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Review article

A review on multi-objective optimization of building performance - Insights from bibliometric analysis

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ABSTRACT

The optimization of building performance has gained significant attention over the past two decades, driven by the need for energy efficiency, occupant comfort, and environmental sustainability. This paper conducts a comprehensive bibliometric analysis of multi-objective optimization (MOO) for building performance, spanning research publications from 2003 to 2023. Utilizing advanced bibliometric tools such as CiteSpace, VoSviewer, and Bibliometrix, we analyzed 1604 documents from the Web of Science Core Collection to map collaborative networks, research trends, and citation patterns. The study identifies notable advancements in the integration of sophisticated optimization algorithms, including genetic algorithms and particle swarm optimization (PSO), with simulation platforms like EnergyPlus and MATLAB, while utilizing Artificial Neural Networks (ANN) for enhanced predictive capabilities. These integrations have markedly enhanced the efficiency and accuracy of optimizing key building performance metrics, including energy efficiency, thermal comfort, indoor air quality (IAQ), and cost-effectiveness. China and the United States emerged as leading contributors, with higher education institutions playing a critical role in research outputs. Key research hotspots identified include energy consumption, thermal comfort, life cycle assessment, and simulation-based optimization. The effectiveness of genetic algorithms in managing complex multi-objective problems has led to their widespread adoption. Looking forward, future research is anticipated to focus on the development of more integrated and intelligent optimization algorithms that leverage real-time data and user behavior, thus improving the adaptability and sustainability of building performance optimization. This study provides a detailed insight into the evolution and current trends in MOO research, laying a strong foundation for future investigations aimed at advancing building performance in the context of energy efficiency and environmental sustainability.

1. Introduction

Energy plays an indispensable role in the promotion of social progress and global economic growth. However, escalating energy consumption has triggered concerns such as resource depletion, environmental degradation, and climate change [1–4]. According to the International Energy Agency, building operations globally account for approximately 36 % of the total societal energy use in 2020, with carbon dioxide emissions from this sector contributing to 37 % of total emissions [5,6]. In Europe [7] and the United States [8],

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the building sector's share of energy consumption relative to primary energy was 39 % and 40 %, respectively. Given its significant impact on global energy consumption and carbon emissions, the building industry is pressured to enhance its energy efficiency.

Recent technological advancements have enhanced building energy efficiency, offering solutions to mitigate greenhouse gas emissions, reduce energy costs, and foster economic benefits in line with global sustainable development goals. With the escalating urgency to combat climate change and reduce energy consumption coupled with the persistent demand for superior indoor environmental quality, there has been a surge in interest in optimizing building performance through MOO techniques.

These techniques address many conflicting objectives, including energy efficiency, thermal comfort, IAQ, and cost-effectiveness. The MOO of building performance involves navigating complex interactions among diverse parameters, ranging from building design and material selection to the integration of renewable energy systems. To address this complexity, advanced optimization algorithms capable of simultaneously handling multiple objectives have emerged, such as genetic algorithms, PSO, and others. The evolution of these algorithms underscores the evolving complexity and specialization of the problems addressed within this field.

Some studies have explored MOO for building renovation and facade optimization. However, traditional literature reviews may focus on a limited number of studies, making it difficult to capture a broader range of available evidence [9,10], and may rely on personal biases, leading to selective citations [11]. Previous studies have highlighted the importance of regularly updating systematic reviews to maintain their relevance and accuracy, advocating for the use of objective and rigorous methods to ensure the ongoing validity of literature review findings [12–15]. To address these limitations, this study employs bibliometric analysis, offering an objective and systematic approach to collecting and organizing a vast amount of literature while applying quantitative analysis and

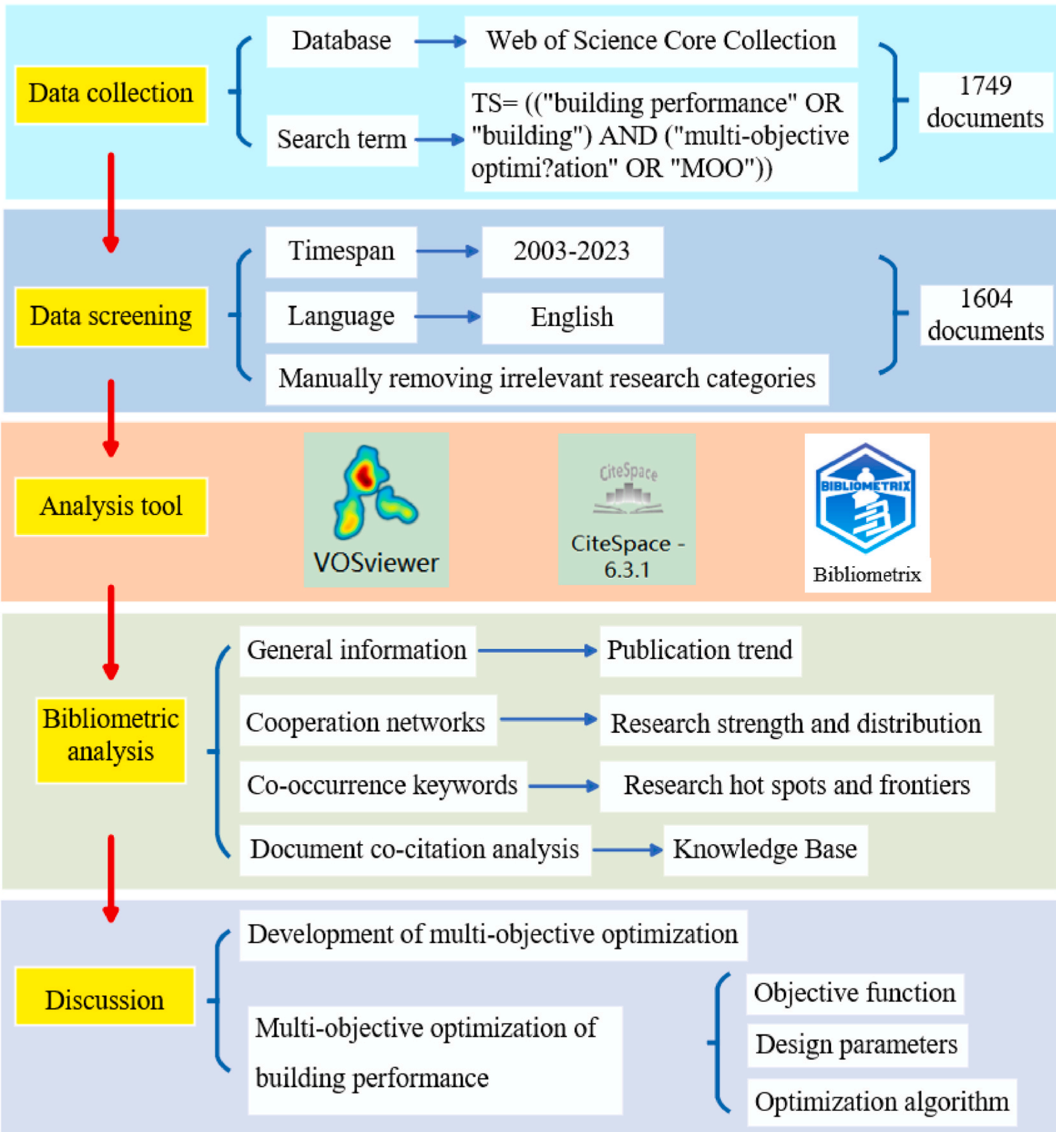

Fig. 1. Document selection and flow diagram.

statistical methods. The primary objective is to identify trends, critical contributions, and future directions in the MOO of building performance.

In this review, we systematically analyze collaborative networks, keyword hot studies, and citation networks within MOO for building performance. Utilizing tools such as CiteSpace, VoSviewer, and the Bibliometrix R package, we explored the knowledge base, research hot spots, and emerging research frontiers. Through this analysis, our study aims to provide valuable insights into the application of MOO to enhance building performance.

2. Data collection and bibliometric analysis

2.1. Data collection and screening

Web of Science databases are internationally recognized databases that reflect the standard of scientific research by allowing access to world-class scholarly journals, books, and conference proceedings in the sciences, social sciences, arts, and humanities and browsing the complete citation network. Because of the completeness and high quality of its entries, the Web of Science Core Collection was selected as the data source for this study. Data retrieval was conducted on April 12, 2024, using the search terms TS= (("building performance" OR "building") AND ("multi-objective optimi?ation" OR "MOO")). A total of 1749 documents were retrieved. The language was then restricted to English and irrelevant categories were manually eliminated and filtered. Based on the literature search results, the first study was published in 2003, and the period was determined from 2003 to 2023.12.31. Finally, 1604 documents were retained for bibliometric analysis. A detailed screening and work flow chart are shown in Fig. 1.

2.2. Bibliometric analysis

The bibliometric analysis in this study was consistent with that of previous studies [16]. CiteSpace (version 6.3.1), VoSviewer (version 1.6.20), and R package Bibliometrix (version 4.3.3) were chosen as the primary tools for analysis and visualization. Each tool was chosen for its unique strengths to ensure a comprehensive evaluation of the research field. CiteSpace and VOSviewer provide intuitive visualizations of the research landscape, helping to identify key literature, track the evolution of hotspots, and explore research frontiers. Specifically, CiteSpace is used for detecting emerging trends and conducting co-citation analysis, mapping the development of the research field over time. VOSviewer is employed to create visualizations of collaboration networks among authors, institutions, and countries. Additionally, Bibliometrix offers precise bibliometric data indicators for statistical analysis. By integrating these tools, this study thoroughly explores the dynamics of the research field while ensuring data accuracy. VOSviewer was used to generate collaboration network diagrams, CiteSpace for keyword clustering analysis and co-citation mapping to reveal research hotspots' evolution, and Bibliometrix for statistical data results. In the analysis process of the CiteSpace software, the slice length was set at one year, and the nodes were merged, deleted, and adjusted manually using the pathfinder function in pruning.

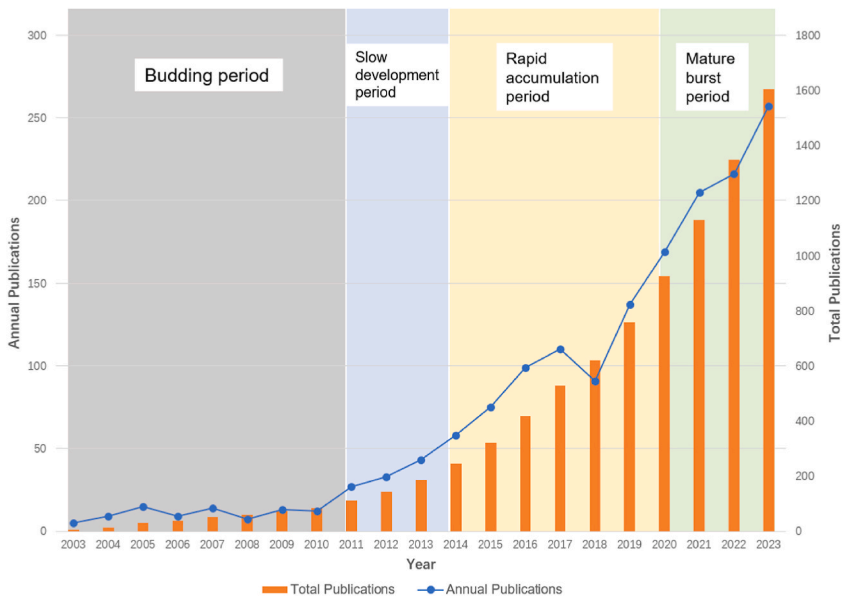

Fig. 2. Annual and total publications in the field over time.

3. Results of bibliometric analysis

3.1. Dataset overview

Fig. 2 displays the annual and total number of publications. Since its inception in 2003, a total of 1604 papers have been published in this field over more than 20 years (Table 1). When plotted on a logarithmic scale, the total publication volume exhibits an exponential growth trend, indicating rapid expansion and increasing scholarly attention. The research trajectory can be categorized into four distinct phases: the budding period, slow development period, rapid accumulation period, and mature burst period.

The period from 2003 to 2010 marks the germination phase of the initial research and is characterized by fewer than 20 publications annually. The subsequent phase, from 2011 to 2013, witnessed a slow development phase in which research began to receive more attention from scholars. However, overall development is still relatively slow. The years from 2014 to 2019 represented a phase of rapid accumulation, where the yearly publication volume increased by more than 50 times. The annual publication volume increased almost linearly during the accumulation period, with the exception of a slight decrease in 2018. Concurrently, research hotspots and frontier directions have proliferated, while knowledge accumulation and technological innovation have expanded.

Post-2020, research transitioned into a mature and explosive phase. More research institutions and scholars have begun to focus on this field, which has resulted in increased research output. Additionally, relevant theories and methodologies have gradually matured, with research findings increasingly being applied to address practical problems.

Fig. 3 presents a keyword time zone map. The node position of this map represents the year in which the keywords first appeared in the analyzed dataset. In contrast, node size represents the cumulative frequency of appearance, indicating the intensity of the research activity associated with that keyword. The connecting lines between the nodes illustrate the inheritance relationship and temporal evolution of keywords. The keyword time-zone map effectively shows the development history and evolution trend from the time dimension.

The development of MOO algorithms for building performance has evolved significantly over the years. In 2002, Deb et al. proposed non-dominated sorting genetic algorithm II (NSGA-II) [17], bringing genetic algorithms into the spotlight within the field of construction. In 1995, Kennedy and Eberhart proposed the PSO algorithm, which began to be applied to the construction field in the mid-2000s and was used for MOO of building performance.

These foundational algorithms paved the way for further advancements. Enhanced versions, such as improved genetic algorithms (e.g., NSGA-II) and particle swarm algorithms (e.g., NSPSO), were developed to improve optimization performance and convergence speed. In 2014, Kalyanmoy Deb et al. introduced NSGA-III [18], an extension of NSGA-II, designed to handle optimization problems with a larger number of objectives. After 2015, NSGA-III gradually began to be applied to building energy optimization. For example, in 2015, NSGA-III was used to address multi-objective hydro-thermal-wind scheduling problems, optimizing wind power costs [19]. Subsequently, it was employed in smart building scenarios to optimize energy management by balancing energy costs, CO_2 emissions, and occupant comfort, demonstrating superior performance over other evolutionary algorithms [20]. NSGA-III has also been applied in building retrofit planning, optimizing objectives such as energy efficiency, greenhouse gas emissions, and total cost [21]. These applications highlight NSGA-III's growing integration into building energy and comprehensive building performance optimization, establishing its significance in multi-objective optimization tasks within this field [18].

More recently, machine learning methods such as neural networks and support vector machines have been applied to MOO problems. These methods enhance optimization by learning historical data and patterns to improve efficiency and accuracy. As a result, the efficiency and performance of MOO for building performance continues to improve.

As illustrated in the time-zone diagram, the early MOO of building performance mainly focused on energy, design, and cost control. Over time, the scope has expanded to include thermal comfort, IAQ, and other research areas. Initial optimization methods mainly involve genetic algorithms, analytic hierarchy process, evolutionary algorithms, neural networks, particle swarm optimization, differential evolution, artificial neural network optimization, differential evolution, artificial neural networks, and machine learning.

After 2011, research began to diversify into optimal design, dynamic simulation, distributed energy systems, cost-optimal analysis, model predictive control, and other topics. The literature on MOO for building performance has been published in 628 different sources. Energy and Buildings ranked first with 131 articles, followed by Applied Energy and the Journal of Building Engineering with 74 and 61 articles, respectively. Table 2 lists the top 10 journals in terms of publications.

The research is mainly distributed across various disciplines, including energy fuels, construction building technology, civil

Table 1
Primary information of the data set.

Main information	
Timespan	2003:2023
Sources (Journals, Books, etc)	628
Documents	1604
Annual Growth Rate %	21.77
Average citations per doc	22.51
References	48970
Keywords Plus (ID)	2066
Authors	4479
International co-authorships %	29.11

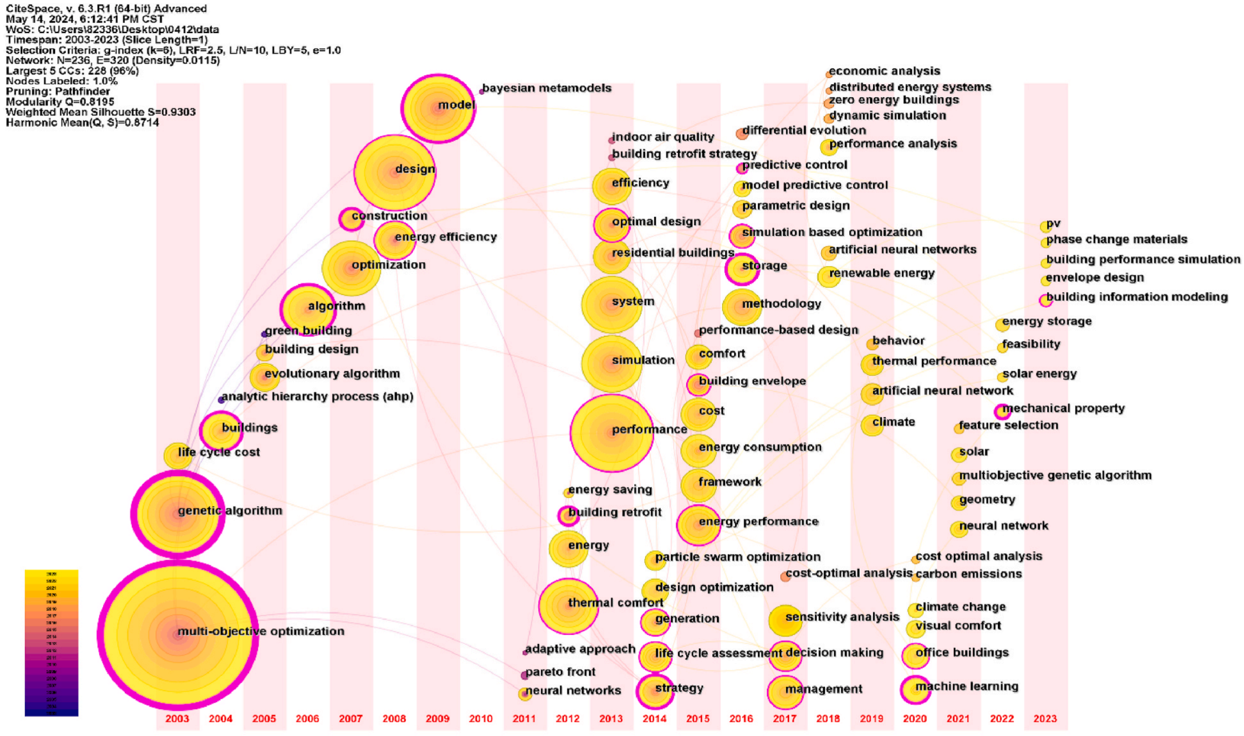

Fig. 3. Keywords time zone mapping.

Table 2
Top 10 journals by publications.

Sources	Articles	TC	h-index	g-index	IF
ENERGY AND BUILDINGS	131	6648	46	79	6.7
APPLIED ENERGY	74	4907	37	70	11.2
JOURNAL OF BUILDING ENGINEERING	61	1175	19	32	6.4
BUILDING AND ENVIRONMENT	57	2376	26	48	7.4
ENERGY	57	2522	27	49	9
JOURNAL OF CLEANER PRODUCTION	45	815	17	27	11.1
ENERGIES	40	454	13	19	3.2
ENERGY CONVERSION AND MANAGEMENT	36	1244	20	35	10.4
SUSTAINABILITY	33	330	9	17	3.9
AUTOMATION IN CONSTRUCTION	27	1141	19	27	10.3

*TC and IF represent total citations and impact factors.

engineering, green sustainable science technology, thermodynamics, computer science artificial intelligence, engineering environment, engineering science artificial intelligence, engineering environment, engineering electrical electronics, and environmental sciences. This wide distribution reflects the multi-disciplinary nature of the field, highlighting the diverse research backgrounds that contribute to advancements in building performance optimization.

3.2. Cooperation networks (authors, institutions, countries)

Fig. 4 displays the organization-author-keyword Sankey diagram generated by Rstudio. Sankey diagrams help to visualize data flows or relationships between different entities, with the thickness of the flow lines representing the strength of the connection between the variables [22]. This diagram sequentially characterizes the flow from institutions to authors to keywords from left to right.

The leftmost side represents different universities or institutions, such as the University of Naples II, the University of Aalto, and Tongji University. The middle section represents researchers affiliated with each institution, and the rightmost section lists the most popular keywords in the field, such as MOO, genetic algorithms, thermal comfort, energy efficiency, machine learning, life cycle cost, and sustainability.

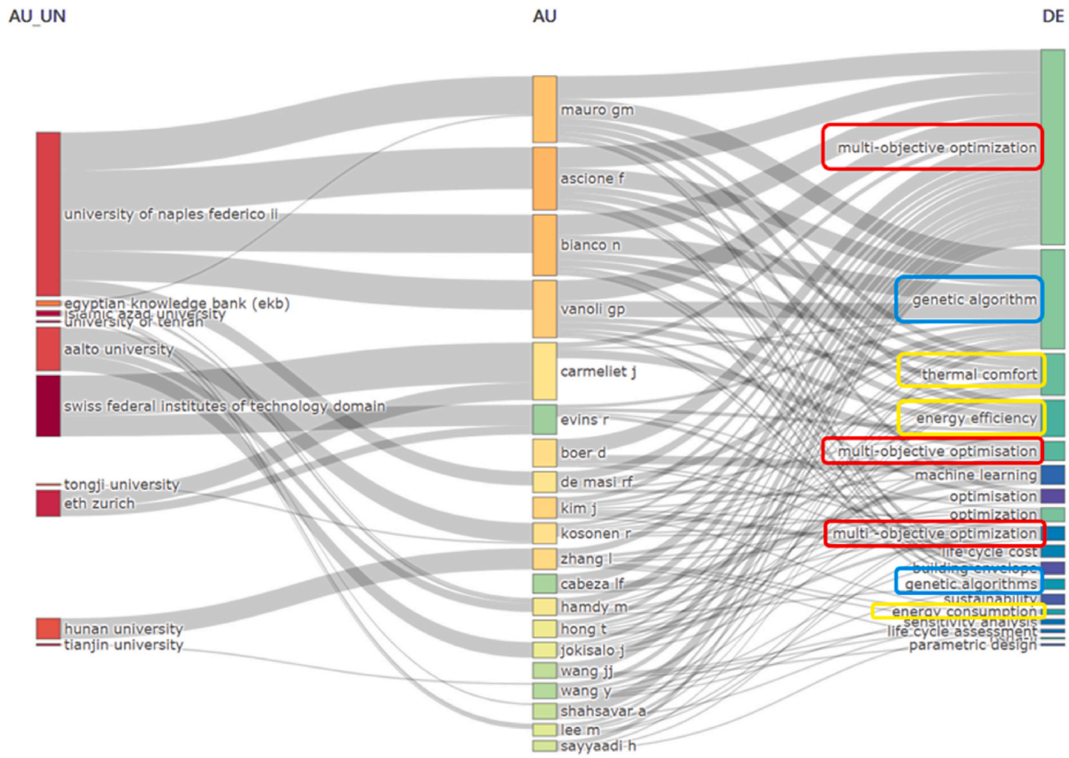

Fig. 4. Sankey diagram of institution-author-keywords.

The flow from institution to author represents affiliations, while the flow from author to keyword illustrates their primary research areas and contributions. Keywords on the far right are categorized in color-coded boxes: the red box highlights MOO, the most concentrated research area in the field; the blue box indicates the genetic algorithm, a key focus; and the yellow box marks the primary objectives of building performance optimization, particularly thermal comfort and energy efficiency. Notably, the highest streamline intensity is seen among researchers from the University of Naples II, underscoring the institution's strong emphasis on these research areas.

We used VOSviewer to generate a collaborative network map of countries (Fig. 5A), authors, and institutions to better understand collaborations within the field. In this visualization, node size is proportional to the number of articles published by a country. The thickness of the connecting line is positively correlated with its LINK STRENGTH, and the color of the connecting line represents the average year of the first co-publication of an article by the two countries.

MOO of building performance is of global interest, particularly given the increasing share of energy consumption by buildings and growing interest in indoor environmental comfort. Scientists from 88 countries have contributed to this research field. However, the extent of contributions inevitably varies from country to country, depending on factors such as building design philosophy, level of economic development, industrial technology, energy efficiency standards, and policymaking. East Asia, North America, and Europe have higher research output. The leading countries in terms of publications were China, the United States, Iran, Italy, England, Canada, and Australia (Fig. 5B).

China has ranked first with 434 publications (based on Corresponding Authors' countries) over the last two decades, accounting for 25.8 % of multiple-country production (MCP) and leads with 7189 citations. China is facing severe environmental pressures and energy challenges, which have prompted the country to focus on reducing energy consumption and improving indoor environmental quality. This dual pressure has driven China to continue advancing research and applications in the field of MOO optimization of building performance [23].

In addition, the accelerated rate of urbanization in China has led to a large number of newly constructed buildings, coupled with the demand for retrofitting existing buildings, which has increased the demand for building performance optimization and provided a large amount of case data for researchers [24]. The Chinese government's energy-saving and emission-reduction strategy at the national level also provides policy and financial support for this research. These factors collectively contribute to the abundance of research results in the area of building performance optimization in China.

The data in Fig. 5C indicate that the United States was one of the first countries to start research on the MOO of building performance. With 154 published papers, it is the world's second most prolific country, underscoring its essential role in the global research field of building performance optimization. The American Society of Heating, Ventilation, Air Conditioning and Refrigeration (ASHRAE) has also contributed significantly to building performance optimization, and its research results have significantly impacted the industry's development. Other countries, such as Iran, Italy, the United Kingdom, Canada, and India, have also made significant

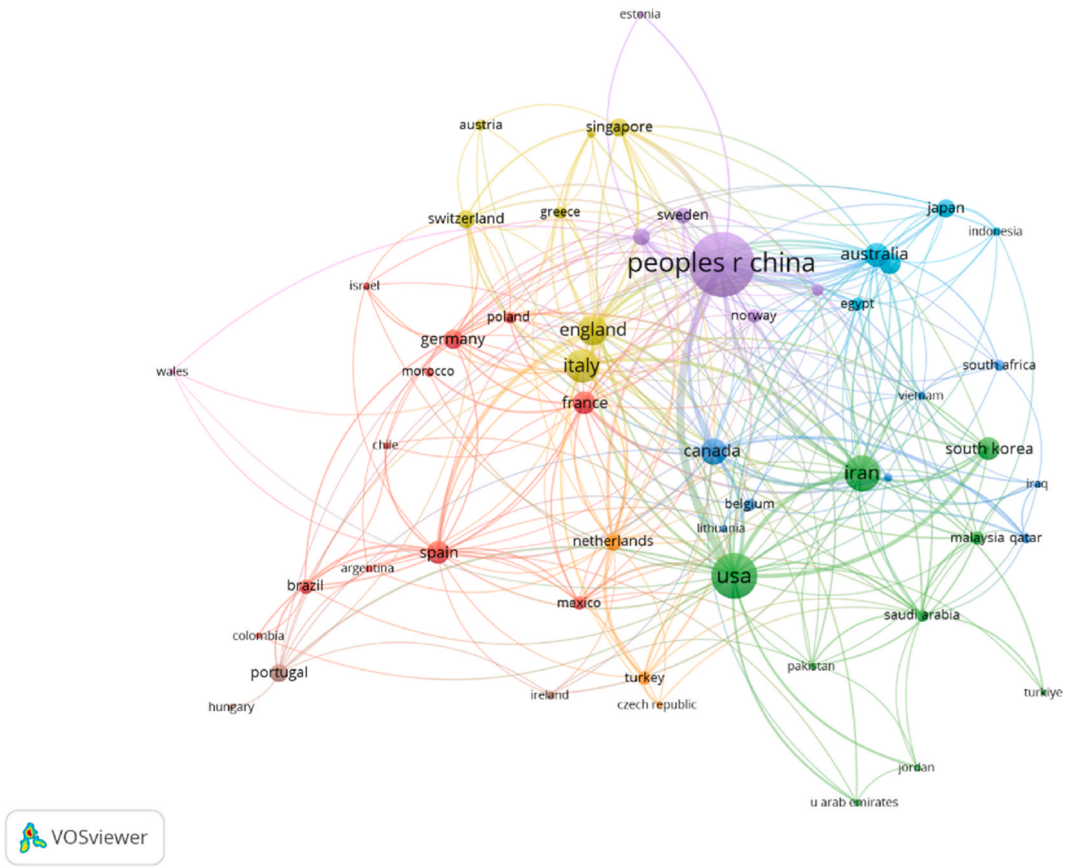

Fig. 5a. Cooperation networks of countries.

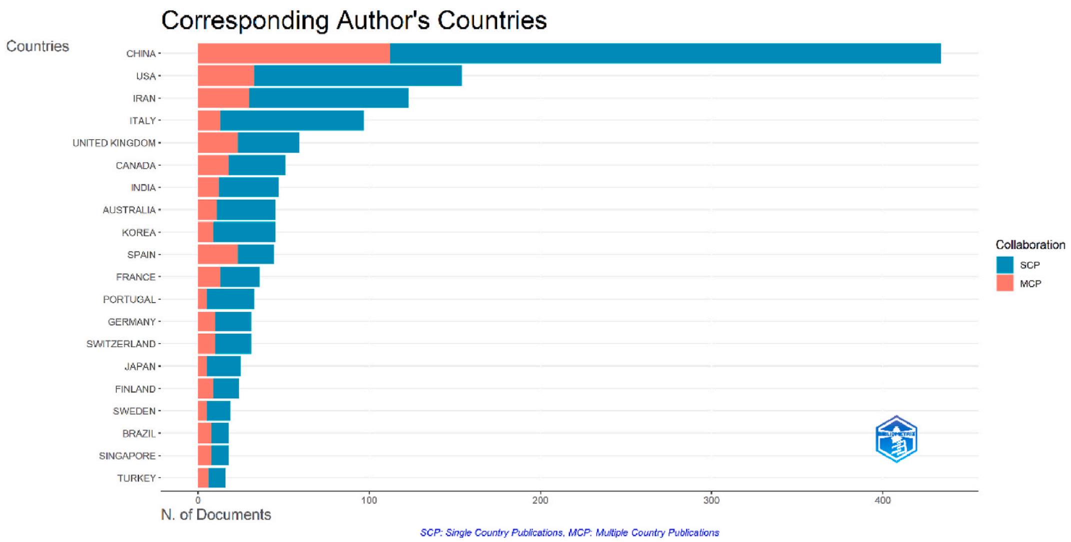

Fig. 5b. Corresponding authors' country contributions.

contributions to the field, with 123, 97, 59, 51, and 47 publications, respectively.

Based on the country collaboration network diagram (Fig. 5A), it can be seen that the most apparent significant collaborations come from China and the United States, which are the two countries that have contributed the most to the field. The ratio of MCP characterizes the collaborative relationship between countries. China has the first level of single-country production (SCP) and MCP.

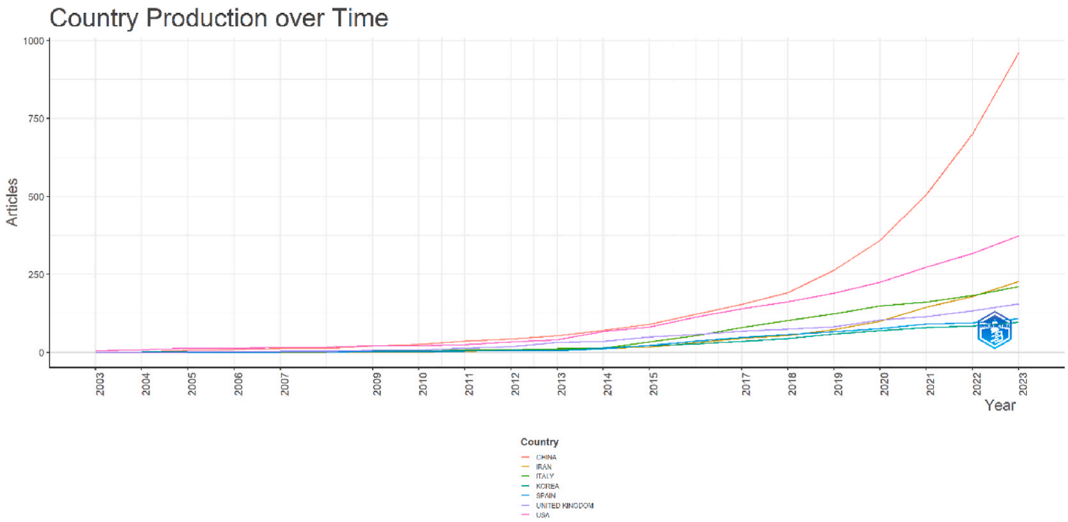

Fig. 5c. Country production over time.

However, SPAIN had the highest rate of international cooperation (52.3 %) in the MCP ratio (Table 3).

Regarding the involvement of research institutions (Fig. 6), higher education institutions, primarily schools of architecture and environmental engineering, are the leading forces in research on the MOO of building performance. By contrast, private companies and research institutes have not yet shown significant leadership in this field. The University of Sannio (Italy), the National University of Singapore (Singapore), Islamic Azad University (Iran), and the University of Naples Federico II (Italy) are the top institutions in the collaborative network, having the most vital link strengths with other institutions.

In the last three years, more research institutions from China have emerged in this field, including Hong Kong Polytechnic University, Hong Kong University of Science and Technology, Huazhong University of Science and Technology, Hunan University, Southeast University, Tongji University, Chongqing University, and other institutions. Analyzing the collaborative network of research institutions through VOSviewer reveals that while there is a relative frequency of inter-institutional collaboration within the same region, there is still room for strengthening the overall collaborative network from a global perspective.

Alfred J. Lotka summarized Lotka's Law in 1926, which concerned researchers' scientific output [25]. Lotka's law implies the presence of a few prolific and poorly published authors in a given academic field. This law has been primarily used to assess research productivity and the distribution of scientific contributions within a field. The MOO of building performance conforms to the primary form of Lotka's law. Furthermore, we analyzed the top 10 researchers worldwide in terms of the total number of publications. Table 4 presents specific information.

Fig. 7 illustrates the author collaboration network, showcasing the connections between key researchers in the field of building performance optimization. It is worth mentioning that the top four authors, Fabrizio Ascione (NP = 21, TC = 1492, h-index = 17), Nicola Bianco (NP = 20, TC = 1352, h-index = 16), Gerardo Maria Mauro (NP = 20, TC = 1250, h-index = 16), and Giuseppe Peter Vanoli (NP = 18, TC = 1306, h-index = 16) formed a very close collaboration and were the most influential research teams in the field. Together, they have significantly contributed to scientific research and practical innovation in optimizing energy retrofitting and building design. This collaborative network was connected through Mohamed Hamdy (NP = 9, TC = 563, h-index = 8) with the network formed by Risto Kosonen (NP = 11, TC = 310, h-index = 9). Thus, the most influential collaborative network in the field was formed. This collaborative network has developed MOO methods combining tools such as EnergyPlus, MATLAB, Genetic Algorithms, and Artificial Neural Networks to customize energy-efficiency optimization solutions for different climates and building types.

In 2015, Ascione et al. introduced an optimization method that integrates genetic algorithms, EnergyPlus, and MATLAB, with a

Table 3
Production and international collaboration by countries.

Country	Articles	SCP	MCP	Freq	MCP-Ratio
CHINA	434	322	112	0.271	0.258
USA	154	121	33	0.096	0.214
IRAN	123	93	30	0.077	0.244
ITALY	97	84	13	0.060	0.134
UNITED KINGDOM	59	36	23	0.037	0.390
CANADA	51	33	18	0.032	0.353
INDIA	47	35	12	0.029	0.255
AUSTRALIA	45	34	11	0.028	0.244
KOREA	45	36	9	0.028	0.200
SPAIN	44	21	23	0.027	0.523

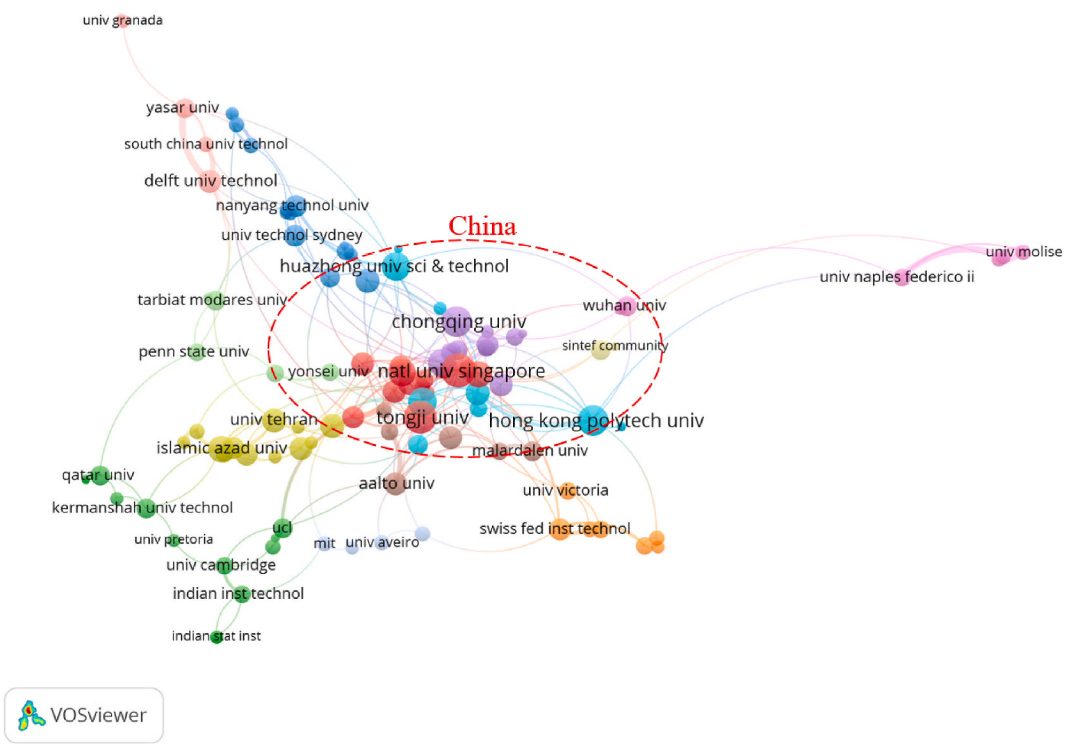

Fig. 6. Cooperation network of institutions.

Table 4
Information on the top ten researchers by total number of publications.

Authors	Institutions	h-index	g-index	TC	NP	PY-start
Fabrizio Ascione	University of Naples Federico II	17	21	1492	21	2015
Nicola Bianco	University of Naples Federico II	16	20	1352	20	2015
Gerardo Maria Mauro	University of Naples Federico II	16	20	1250	20	2015
Giuseppe Peter Vanoli	University of Sannio	16	18	1306	18	2015
Jan Carmeliet	Swiss Federal Institute of Technology Zurich	9	10	730	10	2016
Jimin Kim	Seoul National University of Science and Technology	9	12	251	12	2015
Risto Kosonen	Aalto University	9	11	310	11	2017
Dieter Boer	Universitat Rovira i Virgili	8	11	347	11	2014
Mohamed Hamdy	Norwegian University of Science and Technology (NTNU)	8	9	563	9	2010
Taehoon Hong	Yonsei University	8	9	268	9	2015

focus on energy retrofitting for both new and existing buildings. This method helped identify the most cost-effective energy-saving measures [26]. Building on this work, in 2016, the team developed a multi-objective optimization framework for hospital buildings. This approach adjusted retrofit measures through hierarchical steps, optimizing both energy efficiency and cost [27]. Additionally, they explored strategies for optimizing building envelope design in Mediterranean climates to reduce energy consumption while maintaining thermal comfort [28]. By 2017, the team introduced the CASA framework, which combines genetic algorithms, artificial neural networks, and EnergyPlus to maximize cost savings and minimize thermal discomfort during energy retrofits [29]. Through their use of advanced simulation tools and optimization algorithms, the team has provided highly adaptable and customized solutions for a wide variety of building types and climates, significantly advancing multi-objective optimization in building performance.

Hamdy's research focuses on the MOO of building designs to improve energy efficiency and minimize the environmental impact. By combining simulation and optimization algorithms, Hamdy addressed the complex design challenges of near-zero energy buildings (nZEBs) [30]. His work balances operating costs, energy consumption, and carbon emissions and plays a vital role in advancing the development of methodologies for cost-optimized solutions for building retrofits [27]. Through extensive simulation scenarios, Hamdy tested different building performance variables, pushing the frontiers of sustainable building design and retrofitting strategies.

Kosonen's research addressed the challenge of meeting CO_2 reduction targets in the Finnish building sector [31]. They explored cost-optimal solutions for energy performance and environmental impact analysis using simulation-based multi-objective optimization. His work proposed in-depth energy renovation configurations for different types of buildings [32,33] aiming for significant reductions in energy consumption and CO_2 emissions. His research also involved the use of simulation-based multi-objective

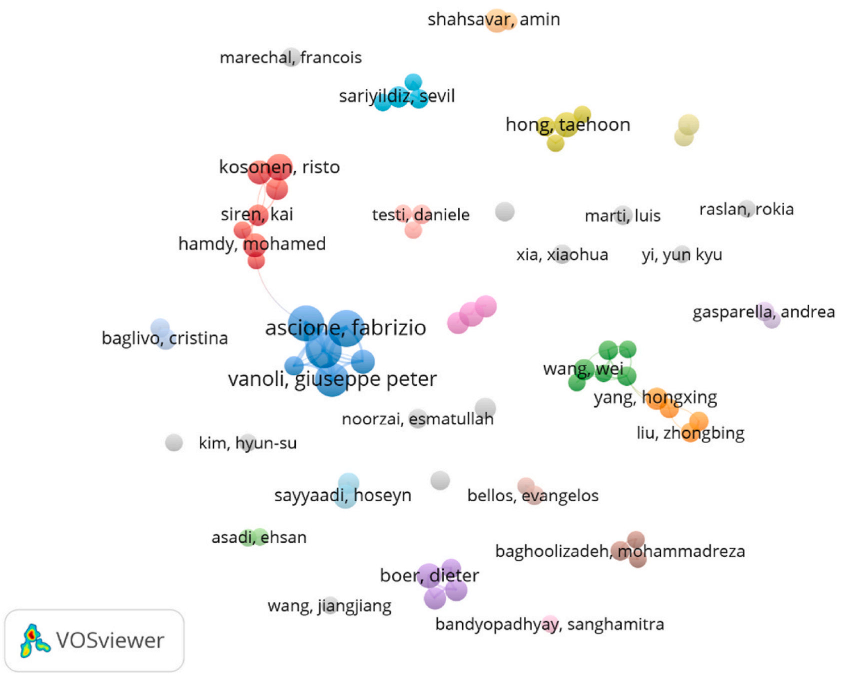

Fig. 7. Author collaboration network.

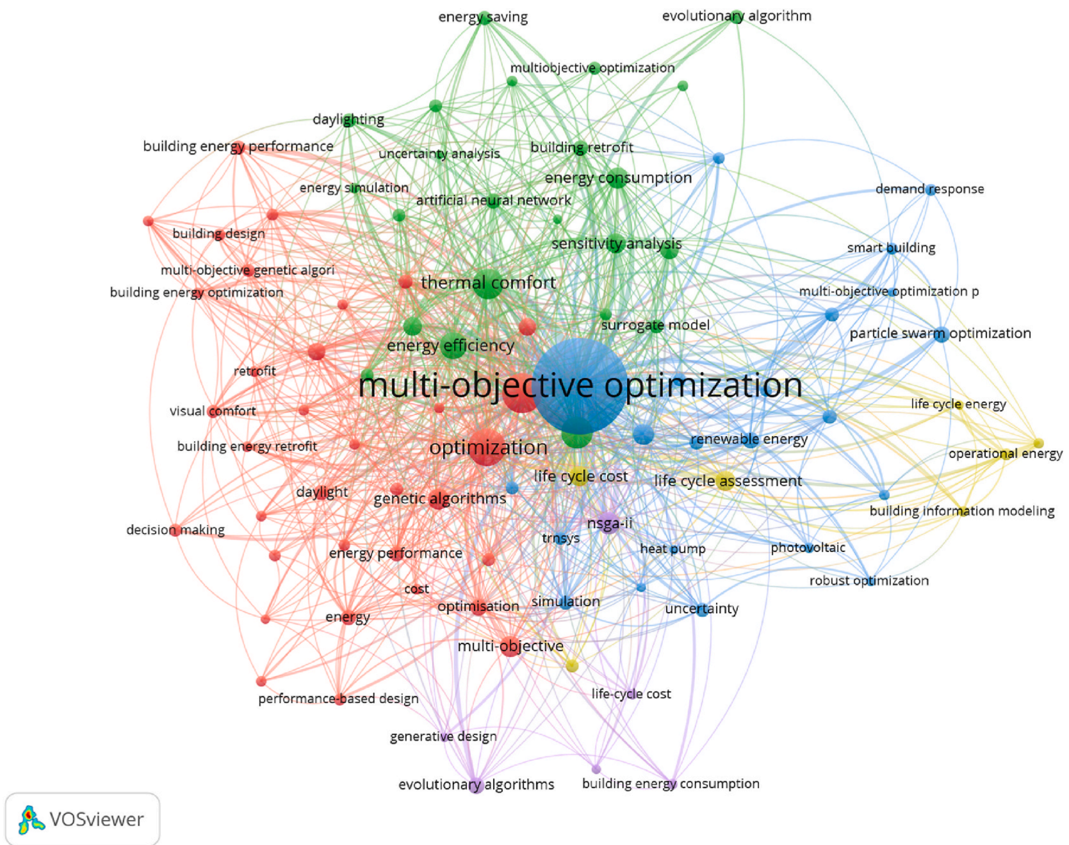

Fig. 8. Keywords co-occurrence network visualization.

optimization for different types of buildings [34] and to estimate future changes using a building bank model based on Finnish statistical data [35].

Another collaborative network was created by Dieter Boer (NP = 11, TC = 347, h-index = 8), which focuses on the energy retrofit of buildings, especially in the combined application of MOO and full life cycle assessment research [36–39], and has emphasized the integration of economics and environmental sustainability at the building design stage. This involves using mixed-integer linear programming models to identify strategies to reduce environmental impacts and quantify the environmental benefits of these strategies through life cycle assessment.

Carmeliet's (NP = 10, TC = 730, h-index = 9) research has focused on developing and applying MOO methods to enhance the building and performance of urban energy systems. His research at the residential community level covers the simultaneous optimization of the building envelope and energy systems to reduce life cycle costs and greenhouse gas emissions [40]. Furthermore, his research extends to the optimization of urban energy systems, including the simultaneous optimization of system sizing, operation, and district heating network layouts for cost-effectiveness and carbon emission reduction [41]. These results provide theoretical and practical guidance for the design of more efficient and sustainable energy systems.

Jimin Kim (NP = 12, TC = 251, h-index = 9) and Taehoon Hong (NP = 9, TC = 268, h-index = 8) focused on MOO for improving building energy efficiency and PV system integration model development and application [42,43]. Their research extensively used simulation tools and genetic algorithms to explore and optimize various aspects of building performance, including window-to-wall ratios, rooftop PV system implementations, and solar thermal systems. Notably, their work addressed the trade-offs between energy performance, economic costs, and environmental impacts [44–46], providing new buildings and retrofit strategies.

In China, a collaborative network has been formed by Hongxing Yang, Wei Wang, and Zhongbin Liu involves The Hong Kong Polytechnic University, Tongji University, Xiamen University, Southeast University, Hunan University, Changsha University of Science and Technology, and other institutions. Hunan University and Changsha University of Science and Technology are forming the largest collaborative network in China.

3.3. Research trending topics

Keywords summarize a paper's topic to a high degree, and their frequency and relevance in different periods reflect the research hotspots and evolutionary trends in the field. In this study, keywords were extracted using CiteSpace, and then a keyword co-occurrence network, keyword clustering network, and keyword burst detection were established.

3.3.1. Trend topics based on keywords co-occurrence and clustering

Fig. 8 presents a keyword co-occurrence network generated using VOSviewer, which visually represents the relationships between research topics related to 'multi-objective optimization.' The colors correspond to thematic clusters within the research field. The red cluster is primarily associated with building performance and algorithms, the green cluster focuses on optimization tools and objectives, the blue cluster highlights emerging technologies and smart buildings, and the yellow cluster emphasizes lifecycle analysis and cost optimization. The connections between keywords illustrate the interactions and overlaps between different research areas. Optimization algorithms, smart technologies, and lifecycle assessments are key factors in improving building performance and advancing sustainable development.

According to Table 5, excluding the keywords used for querying, MOO, and performance, the remaining highest frequencies are as follows: genetic algorithm (327 times), design (289 times), model (207 times), simulation (188 times), system (181 times), optimization (173 times), algorithm (139 times), thermal simulation (188 times), system (181 times), optimization (173 times), algorithm (139 times), thermal comfort (138 times), etc., which are popular research topics in this field. In addition, some essential keywords

Table 5
Most frequently occurring keywords.

Count	Centrality	Year	Keywords
327	0.5	2003	genetic algorithm
289	0.16	2008	design
207	0.28	2009	model
188	0.09	2013	simulation
181	0	2013	system
173	0.11	2007	optimization
139	0.26	2006	algorithm
138	0.15	2012	thermal comfort
81	0.17	2008	energy efficiency
76	0.16	2015	energy performance
54	0.22	2014	strategy
45	0.2	2014	life cycle assessment
42	0.17	2014	generation
35	0.21	2005	evolutionary algorithms
30	0.18	2016	envelope
27	0.24	2020	machine learning
24	0.16	2016	simulation-based optimization

connect different research directions, which rely on the measure of mediating centrality (between centrality), genetic algorithm (centrality = 0.5), model (centrality = 0.28), algorithm (centrality = 0.26), machine learning (centrality = 0.24), strategy (centrality = 0.22), evolutionary algorithms (centrality = 0.21), life cycle assessment (centrality = 0.2), envelope (centrality = 0.18), energy efficiency (centrality = 0.17), generation (centrality = 0.17), design (centrality = 0.16), energy performance (centrality = 0.16), simulation-based optimization (centrality = 0.16), thermal comfort (centrality = 0.15) are all critical nodes with mediator centrality greater than 0.1.

Notably, the genetic algorithm is ranked highest in terms of both frequency and mediator centrality. Building performance objectives are characterized by multi-dimensionality and need to be processed in parallel. Algorithm-based optimization design can solve such complex nonlinear problems, which is one of the research hotspots in this field. The mainstream MOO algorithms include genetic, particle swarm, and ant colony algorithms. The results of keyword co-occurrence mapping show that the genetic algorithm has been the most widely used core optimization algorithm since 2003. Nguyen et al. have counted 16 algorithms applied to the optimal design of building performance and concluded that genetic algorithms are the most frequently and effectively used [47].

Owing to the uncertainty, large number, and discrete nature of building design variables, the final selection of optimization algorithms must be based on specific optimization objects and objectives. Keywords such as thermal comfort, cost, life cycle assessment, simulation-based optimization, and decision-making have been gradually used since 2012. Optimization, decision-making, and other keywords have gradually become research hotspots; people pay increasing attention to the psychological feelings of the house occupants, as well as from the perspective of the whole life cycle of the building, life cycle cost, energy efficiency, etc., to consider the architectural design scheme and make decisions.

Cluster analysis is a statistical technique used to classify research objects into relatively homogeneous groups (i.e., clusters). CiteSpace analyzes the keyword network by clustering, and ultimately obtains the cluster labeling map shown in Fig. 9. Cluster ID is the number of clusters, which are arranged according to the size of the size starting from #0; size indicates the number of documents contained in the cluster; silhouette suggests the homogeneity of the cluster; and >0.7, suggesting that it is convincing. Size indicates the number of documents contained in the cluster, Silhouette suggests the homogeneity of the cluster, and >0.7 suggests that it is convincing. The mean year indicates the average year of document information, and the Top Term indicates the keyword with the highest frequency of occurrence in the cluster. Unlike most previous studies, which are based on the authors' subjective understanding of a particular domain, cluster analysis provides a more objective way to perceive the overall structure of a knowledge domain [48].

To better present the research topics in this field, we have introduced a four-quadrant diagram based on the dimensions of development degree and relevance degree for analysis. Table 6 categorizes research topics into four types: motor themes, niche themes, basic and transversal themes, and emerging or declining themes. This analytical framework allows for a comprehensive evaluation of

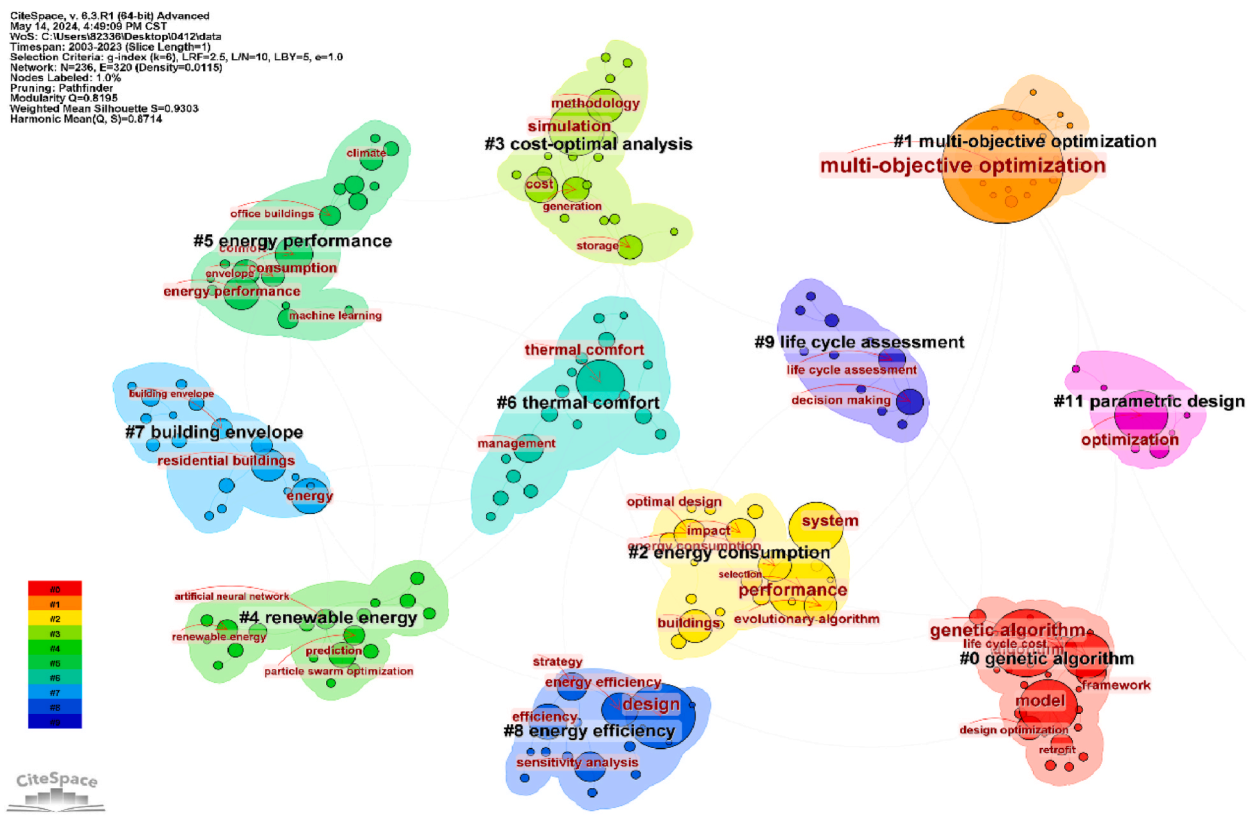

Fig. 9. Keywords clustering map.

Table 6
The #0~#11 cluster labels of the co-occurrence keyword.

Cluster-ID	Size	Silhouette	Mean year	Top Term
#0	30	0.974	2009	genetic algorithm
#1	24	1	2007	multi-objective optimization
#2	24	0.909	2013	energy consumption
#3	21	0.896	2018	cost-optimal analysis
#4	19	0.923	2018	renewable energy
#5	19	0.854	2018	energy performance
#6	19	0.831	2016	thermal comfort
#7	18	0.946	2017	building envelope
#8	16	0.967	2015	energy efficiency
#9	11	0.991	2019	life cycle assessment
#10	10	0.997	2003	oxygen
#11	8	0.916	2010	parametric design

research trends in building energy efficiency optimization, helping to highlight both current major directions and areas with future research potential.

The analysis of Table 6 is as follows: Motor Themes represent topics that are both highly developed and of critical importance within the research field. For example, genetic algorithm (#0, size = 30, mean year = 2009) and multi-objective optimization (#1, size = 24, mean year = 2007) are key motor themes. These topics were instrumental in the early stages of building optimization research and have evolved to tackle more complex goals and constraints. As technology has progressed, these methods have become central to optimizing building design and performance by effectively balancing energy efficiency, cost, and occupant comfort.

Basic and Transversal Themes include foundational topics such as energy consumption (#2, size = 24, mean year = 2013), thermal comfort (#6, size = 19, mean year = 2016), and energy efficiency (#8, size = 16, mean year = 2015). These themes are essential to building performance optimization, as they directly impact energy savings and occupant well-being. As these topics increasingly intersect with emerging research areas, they are expected to gain even more attention in the coming years.

Niche Themes focus on specialized areas of research that hold high value in specific contexts. One example is parametric design (#11, size = 8, mean year = 2010), which has shown great potential in optimizing building geometry to enhance energy efficiency. Although niche in scope, these themes provide important insights for innovative approaches in building performance.

Emerging Themes identified in Table 6 are topics that are gaining momentum due to evolving global priorities around sustainability. These include renewable energy (#4, size = 19, mean year = 2018), cost-optimal analysis (#3, size = 21, mean year = 2018), and life cycle assessment (#9, size = 11, mean year = 2019). The growing focus on sustainability and carbon reduction is driving research in these areas, particularly in efforts to integrate renewable energy systems and optimize lifecycle costs for better energy efficiency and environmental performance. In contrast, Declining Themes are those that are losing relevance as new technologies and standards emerge. For instance, oxygen (#10, size = 10, mean year = 2003) is an example of a theme that has seen decreasing attention as more advanced methods and materials take their place in the field.

(1) Genetic algorithm (optimization method)

The maximum #0 keyword clustering is for genetic algorithms. The genetic algorithm is a landmark algorithm as a mature optimization tool, and many architects and engineers regard it as the first choice for solving design optimization problems. Checking the trend of literature publication, 2003–2012 belongs to the primary development stage, and since 2013, genetic algorithms have been widely used in the MOO of building performance.

Genetic algorithms are widely recognized for their ability to address complex design problems by leveraging principles of natural selection and genetic variation. These algorithms are well-suited to handling diverse building constraints and performance criteria, effectively balancing conflicting objectives such as energy efficiency, cost, and aesthetics by generating multiple sets of solutions [49]. They are often integrated with building simulation tools like EnergyPlus and TRNSYS, enabling a comprehensive assessment of building performance. This integration allows for dynamic interactions between design variables and performance outputs, facilitating a more thorough evaluation of building efficiency [49].

Most building design process decisions must be made in the early design phase, and the design team must balance the multiple objectives and constraints. Genetic algorithms can perform multi-objective searches in the early design phase, quickly generate and evaluate various design options, iterate, and find the optimal solution [50]. F. Ascione et al. coupled a genetic algorithm with EnergyPlus and MATLAB to propose a simulation-based Model Predictive Control (MPC) approach for MOO of heating, ventilation and air-conditioning (HVAC) system control strategies. Based on forecasts of weather conditions and occupancy profiles, the hourly set point temperature was optimized with an ahead planning horizon to achieve MOO of the operating cost for space conditioning and thermal comfort [51].

Moreover, genetic algorithms can be considered in combination with artificial neural networks. The ability of the ANN to quickly evaluate building performance models was used to optimize the genetic algorithms search process and improve the computational efficiency. This approach can significantly reduce the model runtime, making it possible to handle large-scale optimization problems within a reasonable timeframe [52].

(2) Cost-optimal analysis (optimization object)

Several studies have emphasized the integration of design and operational strategies to achieve cost-optimal results. This often involves balancing costs with factors, such as energy efficiency and thermal comfort [53]. A cost analysis needs to assess the overall cost of the building over its life cycle, considering both upfront and operational costs to ensure energy and economic sustainability [54]. In particular, MPC can be integrated into an optimization framework. By predicting and adjusting operations based on real-time data, the MPC can support the realization of cost-optimized energy consumption and operational efficiency [53].

(3) Renewable energy (optimization object)

Several studies have emphasized the importance of hybrid renewable energy systems. The use of MOO models, especially those involving genetic algorithms and other advanced techniques, facilitates the optimal sizing and operation of these systems to balance economic costs and environmental benefits [55,56]. This research emphasizes the integration of renewable energy sources, such as solar and wind, to reduce the dependence on non-renewable energy sources and improve building energy sustainability. Model predictive control methods can shift controllable loads to production periods by adjusting the heating and cooling demands based on fluctuating renewable energy generation [57].

Ebrahimi et al. proposed a multi-objective model to optimize the sizing of a renewable energy hybrid system that employs a NSGA-II methodology to solve the optimization problem to maximize renewable energy efficiency and minimize the net present value cost and CO_2 emissions. The renewable energy efficiency of this hybrid renewable energy system is close to 80 % under the selected climatic conditions and building parameters [55]. Artificial Intelligence (AI) and Internet of Things (IoT) technologies contribute to the integration of renewable energy sources and improve energy efficiency. The energy flows are managed based on grid tariffs, predictive data (photovoltaics and weather conditions), and user preferences. Simultaneous cost minimization and comfort maximization were achieved using AI-based MOO algorithms [56]. Exploring the optimal strategy for building owners based on a MOO model to achieve the required carbon reductions at a minimal incremental cost.

Song et al. [58] suggested that policy adjustments to promote renewable energy sources should be made to support the economic viability of renewable energy technologies in the building sector. Studies often discuss the dual goals of minimizing costs and environmental impacts. Economic analyses show that while initial investments may be high, long-term benefits, such as reduced energy bills and lower carbon footprints, justify upfront costs. Policy measures such as subsidies and incentives are also emphasized as key to facilitating renewable energy integration [59]. Advanced optimization methods, including multi-objective decision-making frameworks, are essential for dealing with the complexity of building energy systems integrated with renewable energy sources. It helps determine the optimal trade-offs between various performance indicators, such as cost, energy efficiency, and CO_2 reduction.

(4) Energy performance/energy consumption (optimization object)

Building retrofits are a practical and impactful way to improve energy efficiency, especially in existing buildings, where such improvements can significantly reduce energy consumption and operating costs [26,60]. Dynamic simulation tools, such as EnergyPlus, in combination with optimization frameworks, are prevalent in research on predicting and improving the energy efficiency of building energy efficiency retrofit strategies. These tools enable detailed analysis and exploration of various retrofit scenarios before implementation, ensuring tailored solutions for specific climatic conditions and building types [61]. Economic feasibility studies, including life-cycle cost analyses, are often discussed in conjunction with energy efficiency measures to ensure financial sustainability over the life-cycle of a building [61].

Integrating photovoltaic systems and other renewable energy technologies is a standard means of improving the energy performance of buildings. These systems can be incorporated into building design through MOO to balance energy production, cost, and environmental impact [62]. Optimizing both passive and active design elements is essential for improving energy performance. Futrell et al. performed a bi-objective optimization of thermal and lighting performance by balancing the needs of passive lighting and thermal comfort with the energy needs of heating, cooling, and artificial lighting [63].

Buildings are designed to adapt to specific climatic conditions, and energy performance optimization is most effective when local weather patterns and environmental conditions are considered. Studies have shown that regional factors affect the choice of insulation, window types, and other building components [61]. Optimizing the building envelope (insulation, windows, and orientation) is critical for minimizing energy consumption. Studies have shown that a well-designed envelope can significantly reduce the need for artificial heating and cooling, thereby reducing overall energy demand [64].

Advanced algorithms, such as genetic algorithms and PSO, are widely used to solve complex MOO problems related to building energy efficiency. These methods help to minimize energy consumption while maximizing other performance aspects, such as comfort or cost-effectiveness.

Sensitivity analysis helps to accurately customize energy-efficient and cost-effective building solutions. It is critical to determine the design variables that significantly affect energy consumption. To conduct a sensitivity analysis, Vukadinović et al. discussed advanced methodological approaches including multiple linear regression and Latin hypercube sampling. These methods help determine how design parameter changes affect building performance and facilitate informed decision-making in the design process [65].

Moreover, sensitivity analysis extends the understanding of how different climatic conditions affect the building performance. This is particularly important for optimizing designs that are effective across various climate zones, ensuring that buildings perform optimally in their respective environments [66]. Passive design elements can be effectively optimized by quantifying their impact on energy efficiency, enabling buildings to maximize the use of natural resources, reduce reliance on mechanical systems, and increase sustainability [67].

A sensitivity analysis informs economic decisions by identifying the most impactful variables, guiding investments in technologies, and designing features that offer the best return on energy savings and cost-effectiveness.

(5) Thermal comfort (optimization object)

Thermal comfort and energy efficiency are the most frequently mentioned objective performances in the MOO of buildings [68]. Optimization algorithms and simulation tools adjust the design parameters to optimize thermal comfort and energy efficiency. Passive design elements, such as shading devices, window glazing, and building orientation, are critical for naturally regulating indoor temperatures, and they can reduce energy demand by improving comfort [69].

The integration of renewable energy technologies, particularly photovoltaics, is analyzed for its impact on thermal comfort by stabilizing indoor temperatures and reducing reliance on conventional energy sources [49]. Dynamic simulations are crucial for predicting and improving thermal comfort in various design scenarios. This approach supports a detailed exploration of different configurations before implementation, ensuring that optimal comfort levels are achieved. Adaptive comfort models that accommodate individual preferences and real-time feedback are required. These models help tailor the indoor environment to the actual usage

Table 7
Top 20 keywords with the strongest citation bursts.

Keywords	Year	Strength	Begin	End	2003–2023
evolutionary algorithms	2005	4.57	2005	2016	
multi-objective optimization	2003	14.37	2007	2012	
energy efficiency	2008	4.51	2008	2015	
building retrofit	2012	3.22	2012	2018	
genetic algorithm	2003	7.6	2013	2016	
optimal placement	2013	3.26	2013	2014	
building envelope	2015	4.4	2015	2017	
building simulation	2016	3.97	2016	2017	
differential evolution	2016	3.97	2016	2017	
simulation-based optimization	2016	3.89	2016	2020	
methodology	2016	5.4	2017	2019	
strategy	2014	3.73	2017	2018	
performance analysis	2018	3.58	2018	2019	
retrofit	2016	4.25	2019	2021	
building energy	2019	3.58	2019	2021	
ventilation	2019	3.25	2019	2021	
behavior	2019	3.25	2019	2021	
prediction	2020	6.37	2021	2023	
artificial neural network	2018	4.52	2020	2023	
multi-objective genetic algorithm	2021	3.75	2021	2023	

patterns and preferences of occupants, thereby enhancing comfort and satisfaction [69]. Economic and environmental considerations are integrated into the optimization process to ensure that thermal comfort enhancements are cost-effective and sustainable. Life-cycle cost analysis is often used to justify investments in energy-efficient measures to improve comfort [70].

(6) Building envelope (optimization object)

Building envelopes can achieve nZEBs by minimizing energy consumption and enhancing sustainability. Therefore, optimizing envelope design is critical for meeting stringent energy standards and sustainability goals [28]. The optimization of building envelope components (e.g., insulation, windows, and wall materials) helps to balance energy efficiency, cost, and environmental impacts. This improved the overall building performance [71]. Advanced materials such as integrated phase change materials (PCMs) and new glazing technologies help maintain indoor thermal comfort while reducing a building's energy demand [72].

There is an increasing emphasis on a user-centred design approach in the design process, focusing on occupant comfort and satisfaction. By optimizing the building envelope, designers can significantly influence the quality of the indoor environment and enhance occupant comfort and productivity [73].

Life cycle costs and environmental impacts need to be integrated into the optimization process to ensure that the building envelope design is not only effective in terms of performance but also economically and environmentally sustainable [74]. The design of the building envelope considers the local climatic conditions and regulatory requirements, ensuring that the design is both practical and compliant with regional standards [75].

3.3.2. Evolution of hot topics

The evolution of research hotspots can reflect dynamic changes in the focus of scientists and the emphasis of scientific research at different times, manifested in new trends, directions, and themes in the field of study. Research frontiers will be converted into knowledge bases over time and new ones will emerge simultaneously. Co-word (keyword) mapping helps analyze research hotspots and their evolution, especially with the use of the burst term function, an algorithm for detecting frequency bursts proposed by Kleinberg in 2002. If a keyword shows a sharp increase in a specific period, it is called a burst keyword [76]. Table 7 shows the top 20 keywords with the Strongest Citation Bursts in this field, sorted according to the year they started to burst. These were the hot topics of research that year.

Based on the results in Table 7, it can be summarized that in terms of optimization algorithms, the genetic algorithm (burst strength = 7.6) runs from 2003 to the present day and has attracted significant attention from researchers from 2013 to 2016; the evolutionary algorithm (burst strength = 4.57) was applied to building performance optimization in 2005, began to be used for building performance optimization, and continued to explode from 2005 to 2016; differential evolution algorithm differential evolution (burst strength = 3.97) is a population-based evolutionary algorithm, which became a research hotspot in 2016–2017; with an artificial neural network (burst strength = 4.52) as a machine learning algorithm and multi-objective genetic algorithm (burst strength = 3.75) have become popular research directions in recent years. Keywords in the order of explosion after 2017: methodology, strategy, performance analysis, behavior, prediction strategy, performance analysis, behavior, prediction, characterization of hot research changes in this field.

To gain a deeper understanding of research trends in building performance optimization, we have analyzed keyword bursts to uncover research hotspots across various time periods. This method allows us to pinpoint key technologies and methods that have been the focus of research and to observe how these technologies evolve in response to industry demands and policy changes.

In the early stages, keyword bursts related to *multi-objective optimization* and *evolutionary algorithms* highlight their central role in optimizing building design. These methods, initially groundbreaking, have been applied to increasingly complex scenarios, establishing themselves as core tools in the field. Although their prominence has diminished in recent years, they have significantly shaped the development of building performance optimization and set the stage for subsequent advancements.

The bursts of terms such as *energy efficiency*, *building envelope*, and *building retrofit* from 2008 to 2017 highlight the construction industry's increasing emphasis on enhancing building performance and optimizing structural design. This period reflects a global push towards reducing energy consumption and improving sustainability in building design and renovation, driven by climate change concerns and policy initiatives. Researchers and practitioners focused on optimizing building envelopes and retrofitting structures to minimize energy loss and lower carbon emissions. The research conducted during this time laid the foundation for energy-saving measures, green building standards, and sustainable development practices that followed.

From 2016 to 2017, the rise of terms like *building simulation* and *differential evolution* signifies a growing emphasis on multi-objective optimization in building performance. Researchers increasingly integrated simulation tools with optimization algorithms to achieve more precise design outcomes. This period marked a transition towards more applied, intelligent, and systematic approaches to building performance optimization. Building simulation underscored the importance of assessing performance through advanced technologies, while the focus on differential evolution indicated a trend towards utilizing sophisticated algorithms to tackle complex, constraint-laden optimization problems. Furthermore, the burst of *simulation-based optimization* from 2016 to 2020 reflects a rising demand for intelligent integration of technologies to address multiple objectives, such as energy efficiency, comfort, and cost. These trends illustrate a shift towards algorithm-driven solutions in building performance optimization, driving significant advancements in the field.

Between 2017 and 2019, keywords such as *methodology*, *strategy*, and *performance analysis* gained prominence in the field of building performance optimization. This period saw a shift towards more systematic and scientific approaches, with researchers adopting advanced computational models, simulation tools, and data-driven techniques. These developments enhanced analytical precision and improved decision-making processes. Optimization strategies became increasingly diverse and adaptable, addressing various project needs and goals, including overall design strategies, material selection, and energy use. These strategies were applied not only to new construction projects but also to the renovation of existing buildings, helping decision-makers identify the most effective design and operational solutions. The rise of performance analysis also marked a transition from traditional energy consumption metrics to a broader set of performance indicators. These indicators included indoor thermal comfort, IAQ, lighting comfort, acoustic environment, pollutant concentration, building costs, operational efficiency, and sustainability performance, including life cycle assessment.

Since 2019, the term *behavior* has emerged as a significant keyword, reflecting a growing interest in how occupant behavior influences building systems. Through behavioral modeling and data analysis, building systems can now more effectively respond to real-time needs by dynamically adjusting parameters such as temperature, lighting, and other environmental factors. This focus on behavior underscores the industry's shift towards smart buildings, where occupant behavior models inform personalized optimization strategies within building management systems. In 2020 and beyond, *prediction* has become a central theme, gaining momentum, particularly after 2021. The rise of prediction models, especially those utilizing machine learning and big data, highlights the evolving trends in construction industry policies and technologies. These models enable the forecasting of building system performance and facilitate real-time adjustments based on external conditions and usage patterns. As global demand for energy-efficient and sustainable building solutions increases, there is a growing emphasis on smart control systems and data-driven optimization methods to enhance both energy performance and occupant comfort. The surge in these keywords reflects the field's heightened focus on behavioral analysis and predictive techniques, driving significant advancements in building performance optimization.

Since 2018, ANNs have become a major focus in building performance prediction and assessment, with a notable surge in interest in 2020. As a powerful machine learning tool for performance prediction, ANNs have rapidly permeated various aspects of building design and performance simulation. Their integration with Building Information Modeling (BIM) and the IoT has enhanced prediction accuracy and computational efficiency in smart building management systems and adaptive design approaches. This surge underscores ANN's pivotal role as a predictive tool in current research and its potential to shape future trends in the field. The continued prominence of ANNs in performance prediction suggests that other AI-related technologies will also see expanded applications in the construction sector, offering new research opportunities and potential breakthroughs.

Since 2021, Multi-Objective Genetic Algorithms (MOGAs) have emerged as a significant research topic, indicating a growing interest in refining these algorithms for larger-scale building systems and complex design scenarios. As smart technologies evolve, integrating MOGAs with cutting-edge techniques such as machine learning and deep learning could enhance the efficiency and intelligence of optimization processes. Future research is expected to focus on improving selection mechanisms and fitness evaluation criteria to boost computational speed and accuracy, addressing the demands of increasingly complex building systems. Researchers will likely explore both practical applications and deeper insights into MOGA's underlying mechanisms and innovative optimization strategies, aiming to provide more effective solutions for building design.

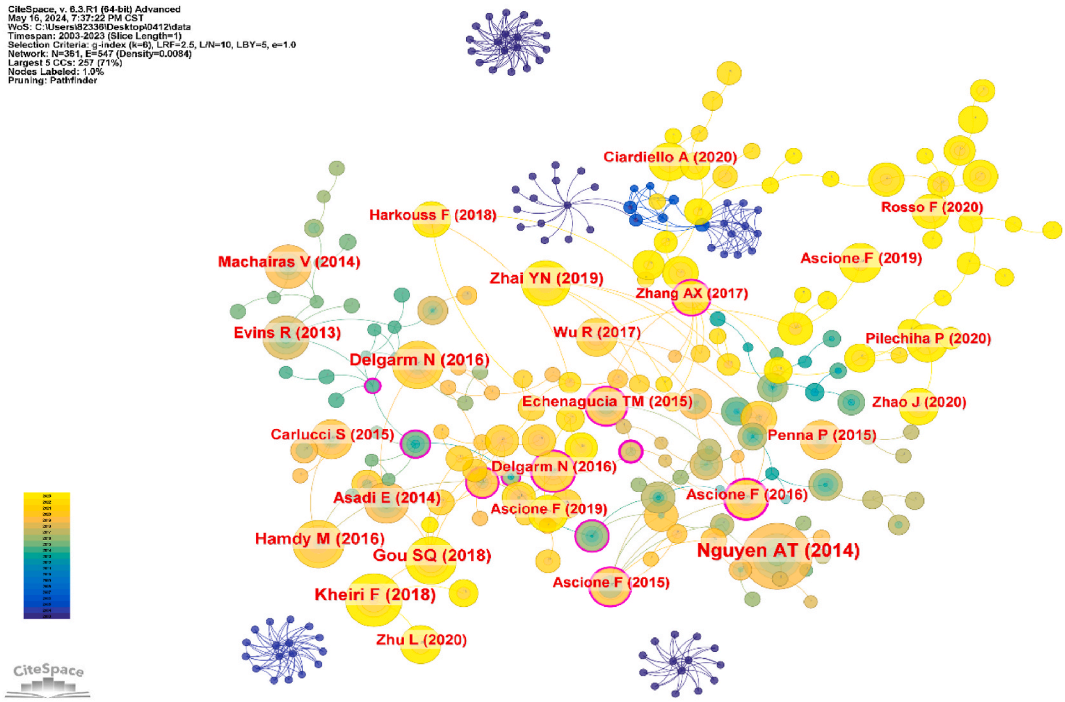

Fig. 10. Documents co-citation network.

The ongoing prominence of keywords like *prediction models*, *ANN*, and *MOGA* signals that these areas will lead future research in building performance optimization. Prediction models, empowered by machine learning and big data, will become essential for supporting the optimization of building performance through real-time monitoring and dynamic adjustments. In particular, ANNs, as powerful prediction tools, will play a critical role in forecasting building system behaviors, while MOGAs will continue to advance as optimization algorithms, driving further improvements in performance and efficiency for complex building systems. These developments will enhance the precision and intelligence of building performance optimization, offering more effective solutions and setting the stage for future innovations in the field.

3.4. Analysis of knowledge base and hottest cited literature

3.4.1. Analysis of document co-citation networks

In 1973, American intelligence scientist Small first proposed the concept of co-citation as a research method for measuring the degree of relationship between documents. When other documents jointly cite two papers, the relationship between them is the co-citation relationship, and the number of co-citations is called the association strength between the two papers. The greater the association strength, the more similar the research topics of the two papers are and the closer the research content is.

Fig. 10 shows a literature co-citation network containing 361 nodes and 547 links. Each node represents a piece of literature and each link represents a co-citation relationship between two pieces of literature. The purple circles in the figure show literature with high centrality. These are essential representative papers in the field. The top five most frequently cited documents were analyzed separately.

Nguyen et al. [47] provided an overview of the simulation-based building performance optimization process and discussed the classification of the optimization problem and the various algorithms and simulation tools used. They also provided a comparative analysis of the efficiency of different approaches for improving building performance. Emphasizing the need for the efficient selection of optimization algorithms based on the requirements of a specific problem, it is suggested that future research directions focus on improving the efficiency of search techniques, improving surrogate models, and reducing the computational effort of simulation-based optimization.

Kheiri discussed the impact of building envelope parameters and geometric configurations on energy performance, emphasizing the need to achieve optimal trade-offs between different design configurations and the complexity of attaining optimal trade-offs between different design configurations to improve energy efficiency. The study also delves into MOO, outlining the decision-making process for integrating multiple criteria to achieve a balanced and sustainable building design, and highlighting the potential for integrating more comprehensive simulation tools and advanced optimization algorithms [77].

In a separate study, Hamdy et al. [78] evaluated seven MOO algorithms commonly used to solve nZEBs design problems. These include a non-dominated sorting genetic algorithm with a passive archive (NSGA-II), multi-objective particle swarm optimization (MOPSO), two-phase optimization using the genetic algorithm (PR-GA), elitist non-dominated sorting evolution strategy (ENSES), and so on. This study compared the repeatability, convergence, solution diversity, and stability of the algorithms. The results show that two-stage optimization using genetic algorithms performs superiorly in terms of repeatability and solution diversity, and can achieve near-optimal solutions.

Delgarm et al. [79] combined PSO and EnergyPlus to optimize the energy efficiency of buildings. This study focuses on the impact of building design parameters (orientation, shading, windows, glazing, and wall materials) on energy consumption. The results show that the optimized building design significantly reduces energy consumption, including the reduction in cooling energy consumption and the corresponding adjustment of heating and lighting requirements. The optimization process produces Pareto optimal solution fronts that show trade-offs between different design parameter choices.

Gou et al. [69] investigated the optimization of the passive design of a residential building by employing a MOO framework that integrates the NSGA-II optimization algorithm with an ANN surrogate model. In this framework, NSGA-II served as the optimization algorithm to explore and identify optimal passive design solutions, while ANN acted as a surrogate model to approximate simulation outputs, significantly reducing computational time during the optimization process. The framework was used to improve indoor thermal comfort while reducing building energy consumption. A new assessment metric, the comfort time ratio, was developed to evaluate and optimize building performance. The combination of simulation tools and optimization algorithms provides strong technical support for achieving MOO of building performance.

According to the summary of the five most frequently cited papers, combining simulation tools and optimization algorithms is the mainstream method for solving the MOO of building performance. The selection of optimization algorithms must be matched to specific performance requirements.

Betweenness centrality is a significant metric for measuring nodes; it discovers and measures the significance of the literature. Nodes with a betweenness centrality greater than 0.1 are considered significant key nodes and are surrounded by purple circles in the figure. Interestingly, four of the top five articles with the highest betweenness centrality were the studies by Ascione et al.

In 2015, Ascione et al. proposed a new methodology that combines the genetic algorithms EnergyPlus and MATLAB through a structured process of preprocessing, optimization, and post-processing phases to achieve energy efficiency at an optimization level. This method is specifically designed to optimize the retrofitting of new and existing buildings, enabling the identification of the most cost-effective combination of energy-efficiency measures [26]. In 2016, Ascione et al. developed a multi-stage, MOO method for energy retrofitting, focusing on hospital buildings. The methodology adapts retrofit measures through hierarchical steps of preliminary analysis and bi-objective and tri-objective optimization to reduce thermal energy demand and achieve cost optimization. Their approach evaluated a variety of retrofit scenarios, demonstrating how strategic upgrades can align economic and environmental goals to promote significant improvements in building energy efficiency [80].

Subsequently, they explored the optimization of building envelope design to meet nZEBs standards in a Mediterranean climate. Dynamic simulation tools and MOO algorithms were employed to analyze various passive strategies, including phase-change materials and cool roofs. The methodology aims to ensure thermal comfort across seasons while minimizing energy demand, providing guidance for the effective integration of passive design in energy-efficient residential buildings [30]. These findings offer valuable insights into incorporating passive design elements for energy-efficient residential construction. However, the challenge remains: how can we robustly assess cost-optimal solutions that are feasible for any building?

In 2017, Ascione et al. answered this question by proposing a new multi-stage framework for cost-optimal analysis using MOO and artificial neural networks known as CASA. This framework combines the genetic algorithms EnergyPlus and MATLAB to minimize energy consumption and thermal discomfort, while maximizing cost savings. This research uses artificial neural networks combined with sensitivity and uncertainty analysis to allow rapid evaluation and adaptation of retrofit strategies for different building categories, making the CASA framework a scalable solution for energy-efficient building retrofits. Finally, it was validated in office buildings, where the results showed that cost savings could be realized while significantly reducing energy consumption, heat discomfort hours, and pollution emissions. The framework innovatively addresses the challenge of scaling up building energy retrofits, providing a cost-optimized energy retrofit solution for any building [29].

Overall, Ascione and his team contributed a forward-looking approach to multi-objective building performance optimization. The extensive use of simulation and computational tools such as EnergyPlus and MATLAB, combined with state-of-the-art algorithms such as genetic algorithms and artificial neural networks, enabled research to find optimal solutions in complex MOO problems of building performance. In particular, customizing solutions for different climates and types (e.g., office buildings, hospitals, and residences) emphasizes the adaptability of the solutions. This research advocates using integrated, multi-objective strategies that utilize advanced simulation and optimization tools to tailor energy retrofit and design solutions to specific building types and climates, ultimately enhancing the sustainability and cost-effectiveness of buildings.

In another critical study, Delgarm et al. combined NSGA-II with EnergyPlus to optimize building energy efficiency performance in different climates. This study highlights the importance and criticality of climate and building design parameter selection in reducing building energy consumption and demonstrates the effectiveness of optimization methods as a decision-making tool for improving energy efficiency in the early building design phase [81].

3.4.2. Analysis of knowledge base

Literature with more co-citations usually has a higher impact on the research field, reflecting the essential theories, methods, or discoveries that form the field's core knowledge structure and foundation. The citation counts of the most locally cited references in this field were 393 [17], 162 [47], 117 [82], 109 [83], 96 [84] and 85 [85].

Deb et al. improved the original NSGA algorithm to address issues such as high computational complexity, the absence of an elite strategy, and the need to specify a sharing parameter to maintain the diversity of the solution set. They proposed the NSGA-II algorithm, which introduces fast nondominated ordering, an elite strategy, and a parameter-free congestion distance method. These enhancements can effectively improve the computational efficiency of the algorithm and solution set diversity.

Simulation tests demonstrated that NSGA-II outperforms other contemporary multi-objective evolutionary algorithms, such as pareto archival evolutionary strategies and strength pareto evolutionary algorithms (SPEA), in MOO problems in terms of preserving the diversity of the solution set and converging to the true Pareto frontier. These features make NSGA-II valuable and influential in solving practical MOO problems.

This paper, published in 2002, has been cited 393 times and has become the basis for research on optimization algorithms in this field. Since then, the NSGA-II has been extensively used in engineering design, building design, and performance optimization [17].

Nguyen et al. reviewed the simulation and optimization methods for building performance in their 2014 article, emphasizing the importance of selecting appropriate optimization algorithms and exploring MOO and optimization under uncertainty. This study analyzed the efficiency of the simulation procedures and optimization tools. This indicates that future research should improve the efficiency of search techniques and approximation methods, reduce the time and labor intensity, and improve the robustness of the optimal solution. This study provides an essential guide and reference for the development of optimization techniques for building design [47].

Evins 2013 summarized the computational optimization methods applied in sustainable building design, covering key areas such as building shells, system configurations, and renewable energy sources, focusing on the overall optimization of dwellings and renovations. This article discusses improvements in the optimization process, trends in MOO, and future directions. This review provides a systematic theoretical framework and practical guidance for the study and practice of building design optimization [82]. A comprehensive review of the optimization algorithms used in building design, including evolutionary algorithms, derivative-free search methods, and their hybrid forms, was presented by Machairas et al. These algorithms mainly improve the building performance and design efficiency, focusing on MOO problems. The literature indicates that these methods suffer from complex algorithmic choices and high computational resource requirements in practical applications, providing a direction of development for improving and applying optimization algorithms in building design [83].

In 2010, Magnier and Haghighat proposed a fast and efficient MOO strategy that significantly reduced energy consumption and improved thermal comfort by combining TRNSYS simulations with an ANN surrogate model and the NSGA-II optimization algorithm. In this framework, NSGA-II served as the optimization engine to explore trade-offs between energy consumption and thermal comfort, while ANN acted as a surrogate model to approximate TRNSYS simulation outputs, drastically reducing computational time. This study highlights the potential of integrating simulation tools and optimization algorithms to enhance building performance and identify optimal design solutions [84].

In his influential book "Multi-Objective Optimization Using Evolutionary Algorithms," Kalyanmoy Deb meticulously synthesizes the theory and application of evolutionary algorithms to address MOO problems. Deb's work is a cornerstone in the field, offering an extensive examination of the methodologies and frameworks for balancing competing objectives within optimization tasks. The text has progressed from foundational concepts and strategies in evolutionary computation to complex real-world applications. The comprehensive discussions encapsulate theoretical underpinnings and algorithmic developments, particularly on elitist strategies, such as NSGA-II, prioritizing the preservation and propagation of superior solutions. This work not only charts the evolution of the domain, but also anticipates future research directions, positioning itself as an indispensable resource for academic and applied research in computational optimization [85].

4. Discussion

4.1. Development of multi-objective optimization (MOO)

The initial MOO problems concerned theoretical foundations such as Pareto optimal solutions. At this time, researchers were mainly concerned with how to define and identify optimal solutions in multi-objective issues and how to construct simple methods that can deal with two or three objectives; with the advancement of computational technology into the period of heuristic and classical techniques, the first generation of MOO algorithms appeared, such as vector optimization methods, goal programming, and hierarchical ranking.

The rise of evolutionary algorithms has marked a turn in this field; a series of evolutionary algorithms (e.g., genetic algorithms, evolutionary strategies, and evolutionary planning) have been applied to MOO problems. Representative algorithms include the NSGA, SPEA, and MOGA. These algorithms generate diverse Pareto optimization solutions that are suitable for solving complex optimization problems in practice.

Subsequent advancements have led to the development of newer algorithms, such as NSGA-II and SPEA2, which provide higher-efficiency and better-quality solution sets. In addition, researchers have begun to focus on other aspects of MOO problems, such as dynamic MOO, multi-objective decision-making support, and practical applications of MOO problems. In recent years, MOO techniques have been widely used in industrial engineering, energy management, transportation, and ecological environments. Meanwhile, many software and tools have been developed to solve MOO problems.

The MOO of building performance is a specialized application area that involves the optimization of multiple performance metrics, such as building design parameters, to balance various objectives, such as energy efficiency, indoor comfort, cost-effectiveness, environmental friendliness, and building functionality. The earliest MOO mainly focused on industry and economics, with relatively few applications in architecture. In the 1970s, the initial phase of the architectural field mainly focused on optimizing a single performance metric using linear and nonlinear planning techniques. With the development of computer technology and the popularity of simulation software, architects have begun to use computers to simulate and evaluate building energy consumption and indoor microclimates. They explored MOO based on rule-based systems and simple optimization algorithms.

By the early 2000s, evolutionary and heuristic algorithms had been applied to the MOO of building performance. Researchers have utilized these algorithms to address multiple conflicting objectives in building design, such as cost, energy efficiency, environmental

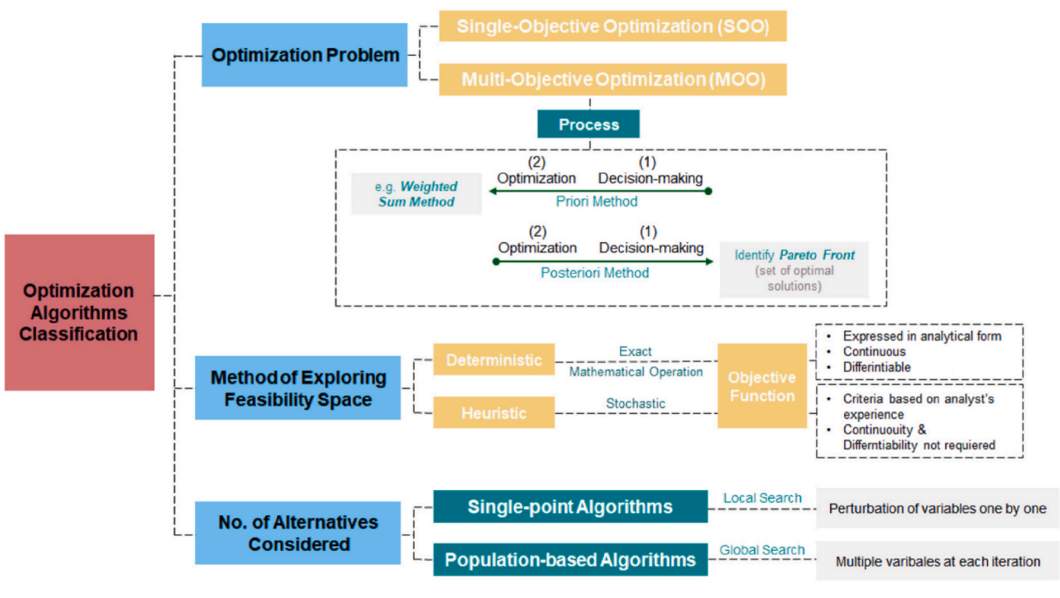

Fig. 11. Optimization algorithms classification [86].

impact, and user comfort. Representative algorithms include genetic algorithms, PSO, and simulated annealing. More complex and efficient MOO algorithms, such as NSGA-II and SPEA2, have been developed. These algorithms can generate diverse Pareto optimal solutions to help building designers make the best choices among the many design options. The current research combines artificial intelligence and machine learning techniques and integrates the effects of user behavior, environmental changes, and socioeconomic factors.

4.2. Optimization algorithms and objectives

Over time, various optimization methods and algorithms have been proposed to address the unique characteristics of MOO problems. Some of the most commonly used methods include the Pareto frontier method, the weighted sum method, the ε-constraint method, and the analytic hierarchy process. Among these, the Pareto frontier method has gained widespread popularity due to its ability to provide multiple balanced solutions, making it the most mainstream approach. Once the appropriate optimization method is selected, the next critical step is choosing a suitable algorithm to execute the iterative optimization process. This choice depends on several factors, such as the type of optimization problem, the complexity of the objective function, the number of variables, and the method used to explore the feasible solution space, as illustrated in Fig. 11.

In MOO, algorithms are generally classified into two categories based on the optimization and decision-making process: a priori methods, where preferences are defined before the optimization process, and a posteriori methods, where preferences are determined after generating a set of solutions. Additionally, algorithms can be categorized as deterministic (precise) or heuristic (stochastic), depending on how the objective function is expressed. Deterministic methods require the objective function to be continuous and differentiable, while heuristic methods rely more on the expertise of the optimizer to guide the process. In building performance optimization, these algorithms are mainly divided into deterministic algorithms and population-based stochastic algorithms. Deterministic approaches simplify multi-objective problems by converting each objective into a scalar value, whereas population-based stochastic algorithms are more commonly employed in complex, constrained optimization problems. Among these, genetic algorithms and PSO are two of the most frequently used algorithms [86].

Currently, genetic algorithms are widely applied in MOO for building performance. Genetic algorithms evolve solutions through an iterative process, guiding them toward an optimal outcome. In 1994, Srinivas and Deb introduced the NSGA, which is based on the Pareto optimal concept. This was further improved in 2002 by Deb and colleagues, resulting in NSGA-II, which enhanced both the speed and accuracy of optimization [17]. Due to its fast convergence and strong performance, NSGA-II has since become one of the most widely used genetic algorithms in MOO. However, when the number of objectives exceeds four, the performance of NSGA-II declines significantly [87]. To overcome this limitation, Deb et al. introduced NSGA-III, a more advanced and efficient algorithm capable of handling complex problems with higher-dimensional objectives. Research has demonstrated that NSGA-III consistently outperforms NSGA-II in high-dimensional multi-objective problems [88].

The PSO algorithm, introduced by Eberhart and Kennedy in 1995, emerged as a powerful tool for optimization but was only applied to MOO problems after 2002. Like genetic algorithms, PSO is a population-based algorithm that begins with random solutions and iterates toward an optimal solution by evaluating their quality through a fitness function. The algorithm continues this iterative process until a satisfactory solution is found. An example of PSO's application in building design is Liu et al.'s use of an improved PSO to balance life-cycle carbon emissions and costs. Their study demonstrated that the enhanced PSO not only improved computational speed but also mitigated premature convergence issues, a common challenge in evolutionary algorithms [89]. Similarly, in 2001, Zitzler and Thiele introduced SPEA2, an advanced version of the SPEA, which improved the fitness assignment process, individual distribution evaluation, and the management of non-dominated solution sets—further expanding the range of applicable optimization techniques.

The diversity of optimization algorithms employed in building performance optimization reflects the complexity and variety of the problems faced. No single algorithm is universally applicable to all building optimization problems due to the wide range of objectives, constraints, and performance metrics [90]. The selection of an appropriate algorithm depends heavily on the specific characteristics of the problem, including the type of objective functions (linear or non-linear), the balance between global and local search requirements, computational resource availability, time constraints, and the overall complexity of the optimization task. The number of objectives is also a critical factor in choosing an optimization method.

For single-objective optimization, standard algorithms like genetic algorithms or PSO are widely used due to their efficiency in finding optimal solutions. However, as the number of objectives increases, the optimization task becomes more complex. In cases of two-objective optimization, algorithms like NSGA-II or Multi-Objective Particle Swarm Optimization (MOPSO) are commonly employed. These methods are designed to balance multiple conflicting objectives, providing trade-off solutions that make them well-suited for complex optimization scenarios. NSGA-II remains a popular choice for two-objective and three-objective problems because of its ability to generate a well-distributed Pareto front. However, as the number of objectives grows, the complexity of the problem increases, making NSGA-III a more suitable option. NSGA-III, designed for handling high-dimensional objective problems, excels in generating diverse solutions while ensuring that all objectives are effectively optimized. This makes it particularly valuable for building system optimization problems, where large datasets and multiple conflicting objectives are common.

For multi-objective problems involving three or more objectives, algorithms like MOGA and NSGA-III are often employed. When the number of objectives reaches four or more, the problem complexity increases significantly, and the use of heuristic or population-based algorithms becomes advantageous. For instance, Differential evolution is a robust option for large-scale, complex-constrained optimization problems in building design, as it does not require the objective function to be differentiable or continuous. Additionally, combining MOGA with machine learning techniques in complex building design scenarios can further enhance the adaptability and efficiency of the optimization process, allowing for more precise solutions in highly dynamic and intricate environments.

The process of building optimization essentially involves finding optimal solutions that meet various objectives, which include, but are not limited to, minimizing environmental impact, reducing the consumption of energy, building materials, and other resources, minimizing construction and operational costs, and maximizing building performance, such as thermal comfort, natural lighting effectiveness, and IAQ [91]. Broadly speaking, optimization objectives can be categorized into the following key areas: building energy consumption, indoor environmental quality (thermal, lighting, and acoustic environments, and IAQ), economic indicators, environmental indicators, and others. Among these, energy efficiency optimization remains a primary focus in current research, targeting areas like HVAC, heating, and lighting energy consumption.

Another key area of interest is indoor environmental comfort, encompassing thermal conditions, lighting, and air quality. A recent review indicates that the most frequently selected MOO targets are energy consumption, thermal comfort, and IAQ [86]. Other common objectives include visual comfort, productivity, lighting quality, and life cycle cost, among others. The main indicators used to assess energy consumption, thermal comfort, and IAQ are energy consumption, PMV, and CO_2 concentration levels, likely due to their standardization, direct correlation with objective functions, as well as data accessibility and measurability. According to data derived from another review study, 66 % of the studies addressed two optimization objectives, while 31 % dealt with three objectives. Only approximately 3 % of the literature proposed the simultaneous optimization of four or more variables [92]. Furthermore, nearly 83 % of the studies included improving building energy performance as one of the objectives, followed by thermal comfort, visual comfort, life cycle cost, and life cycle emissions.

4.3. Multi-objective optimization of building performance

In the realm of MOO of building performance, objective functions can be broadly classified into several key categories. First, there is energy efficiency optimization, which entails the minimization of energy consumption across various aspects such as heating, cooling, lighting, and equipment usage. Second, optimizing indoor environmental quality and occupant comfort is crucial, focusing on factors such as air quality, lighting, acoustic environment, and thermal comfort. Additionally, economic considerations come into play, aiming to minimize construction and operation costs, along with optimizing life cycle costs. Finally, environmental impacts are a significant concern, covering aspects such as reducing greenhouse gas emissions and the ecological footprint.

Across many studies, performance objectives emphasize energy, the environment, comfort, and the economy. This is reflected in the combined reduction in energy consumption, optimization of thermal comfort, minimization of environmental impacts, and achievement of cost-effectiveness. Balancing these goals often requires trade-offs, and complex interactions exist between various goals [93]. Sustainable development, such as improving energy efficiency, reducing environmental impacts, and integrating renewable energy sources, is consistent with global sustainable development goals [94].

The integration of optimization algorithms with building performance simulation tools is essential for accurately modeling the effects of various design choices on building performance. However, this integration faces several significant challenges. One major issue is the high computational intensity required by high-fidelity simulations and advanced optimization algorithms, which often limits their applicability to resource-intensive scenarios, making them impractical for projects with limited computational capacity [95]. Additionally, simulation outputs often exhibit discontinuities and non-linearities, further complicating the optimization process [47]. Many existing studies lack real-time adaptability, reducing their effectiveness in dynamic environments where conditions change rapidly [96]. Furthermore, the reliability of optimization outcomes depends heavily on the fidelity of the simulation tools and surrogate models, which may fail to adequately capture the complexities of real-world building dynamics [97]. Addressing these challenges requires developing lightweight and adaptive optimization frameworks, improving surrogate models, and integrating real-time data and user behavior to enhance both computational efficiency and practical relevance [47].

To address these challenges, future research should focus on addressing these limitations by developing optimization frameworks that strike a balance between computational efficiency and accuracy. For instance, lightweight optimization frameworks and adaptive algorithms that can integrate real-time data and user behavior could significantly enhance the relevance and flexibility of solutions in practical applications [98]. Hybrid optimization methods that combine machine learning techniques with traditional evolutionary algorithms present a promising direction for improving both precision and robustness in optimization outcomes [99]. Furthermore, it is essential to tackle uncertainties in input parameters and climate data to ensure that the results of optimization processes are reliable and applicable across a variety of scenarios [100–102].

In practical applications, the design parameters are variables that can be adjusted during the optimization process, and the parameter values directly affect the performance of the building in terms of energy consumption, cost, and comfort. The design parameters included (1) building floor plan layout and orientation; (2) building envelope, including wall, roof, and floor materials, window-to-wall ratios, and glazing thermal coefficients; (3) building energy system choices, including HVAC system types and efficiencies, lighting system choices, and renewable energy systems; and (4) building control systems and automation. Simulation software usually evaluates design parameters during the MOO process to determine their impact on building performance and to find the optimal equilibrium to satisfy multiple performance objectives by adjusting the design parameters.

Design variables, such as building geometry, envelope characteristics, and material selection, have a significant impact on the energy efficiency and environmental impact of a building, especially the choice of insulation materials and the design of windows to balance light transmission and thermal resistance. Optimal design solutions can improve energy efficiency but require a deep understanding of material properties and their interaction with climatic conditions [103]. Designers can maximize environmental, economic, and comfort criteria by optimizing physical characteristics and configurations, considering local climatic conditions, and the intended use of the building [94]. Effective facade design is essential for improving energy efficiency and reducing environmental impacts while ensuring occupant comfort and visual appeal [104]. Advanced simulation tools are necessary for managing the complex relationships between various design parameters, allowing detailed exploration of parameter impacts, and fine-tuning design decisions to facilitate trade-offs between optimization objectives. Some studies have called for more customized solutions that consider the local climate, usage patterns, and available technologies [94,103].

Various optimization algorithms have been employed to address the multi-dimensional challenges of building design. Genetic algorithms, particle swarm optimization, and simulated annealing are widely used. These algorithms are essential for managing multiple, often conflicting, objectives and provide a powerful tool for exploring different design options and determining optimal tradeoffs. Table 8 summarizes key studies that have utilized multi-objective optimization models in building performance, including different building types, optimization objectives, methods, and parameters considered. This table highlights how algorithms like genetic algorithms and particle swarm optimization have been applied to optimize energy consumption, thermal comfort, and indoor air quality in various contexts.

Integration with building performance simulation tools is essential for practical evaluation and refinement of design strategies through iterative testing and tuning [104]. Algorithms such as genetic algorithms and particle swarm optimization are particularly praised for their robustness in balancing conflicting objectives such as cost, energy efficiency, and environmental impact. Owing to their computational demands, the computational intensity and expertise required to apply these algorithms effectively may not be appropriate for every design scenario [94].

Combining optimization algorithms and building performance simulation tools is essential for accurately modeling the impact of different design choices on building performance. Nevertheless, Zemero et al. critically assessed the limitations of current simulation tools in handling real-time data and complex dynamic simulations, which can improve the predictive power of the optimization process [103]. Similarly, optimization algorithms must be adapted to various building types and climatic conditions. Although algorithms such as genetic algorithms and PSO are generally adaptive, their effectiveness can vary greatly depending on the building context and environmental factors. This requires dynamic adaptation to suit the needs of a particular project.

Building upon these theoretical and practical considerations, future optimization algorithms will be more integrated and intelligent, simultaneously dealing with multiple aspects of building design and operation while balancing energy efficiency, cost, and environmental sustainability. In addition, as a significant challenge for future research, algorithms that more effectively incorporate user behavior and real-time ecological changes are required [93].

5. Conclusion and outlook

This study presents a comprehensive bibliometric analysis of MOO for building performance, covering research publications from 2003 to 2023. Using tools such as CiteSpace, VoSviewer, and Bibliometrix, we analyzed 1604 documents from the Web of Science Core Collection to map collaborative networks, research trends, and citation patterns.

The findings show significant progress in MOO for building performance, with advanced optimization algorithms like genetic algorithms and PSO improving efficiency and accuracy in optimizing metrics such as energy efficiency, thermal comfort, IAQ, and cost-effectiveness. ANN has been used to work in coordination with these algorithms by providing accurate predictive models that support the optimization process, thereby indirectly contributing to the improvement of optimization outcomes. The analysis identifies China and the United States as the leading contributors to the field, with significant research output from higher education institutions. Researchers like Fabrizio Ascione, Nicola Bianco, and Mohamed Hamdy have played pivotal roles in advancing MOO methodologies for building performance optimization. Energy consumption, thermal comfort, life cycle assessment, and simulation-based optimization have been identified as key research hotspots. Genetic algorithms have been particularly prominent due to their effectiveness in handling complex multi-objective problems. The methodologies for MOO have evolved from traditional optimization techniques to more sophisticated approaches that incorporate real-time data and user behavior, enhancing the adaptability and sustainability of building performance optimization.

While this study provides valuable insights, several limitations must be acknowledged. The choice of databases, search criteria, and keywords may influence the comprehensiveness of the analysis. Although the Web of Science Core Collection is a powerful database, its exclusive use might omit relevant studies indexed in other databases, such as Scopus or Google Scholar. This could affect the completeness and representativeness of our results. Additionally, interpretations of collaborative networks, research trends, and citation patterns may carry potential biases. The methodologies employed, including the tools and parameters used, might also impact the generalizability of the findings. Future research could benefit from integrating multiple databases to ensure more comprehensive literature coverage, thereby enhancing the robustness of the analysis.

Future research should focus on developing more integrated and intelligent optimization algorithms that incorporate real-time data and user behavior. This will enhance the adaptability and sustainability of building performance optimization. Enhancing interdisciplinary collaboration will be crucial. Bridging the gap between academia, industry, and policy-making can foster the practical application of MOO methodologies in real-world scenarios. Leveraging advanced simulation tools and data analytics will be vital. Incorporating IoT and AI technologies can provide real-time monitoring and optimization, continuously improving building performance. Continued policy and financial support, particularly in countries like China and the United States, will drive further advancements in this field. Government initiatives promoting energy efficiency and sustainability in the building sector will be instrumental.

In conclusion, this study lays a robust foundation for future research aimed at enhancing energy efficiency, occupant comfort, and environmental sustainability in the built environment. Acknowledging the study's limitations provides a balanced view, highlighting both the strengths and potential areas for improvement in future research endeavors.

Table 8
Multi-objective optimization of building performance.

Literature	Type of buildings	Objective function building method	Optimization methods	Optimization objectives	Optimization parameters								
					Energy consumption	Temperature	Relative Humidity	PMV	CO_2 concentration	PM2.5	Illuminance	IAQ satisfaction	Other
[105]	Office building	Establishing performance index J through functional equations	Gradient-based MOO	Energy consumption + thermal comfort + IAQ	✓			✓	✓				
[106]	Residential building	JEPLUS + EA software	NSGA-II	Annual electricity consumption cost + CO_2 concentration	✓				✓				
[49]	A detached net-zero-energy house (Southern Italy)	EnergyPlus	NSGA-II	Energy consumption + thermal comfort + visual comfort	✓								Long-term percentage of dissatisfaction index (LPD); Useful daylight illuminance (UDI); Discomfort glare index (DGI)
[107]	Offices	IDA-ICE 4.0	genetic algorithm	Energy use + cooling equipment size + thermal comfort levels	✓								The indoor operative temperature is the average room-cooling beam size.
[108]	Not mentioned	White-box model	PSO algorithm	Energy consumption + CO_2 concentration + thermal comfort + visual comfort	✓	✓			✓		✓		
[109]	Office room	CFD (Airpak 3.0)	Taguchi optimization algorithm	Thermal comfort + IAQ + energy consumption	✓			✓					The IAQ is characterized by the mean age of air (MAA) index.
[110]	Office building	Computational fluid dynamics (CFD)	Genetic algorithms	Energy saving + thermal comfort + IAQ	✓			✓	✓				
[111]	Office room	Computational fluid dynamics (CFD)	NSGA-II	Thermal comfort + IAQ + energy costs of HVAC system	✓								PMV-PPD model, ventilation effectiveness (ε_v)

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Table 8 (*continued*)

Literature	Type of buildings	Objective function building method	Optimization methods	Optimization objectives	Optimization parameters								
					Energy consumption	Temperature	Relative Humidity	PMV	CO_2 concentration	PM2.5	Illuminance	IAQ satisfaction	Other
[69]	Models	Computational fluid dynamics (CFD)	Adaptive multi-objective particle swarm optimizer (AMOPSO) algorithm	Indoor air quality (IAQ)					✓	✓			
[112]	Small and medium-sized commercial buildings	EnergyPlus	The Hooke-Jeeves Particle Swarm Optimization (HJPSO)	Energy cost + thermal comfort	✓			✓					
[113]	Office building	MATLAB	The weighted sum method	Energy costs + office workers' productivity	✓								Position-based productivity
[114]	Commercial Buildings	MATLAB	Weighted sum method	Energy costs + occupants' productivity	✓								Occupant productivity in commercial buildings
[115]	Office building	MATLAB	Weighted sum method	Energy costs + productivity of office workers	✓								Collective productivity of office workers
[116]	Museums	TRNSYS	The achievement function approach is adopted as the scalarizing method	Visitors' comfort + energy consumption + artwork integrity	✓								Lifetime multiplier for artwork preservation, predicted percentage of dissatisfied (PPD)
[117]	Public buildings	Designbuilder	NSGA-II	The thermal environment + IAQ + energy conservation	✓	✓	✓		✓				
[118]	Classroom	Grasshopper + EnergyPlus	NSGA-II	Thermal comfort + energy use	✓	✓	✓						Air speed
[119]	Residential building	Establishing a functional relationship based on theory	YALMIP Toolbox	The system economy + the occupants' comfort		✓			✓		✓		The operation economy
[120]	Not mentioned	Multi-agent control system (MACS)	Genetic algorithms	Building energy consumption	✓	✓			✓		✓		

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Table 8 (*continued*)

Literature	Type of buildings	Objective function building method	Optimization methods	Optimization objectives	Optimization parameters								
					Energy consumption	Temperature	Relative Humidity	PMV	CO_2 concentration	PM2.5	Illuminance	IAQ satisfaction	Other
				+ thermal comfort + visual comfort + IAQ									
[121]	Classroom	Radiance, Daysim, and EnergyPlus	NSGA-II	Lighting + energy consumption + visual comfort	✓								Useful Daylight Illu- minance (UDI) and spatial Daylight Autonomy (sDA); Daylight glare probability (DGP), Window view satisfaction (WVS), Luminance ratio of blackboard and desktop (LRBD), Uniformity ratio of illuminance (URI)
[122]	Kitchen	Computational Fluid Dynamics (CFD)	NSGA-II	comfort (air quality and thermal comfort) + energy consumption + gradient (in temperature and CO_2 concentration profiles)	✓	✓			✓				Temperature and CO_2 concentration gradients
[123]	Energy Resource Station	The sampled data (training and testing parts)	A modified PSO based on two levels of non-dominated solutions	Indoor air quality + energy consumption	✓	✓	✓		✓				
[124]	Residential buildings	Energyplus	GA-BP (Genetic algorithm-Back propagation)	Energy consumption + indoor thermal comfort status	✓								The percentage of thermal comfort hours throughout the year

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Table 8 (*continued*)

Literature	Type of buildings	Objective function building method	Optimization methods	Optimization objectives	Optimization parameters								
					Energy consumption	Temperature	Relative Humidity	PMV	CO_2 concentration	PM2.5	Illuminance	IAQ satisfaction	Other
[125]	Campus gymnasium	EnergyPlus + Eppy	NSGA-II	Thermal comfort + energy efficiency	✓								The cooling and heating degree hours
[126]	School	DesignBuilder	An integrated design approach coupling verification experiment with a numerical simulation network	Energy saving + thermal comfort	✓								The physiological equivalent temperature (PET)
[127]	School building	EnergyPlus + Radiance	Octopus (based on SPEA2)	Energy use + thermal performance + daylight performance	✓								Summer thermal comfort time, UDI
[128]	Teaching building	DesignBuilder + least square support vector machine (LSSVM)	NSGA-II	Building energy consumption + indoor thermal comfort	✓			✓					
[69]	Residential buildings	EnergyPlus	NSGA-II	Indoor thermal comfort + building energy demand	✓								Comfort time ratio

CRediT authorship contribution statement

Rong Li: Writing – original draft, Visualization, Software, Investigation, Data curation. **Zalina Shari:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Mohd Zainal Abidin Ab Kadir:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Data availability statement

Data will be made available on request. For requesting data, please write to the corresponding author.

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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