear optimization techniques have been widely used, there are still different techniques to be explored, where more advanced heuristic algorithms will appear. Applying them to the HVAC MPC method can further improve system optimization performance.

Regarding the control and prediction ranges, it is important to explore and select the appropriate range and control range. The HVAC system's prediction range should be set long enough to capture transient dynamics. Generally, the control prediction range or sampling time is defined by the behavior and time step of the controlled process. Most of the studies mentioned by the authority show that the sampling time of the HVAC system is generally 5 min to 1 h, and the prediction range is generally 24 h. Some researchers also consider a large sampling time, such as 6 h, and the prediction range is greater than 24 h, such as 48 h and 96 h. Weather forecasts and other climate disturbances are usually updated at an interval of 1 h. The relatively short time step and sampling time used in the optimization process can help MPC adapt to the changes in the HVAC system faster, but the shorter control interval will lead to more intervals within the prediction range and ultimately increase the burden of solving the optimization process.

For some large-scale centralized systems, the control effect deteriorates under extreme weather conditions with the application of MPC. The use of distributed control will also be one of the most popular research methods in the future, and it can save energy consumption compared to the current common control method based on a relay. Similarly, researchers can develop a distributed or decentralized MPC controller for heating systems to independently control each room's heating terminal, which may be more conducive to large buildings than using a centralized controller to control all rooms. Generally, the research work on heating systems focuses more on the consideration of thermal inertia and hysteresis, such as radiant floor heating, urban central heating networks, which includes the occupancy rate that is more difficult to predict, the impact of internal heat revenue, and the adaptive update of multi-room control model over time. It is easy to find the optimal local solution of each subsystem using distributed MPC, where searching for the optimal global solution is worth studying. In this regard, the suboptimal solution is adopted in the above research content. For actual buildings, the proposed suboptimal solution method is challenging to carry out a directional measurement or comparative analysis and has significant limitations. Therefore, in terms of heating, applying the distributed MPC method in reality and its complete experiment are still a gap in the literature, and further testing in actual buildings is important. More research on the performance evaluation and comparison of centralized, decentralized, and distributed MPC control strategies also needs further development.

The use of renewable energy and new air energy heat pump is of great significance for developing energy conservation and emission reduction. In order to give full play to the potential of the MPC strategy, the matching optimization design of the renewable energy storage system is studied, and the overall heating system is optimized according to the solar energy utilization efficiency of photovoltaic panels or solar thermal collectors. In the hybrid renewable energy HVAC system with MPC, exploring its combination with a photovoltaic power supply system will become a future research and development direction. Generally, the photovoltaic system can be divided into an independent photovoltaic system and a grid-connected photovoltaic system, and the two power supply systems apply to different regions. If the selected HVAC system application area contains a municipal grid and has an online revenue policy, grid-connected photovoltaic and HVAC systems will be highly recommended. In addition, the synergy with other flexible energy sources in the building is also essential. For example, the combination of battery storage capacity and photovoltaic grid can be considered to expand the flexibility of supply to meet various challenges in the photovoltaic system. Some researchers plan to expand the municipal power grid to an interactive multi-energy mode using the MPC method and consider the information delay and faults in MPC communication, such as data loss. Therefore, it is significant to investigate and develop a more robust network physical interaction mechanism's MPC method to ensure the safe and economic operation of the hybrid HVAC system. The development of various composite renewable energy microgrid technologies has gradually received the favor of many researchers. The building can be considered an independent microgrid, including an HVAC system, electric vehicles, electrical appliances, wind power generation, and other flexible building loads. In this case, special attention should be paid to the active/reactive power flow to ensure that the power constraints in MPC are met, such as the Micro-CSP system. In addition, there is still a lack of research on applying the MPC method involved in many composite systems in reality. For example, the XMPC controller mentioned above has achieved a good simulation effect, but the real-time demonstration and the experiment on the actual test bench must be performed further [85].

In terms of software development, for implementing some innovative HVAC systems or deriving new MPC strategies using MPC methods in real life, it is necessary to set up corresponding computing equipment locally and distribute the control signals of each system reasonably. In order to achieve this, all data communication facilities and structures should be established, so the corresponding technical barriers and practical problems need to be solved. In building energy management systems, testing the MPC framework in the laboratory environment of existing energy equipment or applying it to experimental research in actual buildings is more significant than that of MPC only for an HVAC system. Therefore, more field studies are needed to determine the uncertainties in the physical models of buildings, systems, and micro-climates, increase the critical predictability methods, and incorporate the measured values and predicted data of various types that are easy to measure into the algorithm or process of MPC formula.

In terms of predictive maintenance, the main goal of implementing predictive maintenance strategies in HVAC systems is to proactively predict when HVAC equipment might fail. The success of this strategy hinges on building accurate failure mode models and predicting their future trends. HVAC system failures can cause significant financial losses for the operation and maintenance departments in the construction industry. Therefore, effectively managing and addressing failure modes through predictive maintenance strategies is crucial for Facility Management and Maintenance (FMM). To ensure efficient building operation and occupant comfort, research and practice in automatic fault detection and maintenance planning for HVAC equipment should be strengthened [290]. Implementing predictive maintenance can effectively reduce equipment downtime, improve system reliability, lower maintenance costs, and extend equipment lifespan [291]. Currently, the application of machine learning (ML) and deep learning (DL) in HVAC failure mode management (FMM) requires further research. Although these technologies have significant theoretical advantages, in practice, the lack of open databases containing building operation data makes constructing predictive maintenance models difficult and costly. Additionally, implementing predictive maintenance often requires substantial time for data collection, model training, and validation. This lengthy implementation process presents significant challenges for facility managers in investment decisions, as these solutions may take a long time to demonstrate economic benefits. In terms of algorithm selection, current practices often rely on the developer's experience, which can increase the variability of prediction results. Using a single predictive method may not achieve ideal prediction results. Therefore, it is recommended to use ensemble learning or hybrid model strategies, combining multiple ML or DL models to improve prediction accuracy and robustness [292–294].

To sum up, according to the researchers' exploration of using the MPC method in various HVAC systems, although different nonlinear optimization technologies have been widely studied or used, their development is still immature. The linear MPC method accounts for most of the current research, so the nonlinear method still needs to be explored and improved. Various new intelligent algorithms can be used in various MPC optimizations for better performance. Using different system forms and proposing corresponding high-precision prediction models is also very important. Further improvement of prediction accuracy will also help improve the MPC's overall performance. The combination of MPC and AI technology can become the future research goal of intelligent buildings, including HVAC systems. With the emergence of many MPC research contents, many types of MPC have been born. Researchers must continue exploring the applicability of various derived new MPC methods in HVAC systems. Indeed, there is room for further exploration and optimization of the design parameters that affect the MPC control scheme in basic research, such as prediction range, control range, and sampling time. Many MPC methods also have certain generality. These methods can be extended to more types of buildings, HVAC systems, and even more extensive fault diagnosis. In addition to applying MPC to the HVAC system of future green buildings, it is also worthwhile to investigate the reconstruction of the HVAC systems in older buildings. Some measures can be taken to modify the existing control algorithm, and MPC can be achieved in older buildings.

5.2. MFPC

Based on the research results of various literature sources, many HVAC systems use the model-free method to save energy and improve the control effect compared to the traditional control methods. However, the model-free control methods proposed in some research contents are not universal, and many reinforcement learning control algorithms have space for improvement. The model-free method is usually processed and iterated discretely, the traditional model-free method, such as Q-learning, is computationally complex, and it is not easy to propose a model-free method with general properties. Therefore, according to the difference in HVAC systems of various users, the agent used in model-free control should be able to automatically switch between different system control modes or learn different set point schedules customized by users to obtain a long control cycle and provide flexible control strategies.

The results of some literature on heat pump heating show that the efficiency of the heat pump system can be continuously optimized in a model-free and cost-effective way, which has great value for the actual operation of the system. When model-free is applied to some special HVAC systems, such as door and window control, natural ventilation can be used as much as possible to adjust indoor thermal comfort and reduce the energy consumption of the air conditioning system, with a significant energy-saving effect. Nevertheless, more indoor-related parameters still need to be introduced to further improve the algorithm.

Most of the research on the system of model-free control is still based on theoretical analyses, where the transformation from simulation to implementation is very complicated. Therefore, more research is needed to further illustrate the advantages of the new model-free method in applying various aspects of the system through experimental verification. Indeed, some research results have been verified in practice and achieved good results. Future researchers are expected to obtain real building data and more accurate quantitative results or integrate more system parameter variables to improve the control system and further tap the significant potential of real-time energy efficiency of model-free control.

To sum up, no matter what form of the HVAC system, the control accuracy of the model-free predictive control method applied by them must be further improved. Intelligent algorithms are developing rapidly; hence, machine learning, reinforcement learning, and deep reinforcement learning will be further improved. In future research, more advanced intelligent algorithms can be introduced to improve the effect of model-free control and the adaptability of the deep reinforcement learning technology's application to the HVAC system. In the model-free method, the value-based method is more suitable for discreteness, while the strategy-based method is more suitable for continuity. Future research can focus on combining the two, but the computational complexity is slightly higher after the combination. Similar to the adaptive method, the control strategy is improved by continuously adjusting the HVAC system training process parameters. In addition, compared to the MPC, the model-free method was more recently introduced as experimental research, where practical application research is a critical topic that researchers must focus on in the future. It is still necessary to enrich the application of various new model-free control methods in actual HVAC systems, reflecting their different application characteristics from MPC.

6. Conclusion

This study introduces the research progress of model predictive control and model-free control in the field of HVAC control strategy over the past 12 years, especially the improved methods of their application in different forms of HVAC systems. The optimal control schemes for efficient energy operation in buildings and their HVAC systems provided in previous papers are classified, and the different predictive control methods used in different system forms are comprehensively analyzed and compared. The main conclusions are as follows.

(1) MPC in cooling systems reduces energy consumption and improves operational efficiency by precisely controlling equipment like cooling towers, condensers, evaporators, and pumps. This makes it particularly suitable for multi-area and residential buildings. To address the increasing complexity of cooling systems, researchers have adopted methods like Distributed MPC and Multi-scale modeling. These methods simplify model optimization and adapt to dynamic changes.
(2) Reinforcement learning and its derivative technologies in MFPC, like Multi-agent Strategies and Deep Deterministic Strategy Gradients, have shown potential to improve cooling system performance, and reduce energy consumption and costs.
(3) MPC is mainly applied in centralized heating systems, focusing on factors like heating temperature and auxiliary heat source control. Research focuses on building accurate dynamic models of water and heat balance, ensuring supply-demand balance, reducing energy consumption, and addressing the volatility of renewable energy. Researchers address these challenges using advanced modeling technology, Distributed MPC strategies, and other methods.
(4) MFPC researchers have explored model-free algorithms like deep reinforcement learning to achieve precise control of multiple points in heating systems. They have also focused on applying multi-agent model-free methods in building or room temperature control.
(5) The application of MPC in integrated HVAC systems involves optimizing operating modes, reducing energy consumption, and adjusting thermostat settings. In Building Energy Management Systems, MPC coordinates and optimizes multiple control points like indoor temperature and energy supply using multi-objective optimization and decision support tools. MPC promotes seamless integration and energy flow optimization of renewable energy in composite HVAC systems, achieving efficient management and scheduling of multiple energy points. Additionally, MPC integrates with ventilation systems to optimize indoor air quality and improve energy system stability and reliability.
(6) MFPC reduces total energy consumption and load transfer, improving system operation through model-free control and automatic grading strategies. Research focuses on multi-agent methods, innovative model-free control algorithms, and developing model-free adaptive control strategies.
(7) Over the past 12 years, MPC methods have been the most popular control strategy in architecture and HVAC. MPC shows significant control accuracy when equipped with high-quality historical data. However, due to high computational costs, MPC is suitable for moderate-sized and relatively simple systems. Model-free control methods achieve lower computational costs and higher local control accuracy but may generate significant errors in special environments. This makes them suitable for complex systems with relatively low control accuracy requirements.

Although MPC has shown significant maturity and advantages in many practical applications, its use in HVAC system control still faces various challenges and difficulties. Limited research exists on the practicality and experimental advantages of MFPC, and it lacks integration with real-world applications. For complex control systems, combining reinforcement learning and its derivative methods with MPC in model-free systems is a key future exploration. In the future, researchers should select the most appropriate control mode according to the specific HVAC system form, application scenarios, functional requirements, and other aspects to obtain the best control performance and meet the requirements of thermal comfort, energy saving, peak load reduction, carbon emissions reduction, and other requirements.

CRediT authorship contribution statement

Xin Xin: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Zhihao Zhang:** Writing – review & editing, Investigation. **Yong Zhou:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Yanfeng Liu:**

Supervision, Project administration, Funding acquisition. **Dengjia Wang:** Project administration, Funding acquisition. **Shuo Nan:** Writing – review & editing, Validation.

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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Appendix A. Supplementary Table

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