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Review

A review of research on intelligent technology in building air conditioning system optimisation

Bo Li [a,b,*], Jonathan Chung Ee Yong [b,*], Lih Jiun Yu [b], Ezutah Udoncy Olugu [c], Xiaoqing Yang [b], Zhiming Zhang [b], Mohammed W Muhieldeen [b,*]

[a] School of Architectural Engineering, Zhejiang Industry Polytechnic College, Shaoxing City, Zhejiang Province, China
[b] Mechanical Engineering Department, Faculty of Engineering, Technology & Built Environment, UCSI University, Kuala Lumpur, 56000, Malaysia
[c] School of Mechanical, Industrial and Aeronautical Engineering, University of the Witwatersrand, Johannesburg, South Africa

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ABSTRACT

The Sustainable Development Goals (SDGs) aim to enhance cities and communities more comfortable, safe, and environmentally friendly. The SDGs state that the construction sector should take a low-carbon and sustainable development path. During the operation phase of buildings, the energy consumed by air conditioning systems makes up approximately 22 % of the overall energy consumption of a building. The optimisation of the air conditioning operation control strategy is significant for saving energy and cutting emissions. However, a building air conditioning system is a complex system with multiple parameters, nonlinearity, time variance, and multiple objective values. Traditional air conditioning control methods cannot meet the complex needs of energy saving and comfort improvement in a dynamic environment. Currently, many researchers are studying intelligent technologies for optimising building air conditioning systems. This literature review categorises the relevant articles in this field in recent years, discusses the aspects of optimisation of control methods and the application of intelligent technologies, and focuses on the analysis of the characteristics of various intelligent technologies such as Model Predictive Control, Machine Learning, Deep Learning, and intelligent optimisation algorithms, and their advantages in the domain of optimising control for building air conditioning systems.

1. Introduction

Energy preservation and pollutant reduction are crucial matters confronting nations globally. The SDGs espouse a commitment to the global promotion of environmental protection, including energy saving and emission reduction, and their 11th objective advocates enhancing energy efficacy and comfort within buildings (Di Foggia, 2018). Technologies such as the Internet of Things (IoT), Cloud Computing (CC), Big Data (BD), and Artificial Intelligence (AI) are used to create green, efficient, and economical buildings and environments. New technology has played an ever-more important role in the achievement of SDGs, and SDG-11 states the requirement to “Make cities and communities more comfortable, safe, and environmentally friendly” (Sengupta and Sengupta, 2022).

The entire life cycle of buildings includes four stages: production of materials, construction, operation, and demolition. It is calculated that buildings account for 30 to 40 % of the consumption of primary energy and are responsible for 40 % of the greenhouse gas emissions that lead to global warming. Additionally, the energy consumed during the operation phase makes up approximately 85 % of the total energy utilised throughout the life cycle of a building (Minde et al., 2023). Carbon emissions during the building operation stage mainly include indirect emissions from the electricity consumption of various building facilities and equipment, such as lighting, air conditioning (AC), heating, and water pumps. AC systems constitute 40 %–60 % of the energy utilisation within buildings (Asim et al., 2022).

The optimisation of an AC control strategy can remarkably enhance energy effectiveness and fulfil energy-conservation targets. An AC system in a building is a complex, nonlinear, time-varying system with multiple parameters and objectives (Sun et al., 2022). Different areas have varying temperatures, humidities, and ventilation needs, while external factors such as outdoor temperature, humidity, wind speed, and sunlight influence the indoor environment. Changes in occupancy, equipment, and heat sources further cause dynamic shifts in indoor loads, with many parameters being coupled and delayed (Zhao et al., 2022). Traditional AC system design and AC control face several issues:

* Corresponding authors.
E-mail addresses: 740123553@qq.com (B. Li), jonathanyong@ucsiuniversity.edu.my (J.C.E. Yong), al-gailani@ucsiuniversity.edu.my (M.W. Muhieldeen).

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Nomenclature

Acronyms

ABC	Artificial Bee Colony
AC	Air Conditioning
ACB	Active Cold Beam
ACO	Ant Colony Optimisation
AHU	Air Handling Unit
AI	Artificial Intelligence
ANN	Artificial Neural Network
AQ	Air Quality
BB-BC	Big Bang-Big Crunch optimisation algorithm
BD	Big Data
BDA	Big Data Analysis
BEM	Building Energy Model
BIM	Building Information Modelling
BMS	Building Management Systems
CAC	Central Air Conditioning
CC	Cloud Computing
CFT	Comfort
CHAID	Chi-square Automatic Interaction Detection
CNN	Convolutional Neural Network
CSA	Cuckoo Search Algorithm
CSI	Channel State Information
DCS	Distributed Control System
DD	Data-Driven
DDPG	Deep Deterministic Policy Gradients
DL	Deep Learning
DM	Data Mining
DMPC	Distributed Model Predictive Control
DNN	Deep Neural Network
DPC	Data-driven Predictive Control
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
DT	Digital Twin
DTR	Decision Tree Regression
DX	Direct eXpansion
EC	Energy Consumption
EFF	Efficiency
ETM	Event-triggered Mechanism
FA	Firefly Algorithm
FCM-ANFIS	Fuzzy Clustering ANFIS Model
FLC	Fuzzy Logic Control
FNN	Feedforward Neural Network
FPGA	Field Programmable Gate Array
GA	Genetic Algorithm
GMDH	Grouped Method of Data Handling
GSA	Gravitational Search Algorithms
GWO	Grey Wolf Optimisation
HP	Heat Pump
HVAC	Heating, Ventilation, and Air Conditioning
IASO	Improved Alpine Skiing Optimisation
IEQ	Indoor Environment Quality
IGPSO	Improved Global Particle Swarm Optimisation
IOA	Intelligent Optimisation Algorithm
IoT	Internet of Things
IntelTech	Intelligent Technology
KNN	K-nearest Neighbours
LHS	Latin Hypercube Sampling
LSTM	Long-Short-Term-Memory
MFNN	Multi-layer Feedforward Neural Network
MIMO	Multi-Input and Multi-Output
ML	Machine Learning
MLPANN	Multilayer Perception Artificial Neural Network
MOGA	Multi-Objective Genetic Algorithm
MOIP	Multi-Objective Integer Programming
MOPSO	Multi-Objective Particle Swarm Optimisation
MPC	Model Predictive Control
NN	Neural Network
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PCA	Principal Component Analysis
PID	Proportional Integral Derivative
PMV	Predicted Mean Vote
PSO	Particle Swarm Optimisation
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SDGs	Sustainable Development Goals
SL	Supervised Learning
SSL	Semi-Supervised Learning
SVM	Support Vector Machine
SVR	Support Vector Regression
TC	Thermal Comfort
TIEO	Tribal Intelligent Evolutionary Optimisation
USL	Unsupervised Learning
VAV	Variable Air Volume
WO	Whale Optimisation Algorithm

i. Systems are often over-designed, but inefficient most of the time.
ii. AC systems operate at constant loads without adjusting to actual demands.
iii. Real-time monitoring and feedback mechanisms are lacking.
iv. Response to environmental changes is slow, limiting adaptations to internal and external load variations.
v. AC systems operate independently, lacking integration with lighting and ventilation systems.
vi. AC systems cannot predict future demand or adjust operations in advance.

Intelligent technology addresses these difficulties by facilitating self-awareness, acquisition of knowledge, decision-making, implementation, and accommodation. Adjusting the set parameters of AC in real time according to the ambient temperature and humidity, light intensity, seasonal changes, and personnel activities, and dynamically optimising the AC operation strategy can avoid unnecessary energy waste. This paper examines the utilisation of diverse intelligent techniques in the control and optimisation of AC systems in buildings, compares the characteristics and applicability of AC systems, and explores the necessity of further combining technologies such as the IoT.

In recent times, intelligent technology has been extensively studied in energy-saving and AC system optimisation. Google Scholar searches using the keyword phrases Building air conditioning, Multi-objective optimisation, Energy saving, Thermal comfort, and Intelligent technology show a steady growth pattern in related publications over the past 20 years with a sharp rise in recent years, as shown in Fig. 1.

Fig. 2 shows the changing trend of the research focus of relevant literature in the past decade. As can be seen from the figure, the application of artificial intelligence technology is on a rapid upward trend and is a hot research object in this field.

The main innovation of this article is that it provides a relatively comprehensive and systematic review of the application of intelligent technology in the field of dynamic multi-objective optimisation of building air conditioning, and specifically discusses the impact of external dynamic factors such as personnel behaviour and occupancy information, extreme weather and power grid fluctuations, as well as the integration of intelligent technology with technologies such as the

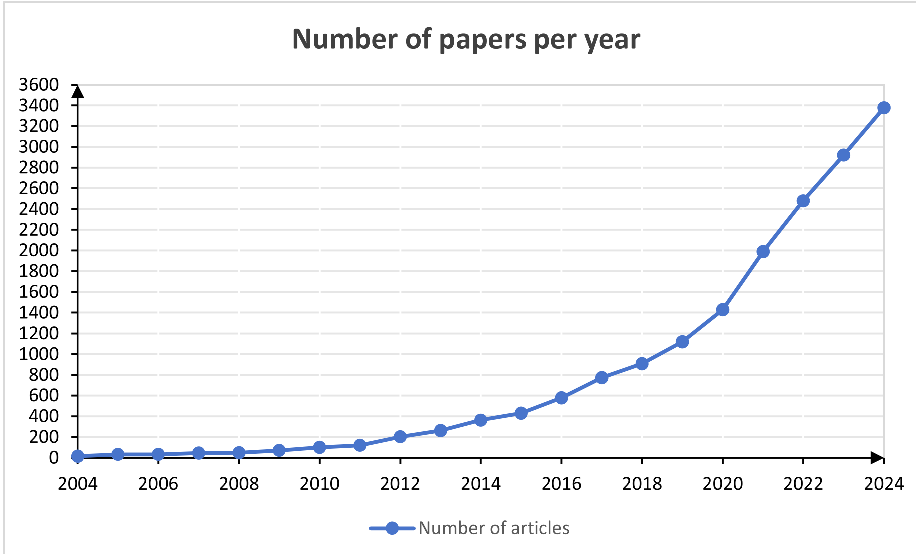

Fig. 1. Number of papers in the field between 2004 and 2024.

Fig. 2. The changing trend of the research focus in the past decade.

Internet of Things and digital twins.

2. Review methodology

This literature review methodically explores the ways in which artificial intelligence is capable of augmenting the thermal amenity and energy effectiveness within the AC systems in buildings. Key terms and phrases include building air conditioning, energy saving, thermal comfort, artificial intelligence, dynamic control, multi-objective optimisation, occupants, and real-time. The search was conducted using databases and platforms such as Google Scholar, Elsevier, ResearchGate, and China National Knowledge Infrastructure.

A total of 257 articles were initially gathered, and after applying specific criteria, 130 articles were selected. The selection criteria were:

i. The research focuses on the AC or heating, ventilation, and air conditioning (HVAC) systems in buildings.
ii. The main topic involves AI applications for energy saving and thermal comfort in AC systems.
iii. The articles include detailed descriptions of the research methods, model design, and data analysis.
iv. The publications are from 2018 to 2025.

Fig. 3 illustrates the article selection process.

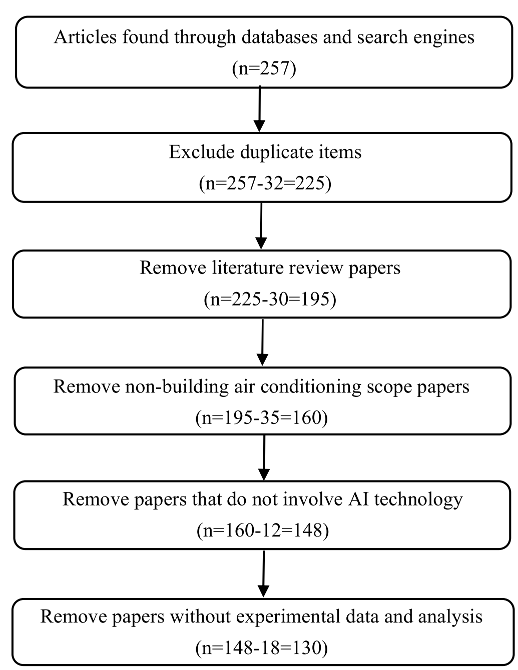

Fig. 3. Diagrammatic representation of the article selection procedure.

3. Results

The AC system in a building mainly includes HVAC and direct expansion systems (e.g., split and window AC). HVAC dominates commercial and public buildings, while split AC is prevalent in the residential market. In energy-saving optimisation research, 60 % of the research is focused on HVAC due to its high energy consumption in large buildings, especially in commercial settings. HVAC systems have multiple subsystems (refrigeration, heating, ventilation, and air treatment), offering more control parameters and optimisation potential compared to simpler split AC systems. This makes HVAC the primary target for energy-saving efforts. Some HVAC systems integrate radiant cooling, variable air volume (VAV) chillers, and dedicated air systems. Nasruddin et al. (2019) incorporated parameters (e.g., thermostat settings, passive solar design, chiller operation control) as decision variables. Qiu et al. (2019) proposed a stochastic optimised chiller operation strategy, as chillers are responsible for nearly 30–40 % of the energy consumption of an HVAC system This article mainly discusses the HVAC systems of commercial buildings with more complex control variables and dynamic parameters. However, for residential split air conditioners, although the control is relatively simple, human activities and occupancy information are relatively important influencing factors, which will be explained in the following chapters. An HVAC system control schematic is shown in Fig. 4.

Energy consumption is the main optimisation focus (96 % of the literature), followed by comfort (58 %), while factors such as investment cost, management efficiency, or air quality have been studied less often. This is because AC is among the systems with the highest energy consumption in buildings, particularly in commercial and public structures. In addition, a comfortable environment is essential for user health and productivity. Kawakubo et al. (2023) discovered that productivity for men peaked in neutral to somewhat cooler conditions, while productivity for women was the highest in neutral to somewhat warmer conditions. All of these factors have led research to prioritise balancing energy use and comfort.

With the rise of technologies, such as computers, Big Data (BD), IoT, and AI, new approaches are transforming traditional building energy management, especially in AC energy-saving and optimisation control. Active, dynamic, and intelligent methods are replacing the old passive, static, and broad control strategies. The utilisation of machine learning (ML) or deep learning (DL) for the modelling of intricate AC systems, optimisation with heuristic algorithms, and the integration of IoT and digital twin (DT) technologies to enhance real-time performance and efficiency are key trends in this field. Halhoul Merabet et al. (2021) indicated that the employment of AI methods and individualised comfort models led to an average energy reduction ranging from approximately 22 % to 44 %, along with an average comfort enhancement varying from approximately 22 % to 88 %. In the next section, we provide a comprehensive discussion of the utilisation of diverse intelligent techniques in the field of AC control and optimisation for buildings. Fig. 5 summarises the distribution of research objects in the reviewed literature.

4. Analysis and discussion

The discussion in this section mainly starts from three aspects: the discussion of control methods, the application of intelligent technology, and the analysis of the impact of dynamic factors. Fig. 6 shows the content structure of this section.

4.1. Building AC control methods

Building AC control methods conventionally encompass five principal approaches: constant temperature regulation, proportional-integral-derivative (PID) control, fuzzy logic control (FLC), distributed control systems (DCS), and model predictive control (MPC). Contemporary analyses typically classify constant temperature regulation as obsolete in modern applications due to its characteristically high energy intensity and suboptimal thermal comfort outcomes. While PID, FLC, and DCS remain operational in legacy systems, these conventional strategies exhibit limitations in addressing the dynamic complexities of contemporary building energy management, particularly regarding adaptability to stochastic occupancy patterns and transient environmental conditions. In contrast, MPC has emerged as the predominant paradigm for advanced applications, demonstrating superior dynamic optimisation capabilities and adaptability to time-varying operational constraints.

4.1.1. Traditional control methods

(i). PID Control

PID control is widely used to adjust an AC temperature to a set target value, consisting of three parts: proportional (P), integral (I), and differential (D). The total output is:

$$u(t) = K_p \times e(t) + K_i \times \int e(t)dt + K_d \times \frac{de(t)}{dt} \tag{1}$$

where K_p is the proportional coefficient, K_i is the integration coefficient, K_d is the differential coefficient, and e is the current error. K_p needs to balance the response speed and actuator saturation to avoid frequent start and stop leading to increased energy consumption, K_i needs to suppress integral saturation, and K_d needs to cooperate with low-pass filtering to weaken the influence of noise and time lag.PID control

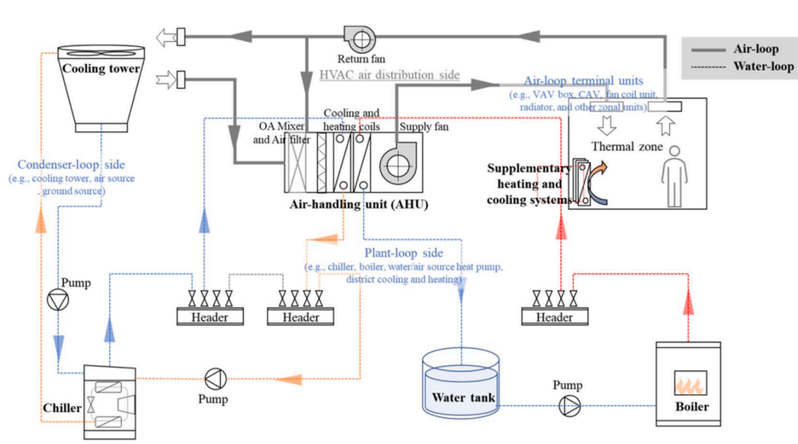

Fig. 4. HVAC system control schematic (Dongsu et al., 2022).

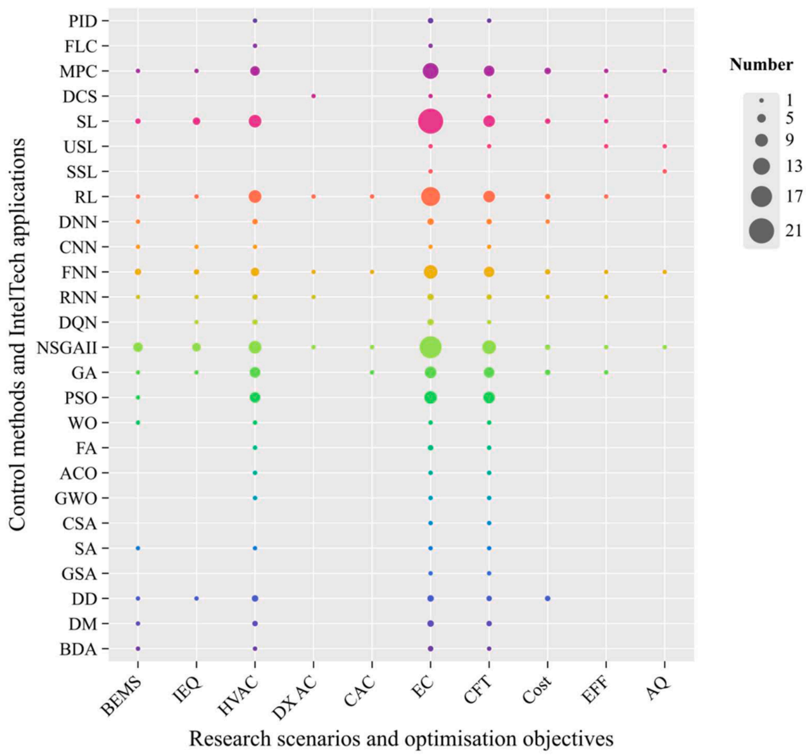

Fig. 5. Distribution of research objects.

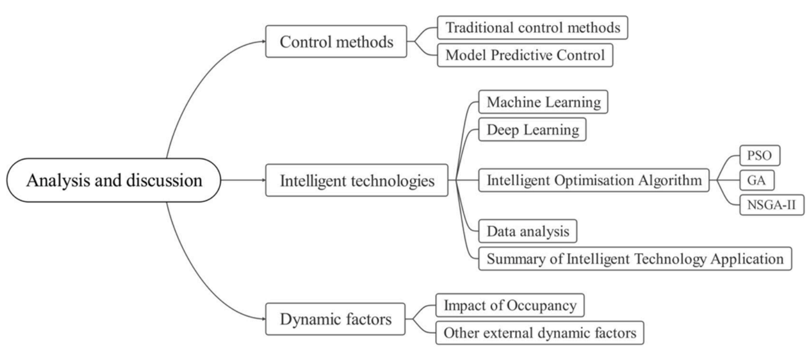

Fig. 6. Content structure of this section.

boasts the merits of a straightforward structure, rapid response, and convenient implementation.

Due to the nonlinear and time-varying characteristics of AC systems, it is challenging to tune PID controllers for optimal tracking performance. Researchers have explored parallel processing and gradient calculation methods to improve the processing speed and efficiency of PID control. Field programmable gate array (FPGA) technology combining the Big Bang-Big Crunch (BB-BC) optimisation algorithm was used to accelerate PID parameter tuning, leveraging the efficiency of FPGA parallel processing (Almabrok et al., 2018). Homod et al. (2020) used a virtual building simulator with automatic PID tuning that combined Deep Deterministic Policy Gradients (DDPG) to find optimal control parameters.

(ii). Fuzzy Logic Control

Fuzzy logic control (FLC) employs the fuzzy set principle, verbal variables, and fuzzy logic inference to obtain precise control through a series of imprecise adjustments based on prior knowledge. FLC is well-suited for handling nonlinear systems and complex environments without a requirement for exact mathematical models. However, similar to PID control, FLC adjusts reactively, making it less effective for systems with significant delays such as the AC in a building. Combining FLC with predictive control can improve performance. Hang and Kim (2018) proposed an enhanced MPC system using FLC and incorporating the Predicted Mean Vote (PMV) index and outdoor IoT data to develop control rules.

(iii). Distributed Control System

Distributed control system (DCS) for the AC in a building involves dividing the building into multiple independent zones, for which each zone's controller autonomously adjusts the AC equipment (e.g., fan coil devices and adjustable air volume systems) based on local conditions and needs. Li and Wang (2020) recommended a decentralised system built on multiple intelligent agents for the optimisation of multi-zone ventilation, breaking down complex optimisation into simpler sub-problems to improve the system's scalability, reconfigurability, and robustness. Ma et al. (2022) proposed a distributed control with priority coordination for a multi-zone HVAC system, transforming the optimisation problem into a consensus problem for fully distributed operation. Li et al. (2021) developed a multi-agent distributed optimisation scheme that resolves the target problem through decentralised computation, enabling deployment of local control devices with limited processing capacity. DCS enhances system flexibility, reliability, and efficiency but comes with high initial setup costs and complex system structures.

4.1.2. Model predictive control

Model predictive control (MPC) utilises the mathematical model of a system to forecast the future behaviour of the system and creates current control actions according to these forecasts. The prediction time domain is set to *N* steps, the control input is set to *u(k)*, the system output is set to *y(k)*, and the reference value is set to *r(k)*. MPC determines the control input by solving the following optimisation problem:

$$\min_{u(k),\dots,u(k+N-1)} \sum_{i=0}^{N-1} \left[(y(k+i) - r(k+i))^2 + \lambda \cdot u(k+i)^2 \right] \quad (2)$$

In the expression, λ is the weight parameter of the control input, which is used to balance the output error and the size of the control input. N is the prediction horizon, the step size for predicting future system behaviour.

MPC can handle multiple input and output variables at the same time and is suitable for complex systems with multiple variables and multiple objective values such as building air conditioning systems. IoT technology has been used to provide real-time variable data for MPC systems for real-time control (Carli et al., 2020). Yang et al. (2018) developed a multi-objective MPC controller with a runtime of less than 0.1 s per optimisation, making it suitable for real-time BAC applications. Ma et al. (2021) proposed a collaborative technique of distributed model predictive control (DMPC) for the management of an air handling unit (AHU) and variable air volume (VAV) boxes within multi-zone constant temperature and humidity systems. Shao et al. (2023) presented an economical and practical MPC algorithm for DX A/C systems. Du et al. (2022) proposed a multi-region building energy-saving MPC based on multi-objective optimisation and built a large full-link control model from the demand and application layers to the control layers. In addition to energy consumption and comfort, MPC is used to predict and optimise other objective values such as the real-time dynamic electricity tariffs in smart grids by means of the frequency-dependent MPC approach (Hu et al., 2019).

The literature shows that MPC effectively addresses the issue of large hysteresis in AC systems, with researchers noting shorter response times, improved real-time performance, and faster control frequency. This can be verified through a simple experimental model that simulates PID and MPC in MATLAB. As shown in Fig. 7, the PID controller exhibits significant overshoot and slow convergence, while the MPC controller has minimal overshoot, faster stabilisation, and overall better performance.

Jing et al. (2021) combined load forecasting and delay characteristics and used the TRNSYS-MATLAB joint simulation platform to verify the effectiveness of MPC in timing matching and energy consumption optimisation. Compared with traditional feedback control and fuzzy feedforward strategy, its summer energy consumption was reduced by 9.56 % and 5.30 %, respectively, and the winter energy consumption was reduced by 7.75 % and 2.61 %, respectively. Jing et al. (2022) quantified the startup process delay time (SPDT) and the integrated delay time (IDT) during operation, dynamically adjusted the prediction interval and rolling optimisation step of MPC, and constructed a short-term load forecasting model based on delay compensation. Compared with the traditional constant temperature control and PID methods, the energy consumption was reduced by 14.89 % and 8.51 % respectively. Zhang et al. (2018) developed a MPC-based temperature regulation framework, specifically designed for real-time optimisation, which demonstrated a 18.2 % reduction in energy consumption compared to PID control strategies. Yang et al. (2020) developed a novel MPC to coordinate multiple cooling coils, achieving 18 % electricity savings compared to a conventional feedback-control-based building management system (BMS). Combining MPC with IoT and leveraging real-time data for optimisation can further enhance system responsiveness.

From the literature review results, it can be seen that 37 articles attempted to optimise the control method. The distribution of the methods discussed in these articles is shown in Fig. 8.

As shown in Fig. 8, optimisation research based on the MPC method has been in a dominant position in recent years for two main reasons:

i. Ability to handle MIMO systems

While PID control is simple, it is unsuitable for multi-objective optimisation in complex Multi-Input and Multi-Output (MIMO) systems such as AC systems for buildings. MPC, by contrast, optimises multiple objectives and handles MIMO complexity.

ii. Prediction capability

AC systems for buildings have significant time-varying and hysteresis characteristics. For example, temperature changes occur with a delay after adjustments. PID and FC rely on ‘post-feedback’ adjustments, which require waiting for results before the next action. With rolling updates, dynamic prediction, and advanced optimisation, MPC effectively manages the time-varying and hysteresis features of AC systems for buildings.

4.2. Application of intelligent technology

Intelligent technology (IntelTech) encompasses AI, machine learning, data analysis, and other advanced computing methods to enable automation, optimisation, and intelligent decision-making. The literature review highlights the significant role of IntelTech in AC optimisation control for buildings, making it a prominent research focus in the field of multi-objective AC system optimisation. Fig. 9 summarises the IntelTech components relevant to AC system optimisation for

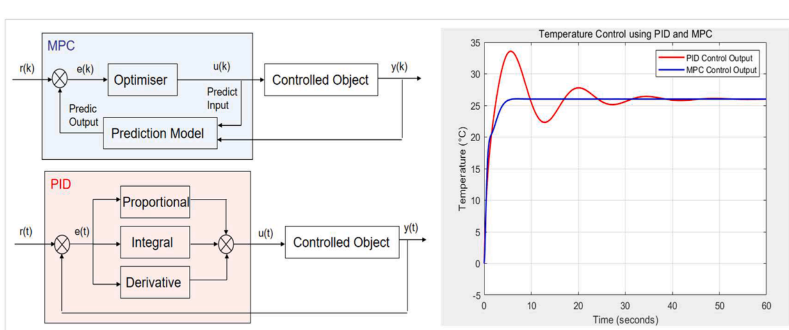

Fig. 7. Comparison of simulation results for MPC and PID controllers.

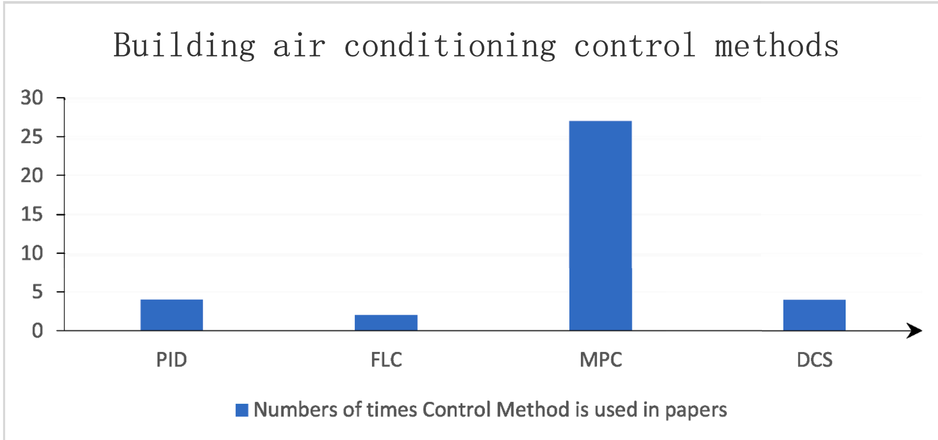

Fig. 8. The distribution of building AC control methods.

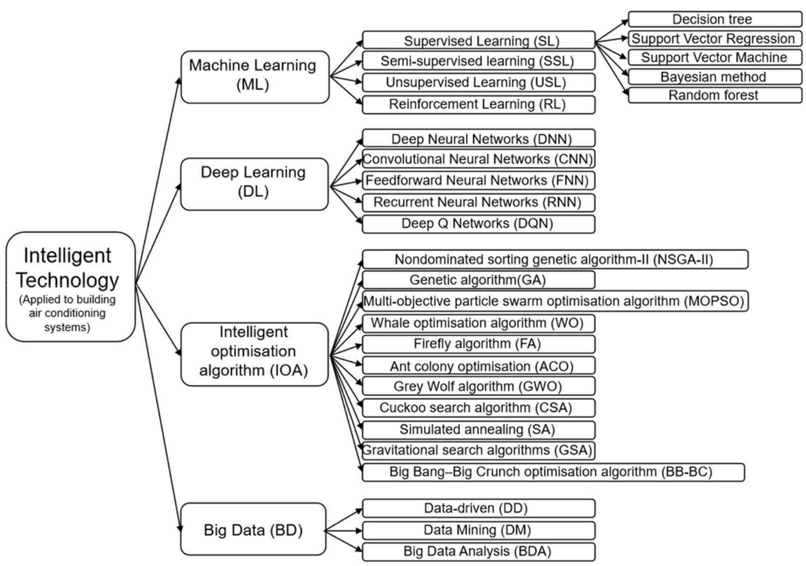

Fig. 9. IntelTech is involved in the review of the literature.

buildings from the reviewed literature (although IntelTech covers a broader scope, only the items related to this study are shown in the figure).

Among them, machine learning (ML) technology can analyse the mapping relationship between building thermodynamic parameters and equipment operating status in real time by establishing an energy consumption prediction model. Especially in dynamic personnel flow scenarios, it can be combined with reinforcement learning algorithms to realise online self-correction of air-conditioning parameters; deep learning (DL) can accurately identify the spatiotemporal coupling characteristics of building thermal inertia and environmental disturbances by processing multi-source heterogeneous data. For example, it can realise directional regulation of local microenvironment by identifying regional temperature field distribution based on thermal infrared images; intelligent optimisation algorithms (IOA) have unique advantages in multi-objective games. Under multi-dimensional constraints such as energy consumption, comfort, and equipment life, they can obtain non-inferior solution sets through Pareto frontier optimisation, and can also be combined with digital twin technology to realise virtual verification of dynamic strategies; big data (BD) technology can extract potential operating laws by mining historical data, diagnose operating faults by analysing real-time data, and perform dynamic control through data-driven, thus forming an iterative optimisation chain of air-conditioning control.

Intelligent technology offers capabilities such as self-awareness, self-acquisition of knowledge, autonomous decision-making, self-implementation, and self-modification. For example, IntelTech employs deep learning and reinforcement learning to optimise control strategies for adaptive adjustments and employs machine learning along with algorithms to dissect historical and real-time data to forecast equipment failures. IntelTech also applies heuristic optimisation algorithms to find the optimal solutions for multi-objective systems in dynamic operation. Fig. 10 illustrates the applications of these intelligent technologies in the reviewed literature.

4.2.1. Machine learning

Machine learning utilises learning algorithms to accumulate experience from data and generate models through training. The data used in training are called training data. The model can then help the computer make judgments and take action. The ML process includes the following steps, shown in Fig. 11.

ML can be categorized into supervised learning (SL), unsupervised learning (USL), semi-supervised learning (SSL), and reinforcement learning (RL). SL, USL, and SSL all require training data. The main difference is how much the data is labelled. Since the training data for AC systems in buildings are sufficient and have clear labels, the training of

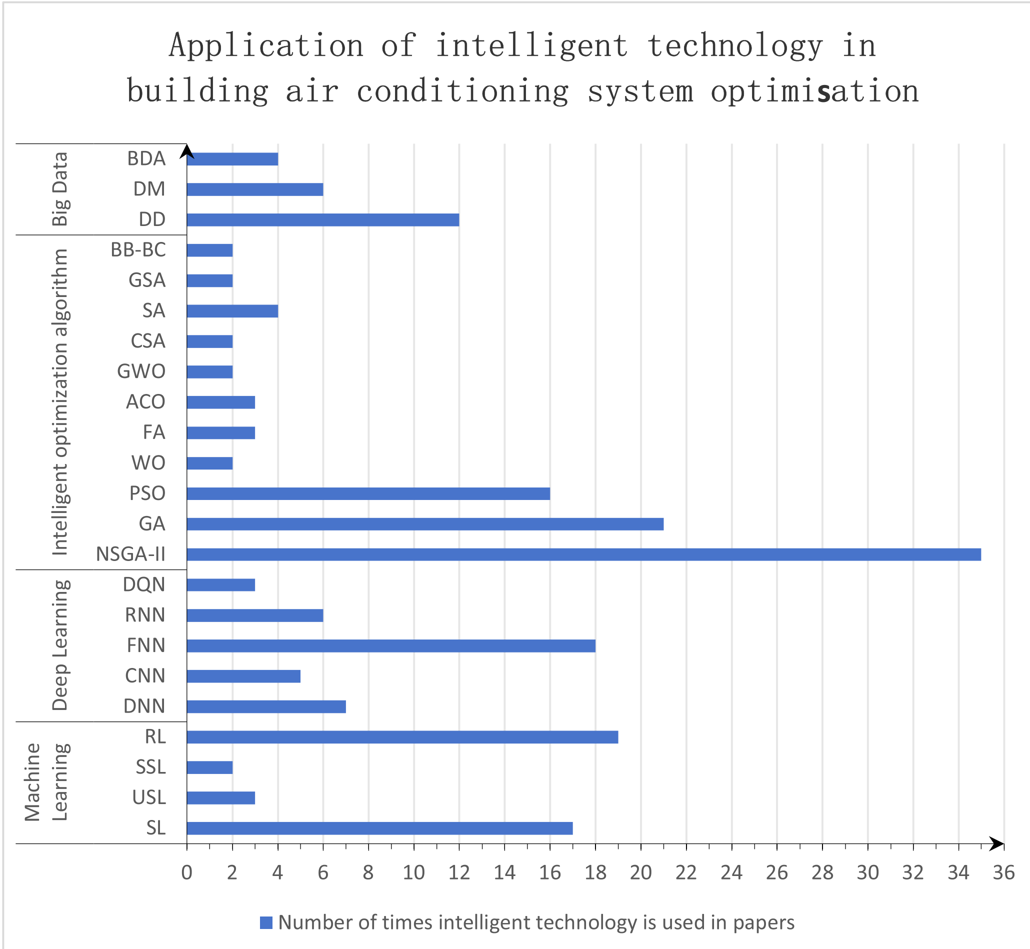

Fig. 10. Application of IntelTech in AC system optimisation for buildings.

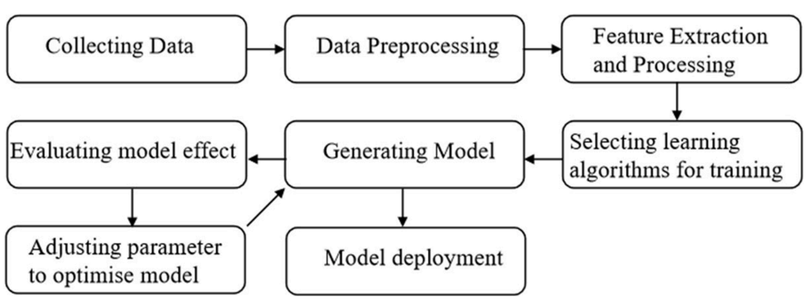

Fig. 11. Machine learning process.

SL models is usually more efficient. SL models can learn faster and be more quickly applied to actual scenarios than USL and SSL. Table 1 is a comparison of SL, USL, SSL, and RL in terms of data requirements, computational complexity, and adaptability.

RL learns by maximising rewards through experience without relying on pre-prepared data. In AC optimisation for a building, RL is widely used because it learns optimal strategies by interacting with the environment, making it ideal for complex systems that are difficult to model with precision. A conventional building energy model (BEM), which is a physics-based approach for simulating building energy, has high-level complexity and sluggish computation speed restricting its practical use in real-time HVAC optimal control. In contrast, a DRL-based BEM can reduce heating demand by approximately 17 % with a probability exceeding 95 % compared to the former rule-based control (Zhang et al., 2019). Zeyang et al. (2022) proposed a demand response strategy based on time-of-day electricity prices, using an RL algorithm to optimise the temperature set point of a thermal storage AC system, which can save approximately 9.17 % of operating costs. Valladares et al. (2019) proposed an artificial intelligence algorithm based on deep reinforcement learning (DRL), trained it with a 10-year real environment data set, and attained a 10 % reduction in CO2 levels compared to the existing control system, with an approximate 5 % decrease in energy consumption. The benchmark for this comparison is a traditional rule-based control system without active CO_2 intervention. DRL dynamically optimises air conditioning temperature and ventilation strategies to balance CO_2 control, energy consumption and thermal comfort. The CO_2 concentrations of the DRL agent and traditional control are compared in the same experimental environment to verify the control effect. The results show that

Table 1
Comparison of SL, USL, SSL, and RL.

	SL	USL	SSL	RL
Data Requirements	High (needs a lot of labeled data, with clear labels)	Low (no labeled data required)	Medium (partially labeled data)	No need for pre-stored data (acquired in real time through environmental interaction)
Computational Complexity	Low-Medium (high training efficiency, relatively simple model structure)	Medium-high (relies on discovering intrinsic structure in the data)	Medium-high (need to process both labeled and unlabeled data, high algorithm complexity)	Very high (requires large-scale simulation training)
Adaptability Typical	Applicable to static scenarios with sufficient data and clear labels	Suitable for exploratory data analysis, but limited adaptability to dynamic environments	Suitable for scenarios with high labeling costs, but dynamic adaptability is still limited	Very strong (can adapt to dynamic environments in real time)
Cross-Validation	Directly use labeled data to split the training set and validation set	Rely on internal evaluation metrics instead of label verification	Dynamically adjust the verification ratio of label data, label data is used for verification first	Verification requires a simulated environment, and data is dynamically generated through environmental interaction
Hyperparameter Optimisation	Minimise supervised loss and optimise model complexity	Rely on internal indicators or downstream tasks for indirect optimisation	Balancing the contribution of labeled and unlabeled data	Adjust learning rate, experience replay buffer size, etc.
Application Scenarios	Qin and Wang (2022) obtained a large amount of simulation data through computational fluid dynamics software and collected real-time data through sensors. Based on the massive data, they used support vector regression (SVR) to establish an environmental prediction model. Tian et al. (2019) replaced EnergyPlus with the Decision tree regression (DTR) model for building climate prediction, and the computation time for a large office was cut down from approximately 640 min to 24 min.	Yang et al. (2022) used the K-Means algorithm for pattern recognition, using the data from the historical operation data of central AC in a commercial building in Shenzhen.	Cheng et al. (2024) developed an SSL data-driven model in HVAC fault diagnosis to autonomously discover knowledge from unlabeled building operation data. The results showed that active learning can effectively identify valuable fault diagnosis data samples and reduce the annotation cost by about 50 %.	Lee et al. (2023) applied DRL technology and the deep deterministic policy gradient algorithm, leveraging limited system operation data to identify the optimal control parameters for the AHU system in under three hours without any system downtime.

the CO_2 concentration in traditional control frequently exceeds the standard when the agent is not enabled, reaching 1407 ppm at the peak, while the CO_2 concentration in DRL agent control is always below 800 ppm, which is about 10 % lower than traditional control.

Charalampos et al. (2024) explored the advantages and limitations of various DRL algorithms in residential energy management and comfort control. In terms of advantages, deep reinforcement learning effectively integrates multi-source environmental information such as temperature, humidity, and occupancy rate through the high-dimensional data processing capabilities of deep neural networks, and constructs complex state-action mapping relationships. For instance, the algorithm employs entropy maximisation strategies to enhance exploration capabilities, achieving 39.88 % energy savings while balancing energy efficiency and comfort, demonstrating its adaptability to continuous action spaces. Meanwhile, the algorithm maintains low PPD (6.5 %) across various weighting scenarios through its policy clipping mechanism, underscoring algorithmic robustness. Compared with traditional rule-based control, DRL's dynamic learning characteristics enable real-time adaptation to uncertainties like abrupt weather changes and equipment performance fluctuations, thereby mitigating energy wastage inherent in static strategies. Furthermore, the flexible design of multi-objective reward functions (e.g., adjustable weighting parameters α and β) facilitates bespoke optimisation.

Regarding limitations, the study highlights persistent constraints in practical DRL implementation. Primarily, algorithm training necessitates extensive simulation data and computational resources – exemplified by DDPG's requirement for million-scale experience replay buffers, potentially hindering real-time deployment efficiency. Secondly, pronounced hyperparameter sensitivity emerges as a critical challenge: clipping threshold (ε=0.2) and temperature coefficient (α) demand meticulous tuning to avoid policy oscillations or convergence issues. The algorithms' generalisability is further constrained by disparities between simulated environments and real-world conditions, where architectural heterogeneity and equipment variability may degrade performance. This is evidenced by DQN's energy efficiency fluctuations (−8.61 %) in discrete action spaces, revealing inherent limitations in continuous control adaptation. Finally, while weight parameters simulate user preferences, the absence of mature dynamic integration mechanisms for real-time occupant feedback remains a barrier. The challenge of seamlessly incorporating residents' instantaneous comfort responses into policy updates persists as a crucial research frontier. These limitations suggest that comprehensive DRL implementation in building energy systems requires synergistic integration with digital twin architectures and edge computing infrastructures to achieve harmonious algorithm-hardware co-optimisation.

4.2.2. Deep learning

In recent years, deep learning (DL) has been the fastest-growing branch of machine learning, so this is discussed in a separate section. DL is a method of using artificial neural networks (ANN) to imitate the human brain. Its core process mainly includes three steps: selecting a neural network architecture, determining learning goals, and beginning learning.

$$\Delta w_j = \eta \sum_{i=1}^{n} (y_i - \widehat{y}_i) x_{ij} \tag{3}$$

$$w_j \leftarrow w_j + \Delta w_j \tag{4}$$

In the expression, x_{ij} is the input of the linear unit, $\widehat{y}_i$ is the output, y_i is the target value of the training sample, η is the learning rate, Δw_j is the weight update rule, and $j = 1,2,\ldots,m$. First, an initial weight vector is randomly selected, the output of all training samples is calculated through the linear unit according to Formula (3), the Δw_j of each weight is calculated, and then each weight is updated according to Formula (4). This process is repeated to train the gradient descent of the linear unit.

At present, the major ANN architectures include deep neural networks (DNN), convolutional neural networks (CNNs), recurrent neural networks (RNNs), feedforward neural networks (FNNs), and deep Q networks (DQNs). FNNs and RNNs are widely used to optimise AC systems for buildings.

An FNN has a simple structure that is suitable for processing the mapping connection between input and output. For example, various system parameters can be directly input into an FNN to optimise HVAC systems. The output results include temperature setting values, wind speed adjustment, and other measures. An FNN can process multi-dimensional input data, which is suitable for integrating and processing different sensor data in AC systems for buildings. Yao and Huang (2019) employed FNN models to acquire the power consumption patterns of chillers and AHUs along with the cold air temperature at the AHU outlet using field-recorded data. At the same time, both the stabilisation of the AC system's energy consumption and the rack intake air temperature were designated as two goals for multi-objective optimisation. Gao et al. (2020) put forward a building thermal comfort control approach named DeepComfort that was grounded on DRL. It utilised a deep FNN to forecast the thermal comfort of occupants and applied deep deterministic policy gradients (DDPGs) to determine the optimal thermal comfort control technique. Chegari et al. (2021) used TRNSYS software to perform a dynamic thermal simulation to create a database. This resulted in diverse suggested remedies regarding the building envelope design for the FNN to conduct its learning process. This approach is more efficient when multiple objectives need to be compared and multiple design variables need to be considered simultaneously.

An RNN excels at processing time series data by remembering previous states, making RNNS ideal for handling dynamic changes in HVAC systems such as hourly temperature and energy trends. Long Short-Term Memory (LSTM), which is a special type of RNN structure, is commonly used for learning time series data. Zou et al. (2020) used an LSTM network to build a DRL training environment, and they obtained an average mean square error of 0.0015 on 16 standardised AHU parameters and achieved approximately 30 % energy savings. Lu et al. (2023) proposed a central AC system energy regulation network framework design based on the LSTM prediction model.

4.2.3. Intelligent optimisation algorithm

Many bio-inspired algorithms have been devised to tackle complex optimisation issues, including genetic algorithms (GAs), Non-dominated Sorting Genetic Algorithm II (NSGA-II), Particle swarm optimisation (PSO) algorithms, Ant colony optimisation (ACO) algorithms, whale algorithms (WAs), firefly algorithms (FAs), cuckoo algorithms (CAs), and grey wolf algorithms (GWAs). These algorithms simulate biological group behaviour to model natural phenomena. Among them, the NSGA-II, GAs, and PSO are the most commonly used algorithms for the optimisation of AC operations in buildings.

4.2.3.1. Particle swarm optimisation. PSO is an evolutionary algorithm that mimics bird flock foraging. Starting from a random solution, it iteratively searches for the optimal solution by evaluating solution quality via fitness. PSO can converge easily and quickly. The following formula updates each particle's speed in PSO:

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (pbest_i - x_i(t)) + c_2 \cdot r_2 \cdot (gbest - x_i(t)) \quad (5)$$

In the expression, $v_i(t)$ is the velocity vector of particle i in generation t, w is the inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are two random numbers that are uniformly distributed between [0, (Di Foggia, 2018)], $pbest_i$ is the individual optimal position of particle i, $gbest$ is the global optimal position, and $x_i(t)$ is the position vector of particle i in generation t. The particle position update formula is as follows:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (6)$$

Morteza et al. (2023) used an ANN and PSO fusion model to achieve high-precision thermodynamic property prediction. In multi-objective optimisation, improving one objective often compromises others. For example, increasing comfort in the AC systems in buildings typically raises energy consumption. Multi-objective optimisation seeks non-inferior solutions, called the Pareto set. Multi-objective particle swarm optimisation (MOPSO) simulates particle collaboration to quickly converge on the Pareto frontier. It is ideal for dynamic AC system optimisation in a building, though the choice of the optimal value usually hinges on the preferences and demands of actual applications. Specifically, hard constraints are used to determine the driving priority, such as grid demand response as a rigid constraint, and optimisation with energy consumption as a hard constraint to maximise comfort within the allowable energy consumption range. Soft constraints can also be used for adjustment, and the Fuzzy Membership Function is introduced to convert the user's subjective preferences into the weight of the optimisation target, guiding the algorithm to search in a specific area. The "inflexion point" of the Pareto frontier (the mutation point of the target marginal substitution rate) usually represents the comprehensive optimal solution. The fuzzy decision method is used to quantify the decision maker's satisfaction with the target through the membership function, and the solution with the highest comprehensive satisfaction is selected, such as defining the satisfaction function of energy consumption and PMV, and calculating its geometric mean or weighted sum. Franco et al. (2021) analysed Pareto frontiers for global energy demand and annual average PPD under static versus dynamic weighting strategies. At equivalent thermal comfort levels, dynamic weighting reduces energy demand by 10.7 %. Conversely, at matched energy consumption, it decreases occupant dissatisfaction rates by 19.2 %.

Ding et al. (2019) generated a Pareto frontier based on system efficiency and operating costs as the two primary objectives and determined the final optimal state point based on occupant thermal comfort. Schito et al. (2020) employed the Pareto optimisation method to address multiple objectives, including the equivalent lifespan multiplier for museum artefact preservation, predicted dissatisfaction rate, and energy consumption. Haniff et al. (2018) used an improved global particle swarm optimisation (IGPSO) to achieve faster convergence and hence delivered faster results than the original GPSO.

While Pareto-based algorithms have achieved significant progress in multi-objective optimisation of air conditioning systems, practical applications still face challenges in real-time computational efficiency, robustness under dynamic environments, hardware coordination reliability, and dynamic coupling of user preferences. Bagheri-Esfeh and Dehghan (2022) addressed computational complexity by constructing polynomial surrogate models, enabling rapid generation of Pareto solutions and transforming complex building energy consumption simulations into efficient optimisation problems. Reza and Mohammad (2024) highlighted that partial Pareto-optimal solutions may become infeasible due to dynamic economic policy constraints, necessitating multi-scenario analysis through dynamic adjustment of objective weights. Alejandro et al. (2021) developed a data-driven multi-objective optimisation simulation environment to emulate real hardware responses, providing a bridge for algorithm-hardware co-validation, though long-term stability testing on physical devices remains unexplored. Lin et al. (2022) incorporated human-robot collaboration variables into their multi-objective optimisation framework but did not further investigate dynamic user feedback mechanisms. Future research could adopt a participatory Pareto decision-making paradigm by developing interactive interfaces that allow users to adjust objective weights in real time, thereby enhancing the personalisation and acceptability of solutions.

4.2.3.2. Genetic algorithm. A GA, which is a search algorithm rooted in Darwin's evolution theory, employs selection, crossover, and mutation to probe the solution space. Beginning with an initial population, it conducts iterative evolution to identify optimal or near-optimal solutions fulfilling the termination conditions.

$$f(x) = ObjectiveFunction(x) \quad (7)$$

In the expression, *f(x)* is the fitness function that is used to evaluate the quality of individual *x*, and the Objective Function represents the objective function of the problem.

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{8}$$

In the expression, f_i is the fitness value of the individual, N is the total number of individuals in the population, and P_i is the probability of each individual being selected. For two individuals P_1 and P_2, a random crossover point is selected, the genes before the crossover point are passed from P_1 to the offspring, and the genes after the crossover point are passed from P_2 to the offspring. The formula is expressed as:

$$Child_1 = [P_1[1 : crossoverpoint], P_2[crossoverpoint + 1 : N]] \tag{9}$$

$$Child_2 = [P_2[1 : crossoverpoint], P_1[crossoverpoint + 1 : N]] \tag{10}$$

The GA simulates natural selection to perform a global search, avoiding local optima. It does not require gradient information and can handle discrete, nonlinear, and multi-peak functions, making it suitable for the optimisation of AC systems in buildings with diverse input and control variables. Hosamo et al. (2022) simulated the natural selection mechanism by GA and performed multi-objective optimisation on multiple input variables and control parameters of HVAC system. The study embedded GA into the multi-objective optimisation framework (MOGA) and took the key control variables of the HVAC system (such as supply air temperature, static duct pressure, air flow rate, hot and cold water flow, etc.) as decision variables, whose value range was based on the real-time monitoring data of the building management system (BMS). An artificial neural network (ANN) was used to construct a prediction model of energy consumption and PPD (R^2=0.93, RMSE=0.027), which was used as the fitness function of MOGA to drive the optimisation process. MOGA generated the Pareto frontier through population iteration and selected the optimal solution through the ideal point method. The results showed that after optimisation in summer, energy consumption was reduced by 22 % and PPD was reduced to 3.4 %, and energy consumption was reduced by 15.6 % and PPD was reduced to 6.2 % in winter, which were significantly better than traditional control strategies. Sajjadi. et al. (2024) used GA for multi-parameter optimisation, and the optimised fin design could improve the heat transfer efficiency of the AC heat exchanger and reduce energy consumption. Mohammad et al. (2024) optimised the operating parameters of a natural gas combined heating and power system based on GA and multi-objective decision-making method, and analysed and predicted the overall efficiency of the system.

4.2.3.3. Non-dominated sorting genetic algorithm II. Non-dominated Sorting Genetic Algorithm II (NSGA-II) is an evolutionary computation-based multi-objective optimisation method. Its core concept lies in emulating the genetic and selection mechanisms observed in biological populations to progressively approximate the optimal solution set for a given problem. The algorithm initiates by randomly generating a set of initial solutions (referred to as a population), each representing a potential parameter configuration. Subsequently, a non-dominated sorting process stratifies all solutions into hierarchical tiers: Solution A is defined as dominating Solution B if A is non-inferior to B across all optimisation objectives and superior in at least one objective. Solutions not dominated by any others form the first-tier non-dominated set (Pareto front), with remaining solutions subsequently stratified according to their dominance relationships. To preserve solution diversity, NSGA-II introduces a crowding distance metric, which quantifies the distribution density of solutions within the same tier across the objective space. This mechanism prioritises the retention of individuals situated in sparsely populated regions, thereby preventing excessive clustering of optimised results. Throughout the iterative process, the algorithm incorporates an elitist preservation strategy that combines parental and offspring populations before selecting superior individuals for the next generation. Concurrently, genetic operations such as crossover and mutation facilitate continuous exploration of the solution space until convergence criteria are met or predefined iteration limits are reached. This methodology ensures comprehensive coverage of the Pareto front while significantly enhancing computational efficiency, rendering it particularly suitable for complex optimisation problems characterised by high dimensionality, non-linearity, and conflicting objectives. The formula is as follows:

$$I_d(i) = \sum_{j=1}^{m} \left(\frac{f_j(i+1) - f_j(i-1)}{f_j^{\max} - f_j^{\min}} \right) \tag{11}$$

In the expression, I_d is the crowding distance measuring solution set distribution uniformity. $f_j(i)$ represents the value of the *i*th individual on target j after sorting, $f_j^{\max}$ and $f_j^{\min}$ are the maximum and minimum values of target *j*, respectively, and $I_d(i)$ is the crowding distance of the *i*th individual.

Among the different genetic algorithms, the NSGA-II is the most influential and commonly adopted genetic algorithm for multi-objective optimisation, making it ideal for AC systems in buildings with multiple goals. Using the same test model, population size, and iterations, MATLAB simulations show that when the population diversity is insufficient, PSO tends to fall into local optima. Fig. 12 is a snapshot of the input and output commands.

Under identical experimental conditions (population size: 100; maximum iterations: 200), the NSGA-II algorithm, implemented via MATLAB's built-in multi-objective genetic solver gamultiobj, reliably converges to the expected Pareto-optimal frontier. In this framework, x_nsga denotes the Pareto-optimal solution set, while fval_nsga quantifies the corresponding bi-objective trade-offs between energy consumption and thermal comfort. By contrast, the particle swarm optimisation (PSO) approach, executed using MATLAB's particleswarm function, yields a singular optimal solution (x_pso) derived from a scalarised fitness function. Fig. 13 illustrates the comparative simulation outcomes, wherein NSGA-II demonstrates superior capability in characterising the complete Pareto front, thereby systematically elucidating the inherent compromises between conflicting objectives.

Bagheri-Esfeh et al. (2020) utilised EnergyPlus to create neural network input data. They obtained cooling and heating load polynomials via an ANN and then applied the NSGA-II to determine the Pareto optimal points by means of these polynomials. Yue et al. (2021) integrated the NSGA-II and a multilayer perceptron artificial neural network (MLPANN) meta-model and utilised the Latin hypercube sampling (LHS) method along with principal component analysis (PCA) to enhance the architectural performance of a campus gymnasium. Wu et al. (2021) employed an empirical energy model along with an evolutionary NSGA-II to optimise the balance between energy use and thermal comfort, achieving up to 39 % energy savings and a 12 % PPD reduction. Gao et al. (2023) integrated jEPlus+ with the NSGA-II and utilised real-time energy consumption data from building HVAC systems for model training and construction, thus guiding operators to optimise energy savings and operation parameters in future climates. Nateghi and Kaczmarczyk (2023) used jEPlus + EA combined with NSGA-II to perform multi-criteria optimisation of objective functions and decision parameters to improve the indoor environment. The NSGA-II has great advantages in multi-objective optimisation, including energy consumption, carbon emissions, comfort, economic cost, air quality, optimisation efficiency, and other aspects.

NSGA-II has shown significant advantages in the field of multi-objective optimisation, especially in dealing with complex engineering problems. It has higher applicability and efficiency than algorithms such as SPEA2 and MOEA/D. Pamela and Robert (2022) used a hybrid algorithm (MOPSO—NSGA II) that combines NSGA-II with MOPSO, which has better convergence performance. The computational efficiency is better than the hybrid framework of SPEA2 or MOEA/D. Alberto et al.

```
function multiobjective_optimisation
    % Define lower and upper bounds for the optimisation problem
    lb = [16, 18];  % Lower boundary
    ub = [30, 40];  % Upper boundary

    % Multi-objective optimisation using NSGA-II
    options = optimoptions('gamultiobj', 'PopulationSize', 100,...
                          'Generations', 200,'Display', 'iter');

    [x_nsga, fval_nsga] = gamultiobj(@ac_objectives, 2, [], [], [], [], lb, ub, options);

    % Multi-objective optimisation using PSO
    options_pso = optimoptions('particleswarm', 'SwarmSize', 100, ...
                              'MaxIterations', 200, 'Display', 'iter');

    [x_pso, ~] = particleswarm(@(x)pso_fitness(x, lb, ub), 2, lb, ub, options_pso);
    fval_pso = ac_objectives(x_pso);
```

Fig. 12. Core code modules for algorithmic performance comparison.

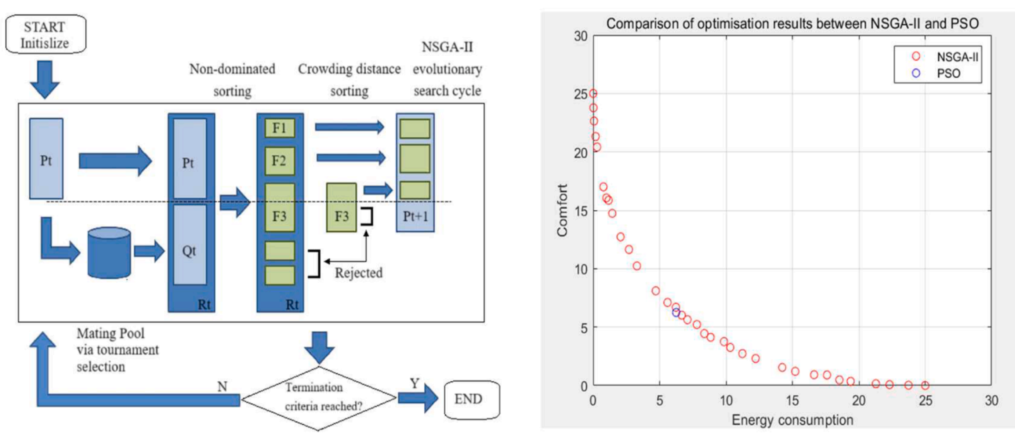

Fig. 13. NSGA-II workflow and simulation test.

(2021) compared multiple algorithms in the dynamic optimisation of HVAC systems and found that NSGA II is better than the SPEA2 algorithm in key indicators such as hypervolume and generational distance, and can more efficiently generate high-quality non-dominated solution sets. In general, the advantages of NSGA-II are reflected in two aspects: first, its elite retention mechanism and fast non-dominated sorting improve the convergence speed and solution set quality; second, the lower algorithm complexity makes it easier to integrate with other optimisation strategies (such as simulated annealing and particle swarm) to form an efficient hybrid framework.

4.2.4. *Data analysis*

In the optimisation of AC in buildings, data-driven (DD) technologies such as data mining (DM) and big data (BD) analysis use historical data to predict cooling, heating loads, and energy consumption. Unlike traditional models, DD models flexibly adapt to different buildings and dynamic changes. Integrated with IoT and real-time data, DD technology enables real-time AC monitoring, optimisation, and personalised control based on user behaviours. This makes DD technology suitable for the optimisation of AC systems in buildings.

Su et al. (2021) proposed an operation optimisation method for subway air conditioning water systems based on DM and dynamic system models, and they achieved 9.5 % energy savings by obtaining the optimal system parameters through feedforward control. Tsolkas et al. (2023) suggested a modular method that involved applying a DD algorithm to dynamically arrange the operation time of a building's heating and cooling system via thermal comfort prediction. Soleimani et al. (2024) put forth a multi-objective optimisation approach for building HVAC systems that employed DD predictive control (DPC) and local loops with PI controllers. Lork et al. (2020) proposed a DD uncertainty-aware approach to control split-type inverter ACs of residential buildings.

4.2.5. *Summary of intelligent technology application*

This review of intelligent technology applications in the AC optimisation of buildings leads to the following conclusions:

i. ML is ideal for predicting and modelling tasks, such as cooling/heating loads, energy consumption, and thermal comfort, while RL excels in complex systems without relying on precise models.
ii. DL handles complex, high-dimensional tasks. RNNs, for example, capture temporal relationships in dynamic, nonlinear control, thus making them effective for managing hourly temperature changes and long-term energy trends in AC systems.
iii. IOA solve multi-objective problems by finding near-global optimal solutions in nonlinear spaces. The NSGA-II is

particularly suited for an AC system in a building that has multi-objective optimisation.

Table 2 is a comparison table of the training data selection, model parameter differences and their impact on prediction accuracy of ML, DL and IOA in air conditioning energy saving optimisation.

The typical multi-objective optimisation targets in building AC systems comprise thermal comfort (e.g., PMV-PPD indices), system energy consumption (encompassing refrigeration/heating plant and distribution systems), equipment lifespan (such as compressor start-stop frequency optimisation), initial deployment costs (involving equipment selection and redundancy design), and operational efficiency (performance parameters including COP and EER). Table 3 is a comprehensive quantitative comparison of the optimisation efficiency of various intelligent technologies in the field of AC multi-objective optimisation.

Table 2
Comparison of the impact of various IntelTech on prediction accuracy.

Method	Key points for data selection	Model parameter complexity	Prediction accuracy characteristics	References
ML	Features need to be manually screened (such as temperature, energy consumption, time series), and data balance is required	Few parameters (such as the kernel function of SVM and the depth of decision tree)	Stable performance under small samples, limited ability to model complex nonlinear relationships	Xue et al. (2022) pointed out that the high dimensionality of building energy consumption datasets would reduce the accuracy and generalisation ability of machine learning models, while the use of packaging methods could improve the accuracy of machine learning models.
DL	Sensitive to the quality of raw data (need to be cleaned and standardized), support multi-dimensional time series data (such as sensor series)	Very many parameters (such as the number of network layers, the number of neurons, the learning rate, the regularisation term)	High accuracy under large data (captures complex patterns), small data is prone to overfitting	Ziwei et al. (2022) developed long and short-term memory (LSTM) models based on historical data to predict the day-ahead hourly energy consumption of HVAC systems and analysed the impacts of feature selection, training set volumes and update frequency of models.
IOA	Depends on the definition of optimisation goals (such as energy consumption, comfort), and can generate data in combination with simulation or physical models	Parameters are related to the algorithm type (such as the population size and mutation rate of genetic algorithms)	Accuracy depends on optimisation goals and constraint design, more suitable for global optimisation rather than direct prediction	Zakia et al. (2022) used the PSO algorithm for solution and optimisation based on the model's complexity, prediction accuracy, and ease of use in practical systems.

Various intelligent technologies also exhibit limitations and shortcomings in practical applications.

ML has problems such as low computational efficiency caused by complex models and high requirements for data quality. Researchers have tried to solve these problems using simplified models, hardware acceleration, data preprocessing, data enhancement, feature engineering, and other methods. For example, the use of the Hook–Jeffers algorithm to improve DRL can improve the convergence speed and accelerate the learning process through efficient step size adjustment and the optimisation path.

DL has problems such as model overfitting, hyperparameter tuning, and model interpretability. For example, DL typically requires large datasets for training. In AC control optimisation, data from building environments is often limited by factors such as specific building usage, sensor layout, and extended data collection periods. Limited datasets may lead to models that perform satisfactorily with a training set yet perform inadequately with test sets or in real-world situations, leading to overfitting. Researchers have tried to solve these problems using regularisation, cross-validation, automatic machine learning, grid searching, and interpretability technology. Software co-simulation demonstrates practical implementation potential. Fang et al. (2022) employed an EnergyPlus-Python co-simulation framework to train and validate a DQN control strategy, achieving optimised setpoints for supply air temperature and chilled water temperature in a multi-zone VAV system.

Heuristic optimisation algorithms have problems such as high computational complexity, difficulty with balancing solution diversity and convergence, and susceptibility to local optima. To address these challenges, researchers have explored parallel computing, hybrid algorithms, improved population selection, dynamic parameter adjustment, multi-strategy collaboration, global search strategies, and dimensionality reduction techniques. For example, the NSGA-II faces computational bottlenecks, particularly regarding sorting and crowding distance calculations. To enhance its efficiency, efforts have focused on improving convergence, diversity balance, distributed computing, and multi-strategy collaboration. Some scholars have also explored new metaheuristic optimisation algorithms. Yurun et al. (2023) compared 10 optimisation algorithms and verified them with 24-hour measured data in an actual HVAC energy model. They found that the artificial bee colony (ABC) algorithm showed better performance. Ye et al. (2025) proposed a new metaheuristic algorithm, the Tribal Intelligent Evolutionary Optimisation (TIEO), which dynamically balances global search and local search capabilities by simulating the splitting (exploring new solutions) and unification (developing high-quality solutions) of the tribe. Xiaoxi et al. (2025) compared the performance of TIEO with 7 other algorithms in the optimisation of the district cooling system, and verified through engineering cases that TIEO is superior in optimisation accuracy, stability and computational efficiency.

4.3. Impact of dynamic factors

The energy-saving optimisation of AC systems faces substantial challenges arising from the complexity and uncertainty of time-varying external factors, including occupancy patterns, occupant activity profiles, meteorological variations, extreme weather events, and electrical grid instabilities. To address these challenges, contemporary energy efficiency enhancement strategies typically employ a hierarchical control framework incorporating three principal components: (1) IoT-enabled real-time environmental monitoring, (2) digital twin-based system modelling, and (3) reinforcement learning-driven adaptive control algorithms. This integrated approach facilitates dynamic

Table 3
Comparison of the optimisation efficiency of various IntelTech.

Refs.	Year	Author	ML	DL	IOA	Optimisation efficiency
(Hong et al., 2019)	2019	Hong et al.			√	Buildings achieved substantial energy efficiency gains, with optimal solutions determined in 2 s per scenario.
(F. Ascione et al., 2019)	2019	Ascione et al.	√		√	Maximum reductions: 43.9 kWhp/m²a (primary energy), 63.9 €/m² (global costs, 3 % discount rate), and 12.3 kg/m²a (CO_2-eq emissions).
(F. Ascione et al., 2019)	2019	Ascione et al.			√	Achieve lower primary energy consumption (PEC: 62.0–91.9 kWh/m²/yr) and global cost (GC: €456–665/m²), varying by location.
(Ahn and Park, 2019)	2019	Ahn & Park		√		DQN reduced total energy use by 15.7 % versus baseline operations, sustaining indoor CO_2 <1000 ppm.
(Al-Azba et al., 2020)	2020	Azba et al.		√		Compared to the optimum case, energy savings reach 30.16 % at 29 °C and 55.45 % at 38 °C outdoor temperatures.
(Nam et al., 2020)	2020	Nam et al.		√		8.68 % energy efficiency improvement achieved without compromising indoor air quality standards.
(S. Yang et al., 2020)	2020	Yang et al.	√			Model predictive control reduced cooling loads: 58.5 % thermal energy savings (office) and 36.7 % electrical savings (lecture theatre).
(Harish and Kumar, 2020)	2020	Harish & Kumar			√	17 % overall comfort enhancement with 2.5 %/7.7 %/17.9 % daily/weekly/monthly energy reductions.
(Wang et al., 2021)	2021	Wang et al.	√		√	7.09 % total energy reduction versus PID controllers in proposed model.
(Yang and Shao, 2021)	2021	Yang et al.			√	Demonstrates high-accuracy predictions with robust optimisation capabilities, enhancing operational energy efficiency.
(Ruiz et al., 2021)	2021	Ruiz et al.			√	Using the NSGA II optimizer can save about 19 % of energy.
(Yang et al., 2021)	2021	Yang et al.		√		RNN-based approximate MPC delivers control commands >100 × faster than conventional model predictive control.
(Amasyali and El-Gohary, 2021)	2021	Amasyali et al.	√		√	Experimental results demonstrated 11–22 % behavioural energy savings alongside significant occupant comfort improvements.
(Zhou et al., 2021)	2021	Zhou et al.			√	Against PSO- and FA-based strategies, the IFA-based strategy reduces energy losses by 31.64 % and 25 %, with cost savings of 4.97 % and 1.55 % respectively.
(Homod et al., 2023)	2023	Homod et al.	√			Agents enhance indoor thermal conditions with 44.5 % energy savings versus conventional methods through smart building behaviour manipulation.
(Guo et al., 2023)	2023	Guo et al.			√	Only 118 samples were used in the optimisation process of the air supply parameters of a dual-aisle, single-row cabin.
(Tariq et al., 2023)	2023	Tariq et al.		√	√	The optimised total water footprints are 45.17 kg/h with a system of 3.32 tons of refrigeration.
(Z. Li et al., 2023)	2023	Li et al.		√		Dynamic temperature setpoints save 2.8 % electricity and 3.73 % operational costs versus fixed setpoint strategies while ensuring thermal comfort.
(Maheshwari et al., 2023)	2023	Maheshwari et al.			√	The pre-optimisation energy consumption stands at approximately 508,003 kWh, with post-optimisation

(continued on next page)

Table 3 (*continued*)

Refs.	Year	Author	ML	DL	IOA	Optimisation efficiency
						consumption reducing to 20,000–25,500 kWh.
(Liu et al., 2023)	2023	Liu et al.			√	RF-NSGA-II algorithm reduces lifecycle carbon emissions (LCCE) by 16.6 %, energy consumption per m^2 by 2.0 %, and improves thermal comfort by 18.3 %.
(Li et al., 2024)	2024	Li et al.			√	The energy consumption is reduced by about 10 %, and the comfort satisfaction degree is increased by about 8 %.
(Zhao et al., 2024)	2024	Zhao et al.		√	√	The multi-objective optimisation strategy reduces energy use by 25 % and costs by 20.9 % versus storage-priority control.

compensation for external disturbances while maintaining thermal comfort requirements. Furthermore, the implementation of coordinated multi-energy system integration - particularly through synergistic operation with thermal storage systems and renewable generation infrastructure - has been demonstrated to enhance both operational energy efficiency and system resilience under variable boundary conditions.

4.3.1. Impact of occupancy

Occupancy density affects indoor heat load, humidity, and CO2 levels, while activity intensity affects heat release and humidity. For example, greater amounts of cooling and ventilation are required in a gymnasium with a high-activity environment. Occupancy data are crucial for the optimisation of AC control. Occupancy-based control systems may trigger peak demand issues and could increase peak energy consumption by up to 10 % (Esrafilian-Najafabadi and Haghighat, 2021). Although daily energy savings vary with occupancy sensor accuracy and outdoor environmental conditions, the weekly average energy savings from occupancy-based control can be maintained between 17 % and 24 % (Kong et al., 2022). Fig. 14 summarises the literature review results. Overall, 82 % of studies did not consider occupancy in AC optimisation, while 18 % did.

Yan et al. (2023) established systematic personnel behaviour modelling methodologies with corresponding flowcharts. Wang et al. (2020) constructed a simulation platform using an occupancy simulator to assess the influence of occupancy data. Sajjadi. et al. (2023) used the Taguchi method to optimise the location of the heating/cooling system and dynamically adjust the equipment layout based on occupancy information. This research has also been used in high-density places such as hospitals and office buildings to reduce the deposition of suspended particles and reduce ventilation energy consumption while ensuring air quality (Hasan et al., 2024). Png et al. (2019) proposed three occupancy-based overlapping operation strategies to optimise the energy efficiency of VAV systems. Salimi and Hammad (2020) proposed a local control strategy for open offices that was based on occupancy dynamics data. Advances in IoT, ML, and multi-source data fusion technologies have significantly enhanced the energy efficiency of AC systems through real-time occupant behaviour monitoring, mobility pattern modelling, and adaptive preference optimisation.

(i). Adaptive preference learning and personalised control

Occupancy information significantly affects AC control strategies, but research is limited due to the randomness and uncertainty of this information. However, with advances in DL, researchers are no longer bound by strict model requirements, enabling more studies to be performed. DL methods have performed well in research areas such as user thermal preference differences and adaptive behaviour. Seunghoon et al. (2022) developed an LSTM-based model to learn user preferences from historical thermostat adjustments, dynamically tuning setpoints to reduce overcooling/heating in homes by 19 %. Nour et al. (2023) proposed a selective reinforcement graph mining framework, constructing user-device interaction networks to prioritise AC optimisation in zones with frequent manual adjustments. This approach yielded 80 % energy savings. Lei and Ye (2021) developed a K-nearest neighbours (KNN)-based thermal comfort model to establish a personalised adaptive thermal comfort environment to adapt to the preferences of the occupants. The test results manifested that the percentage accuracy of the KNN model with 1000 sets of training data could reach up to 88.31 % and can meet practical demand. Li et al. (2019) proposed an indoor thermal environment optimal control method based on the online monitoring of thermal sensation.

(ii). Real-time occupant behaviour detection technologies

Current studies often use pre-set occupant numbers instead of real-time data. With the rise of IoT and sensor technologies (e.g., cameras,

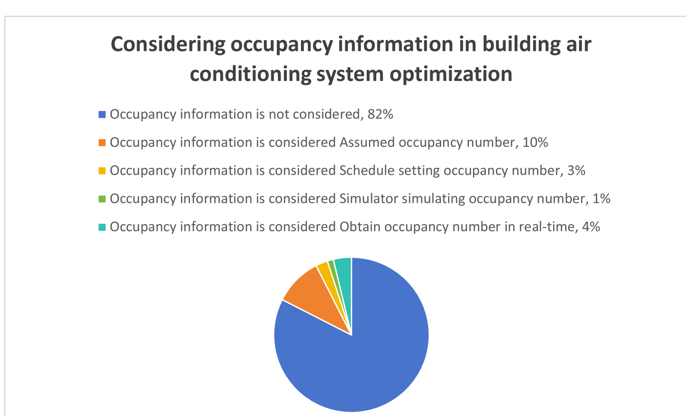

Fig. 14. Considering occupancy information in AC system optimisation in buildings.

infrared sensors, radar devices, and thermal imagers), real-time occupancy data can now be utilised for large-scale model training and analysis. Some studies predominantly employ multi-modal sensors (e.g., CO_2, temperature, Wi-Fi, depth imaging) to capture occupancy status, activity intensity, and thermal preferences. Wi-Fi sensing excels due to its non-intrusiveness and affordability. Samareh et al. (2022) demonstrated that commercial Wi-Fi-derived mobility patterns could calibrate traditional energy simulation models, reducing prediction errors from 22 % to 9 %. Styliani et al. (2021) validated a physics-informed pattern recognition model, combining CO_2 and temperature sensors to detect multi-room occupancy (97 % accuracy) and reduce AC energy use by 21 % through dynamic zoning. Tao et al. (2025) proposed a synchronisation-asynchronisation framework for AC control, using infrared sensors and Wi-Fi positioning to detect room-level occupancy. Their findings revealed that synchronous control strategies (activating AC only during occupancy) achieved 16–30 % energy reduction, albeit requiring trade-offs between comfort and response latency. In contrast, depth imaging sensors offer superior spatial resolution for activity recognition. Omar et al. (2023) optimised airflow direction and speed via depth imaging sensor-captured posture and movement trajectories, mitigating localised overcooling/overheating in offices and achieving 15 % energy savings. However, privacy concerns and deployment costs limit their scalability.

(iii). Mobility pattern modelling and spatial-level optimisation strategies

Most reviews focus only on occupant numbers, yet factors such as activity intensity, movement speed, and local concentration also affect indoor environments. Research should include location, speed, and trajectory for precise, demand-based control, though these types of studies remain rare. Ying et al. (2024) introduced a behaviour-environment integration framework, fusing Bluetooth beacons with humidity data to generate spatial occupancy heatmaps. Coupled with genetic algorithm-optimised zoning strategies, this approach reduced energy consumption by 23 % in commercial buildings. Arianna et al. (2021) analysed Wi-Fi-derived trajectories in activity-based workplaces, showing that the actual cooling demand was 9 % lower than predicted. Alfonso et al. (2021) proposed virtual agent organisations to extract multi-user behaviour patterns and apply game theory to optimise AC scheduling, achieving 15 % peak load reduction in heterogeneous scenarios. Anand et al. (2019) proposed occupancy-based overlapping operational strategies and studied the implications of VAV systems on energy efficiency and Indoor Air Quality (IAQ) when controlled using occupancy.

(iv). Multi-sensor fusion technologies

In the field of AC energy-saving control strategy optimisation based on human activity and occupancy information, sensor fusion technology has significantly enhanced prediction accuracy by integrating multi-source heterogeneous data, emerging as a core research focus in recent years. Li et al. (2020) proposed a strategy for controlling HVAC in irregularly occupied spaces through temperature and CO2 concentration sensors. The EMSS framework proposed by Nirupam Sannagowdara et al. (2024) achieved multi-level data fusion on an edge-cloud platform by integrating environmental sensors, cameras, and plug-load data, generating real-time personalised energy-saving recommendations. Comparative experiments on its decision engine validate the effectiveness of machine learning and deep learning algorithms in processing fused data. Rafi et al. (2024) introduced Deep Weighted Fusion Learning (DWFL), which dynamically assigns weights to cameras, CO_2, and passive infrared (PIR) sensors based on room conditions to optimise feature fusion, achieving a 94 % occupancy detection accuracy—a 3 % improvement over traditional methods. Alma et al. (2024) focused on feature fusion of environmental sensors (temperature, humidity, barometric pressure) combined with semi-supervised learning. By employing Chi-squared tests for feature selection and a self-training model, they attained high precision with only 14 % labeled data, validating the potential of environmental data fusion under low annotation costs. Kailai (2024) proposed the DMFF method, which leverages pre-trained Transformer encoders to extract multimodal features (e.g., visual, acoustic) and fuses cross-modal correlations through a self-attention mechanism, outperforming CNN-based models in real-world datasets and highlighting the value of multi-temporal fusion for energy efficiency optimisation. In summary, current research trends demonstrate that integrating environmental, thermal, visual, and other multi-sensor data with advanced algorithms—such as weighted fusion, Transformer architectures, and semi-supervised learning—effectively addresses challenges related to privacy, noise, and complex scenarios. This integration drives the development of air-conditioning energy-saving control systems toward higher accuracy, lower costs, and enhanced generalisation capabilities.

4.3.2. Other external dynamic factors

Climate variability and power grid fluctuations, as two predominant dynamic disturbance sources, are inducing paradigm shifts in the operational optimisation frameworks of air-conditioning systems. The increasing frequency and intensity of extreme weather events have exposed critical limitations in conventional load forecasting methodologies. This necessitates the integration of real-time meteorological data assimilation with advanced short-term prediction algorithms to enable dynamic parameter calibration in optimisation strategies. He et al. (2023) proposed a central air conditioning optimisation control method based on deep reinforcement learning, which enhances the robustness to climate variability by simulating noise interference in the environment.

The integration of high-penetration renewable energy systems introduces significant power intermittency, driving the transition of air-conditioning systems from passive loads to grid-responsive flexible assets. This transformation requires the development of a multivariate optimisation framework that simultaneously addresses dynamic electricity pricing signals, equipment degradation dynamics, and multi-stakeholder coordination. Recent advancements in game theory-based distributed control strategies demonstrate the capability to reconcile user comfort requirements with grid stability constraints through Nash equilibrium solutions. Byungkwon et al. (2023) proposed a demand response strategy based on location marginal carbon emissions, which optimises the carbon emissions of the distribution network through dynamic adjustment of flexible loads such as air conditioning clusters. Simulations show that this method can reduce peak load carbon emissions by 15 % in the IEEE standard distribution network while balancing user comfort and grid stability. Wenqiang et al. (2022) proposed an air conditioning load forecasting model based on a GRU neural network and an improved alpine skiing optimisation algorithm (IASO), combined with energy flexibility to correct terminal energy consumption.

5. Future directions

Based on the literature analysis, the following directions are suggested for future research.

(i). Combining MPC and ML

Because MPC relies on a physical model of a controlled object, its accuracy depends on the model's precision. Traditional MPC cannot adapt to changes in an object or the environment. The AC systems in buildings are complex and nonlinear, making it beneficial to combine MPC with machine learning (ML). Norouzi et al. (2023) explored the integration of ML and MPC, and they proposed that ML could enhance MPC performance by supplying an accurate model with lower computational expense. ML can train models from data, improving prediction accuracy and automatically learning complex nonlinear relationships through artificial neural networks (ANNs). Sihao et al. (2023) proposed a machine learning-based MPC framework, which built a high-precision energy consumption prediction model (MAPE = 2.5 %) by combining support vector regression (SVR) with PSO. Compared with traditional empirical rules or linear models, the introduction of ML significantly improves the reliability of disturbance prediction, making the control error of MPC only 0.4 % lower than the ideal input scenario. Aryan et al. (2024) used ANN to update thermodynamic model parameters in real time and dynamically adjust the closed-loop control setpoints of AHU. The real-time learning capability of ML enabled MPC to adapt to dynamic environments and break through the limitations of traditional MPC that rely on static models. Shiyu et al. (2023) designed an event-triggered mechanism (ETM) through machine learning. Compared with the traditional time-triggered MPC, ETMPC reduced the number of optimisation runs by 77.6 % to 88.2 % while maintaining similar energy-saving effects (9.3 %) and thermal comfort. In this process, ML dynamically judged the optimisation requirements through the cost function of comprehensive historical, current and future information, significantly reducing the computational load of MPC. The deep integration of ML, DL and MPC provides a new paradigm for the dynamic optimisation of HVAC. Such methods show significant potential in improving control accuracy, enhancing system adaptability and optimising computing efficiency.

(ii). Combining IoT, DT, and AI

Both ML and big data (BD) require large datasets. The literature highlights three main data sources: historical operational data, simulation data, and real-time data. Due to limitations, large amounts of historical data can be difficult to obtain. Simulation software programs such as EnergyPlus and TRNSYS are widely used for model verification and optimisation. With the growth of IoT and digital twin (DT) technologies, real-time data from digital buildings are now more accessible. Future research should focus on better integrating IoT, DT, and AI to enhance energy-saving and optimisation in the AC systems in buildings. Clausen et al. (2021) proposed a building DT framework comprising parameterised models embedded within a generic control algorithm. This algorithm integrates weather forecasts, real-time/planned occupancy data, and environmental states to execute model predictive control MPC, with a unified data layer ensuring standardised data retrieval across systems

The integration of technologies such as IoT, DT, and AI faces multifaceted challenges, particularly in network and data security, deployment and computational costs, and system integration and interoperability. IoT devices and sensors, which are integral to real-time data collection and transmission, can become vulnerable entry points for cyberattacks. For instance, sensors in HVAC systems lacking encryption measures may expose sensitive data to leakage or enable malicious manipulation of the system. Surendra (2023) highlighted the need to address these risks by strengthening encryption protocols and access control mechanisms. Nitin et al. (2023) emphasised that integrating IoT sensors and AI models with existing Building Management Systems (BMS) often requires custom interface development, leading to substantial upfront costs. Furthermore, divergent protocols and standards across IoT devices, AI platforms, and DT models from different manufacturers create interoperability barriers that complicate data exchange. Ibrahim et al. (2025) underscored that digital twins must achieve real-time synchronisation with physical systems, demanding higher interface compatibility and lower latency. To address these challenges, future research should focus on developing lightweight AI models, integrating edge computing and blockchain technologies, and establishing cross-industry standards to ensure the sustainable implementation of these technologies..

(iii). AI in occupancy information

This paper reviews the current research on occupancy information in the optimisation of the AC systems in buildings. The literature shows that most studies have focused on basic data such as the number and density of people in a room, with little research on the factors of occupant behaviour, activity levels, movement speed, aggregation, and real-time satisfaction feedback, which have a greater impact on AC and ventilation systems. Few prediction models have accounted for the influence of the stochastic elements associated with the AC usage behaviour of building occupants, resulting in diminished accuracy (Li et al., 2023; Seghier et al., 2022; Sha Lan and Razmjooy, 2024). There is significant potential for further exploration in these areas.

Of course, the practical deployment barriers of intelligent AC control systems that integrate dynamic occupancy information (such as high computing costs, data acquisition problems, and the need for dedicated sensors) are challenges that cannot be ignored in future research. The acquisition of real-time occupant information data traditionally relies on high-density sensor networks. To address this limitation, Anisha et al. (2022) proposed a device-free sensing approach utilising WiFi Channel State Information (CSI), effectively reducing the dependence on dedicated sensors. Regarding the low accessibility of real-time building performance data, Giuseppe et al. (2021) implemented BIM-IoT integration to enable dynamic data exchange through API interfaces and visual programming platforms. For computationally intensive algorithms such as deep learning and Model Predictive Control (MPC), David et al. (2022) developed open-source toolchains to automate control model generation, thereby minimising manual modelling efforts. In complex indoor environments where multipath effects and furniture arrangements compromise sensing accuracy, Muhammad et al. (2024) introduced a CSI-based occupancy detection system demonstrating adaptive capabilities to environmental variations. Future research directions should prioritise multimodal data fusion combining environmental sensors with user behaviour analytics, along with edge computing architectures, to enhance system real-time performance and robustness.

(iv). AI in heat transfer prediction

In addition to being applied to the optimisation of AC system control modes and operation strategies, AI technology can also be used to optimise AC system design to achieve energy-saving effects, especially in heat transfer prediction. Mohammad et al. (2023) compared the multi-layer perceptron (MLP) with the fuzzy clustering ANFIS model (FCM-ANFIS) optimised by simulated annealing to predict parameters such as heat transfer coefficient under ultrasonic turbulent inlet conditions. The model can be used for air-conditioning duct design to optimise air flow distribution and heat transfer efficiency. Pedram et al. (2023) established a regression model based on experimental data to predict the optimal configuration of the heat exchanger and reduce the energy consumption of the air-conditioning hot water circulation system. Mostafa et al. (2020) optimised the dual intake manifold geometry through 1D-3D coupling simulation and numerically verified the influence of air-conditioning compressor design parameters on thermodynamic performance.

6. Conclusion

This paper comprehensively reviews the utilisation and exploration of intelligent technology in the control and optimisation of AC systems in buildings. To ensure the accuracy of this review and evaluation, we collected a large number of relevant literature studies in the database and search engine according to the set keywords and search conditions, and we carefully screened, sorted, and compiled the studies. The review shows that AI, especially ML, DL, and intelligent algorithms, has been widely utilised for energy savings and the enhancement of AC systems in buildings. Through data-driven AI model construction, AC systems in buildings can perform intelligent control, load forecasting, and multi-objective optimisation, such as the trade-off between energy utilisation and comfort level. However, there are also common problems in this process, such as difficulty in data acquisition, weak real-time response capabilities, and insufficient complex behaviour modelling. Researchers have been actively improving algorithms, introducing parallel processing modes, and integrating IoT technologies. This also represents the trend for forthcoming research efforts.

CRediT authorship contribution statement

Bo Li: Writing – original draft, Methodology, Investigation. **Jonathan Chung Ee Yong:** Writing – review & editing, Supervision, Conceptualization. **Lih Jiun Yu:** Writing – review & editing, Supervision, Project administration. **Ezutah Udoncy Olugu:** Writing – review & editing, Supervision. **Xiaoqing Yang:** Writing – review & editing, Resources. **Zhiming Zhang:** Writing – review & editing, Project administration. **Mohammed W Muhieldeen:** Writing – review & editing, Visualization, Supervision, Resources.

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.

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