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Energy, thermal comfort, and indoor air quality: Multi-objective optimization review

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ABSTRACT

The reliance on optimization techniques for robust assessments of environmental and energy-saving solutions has been largely driven by the increasing need to comply with international energy policies. However, numerous challenges arise from inherently conflicting objectives for a sustainable built environment, that is, maximizing thermal comfort, and indoor air quality, while minimizing energy consumption, forming a multi-objective optimization problem. Consequently, studies seeking multi-faceted optimality in the design and/or operation of low-energy buildings have exponentially increased over the past few years. This research critically reviews the latest multi-objective optimization studies that present energy consumption, thermal comfort, and indoor air quality as competing targets. By examining 82 records between 2013 and 2022, key discussions focused on commonly investigated objective functions, design variables, and performance metrics. The review also investigates the latest research trends, optimization techniques, algorithms, and tools, and identifies gaps in knowledge and potential future research directions. The review results showed that most studies used a holistic approach that targeted all three objective functions, with the largest portion performed on office and residential buildings. The most commonly investigated design variables are system-related variables, whereas building-related and occupant-related variables are often overlooked. Coupling simulation tools and optimization algorithms is the most widely utilized optimization approach, with genetic algorithms being the most employed. These findings suggest a promising area for future research on methodological optimization approaches, which are expected to be significantly transformed with the rapid development of artificial intelligence technologies.

Nomenclature

ANN	Artificial Neural Network	ML	Machine Learning
ANOVA	Analysis of Variance	NN	Neural Network
AI	Artificial Intelligence	NSGA-II	Non-dominated Sorting Genetic Algorithm
BPO	Building Performance Optimization	NSPSO	Nondominated Sorting-based Particle Swarm Optimization
BPS	Building Performance Simulation	NZEBs	Net-Zero Energy Buildings
CFD	Computational Fluid Dynamics	nZEBs	Nearly Zero Energy Buildings
CO_2	Carbon Dioxide	PMV	Predicted Mean Vote
EUC	Energy Utilization Coefficient	PPD	Percentage of People Dissatisfied
GA	Genetic Algorithms	PSO	Particle Swarm Optimization

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HVAC	Heating, Ventilation and Air Conditioning	RC	Resistance–Capacitance
IAQ	Indoor Air Quality	S/N	Signal-to-Noise
MAA	Mean Age of Air	TOPSIS	Technique of Order Preference by Similarity to Ideal Solution
Symbols			
T_s	Air supply temperature (°C)		
T_e	Exhaust air temperature (°C)		
T_r	Occupied zone temperature (°C)		
L	Thermal load		
M	Metabolic rate (W/m^2)		
τ	The age of air		
x_j	j coordinate		
$\Gamma\rho$	The diffusion coefficient		

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1. Introduction

Efforts to reduce the environmental impact of buildings have led to the development of various codes and standards devised to lower energy consumption in buildings, and the introduction of paradigms such as net-zero energy buildings (NZEBs), nearly zero energy buildings (nZEBs), and highly energy-efficient buildings. This regulatory shift imposed stringent requirements on the building industry and created a need to transform the way buildings are designed, controlled, and operated [1]. Building optimization, an automated process that performs an infinite number of computations to identify the best solutions while meeting performance requirements [2], has become an essential research tool supporting in decision-making processes [3].

Most building optimizations target energy consumption as the central objective function, aiming for highly energy-efficient buildings that satisfy indoor comfort standards and require a multi-faceted solution to guarantee a fair trade-off [4]. The significance of other fundamental optimization objectives related to the quality of indoor environments, such as thermal comfort and indoor air quality (IAQ), which appear to conflict with energy reductions targets, has been highlighted in the literature [5]. Addressing this multimodal problem has been driven by advancements in numerical simulations and mathematical optimization methods [6].

Several studies in the literature had previously reviewed building optimization research; nevertheless, these reviews had limitations in:

- Scope/context: Several reviews have investigated building optimization in a limited scope, for example, confining research to smart homes [7], smart buildings [4,8], low-energy buildings [1], nZEBs, NZEBs, and high-energy performance buildings [2], which were mainly target optimized energy consumption.
- Topics/themes: Heating, ventilation, and cooling (HVAC) system optimization [9], the use of computational intelligence techniques for HVAC systems [10], control systems for building energy and comfort management [4], and using artificial intelligence (AI)-based techniques for optimizing energy consumption and thermal comfort [11] are a few examples of themes or topics that have been the subject of several reviews. Hence, many studies that performed optimization research for other systems or used other techniques have been dismissed.
- Optimization objectives: Energy consumption optimization [1,9], energy consumption and thermal comfort optimization [8,11], energy use and comfort index [4,7,9], or studies that were not geared toward one or more optimization objectives [6,10] were generally the subject of earlier reviews. This demonstrates that review articles have not comprehensively covered studies that optimized IAQ in conjunction with energy consumption and/or thermal comfort. Even with the inclusion of all three goals, a full analysis of the state of building optimization research, which strives to minimize energy consumption while improving thermal comfort and IAQ, is still restricted by topics or scope limits.

To the best of authors knowledge, no review has assessed building optimization research in a holistic manner that simultaneously integrates energy use, thermal comfort, and IAQ targets without being restricted to a specific theme or scope. Thus, the goal of this research is to offer an in-depth investigation of multi-objective optimization studies targeting the three key sustainable building goals. Consequently, this study aims to make the following contributions:

- Provide an up-to-date insight into building performance optimization (BPO).
- Investigate the application of multi-objective optimization research in different building types and geographical contexts.
- Highlight commonly investigated objective functions, design variables, and performance metrics.
- Investigate the state-of-the-art optimization techniques, algorithms, and tools.
- Identify emerging trends, technological advances, knowledge gaps, and potential opportunities for future research.

Section 2 provides an overview of the BPO procedure, terminologies, components, and algorithms in. Section 3 provides a description of the review methodology, search strategy, and selection criteria adopted in this study, along with an overview of the literature distribution. Section 4 provides the main literature review findings, and discussion. Finally, Section 5 summarizes the main research conclusions and future research directions.

2. Background

2.1. Building performance optimization

Building performance simulation (BPS) programs are indispensable in guiding early design decisions, enhancing building operations and control, and providing refurbishment strategies for existing buildings [12,13]. A strategy that involves adjusting variable inputs to observe their impact on design objectives while maintaining the other variables constant is sometimes utilized to improve building performance. This parametric simulation method is typically repeated multiple times to test different variables at each iteration [6]. However, this iterative trial-and-error procedure can be time-consuming and may only offer limited improvements owing to the complexity of the problem and the nonlinearity between input factors [6,14]. BPO can overcome these issues by automating this procedure [2]. In a BPO process involving modelling, computation, and search algorithms, an optimal solution to a single- or multi-objective problem is found by running limitless calculations within a search space. This strategy is commonly used to enhance the design, aesthetics, operation, and/or control of buildings by targeting outcomes related to their geometry, structure, energy, comfort, and economic aspects [2].

Numerical simulations are commonly coupled with mathematical optimization to solve optimization problems; this is an approach called simulation-based or numerical optimization. The coupling approach between BPS and BPO through simulation-based optimization is the most time- and labor-efficient approach [2,6]. Building optimization problems can also be solved without using simulation tools with the rather challenging inverse modelling approach, utilizing mathematical or predictive models that define the mathematical relationship between inputs and outputs [10,15].

2.2. Optimization process & components

The optimization process is performed by identifying an optimal solution from a set of available scenarios for a predefined criterion. The performance criterion of any optimization problem, known as the objective function, is expressed mathematically and subjected to optimization [2]. When there are two or more objective functions to be met, this process becomes a multi-criterion or multi-objective optimization [1]. Multiple objective functions can be optimized (i.e., maximized or minimized) using one or more algorithms, and evaluated using quantitative metrics called performance evaluation indicators. For example, the annual or hourly energy consumption in kilowatt hours can be used to evaluate the objective function for minimizing building energy usage. A multi-objective optimization problem also comprises constraints and dependent variables, either discrete with selection-type constraints or continuous with box-type constraints that are confined between the upper and lower boundary values [14].

The process of any optimization problem concludes with an optimum solution representing the global maximum or minimum defined by the optimization objective function. However, for multi-objective optimization, where two or more objectives must be simultaneously met, there is no single optimum solution that can minimize or maximize each objective function at the same time. Thus, two steps are executed: optimization and decision making [1]. When optimization is performed first, the possible solutions will reach the limit values, whereas further improvement in one objective function will impair the optimization of the other objective functions. In this approach, optimization algorithms are used to obtain a set of optimal solutions plotted along a tradeoff curve, referred to as the Pareto Front, to facilitate the decision-making process and selection of the optimal solution, which can be determined based on experience, function, or preference [2,16]. However, if decision-making occurs prior to optimization, referred to as the weighted sum approach, the order and weight of each objective function must be determined first to convert the problem into a single-objective optimization problem, eventually leading to an optimal solution instead of an entire Pareto Front of optimal solutions [1,16].

2.3. Optimization algorithms

Algorithms generally vary depending on the type of optimization problem, method of exploring the feasibility space, and the number of alternatives. Fig. 1 illustrates the various methods by which these algorithms can be categorized. According to the optimization objective function, algorithms are responsible for solving either single- or multi-objective optimization problems. The direction of the processes (i.e., optimization and decision-making) involved in handling multi-objective optimization problems demonstrates a different method of categorizing multi-objective algorithms as a priori or a posteriori method. Depending on how the objective function is expressed, algorithms can be deterministic (exact) or heuristic (stochastic). The objective function, which is expressed in an analytical form in the deterministic approach, must be continuous and differentiable. In the heuristic approach, it does not have to be either and is primarily expressed based on the experience of the specialist performing the optimization. Depending on the number of variables considered in each iteration of the optimization process, algorithms can be either single-point (by performing a local search and looking at variables one at a time) or population-based (by performing a global search and considering a set of variables in each iteration) [1].

The type of optimization approach, selection of algorithms, and modelling techniques depend on the optimization problem and nature and complexity of its variables, objectives, and constraints. Therefore, given the complex nature of optimization problems, it is often impossible to provide a generalized criterion for algorithm selection [6]. Algorithms for multi-criteria building optimization fall into two categories. The first category comprises deterministic algorithms that simplify multi-objective problems by translating each objective function into a scalar measure; the measure is then calculated using the weighted sum of its criteria [6,17]. The second category includes population-based stochastic algorithms, which are widely utilized in complex and constrained multi-objective optimization problems as they require less computational time and have fewer mathematical properties than other algorithms [6]. Particle swarm optimization (PSO) and genetic algorithms (GA) are common population-based algorithms [1].

3. Methodology

3.1. Overview

Building optimization research focusing on energy consumption, thermal comfort, and IAQ was investigated through a systematic review methodology to comprehensively assess the available literature on multi-objective optimization over the last ten years. Through this review, a comprehensive and up-to-date summary of the knowledge in this area was presented by identifying popular themes, methods, and approaches. The key review outcomes within the scope of the proposed research are shown in Fig. 2.

3.2. Search strategy and criteria

This review addresses studies that seek optimal solutions through optimization techniques for at least two of the following three objectives: minimizing building energy consumption, maximizing occupant thermal comfort, and maximizing IAQ. Studies investigating iterative improvements, monitoring, scenario assessments, and those performing parametric analyses were excluded from this review. In addition, to capture the latest optimization approaches in the literature, only studies published in the last decade (i.e., from 2013 to 2022) were considered.

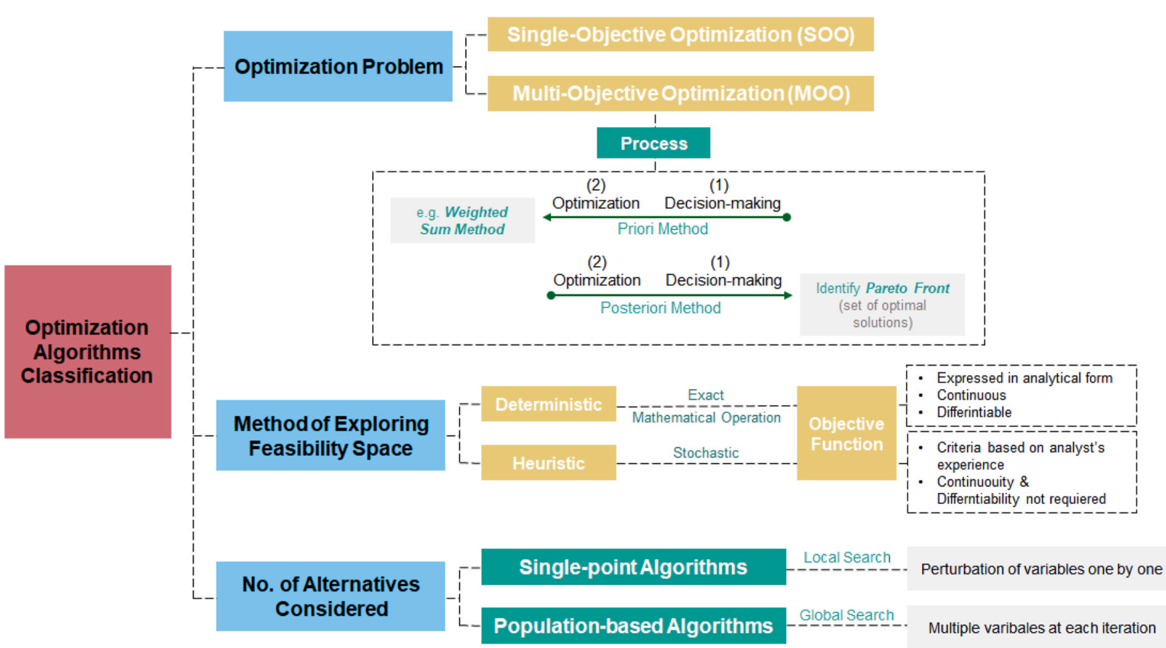

Fig. 1. *Optimization algorithms classification (extracted from* Refs. [1,6]*).*

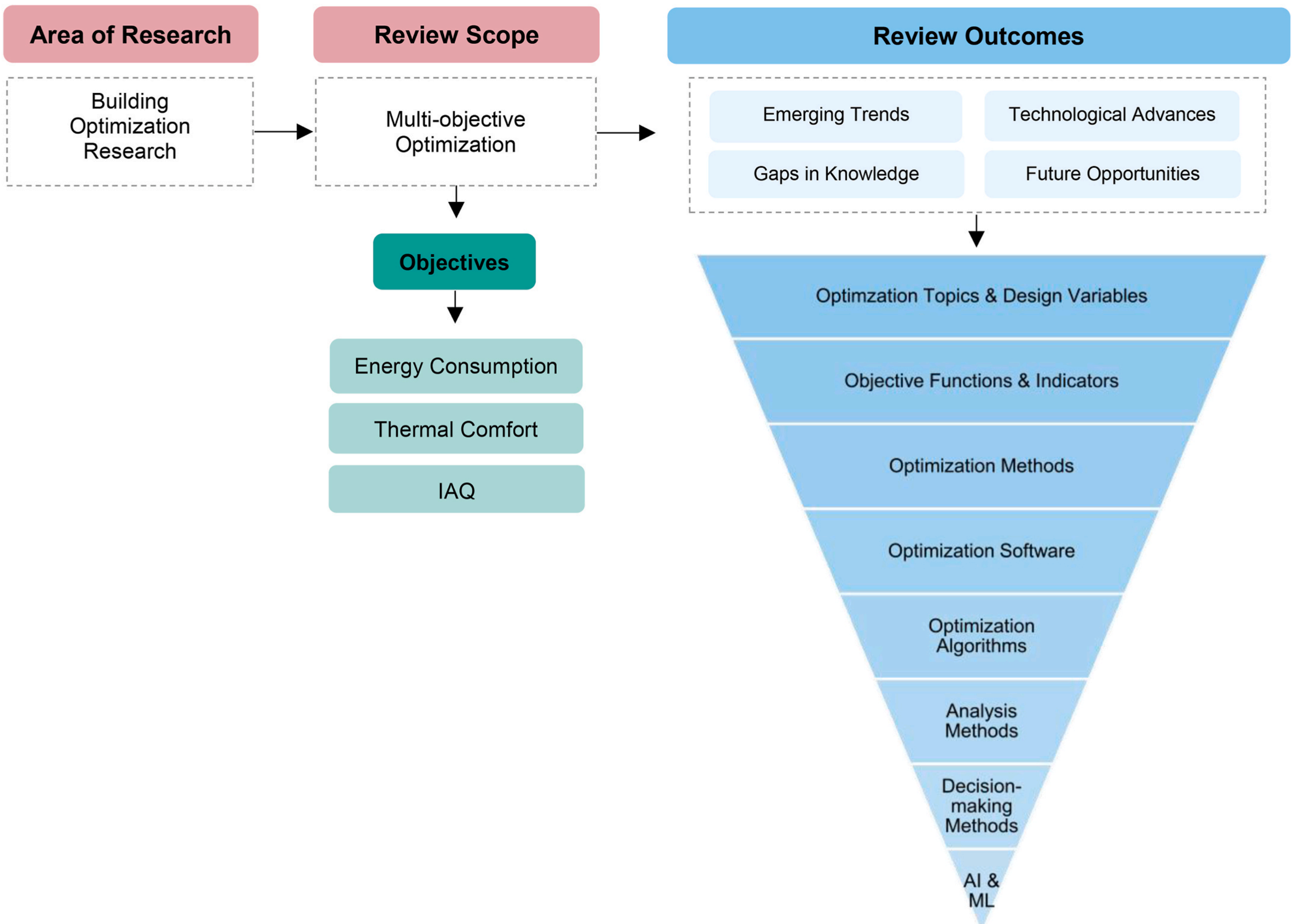

Fig. 2. The review proposed scope and outcomes.

As shown in Fig. 3, the search of the literature was conducted in the internationally recognized "Web of Science" database using a combination of keywords: "optimization," "multi-objective optimization," "optimal," "optimized," "thermal comfort," "comfort," "Indoor air quality," "IAQ," and "energy." The literature search began in early 2023; therefore, articles published until the end of 2022 were included in this review.

3.3. *Literature distribution*

Initially, 494 publications were obtained, including 36 review articles that, although examined and cited in some sections of this review, were not part of the literature analysis or the results reported in this study. Furthermore, screening the titles and abstracts of the remaining 458 publications followed by a thorough evaluation of the exclusion criteria resulted in 82 publications that formed the foundation of this review. The examined studies were published in several leading journals and conferences (75 journal articles and 7 conference proceedings) with the highest number of publications from papers featured in Building and Environment, Applied Energy, and Energy and Buildings Journals (Fig. 4). A summary of the literature review is presented in Table 1 and is categorized based on the reference, year of publication, location, building type, and basic optimization parameters, such as objective functions, simulation tools, optimization methods, algorithms, and optimization tools utilized.

The popularity of BPO has increased in the last ten years, peaking in 2022. Office buildings ranked first among all the building sectors investigated in the literature (approximately 43 % of buildings), followed by residential and educational buildings (approximately 17 % and 11 %, respectively). Although most studies (approximately 55 %) have not been linked to a specific geographic location, most optimization studies have focused on buildings in the US and China, accounting for 10 %, and 9 % of all studies, respectively, compared with fewer in Lebanon, Korea, Malaysia, Poland, Canada, Qatar, Egypt, Portugal, France, Cyprus, Taiwan, South Africa, Australia, India, and Italy. The distribution of the years, building sectors, and countries covered by the analyzed literature is illustrated in Fig. 5.

4. Results

4.1. *Main optimization topics and parameters*

Presenting the methodological novelty is one of the primary contributions of the reviewed optimization research. Numerous attempts have been made to experiment with different optimization algorithms, test them, and propose new methodologies. For instance, the main goal of several studies was to develop an optimization methodology, scheme, or framework (e.g. Refs. [45,46]); develop an optimization model (e.g. Refs. [61,62,78]); or propose a new control method (e.g. Refs. [44,52, 80,83]). Other studies have performed comparative analyses between different algorithms or prediction techniques [15,53,87], proposed a hybridization model between two algorithms [64], or assessed the use of a novel combination of algorithms, simulation techniques, predictions, and/or statistical methods (e.g. Refs. [51,67,68]).

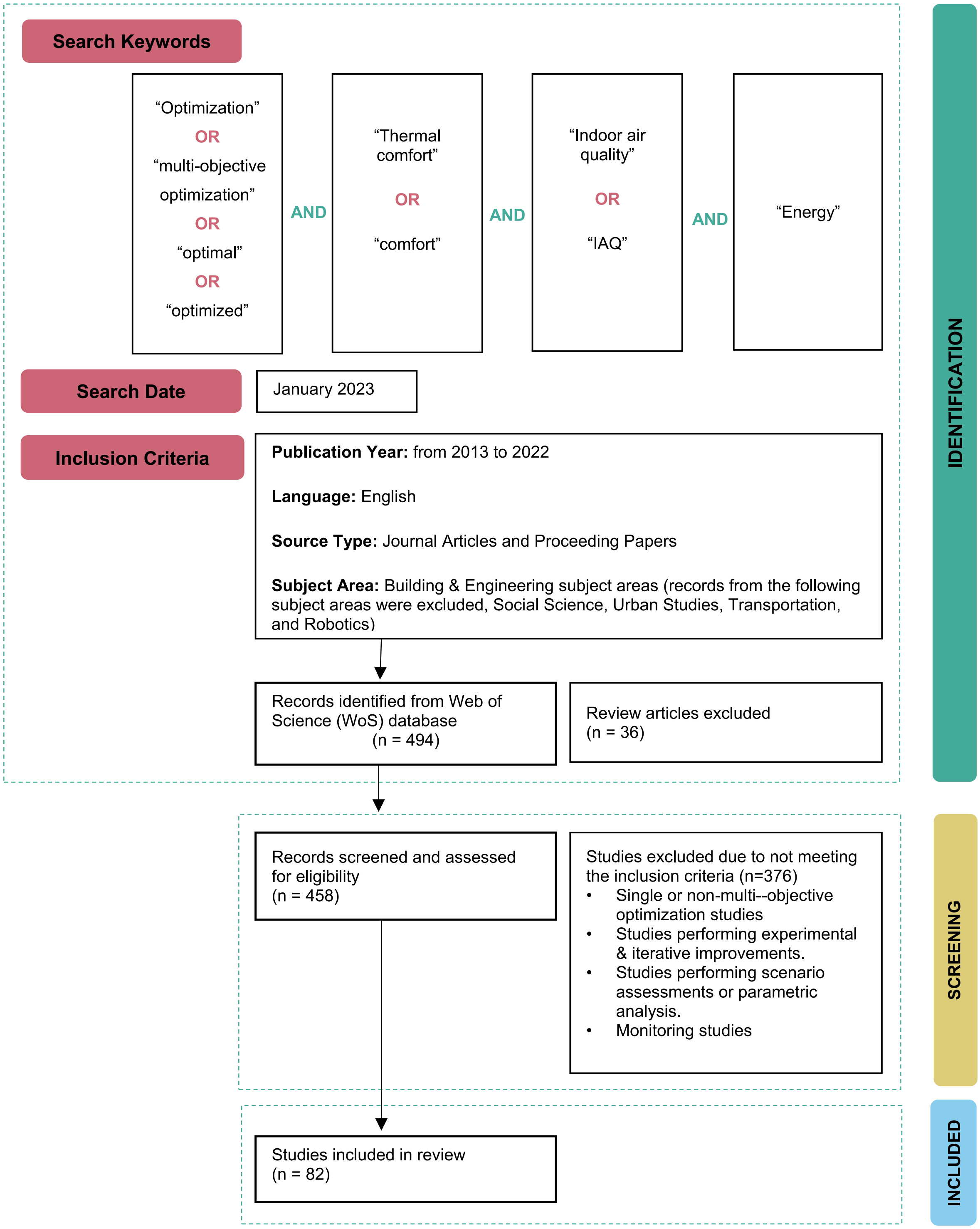

Fig. 3. Flowchart of the literature review selection and screening process.

The key topics identified in the evaluated studies were divided into six categories: Half of the reviewed studies investigated the optimal system control schemes, strategies, and settings to achieve optimized energy consumption, thermal comfort, and IAQ. For system design and operation (approximately 33 % of the literature), the principal investigation was to determine the optimal system-specific design variables, including the inlet air temperature, velocity, flow angle, and system component dimensions. The reviewed studies less frequently considered the following optimization topics: optimal building and envelope design (9 %); optimal building design and system control (5 %); optimal occupant behavior (2 %); and optimal system design, operation, and control (1 %), as shown in Fig. 6.

Since system control, system design, and operation were the most studied topics, it was expected that most studies (82 % of the reviewed work) would investigate system-related variables (Fig. 7). Examples of the commonly used system-related variables include temperature set points, supply air temperature, velocity, humidity, different control strategies, ventilation strategies, and ventilation rates. These variables are largely connected to HVAC and ventilation systems, which have been the most investigated systems in the last decade. Indoor and

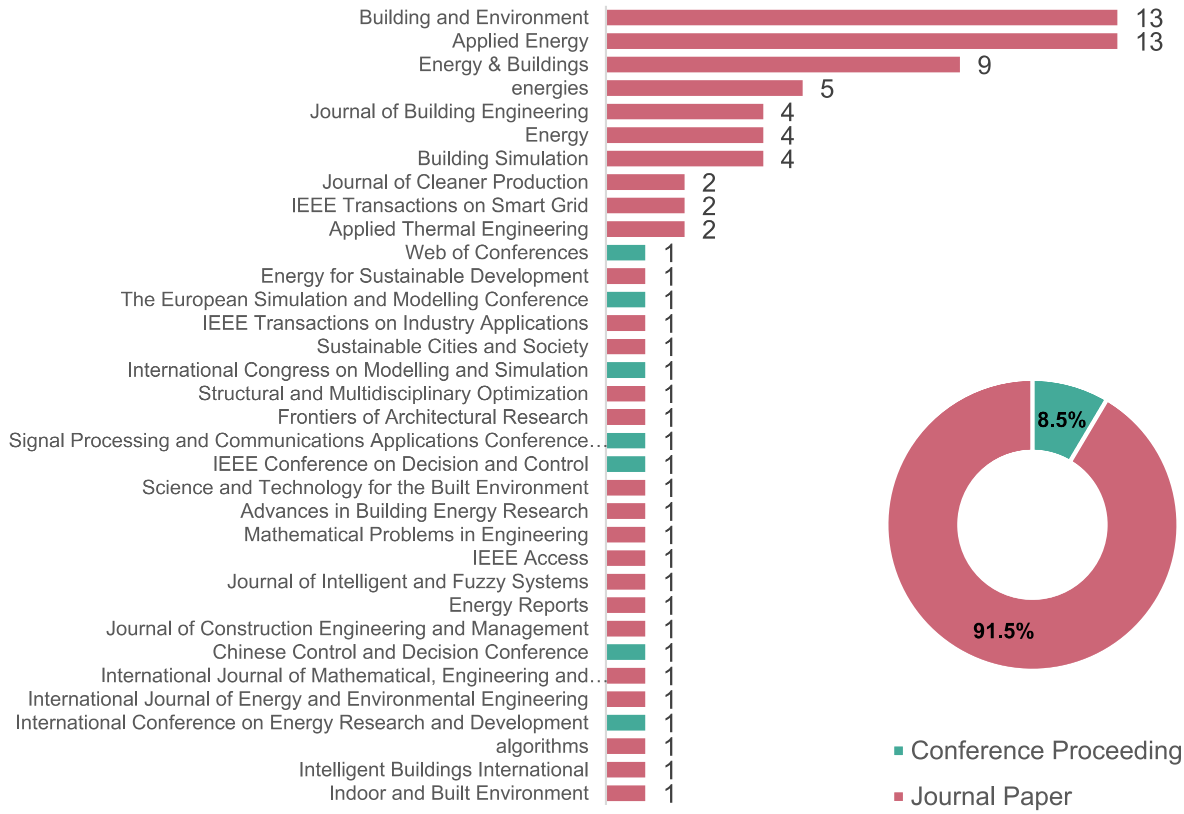

Fig. 4. Distribution of publications across journals and conference proceedings.

outdoor environmental-related variables, which are generally considered during building simulations, have only been reported in 40 % of the reviewed studies in the form of outdoor and indoor environmental parameters (e.g., seasonal variations, different locations, climates, and weather conditions). Occupancy-related variables (e.g., number of occupants, presence, positions, preferences, behaviors, and activities) and building-related variables (e.g., building orientation, envelope components, window design, building material and insulation) were the least explored and examined in only 21 %, and 17 % of publications, respectively. Additional design variables were rarely addressed (11 % of reviewed studies). These included energy and electricity prices, market uncertainty, internal heat gains, and neighborhood locations.

Various approaches have been used to investigate occupant-related variables, including number of occupant [40,88]; occupancy density [55]; occupant behavior [98]; occupant numbers and actions [70]; specific occupancy scenarios [52]; occupancy status (i.e., occupied and unoccupied modes) [18,20,22,73]; user preference profiles [90]; and occupant presence, activities, and/or preferences [59,63,83]. Furthermore, several studies considered occupant-related variables by investigating the impact of varying occupant clothing insulation during winter and summer on design objectives, as employed in Refs. [49,79] or the impact of different occupant seating distributions, as performed in Ref. [45]. This demonstrates that in comparison to other design variables, there is a variable selection of design parameters reflecting occupancy in the reviewed literature, particularly given that some were based on real-time data, whereas others were predicted or assigned data.

The most investigated building parameters were the envelope components, materials (e.g. Refs. [77,84]), and window design (e.g. Refs. [30,33,38]). The reviewed works also explored the impact of different building types [74,90]; building sizes [38,75]; building orientations [33,81]; and interior layouts [95]. Despite variations in optimization objectives and techniques, all studies examining building-related variables have used a simulation and algorithm-based optimization approach. The selection of this approach can be ascribed to the capacity of the simulation tools to provide a full and accurate representation of the building design, envelope, and materials before performing the optimization procedure.

4.2. Optimization objective functions and indicators

Most reviewed studies performed multi-objective optimization research aimed at improving energy, thermal comfort, and IAQ (55 out of 82), accounting for approximately 67 % of all reviewed studies. The combination of the following optimization objectives "energy and thermal comfort," "energy and IAQ," and "thermal comfort and IAQ" have only constituted 17 %, 9 %, and 7 %, respectively. Assessing the yearly distribution of optimization objectives over the last decade reveals that optimizing all three objective functions has continued to be the primary target for optimization studies (Fig. 8). Additional optimization objectives were also explored in approximately 28 % of the literature, with the most common being visual comfort (in 16 % of the studies), primarily as a fourth objective, followed by productivity (in 5 % of the studies). The use of ventilation [81]; lighting quality [81,97]; academic performance [69]; life cycle cost [97]; neighborhood quality [97]; water consumption [71]; interference with daily routine [70]; durability [91]; and artifacts conservation [17]; were other less frequently employed objective functions.

The predominant performance metric for energy-related objectives is "Energy Consumption," adopted in 47 % of studies (i.e., studies with energy consumption as one of the objective functions), followed by "energy cost" and "energy utilization coefficient (EUC)" in 13 %, and 5 % of studies, respectively. The following are brief descriptions of the three most popular energy metrics adopted in literature.

- Energy consumption or use can be calculated on an hourly, daily, weekly, monthly, or annual basis. The energy consumed by a building, HVAC system owing to cooling, heating load, ventilation power, or any other building system is a straightforward method to

Table 1
Summary of the studies performing multi-objective optimization of energy, thermal comfort, and IAQ between 2013 and 2022.

Energy, Thermal Comfort, and IAQ Optimization												
Ref.	Year	Location	Building Type	Optimization Objectives				Simulation Tools		Optimization Method	Optimization Algorithm (s)	Optimization Tools
				Energy	Thermal Comfort	IAQ	Other	Energy Tools	CFD Tools			
[18]	2013	USA	Office Building	✓	✓	✓	N/A	RC Network Model (MATLAB)	N/A	Simulation & Algorithm-based Method	Control Algorithms	IPOPT
[19]	2013	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (Airpak)	Simulation & Algorithm-based Method	GA	N/A
[20]	2014	USA	Office Building	✓	✓	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Iterative relaxing Algorithm & Control Algorithms	N/A
[21]	2015	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (ANSYS CFX)	Simulation & Algorithm-based Method	NSPSO	N/A
[22]	2015	USA	Commercial Building	✓	✓	✓	N/A	RC Network Model (MATLAB)	N/A	Simulation & Algorithm-based Method	Control Algorithms	IPOPT
[23]	2015	Lebanon	Office Building	✓	✓	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	GA	N/A
[24]	2016	Lebanon	Office Building	✓	✓	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	GA	MATLAB
[25]	2016	Korea	Office Building	✓	✓	✓	N/A	EnergyPlus	N/A	Simulation & Algorithm-based Method	GA	MATLAB
[26]	2017	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (ANSYS CFX)	Simulation & Algorithm-based Method	NSPSO	MATLAB
[27]	2017	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (Airpak)	Simulation & Algorithm-based Method	NSGA-II	MATLAB
[28]	2018	N/A	N/A	✓	✓	✓	N/A	N/A	CFD	Simulation & Algorithm-based Method	GA	N/A
[29]	2018	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (Airpak)	Simulation & Algorithm-based Method	Taguchi Method	N/A
[30]	2019	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (Star-CD)	Simulation & Algorithm-based Method	GA	N/A
[31]	2019	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (Airpak)	Simulation& TOPSIS-based Method	N/A	N/A
[32]	2019	N/A	Train Cabin	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	NSPSO	New MOO Platform
[33]	2019	N/A	N/A	✓	✓	✓	N/A	EnergyPlus & Autodesk Ecotect	N/A	Simulation & Algorithm-based Method	GA	MATLAB
[34]	2020	N/A	N/A	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	GA	MATLAB
[35]	2020	China	Office Building	✓	✓	✓	N/A	EnergyPlus	CFD (Airpak)	Simulation & Algorithm-based Method	Marquardt Method	MATLAB

(continued on next page)

Table 1 (*continued*)

[36]	2020	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation& TOPSIS-based Method	N/A	N/A
[37]	2020	N/A	Educational Building	✓	✓	✓	N/A	N/A	CFD (Airpak)	Simulation & Algorithm-based Method	Taguchi Method	N/A
[38]	2020	Cyprus	Office Building	✓	✓	✓	N/A	TAS Engineering	N/A	Simulation & Algorithm-based Method	Taguchi Method	N/A
[39]	2021	N/A	Sleeping Environment	✓	✓	✓	N/A	N/A	CFD	Simulation& TOPSIS-based Method	N/A	N/A
[40]	2021	N/A	Commercial Building	✓	✓	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Control Algorithms	Python
[41]	2021	China	Office Building	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	Taguchi Method	N/A
[42]	2021	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (Airpak)	Simulation & Algorithm-based Method	Taguchi Method	N/A
[43]	2021	N/A	N/A	✓	✓	✓	N/A	Co-simulation (TRNSYS-MATLAB)	N/A	Simulation & Algorithm-based Method	ADMM & GA	Co-simulation (TRNSYS-MATLAB)
[44]	2022	N/A	Sleeping Environment	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	GA	N/A
[45]	2022	N/A	Educational Building	✓	✓	✓	N/A	eQUEST	CFD (Autodesk)	Simulation & Algorithm-based Method	GWO Algorithm	N/A
[46]	2022	N/A	Residential Building	✓	✓	✓	N/A	N/A	CFD (FloVENT)	Simulation & Algorithm-based Method	NSGA-II	MATLAB
[47]	2022	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation& TOPSIS-based Method	N/A	N/A
[48]	2022	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation& TOPSIS-based Method	N/A	N/A
[49]	2022	USA	Residential Building	✓	✓	✓	N/A	EnergyPlus	N/A	Simulation & Algorithm-based Method	NSGA-II	jEPlus + EA
[50]	2022	Poland	Residential Building	✓	✓	✓	N/A	Co-simulation (EnergyPlus & Contam)	N/A	Simulation & Algorithm-based Method	NSGA-II	Python
[51]	2022	N/A	N/A	✓	✓	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	PSO	MATLAB
[52]	2022	Qatar	Sports Facilities	✓	✓	✓	N/A	DesignBuilder (EnergyPlus)	N/A	Simulation & Algorithm-based Method	Bayesian Optimization Algorithm	Co-simulation (EnergyPlus-MATLAB)
[53]	2022	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation& TOPSIS-based Method	N/A	N/A
[54]	2018	South Africa	Office Building	✓	✓	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Control Algorithms	MATLAB
[55]	2020	China	Different Types	✓	✓	✓	N/A	DesignBuilder (EnergyPlus)	N/A	Simulation & Algorithm-based Method	NSGA-II	MATLAB
[56]	2021	N/A	Office Building	✓	✓	✓	N/A	N/A	CFD	Simulation & Algorithm-based Method	Scalarization Method	N/A
[57]	2014	China	Intelligent Buildings	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	GA	N/A

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Table 1 (*continued*)

[58]	2016	China	Office Building	✓	✓	✓	Visual Comfort, Acoustic Comfort, & Cost	EnergyPlus	N/A	Simulation & Algorithm-based Method	NSGA-II	MATLAB
[59]	2016	Canada	Office Building	✓	✓	✓	Productivity	RC Network Model (Matlab)	N/A	Simulation & Algorithm-based Method	Scalarization Method	MATLAB
[60]	2017	N/A	Educational Building	✓	✓	✓	Visual Comfort	EnergyPlus	N/A	Simulation & Algorithm-based Method	Hybrid Optimization Algorithm	GenOpt
[15]	2017	N/A	Residential Building	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	GA	N/A
[61]	2018	N/A	N/A	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Intelligent Algorithms (various)	MATLAB (YALMIP Toolbox)
[62]	2019	N/A	Vehicle	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	BAT Algorithm	MATLAB
[63]	2019	Canada	Office Building	✓	✓	✓	Visual Comfort & Productivity	RC Network Model (Matlab)	N/A	Simulation & Algorithm-based Method	Scalarization Method	MATLAB
[64]	2020	N/A	Residential Building	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Hybrid Optimization Algorithm	MATLAB
[65]	2020	Malaysia	Residential Building	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Bat Algorithm	MATLAB (Fuzzy Logic Toolbox)
[66]	2020	N/A	N/A	✓	✓	✓	Visual Comfort	White Box Building Energy Model	N/A	Simulation & Algorithm-based Method	Hybrid Optimization Algorithm	N/A
[67]	2022	N/A	Residential Building	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Hybrid Optimization Algorithm	N/A
[68]	2022	Malaysia	Residential Building	✓	✓	✓	Visual Comfort	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Bat Algorithm	N/A
[69]	2022	Taiwan	Educational Building	✓	✓	✓	Academic Performance	EnergyPlus	N/A	Simulation & Algorithm-based Method	GA	N/A
[70]	2019	France	Office Building	✓	✓	✓	Interference with Daily routine	Mathematical/ Predictive Models	N/A	Algorithm-based Method	AGE-II Algorithm	Python
[71]	2021	Lebanon	Educational Building	✓	✓	✓	Water Consumption	Mathematical/ Predictive Models	N/A	Algorithm-based Method	GA	MATLAB

Energy, and Thermal Comfort Optimization

Ref.	Year	Location	Building Type	Optimization Objectives Energy	Thermal Comfort	IAQ	Other	Simulation Tools Energy Tools	CFD Tools	Optimization Method	Optimization Algorithm (s)	Optimization Tools
[72]	2013	N/A	Office Building	✓	✓	N/A	N/A	Simulink	N/A	Simulation & Algorithm-based Method	Control Algorithms	MATLAB
[73]	2013	USA	Educational Building	✓	✓	N/A	N/A	RC Network Model (MATLAB)	N/A	Simulation & Algorithm-based Method	Control Algorithms	IPOPT
[74]	2015	N/A	Different Types	✓	✓	N/A	N/A	Co-simulation (EnergyPlus & Matlab)	N/A	Simulation & Algorithm-based Method	Scalarization Method	N/A
[75]	2016	USA	Office Building	✓	✓	N/A	N/A	EnergyPlus	N/A	Simulation & Algorithm-based Method	Hybrid Optimization Algorithm	GenOpt
[76]	2017	Portugal	Educational Building	✓	✓	N/A	N/A	EnergyPlus	N/A	Simulation & Algorithm-based Method	Hybrid Optimization Algorithm	EMS Application Code

(*continued on next page*)

Table 1 (*continued*)

[77]	2020	Poland	Residential Building	✓	✓	N/A	N/A	EnergyPlus	N/A	Simulation & Algorithm-based Method	NSGA-II	MATLAB
[78]	2021	N/A	Manufacturing Facility	✓	✓	N/A	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	GA & SVR Algorithm	N/A
[79]	2021	USA	Educational Building	✓	✓	N/A	N/A	ClimateStudio (EnergyPlus)	N/A	Simulation & Algorithm-based Method	NSGA-II	Grasshopper
[80]	2022	Egypt	Office Building	✓	✓	N/A	N/A	TRNSYS	N/A	Simulation & Algorithm-based Method	NSGA-II	MATLAB
[81]	2016	China	Residential Building	✓	✓	N/A	Ventilation & Lighting	EnergyPlus	N/A	Simulation & Algorithm-based Method	NSGA-II	jEPlus
[82]	2017	N/A	Office Building	✓	✓	N/A	Productivity	IDA ICE	N/A	Simulation & Algorithm-based Method	NSGA-II	MOBO
[17]	2020	Italy	Museum	✓	✓	N/A	Artifacts Conservation	TRNSYS	N/A	Simulation & Algorithm-based Method	Scalarization Method	N/A
[83]	2022	Korea	Smart Buildings	✓	✓	N/A	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Control Algorithms	N/A
[84]	2021	Australia	Prefabricated Buildings	✓	✓	N/A	Visual Comfort	TRNSYS	N/A	Simulation & Algorithm-based Method	NSGA-II	jEPlus + EA
Energy, and IAQ Optimization												
Ref.	**Year**	**Location**	**Building Type**	**Optimization Objectives**				**Simulation Tools**		**Optimization Method**	**Optimization Algorithm (s)**	**Optimization Tools**
				Energy	**Thermal Comfort**	**IAQ**	**Other**	**Energy Tools**	**CFD Tools**			
[85]	2013	N/A	N/A	✓	N/A	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	PSO	N/A
[86]	2014	USA	Office Building	✓	N/A	✓	N/A	EnergyPlus	N/A	Simulation & Algorithm-based Method	Hybrid Optimization Algorithm	GenOpt
[87]	2015	N/A	Office Building	✓	N/A	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	PSO	N/A
[88]	2018	N/A	N/A	✓	N/A	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Q-learning Algorithm	N/A
[89]	2020	Korea	Subways	✓	N/A	✓	N/A	Mathematical/ Predictive Models	N/A	Algorithm-based Method	Iterative Dynamic Programming Algorithm	N/A
[90]	2019	N/A	Office Building	✓	N/A	✓	Productivity	EnergyPlus	N/A	Simulation & Algorithm-based Method	Gradient-based Interior Point Algorithm	MATLAB
[91]	2021	China	Educational Building	✓	N/A	✓	Durability	Mathematical/ Predictive Models	N/A	Algorithm-based Method	GA	N/A
Thermal Comfort, and IAQ Optimization												
Ref.	**Year**	**Location**	**Building Type**	**Optimization Objectives**				**Simulation Tools**		**Optimization Method**	**Optimization Algorithm (s)**	**Optimization Tools**
				Energy	**Thermal Comfort**	**IAQ**	**Other**	**Energy Tools**	**CFD Tools**			
[92]	2014	N/A	Office Building	N/A	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	GA	N/A
[93]	2017	N/A	Laboratory Facility	N/A	✓	✓	N/A	N/A	CFD	Simulation & Algorithm-based Method	PSO	N/A

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Table 1 (*continued*)

[94]	2019	N/A	Aircraft Cabin	N/A	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	GA, Proper Orthogonal Decomposition & Adjoint Method	GenOpt
[95]	2020	India	Residential Building	N/A	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	NSGA-II	MATLAB
[96]	2021	N/A	Office Building	N/A	✓	✓	N/A	N/A	CFD (ANSYS Fluent)	Simulation & Algorithm-based Method	GA	MATLAB
[97]	2014	N/A	Residential Building	N/A	✓	✓	Lighting Quality, Life Cycle Cost & Neighborhood Quality	EnergyPlus	N/A	Simulation & Algorithm-based Method	GA	MATLAB

evaluate energy consumption optimization. This explains why this evaluation metric was utilized in almost 50 % of the optimization studies that sought to reduce energy use.

- Energy cost is typically linked to the utility or energy price from electricity, gas or both and is mainly expressed in monetary units (e.g. Refs. [40,49]). The energy cost was calculated as the sum of the fan power and the cooling energy consumption in Ref. [34] and as the sum of the water and electrical energy consumption costs in Ref. [71].
- The EUC is used to evaluate the effectiveness of the energy utilization. Although the recommended EUC values may differ across various systems, higher values indicate greater efficiency. Several optimization studies [31,39,41,53] have employed the EUC indicator to assess the energy performance. The EUC can be calculated using Equation (1):

$$EUC = Ts - Te \;/\; Ts - Tr \tag{1}$$

where Ts is the air supply temperature (°C), Te is the exhaust air temperature (°C), and Tr is the occupied zone temperature (°C).

Thermal comfort was mostly evaluated using the predicted mean vote (PMV) indicator either exclusively in 21 % of studies (i.e., studies with thermal comfort as one of the objective functions), in combination with the percentage of people dissatisfied (PPD) in 3 % of studies, or coupled with other indicators such as draft rate, temperature difference between head and ankle, PPD of draft sensation, relative humidity, temperature gradient, or thermal sensation. In addition, numerous studies have evaluated thermal comfort solely using the indoor air temperature (in 17 % of studies), or PPD (in 15 % of studies). Brief descriptions of the two most frequent and closely related metrics used to evaluate thermal comfort are as follows:

- The PMV index was developed by Fanger, based on the steady-state heat balance of the human body. This model considers two influential human parameters: metabolic rate and clothing insulation, and four objective parameters: mean radiant temperature, air temperature, relative humidity, and air velocity. The PMV mainly seeks thermal neutrality by utilizing a thermal sensation scale to represent the occupant's mean thermal satisfaction and determine the indoor conditions where occe calculatedupants feel thermally neutral. The PMV value of a space can then b using Equation (2) to determine the occupant acceptance rate of an indoor environment [99]. ASHRAE Standard 55 has identified an acceptable PMV value between - 0.5 and +0.5, which refers to a 90 % acceptance rate [99,100].

$$PMV = [0.303 \exp(-0.036\, M) + 0.028] * L \tag{2}$$

where L is the thermal load and M is the metabolic rate (W/m^2).

- The PPD is another widely used index developed by Fanger. This index, which represents the number of people thermally dissatisfied with their environment by feeling too hot or cold, is calculated using the PMV value in Equation (3):

$$PPD = 100 - 95 \exp(-0.03353 * PMV\hat{}4 - 0.2179 * PMV\hat{}2) \tag{3}$$

Accordingly, this model targets the lowest value possible to achieve thermal comfort with an acceptable threshold of 20 % as recommended by ASHRAE Standard 55, which corresponds to a PMV value of $-0.85 <$ PMV $<+0.85$ [100]. A more stringent thermal comfort requirement is sometimes used by limiting the PPD value to 10 %, which corresponds to a PMV value between -0.5 and $+ 0.5$.

Most studies that incorporated IAQ as one of the objective functions either adopted the carbon dioxide (CO_2) concentration exclusively as the evaluation criterion (41 %) or in combination with the airflow rate (3 %), mean age of air (MAA; 3 %), and total volatile organic compound concentration levels (3 %), as illustrated in Fig. 9. The MAA was used to evaluate IAQ performance in 13 % of studies. The following are brief

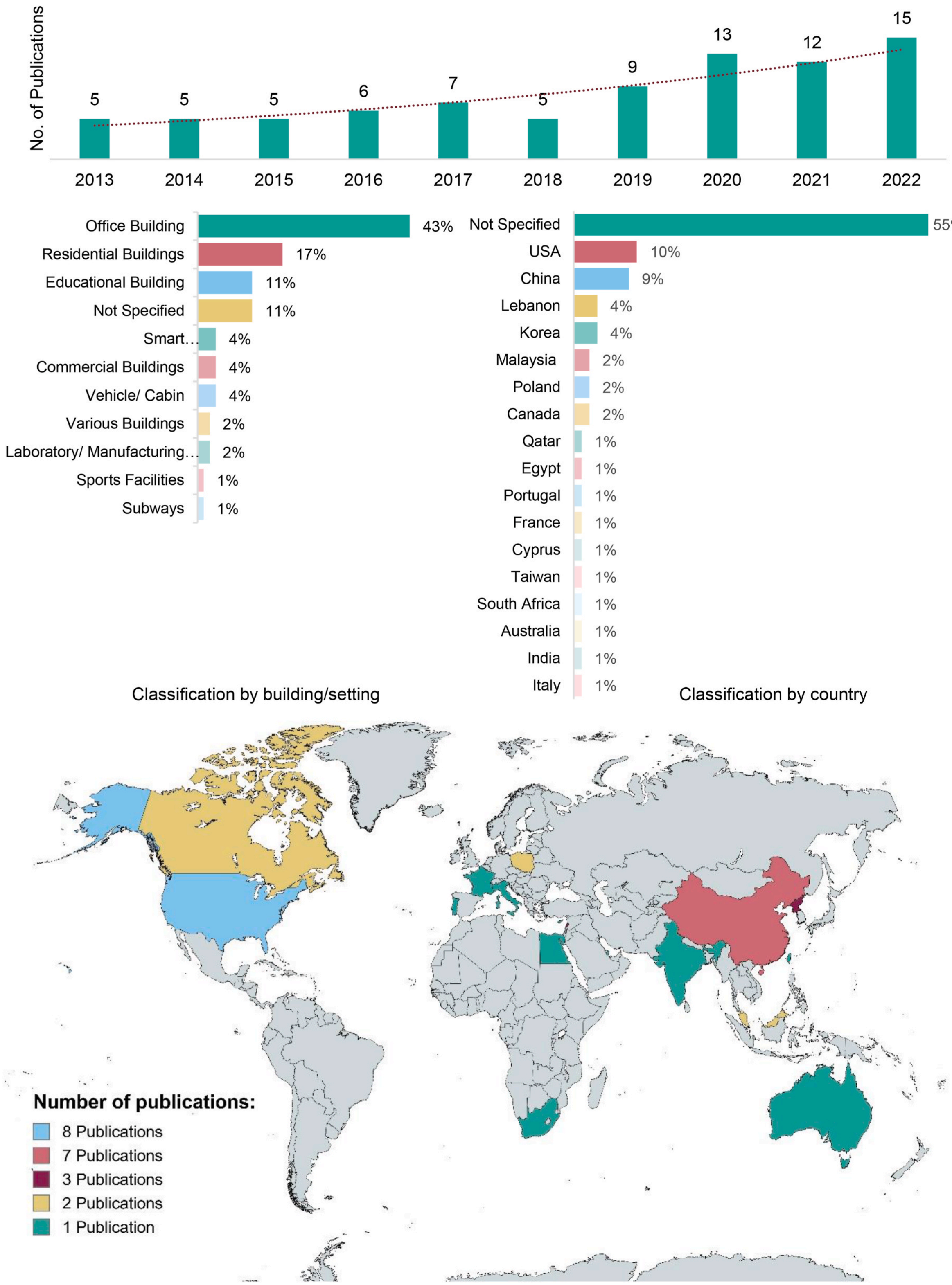

Fig. 5. Number of optimization studies published between 2013 and 2022 and their classification based-on country and building type or setting.

descriptions of the two most commonly used IAQ indices.

- CO_2 concentration levels have been widely used to evaluate IAQ in parts per million (ppm) units. International guidelines and standards such as those set by the World Health Organization, ASHRAE Standard 62.1, and EN 15251 suggest that CO_2 levels should be maintained below 1000 ppm as a measure of acceptable IAQ [101–103].
- The MAA is used to indicate the level of air freshness in naturally or mechanically ventilated buildings by calculating the average time the air has spent in a room, a single zone, or at occupant's breathing

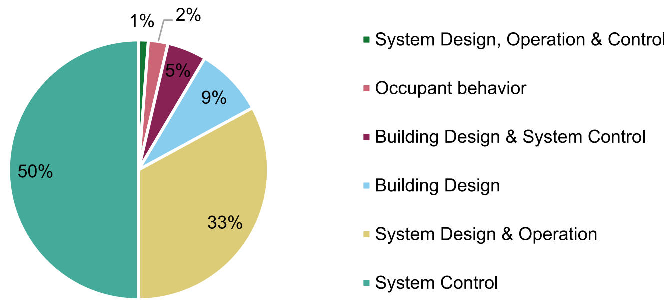

Fig. 6. Common optimization topics in the reviewed works between 2013 and 2022.

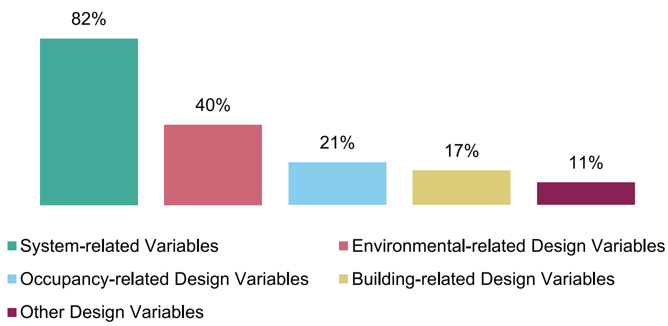

Fig. 7. Common design variables in the reviewed works between 2013 and 2022.

zone. Lower values of MAA indicate fresher indoor air; thus, they are preferable to higher values. For a 2 m^3 office space, for instance, it is recommended that the MAA be less than 125 s, with the maximum age of the air value not exceeding 250 s [92]. The MAA is typically determined using a user-defined computational fluid dynamics (CFD) program; however, it can also be calculated using Equation (4):

$$\frac{\partial_\tau}{\partial_{x_j}} = \frac{\partial}{\partial_{x_j}}\left[\Gamma_\rho \quad \frac{\partial_\tau}{\partial_{x_j}}\right] + 1 \tag{4}$$

where τ is the age of air, x_j is the j coordinate, and $\Gamma\rho$ is the diffusion coefficient [34].

MAA typically assesses ventilation conditions inside buildings; thus, all optimization studies that employed MAA to evaluate IAQ examined the optimal system design and operation by investigating system-related design variables [34,37,42].

Fig. 9 shows the most common performance indicators utilized over the last ten years to evaluate the three optimization objectives. The amount of energy consumption, PMV, and CO_2 concentration levels were the main indices to assess energy consumption, thermal comfort, and IAQ, presumably due to their standardization, direct connection to objective functions, data accessibility, and measurability.

4.3. Optimization methods

To perform multi-objective optimization, it is common practice to adopt a simulation-based optimization approach by coupling optimization algorithms with energy simulations and/or CFD. The values of the design objectives are computed using a simulation tool, and the optimal design variables are obtained using optimization algorithms. Thus, it was expected that most reviewed studies utilized BPS tools in combination with optimization algorithms (65 %) or the technique of order preference by similarity to ideal solution (TOPSIS) optimization method (7 %) to tackle the multi-objective optimization problem, whereas 28 % relied solely on optimization algorithms (Fig. 10).

Simulation and algorithm-based optimization: Building optimization is performed using either simulation-based tools, which act as fully functioning simulation-optimization platforms to solve multi-objective optimization problems (e.g., BeOpt and Opt-E-Plus), or standalone tools (e.g., GenOpt and MATLAB optimization toolbox), which are normally coupled with BPS software such as EnergyPlus, TRNSYS, and IDA ICE. As shown in Fig. 11, most reviewed studies (approximately 72 %) favor the coupling approach, combining optimization tools with energy simulation software, CFD software, or both, which is the case for all studies aimed at optimizing thermal comfort and IAQ.

Algorithm-based optimization: The multi-objective optimization process was performed using optimization algorithms and predictive or mathematical models without the use of simulation tools in 28 % of the studies. This approach is referred to in the literature as the inverse modelling approach and can be applied by defining the mathematical relationships between the inputs and outputs of the problem [15].

Simulation and TOPSIS-based optimization: Coupling simulation tools with the TOPSIS method has been the least used optimization method, adopted in 6 of the 82 optimization studies (7 % of publications). The TOPSIS method is a multi-objective decision-making technique that uses statistical analysis to make multiple-attribute decisions for optimizing design variables [36]. The optimal solutions in the TOPSIS method are obtained when they are closest to the positive ideal solutions, while also being the furthest away from the negative ideal solutions [104]. Based on the reviewed studies, CFD simulations were utilized in conjunction with the TOPSIS method to investigate and optimize ventilation systems such as the stratum ventilated heating system in Refs. [31,39]; stratified air distribution ventilation system in Ref. [48]; underfloor air distribution system in Ref. [47]; and impinging jet ventilation systems in Refs. [36,53].

4.4. Simulation & optimization software

Building energy tools: A coupling technique that combines BPS and optimization tools has been the primary approach for optimizing energy, thermal comfort, and IAQ. This can be attributed to the ability of the simulation tools to provide a thorough and realistic image of building performance, thereby capturing the complexity of building systems and producing more accurate optimization outcomes. The reviewed studies

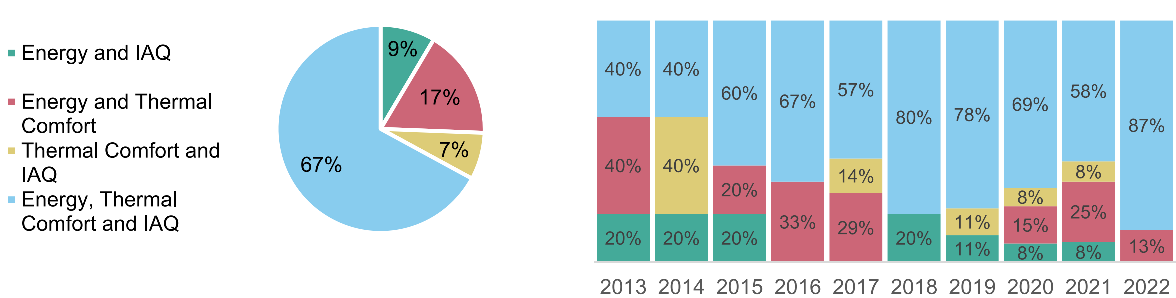

Fig. 8. Main multi-objective functions in the reviewed works between 2013 and 2022.

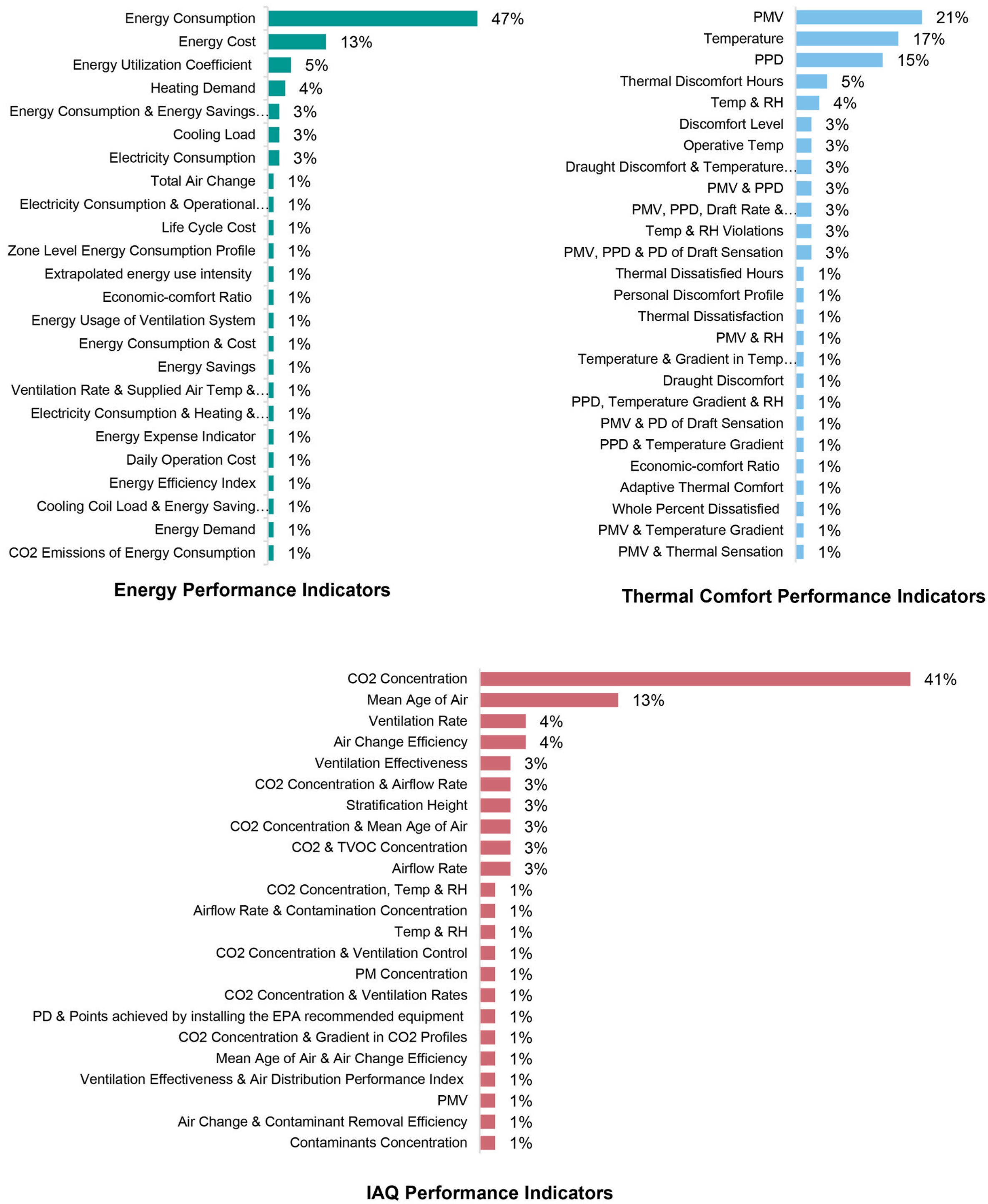

Fig. 9. Common performance metrics adopted to evaluate energy, thermal comfort, and IAQ in the reviewed publications between 2013 and 2022.

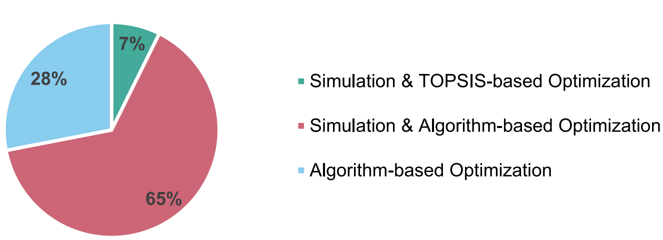

Fig. 10. Common optimization methodologies employed between 2013 and 2022.

that adopted this approach employed energy performance simulation tools, CFD simulation tools, or both.

1. Energy modelling software: As illustrated in Fig. 12, 38 % of the studies predict building performance using popular energy simulation software such as EnergyPlus (including various graphical user interfaces for its engine, e.g., DesignBuilder, Autodesk Ecotect, and ClimateStudio), TRNSYS, eQUEST, and IDA ICE. A comparative analysis of energy modelling tools reveals a blend of shared and distinctive features. EnergyPlus and TRNSYS demonstrated similarities in their text-based input/output formats, validation, and

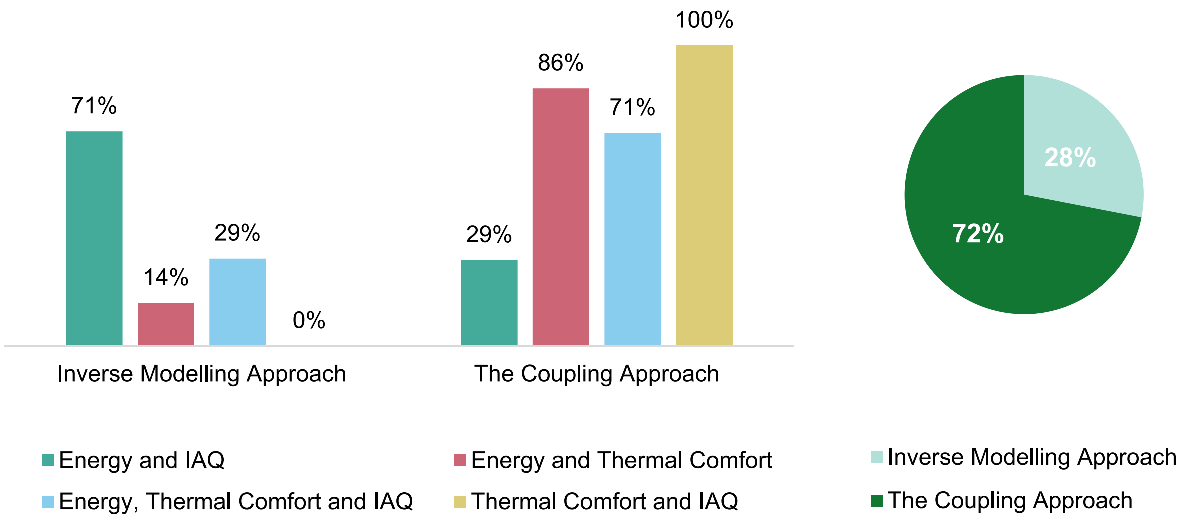

Fig. 11. Classification of BPS tools utilized between 2013 and 2022.

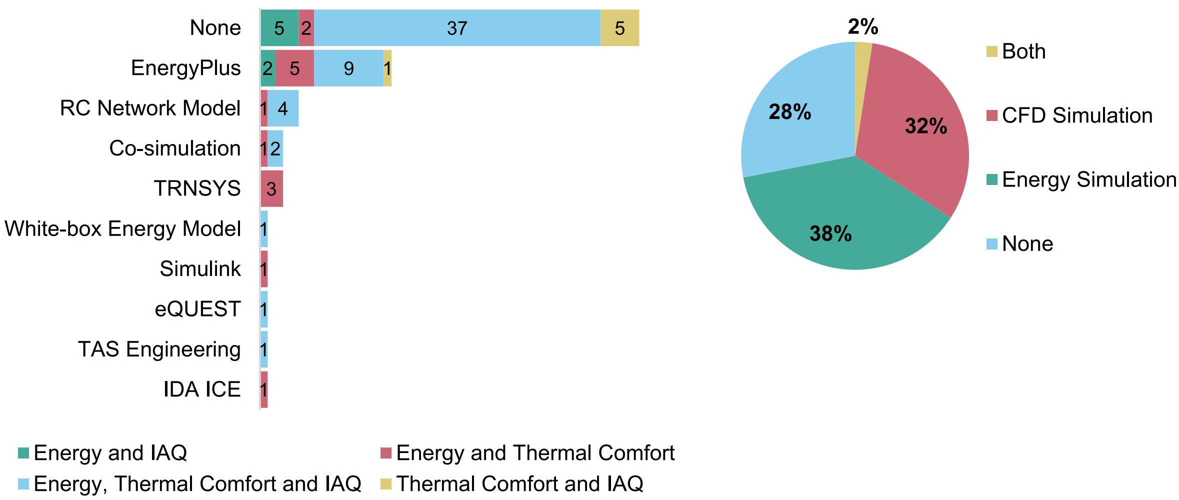

Fig. 12. Common building energy simulation tools employed in optimization studies between 2013 and 2022.

sustained support from vibrant user communities, particularly in terms of energy and thermal analysis, and their ability to model airflow networks and CO_2 concentrations. EnergyPlus distinguishes itself with its research-grade status, provision of generic models, and seamless compatibility with third-party interfaces, whereas TRNSYS stands out for its user-friendly approach and proficiency in modelling transient systems. Alternatively, eQUEST is praised for its emphasis on user-friendliness and reliability, particularly in the context of LEED compliance modelling; however, it exhibits constraints in undertaking detailed analyses of thermal comfort, airflow dynamics, and CO_2 dispersion. IDA-ICE is another software that excels in conducting a wide range of indoor climate and thermal comfort simulations owing to its validation and use of a Neutral Model Format language. However, IDA-ICE has limitations when it comes to modelling airflow networks [105].

2. Simplified resistance–capacitance (RC) network thermal modelling: The RC-network model, primarily developed in MATLAB, has been utilized in numerous optimization studies [18,22,59,63,73]. Unlike the conventional white-box modelling tools discussed earlier, this simplified thermal model is acknowledged for its computational efficiency while utilizing model simplification techniques to simulate energy and hygrothermal dynamics.
3. Co-simulation techniques: For comprehensive modelling, co-simulation techniques between MATLAB and some renowned energy simulation software, such as EnergyPlus or TRNSYS, and a co-simulation between CONTAM and EnergyPlus have been employed, demonstrating the strategic integration of diverse simulation tools, as demonstrated in Refs. [43,50,74].

CFD tools: As depicted in Fig. 12, approximately one-third of the studies (32 % of publications) utilize CFD models to predict building performance pertaining to thermal comfort and IAQ goals, or all three goals together. As shown in Fig. 13, the CFD tools ANSYS Fluent and Airpak are the most widely employed, accounting for 43 % and 25 % of the studies, respectively.

Optimization tools: After running the BPSs, stand-alone optimization tools were used to optimize two or all three objective functions: energy, thermal comfort, and IAQ. Fig. 14 shows that most studies (32 % of publications), notably those conducted in recent years, use MATLAB to optimize all three goals. The extensive optimization capabilities of MATLAB have contributed to its popularity as an optimization platform. However, it can be difficult to master, and the execution speed can vary depending on the complexity of the optimization. Furthermore, the use of GenOpt and jEPlus + EA to perform the optimization process in 5 % and 4 % of the examined studies, respectively, is most likely related to

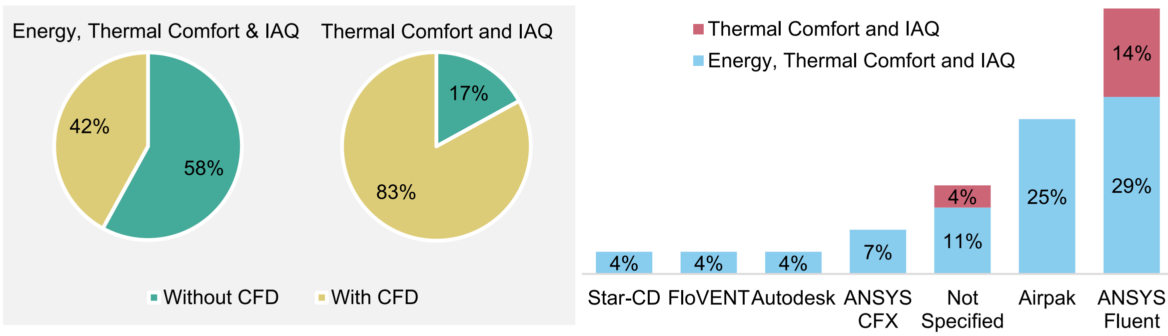

Fig. 13. The utilization of computational fluid dynamics (CFD) tools in optimization studies between 2013 and 2022.

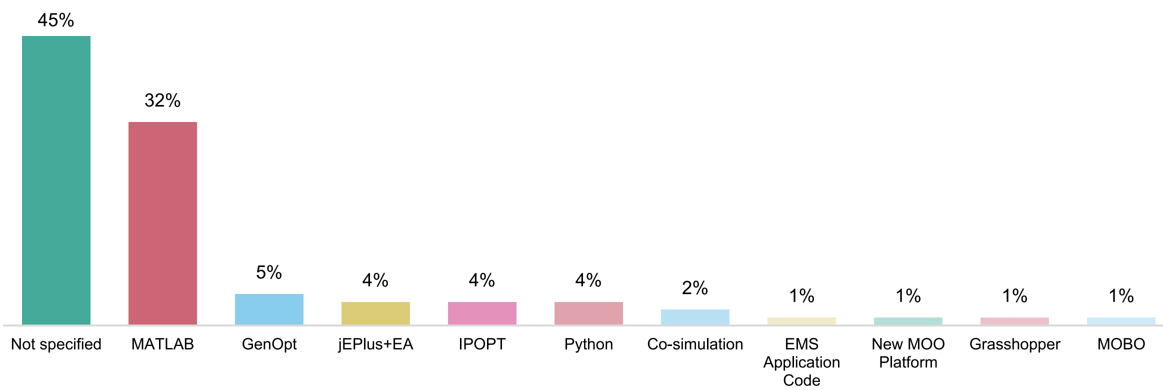

Fig. 14. Optimization tools utilized by the reviewed publications.

the increased use of GAs for multi-objective optimization. GenOpt stands out for its specialized design focused on EnergyPlus, which ensures ease of use and tailored functionality for simulating building energy dynamics. Similarly, jEPlus + EA offers seamless integration with EnergyPlus, emphasizing user-friendly operation. However, the scope of these tools is primarily confined to EnergyPlus simulations, distinguishing them from the broader functionality of general-purpose programs like MATLAB.

4.5. *Analysis-coupled approach*

Prior- and/or post-analysis techniques may provide useful insights and improve the performance of multi-objective optimization processes. A preliminary analysis conducted prior to the optimization process can enhance the understanding of the significant factors influencing building performance and eliminate inconsequential factors, resulting in improved model reliability and validity. One such basic analysis is the sensitivity analysis, which is a technique for determining how changes in a model's outputs can be attributed qualitatively and/or quantitatively to changes in a collection of input variables by evaluating different scenarios [106]. Post-processing analysis can also be beneficial for evaluating solution stability and robustness and offering a deeper understanding of the optimization problem and trade-offs between objectives, which in turn enhances the decision-making process and creates appropriate expectations and goals.

However, this analysis-coupled strategy has not always been adopted in the studies examined. As shown in Fig. 15, approximately 38 % of the studies perform some form of prior- or post-analysis along with the optimization process. This allowed the generation of a random sampling of design variables or modelling datasets (e.g. Refs. [53,80,95]), studying the effect of parameters and determining the most influential ones (e.g. Refs. [49,69]), testing the correlation and identifying relationships between parameters (e.g. Refs. [45,55,89]), and determining the optimal levels of parameters (e.g. Refs. [37,42]). The types of analyses that have been mostly performed in the compiled research are sensitivity analysis (16 %), sampling (9 %), regression analysis (5 %), analysis of variance (ANOVA) (2 %), correlation analysis (2 %), causality analysis (1 %), a combination of regression analysis and

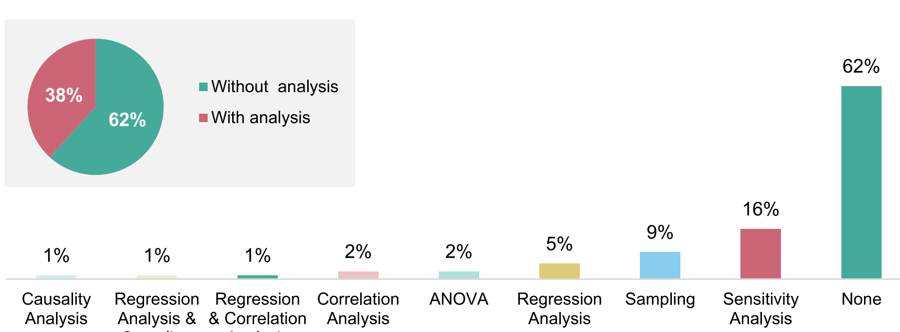

Fig. 15. Types of analysis performed by the reviewed publications.

correlation (1 %), and a combination of regression analysis and sampling (1 %).

4.6. Optimization algorithms

The most common optimization algorithms used over the last 10 years were GAs and non-dominated sorting genetic algorithms (NSGA-II; 37 %), PSO algorithms and non-dominated sorting-based particle swarm optimization algorithms (NSPSO; 9 %), hybrid algorithms (9 %), control algorithms (9 %), the scalarization method (6 %), and the Taguchi method (6 %), as shown in Fig. 16. Studies that performed optimization without using a specific algorithm (7 % of the literature) employed simulation- and TOPSIS-based optimization approaches, as discussed in Section 4.3. The following are brief descriptions of the top six types of optimization algorithms and their applications in the reviewed literature.

1. GAs are inspired by the natural selection process and are founded on the Darwinian principles of biological evolution and the survival of the fittest [34,107]. For GA, data evolution begins by transforming the data population into a new generation with higher average fitness values that are closer to the optimal results. Each generation is evaluated, and when the data fails to satisfy the optimization criterion, a new population of data will be generated using three GA operators: selection, crossover, and mutation. The procedure for evaluating and generating the data is repeated until the evaluation criteria are satisfied [28,92]. Accordingly, and as it is not necessary to express the objective function, variables, and constraints analytically, multi-objective GAs appear to be the most preferred optimization method for the coupling approach between the BPS and optimization. GA-based optimizations were coupled with simulation tools in 65 % of the reviewed studies. For instance, CFD simulations were employed in combination with GAs in Refs. [34,44,96]; whereas energy simulations and GA-based optimizations were performed in Refs. [25,33,69]. However, other studies have relied on an inverse modelling approach that uses predictive mathematical models to simulate indoor environmental conditions or systems operations as reported in Refs. [15,71,91].

The NSGA-II, an advanced meta-heuristic version of the GA, is developed using non-dominated sorting, sharing, and crowding distance methods, which demonstrated higher computational and search efficiency than other GA methods [108]. The NSGA-II was used in 16 % of the reviewed literature, indicating its notable popularity in optimization studies, particularly in recent years (e.g. Refs. [46,49,50,80]). The reviewed work utilizing NSGA–II–based optimization was performed in various types of buildings; however, NSGA-II was always coupled with a simulation tool, principally with energy simulation software (in 77 % of studies). MATLAB and jEPlus + EA optimization tools were widely used (in 77 % of studies) to perform multi-objective optimization using the NSGA-II.

The review shows that GAs are the most popular non-gradient-based algorithms, exhibiting unparalleled versatility and the capability to handle a wide spectrum of complex, nonlinear, and multimodal optimization problems across diverse domains. Given their robustness and universal applicability, GAs are considered powerful search tools with higher computational efficiency. GAs have also demonstrated an enhanced probability of generating optimal solutions, particularly when coupled with CFD simulations to optimize indoor environments. Additionally, the integration of GAs with artificial neural networks (ANN) allows for a comprehensive exploration of the global optimum within a parametric search space.

2. PSO algorithms, used in approximately 9 % of the reviewed studies, are ranked second to GAs. These algorithms use intelligent techniques inspired by nature to address a wide range of complex engineering problems. A particle in PSO represents a potential solution and has two vectors: location and a velocity. By continuously modifying the velocity vector, a particle approaches its best local position. The best global position can then be obtained using the weights and acceleration constants [85]. For multi-objective optimization applications, a more advanced version of the algorithm was developed by introducing a non-dominated sorting method in which the personal and the global best selections were updated for a better distribution of solutions along the Pareto-optimal Front. The NSPSO algorithm was employed in three studies (4 % of the reviewed work) to optimize energy consumption, thermal comfort, and IAQ in a typical and a train cabin [21,26,32]. However, other studies (5 % of the reviewed work) preferred to utilize the original version of the algorithm (i.e., PSO) [51,85,87,93].

Similar to GAs, PSO algorithms have demonstrated their capabilities

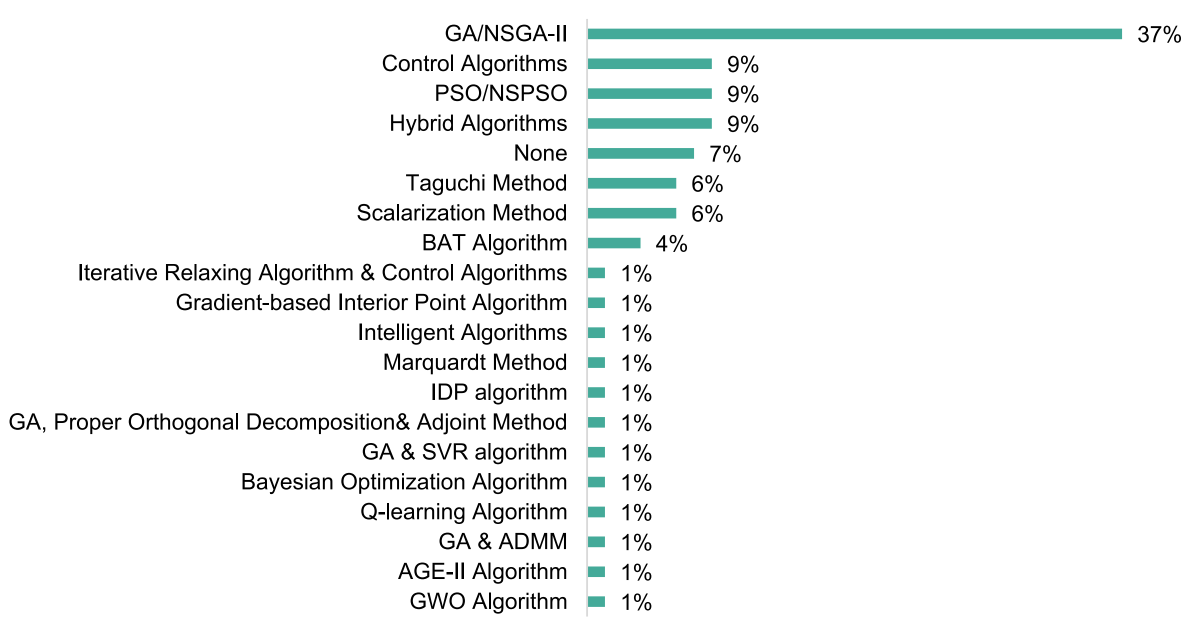

Fig. 16. Common optimization algorithms used in reviewed literature.

in solving nonconvex and multimodal problems, offering speed, accuracy, and faster convergence. As PSO requires less memory and is user-friendly, it has been particularly effective in optimizing HVAC design when paired with CFD simulations. Moreover, the integration of PSO-CFD methods with predictive models and data mining techniques, such as neural networks (NN), shows promising potential for accurately portraying system performance in response to various design parameters.

3. Hybrid algorithms have been developed to enhance the performance of optimization algorithms by combining two or more algorithms. Developing a hybrid optimization algorithm by leveraging the strengths and overcoming the limitations of individual algorithms is a promising approach to accelerate convergence, enhance solution quality, boost robustness, and manage challenging optimization problems better. Efforts to develop new hybrid approaches and investigate new combinations of optimization techniques to solve more complex problems have been vividly captured in the reviewed literature and may still be an active area of research in the future. The use of hybrid optimization algorithms was reported in 9 % of the reviewed works to achieve optimization objectives through optimized control schemes (e.g. Refs. [64,66,67]), building construction materials [76], or occupant behavior [98]. As highlighted in recent studies, hybrid algorithms consistently outperform traditional optimization techniques [64,67]. This review also highlights their enhanced efficacy and superior performance across diverse applications, including residential, educational, commercial, and smart buildings.
4. Control algorithms and methodologies have been explored to optimize the control schemes for HVAC systems in commercial settings. The control input devised by control algorithms is usually determined by measurements or predictions of indoor environmental parameters, as in Refs. [54,72], or together with occupancy information, as in Refs. [18,22,40,73]. Conventional control algorithms, such as rule-based feedback controllers, are cost-effective and operationally comparable to their more sophisticated model predictive control counterparts [18,22,73]. However, intelligent control algorithms, such as fuzzy model predictive controls, demonstrate notable efficacy in enhancing energy efficiency and indoor environmental conditions [72]. Considering the limitations of model-based approaches, particularly their dependence on specific building environments, there has been a growing inclination toward model-free methods. By leveraging learning-based techniques, such as deep reinforcement learning [40], these model-free methods hold significant potential for integration into HVAC control strategies, offering adaptability to diverse and dynamic operational contexts.
5. The scalarization method is a deterministic optimization method that uses a scalarization function to convert a multi-objective optimization problem into various single-objective problems (e.g. Ref. [17]). The weighted sum approach is a common scalarization technique that primarily aggregates single objective functions after multiplying each by a weighting coefficient. The weighted sum approach was used to optimize the energy consumption and thermal comfort of various types of buildings [74] and to optimize an office building's energy consumption, occupants' thermal comfort, and IAQ [59,63].
6. The Taguchi method, or factorial design, is a powerful optimization technique based on the design of experiment approach. Investigating all possible scenarios for a full factorial design requires an assessment of various design variables and their possible values, which can result in multiple experiments. The number of experiments required for optimization can be reduced by determining the most significant operational parameters via sensitivity analysis and proposing a set of orthogonal arrays representing the number of factors and their levels [109]. Although this method has a wide range of applications, optimizing the operating characteristics of a ventilation system appears to be the main use of this algorithm. For example, studies have considered optimizing a mixed-mode ventilation system [38]; an underfloor air distribution system [37,42]; and an impinging jet ventilation system [29,41]. In addition, all studies performed a sensitivity analysis using either signal-to-noise (S/N) ratio analysis [37,42]; ANOVA [29]; or both [38,41] to identify significant variables and determine the optimal level of each variable.

4.7. Decision-making methods

Two processes, optimization and decision-making, are required to solve a multi-objective optimization problem. The sequence in which these are completed determines the method utilized to solve the optimization problem, whether it is a Pareto Front, weighted sum approach, or another. When the decision-making process occurs before optimization, as in the weighted sum approach, the order and weight of each objective function are determined and the problem is transformed into a single-objective optimization problem. This indicates that the weighted sum approach yields a single solution for each set of weights. In contrast, optimization prior to the decision-making process is more common, and a range of optimal solutions is obtained on a trade-off curve known as the Pareto Front, reflecting the best compromise between the optimization objectives [16]. According to the Pareto Optimality concept, a solution is considered optimal if no alternative improves one of the objectives without worsening at least one other objective [2].

Fig. 17 shows that Pareto optimality was used in approximately 35 % of the reviewed studies, with the majority concentrating on energy and thermal comfort, or all three goals. However, the number may be higher, given that approximately 24 % of the reviewed articles failed to specify the decision-making process used for multi-objective optimization. Approximately 15 % of the publications used weights to facilitate the decision-making process, most of which involved energy, thermal comfort, and IAQ optimization. This was primarily accomplished using a simulation and TOPSIS-based optimization method. Some statistical analysis techniques have also been employed for decision-making, such as S/N ratio analysis in Refs. [37,38,42]; Pearson Correlation analysis in Refs. [33,98]; regression analysis in Ref. [35]; and ANOVA in Ref. [29].

4.8. Artificial intelligence & machine learning prediction approaches

The enormous computational cost of optimization studies that compute all possible solutions in a very large solution space is time intensive when more than one objective is targeted. Learning-based techniques have been used to accelerate the exploration of the design space and reduce computational burden without compromising the accuracy of the results. These techniques serve as surrogate models that mimic the behavior of the original model while accelerating time-consuming simulations. Accordingly, 18 of the 82 publications (approximately 22 % of the reviewed studies) included learning-based prediction techniques in their optimization research, most of which were optimizing energy, thermal comfort, and IAQ (Figs. 18 and 19). Half of those studies, predominantly over the last few years, used NN to predict the values of the design objectives and reduce the computational cost (e.g. Refs. [28,34,40,52,56]). The NN prediction method is a machine learning (ML) process inspired by biological neurons in the human brain. Common types of NN using the feed-forward learning process have been adopted in the reviewed literature, including multi-layer perceptron NN in Ref. [87], multi-input multi-output multi-layered perceptron NN in Ref. [80], one-dimensional convolutional NN in Ref. [83], and extreme learning machine in Ref. [45].

Furthermore, powerful estimation algorithms that act as observers have been incorporated in some optimization studies to enhance the data prediction, smoothing, and noise removal performance. For example, the Kalman filter and extended Kalman filter were used in Refs. [15,18,22,73] to filter noise and uncertainties, whereas the Alpha Beta filter was utilized [65] for estimation and smoothing, both of which were performed to improve the accuracy of the predictions. Moreover,

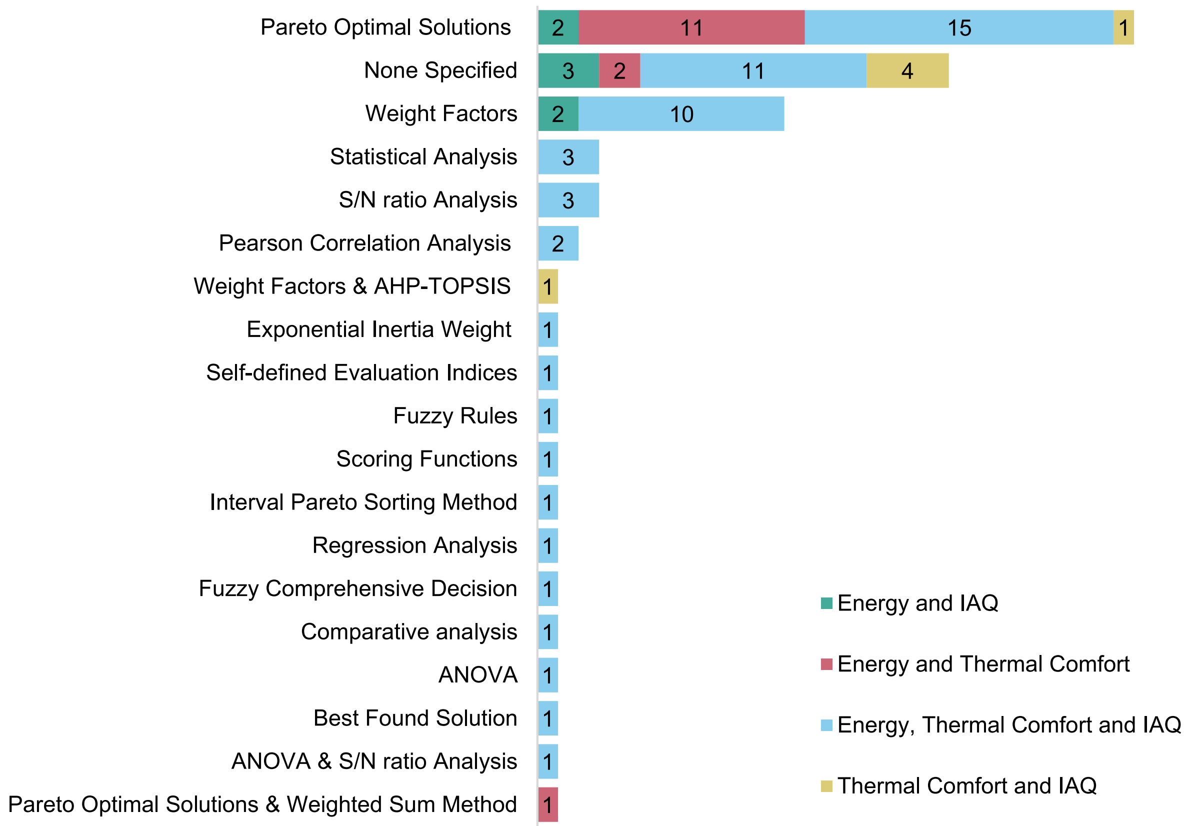

Fig. 17. Common decision-making methods employed between 2013 and 2022.

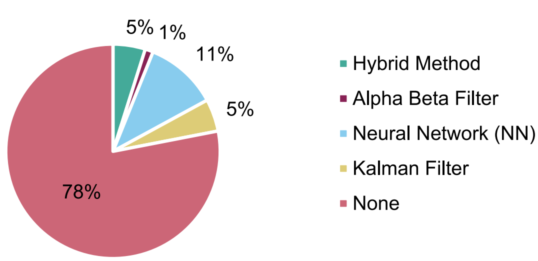

Fig. 18. Common AI/ML prediction approaches adopted between 2013 and 2022.

the fusion of intelligent techniques with other common advanced techniques has shown remarkable capabilities in reducing the computational cost of optimization. Examples of the application of this integrated approach include combining ANN and fuzzy logic, as shown in Ref. [93], ANN and response surface methodology in Ref. [53], feed forward back propagation NN and Kalman filter in Ref. [62], NN and nonlinear autoregressive exogenous in Ref. [51]. This demonstrates how the field of multi-objective optimization research has been significantly impacted by the use of AI/ML prediction techniques. However, as the field of predictive modelling and optimization develops and these cutting-edge methods are explored further, this ongoing advancement will undoubtedly yield more realistic and effective solutions for high-performance sustainable buildings.

5. Conclusions and future research directions

A comprehensive overview of the landscape of BPO research targeting key sustainability goals (i.e., reduced energy usage, improved IAQ, and thermal comfort) is presented in this review by examining the literature published between 2013 and 2022 (82 publications). This review systematically analyzes and discusses the existing optimization approaches, objective functions, performance indicators, tools, algorithms, decision-making methods, analyses, and prediction techniques, providing a clear picture of the latest research movements, advancements, and ways to move forward.

The reviewed work showed notable interest in optimizing energy consumption, thermal comfort, and IAQ collectively, rather than targeting a pair of objectives, reflecting a more comprehensive approach to conducting sustainable building research. Previous studies commonly

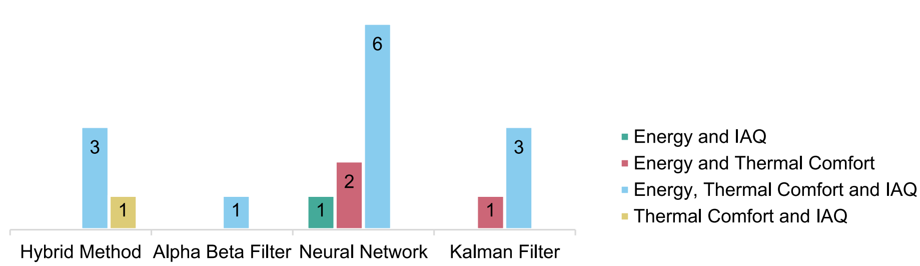

Fig. 19. Number of studies adopting AI/ML prediction approaches between 2013 and 2022 based on optimization objectives.

used the following key performance indices: energy consumption, PMV, and CO_2 concentration levels, as they are practical, comparable, and clearly connected to the key optimization objectives. However, the primary knowledge gaps remain unresolved. For instance, as most research has focused on office and residential buildings, more research on other commercial, educational, and public buildings is needed. Addressing research gaps concerning building- and occupancy-related variables and examining their association with the three optimization goals of reduced energy use, enhanced thermal comfort, and IAQ are also warranted, particularly because most optimization studies have focused on specific systems and/or environmental variables to address the optimization problem.

From a methodological outlook, studies in the BPO field have progressively experimented with various optimization algorithms, hybridization approaches, data-driven models, and testing new methodologies. The coupling approach between BPS and optimization tools has been the primary optimization method adopted in the literature. Only 38 % of the reviewed studies adopted an analysis-coupled approach. Nevertheless, techniques such as sensitivity analysis that were utilized before or after the optimization process can greatly enhance the ability of decision makers to respond more intelligently to the dynamic and complex problems of building environments. This review also demonstrates the primacy of evolutionary algorithms, specifically GAs and NSGA-II, in optimizing building energy consumption, thermal comfort, and IAQ owing to their universal use and ability to handle multi-criteria problems that require a population of solutions. Although the use of AI prediction techniques in the reviewed studies was limited to only 21 %, the application of learning and prediction-based techniques has grown in popularity in last few years and is expected to continue evolving with the rapid development seen today in the fields of AI and ML technologies. As the potential of AI/ML prediction techniques in multi-objective optimization research has not yet been completely realized, this presents a promising area for further research. Hence, methodological optimization approaches are expected to evolve further in tandem with these emerging advanced technologies.

Although this review provides an in-depth examination of building optimization research, certain limitations must be acknowledged such as the consideration of all indoor environmental quality components, namely, thermal comfort, IAQ, visual comfort, lighting quality, and acoustic quality, as optimization targets that could provide a broader and more thorough analysis of the sustainable building optimization research. However, owing to the subject's breadth and its evolving and dynamic nature, it was necessary to focus on studies published in the last decade with three primary optimization targets to acquire representative conclusions. Thus, this review offers a valuable foundation for future research in which other indoor environmental quality components are incorporated as objective functions.

CRediT authorship contribution statement

T. Al Mindeel: Conceptualization, Methodology, Investigation, Writing – original draft, Visualization. **E. Spentzou:** Conceptualization, Writing – review & editing, Supervision. **M. Eftekhari:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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