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Review

Gaps and requirements for applying automatic architectural design to building renovation

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ABSTRACT

The renovation of existing buildings provides an opportunity to change the layout to meet the needs of facilities and accomplish sustainability in the built environment at high utilisation rates and low cost. However, building renovation design is complex, and completing architectural design schemes manually needs more efficiency and overall robustness. With the use of computational optimisation, automatic architectural design (AAD) can efficiently assist in building renovation through decision-making based on performance evaluation. This paper comprehensively analyses AAD's current research status and provides a state-of-the-art overview of applying AAD technology to building renovation. Besides, gaps and requirements of using AAD for building renovation are explored from quantitative and qualitative aspects, providing ideas for future research. The research shows that there is still much work to be done to apply AAD to building renovation, including quickly obtaining input data, expanding optimisation topics, selecting design methods, and improving workflow and efficiency.

1. Introduction

Renovation is an opportunity to enhance a building's overall technical performance [1]. It can change the layout to meet the needs of facilities and accomplish sustainability in the built environment at relatively high utilisation rates and low-cost [2]. Therefore, many countries have prioritised building renovation [3]. However, the task of building renovation design is complex and represents a challenge to human cognition. On the one hand, complexity is due to the softness and imprecision of the design objectives. On the other hand, complexity arises due to combinatorial explosion and sophisticated non-linear relationships between the object properties and their abstractions, whether objectives or constraints [4]. Building renovation design can be described as follows: building components can be repaired, replaced, removed, modified, and refurbished by developing and using renovation scenarios by adding building facilities and elements [5]. Experienced designers can use their knowledge to complete architectural design schemes that meet requirements manually, but this building renovation approach needs more efficiency and overall robustness [6].

With the continuous development of computer technology, many manual design tasks can be completed by computers. Architectural design tasks can be executed automatically through the aid of computational optimisation. This review paper refers to this technology as Automatic Architectural Design (AAD). Under normal circumstances, the components of AAD include design variables, constraints, design rules, generative algorithms, and optimisation objectives [7]. Moreover, the workflow of AAD for the early design stage can be divided into three categories: the forward optimisation workflow, the inverse optimisation workflow, and the bidirectional optimisation workflow. The forward optimisation workflow is a work process in which a design plan is proposed in advance and then evaluated to determine whether it is selected for implementation. Designers can optimise building design based on feedback collected from the performance metrics [8]. However, the reverse optimisation workflow is just the opposite. The optimal design plan can be found with the aid of computers. As can be seen in Fig. 1, an inverse optimisation workflow of AAD consists of four steps in general: 1) Choose an appropriate method to represent the parametric model; 2) Select design variables, optimisation objectives, and appropriate architecture generation rules; 3) Generate architectural design; 4) Evaluate the generated architectural design according to the optimisation objectives, and determine whether the stop criterion is met. If yes, the process ends, and the architectural design is the solution; if not, the design is transformed to find a better solution [9]. The bidirectional optimisation workflow combines the forward and inverse optimisation

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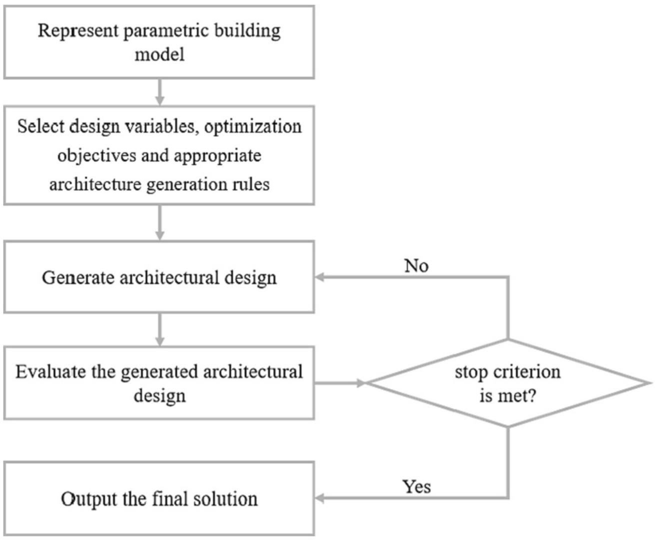


Fig. 1. Inverse optimisation workflow of AAD.

workflows. As shown in Fig. 2, the outer circle arrows are a forward optimisation workflow: users perform a performance analysis based on the existing design and modify the design according to the results. The inner-circle arrows indicate the inverse optimisation workflow: users set goals and find the optimal solution through design rules. It provides rapid feedback from building performance metrics and allows designers to search for optimal solutions, using optimisation algorithms to support design decisions [8].

AAD methods include machine learning, mature generative design systems, and other technologies. As a whole, AAD methods can be divided into two categories: the rule-based method and the data-based method. The rule-based approach is to realise the AAD by pre-setting design rules. On the contrary, the data-based process does not need to set design rules and achieves the automatic design through the design of the given data. The rule-based and data-based methods can be divided into six categories and two types, respectively. The specific classifications are shown in Table 1.

Currently, the overview of existing AAD studies is as follows. Ekici et al. [7] developed a collective understanding of high-performance computing architectures optimised using swarm and evolution. This research divides related studies into four categories: sustainability, cost, functionality, and structure. At the same time, it analyses form-finding parameters, performance goals, and topics for each reviewed literature. However, it focuses on sustainability and cost-related studies, and the analysis of functionality and structure studies is relatively brief. Du et al. [9] classified the automatic generation of space layouts (GSL) methods about the functionality topic and evaluated them. Many AAD studies have used generative design systems to reduce the programming burden in civil engineering. So BuHamdan et al. [10] provided a systematic summary of the applications of generative systems in the architecture, engineering, and construction (AEC) industry and proposed future research directions based on a review of the peer-reviewed literature published between 2009 and 2019 on this topic. It can be seen from the description of the above studies that the existing AAD reviews mainly focus on some optimisation topics or specific aspects, and a comprehensive and in-depth introduction to AAD research needs to be improved. At the same time, the application of AAD technology has gradually extended to the process of building renovation and has had a significant effect on the process [11], effectively solving the problem of substantial design complexity in engineering [12] and architecture [13,14]. For example, Costa-Carrapiço et al. [6] presented a considerable evidence base to evaluate the potential of multi-objective optimisation (MOO) by adopting a genetic algorithm (GA) to support the development of renovation strategies and their decision-making (DM) processes for the first time. However, there are only a limited number of studies and a narrow range of applications for the use of AAD in building renovation design. So, it is necessary to summarise how AAD technology can be applied to building renovation and identify potential future research areas.

To enable researchers to have a detailed and in-depth understanding of AAD technology and remove the barriers between AAD technology and building renovation design as much as possible, this paper comprehensively summarises AAD's research status in recent years and analyses how to apply AAD technology to building renovation. Because the most attention is paid to functionality [15,16], energy-related performance [17–21], and economy [22–24] in the renovation design task, this paper summarises AAD studies according to the above three topics. Moreover, considering the limitations of building renovation, the

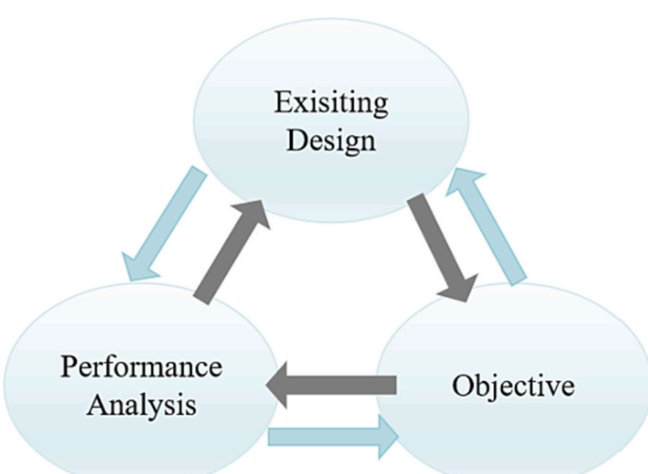


Fig. 2. Bidirectional optimisation workflow of AAD.

Table 1
AAD methods.

Classification	Method	Explanation of method
Rule-based architectural design	Programming design directly (PDD)	Direct programming based on predefined rules to generate layout design.
	Discrete event simulation (DES)	Determine architectural design by computer simulation of different discrete designs.
	Graph theory algorithms (GTA)	Convert the spatial adjacency into a floor plan, and use GTA to convert the floor plan into a feasible spatial layout.
	Building mathematical models (BMM)	By converting the design parameters and constraints into formulas and changing the location and size of the space, a feasible design can be obtained by satisfying all the constraints.
	Space discretization (SD)	Building geometry is pre-defined and divided into discretized unit grids, and space distribution is realized by the distribution of the unit grids.
	Based on a generative design system (BGDS)	Combination of modelling software that can generate parameterized models and artificial intelligence algorithm tools.
Data-based architectural design	Machine learning	The building design is generated automatically by learning many sample data.
	Based on individual data	The building design is generated automatically by learning single sample data.

content of architectural design covers the layout design and envelope design of buildings, excluding the design of building shape.

The structure of this paper is as follows: Section 2 provides a bibliographic analysis of the AAD literature; Section 3 analyses the AAD studies from multiple perspectives; Section 4 presents how AAD technology is applied in the process of existing building renovation, and a detailed analysis of existing studies on using AAD technology to building renovation; Section 5 analyses gaps and requirements of applying AAD technology to building renovation; Finally, section 6 summarises the research contribution of this paper, and proposes future research directions.

2. Bibliographic analysis

This paper is dedicated to a comprehensive and in-depth understanding of research trends, identifying research challenges and the potential to apply AAD technology to building renovation. The literature is reviewed using bibliometric analysis (i.e., quantitative analysis) and systematic reviews (i.e., qualitative research). This hybrid review approach allows for the convergence and confirmation of the conclusions driven by quantitative and qualitative methods while providing a convincing conclusion in case of any paradox or contradiction in the analysis [25,26]. Additionally, the research using this hybrid review approach can be analysed from different perspectives to increase the breadth and depth of the review conclusions.

It is essential to carefully acquire studies related to this paper's subject, particularly through bibliometric analysis, to provide a quantitative explanation of the field of knowledge. For this reason, according to the recommendation of [27], the following data collection criteria are used when collecting academic articles:

1) Database selection: Compared with the Web of Science and other databases, Scopus includes more publications and a quick update. Therefore, this paper selects Scopus as the source of the literature search.
2) Contemporary and relevance: All selected studies were published between 2014 and mid-2022, and titles, keywords, and abstracts should be manually reviewed to ensure their relevance to the research area.
3) Quality assurance: Journal papers are usually published for comprehensive, self-contained research results after several rounds of peer review. However, conference papers are typically prepared to share preliminary research findings and to indicate that further work will be undertaken to further the specific research objectives. Journal papers provide more rigorous higher-quality information than conference papers [28]. Including only journal articles in literature reviews is a recognised method to ensure consistency and high quality of review work [29–31]. So, almost all references included in this paper are peer-reviewed articles from leading international journals.

The keywords of the literature search are shown in Table 2. According to the review methodology in Fig. 3 and the standard method used in the literature, the search process for AAD studies is divided into the following five phases. In the first phase, Term 1 and Term 2 are used as keywords to search for AAD studies based on the three data collection criteria described above. The initial search results include 6968 studies. The second phase reviews study titles and delete the following studies:

Table 2
Keywords of the literature search.

Term	Keywords
Term 1	(Architectural design) OR (floor plan) OR floorplans OR (space layout) OR (space allocation) OR (spatial layout) OR (facility layout)
Term 2	Automation OR generation OR algorithm
Term 3	Renovation OR retrofit

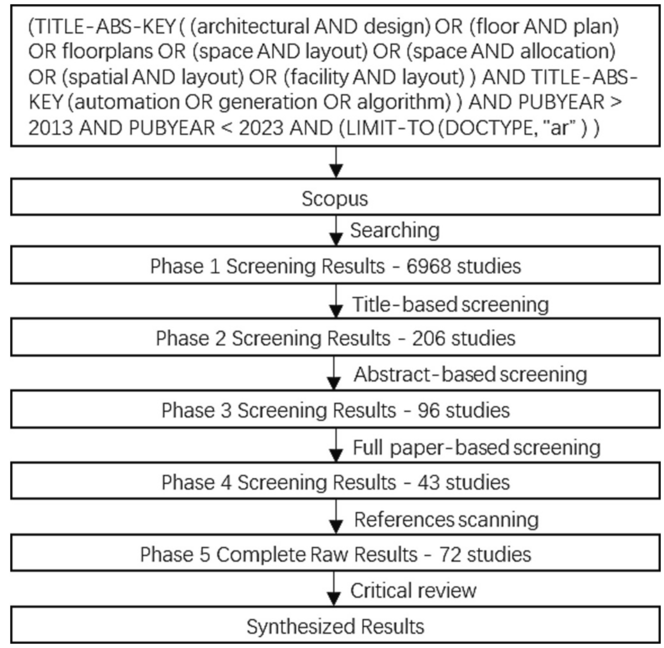


Fig. 3. Methodology for identifying relevant research literature.

(1) Studies that do not belong to the field of civil industry, such as "Surface Structure State Perception System Based on FBG Array"; (2) Studies belonging to the journal Q4; (3) Studies that are inconsistent with the research topic of this paper, such as "urban planning", etc. The result is 206 studies. The third phase scans abstracts, removing studies whose topics are not within the scope of this paper, such as "the design of building shape", resulting in 96 articles. The fourth phase investigates the entire body of each study, screening out studies most closely related to the research topic and resulting in 43 articles. Using these steps, the results from Scopus miss many essential studies. The fifth phase improves the results by reviewing the references of the 43 studies mentioned above. This process appends an additional 29 studies to the list of relevant studies, increasing the total to 72.

Term 1 and Term 3 are used as keywords to search for related studies on applying AAD technology to building renovation based on the three data collection criteria described above. Identifying the relevant research literature is the same as Fig. 3, and 23 related studies are obtained.

72 studies about AAD technology were imported into VOSviewer. Then, keywords with similar meanings were merged into one. The resulting keywords' co-occurrence map is shown in Fig. 4. The clustering and description of keywords with high frequency are shown in Table 3.

Through the analysis of Fig. 4 and Table 3, this paper can draw the following conclusions:

- According to the optimisation objectives, the above references can be divided into three categories, i.e., functionality, energy-related performance, and economy. Among them, energy-related performance is the most researched topic, followed by functionality and economy the least.
- The AAD studies with the energy-related performance topic mainly focus on optimising the architectural envelope, and the AAD studies with the functionality topic mainly optimise the architectural layout.
- In the optimisation process, the researchers usually use multi-objective optimisation and refer to the principle of the Pareto front; the standard optimisation algorithm is GA, represented by a non-dominated sorting genetic algorithm (NSGA-II); the optimisation process is often linked with simulation.

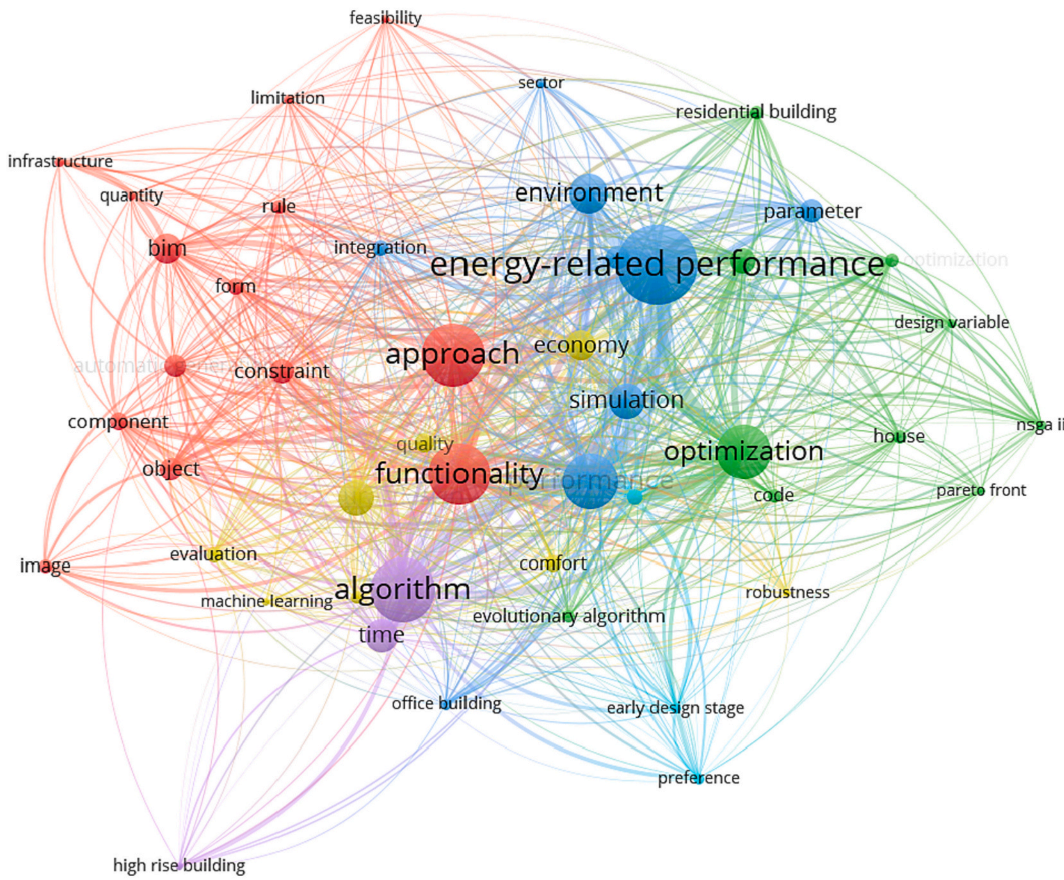


Fig. 4. Resulting term co-occurrence map generated by VoSViewer.

- Machine learning and image-based related studies mainly focus on the functionality topic.
- Studies on the energy-related performance topic are often related to environmental factors.
- Robustness is closely related to studies on economic topic.
- The research objects of AAD studies are mainly residential buildings, office buildings, and high-rise buildings.

3. Clusters of AAD studies

According to the groups of AAD analysed in Fig. 4. and Table 3, this paper classifies the studies in the AAD field into the following three optimisation topics: functionality, energy-related performance, and economic aspects.

3.1. Functionality

Functionality is one of the most exciting optimisation objectives in architectural design. In recent years, the requirements met by building design of functionality mainly include topological and geometric requirements. Topological requirements refer to the relative relationship between spaces, including connections, adjacency, separation, orientation preferences, etc. Geometric requirements are requirements related to size information of space and boundaries, including width, depth, length, area, compactness, etc. In addition, it should also meet the requirements of non-overlapping and non-overflow: non-overlapping intends that two spaces cannot overlap each other; non-overflowing intends that the space cannot overflow the boundary [9].

This section selects 30 representative articles and summarises the design methods, design variables, constraints, optimisation algorithms, objectives, and design levels, as shown in Table 4.

Considering that the AAD studies with the functionality topic are mainly carried out in the reverse optimisation workflow, this section will not discuss the classification of optimisation workflow, focusing on a detailed classification and introduction of design methods and optimisation levels.

3.1.1. Design methods

3.1.1.1. Rule-based architectural design. In summary, the rule-based method can be divided into the following six categories: programming design directly (PDD), discrete event simulation (DES), graph theory algorithms (GTA), building mathematical models (BMM), space discretisation (SD), and based on a generative design system (BGDS).

There have been some related studies about AAD utilising the PDD method. In 2014, Shekhawat proposed an algorithm for building the best-connected rectangular floor plan [32]. Based on this study, he proposed a set of algorithms for creating a floor plan of a given shape for the given spaces and adjacencies among the areas in 2015. From the point of connectivity, the obtained floor plans were one of the best arrangements of spaces inside a rectangle, proven by a mathematical formula [33]. Besides that, Song et al. [34] suggested an alternative evolutionary-based apartment building design approach by adopting the Implicit Redundant Representation Genetic Algorithm (IRRGA), which was ideal for exploring unstructured representations of problems like conceptual design. The design goals were selectively applied in symmetry, structure, circulation, and façade. Shi et al. [35] proposed an algorithm that utilised reinforcement learning with off-policy Monte-Carlo Tree Search to generate early-stage floor plan designs with highly dense adjacency and non-adjacency constraints. The results showed that the proposed algorithm was advantaged in causing targeted problems in the highly-dense adjacency constraint plan and had higher time

Table 3
Clustering and description of keywords with high frequency.

Topic	Important keywords	Description
Functionality (red in Fig. 4, 14 items)	Approach, functionality, architectural design, automatic generation, bim, constraint, evaluation, evolutionary algorithm, rule, machine learning, image, ……	AAD with "functionality" topic focuses on the research of design "approach". The main components and generation process of design "approach" include but not limited to "rule", "constraint", "evolutionary algorithm", "automatic generation", "evaluation", "machine learning" and "image". The design "object" of this topic focuses on building "form", and most of the models used are "bim" models.
Energy-related performance (blue in Fig. 4,16 items)	Building, design variable, energy (energy-related performance), envelope, environment, genetic algorithm, multi-objective optimization, Pareto front, residential building, simulation, ……	AAD with "energy-related performance" topic is often a process of "multi-objective optimization", and a "genetic algorithm" is often used to make the design solution "Pareto front". Objects of AAD studies are mostly "residential building". It focuses on building "envelope" design. The design process focuses on the selection of the "design variable" and the "simulation" after the program is generated.
economy (yellow in Fig. 4, 3 items)	Economy, robustness, sustainability	AAD with the"economy" topic often considers the "robustness" and "sustainability" of the design plan.
others (purple and green in Fig. 4, 10 items)	Algorithm, comfort, high rise building, office building, time, workflow, preference, early design stage	AAD technology is not only applied to ordinary residential buildings but also applied to "high rise building" and "office building". "Comfort", design "time" design "preference", and "workflow" will also be considered in AAD studies.

efficiency and more lightweight implementation ability than evolutionary strategies and traditional strategy search methods.

People always combine space syntax analysis (SSA) when it comes to the DES method. For example, Morgareidge et al. [36] presented a case study utilising DES and SSA to optimise care processes and design hospital spaces. SSA was used to calculate connectivity and integration to compare new designs with existing layouts and assess new designs' effectiveness in supporting visual monitoring and care coordination. Also, Wang et al. [37] introduced space syntax theory to renovate existing industrial buildings. With convex space as the centre, the space model of Chongqing Industrial Museum & Creative Park was constructed, and the spatial connectivity, depth, and integration of the space were used to measure the permeability, convenience, and distribution of the space, quantitatively analyse its spatial form and explore the impact of spatial arrangement on function.

A rectangular floorplan (RFP) is a floor plan in which the plan's boundary and each room is a rectangle. With the aid of the GTA method, Shekhawat [38] presented a generic solution to construct an RFP for the given adjacency requirements. Wang et al. [39] introduced a framework for automatically generating floor plans based on adjacency between rooms. The adjacency relations could be generated from user-specified design requirements in the form of graphical grammar. The solution overcame the limitation of previous approaches that generate only RFPs and can generate non-rectangular floor plans. Upasani et al. [61] proposed a method for automatically constructing RFPs while addressing dimensional constraints and adjacency. Adjacency relations were performed in a dimensionless rectangular arrangement (RA) to ensure the presence of RFPs. At the same time, dimensional constraints were given according to the minimum width and aspect ratio range for each room. A linear optimisation model was then proposed to obtain a feasible size RFP with user-defined constraints. The proposed model could generate viable solutions for every possible RA in a reasonable time.

Many studies obtain the optimal facility layout by the BMM method in the manufacturing industry. The construction industry borrows this method and applies it to allocate different functional spaces. For example, Abbasi et al. [45] showed a model for solving hospital layout design problems in which material handling cost, connectivity, and department shape ratio were considered. Nisztuk et al. [48] applied hybrid evolutionary and greedy-based algorithms to automatic floor plan generation problems. The aim is to generate various layout options to support design diversity. Still, it only has two parameters: the scale factor matrix that defines a value for each room and the sequence representing the room sort sequence. Baki, Abdulbaqi, and Mohialden [47] combined Monte Caro Density with the firefly algorithm (MDB-FA) to propose a novel approach to space planning. According to the customer's space conditions and needs, furniture location was generated to maximise the use of furniture space and its function and comfort requirements.

SD method is often used in the process of space allocation. Chen et al. [43] attempted to maximise space utilisation by maximising the size of the open workspace. They proposed a lightweight tool that used a nested GA optimisation with two layers to automatically generate an open-plan office layout with the inner layer algorithm embedded in the outer one. A local search enhanced the result. The furniture arrangement inside rooms is also one of many architectural design problems. An optimal spatial layout design will facilitate the movement of people within the space, thereby reducing any possible injuries. So Hassan et al. [42] studied the application of GA in solving problems of spatial layout design. Considering several constraints, it found the optimal placements for the furniture in a given space. Non-overlapping objects are one of the main constraints in spatial layout design requirements, which can be used as a fitness function to help evaluate the quality of the resulting solutions. Besides, this method can optimise functionality and energy-related performance simultaneously. Zawidzki and Szklarski [44] proposed a framework in which architectural functional layout (FL) was optimised for the following objectives: functionality (defined by users), sunlight (calculated based on geographical conditions), external view attraction (site assessment), and external noise (measured on-site). The proposed framework was tested through a realistic case study of a 14-room single-family house on an existing building plot. From an architectural design perspective, the results were feasible.

Many studies about AAD adopt the GBDS method. For example, Coorey et al. [51] presented the generative spatial performance design system (GSPDS), which integrated a sequence of parametric logic models into a system for design exploration. It consisted of the following four models and functions: analysis model, evaluation model, synthesis model, and optimisation model. The system was configured for the specific and significant residential space design architectural problem. Cellular automata, swarm intelligence, shape grammars, and so on are often used to enhance designers' abilities during the design process [62]. Khalili Araghi et al. [52] examined the potential of the cellular automata (CA) to produce a range of architectural forms in architecture that meet architectural requirements. It extended the dynamical behaviour of classical CA through the versatility of cellular properties, especially neighbourhood and unit type versatility. This generative design process addressed two challenging architectural requirements for high-density buildings: accessibility and natural light. Utilising the existing generative design system can help architects free themselves from complex computer programming work and apply more energy to finding

Table 4
Detailed analysis of AAD studies on the functionality topic.

Topic	Opt. obj	Article	Author	Year	Methods	Level	Design variables				Algorithm	Constraints
							Geo.	Top.	Fur.	Ori		
Functionality	Adjacency	[32]	Shekhawat	2014	PDD	Single floor		■			The spiral algorithm	–
Functionality	Adjacency	[33]	Shekhawat	2015	PDD	Single floor		■			The spiral algorithm	Adjacency matrix
Functionality	Symmetry, structure, circulation, and facade	[34]	Song et al.	2016	PDD / BGDS	Multi-floor	■	■			Implicit Redundant Representation Genetic Algorithm (IRRGA)	the relationship between the unit and the staircase; the number of units
Functionality	Adjacency and non-adjacency	[35]	Shi et al.	2020	PDD	Single floor		■			Monte-Carlo Tree Search	Adjacency and non-adjacency constraints
Functionality	Connectivity and integration	[36]	Morgareidge et al.	2014	DES	Single floor		■			Solved directly by computer	Adjacency matrix
Functionality	Connectivity, depth, and integration	[37]	Wang et al.	2017	DES	Site Planning		■			Solved directly by computer	Adjacency matrix
Functionality	Adjacency	[38]	Shekhawat et al.	2018	GTA	Single floor		■			Custom algorithm	Adjacency matrix
Functionality	Adjacency, orientation, and aspect ratio	[39]	Wang et al.	2020	GTA	Single floor	■	■		■	Custom algorithm	Adjacency matrix
Functionality	Adjacency and dimension	[40]	Upasani et al.	2020	GTA	Single floor	■	■			Custom algorithm	Adjacency matrix
Functionality	Constraint objective	[41]	Dino et al.	2016	SD	Multi-floor	■	■			EA	The space size, absolute dimension, compactness, jaggedness, convexity; Façade constraint; Floor constraint; Neighbourhood constraint; Separation constraint
Functionality	Non-Overlapping Ratios	[42]	Hassan et al.	2017	SD	Furniture			■		GA	non-overlapping requirement
Functionality	Space utilisation	[43]	Chen et al.	2020	SD	Single floor	■	■			GA	1. Exits cannot be blocked. 2. Open areas cannot be divided into isolated areas. 3. All rooms should be accessible from the open area. 4. The channels are straight and should be connected.
Functionality; ERP	Layout functionality; Sunlight in selected rooms; External view attraction in selected rooms; External noise shielding in selected rooms	[44]	Zawidzki and Szklarski	2020	SD	Single floor	■	■		■	The depth-first backtracking search algorithm	No room-to-room overlap; no room beyond the building; every room is accessible via corridors
Functionality; economy	Cost, connectivity, and departments shape ratio	[45]	Abbasi et al.	2017	BMM	Single floor	■	■			Solved directly by computer	Operation relation chart and department relationship
Functionality	Desk counts	[46]	Anderson	2018	BMM	Furniture			■		Rotation layout algorithm; Left-right layout algorithm; Brute force layout algorithm	Minimum table-to-door distance; Sufficient space around chairs for people to enter and exit; Minimum distance from the end of the table to other tables; Table

(continued on next page)

Table 4 (*continued*)

Topic	Opt. obj	Article	Author	Year	Methods	Level	Design variables				Algorithm	Constraints
							Geo.	Top.	Fur.	Ori		
												and its clear area do not overlap any obstructions
Functionality	Living comfort	[47]	Abdulbaqi and Mohialden	2018	BMM	Furniture			■		MDB-FA	–
Functionality	A variety of layout options	[48]	Nisztuk et al.	2019	BMM / BGDS	Single floor	■	■			Hybrid Evolutionary Algorithm	Architectural design guidelines (adjacency, range of room size, range of room area)
Functionality; economy	The total material handling cost; A variety of layouts	[49]	Mariem Besbes et al.	2020	BMM	Single floor	■	■			GA + A* Algorithm	The location of the obstacle
Functionality; economy	The total square footage cost; the patient blocking time	[50]	Farouq Halawa et al.	2021	BMM	Single floor	■	■			GA	Dimension constraints of outpatient clinic spaces
Functionality	A variety of apartment layouts	[51]	Coorey et al.	2014	BMM / BGDS	Single floor	■	■			Through the parametric plugin Kangaroo	–
Functionality	Accessibility and natural light	[52]	Khalili Araghi, et al.	2015	SD / BGDS	Multi-floor		■			GA	CA rules
Functionality	Dimension; building shape	[53]	Guo et al.	2017	BGDS	Single floor	■	■			Adjust attraction and repulsion strength; swap space locations; compress building geometry	Space connections
Functionality	A variety of apartment layouts	[54]	Veloso et al.	2018	BGDS	Single floor	■	■			Depth-first search	Custom rules by architects (such as adjacency, windows minimum size……)
Functionality	Room size, room quantity; orientation; apartment types, and room area indicators	[55]	Liu Yong and Hao Chibiao	2022	BGDS	Single floor	■	■		■	GA	–
Functionality	Topological and geometrical benchmarks	[56]	Wu et al.	2019	Machine learning	single floor		■			CNN	–
Functionality	Topological and geometrical benchmarks	[57]	Rahbar et al.	2019	Machine learning	Single floor		■			Conditional-GANs	–
Functionality	Topological and geometrical benchmarks	[58]	Morteza Rahbar et al.	2022	Machine learning	Single floor	■	■			cCANs	Topological constraints
Functionality	Adjacency	[59]	Hua	2016	Individual data	Single floor	■	■			Custom algorithm	Adjacency matrix and space size
Functionality	Perceived density	[60]	Fisher-Gewirtzman and Polak	2019	Individual data	Single floor			■		Crowdsourcing	Unit area and function space
Functionality	Adjacency, room area	[61]	AlOmani and El-Rayes	2020	Individual data	Single floor	■	■			Custom algorithm	Adjacency matrix and space size

Header: Opt. obj, Optimization objective; Geo., Geometry of layout; Top., Topology of layout; Fur., furniture layout; Ori, Orientation.
Methods: PDD, programming design directly; BGDS, based on a generative design system; GTA, graph theory algorithms; SD, space discretisation; BMM, building mathematical models.
Algorithm: EA, evolutionary algorithm; GA, genetic algorithm; MDB-FA, Monte Caro Density-Based correlated with the firefly algorithm; CNN, Convolutional Neural Network.
Constraints: CA, cellular automata.

architectural design requirements and optimising design logic. Veloso et al. [54] described a design customisation system to implement Computer-Aided Architectural Design (CAAD). The workflow of this system begins with the architect defining shape syntax rules. These rules were then automatically imported into a user interface, allowing future owners to customise their apartment plans interactively. This workflow could contribute to customising houses and other simple architectural programs, ensuring the quality of the results through shaping grammar rules. In generative design systems, researchers can also use agents to assist research. Guo et al. [53] presented a method to generate spatial architectural layouts from user-specified architectural programs automatically. The proposed method combines a multi-agent topology finding system and an evolutionary optimisation process. The former produced a topology that satisfied arrangements for further optimisation, while the latter focused on optimising the layouts to achieve predefined architectural standards. This dual operation shortened the time cost, but non-orthogonal layouts were difficult to generate, and curve-shaped rooms could not be achieved. Using BGDS, Liu et al. simplified the design process to a mathematical model starting with spatial shapes and used Rhino and Grasshopper to complete the algorithm development [55].

3.1.1.2. Data-based architectural design. As seen from the publication date of the cited literature in Table 4, the data-driven approach to architectural layout design has become increasingly popular in recent years.

Rahbar et al. [57] applied a data-driven generative method to generate a synthetic space allocation probability layout. A specific training dataset, including 300 existing apartment layouts coloured with low feature representations, was developed to train the conditional-Generative Adversarial Network (cGAN) model. The trained model was evaluated by the quality of the layouts they generated, involving five predefined topological and geometrical benchmarks (orthogonal design, space dimensions, space area ratios, entrance identification, and space allocation logic). At the same time, Wu et al. [56] also proposed a novel data-driven technique to automatically and efficiently generate floor plans for residential buildings with given boundaries. Depending on personal preferences and requirements, users first choose the locations for several specific rooms within the given limit. Then their method generated additional rooms and respected the user's design intent. In addition to data-driven using pre-collected layout maps, a data-driven process can also be achieved through "crowdsourcing." Fisher-Gewirtzman and Polak [60] presented a learning model for the automatically generated built environments, and it was demonstrated by creating the smallest apartments located in dense urban environments. Using parametric modelling, multi-criteria optimisation, and supervised machine learning, this study utilised "wisdom of the crowd" to define functional layouts to provide a 3D configuration of the smallest apartment with improved visibility.

In addition to machine learning using a large amount of data to generate architectural layout designs, there are some studies about the automatic generation of architectural layout designs based on individual data. This type of research primarily aims to produce irregular architectural layouts. Hua et al. [59] presented a program that automatically constructs irregular floor plans. The program generated various layouts to meet users' geometric and topological requirements given image patterns. The program extracted irregular regions from images by statistical region merging and employed simulated annealing to build topologically viable layouts. AlOmani and El-Rayes [61] presented the development of an innovative approach to supporting architects and designers in automatically generating thematic architectural layout designs inspired by natural images. The method utilised image processing to segment the naturally inspired image and analysed the segmented image using a region and boundary extraction algorithm to generate a region. The technique also integrated two innovative optimisation algorithms designed to optimise room allocation in the resulting layout to maximise compliance with the adjacency requirements specified by the designer and optimise the room area to maximise the functionality and operational performance of the building layout.

3.1.2. Levels of detail

Current studies can also be classified based on the subject's level of detail. According to the optimisation levels, the related studies can be classified as furniture optimisation, single-floor optimisation, multi-floor optimisation, and site planning optimisation. Most studies are designed for single-floor optimisation [33,35,36,38–40,43–45,48,51,53,54,56,57,59–61]. Studies on multi-floor optimisation often consider connectivity between floors. For example, Khalili Araghi et al. [52] adopted cellular automata (CA) to generate various building forms. Cell types included circulation units, studios, and one- and two-bedroom apartments and were assigned according to their adjacency to circulation units. In exploring multi-floor layout design, Dino [41] presented a Precedence-Based Layout Configuration Heuristics (P-LCH) approach. This approach could satisfy the rigid constraints of space overlaps and empty areas to solve multi-floor, unequal area 3D space layout problems. Generated layouts were evaluated by several constraints that quantify the size, geometry, placement, and topology. The optimisation of the furniture layout is widely used in residential and office buildings. Anderson [46] developed a set of procedural algorithms for commercial office space planning to maximise the number of desks. These algorithms, benchmarked against 13,000 actual offices designed by human architects, performed as well as an architect in 77% of offices and achieved a higher capacity in another 6%. Hassan et al. [42] solved furniture layout problems in which non-overlapping objects were one of the main constraints in spatial layout design requirements. Considering site planning, Wang et al. [37] studied the layout design of an existing industrial park based on space syntax theory.

3.2. Energy-related performance

This section provides a detailed analysis of 31 representative studies with energy-related performance as the main topic, as shown in Table 5.

The AAD studies with the energy-related performance topic mainly adopt the BGDS method. Therefore, this section no longer classifies the design methods but analyses workflow, optimisation objectives, simulation methods, and tools in detail.

3.2.1. Workflow

In this section, the forward optimisation workflow is a workflow that optimises the building scheme by evaluating building performance metrics through integrating modelling platforms and simulation engines. The definition of the inverse optimisation workflow is that single or multiple building performance metrics are taken as the target functions, and the optimal solution is then found through integrating optimisation algorithms and simulation engines. Since forward optimisation is relatively common, this paper mainly introduces the related studies of reverse optimisation and bidirectional optimisation.

Many studies [4,63–87] use the inverse optimisation workflow. For example, Conceicao Antonio et al. [63] proposed a mathematical model to optimise annual solar irradiation availability by maximising incident solar irradiation on buildings' roofs and facades. The dynamic simulation interaction of buildings based on GA was implemented to hunt for optimal topological solutions for the urban grid. But only a few studies on building performance optimisation involve the bidirectional optimisation workflow. Li et al. [8] proposed a bidirectional workflow for creating performance optimisation at the early design stage. This approach could provide rapid feedback from building performance metrics and allow designers to use GA to find the best solution to support early design decisions. The bidirectional workflow improved performance optimisation in the early design phase compared to previous studies. But it can only be applied to a few common forms of office buildings, not to more complex free forms.

3.2.2. Optimisation objectives

In detail, optimisation objectives on energy-related performance topics can be divided into energy, daylighting, thermal comfort, solar radiation, and comprehensive sustainability.

In terms of energy as an optimisation objective, a method for simulation-based multi-criteria optimisation is presented by Harkouss [76]. Its main features include four steps: building simulation, optimisation process, multi-criteria decision making (MCDM), and solution robustness test. NSGA-II is chosen to minimise thermal and electrical requirements and life cycle cost (LCC) while achieving a net-zero energy balance. Expert systems are usually used to provide decision support

Table 5
Detailed analysis of AAD studies on the energy-related performance topic.

Topic	Opt. obj	Article	Author	Year	Design variables							Methods	Opt. alg	S/M tools	Opt. tools
					Ori	Sha	Geo.	Top.	Env.	MEP.	URE				
ERP	Solar radiation	[63]	António et al.	2014		■		■			■	SD	GA	–	–
ERP	Solar radiation; energy	[64]	Yi	2014			■				■	BGDS	EA; Pareto	Rhino/EnergyPlus and Ecotect	MATLAB
ERP; economy	Energy; daylighting; ICC; LCC	[65]	Negendahl and Nielsen	2015		■						BGDS	GA; Pareto	Rhinoceros; Grasshopper; Radiance; Be10; a new hourly-based quasi-steady-state tool (HQSS)	Octopus of the SPEA2
ERP; economy	Energy; daylighting; ICC; LCC	[66]	Chang and Shih	2015	■				■			BGDS	GA	Rhino, Grasshopper and DIVA 2.0	HLGA
ERP	Energy use; indoor comfort	[67]	Yi	2016			■	■				BGDS	simulated annealing	Ecotect	EASL (Environmental Architecture Space Layout) optimizer
ERP	Energy	[68]	Delgarm	2016	■				■			BGDS	MOPSO algorithm	JEPlus; EnergyPlus	MATLAB
ERP	Daylighting; thermal comfort	[69]	Chen et al.	2016	■	■						BGDS	Latin Hypercube Sampling (LHS); Sensitivity analysis; NSGA-II	Rhinoceros and Grasshopper	Octopus
Functionality; ERP	Space Layout; energy; daylighting	[70]	Dino et al.	2017	■	■	■	■				BGDS	NSGA-II	EnergyPlus and jEPlus	
ERP	Energy; thermal comfort	[71]	Lin	2018					■			BGDS	GA; multi-linear regression (MLR) model and an ANN model; Latin Hypercube Sampling; Pareto front	DesignBuilder	–
ERP; economy	Energy; daylighting; cost	[72]	Sun et al.	2020			■		■			BGDS	Hype algorithm; ANN	Rhinoceros and Grasshopper	Octopus
ERP	Energy	[73]	Bamdadet al.	2017	■	■			■			BGDS	Ant colony algorithm	EnergyPlus	–
ERP	Energy; daylighting	[4]	Chatzikonstantinou and Sariyildiz	2017	■	■			■			BGDS	NSGA-II; ANN	Radiance; EnergyPlus	–
ERP	Energy; daylighting; thermal comfort	[74]	Zhang et al.	2017	■	■	*		■			BGDS	SPEA-2(an improved multi-objective evolutionary algorithm shown to have advantages over NSGA-II in multi-dimensional space)	Rhino, Grasshopper, Ladybug, Honeybee/ EnergyPlus	Octopus
ERP; economy	LCC; energy	[75]	Dhariwal and Banerjee	2017					■			BGDS	GA; RSM	EnergyPlus; Design-Expert	MATLAB
ERP	Energy	[8]	Li et al.	2018			■		■			BGDS	GA	DesignBuilder/SketchUp	–
ERP	Energy	[76]	Harkouss et al.	2018					■	■		BGDS	NSGA-II	TRNSYS	MOBO (a Multi-Objective Building Optimization tool)
ERP	Energy; daylighting	[77]	Chen et al.	2018	■	■			■			BGDS	NSGA-II;Pareto front	Python; GreenMark rating tool	–
Functionality; ERP	Daylight; thermal, energy; structure; architecture	[78]	Yang et al.	2018		■			■			BGDS	NSGA-II	Rhino and Grasshopper	ESTECO's modeFRONTIER
ERP	Thermal comfort	[79]	Sghiouri et al.	2018					■			BGDS	NSGA-II	TRNSYS	JEPlus + EA
ERP	Solar radiation	[80]	Vermeulen et al.	2018				■			■	SD; BGDS	EA	EnergyPlus	–
ERP	Solar radiation	[81]	Youssef et al.	2018					■		■	BGDS	GA	Custom tool (supported by MATLAB)	MATLAB
ERP	Energy	[82]	Zhu	2018					■			BGDS		–	–

(*continued on next page*)

Table 5 (*continued*)

Topic	Opt. obj	Article	Author	Year	Design variables							Methods	Opt. alg	S/M tools	Opt. tools
					Ori	Sha	Geo.	Top.	Env.	MEP.	URE				
													Simulated annealing algorithm		
ERP	Daylighting	[83]	Yi	2019		■			■			BGDS	NSGA-II	Rhino, Grasshopper and DIVA	MATLAB
ERP	Solar radiation	[84]	Chen et al.	2019	■	■			■		■	BGDS	NSGA-II and HGPSPSO	EnergyPlus	JEPlus + GenOpt
ERP; economy	Energy; energy-related LCC	[85]	Ascione et al.	2019	■				■			BGDS	GA	EnergyPlus	MATLAB
ERP	Solar radiation	[86]	Al-Janahi et al.	2020					■	■	■	BGDS	GA	Revit	MATLAB
ERP	Daylighting	[87]	Yang et al.	2020					■			BGDS	NSGA-II	Grasshopper and modeFRONTIER	
ERP; economy	Energy; LCC	[88]	Li et al.	2017	■	■			■			BGDS	NSGA-II; MOPSO; MOGA; MODE; ANN	EnergyPlus	MATLAB; GenOpt
ERP	Daylighting; The total walking distance	[89]	Farouq Halawa et al.	2021			■					BGDS	Placement algorithm; GA-C; PSO	–	Julia + Gourbi
ERP	Daylighting and energy	[90]	Maryam Talaei et al.	2021	■				■			BGDS	GA	Daysim and Read Annual Result	Octopus
ERP	energy consumption	[91]	Jian Dong and Meng Ran	2022			■					BGDS	GA	JEPlus; EnergyPlus	MATLAB

Header: Opt. obj, Optimization objective; Ori, Orientation; Sha, Shading; Geo., Geometry of layout; Top., Topology of layout; Env., Envelope structure; MEP., MEP system of buildings; URE, Using renewable energy (e.g. solar energy); Optimization algorithm, Opt. alg; S/M tools, Simulation/modelling tools; Opt. tools, Optimization tools.
Topic: ERP, energy-related performance.
Optimisation objective: ICC, initial capital cost; LCC, life cycle cost.
Methods: SD, space discretisation; BGDS, based on a generative design system.
Opt. alg: GA, genetic algorithm; MOPSO, multi-objective particle swarm optimisation; NSGA-II, non-dominated sorting algorithm; ANN, Artificial Neural Network; RSM, response surface methodology; MOGA, multi-objective genetic algorithm; MODE, multi-objective differential evolution; HGPSPSO, hybrid generalised pattern search particle swarm optimisation.

Table 6
Detailed analysis of AAD studies on the economic topic.

Topic	Opt. obj	Article	Author	Year	Design variables					Methods	Algorithm	S/M tools	Opt. tools
					Ori	Sha	Geo.	Env.	MEP.				
ERP; economy	Energy; daylighting; ICC	[65]	Negendahl and Nielsen	2015		■				BGDS	GA; Pareto	Rhinoceros; Grasshopper; Radiance; Be10 (a new hourly-based quasi-steady-state tool)	Octopus of the SPEA2
ERP; economy	Energy; daylighting; ICC	[66]	Chang and Shih	2015	■	■				BGDS	GA	Rhino; Grasshopper; DIVA 2.0	HLGA
economy	LCC	[96]	Liu et al.	2015	■			■		BGDS	A revised PSO algorithm	Ecotect	–
economy	ARC; ICC	[97]	Evins	2015				■	■	BGDS	NSGA-II and mixed-integer linear programming;	EnergyPlus	MATLAB
economy	LCC	[98]	Ferrara et al.	2016				■	■	BGDS	PSO	TRNSYS	GenOpt
ERP; economy	LCC; energy	[75]	Dhariwal and Banerjee	2017				■		BGDS	GA; RSM	EnergyPlus; Design-Expert	MATLAB
ERP; economy	Energy; LCC	[76]	Harkouss et al.	2018				■	■	BGDS	NSGA-II	TRNSYS	MOBO, a Multi-Objective Building Optimization tool introduced
economy	LCC	[99]	Hester et al.	2018				■		BGDS	sequential specification; GA	Building Attribute to Impact Algorithm (probabilistic LCA tool)	‘-
ERP; economy	Energy; energy-related LCC	[85]	Ascione et al.	2019	■			■		BGDS	GA	EnergyPlus	MATLAB
ERP; economy	Energy; LCC	[88]	Li et al.	2017	■	■		■		BGDS	NSGA-II; MOPSO; MOGA; MODE; ANN	EnergyPlus	MATLAB; GenOpt
ERP; economy	Energy, daylighting, cost	[72]	Sun et al.	2020			■	■		BGDS	HypE algorithm; ANN	Rhinoceros; Grasshopper	Octopus

Header: Opt. obj, Optimization objective; Ori, Orientation; Sha, Shading; Geo., Geometry of layout; Top., Topology of layout; Env., Envelope structure; MEP., MEP system of buildings; URE, Using renewable energy (e.g. solar energy); Optimization algorithm, Opt. alg; S/M tools, Simulation/modelling tools; Opt. tools, Optimization tools.
Topic: ERP, energy-related performance.
Optimisation objective: ICC, initial capital cost; LCC, life cycle cost; ARC, annual running cost.
Methods: BGDS, based on a generative design system.
Algorithm: GA, genetic algorithm; MOPSO, multi-objective particle swarm optimisation; NSGA-II, non-dominated sorting algorithm; ANN, Artificial Neural Network; RSM, response surface methodology; MOGA, multi-objective genetic algorithm; MODE, multi-objective differential evolution; PSO, particle swarm optimisation.

involving the optimal objective of daylighting. For example, Gagne et al. [92] proposed an interactive, goal-based expert system for daylighting design which consisted of a daylighting knowledge base and a fuzzy rule-based decision-making logic. Yi et al. [83] introduced a design process that can satisfy the qualitative and quantitative properties of the building. And multi-objective evolutionary algorithms were adopted to find solutions. Taking energy and daylight as optimisation simultaneously, Chen et al. [24] integrated cooling systems as variables in the multi-objective building form and envelope design optimisation. It considered two parameters, i.e., the building's shape and window-to-wall ratio, and the most efficient system was selected automatically using NSGA-II. Besides that, Yang et al. [78] suggested and demonstrated a new computational design exploration method that involved multi-disciplinary criteria and complex geometries (e.g., indoor sports buildings). It focused on optimising energy, daylighting, and structure and allowed the designers to prioritise quantitative objectives during cluster filtering. Thus human preferences on the relative importance of each quantitative goal could be integrated.

Regarding thermal comfort, Sghiouri et al. [84] presented a method that combines single-objective optimisation and building energy simulation to study optimised suspension overhangs. Similarly, the optimisation was performed using NSGA-II. Combining energy and thermal comfort as optimisation, Lin et al. [71] presented an optimisation method for building envelope design to minimise heat loads and improve thermal comfort in a two-star green building in Wuhan, China, considering window-to-wall ratio and insulation thickness. Using solar radiation as an optimisation target, Vermeulen et al. [80] proposed a geometric representation of the city as a periodic urban structure. The basic element, called the urban cell, was repeated in each direction, resulting in a sun mask itself. Using an evolutionary algorithm, this representation optimised a district where buildings had variable heights. Referring to the optimisation of comprehensive sustainability, Youssef et al. [81] introduced a novel optimisation method for building-integrated photovoltaics (BIPV) shape development based on the shape grammar theory. The process reformed the given building shapes and envelopes and determined the best placement and matching BIPV systems for the optimised envelopes.

3.2.3. Simulation methods

Simulation methods can be separated into the rule-based method and the data-driven method. The rule-based approach uses TRNSYS, EnergyPlus, and other building performance simulation software to directly simulate the energy-related performance of the built-building model [85]. But considering that the above optimisation scheme may lead to a heavy computational burden and time-consuming problems, data-driven methods also have been widely used. The artificial neural network (ANN) method is used primarily for its excellent performance and simple structure among various data-driven approaches such as support vector machines [93]. ANNs mimic the animal brain's neural network behaviours, composed of layers of parallel neurons and weighted links. They learn the relationship between the input and output variables through the training data [94]. To predict the building's thermal performance and adopt it as a fitness function for a multi-objective genetic algorithm, Lin et al. [67] proposed a multi-linear regression (MLR) and an ANN model for optimising building envelope design. Chatzikonstantinou and Sariyildiz [4] presented an auto-associative decision support system that used an auto-associative neural net to support decision-making in complex environments, such as architectural design and, in particular, to satisfy decision-maker preference optimally. Li et al. [88] investigated the performances of the GenOpt method and ANN method by using a case study of a simple building energy model. Sun et al. [72] proposed an ANN-based many-objective optimisation design approach and implemented an architect-friendly integrated workflow. The system significantly reduces the optimisation time, and the process is very efficient, eliminating the need for manual data conversion between different platforms. Besides using these artificial intelligence techniques to approximate the simulation model behaviour, response surface methodology (RSM) also can be adopted for simulation. RSM is a combination of mathematical and statistical methods grounded on fitting a polynomial equation to the experimental data, which must describe the behaviour of a dataset to make statistical presuppositions. It can be applied well when a response or a set of reactions of interest are affected by multiple variables. The goal is to optimise the levels of these variables simultaneously for optimal system performance [95]. Dhariwal and Banerjee [75] used these methods to approximate the simulation model behaviour and found that it was several orders of magnitude faster than the simulation model.

3.2.4. Simulation and optimisation tools

For building performance simulation, there is a wide range of mature software available, including TRNSYS [76,79], EnergyPlus [4,68,69,73,75,80,84,85,88], DesignBuilder [71], etc. In addition, Rhino + Grasshopper + a performance simulation plug-in (such as DIVA, Radiance, etc.) [66,72,74,78,87] is also a simulation tool many researchers use. To find the optimal design performance with such a simulation engine, numerous state-of-the-art optimisation tools, such as GenOpt [84,88], JEPlus [79,84], Octopus [65,69,72,74], HLGA [66], etc., have been widely used to couple the energy simulation programs with the generic optimisation algorithms. Although MATLAB is not explicitly designed for building optimisation, it is the optimisation tool of choice for AAD associated with energy-related performance [64,68,75,81,83,85,86,88].

In addition, some studies have developed optimisation tools [67,76].

3.3. Economy

In the process of architectural design optimisation, although the number of studies on the economy topic is relatively small compared with functionality and energy-related performance, it is still one of the vital optimisation objectives that need to be considered. This section provides a detailed analysis of 11 representative studies with the economy as the main topic, as shown in Table 6.

Considering that the studies on the economy topic are similar to those on energy-related performance topics, this section will not specifically introduce workflow and design methods. The relationship between the economy topic and other topics will be briefly introduced.

3.3.1. Optimization objectives

In detail, the economy topic can be divided into the life-cycle cost (LCC), and initial capital cost (ICC).

LCC includes all costs incurred during the life cycle of a building, including construction costs, maintaining, operating, and end-of-life-related costs. Liu et al. [96] proposed a BIM-based building design optimisation method to minimise LCC and life cycle carbon emissions (LCCE). Integrating a BIM-based simulation system and particle swarm optimisation (PSO) based system, a case study proved its reliability, effectiveness, and efficiency. Ferrara et al. [44] exploited automated optimisation search procedures to determine optimal LCC by evaluating many design alternatives. The procedure was performed through an iterative input-output process in a computing environment combining the transient system simulation tool TRNSYS and the universal optimiser GenOpt. The method adopted allowed approximately ten thousand building configurations to be simulated in a reasonable computational time. Ascione et al. [85] proposed a multi-objective optimisation approach to solve the problem of energy design of building envelopes. GA was implemented using the coupling between MATLAB and EnergyPlus to minimise primary energy consumption, energy-related LCC, and discomfort hours. Compared with the former two, fewer studies have international costs as the optimisation objective.

ICC mentioned in this paper is construction cost. Negendahl and Nielsen [65] presented a multi-objective optimisation method for early design stages. It combined two different quasi-steady-state approaches for energy and indoor environment assessment. One is a Radiance implementation for daylight simulations, and the other is a scripted algorithm for ICC evaluation. The approach was developed around an integrated dynamic model. It was fast and flexible enough to support the optimisation of building energy, indoor environment, and cost in the early design phase. Chang and Shih [66] developed a parametric design system with Rhino, Grasshopper, and HLGA. The system's effectiveness was verified through an example with energy consumption and ICC as optimisation objectives.

3.3.2. Relationships with other topics

It can be seen from the selected representative studies that the economic topic is often accompanied by energy and environmental impacts. It shows a close relationship between them; cost often increases with increased energy consumption and environmental impact. For example, Evins [97] proposed a methodology that included a multi-objective genetic algorithm and mixed-integer linear programming to solve buildings' design and operation problems and energy systems. The optimisation objective here was annual carbon emissions and annual running costs. Since the prices and carbon factors of grid electricity and gas had very similar ratios, it was found that running costs roughly followed carbon emissions.

Studies on the economic topic also often choose energy-related performance as one of the optimisation objectives [88]. For example, Sun et al. [72] proposed a many-objective optimisation design method to optimise its Energy Use Intensity (EUI), Spatial Daylight Autonomy (SDA), Useful Daylight Illuminance (UDI), and Building Envelope Cost (BEC). This method has been used in a public library building in Changchun City, China, and has achieved good results. Harkouss et al. [76] developed a valuable tool to enhance Net Zero Energy Buildings design in the early design phases. NSGA-II was chosen to minimise LCC while minimising thermal and electrical demands and reaching the net-zero energy balance. In addition to considering energy-related performance, environmental impacts are difficult to ignore in this type of research. Hester et al. [99] explored the potential of efficiently combining parametrised life cycle assessment (LCA) models with optimisation methods to identify designs with minimal environmental impacts and costs. A novel application of information entropy was also proposed to quantify the flexibility of unspecified plans throughout the guided design process.

4. Applying AAD technology to building renovation

Many existing buildings seldom make forward-looking considerations on the sustainable application of space in the design stage and even start construction without confirming their use functions during the construction period. This situation has caused high energy consumption, poor environmental quality, and low space utilisation efficiency when using many established building spaces. The renovation of existing building space is one of the significant challenges for architects.

The design process of building renovation is not far from new buildings, including pre-design, design, construction, and operation phases. However, the main difference is the limitations of having an existing building and building site and existing users of the building [100].

There have been some studies on the design process of project renovation. Bazerman et al. [101] described the ideal steps in a design process as first defining the problem, then identifying goals and criteria, weighting criteria, generating alternatives, rating each option on each criterion, and computing the optimal solution. Ferreria et al. [102] and Alanne [103] also described the design process of renovation projects. In 2016, Nielsen [100] integrated previous views and divided the renovation of a project into six steps: setting the right goals, weighting the criteria, assessing the building state, generating design alternatives, estimating the performance of design alternatives, and evaluating design alternatives, as shown in Fig. 5. Except for the third step, other steps are essentially iterative, e.g., in the individual design process of the architect or engineer where the design scheme is constantly evaluated. This iterative process is relatively time-consuming and brings much workload to the design staff of renovation.

The most common practices for solving building renovation problems lack efficiency and overall robustness [6]. The existing AAD studies can reduce the implementation time of the fourth step - design alternatives generation, reduce the number of iterations of the last three steps, and efficiently assist the renovation of the construction project.

To analyse the research status of AAD application in building renovation, this paper examines 23 references applying AAD technology to building renovation, as shown in Table 7.

5. Gaps and requirements of applying AAD technology to building renovation

From the summary of Table 4 -to Table 7, gaps and requirements of using AAD technology for building renovation are founded by comparing AAD studies with those using AAD technology for building renovation through optimisation topics, design methods, workflow, and efficiency of building renovation design.

5.1. Acquisition of input data

AAD input data typically include spatial location information such as rooms or building exterior contours. For buildings that need to be renovated, their service life is relatively long. The drawings are often difficult to save or have been lost, so the spatial location information is often not directly available. This creates a challenge for applying AAD technology to building renovation.

Therefore, we need to use 3D reconstruction technology based on computer vision to acquire spatial location information automatically. The 3D reconstruction technology based on computer vision can obtain the 3D information of the corresponding scene and reconstruct the object by processing the captured image or video [118]; specific techniques include 3D laser scanning [119], monocular vision [120], stereo vision [121] and so on. The technology is simple, convenient, and fast to reconstruct, and it can help us to quickly obtain accurate information, such as the edges of the external contours of the building. For AAD methods, where the input data is a BIM model, the spatial location information can also be converted into a BIM model with the help of automatic BIM modelling methods, breaking the barrier between building renovation and the application of AAD technology. In future research, the application of AAD technology in building renovation can be quickly realized with the help of 3D reconstruction technology based on computer vision.

5.2. Optimisation topics

In the preceding analysis, this paper divides AAD studies into three topics according to the optimisation objective: functionality, energy-related performance, and economy. Therefore, this section classifies the 23 studies according to the above three topics and compares their distribution with the topic distribution of the representative studies selected in Section 3, as shown in Fig. 6. Here, "a number of occurrences" refers to the number of times different optimisation topics appear in related field studies. For example, in Fig. 6 (a), the "number of occurrences" of "functionality" refers to the number of times the functionality topic appears in the AAD studies analysed in this paper. "percentage of occurrence" refers to the ratio of "number of occurrences" to the number of related field studies.

It can be seen from Fig. 6 that studies on applying AAD technology to building renovation mainly focus on two topics, including energy-related performance and economy, of which functionality is very few. The studies involving AAD technology in functional building renovation

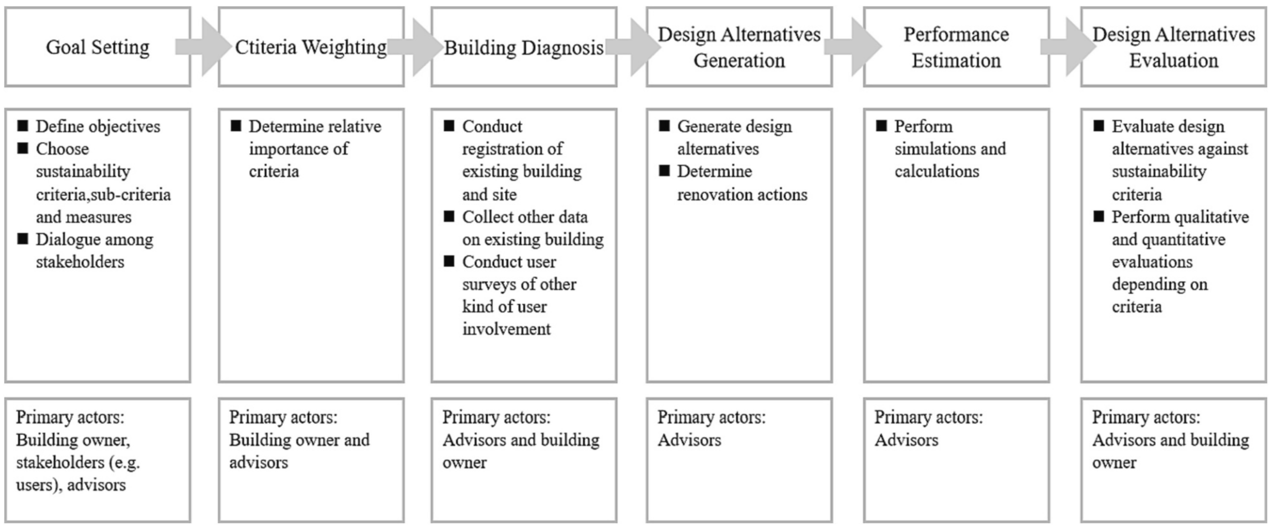


Fig. 5. Whole design process of project renovation [100].

design often combine relevant data on the use of space by building users to determine the objective of functional renovation of existing buildings. For example, in 2015, Dzeng et al. [15] proposed the Function-space Assignment and Movement Simulation (FAMOS) model that integrated radio frequency identification (RFID), fast messy genetic algorithms (fmGA), and motion simulation techniques to solve the function-space allocation problem. The RFID device was specifically designed to track the motion data of occupants in a building, the fmGA was adopted to identify the optimal result of function allocation, and the motion simulation technology was used to verify the development and support decisions on functional space allocation. In addition, the studies applying AAD technology to functional building renovation design are also used in space allocation. Vardouli et al. [104] applied an early algorithm for computing architectural floor plans to carry out the design and plan of the post-war British hospital.

Based on the above analysis, it can be seen that the research gaps in applying AAD technology to functional building renovation design urgently need to be filled. Although it is difficult to change the topological structure of buildings such as ordinary residences during the renovation design process, the research object can be extended to areas with greater spatial freedom, such as libraries, hospitals, office buildings, and stadiums. In addition, the automatic design of the furniture layout can also significantly help during the residence's renovation.

5.3. Design methods

The analysis in Section 3 and Section 4 shows that most of the related studies applying AAD technology to building renovation are based on the BGDS method. For the 8 AAD methods defined in Section 1.2, 7 criteria are used for qualitative analysis to assess whether the AAD method is suitable for building renovation. The suitable types are summarised, as shown in Table 8.

Based on the above analysis, it can be seen that different AAD methods need to be selected for different building renovation objectives. The BGDS method has broad applicability, and most related studies have used it. However, the data-based method is challenging to be applied to actual building renovation due to the uncertainty of its optimisation objectives. In the future, optimisation objectives can be precisely set in combination with methods such as reinforcement learning, which can make the results more meaningful.

5.4. Workflow

The building renovation design often adopts a reverse modelling process, which uses expert decision-making systems, sensitivity analysis, and other methods to find the most suitable design variables and objectives, and then realise automatic design through optimisation algorithms. However, in building renovation design, much knowledge is required, such as knowledge about various needs, broad concepts, and their mutual influence. When decision-makers face many conflicting demands and competing concepts, their understanding of these issues may become more limited. This may result in the design variables, constraints, and optimisation objectives in the parametric model used in building renovation design could be more suitable. Besides, previous studies express quantitative optimisation objectives, but qualitative ones, such as aesthetics, often take more work to say throughout the research process.

Therefore, it is necessary to introduce a dynamic and interactive model reconstruction mechanism to optimise the building renovation plan to realise the re-selection of design variables and optimisation objectives.

5.5. Efficiency of building renovation design

In AAD studies, after establishing a complex parameterised model, simulation software for dynamic simulation puts heavy pressure on the computer. Many studies have introduced ANN into the simulation process to speed up the simulation speed and improve the efficiency of AAD. Although ANN requires significant training data, it can accurately approximate building simulation software results. This method is better than an exhaustive computation and is much faster when operating in a simulation engine.

However, in the current research about building renovation using AAD, the studies combining ANN and GA is relatively inadequate. In future research, the method combining ANN and GA can be incorporated into the renovation decision-making process to improve the efficiency of building renovation.

6. Conclusions and recommendations

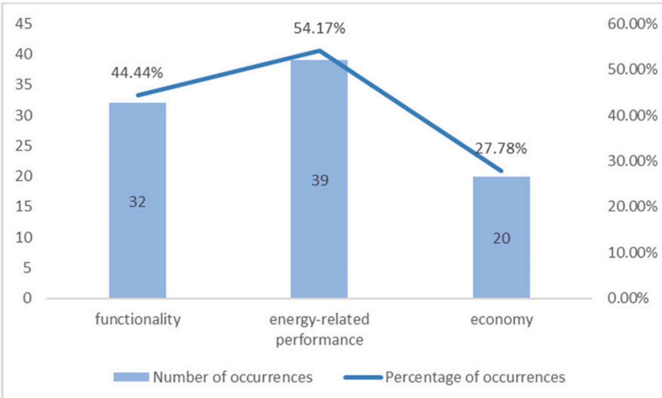
In this paper, we collect and review the studies focusing on AAD and applying AAD technology to building renovation. Based on this, AAD is a promising topic for research, and it can efficiently assist in building renovation. So, we explore gaps and requirements of applying AAD technology to building renovation to provide readers with a detailed and systematic review paper.

The main contributions of this paper are summarised as follows:

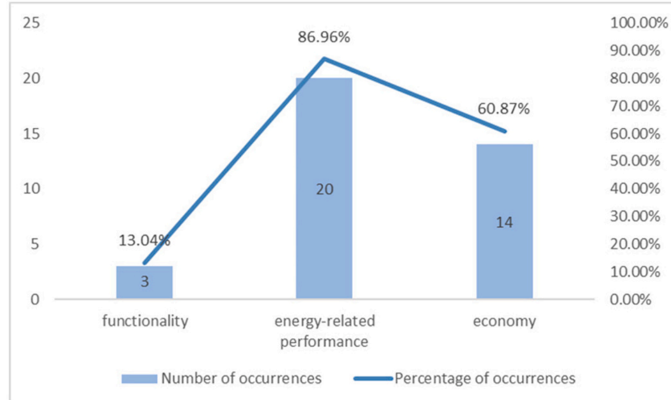
Table 7
Detailed analysis of existing studies applying AAD technology to building renovation.

Topic	Opt. obj	Article	Author	Year	Design variables						Algorithm/methods	Constraints	S/M tools	Opt. tools
					Geo.	Top.	Sha	Env.	MEP.	URE				
Functionality	function-space assignment	[104]	Vardouli et al.	2020	■	■					GA	–	–	–
Functionality	function-space assignment	[15]	Dzeng et al.	2015		■					GA	Space distance; movement relation	FAMOS (customized)	FAMOS (customized)
ERP; economy	Energy consumption; retrofit cost ; thermal comfort	[22]	Asadi, et al.	2014				■		■	GA; ANN	–	TRNSYS; GenOpt	MATLAB
ERP	HVAC energy consumption; conditioned building area; thermal discomfort	[105]	Ascione et al.	2015				■	■	■	GA; ANN	IIC	EnergyPlus	MATLAB
ERP; economy	Thermal energy consumption; NPV; Thermal discomfort	[23]	Penna et al.	2015				■	■		NSGA-II; Mersenne-Twister pseudo random generator	–	TRNSYS	MATLAB
ERP; economy	Energy consumption; ICC; LCC	[106]	Ascione et al.	2016				■	■	■	GA	IIC	EnergyPlus	MATLAB
ERP; economy	Heating and cooling energy demands adjustment; retrofit cost	[24]	Fresco Contreras et al.	2016			■	■			GA; MS Excel programming	Heating/Cooling; Insulation materialsthickness	–	MS Excel solver and GA tool
ERP	Total exergy destructions; consumption of HVAC and DHW generation systems; Thermal discomfort	[107]	García Kerdan, et al.	2016				■	■		NSGA-II;	–	EnergyPlus; Python; SimLab	jEPlus + EA
ERP	Heating and Cooling demand Under different climate scenarios	[108]	Ascione, et al.	2017				■	■		GA	–	DesignBuilder; EnergyPlus	MATLAB
ERP; economy	Energy savings; retrofit cost; payback period	[109]	Fan and Xia	2017				■		■	GA; Nonlinear integer programming	–	–	–
ERP; economy	Exergy destructions; thermal discomfort; retrofit cost	[18]	García Kerdan, et al.	2017				■	■	■	NSGA-II; compromise programming	IIC; Discounted Payback time; Discomfort hours	EnergyPlus; Python; SimLab	ExRET-Opt; jEPlus + EA
ERP	Heating and cooling demand; thermal comfort	[19]	Roberti et al.	2017				■	■		NSGA-II	–	EnergyPlus	C programming
ERP	Heating and cooling demand; exergy need and available	[110]	Bandera et al.	2018				■			NSGA-II	–	EnergyPlus	JEPlus + EA
ERP	Energy savings; payback period	[20]	Fan and Xia	2018				■	■	■	GA	IIC; EPC rating limit; Physical limits (PV installation area, boundary design variables)	–	–
ERP; economy	IIC and operating cost; CO_2 emissions	[21]	Miglani et al.	2018				■	■	■	GA; Mixed integer linear program	Operation levels	3D CAD; EnergyPlus	–
ERP; economy	Energy consumption of heating, cooling, lighting, and appliance; CO_2 emissions; Retrofit cost; thermal cost	[17]	Son and Kim	2018				■			NSGA-II; NSGA-III	–	EnergyPlus	–
ERP; economy	Energy consumption; LCC	[111]	Ascione, et al.	2019				■	■	■	NSGA-II	IIC	EnergyPlus	MATLAB
ERP; economy	Retrofit cost; CO_2 emissions reduction	[112]	Jeong et al.	2019				■	■	■	GA	National CO_2 emission reduction target by 2030	DesignBuilder; EnergyPlus	Excel VBA
ERP; economy	Energy saving; LCC	[113]	Song et al.	2019				■	■	■	GA	Budget limit	–	Excel
ERP; economy	Energy saving; retrofit cost	[114]	Wu et al.	2020					■		GA; Crowdsourcing Model	Requirements of variable boundary and ES	–	–
ERP; economy	Energy consumption; LCC	[115]	Antonio et al.	2020			■	■	■	■	Pareto front	–	DesignBuilder; EnergyPlus	MATLAB
ERP; economy	Annual energy demand; ICC; running cost; CO_2 emissions	[116]	Rosso et al.	2020				■	■	■	NSGA-II	–	EnergyPlus; Python	–
Functionality	Transportation efficiency	[117]	Cemre Cubukcuoglu et al.	2021	■	■					the Iterated Local Search (ILS) algorithm	Edge of rooms	Rhino; Grasshopper	–

Header: Opt. obj, Optimization objective; Shading; Geo., Geometry of layout; Top., Topology of layout; Env., Envelope structure; MEP., MEP system of buildings; URE, Using renewable energy (e.g. solar energy); S/M tools, Simulation/modelling tools; Opt. tools, Optimization tools.
Topic: ERP, energy-related performance; Optimisation objective: ICC, initial capital cost; LCC, life cycle cost.
Algorithm/methods: GA, genetic algorithm; NSGA-II, non-dominated sorting algorithm; ANN, Artificial Neural Network; ES, evolutionary strategy.



(a)



(b)

Fig. 6. Classification and comparison of three types of topics.

Table 8
Qualitative analysis and summary of 8 AAD methods.

AAD methods	Whether a topological relationship can be changed?	Whether internal geometric information can be changed?	Whether structure can remain unchanged?	Whether enclosure structure can be changed?	Whether building systems (such as plumbing, heating, electricity, etc.) can be changed?	Whether internal non-structural components (furniture, etc.) can be changed?	Whether building control strategies can be changed?	Applicable types
Programming design directly (PDD)	yes	yes	yes	no	no	no	no	Suitable for the distribution of a small amount of building space
Discrete event simulation (DES)	yes	yes	yes	yes	yes	no	no	Suitable for positive design with limited and few design variables
Graph theory algorithms (GTA)	yes	yes	yes	no	no	no	no	Suitable for situations where only the topology or geometry of the building space is changed
Building mathematical models (BMM)	yes	yes	yes	yes	no	yes	no	Suitable for situations where optimization objectives can be abstracted into a concrete function
Space discretization (SD)	yes	yes	yes	yes	no	yes	no	Suitable for the situation where a single discretized grid can be used as a separate working space (such as the arrangement of tables and chairs, etc.)
Based on a generative design system (BGDS)	yes	yes	yes	yes	yes	yes	yes	Applicable types are very wide
Machine learning	yes	yes	no	no	no	no	no	A large amount of data of the same type is required for model training, which is suitable for situations with a few constraints, and it is difficult to control whether to change the original building structure
Based on individual data	yes	yes	yes	no	no	no	no	The original building structure cannot be changed, which is suitable for the distribution of building space

(1) This paper classifies and defines the design methods of the parameterised models in the current common AAD studies to help other researchers quickly understand the methods in this field.
(2) This paper divides the recent AAD studies into three categories: functionality, energy-related performance, and economy according to optimisation topics, and analyses their different research characteristics in detail so that readers can clearly understand the current research status of AAD.
(3) By comparing the AAD studies and the studies applying AAD technology to building renovation, this paper summarises the current gaps and requirements of using AAD technology for building renovation from both quantitative and qualitative aspects, providing ideas for subsequent research.

Considering the current development of AAD technology and the needs of the construction industry, this paper formulates some recommendations regarding AAD and applying AAD technology to building renovation.

- AAD

(1) The current AAD studies on functionality topics mainly focus on simple and extensive architectural design. In the future, AAD methods can be combined with specifications and applied to fire protection, green renovation, intelligent renovation, and other aspects of buildings to achieve a delicate architectural design.

(2) AAD technology can be combined with other intelligent construction technologies. Big data, computer vision, natural language processing, and other related technologies can be applied before AAD to provide a data basis for constructing an ideal parametric model; it is also possible to associate AAD with AR/VR/MR to realise the visualisation of design solutions.

- Applying AAD technology to building renovation

The first obstacle to building renovation using AAD technology is acquiring spatial location information. Spatial position information of buildings that need to be renovated is often difficult to save or has been lost. Therefore, it is a valuable and necessary option to use computer vision-based 3D reconstruction technology to obtain accurate information, such as the edges of the external contours of the building. Currently, the number of studies on applying AAD technology for functional building renovation is small, and the gap in this field needs to be filled urgently. When renovating, try to choose buildings with a high degree of spatial freedom. Different AAD methods need to be selected for different building renovation objectives. The BGDS method has broad applicability, and most related studies have used it.

Meanwhile, when designers face many conflicting demands, to design a suitable parametric model, it is necessary to introduce a dynamic and interactive model reconstruction mechanism to optimise the building renovation plan to realise the re-selection of design variables and optimisation objectives. Studies combining ANN and GA should be more present in research on building renovation using AAD. The method combining ANN and GA can be incorporated into the renovation decision-making process to improve the efficiency of building renovation design.

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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