Journal of Building Engineering 106 (2025) 112566

Contents lists available at ScienceDirect

Journal of Building Engineering

journal homepage: www.elsevier.com/locate/jobe

Artificial intelligence algorithms, simulation tools and software for optimization of adaptive facades: A systematic literature review

Resul Özlük [a,*], Fatih Aydın [b], Yusuf Yıldız [a]

[a] Department of Architecture, Balikesir University, Balikesir, Turkey
[b] Department of Computer Engineering, Balikesir University, Balikesir, Turkey

ARTICLE INFO

Keywords:
Adaptive facades
Energy performance
User comfort
Systematic literature review
Artificial intelligence algorithms
Simulation tools

ABSTRACT

In an increasingly digital world, many methods such as AI algorithms, simulation tools, and software are used for performance-based optimization of adaptive facades, and rapid developments are taking place in these areas. Currently, although there are many studies on these topics, they are not yet fully understood and addressed holistically. To fill this gap, this paper conducted a comprehensive review of these researches. In order to accomplish this objective, a bibliometric approach has been conducted with studies published between 2000 and 2023 to systematically analyze the literature on these topics. Using the systematic literature review, the case study location, case study building types, AF movement typologies, sustainability aspects, objectives of the studies and design parameters to achieve these objectives are investigated within the study scope. As a result, among the artificial intelligence algorithms used to optimize the performance of adaptive facades and their typologies, GAs (GA, NSGA-2, MOGA, MOEA) were found as the most widely used algorithms. Furthermore, the common software, simulation and modelling tools required in optimization process are Grasshopper, EnergyPlus and Rhino-Grasshopper, respectively. Finally, this review paper will make a general database for current and emerging AI algorithms and tools used in optimization of adaptive façade.

1. Introduction

Climate change raises concerns all over the world due to its adverse impacts on the environment. The energy demand of the built environment increases the use of non-renewable energy resources and greenhouse gases. These increases cause global warming. According to the 2018 IPCC report, global warming is causing climate change and undesirable weather conditions [1]. For this reason, heat waves, floods, forest fires and structural changes in local climate conditions have begun to occur frequently in many parts of the world [2]. According to the Global Status Report by the International Energy Agency (IEA), the built environment is responsible for 34 % of energy use and almost two-thirds of total emissions [1]. Commercial, office, and university buildings rank first in energy use [2]. Buildings also account for 40 % of direct and indirect CO_2 emissions [3].

Energy use in the building sector is targeted to be reduced by around 30 % by 2050 [4]. Energy savings can be achieved through comprehensive renovations, low-emission energy supply and transition to low-emission materials [5]. With the recent increased emphasis on energy efficiency and the reduction of fossil fuel use, there are also demands for improving the performance and functionality of the building envelope [6].

* Corresponding author.
E-mail address: resul.ozluk@balikesir.edu.tr (R. Özlük).

https://doi.org/10.1016/j.jobe.2025.112566
Received 29 July 2024; Received in revised form 21 March 2025; Accepted 3 April 2025
Available online 10 April 2025
2352-7102/

Building facades form an essential part of the building envelope and are responsible for approximately 20–60 % of energy consumption in buildings [7]. Considering that the envelope is one of the parameters that significantly affect energy consumption in buildings, it is essential to design façade elements to be flexible regarding building energy flow and user comfort. Therefore, building facades play a leading role in providing comfortable living conditions for users [8]. The building facade provides a physical boundary between the inside and outside. Therefore, building facades are exposed to environmental conditions and uncontrollable meteorological variations that significantly affect occupant comfort conditions and building energy consumption. In addition, building facades are responsible for different functions such as shading, artificial lighting, privacy, overheating and daylighting [9]. A static façade has a limited effect in providing indoor comfort conditions in changing climatic conditions [10]; however, in a world where technology advances and climate changes, the requirements of buildings change frequently [11]. The inability of traditional static cladding systems used on facades to respond to environmental changes has increased the application of new software and hardware technologies on facades. Studies draw attention to the development of more dynamic and adaptive cladding systems instead of static facades [12,13]. Therefore, instead of a static façade design, there is a need for adaptive façades where active and passive systems are used together [14], and façade properties change optimally [15]. In recent decades, researchers have attracted significant interest in adaptive facades [16]. Adaptive facades (AF) are building envelopes that can adapt to changing boundary conditions through instantaneous weather fluctuations and daily or seasonal cycles [17]. The main advantages of AFs are their ability to control solar heat gain and daylighting while preventing overheating and glare [18]. Considering that carbon emissions, energy consumption and air temperatures will increase further in the future, the use of AF systems will become more important.

In the literature, there are similar terms for 'adaptive' facades that are used interchangeably and cause confusion. AFs based on the work of Romano [19] and Tabadkani [20] include the following terms: Active facades [21,22], Passive facades [23,24], Biomimetic or bio-inspired facades [25,26], kinetic facades [27,28], intelligent facades [29,30], Interactive or media facades [31], movable facades [32], responsive facades [33,34], smart facades [35,36], dynamic facades [37,38] switchable facades [39], advanced facades [40] and more. The term 'responsive' refers to a system that is the result of automatic dynamic behavior, while the term 'kinetic' refers to a dynamic system that is not automatic [12]. A dynamic façade encompasses different approaches in terms of its functionality, responsiveness and technological integration. For example; Kinetic facades can operate manually or automatically depending on environmental conditions [41]. They involve mechanical movements such as rotating panels, folding elements or sliding panels [20]. Responsive facades can dynamically adjust own components through control systems and sensors. These facade types can include thermochromic glazing and shape memory materials [42]. Bio-mimicry facades are inspired by biological processes. Taking different sources of inspiration from nature helps designers to develop new contexts and creative layers for responsive facades [43,44]. Smart facades are integrated with Internet of Things (IoT) and artificial intelligence technologies and can optimize building performance by learning from user behavior [36,45]. When the functions and features of different adaptive facades are examined, it is seen that the control mechanism may differ depending on the technologies, materials and movement characteristics used. Although these differences bring certain limitations to AF typologies, they also provide advantages. For example, while the primary purpose of the movable facade typology is not to provide user comfort, the ability to generate energy is a significant advantage of this facade type. When supported by appropriate technology and material properties, AF typologies can be upgraded to a more advanced level. It may be possible to upgrade a passive facade to a smart facade, a movable facade to a kinetic facade, and a kinetic facade to a more advanced responsive facade [26]. Among these typologies, facades such as active, passive, biomimetic, kinetic, movable, and smart do not have user interaction. In contrast, smart, interactive, responsive, and changeable facades can have user interaction [11,14,26].

Adaptive facades (AF) are designed for purposes such as improving thermal comfort, visual comfort (daylight, glare, external view), air circulation and reducing energy consumption [9,46]. In this context, criteria such as thermal comfort, visual comfort and energy performance gain importance. In order to evaluate these performance criteria, various approaches such as numerical calculations or estimations [47,48], user surveys [49,50], building performance simulation (BPS) tools [51–55] and experimental methods [56–60] have been adopted in the literature. Each of these methods has its own advantages and limitations. For example, numerical calculations stand out as a convenient method in terms of time and cost. User surveys, on the other hand, require long-term measurements and time to obtain results. Experimental methods provide the most accurate and reliable results, but are costly and usually time-consuming. In experiments carried out with existing equipment, design parameters are often limited [20]. Simulations are more widely used compared to experimental methods and offer a more economical alternative. However, due to the variety of variables, the estimated values may differ significantly from the actual values [17]. Although BPS evaluates the facade design and performance analysis in an integrated manner, it has a complex structure in the early stages of facade design [10].

When the studies on the performance evaluation of AFs are examined, it is seen that building performance simulation (BPS) tools are preferred more frequently than other methods. Especially in recent years, important studies have been carried out that contribute to sustainability goals such as the design of AFs, energy performance, and improvement of thermal and visual comfort. In these studies, optimization has an important place. It is noteworthy that different artificial intelligence (AI) algorithms integrated into BPS tools have been used recently for solving optimization problems [30,61]. Artificial intelligence algorithms such as optimization algorithms [62–65] and machine learning (ML) models [66,67] are used in solving multi-objective problems, estimating the results, and evaluating the performance of AF facades by adapting to real-time data. In addition, these algorithms can be used with BPS programs with additional software or tools, allowing the creation of different design alternatives and optimization scenarios. To better understand these topics, the following subsections examine energy-efficient facades, their key role in improving building energy performance, and the main objectives of this review.

1.1. General background to the artificial intelligence algorithms and the building energy modeling/simulation tools

The following paragraphs provide a brief introduction to the topics.

Artificial intelligence (AI) is intelligence shown by machines, particularly computer systems. [68,69]. Artificial intelligence is used to analyze the performance of the buildings and their sub-components with various algorithms under changing conditions. Thus, AI algorithms play an important role for optimization of adaptive façade to energy efficiency, thermal/visual comfort and other building performance metrics. Optimization algorithms can be roughly categorized under two branches regarding solution guarantee to a problem.

The former is stochastic approaches that are also called modern methods [70] and used in adaptive façade optimization due to their ability to navigate complex, multi-objective search spaces such as Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) [70–72]. GA is based on Darwin's theory of survival of the fittest [73,74]. GAs use various operators such as encoding, selection, mutation and crossover during search [75]. GAs is effective when the optimization problem has many parameters and multi-objective functions [76,77]. Recently, Multi-objective Genetic Algorithms (MOGA) have become more popular than the classical genetic algorithm for solving problems. There are popular multi-objective optimization algorithms such as NSGA-II (Non-Natural Sorting Genetic Algorithm II) and SPEA2 (Strength Pareto Evolutionary Algorithm 2) [78]. In particular, they are widely used in building optimization [79,80]. Thanks to MOGA, many potential design solutions have emerged that provide various trade-offs between thermal comfort and energy consumption [81]. ACO mimics the foraging behavior of ants and solves optimization problems by finding the shortest path between goals [82,83]. The ACO method appears to reduce electricity consumption and increase the comfort of a smart building compared to existing methods [84]. Inspired by the social behavior of birds or fish, PSO seeks optimal solutions by iteratively adjusting particle positions [85]. It has been calculated that the energy consumption of a house optimized using PSO is reduced compared to the existing house [86]. As can be understood from the above, stochastic methods are used to solve optimization problems in different fields of building performance. In real-world applications, adaptive systems often deal with non-deterministic quantities, like environment variables. Stochastic approaches deal with such cases, where the use of random variables is mandatory, and uncertainty is present and not negligible [87].

The latter is deterministic approaches, including gradient descent, Newton's method, interior point method, simplex method, etc. The exact integer programming (IP) algorithms can be used to solve a variety of building-related optimization tasks such as evaluating energy-saving investments [88] and daylight optimization [89]. The deterministic quadratic programming (QP) algorithms are used to solve problems related to energy management system design [90], smart home energy systems [91]. Non-linear programming methods have been used in studies to select suitable building materials and systems for sustainable building design [92] and to optimize the solar gain under different weather conditions [93]. The literature on the adaptive facade optimization is limited due to the difficulties of deterministic methods in handling complex, high-dimensional and multi-objective problems. Furthermore, these kinds of algorithms lack the flexibility to adapt to real-time uncertainties such as changing weather conditions, non-constant parameters and occupancy patterns.

Machine Learning is one of the fastest-growing areas of computer science with wide-ranging applications [94]. Machine learning algorithms can be classified as supervised, unsupervised and reinforcement learning [95]. The number of specific algorithms and approaches supporting Machine Learning (ML) is large and continues to increase. In the building performance literature, ML algorithms such as Artificial Neural Network (ANN), Decision Tree (DT), Random Forest (RF), Gradient Boosting (GB), Linear Regression (LR), Multivariate Adaptive Regression Splines (MARS), K-Nearest Neighbors (KNN), Principal Component Analysis (PCA) are frequently used for purposes such as classification, regression, optimization and control, clustering and dimensionality reduction. In addition to their stand-alone use, machine learning algorithms, especially when integrated with meta-heuristics, provide advantages in processing real-time data and adapting to changing conditions, making them important for adaptive façade optimization [96,97].

Simulation through Building Energy Modeling is a popular method used to reduce the energy demand and increase thermal comfort in individual buildings [98]. A large number of Building Energy Modeling and Simulation tools having different features have been developed over the last six decades. Some of commonly known simulation tools and their features is presented in Table 1. Over time, researchers have increasingly focused on optimizing building energy performance, driven by the need to maximize life cycle

Table 1
Commonly known Building Energy Modeling and Simulation Tools (BEMS).

Tools	Tools Type	Key Features
EnergyPlus	Simulation Engine	highly flexible [100], IDF file support [101], detailed energy analysis [101–103], includes advanced models [102, 104–106]
TRNSYS	Simulation Engine	plugin support [107], dynamic simulation [108,109], limited CAD compatibility [107], coupled with external tools [109,110], detailed control strategies and renewable integration [107,110]
jEPlus	Graphical User Interfaces (GUI)	parametric analysis and optimization [111].
DesignBuilder	Graphical User Interfaces (GUI)	Powerful 3D modeling interface [112,113], simple geometry support [114], useful for parametric and optimization studies, daylighting-CFD-thermal comfort-detailed HVAC [115]
OpenStudio	Graphical User Interfaces (GUI)	large library for templates, open-source, radiance integration, customizable, integrated with Ladybug Tools and cloud computing for optimization [116,117]
Ladybug Tools	Simulation Environments	integration with EnergyPlus, Radiance and OpenStudio, climate data support [118,119]

economic benefits, carbon reduction and occupant comfort while minimizing energy consumption. This increasing interest has led to the use of artificial intelligence algorithms in conjunction with building energy simulation tools. Many simulation tools cannot run artificial intelligence algorithms on their own. Therefore, simulation tools need to be used in together with or within different programming platforms. For example, jEPlus uses Energyplus for parametric analysis and optimization. Limited algorithms are included in DesignBuilder to solve building design optimization problems. It is also important to note that most of the research presented as optimization is actually parametric studies and their results are interpreted as optimized outputs [99].

In light of the definitions and discussions in the previous paragraphs, the following observations are made on conceptual strengths and limitations (Table 2).

- AI algorithms are methods for solving optimization problems. There is no conceptual overlap that leads to misunderstandings about the two topics. AI optimization algorithms and BEMS tools play complementary roles in optimizing building performance [71]. BEMS tools generate data within defined objective functions and constraints. AI optimization algorithms find the optimum solutions in the light of this data.
- There are significant limitations when using building simulation tools, such as the need for detailed information in the modeling process, long computation times due to the large number of input parameters, and the difficulty of reducing the difference between predicted and measured performance [120]. When using optimization algorithms with building simulation tools, the margin of error due to the difference between the predicted and measured result will not change. However, there is growing interest in utilizing artificial intelligence algorithms to generate data quickly and increase the number of data [121].
- Stochastic algorithms try to find better solutions by keeping the best solutions selected in previous iterations [122,123]. ML models can be integrated with stochastic algorithms to improve optimization processes and reduce computation time [124–126]. In addition, ML models can be used in multi-criteria decision support systems in combination with optimization algorithms. Stochastic algorithms are useful for handling large-scale and complex optimization problems, but their computation time can be high depending on the choice of hyperparameters. These algorithms are known for their ease of implementation and their ability to efficiently produce accurate results [72].
- The main differences between AI algorithms are related to the way they solve problems [70]. Stochastic algorithms are initialized by choosing a random initial population and the solution produces a different result in each run. However, the result produced by deterministic algorithms does not change [127]. In addition, deterministic methods usually reach a global solution for convex problems.
- In contrast to deterministic optimization methods that can get stuck at local minima, Stochastic algorithms have global search capabilities, which allows them to find better solutions. Machine learning methods are data-driven. ML methods have the ability to model complex relationships, but they may not be able to perform direct optimization. Examples of the disadvantages of ML models are long model training time in some cases, explainability problem (Black-box problem), low performance without sufficient data. Deterministic methods provide exact solutions but may be inadequate in solving dynamic problems. Moreover, these methods can be time-consuming and require multiple iterations to find different optimal solutions, which increases the computation time [128]. They are not suitable for use in multi-objective optimization problems due to their ability to work with defined constraints [129]. Given the strengths and limitations of each approach, hybrid optimization models that integrate ML models with optimization algorithms have been increasing in recent research.

Table 2
Perceived strengths and limitations of AI Algorithms and BPS in Building Energy Optimization.

	Strengths	Limitations	Application Examples
BEMS	high accuracy and precise results, comparison of design alternatives, performance prediction in the absence of historical data [71,103,130,131].	computational intensity, computational cost, complexity, expertise required, static assumptions, less suitable for existing buildings, real-time application limitations [71,129,132–134].	energy retrofit analysis, climate adaptation strategies, renewable energy integration, energy code compliance, life cycle assessment
Stochastic approaches	flexible and scalable, both single-objective and multi-objective optimization, ease of implementation and efficient production of accurate results, speed and quality of solution, comprehensive exploration of potential solutions [70,72,129,135]	computationally intensive, challenging parameter tuning, limited real-time adaptability [70,72,135].	generating and exploring alternative design scenarios, space utilization, optimizing energy and comfort, indoor air quality management
Machine Learning	adapts to real-time data, fast computation times, handles non-linearity, suitable for optimization processes, comparison of design alternatives, integrate with other AI algorithms [120,132,136–138].	limited to range of training data, ignores uncertainties in measured data, explainability problem (Black-box problem), large training data sets required, computational cost, risk of overfitting [120,122,137,139,140].	climate-responsive design, energy consumption and comfort prediction, occupancy prediction and space utilization, optimize renewable energy usage and storage
Deterministic approaches	excellent for local optimization, providing precise solutions for specific problems, ideal for high-dimensional spaces [70,129,135]	time consuming, require multiple iterations for different optimal solutions, not practical, difficulty with high dimensional and dynamic problems, requires differentiable objective functions, sticking at local minimums [70,129,135]	energy management, material selection, daylight optimization

1.2. Objectives of the review paper

Several review articles on adaptive facades have recently been published, compiled in Table 3. They have primarily focused on future trends of AF technologies [141], factors preventing the growth of the market share of AFs [142], users' interactions with façade systems [143] and review of user-centered strategies [144], approaches and potentials of AFs [35], process and development of AF integration into designs [145,146], evaluation of the sustainability of AFs [147–149], existing typology differences, design approaches and limitations of AFs [20], performance evaluation of AFs [9,150,151]. However, there's no thorough analysis of artificial intelligence algorithms and tools used for optimization of AFs available. Therefore, the main objective of this study is to provide a bibliometric data of published documents on artificial intelligence algorithms, simulation tools, and software used in the optimization of the performance of adaptive façades in order to guide future studies and provide an up-to-date and comprehensive systematic literature review on this topic. To achieve this aim, it has the following objectives.

- review commonly used artificial intelligence algorithms, simulation and modelling/visualization tools related to the subject;
- explore what work takes place on the optimizing the performance of adaptive façades to be a stepping stone for interested researchers who want to publish their work on this subject;
- show future perspectives and possible challenges in the field of artificial intelligence algorithms, simulation and coding languages used to optimize the performance of adaptive façades.

The remainder of this paper is organized as follows. After the introduction, the next section describes the methodological framework of the systematic review and the bibliometric method. The third section provides a detailed content analysis to better understand and interpret the studies on the performance optimization of adaptive facades. The paper concludes by discussing the summary of the findings, gaps in the literature/suggestions for future studies, and strengths/limitations of the study.

2. Methods

2.1. Systematic literature review

A systematic literature review (SLR) was conducted with specific selection criteria and keywords to collect research in the existing literature relevant to the study's purpose. SLR allows the collection of relevant evidence on a given topic that meets predetermined eligibility criteria and provides answers to formulated research questions [157]. SLR can be used to identify knowledge gaps in the existing literature and make inferences that can guide future research. Furthermore, this methodology synthesizes studies analyzed to answer specific research questions [9,158]. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was applied to provide a rigorous and transparent review process. This method provides a comprehensive and structured approach to literature synthesis by guiding the identification, screening and inclusion of relevant studies [45]. The eligibility process based on PRISMA is shown in Fig. 1.

Firstly, highly reputable and recognized databases such as Scopus [159], Web of Science [160], and EBSCO (Environment Complete, Green File) [20] were searched for the scientific studies using a set of inclusion and exclusion criteria as shown in Table 4.

Table 3
List of recent review articles on adaptive facades.

Reference	Topic of the review
Liu et al., 2023 [148]	Investigation of the static and dynamic arrangements of photovoltaic double skin facades (PV-DSF), their design and operation for sustainability.
Zhang et al., 2023 [142]	A review of adaptive facades based on their design, tools, evaluation criteria and control strategy, and the factors preventing the widespread use of adaptive facades.
Shafaghat et al., 2022 [152]	A review based on dynamic façade typologies, technologies and techniques. Investigation of the characteristics, environmental performance and effectiveness of dynamic façade typologies.
Faragalla et al., 2022 [153]	A review of a comprehensive literature review that reviews design approaches to biomimetic façades. In addition, a holistic framework for biomimetic design by examining three methodological frameworks.
Habibi et al., 2022 [149]	Analyzing smart facades' sustainability (economic, environmental and social) performance through a systematic literature review.
Andreeva et al., 2022 [154]	A systematic and bibliometric review on multi-layered adaptive ventilated facades.
Koyaz et al., 2022 [143]	They are investigating the interaction of building users with façade systems and the factors affecting the user experience in a working environment.
Heidari Matin et al., 2022 [33]	Classify the technologies used in responsive façade systems and compare their advantages and shortcomings.
Tabadkani et al., 2021 [144]	A literature review on user-centered control strategies for adaptive facades and an explanation of existing typologies of user-centered control in office buildings.
Tabadkani et al., 2021 [20]	A systematic review of design approaches to adaptive facades and ten commonly used typologies.
Heidari Matin et al., 2020 [155]	Historical factors that play a role in the development of responsive façade systems and their classification.
Tabadkani et al., 2020 [9]	Investigation of automated control strategies based on simulations to ensure user comfort and energy efficiency in adaptive facades.
Bedon et al., 2019 [156]	A review of classification rules, performance measurements and design methods of adaptive façade systems.
Loonen et al., 2017 [151]	A review on analyzing information on BPS tools used for performance prediction of adaptive facades.

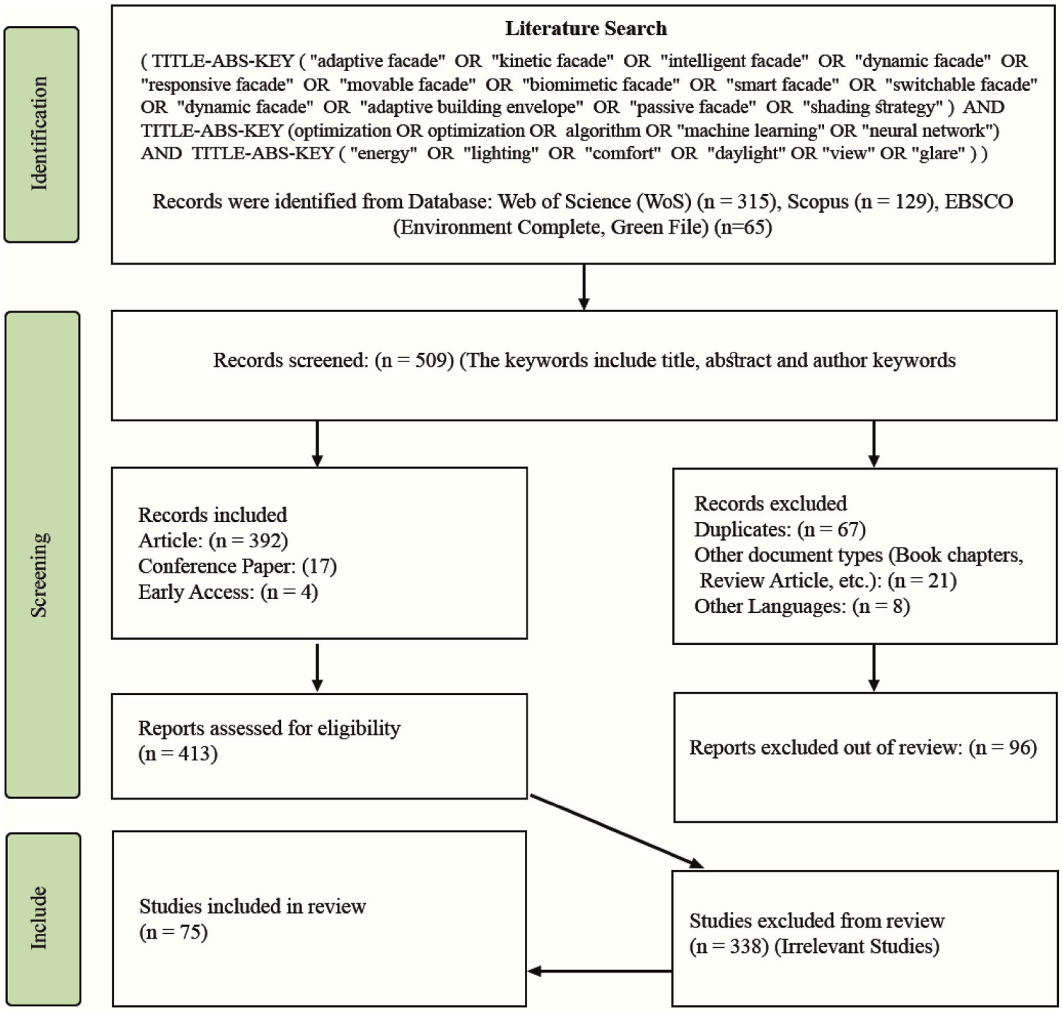

Fig. 1. Framework for eligibility criteria based on PRISMA method.

Table 4
A systematic search summary of databases.

Database	Date of search	Inclusion and exclusion searching criteria in title, abstract and keywords	Number of Documents
Scopus	April 09, 2023/ December 27, 2023	(TITLE-ABS-KEY ("adaptive facade" OR "kinetic facade" OR "intelligent facade" OR "dynamic facade" OR "responsive facade" OR "movable facade" OR "biomimetic facade" OR "smart facade" OR "switchable facade" OR "dynamic facade" OR "adaptive building envelope" OR "passive facade" OR "shading strategy") AND TITLE-ABS-KEY (optimization OR optimization OR algorithm OR "machine learning" OR "neural network") AND TITLE-ABS-KEY ("energy" OR "lighting" OR "comfort" OR "daylight" OR "view" OR "glare"))	129
Web of Science	April 12, 2023/ December 27, 2023		315
EBSCO (Environment Complete, Green File)	April 18, 2023/ December 27, 2023		65

The 'OR' operator used synonyms and alternative spellings, while the 'AND' operator linked main terms from subject terms or headings. Terms, keywords and variables related to the methods used to evaluate thermal comfort, visual comfort and energy performance of adaptive facades and typologies were defined according to certain criteria in the search section of the databases. Fig. 2 shows the distribution of the scientific studies found according to the search results of the above rules between 2000 and 2023. According to the graph, no publications were found between 2002, 2005, 2007 and 2009. In particular, a significant number of studies was observed from 2015 to 2022, and 2022 is the peak year for studies on the subject.

In the first stage, 509 records were found from databases (Scopus, Web of Science and ESBCO). The language of writing was then restricted to English and irrelevant categories were manually eliminated and filtered (n = 29). Most of the articles also appeared in different databases and after removing duplicates (n = 67), 413 publications remained eligible for further detailed review. We then

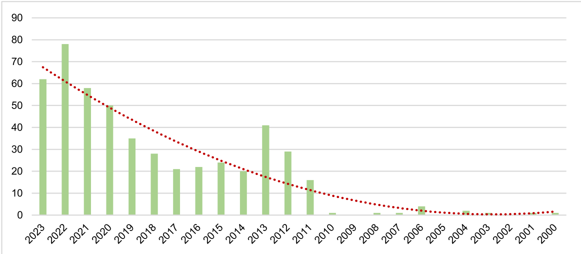

Fig. 2. Distribution of the number of publications related to the studies in the literature by years.

scanned the title and abstracts of each publication and the publications which were not strictly relevant to the topic were excluded (n = 338). After applying all inclusion/exclusion criteria, 75 publications were eligible and considered for this study.

2.2. Bibliometric analysis

Bibliometric analysis is a computer-aided review methodology that can identify basic research and its relationships by covering all publications related to a particular topic or field [161]. This method provides detailed quantitative and statistical information for decision-making processes [162]. A bibliometric review helps visualize the existing literature's structure and connectivity on a given topic and dramatically reduces the time compared to a manual literature search [163]. VOSviewer tool can be used for bibliometric analysis. This software enables the creation and visualization of bibliometric networks based on citations, bibliographic links, co-citation, institutions, countries, researchers and keywords [164]. For this reason, the VOSviewer tool was used in this study to analyze the most frequently occurring terms in the abstract section (Fig. 3), the most frequently occurring terms in the title section (Fig. 4) and the co-occurrence of terms in keywords (Fig. 5). The network diagram in Fig. 3 shows the most frequent words and their interrelationships in the eligible publications. The frequency of a word is reflected in the size of its node and tag. The thickness of a line is proportional to the closeness of the links between two words. Furthermore, these visual network maps use different colors to identify clusters. The analyzed words were repeated at least three times in the selected articles. As a result, the words are clustered under five main groups: (1) visual comfort (blue), (2) strategy/energy consumption (red), (3) optimization (yellow), (4) environment (green) and (5) window (purple). The co-occurrence of these words in the summary section offers some useful insights for analyzing the maps. First, all clusters are interconnected. The words strategy and optimization are the main focus of the studies, indicating that optimization of the energy and visual performance of AFs are objective goals that are often investigated. Energy consumption and visual comfort are the second main focal points in the research of these facades. It is also noteworthy that the performance evaluation of AFs is often linked to office buildings. The occurrence of terms such as daylighting, EnergyPlus, visual comfort, energy consumption, optimization, glare, flexibility and optimal design in the network diagram in Fig. 3 shows that the selected publications are in line with the purpose and focus of the study.

The network diagram in Fig. 4 shows the most frequently occurring words in the title section of the publications that meet the criteria and their interrelationships with each other. As a result, it is seen that words are clustered into four main groups: (1) office

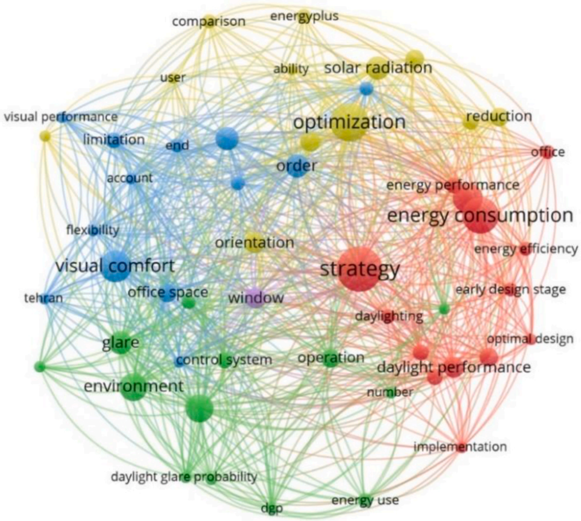

Fig. 3. A network diagram of the words is in the summary section.

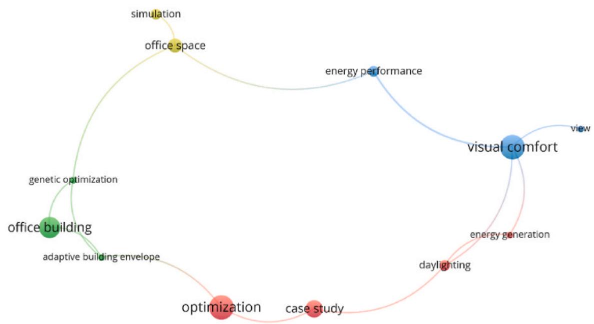

Fig. 4. A network diagram of the words is in the title section of the analyzed studies.

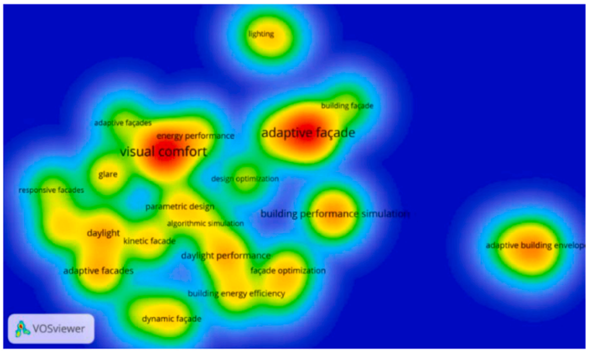

Fig. 5. Density diagram showing the co-use of keywords.

buildings (green color), (2) optimization (red color), (3) visual comfort including daylight, glare and view (blue color) and (4) office spaces (yellow color). When the network diagram is analyzed, it is concluded that the studies are frequently conducted in office buildings. Simulation and optimization studies on visual comfort and energy performance are at the forefront in these buildings.

Fig. 5 shows the cluster density of 20 keywords grouped into six groups. The cluster density view allows the density of items to be displayed separately for each item cluster. The density view shows the general structure of the map. The use of adaptive façade and visual comfort keywords draws attention primarily. The high density of keywords related to "adaptive façade" and "visual comfort" indicates that these topics are prominent in the research field. This indicates that these topics could be current research trends due to their importance in improving building performance and occupant comfort. However, the overuse of these keywords may also indicate that research in these areas has reached saturation. It is noteworthy that while researchers focus on these topics, they may neglect other important but less explored topics. A lower density of keywords in other areas may reveal potential gaps in research and provide opportunities for future research. It can also be seen that there is a distinction between adaptive façade, visual comfort, building performance simulation, lighting and adaptive building envelope. In particular, the use of "building performance simulation" as a separate cluster indicates that simulation tools and methodologies have an important place in the research field. Thus, it may indicate that there is a trend towards data-driven and computational approaches in studies evaluating the performance of AFs.

3. Results and discussion

In this part of the research, as a result of examining the selected studies in the literature, a detailed content analysis was carried out to better understand and interpret the studies on the performance optimization of adaptive facades and their typologies. In this context, reference, year, publication type, building use type, location, design parameters, objectives, adaptive façade movement type, optimization techniques, SIM tools, modelling/visualization software and tools used for optimization are given for the selected studies on the subject. The publication range of the studies that meet the criteria covers the years 2012–2023. Approximately 82 % of the selected studies consist of articles. Fig. 6 shows the distribution of eligible studies published between 2012 and 2023 according to publication type. Most were published in international journals dealing with buildings, solar energy, energy and simulation. These are Journal of Building Engineering (11.2 %), Buildings (8.5 %), Building and Environment and Solar Energy (7 %), Energy & Buildings, Sustainability and Energy (5.6 %), Journal of Daylighting (4.2 %), Energies, Automation in Construction, Applied Energy, Building Simulation (3 %). The remaining studies (18 %) were published in conference proceedings in the fields of building simulation, physics, engineering and energy: IBPSA (International Building Performance Simulation Association) Conference (4.2 %), Journal of Physics: Conference Series (3 %) International Multidisciplinary Conference on Engineering Technology, UrbSys, IEEE conference on, BuildSys'17, International Plea Conference, Energy Procedia, Simulation, Prediction, and Evaluation and ANNSIM (Annual Modelling and

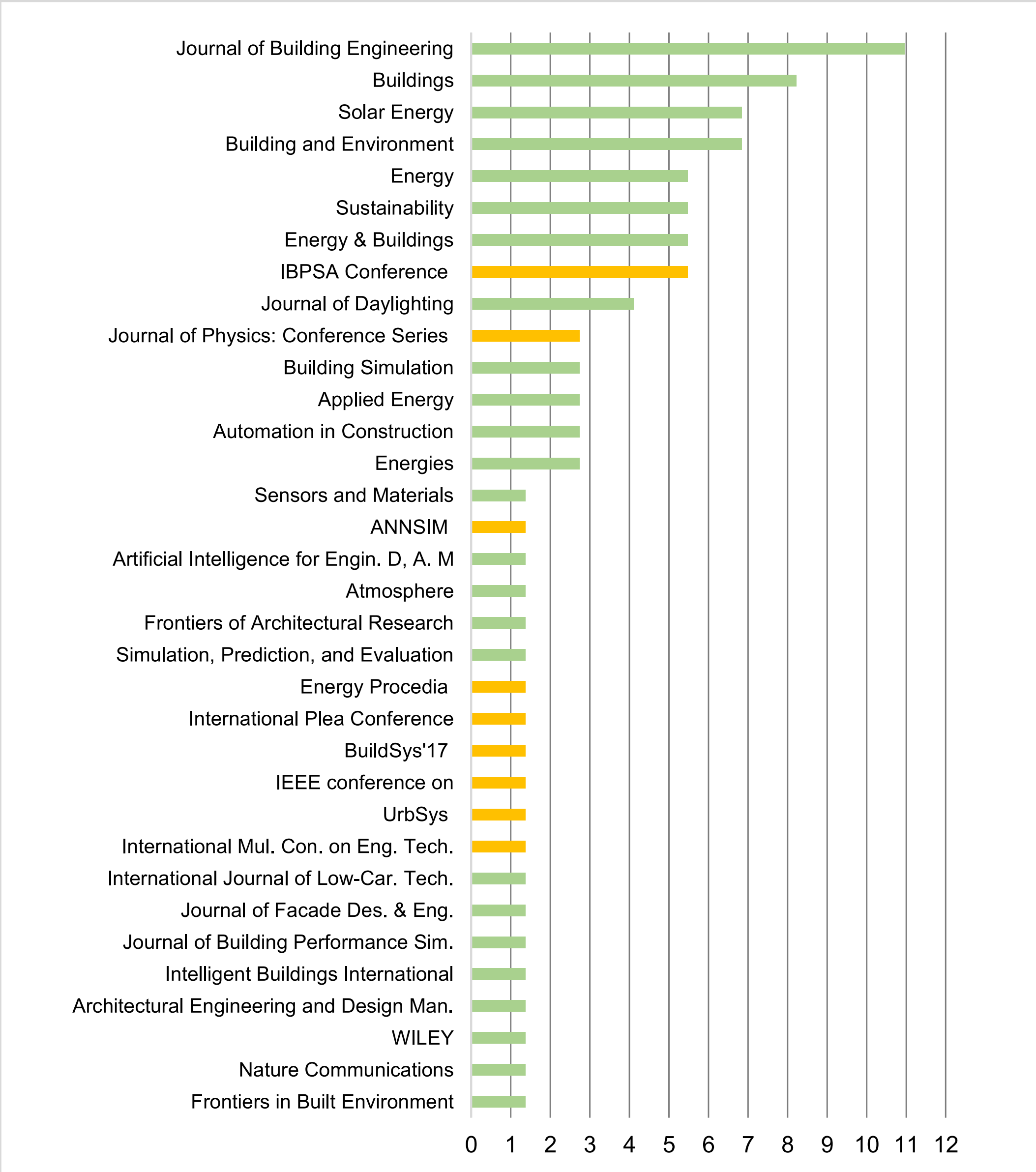

Fig. 6. Percentage distribution of publication types of the studies selected by the criteria.

Simulation Conference). The prominence of journals such as Journal of Building Engineering, Buildings, Building and Environment and Solar Energy indicates that these publications are important platforms for research in building science, energy and sustainability. Researchers target these journals because of their impact in the field and relevance to relevant topics. In addition, the variety of journals and conference proceedings, ranging from building simulation to physics and engineering, indicates that the research has an interdisciplinary approach. This reflects the complexity of work on AFs, which often requires the integration of knowledge from multiple disciplines.

3.1. The characteristics of case studies

This section shows the main characteristics of the studies selected in the literature by the criteria, such as year, reference, publication type, building use type, location and movement towards façade adaptability (Table 5). According to Table 5, the main characteristics of the studies selected by the criteria in the context of AFs are analyzed in detail. The publication range of the studies suitable for the criteria is 2012–2023. However, most of the studies were published in the last three years.

According to Table 5, the types of case studies used are categorized as follows: Office, library, education, residential, hospital, hospital, laboratory, hotel and commercial buildings. The case studies for performance optimization of AFs were most frequently

Table 5
Primary studies focusing on adaptive facade performance optimization, listed chronogical.

Year	Reference	Publication type	Adaptive movable type	Building use type	Case study location
2023	[165] Wen et al.	Conference Paper	Basic movements	Library	China
2023	[166] Liu et al.	Article	Basic movements	Office	China
2023	[167] A. Tabadkani et al.	Article	Folding technique, Venetian blind	Office	Australia
2023	[168] E. C. Lucchino and F. Goia	Article	Passive	Office	Germany
2023	[169] Biloria et al.	Article	Basic movements	Office	Australia
2023	[170] S. Wen et al.	Article	Basic movements	Library	China
2023	[171] Y. Xue and W. Liu	Article	Basic movements, Fixed	Commercial building atrium	China
2022	[172] Gaspari and Fabbri	Article	Basic movements	Residential	Italy
2022	[173] Shi and Pouramini	Article	n/a	Office	Iran
2022	[174] S. Besbas et al.	Article	Folding technique	Hospital	Algeria
2022	[175] Bande et al.	Article	Folding technique	Library	United Arab Emirates
2022	[176] L.E. Hinkle et al.	Article	Basic movements	Office	USA, UK
2022	[177] S.O. Sadegh et al.	Article	Folding technique	Office	Iran
2022	[178] N.H Matin et al.	Article	Basic movements	Office	USA
2022	[54] A. Tabadkani et al.	Article	Folding technique, Venetian blind	Office	Australia
2022	[47] Wang et al.	Article	Folding technique, Basic movements	n/a	China
2022	[179] Zeng et al.	Article	n/a	Office	USA
2022	[180] Valitabar et al.	Article	Basic movements, Light shelf	Office	Iran
2022	[181] R. A. Mangkuto et al.	Article	Fixed, Basic movements	Office	Indonesia
2022	[89] L. Shen and Y. Han	Article	Basic movements, Folding technique	Office	China
2022	[182] N.H Matin and Eydgahi	Article	Basic movements	Office	USA
2022	[183] Sankaewthong et al.	Article	Biomimetic	Office	Thailand
2022	[184] D. M. Le et al.	Article	Roller shade, adaptive glazing	Office	Vietnam, China, South Korea, Germany, Canada and USA
2022	[65] R.P. Khidmat et al.	Article	Venetian blind, Basic movements	Office	UK, Indonesia, Australia
2022	[63] H. Özdemir andB. Y. Çakmak	Article	Folding technique, Fixed	Office	Turkey
2022	[185] S. Wang et al.	Article	Basic movements	Hotel	China
2022	[66] A. Alammar and W. Jabi	Conference Paper	Basic movements	Office	Saudi Arabia
2021	[186] Brzezicki et al.	Article	Basic movements, Fixed	Office	Poland
2021	[67] K. Hiyama and Y. Omodaka	Article	n/a	Office	Japan
2021	[187] A. Tabadkani et al.	Article	Venetian blind	Office	Australia, Egypt, Singapore, India, Germany, Canada, Iran, and Chile
2021	[188] L. Le-Thanh et al.	Article	Folding technique	Office	Viet Nam
2021	[189] M.Ishac and W. Nadim	Article	Light shelf, Venetian blind	Educational	Egypt
2021	[190] R.A. Rizi and A. Eltaweel	Article	Basic movements	Office	Iran
2021	[64] F. Carlucci et al.	Conference Paper	Switchable	Office	European cities (6)
2021	[191] J. Zhu	Conference Paper	Basic movements	Office	USA
2021	[192] Hammoud et al.	Conference Paper	n/a	Office	Lebanon
2021	[26] S. M. Hosseini et al.	Article	Biomimetic	Office	Iran
2021	[193] E. Sorooshnia et al.	Article	Basic movements	Office	Australia
2021	[194] R.P. Khidmat et al.	Article	Basic movements	Office	Japan
2021	[195] H. Bazazzadeh et al.	Article	Folding technique, Basic movements	Office	Iran
2021	[196] A.A.S. Bahdad et al.	Article	Light shelf	Office	Malaysia
2020	[197] H. Kim and M.J. Clayton	Article	Folding technique	Office	USA
2020	[198] A. Tabadkani et al.	Article	Folding technique, Venetian blind, Roller shade	Office	Australia
2020	[199] Z. Luo et al.	Article	Venetian blind	Office	China

(continued on next page)

Table 5 (*continued*)

Year	Reference	Publication type	Adaptive movable type	Building use type	Case study location
2020	[200] X. Shi et al.	Article	Folding technique, Basic movements	Office	Singapore
2020	[201] D.K. Bui et al.	Article	n/a	Office	Australia
2020	[202] T. Mendis et al.	Article	Basic movements	Office	Sri Lanka
2020	[203] S.M. Hosseini et al.	Article	Folding technique, Basic movements	Office	Iran
2020	[204] A. G. Kheybari and S. Hoffmann	Article	Venetian blind, electrochromic glazing	Office	Germany
2020	[205] H. Kim and M.J. Clayton	Article	Folding technique	Office	USA
2020	[206] A.A.S. Bahdad et al.	Article	Light shelf	Office	Malaysia
2019	[62] A. Tabadkani et al.	Article	Folding technique	Office	Iran
2019	[127] H. Yi et al.	Article	Basic movements	Educational	USA
2019	[207] Sharston	Conference Paper	Folding technique	Office	USA
2019	[208] Han and Park	Conference Paper	Switchable	Office	USA
2019	[209] Navarro et al.	Conference Paper	Switchable glazing	laboratory	UK
2019	[210] H. Kim et al.	Article	n/a	Office	South Korea
2019	[211] S. Y. Chen	Article	Folding technique	Office	n/a
2018	[212] A. Tabadkani et al.	Article	Basic movements	Office	Iran
2018	[213] E.S. Mazzucchelli et al.	Article	Basic movements	n/a	Italy
2018	[214] Giovannini et al.	Conference Paper	Switchable	Office	United Arab Emirates, Italy and Sweden
2018	[215] M. Ayoub	Article	Basic movements	Office	Egypt
2018	[216] R. Shan and L. Junghans	Article	n/a	Office	USA
2017	[217] F. Favoino et al.	Article	n/a	Office	China
2017	[218] A. P. Biju et al.	Conference Paper	Basic movements	Office	Netherlands
2017	[219] M. Werner et al.	Conference Paper	Basic movements and Venetian blind	Office	Germany, New Zealand, USA, Brazil
2016	[220] J. Xiong and A. Tzempelikos	Article	n/a	Office	USA
2016	[221] A.H.A. Mahmoud and Y. Elghazi	Article	Basic movements	Office	Egypt
2016	[222] K.S. Lee et al.	Article	Basic movements	Office	n/a
2015	[223] R. Velasco et al.	Article	Basic movements	Office	n/a
2014	[224] Garg et al.	Conference Paper	n/a	Office	India
2014	[225] F. Favoino et al.	Conference Paper	n/a	Office	UK, Italy, Finland
2014	[226] C. Kasinalis et al.	Article	n/a	Office	Netherlands
2013	[227] J. Kim	Article	Basic movements	Office	UK
2012	[228] K. Sharaidin et al.	Conference Paper	Folding technique, Basic movements	Office	Australia

conducted in office buildings (84.2 %). This is followed by library buildings (3 %) and educational buildings are in third place with 2.5 %. Residential, hospital, laboratory, hotel and commercial buildings are the least studied building types (Fig. 7).

In the studies on office buildings, it is seen that an office room [186,226], a section of the office building [169] and, in some cases, the whole building [184,201] are analyzed. Analyzing different scales of spaces within office buildings (e.g. a single room, parts of a building or the whole building) demonstrates a comprehensive approach to understanding the performance of adaptive facades. Investigating these different scales of spaces has provided researchers with the opportunity to examine the effects of adaptive facades at both micro and macro levels. In the context of adaptive façades, office [180,188], education [127,189], library [170,175] buildings, as well as Residential [172], Hotel [185], Laboratory [209], and Commercial [171] buildings have been analyzed. The relatively low percentage of studies on other building types compared to office buildings suggests that these building types have not been sufficiently investigated in the context of adaptive façades. This highlights the need for more studies to understand the performance and optimization of adaptive facades in other building types. However, the fact that different building types have been studied, although in small proportions, shows that adaptive facades have a wide range of applications. This highlights that the technologies and strategies developed for office buildings can potentially be adapted to other building types.

Considering the locations of the analyzed buildings, it is seen that most of them are located in the USA. After the USA, the countries of Iran, Australia, China, UK, Germany, Egypt, Italy, Canada, India, Netherlands, Malaysia, Singapore, Japan, South Korea, Indonesia, United Arab Emirates, Finland, Brazil, New Zealand, Sweden, Sri Lanka, Lebanon, Poland, Saudi Arabia, Turkey, Vietnam, Thailand,

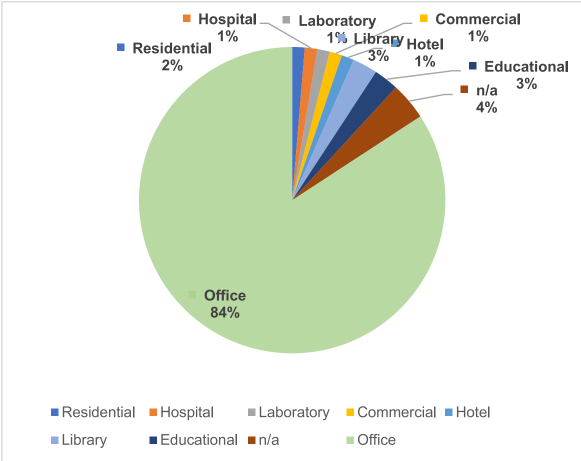

Fig. 7. Building types percentage among case studies in analyzed researches.

Algeria are the locations of the buildings examined in the studies by the criteria.

Adaptive facades are divided into two main groups according to their movement typologies: simple (conventional) and complex (non-conventional) movement types (Fig. 8). Simple movement types are conventional AFs with simple geometries, such as roller and venetian blinds. Their adaptability is limited to rotational and translational movements. Complex motions can be categorized into basic, folding structures and biomimetic skins [20]. Non-conventional AFs with complex movement capability perform better than conventional AFs according to energy consumption, user comfort and daylighting criteria [229]. In the analyzed studies, basic movements [221,223,227], folding technique [62,197], venetian blind [187], light shelf [196], roller shade [184], biomimetic skins [26] and their combined [65,189,198] movement typologies are used. In addition, adaptive typologies such as electrochromic [204] and adaptive glazing [184], which are affected by outdoor conditions, are also included in this study. The studies analyzed basic movements (48 %) and folding technique (27 %) movement typologies more frequently than others. Folding technique and basic movements adaptive movement typologies were mostly used in studies to improve daylight performance [89,203,228]. The two movement typologies have also been compared to determine the best balance between minimum energy consumption and maximum daylight comfort. As a result, folding motion outperformed rotational motion in all four directions [200]. Similarly, it has been confirmed that these dynamic movement types provide better daylight, user comfort and energy efficiency results than fixed shading elements [195].

3.2. *Sustainability scope, objective functions and design variables optimized*

This section of the study describes the reference, sustainability criteria, objectives of the research and design parameters related to the research in evaluating and optimizing the performance of AFs. These characteristics of the selected studies are shown in Table 6. According to Table 6, the objectives, design variables and sustainability scopes of the selected studies in the context of AFs will be analyzed in detail in Section 3.2.1 and Section 3.2.2.

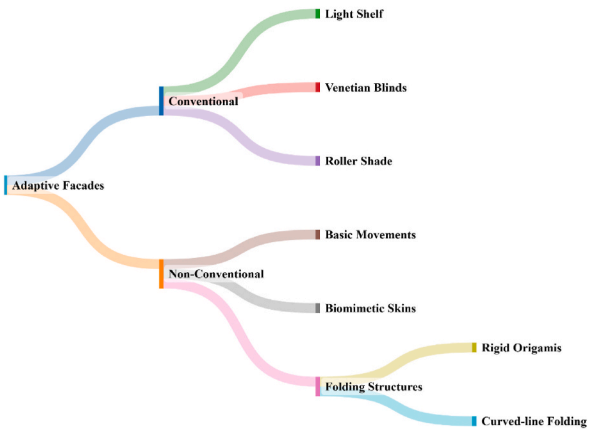

Fig. 8. Classification of AFs according to motion typologies.

Table 6
Objective functions, design variables optimized and sustainability scope.

Reference	Objectives functions	Design variables	Sustainability scopes
[165]	Daylight, Glare	Vertical- horizontal columns, hole diameters, rotation angle, slat width, slat number, window (rotation angle, extension length)	Social
[166]	Energy, Daylight	Building orientation, angle between PV panels and horizontal plane, ratio of the PV panels.	Environmental, Social,
[167]	Visual comfort	Façade module positions, users point, slat angle	Social
[168]	Energy, Thermal comfort, IEQ	Openings of the operable window, fan(on/off), shading angle	Environmental, Social
[169]	Energy, Visual comfort	Time, PV angle, shading type	Environmental, Social
[170]	Daylight, Glare	Number and size of holes, vertical slats, serrated windows with southern and northern orientation	Social
[171]	Visual comfort and Energy	Skylight roof ratio, skylight glass types, fabric Visible transmittance, fabric coverage, louver size and inclination	Environmental, Social
[172]	Energy	Orientation of the façade, opening angle of the flaps	Environmental
[173]	Energy, Visual comfort	Facade type, glass VT and U- value	Environmental, Social
[174]	Daylight, Energy	Glazing ratio, glass materials, module radiance material, modules rotating angle, module distance to glass, sun's position angle	Environmental, Social
[175]	View, Daylight, Energy, Electricity cost calculation	Façade type, structure of the dynamic façade	Environmental, Economic, Social
[176]	Energy	Curve control point, site rotation, window fraction, window head and sill height, L-shape, tower and site location, tower length-width aspect ratio, tower: base building volume fraction, glazing VT and U- value	Environmental
[177]	Daylight	Open, semi-open, and closed configurations, number of nodes in U and V direction, The edge of module for rotational axis, distance of modules to wall	Social
[178]	Visual comfort	Facade angles, configurations, orientations and locations	Social
[54]	Energy, Visual comfort	Shading positions on façade's grid, slat angle	Environmental, Social
[47]	Glare, Thermal comfort	Façade rotating, sun angle	Social
[179]	Energy cost	SHGC of the translucent insulation layer, Thickness of the concrete layer, U-factor of the translucent insulation layer	Economic
[180]	Visual comfort	Shading type, slat's material, light shelve, slat angle, slat view	Social
[181]	Daylight	Facade orientations, shading devices type, slat angles	Social
[89]	Daylight	Blind angle, facade type	Social
[182]	Daylight	Facade orientations, facade locations/climate zones, responsive louvers rotation horizontally or vertically, facade type	Social
[183]	Daylight	Facade type, rotating and twisting façade	Social
[184]	Daylight, Energy and View	Window-wall ratios, glazing materials, Solar Heat Gain Coefficient, Visible transmittance, blind materials, building locations	Environmental, Social
[65]	Daylight, Energy	Building orientation, blade rotation, blade size, spacing, overhang	Environmental, Social
[63]	Daylight, Glare	Facade types, sun position	Social
[185]	Thermal comfort and Energy	Air conditioning (on, off), shading system	Environmental, Social
[66]	Energy	Orientation, building context, façade level height, exterior wall U-value, glazing type U-value	Environmental
[186]	Daylight, Electricity Production	Shading fins, number of shading fins, tracking angle	Environmental, Social
[67]	Glare, Energy	Window direction, operation of electrochromic glass	Environmental, Social
[187]	Energy and occupant visual/ thermal comfort	Building orientation, WWR, building location	Environmental, Social
[188]	Daylight, Energy	Building and facade orientations, variations of the opening size, shape of kinetic shading device	Environmental, Social
[189]	Daylight	Light shelf (depth of internal shelf, depth of external shelf, inclination angle of external shelf, fin depth, fin inclination angle	Social
[190]	Visual and Thermal comfort	Shading type, transforming facade elements	Social
[64]	Energy	Electrochromic windows behaviour, colored state, visible light transmittance in bleached, thermal transmittance	Environmental
[191]	Daylight, Energy	Sky condition, altitude angle and azimuth angle to identify the sun position.	Environmental, Social
[192]	Thermal comfort and Energy	_	Environmental, Social
[26]	Visual comfort	Grid divisions, radius of transitory-sensitive area, hierarchically deformable louvers, sun-timing positions, position of occupants, orientations	Social
[193]	Daylight, Glare	Window dimensions, WWR relative position, sun position, solid angle, horizontal and vertical shade element	Social
[194]	Glare, View	Metal shading attributes: height, length, strand, bond, angle	Social
[195]	Visual comfort, Energy	Shading device type	Environmental, Social
[196]	Visual comfort and Thermal Energy	Light-shelves: position height, external and internal part angle, External and internal depth ratio	Environmental, Social
[197]	Daylight, Energy	Various dynamic and static adaptive building envelope design	Social
[198]	Daylight, Energy	Slat angle, shading type	Environmental, Social
[199]	Visual comfort and Lighting	Tilt angle of the slats	Environmental, Social
[200]	Visual comfort, Energy	Dynamic façade parameters: component size, axis, transmittance	Environmental, Social
[201]	Energy, Visual performance	Facade type, adaptive facade: Tvis and U- value	Environmental, Social

(*continued on next page*)

Table 6 (*continued*)

Reference	Objectives functions	Design variables	Sustainability scopes
[202]	Energy, Solar Irradiation and Economic cost	PV installation strategies: inclined angle, distance-to-length ratios	Environmental, Economic
[203]	Visual comfort	Glass color, kinetic facade angle	Social
[204]	Visual comfort, Thermal comfort and Energy	Facade system, control strategies	Environmental, Social
[205]	Daylight, Energy	Geometric configurations of climate-adaptive building envelopes type, openness	Environmental, Social
[206]	Daylight	Position height, external and internal depth ratio, External and internal part angle	Social
[62]	Visual comfort	Time parameters, timing nodes, hexagonal module materials, indoor view angle	Social
[127]	Daylight, Energy		Environmental, Social
[207]	Daylight and Glare	Degree of shading structure, shading geometry patterns	Social
[208]	Energy, Visual comfort	Window-to-wall ratio, facade material U and SGHC values	Environmental, Social
[209]	Thermal Comfort	Characteristics of the Adaptive Façade: Tsol, Tvis, SHGC, U-value	Social
[210]	Daylight, Energy	Type movable shading device	Environmental, Social
[211]	Daylight		Social
[212]	Daylight and Glare	Rosette rotation motion, distance to façade and radiance material, louver radiance material, louver translation motion, glass material	Social
[213]	Solar Radiation, Energy	Material layer	Environmental
[214]	Visual comfort, Energy	Thermochromic glazing characterized by different five hysteresis widths, building location	Environmental, Social
[215]	Daylight, Energy	Façade configurations	Environmental, Social
[216]	Energy	Glazing types, wall insulation, infiltration, depth of vertical shading elements and window overhang, rotation angle of vertical shading elements	Environmental
[217]	Energy, Thermal comfort	Adaptive insulation design and control parameters	Environmental, Social
[218]	User Comfort, Energy	Tilt angle	Environmental, Social
[219]	Energy	Façade systems, façade area, building location	Environmental
[220]	Visual comfort, Energy	Model-based control strategies	Environmental, Social
[221]	Daylight	Kinetic motion type	Social
[222]	Daylight	Horizontal/vertical angle adjustment of the louver, number of louvers, louver depth, number of window panel divisions in the U and V direction, ratio of remove from the entire window panel, number of seed point patterns, random variable for seed points	Social
[223]	Daylight	Shading facade state, shading rotating angle	Social
[224]	Thermal comfort and Energy	Azimuth Angle, window wall ratio, overhang depth, aspect ratio, glass type	Environmental, Social
[225]	Energy	Building location and orientation, U-wall, U-glazing, g-value, Tvis	Environmental
[226]	Energy, IEQ	Specific heat, thermal conductivity, density, external surface absorptance, window to wall ratio, glazing properties	Environmental, Social
[227]	Daylight	Opening patterns on the building facade	Social
[228]	Daylight	Types of motion	Social

3.2.1. *Optimized objectives in the context of Afs*

Hashempour et al. [217] divided the objectives into three main dimensions of sustainability: environmental (1), economic (2) and social criteria (3). In this study, the objectives of the studies selected by the criteria were analyzed within the scope of sustainability criteria. It was confirmed that 54 % of these studies were single-criteria, 43 % were two-criteria, and 3 % used all three objectives together (Fig. 9).

It is seen that 42 % of the sustainability aspects are environmental and social, 40 % are social, 13 % are environmental, 3 % are environmental, social and economic and the remaining 2 % are environmental, economic and only economic aspects. The objective functions in the reviewed studies are mainly related to energy [270,315,327], visual comfort (glare, view out, daylight) [32,87,265], thermal comfort [308], indoor air quality [266], solar radiation [312], IEQ [24], solar irradiation and energy cost [301] (Fig. 10).

A summary of the objective functions used in the optimization of the performance of AFs is given below.

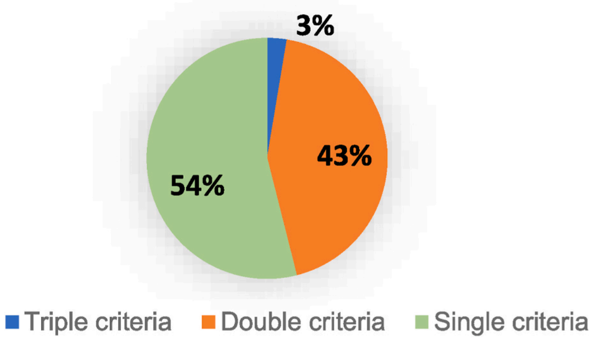

Fig. 9. Percentage of single-criteria, two-criteria and three-criteria sustainability aspects of the analyzed studies.

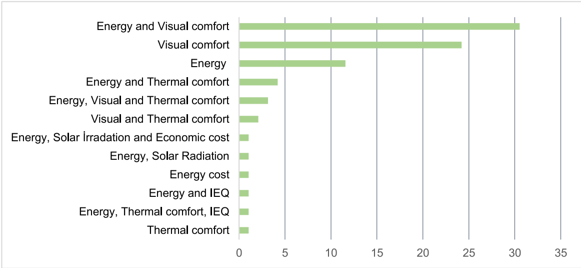

Fig. 10. Percentage distribution of the objectives in the analyzed studies.

- Energy-related (14.7 %): different objective functions have been established for energy consumption [64,216,219,225], energy demand [66,166], energy load minimization [67], energy efficiency and conservation [176,199] and energy intensity [196].
- There are objective functions related to visual comfort and thermal comfort [190,209], but in the studies conducted in the context of AF, the objective functions are mostly related to visual comfort (30.7 %) [26,62,63,170,178,180,203]. Wang et al. [47] used different objective functions for visual comfort, such as maximizing daylight performance and appearance, minimizing glare and uncomfortableness. In addition, daylighting metrics such as mean useful daylight illuminance (UDI) [182], mean daylight autonomy (DA) [177], Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE) [181], daylight factor (DF) [183] are used as objective functions.
- There are objective functions for visual comfort and energy performance (37.3 %) [54,67,169,171,173,175,184,195,196,199–201,208,214,220]. Generally, the most researched objectives in a multi-objective optimization for evaluating the performance of AFs are minimizing energy consumption and maximizing daylight performance (40 %) [65,127,166,174,188,205,210,215].
- Objective functions related to thermal comfort and energy account for 5.3 % of the studies [168,185,192]. In addition, although there are studies on indoor air quality [168], energy cost [187,202,204,213], they are not the most studied objective functions.

Single or multi-objective optimization methods can be used to optimize these objectives. Single-objective optimization addresses only one objective, while multi-objective optimization can address multiple objective functions simultaneously [230]. Multi-objectiveness requires a trade-off between different objectives. This usually leads to Pareto optimal solutions because it can often be challenging to optimize multiple objectives simultaneously. A solution can focus on simultaneously optimizing optimization tasks that involve multiple (conflicting) objectives. Such approaches also allow for the integration of different user-specific objectives [87]. In the context of adaptive facades, the multi-objective optimization process requires a balance of two or more objectives that can be optimized. Simultaneously, optimizing these objectives, such as minimizing energy consumption while maximizing visual and thermal comfort, defines a MOO problem. In the context of the evaluation and optimization of the performance of AFs, it is seen that 53 % of the studies examined used multi-objective optimization and 47 % used single-objective optimization.

3.2.2. Optimized design variables in the context of Afs

In adaptive facades, different design parameters play an essential role in the performance of the facade system. Therefore, various design parameters have been used in adaptive façade optimization. The design parameters commonly used to optimize the performance of adaptive facades in the reviewed studies are given in Table 6. These can be categorized as opaque material properties, window properties, control strategies, airflow, orientation, building location and façade configuration (open, semi-open, and closed configurations). For opaque façades, material selection [181,195,210], windows [174,212,216] and properties related to insulation material [217] have been frequently studied. In window use, glazing type [224,226], coverings [212], number of window panels [222] and window-to-wall ratio [184,208] have been the most interesting design variables. Variables related to window thermal performance are also considered for optimization: visible light transmittance (VLT) (%) [224], solar heat gain coefficient (SHGC) [179,184], total solar energy transmittance (g-value) [226], heat transfer coefficient (U-value). Electrochromic glass properties can vary according to external conditions [64] and user comfort [203]. This way, energy [64] and daylighting performance [203] can be further improved. Adaptive shading systems, blinds, roller shades [198], louvers [182], complex adaptive systems [180] or adjustable panels [166,183] are used as design variables. In the studies, these systems are generally optimized with their distance from the facade [174], rotation angles [183,199], size/depth [216], position on the facade [167,206] and transmittance [64,200] values. In this way, undesirable solar effects and glare can be controlled. Detectors [190], sensors, actuators [191] and control variables [89,180,199] that control the adaptive motion characteristics of the façade are other design parameters used for optimization. Airflow is the variable used to design the adaptive facade to allow controlled natural ventilation [185]. This design variable directly affects indoor air quality, energy consumption and user comfort. The orientation of the building [65,66,166,170] and the configuration of the façade elements (open/closed) [178,215] are other design variables used in the studies. Since these design variables are related to sun exposure and shading, they are also known to impact energy consumption [205] and visual comfort [177]. Finally, climatic characteristics: Sun's position angle [47,174], global solar radiation and direct normal radiation to characterize the sky condition, altitude angle and azimuth angle [191] were used as design variables. Climate-specific conditions such as temperature variations, rainfall and wind conditions impact design decisions.

3.3. Optimization methods, modelling/visualization, simulation and optimization tools

When AF systems are used in buildings, a balance can be achieved between energy efficiency, user comfort and other objectives. In order to achieve this balance, the optimum values of the parameters described in the previous section should be known. In order to determine the most suitable parameters according to the purpose of the study and to determine the optimum values of these variables, an optimization process must be performed. In order to implement the optimization process, simulation, software, modelling programs and optimization tools are needed. The artificial intelligence optimization methods, modelling programs, simulation and optimization tools used to obtain the best performance from AFs are summarized in detail in Table 7. The detailed results and analyses are described in Sections 3.3.1 and 3.3.2, respectively.

3.3.1. Optimization methods in the context of AFs

AI optimization algorithms play an essential role in optimizing the performance of adaptive facades depending on various factors and constraints. The AI optimization algorithms used in the reviewed studies are as follows: Genetic algorithm (NSGA-2, MOGA, MOEA), Brute Force Search Algorithm, Parametric Behavior Map (PBM) algorithm, Fuzzy logic, Generalized Pattern Search (GPS) algorithm, Particle Swarm Optimization (PSO), Machine learning algorithms, Model-based control algorithm (MBC), Raytracing algorithm, Variations-Oriented Algorithm, Simulated Annealing Algorithm, Simulation and-Rule based optimization, Balancing Composite Motion Optimization (BCMO), Deep learning algorithm, Radial Basis Function Neural Network (RBF), Modified Firefly Algorithm (MFA), İnteger Programming Algorithm, Time-Saving Algorithm, Arithmetical Optimization Algorithm, Multi-domain optimization and their combination (Genetic algorithm- ANN, Generalized Pattern Search algorithm (GPS) - Particle Swarm Optimization (PSO) algorithm). In addition to these artificial intelligence optimization algorithms, methods such as parametric simulation, statistical analysis and sensitivity analysis were also used to evaluate the performance of AFs (Fig. 11). Fig. 11 shows the critical role of AI optimization algorithms in the evaluation and optimization of the performance of adaptive facades. The diversity and integration of these methods ((GA- ANN, GPS - PSO)) demonstrates the complexity of the problems for AF systems and the need for innovative and versatile approaches to reach optimum solutions.

The genetic algorithm is the most frequently used optimization method (RQ1 - 35.2 %). Multi-objective evolutionary optimization algorithms such as Multi-objective GA (MOGA) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II) were frequently used in the studies. Genetic algorithms are preferred over other algorithms due to the reduction of optimization computation time [231], the use of evolutionary solvers for parametric design of adaptive facades (Galapagos, Octopus and Wallacei) and their effectiveness in solving nonlinear problems with local minimum and maximum [232]. This is important for AF optimization, where performance metrics (e.g., energy efficiency, thermal comfort, visual comfort) often have non-linear relationships with design variables. In addition, other AI methods such as Particle Swarm Optimization (PSO), Fuzzy Logic, Deep Learning, and Simulated Annealing also play an important role in the evaluation and optimization of the performance of AFs. The use of different AI algorithms meets the need to develop optimal solutions for various design parameters and different purposes. This diversity shows that there is no single best approach. Instead, different studies apply the best performing algorithm for each problem based on specific design constraints, performance criteria, and computational limitations. Moreover, integrating parametric simulation, statistical analysis, and sensitivity analysis in the performance evaluation and optimization process of adaptive facades highlights the need for comprehensive performance evaluation methods as well as AI-based algorithms.

3.3.1.1. Genetic algorithms in the context of AFs. Genetic algorithm (GA) is the most commonly used method in the analyzed studies. Among the multi-objective evolutionary optimization algorithms for solving problems, Multi-objective GA (MOGA) [65,174] and Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [217,226] algorithms are used. Multi-objective Genetic Algorithms are modified versions of GA and differ from GA in terms of fitness function [233]. Adaptive façade systems may need to balance multiple objectives that often conflict with each other. For example, maximizing daylighting while minimizing energy consumption may be desirable. MOGAs can perform well in finding the best trade-offs between conflicting objectives and Pareto-optimal solutions [169,170,197]. There are tools that combine objective and constraint functions from different disciplines and process them simultaneously. For example, genetic algorithms are preferred over other algorithms due to the use of evolutionary solver plugins such as Galapagos [222], Octopus [194] and Wallacei [193]. The use and functionality of Octopus is similar to Galapagos. However, while Galapagos can only generate a shape for one target value, Octopus is suitable for expressing and evaluating multiple targets at the same time [210]. In studies conducted by different researchers [62,207,212], they used Galapagos based on an evolutionary genetic algorithm to achieve maximum visual comfort. Özdemir and Çakmak [63] used genetic algorithm to optimize daylight and glare quality of dynamic shading systems. The method used maximized visual comfort.

Similarly, the optimization of controllable light shelf parameters by genetic algorithm [206] and the configurations of kinetic motions for daylight optimization in the early design phase have been studied [228]. While the above studies focus on the visual performance of AFs, F. Carlucci et al. [64] aimed to minimize the total energy consumption using a genetic algorithm. In addition, Multi-Objective Evolutionary Algorithm (MOEA) [171,183,190,196,197,210], Non-Dominated Sorting Genetic Algorithm (NSGA-2) [169,177,185,193,217,226] and Multi-Objective Genetic Algorithm (MOGA) [65,174] have been frequently used to optimize multiple objectives. Sorooshnia et al. [193] used one of these multi-objective optimization algorithms, NSGA-2, to increase useful daylight and minimize the probability of daylight glare. Similarly, Sadegh et al. [177] developed a system that supports the performance of kinetic facades from the early design stage using Multi-Objective Evolutionary Algorithms (MOEA) and verified that this system improves the natural lighting performance.

Table 7
Optimization methods, modelling/visualization, simulation and optimization tools in the context of adaptive facades.

Reference	Optimization Methods	Modeling/Visualization tools	SIM Tools	Optimization Tools
[165]	MOGA and ANN	Rhino-Grasshopper	Radiance	Grasshopper
[166]	Decision Tree Classifier, Sensitivity analysis	n/a	EnergyPlus	Python
[167]	Fuzzy Logic and Genetic Algorithm	Rhino-Grasshopper	Ladybug-tools, Radiance and DAYSIM	Python
[168]	Multi-domain Optimization	n/a	IDA ICE	Python
[169]	MOEA	Rhino-Grasshopper	Ladybug Tools, EnergyPlus	Grasshopper- Wallacei
[170]	MOGA and ANN	Rhino-Grasshopper	Radiance	Grasshopper
[171]	MOEA	Rhino-Grasshopper	EnergyPlus, Dayism, and Radiance	Grasshopper (octopus)
[172]	Time-Saving Algorithm	IES.VE	IES.VE	Excel software
[173]	Arithmetical Optimization Algorithm	DesignBuilder	EnergyPlus	MATLAB (MLE + toolbox)
[174]	MOGA	Rhino-Grasshopper	EnergyPlus, Radiance	Grasshopper- Octopus
[175]	n/a	Rhino-Grasshopper, Revit	Ladybug Tools, DAYSIM	Grasshopper
[176]	Sequential Search	Rhino-Grasshopper	EnergyPlus	n/a
[177]	MOEA, NSGA-2	Rhino-Grasshopper	EnergyPlus	Grasshopper
[178]	Brute Force Search Algorithm	Rhino-Grasshopper	Radiance	R software
[54]	Parametric Simulation	Rhino-Grasshopper	EnergyPlus	Python
[47]	Convolutional Neural Network	Rhino-Grasshopper	EnergyPlus	Python
[179]	GA, Model predictive control	n/a	EnergyPlus	MATLAB
[180]	Brute Force Search Algorithm	Rhino-Grasshopper	EnergyPlus	Grasshopper
[181]	Parametric simulation	Rhino-Grasshopper	Ladybug, Honeybee, DAYSIM, Radiance	Grasshopper
[89]	İnteger Programming Algorithm and Simulated Annealing Algorithm	Rhino-Grasshopper	Radiance	Grasshopper
[182]	Brute-force search algorithm	Rhino-Grasshopper	EnergyPlus/(DIVA)	Grasshopper
[183]	MOEA	Rhino-Grasshopper (Climate Studio)	Radiance and EnergyPlus (Climate Studio)	Grasshopper (Wallacei X)
[184]	Parametric Simulations, Robust multi-criteria decision-making, Sensitivity analysis	Rhino-Grasshopper	Radiance and EnergyPlus (Climate Studio)	Grasshopper
[65]	MOGA	Rhino- Grasshopper	Radiance and EnergyPlus	Grasshopper (octopus)
[63]	GA	Rhino-Grasshopper	ClimateStudio tools, Ladybug	Grasshopper (Galapagos)
[185]	NSGA-2	Rhino-Grasshopper	DAYSIM, Radiance, and EnergyPlus	Grasshopper (octopus)
[66]	ANN	Rhino-Grasshopper	EnergyPlus	MATLAB
[186]	n/a	SketchUp	EnergyPlus, De Luminae software	n/a
[67]	K-Nearest Neighbor Algorithm	DesignBuilder	EnergyPlus	n/a
[187]	Brute-force search algorithm	Rhino-Grasshopper	EnergyPlus and OpenStudio, Radiance and Daysim	n/a
[188]	Balancing Composite Motion Optimization	Rhino-Grasshopper	DIVA	MATLAB
[189]	Parametric simulation and GA, Sensitivity analysis	n/a	Radiance	n/a
[190]	Parametric simulation and GA	Rhino-Grasshopper	Ladybug-Honeybee	Grasshopper(octopus)
[64]	GA	n/a	EnergyPlus	Python
[191]	Machine learning	Rhino-Grasshopper	DIVA	n/a
[192]	Simulated Annealing Algorithm	n/a	n/a	ASA software
[26]	Parametric simulation	Rhino-Grasshopper	DIVA	Grasshopper
[193]	NSGA-2	Rhino-Grasshopper	Radiance and EnergyPlus	Grasshopper (Wallacei X)
[194]	Multi-Objective Optimization, Sensitivity analysis	Rhino-Grasshopper	Radiance and EnergyPlus	Grasshopper (octopus)
[195]	Multi-objective Optimization	Rhino-Grasshopper	EnergyPlus	Grasshopper (Colibri plugin)
[196]	GA	Rhino- Grasshopper	Radiance and EnergyPlus	Grasshopper (octopus)
[197]	Parametric behavior map, MOEA	Rhino-Grasshopper	EnergyPlus	Grasshopper(octopus)
[198]	n/a	n/a	EnergyPlus	n/a
[199]	Radial Basis Function Neural Network	Rhino-Grasshopper	DIVA	n/a
[200]	Parametric simulation	Rhino- Grasshopper	Radiance and EnergyPlus	Grasshopper
[201]	Modified Firefly Algorithm	Revit	EnergyPlus	Python (Eppy)
[202]	n/a	Rhino-Grasshopper and SketchUp	Radiance and EnergyPlus	n/a
[203]	Parametric simulation	Rhino-Grasshopper	Radiance and EnergyPlus	Grasshopper
[204]	Simulation-based optimization and Rule based optimization	LBNL window software	Radiance and TRNSYS	n/a
[205]	Parametric behavior map algorithm	Rhino-Grasshopper	Ladybug and Honeybee	Grasshopper
[206]	GA	Rhino-Grasshopper	Radiance	Grasshopper (Galapagos)
[62]	GA	Rhino-Grasshopper and SketchUp	EnergyPlus	Grasshopper (Galapagos)
[127]	SVM and Simulated Annealing Algorithm	Rhino-Grasshopper	Radiance	Python

(*continued on next page*)

Table 7 (*continued*)

Reference	Optimization Methods	Modeling/Visualization tools	SIM Tools	Optimization Tools
[207]	GA	Rhino-Grasshopper (DIVA)	DIVA	Grasshopper and Python
[208]	n/a	Rhino- Grasshopper (DIVA) and DesignBuilder	DIVA, EnergyPlus	n/a
[209]	n/a	Rhino- Grasshopper	Radiance and EnergyPlus	n/a
[210]	MOEA	Rhino-Grasshopper	Radiance and EnergyPlus	Grasshopper (octopus)
[211]	ANN	Revit/Dynamo	DOE-2	Neural Builder
[212]	GA	Rhino- Grasshopper	Radiance and DAYSIM	Grasshopper (Galapagos)
[213]	n/a	Rhino and Ecotect	n/a	n/a
[214]	Raytracing algorithm	Rhino- Grasshopper	DAYSIM and EnergyPlus	Grasshopper
[215]	Variations-oriented algorithm	Diva-for-Rhino-Grasshopper and Archsim	Radiance and EnergyPlus	Grasshopper
[216]	GA and AR optimization	Rhino-Grasshopper	Radiance and EnergyPlus	Grasshopper
[217]	NSGA-2	SurfaceControl: MovableInsulation	EnergyPlus	MATLAB
[218]	Facade Optimization System	Rhino- Grasshopper	DIVA	MATLAB
[219]	n/a	DALEC	DALEC	n/a
[220]	Model-based control Algorithm	WINDOW 7 Software	n/a	Matlab v8.5 (R2014b) and LabVIEW Software
[221]	Parametric simulation	Rhino- Grasshopper	DIVA	Grasshopper
[222]	GA	Rhino- Grasshopper	Radiance (DIVA)	Grasshopper (Galapagos)
[223]	Fuzzy Logic, Computational simulations	Rhino- Grasshopper	Radiance	MATLAB
[224]	Generalized Pattern Search algorithm and Particle Swarm Optimization	WinOpt	EnergyPlus	GenOpt
[225]	Hybrid optimization algorithm, (Particle Swarm Optimization with Generalized Pattern Search)	n/a	EnergyPlus	GenOpt/MATLAB
[226]	NSGA-2	n/a	DIVA, TRNSYS	n/a
[227]	Parametric simulation	Rhino- Grasshopper (DIVA)	Radiance	Grasshopper
[228]	GA	Rhino- Grasshopper, Ecotect	Ecotect	Grasshopper (Galapagos)

It is essential to improve the visual comfort of building users and reduce energy consumption. To achieve these objectives, it is necessary to maintain useful daylight levels and reduce glare [193]. Besbas et al. [174] investigated the performance of an adaptive exterior shading system using the multi-objective genetic algorithm to minimize energy use intensity and maximize visual comfort. The results showed that the adaptive façade system is better than the existing system in terms of both visual comfort and energy performance. R.P. Khidmat et al. [65] used a multi-objective optimization (MOO) approach to optimize daylighting and energy consumption in three cities. This approach seems to provide an improvement in daylighting and a reduction in energy consumption. In addition to these studies, Biloria et al. [169] compared the performance of an adaptive photovoltaic shading system with a fixed photovoltaic (PV) system. Using multi-objective evolutionary computational methods, they found that an adaptive PV shading system maximizes the energy produced while maintaining visual comfort.

3.3.1.2. Brute Force Search Algorithm in the context of AFs. Brute Force Search Algorithm are algorithms used to solve pattern search problems [234]. The algorithm searches all solution spaces and paths. It has less iteration time compared to heuristic algorithms. This method shows the results of the objective function heuristically and can directly use possible solutions to calculate the objective function. Brute Force Search Algorithm is slow in solving energy related multi-objective optimization problems [235]. Several researchers have used this method in the evaluation and optimization of the performance of adaptive facades [178,180,182,187]. N.H. Matin et al. [178] used the Brute Force Search algorithm to determine the optimum values of orientations and locations for different façade alternatives to improve natural lighting in interior spaces. Using this method, it was revealed that various parameters increase the amount of indoor natural light in all possible scenarios [182]. Valitabar et al. [180] designed a complex shading system to improve visual comfort and maximize visibility through the Brute Force Search algorithm. The results confirmed that the proposed system improves daylight performance and maximizes outdoor visibility in a glare-free environment. Tabadkani et al. [187] also applied the Brute Force Search method to automatic shading element control scenarios under different climatic conditions and investigated user comfort and energy load regarding objective functions. The results show that different climatic conditions affect the shading element control scenario and the optimum scenario increases the lighting load while increasing the user comfort.

3.3.1.3. Machine learning algorithms in the context of AFs. Machine learning algorithms and their application areas are described in Section 2.3. It is seen that machine learning algorithms such as Decision Tree Classifier (DTC) [166], ANN [66,211], Support Vector Machine (SVM) [127] and K-Nearest Neighbor (K-NN) [67] are used to evaluate the performance of adaptive facades in the reviewed studies. In addition, a comparison of multiple machine learning algorithms (K-NN, SVM, Random Forest (RF)) in a single study was conducted [191]. Liu et al. [166] used DTC, supervised machine learning, to predict the tilt angle of PV panels depending on changing conditions and to develop the Adaptive Control Model (ACM). Weather data and space conditions are used as input parameters in the model. ANN was chosen to build the prediction model. A. Alammar and W.Jabi [66], using existing simulation tools to evaluate the performance of AFs is both a time-consuming and complex process. This study presents an ANN model-based approach that can predict the hourly cooling loads of AF systems in a shorter time compared to existing simulation tools. The prediction results show that the

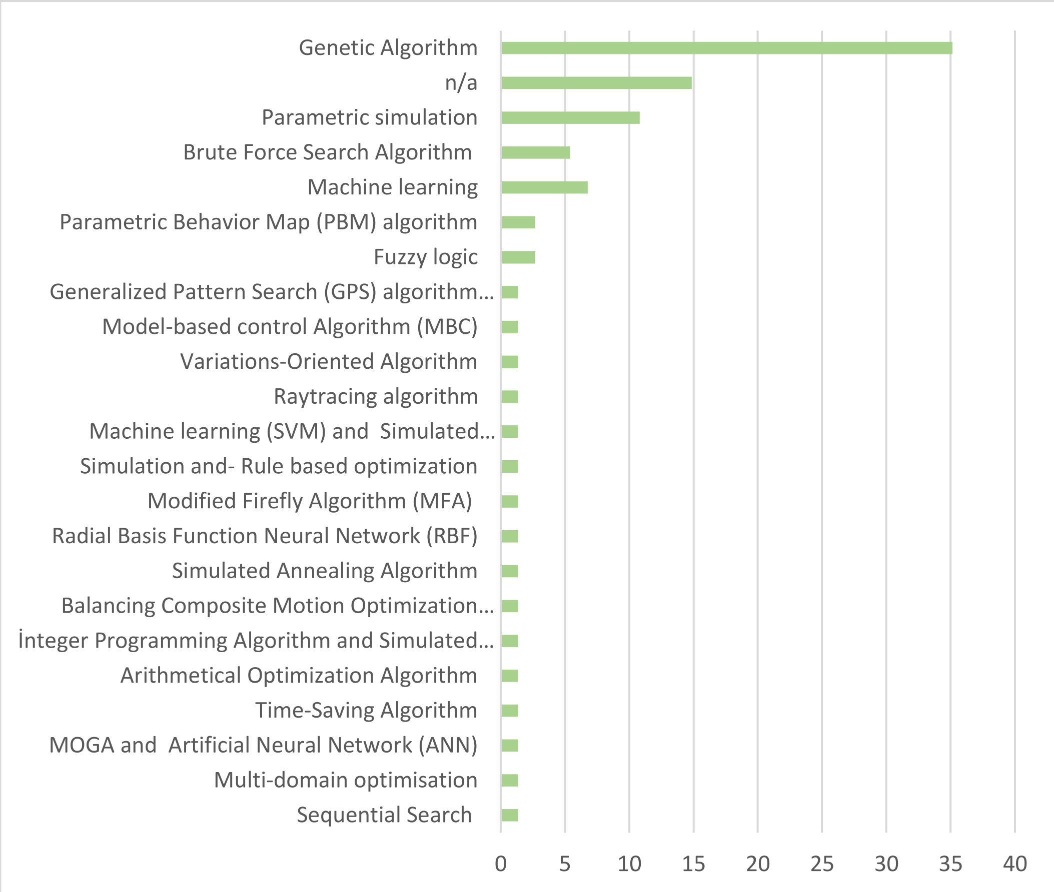

Fig. 11. Percentage distribution of AI methods used in the performance evaluation and optimization of AFs.

proposed model is a reliable model that can predict the cooling loads in a very short time. K. Hiyama and Y. Omodaka [67] used another method, the KNN algorithm, to solve the problem of undesirable cooling processes in certain seasons. The machine learning algorithm successfully solved this problem. In addition to these studies, Zhu [191] used machine learning algorithms such as KNN, SVM and Random Forest (RF) to train prediction models for shading device control with data obtained from daylight simulation. It is verified that the prediction models using machine learning algorithms have high accuracy. In addition, this designed shading system provided significant savings in lighting energy. In general, machine learning algorithms used within the scope of adaptive facades are important algorithms used for purposes such as adaptation to climatic conditions, model prediction, prevention of failures in facades, analysis of data through sensors used, energy efficiency of buildings and ensuring user comfort.

3.3.1.4. Mixed algorithms in the context of AFs. Adaptive facades can have complexities that a single approach cannot always solve. By combining more than one technique, the evaluation of adaptive façade performance and the relationship between various parameters can be better represented. While some studies use only one artificial intelligence optimization algorithm to evaluate the performance of adaptive façades, some studies use hybrid studies in which these techniques are used together. These methods include Multi-Objective Genetic Algorithm (MOGA) and Artificial Neural Network (ANN) [170], Fuzzy Logic and Genetic Algorithm [167], Integer Programming Algorithm and Simulated Annealing Algorithm [89], Parametric simulation and Genetic algorithm optimization [190], Machine learning (SVM) and Simulated Annealing Algorithm [127], Particle Swarm Optimization with Generalized Pattern Search [225], Generalized Pattern Search (GPS) algorithm and Particle Swarm Optimization (PSO) algorithms [224] can be given as examples. Rizi and Eltaweel [190] applied parametric simulation and Genetic algorithm optimization to improve user comfort. Tabadkani et al. [167] used fuzzy logic and genetic algorithm to design adaptive façade modules according to the visual comfort conditions of users. To find the best fuzzy score, a random search process was performed among the pre-recorded datasets and genetic algorithm was applied to find the optimal solution. The results showed that visual comfort for users was significantly improved. Similarly, Wen et al. [170] optimized the design parameters of a shading device using MOGA to improve users' visual comfort. ANN was used to reduce the simulation time for daylighting, while MOGA optimized the design parameters of the shading device. Furthermore, L. Shen and Y. Han [89] combined the fast-linear daylight surrogate model with an integer programming algorithm to evaluate the performance of AFs. This proposed approach has been useful in adaptive façade design. Adaptive facades may involve multiple design parameters, objectives and constraints. These techniques can solve optimization problems where conventional methods are complex. It may be advantageous to use these techniques together to utilize the strengths of each technique. For example, using artificial intelligence optimization algorithms to search for optimal solutions while machine learning algorithms predict the performance of models can speed up the optimization process.

3.3.1.5. Other algorithms in the context of AFs. In addition to the algorithms used above, other methods used to evaluate the performance of adaptive facades can be listed as follows: Time-Saving Algorithm [172], Arithmetical Optimization Algorithm [173], Multi-domain optimization [168], Modified Firefly Algorithm (MFA) [201], Sequential Search [176], Parametric simulation [26,181, 184,200,203,221], Balancing Composite Motion Optimization (BCMO) [188], Fuzzy Logic [223], Model-based control Algorithm (MBC) [220], Variations-oriented algorithm [215], Raytracing algorithm [214], Simulated Annealing Algorithm [192], Radial Basis Function Neural Network [199], Rule Based optimization [204], Parametric Behavior Map (PBM) algorithm [205]. Shi and Pouramini [173] used arithmetic optimization algorithm method integrated with simulation tools to achieve energy efficiency. The proposed approach was applied to office spaces of different sizes. The results showed that energy consumption was reduced in two different offices. Similar to the previous study, Bui et al. [201] proposed a computational optimization approach to improve energy efficiency in buildings. The study's results confirmed that a reduction in energy consumption was achieved. Parametric simulation was used in more than one study to investigate the effect of different kinetic façade configurations on daylighting performance. The simulation results proved that kinetic façade configurations show high performance for improving daylighting performance compared to the existing situation [26,203,221]. Parametric simulations have also evaluated daylighting performance and energy [200] and users' view [184] analyses. The results of the studies have shown that visual comfort performance is achieved and significant savings in building energy consumption can be achieved. In general, in the design of adaptive façade systems, artificial intelligence methods and different integrated methods are used to balance energy efficiency and user comfort. The choice of optimization method for adaptive facades and their typologies will vary depending on the objectives and constraints of the problem, design criteria and available data. When the problem uses these methods, it is seen that the performance of adaptive façade systems is significantly improved.

3.3.2. *Software tools used to evaluate the performance of AFs*

In order to optimize the performance of a building in the context of AFs, simulation, modelling, visualization, and optimization tools are needed. The percentages of optimization tools used in the studies are shown in Fig. 12. Fig. 12 shows that optimization tools such as Python, Grasshopper, Excel software, MATLAB, R software, ASA software, NeuralBuilder and GenOpt are used in the context of adaptive façades. The diversity of optimization tools (Python, MATLAB, R, GenOpt, etc.) used to evaluate the performance of AFs indicates that an interdisciplinary approach has been adopted, including architectural design, building simulation and artificial AI-supported computational methods. Some studies used tools such as Excel [172] and MATLAB [220] for numerical and statistical analysis. These tools are especially preferred for simulation data processing and manual optimization processes. Moreover, the use of AI-assisted tools such as NeuralBuilder shows the increasing use of machine learning in AF optimization [211]. This indicates that predictive modeling and methods using AI algorithms will increase in importance in future studies. Grasshopper (47 %) was the most frequently used tool for optimization in the reviewed studies. Grasshopper, which is a visual programming language and design tool, has become a new generation tool that is frequently used for the design and optimization of adaptive facades among the reviewed studies; (1) its flexibility in design, (2) its ability to perform parametric design, (3) its modelling and visualization features, (4) its ability to work integrated with simulation tools, (5) its integration with tools based on evolutionary-based algorithms such as Galapagos, Octopus and Wallacei for optimization.

Simulation tools are software used to assess building performance (energy consumption, comfort, environmental impacts, etc.), usually in the early design phase [103]. Figs. 13 and 14 show the distribution of different energy simulation tools and building modelling or visualization programs, respectively. When the figures were analyzed, researchers used EnergyPlus (43 %) and Rhino-Grasshopper (68 %) the most. EnergyPlus simulation tool: It has been used for many calculations such as building energy modelling [66,166,173,176], visual [54,177,195] and thermal comfort [180], indoor air quality, climate and daylighting [182,184] analyses. EnergyPlus has become the most widely used software in the optimization process of adaptive facades due to its easy

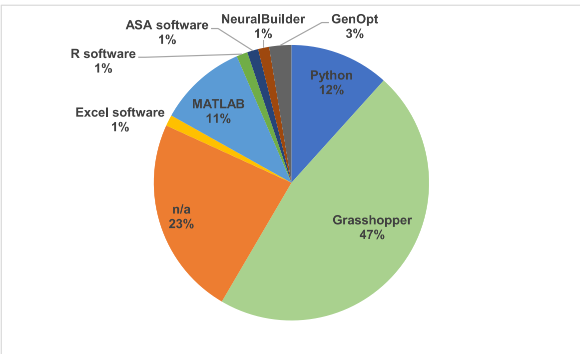

Fig. 12. Percentage of the use of optimization tools among analyzed studies.

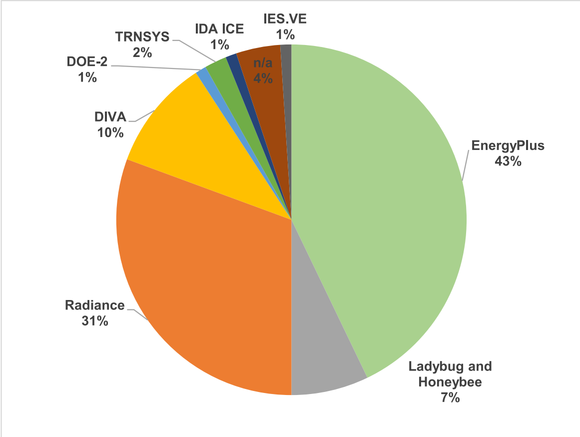

Fig. 13. Percentage of the use of simulation tools among analyzed studies.

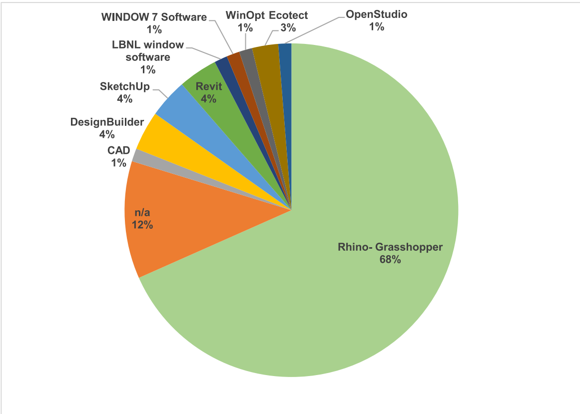

Fig. 14. Percentage of building modelling and/or visualization tools among analyzed studies.

integration into programs that serve as interfaces, the open source of the software [236] and its integration with Building Information Modelling (BIM) [201]. In summary, this has made EnergyPlus an essential tool for evaluating the performance of adaptive facades, which can vary in different scenarios. Also, DOE-2 (1 %) [211], Radiance (31 %) [89,170,174,178,189,202,203,222,223,227], TRNSYS (2 %) [204,226], IESVE (1 %) [172], DIVA (10 %) [26,188,191,199,207,208,218], simulation tools such as IDA ICE (1 %) [168] and Ladybug & Honeybee (7 %) [63,167,169,175,181,190,205] are also used in the optimization process of adaptive facades. These tools are generally used for the calculation of objective functions.

Radiance, another frequently used tool, is a professional toolkit that can analyze lighting. It is a user-friendly software with an extensive library of materials, glass and lighting armatures. It contributes to energy-efficient lighting and natural lighting strategies in building design [237]. Studies show that adaptive facades are widely used in evaluating daylight [89,189,222], glare and view [170,178] performances. DIVA is another natural lighting calculation plugin, but it has been replaced by the newer and more advanced ClimateStudio tool. Integrated with EnergyPlus and RADIANCE tools, ClimateStudio is a fast and reliable simulation software [238]. This simulation tool has been generally used for the calculation of daylight (daylight factor (DF), spatial daylight autonomy (sDA), and annual sunlight exposure (ASE)) indices of adaptive facades [183] and the evaluation of glare performance [63].

TRNSYS is used in building energy performance assessments. TRNSYS is used less in the performance evaluation of AFs than other software. It is seen that the TRNSYS simulation engine is used with Radiance software to evaluate visual comfort, thermal comfort, and energy [204], and DIVA software to evaluate visual comfort, energy, and IEQ performance [226]. Grasshopper's ability to work integrated with different simulation programs [118] has enabled it to be frequently used in single or multi-objective problems of adaptive facades. Ladybug & Honeybee software has been used in more than one study for the evaluation and visualization of daylight [181], thermal comfort [190], energy and visual comfort performances [169,175,205] of adaptive facades. When other simulation tools are analyzed in the context of AFs, IESVE software energy [172], DOE-2 software daylighting [211], IDA ICE software air quality, thermal comfort and energy performances [168]. The simulation tools in this context enable researchers to optimize the design of adaptive facades and typologies for energy efficiency, indoor comfort and overall building performance.

4. Conclusions

4.1. Summary of main findings

Adaptive facades and typologies are building elements that can respond to changing user requirements and external weather conditions. These facades can balance energy consumption by providing insulation, shading and ventilation against adverse external conditions. In addition, balancing indoor temperature fluctuations provides thermal and visual comfort for users. With their adaptability, AFs can make a building resilient to changing conditions, provide aesthetic appearance by including dynamic elements, reduce the need for artificial lighting, and increase visual comfort by optimizing daylight. In summary, adaptive facades and their typologies significantly maximize building performance regarding energy efficiency, comfort, and sustainability. In order to balance these interacting objectives that need to be minimized or maximized, various artificial intelligence optimization methods, a range of simulation tools, software and their combined approaches are needed. For these reasons, this paper aims to provide an overview of the literature on AI algorithms, simulation tools, visualization/modelling tools, and software used to optimize the performance of adaptive façades and their typologies to guide future work. Within the scope of the study, a detailed systematic literature review was conducted using scientific databases such as Scopus, Web of Science, Environment Complete and Green File. The main findings obtained from the analysis of the studies selected by the criteria and the objectives of the study are summarized as follows.

- In most case study locations in the USA, it is observed that the majority of the building type under case study is office building spaces. In studies on office buildings, it is seen that an office room, a section of the office building and, in some cases, the whole building are examined. Library and education buildings are among the most studied building types after office buildings. In addition, residential, hospital, laboratory, hotel and commercial buildings are the least studied building types.
- Simple and complex movement types, which are adaptive façade movement typologies, have been addressed in most studies. The studies observed that basic movements and folding technique typologies, which are complex movement types, were examined more frequently than other typologies.
- In this study, the objectives of the studies selected by the criteria were examined within the scope of sustainability criteria. It has been confirmed that while environmental and social scope are the most frequently addressed scopes together, the least addressed scope is economic. The objective functions in the reviewed studies are mainly related to energy, visual comfort (glare, view out, daylight), thermal comfort, solar radiation, IEQ, solar irradiation and energy cost. Single or multi-objective optimization methods can be used to optimize these objectives. The objectives related to visual comfort (daylight, glare, view) were the most frequently used, while energy costs and IEQ were the least studied. In general, single or multi-objective optimization methods can be used to optimize these objectives. Multi-objective optimization constitutes an essential part of the studies examined in evaluating and optimizing the performance of AFs.
- The design variables that optimize the objectives are opaque material properties, window properties, control strategies, airflow, orientation, building location and façade configuration (open, semi-open, and closed configurations), and climatic characteristics.
- Among the artificial intelligence optimization techniques, GAs (GA, NSGA-2, MOGA) were found to be the most widely used optimization algorithms. GAs are shown to be quite effective in the optimization of adaptive facades (AF) due to their ability to solve complex, low computational time and nonlinear problems [73,75,165]. NSGA-2 and MOGA differ from GA in terms of fitness function. These algorithms are multi-objective genetic algorithms to be applied to optimize multi-objective problems in evaluating the performance of adaptive facades. The widespread use of multi-objective evolutionary algorithms such as NSGA-II and MOGA highlights the importance of balancing multiple performance criteria in optimizing AFs. Moreover, evolutionary-based algorithms [193,194,222] (e.g., Galapagos, Octopus, Wallacei), which can be used as integrated tools in parametric modeling and visual programming language tools, are frequently used in the optimization process of adaptive facades. Parametric simulations, Brute Force Search Algorithm and Machine Learning algorithms are other frequently used methods for evaluating the performance of adaptive fronts. The use of numerous AI optimization algorithms [167,192,225] (e.g., Particle Swarm Optimization, Fuzzy Logic, Deep Learning, Simulated Annealing) in the optimization of AFs shows that researchers have explored various approaches to optimize AF performance. This diversity reflects the complexity of AF systems and the need for different solutions depending on the objective functions within certain constraints. The use of machine learning and deep learning algorithms in the evaluation and optimization of the performance of adaptive facades confirms that these methods are becoming increasingly important. These techniques can improve the prediction accuracy and optimization efficiency of models, often using large data sets. In addition, artificial neural networks from machine learning algorithms are frequently used with other optimization algorithms to minimize the simulation time and estimate the models. The use of hybrid approaches, such as combining Genetic Algorithms with Artificial Neural Networks (ANN) [170] or Generalized Pattern Search with Particle Swarm Optimization (PSO) [224], highlights that integrating multiple AI methods can improve optimization results. This hybrid approach leverages the strengths of different algorithms to address the complexity and challenges in the optimization process.
- When the studies selected by the criteria were examined, two main simulation-optimization approaches were adopted: dynamic simulation modelling methods and static simulation modelling methods [239]. Among the dynamic simulation modelling methods, EnergyPlus accounts for about half of the studies using an energy simulation engine, and Radiance follows it. When we look at the frequency of use of optimization tools, Grasshopper software, which uses Python software in the background, is the most commonly used tool. Although it does not have specific plugins for building optimization, optimization tools such as Python and MATLAB are preferred in the context of adaptive facades. Grasshopper is a plugin that runs on Rhinoceros (Rhino) modelling software. For this reason, Rhinoceros (Rhino) has been the most preferred modelling program for modelling, designing and visualizing adaptive

facades. In addition to the DesignBuilder program, which is especially preferred in building energy modelling, Revit and SketchUp modelling tools come after the Rhino program in modelling adaptive facades. The use of different tools for evaluating the performance of adaptive facades shows that the optimization process is combined with simulation tools (e.g. IES.VE, EnergyPlus, TRNSYS, DOE-2, Radiance) and data-driven approaches (e.g. machine learning techniques in Python and MATLAB).

4.2. Gaps in knowledge and future research needs

This paper is based on a systematic literature review methodology. In general, it reveals the gaps in the existing literature, suggestions for future research and the need for further research on the topic. The study of artificial intelligence optimization algorithms, simulation tools, modelling programs, and tools used to optimize the performance of adaptive façades and typologies is a promising and multidisciplinary field. Some suggestions for future studies are presented as follows.

- Optimization techniques that can balance conflicting objectives in adaptive facades such as energy efficiency, visual comfort, thermal comfort and aesthetics and that can define two or more objective functions should be developed and disseminated.
- Studies should be carried out to address all aspects of comfort in a space (thermal, visual, lighting and acoustic comfort) together.
- In optimizing the performance of adaptive facades, there are uncertainties in studies regarding the criteria according to which design variables are selected. For this reason, feature selection algorithms for design variables before optimization should be widely used in studies.
- Machine learning algorithms are generally used to predict results and reduce optimization time. In addition to these functions, using adaptive facades to optimize control strategies in real-time and create innovative facade designs should be further expanded.
- In order to obtain more accurate and reliable results from the methods used in optimizing the performance of adaptive facades and typologies, sensitivity and uncertainty analyses should be preferred more.
- The accuracy and efficiency of models such as ANN, which will reduce the optimization time, and its effect on multiple artificial intelligence optimization methods should be studied comparatively. Machine learning algorithms, in addition to their stand-alone use, offer significant advantages in terms of real-time data processing and adaptation to dynamic conditions, especially when integrated with meta-heuristic optimization algorithms. However, when the existing literature is examined, the number of studies comparing the performances of more than one machine learning algorithm in the optimization process of adaptive facades is limited. In this context, increasing the number of studies focusing on the comparative analysis of various machine learning algorithms that can work in integration with optimization algorithms (e.g. Artificial Neural Networks (ANN), Decision Trees (DT), Random Forest (RF), Gradient Boosting (GB), Linear Regression (LR), Multivariate Adaptive Regression Splines (MARS), K-Nearest Neighbor (KNN)) will make a significant contribution to the studies on the optimization of adaptive facades. Such studies will provide the evaluation of the performance of different machine learning algorithms by revealing the strengths and limitations of different algorithms.
- Studies on life cycle assessment and cost optimization of adaptive facades should be increased.
- Previous studies generally used parameters related to façade characteristics and environmental conditions to optimize adaptive facades' performance. Including user-centered factors (number of users, user behavior, etc.) in the optimization process will interest future studies and ensure that the results obtained are closer to the actual situation.
- Studies examining climate change and near future weather projection of adaptive facades integrated into the building using different artificial intelligence optimization methods should be expanded.
- In the context of adaptive facades, it has been analyzed that there is a limited number of studies on other building types (such as shopping malls, shops, banks, hotels, residential buildings, museums, and educational and healthcare buildings) compared to office buildings. This highlights the need for more studies that take into account the diverse needs and usage patterns of different buildings to evaluate the performance and optimization of adaptive facades in other building types.
- More than one artificial intelligence optimization methods should be included in the simulation tools to evaluate the performance of AFs and allow algorithm-based comparison.

Finally, when proceeding with optimization in practice, design teams should not rely solely on the optimization technique and should not relegate their knowledge to the background. It should not be forgotten that they are only tools to help the design team in decision-making. These recommendations and identifying gaps will guide future work and future research. By addressing the research gaps identified within the scope of the study, future studies can increase the effectiveness of adaptive façade optimization and enable more sustainable and smarter design of buildings.

4.3. Challenges and limitations

One of the strengths of this article is that there are no related studies in the literature on artificial intelligence optimization methods, simulation tools, or modelling/visualization programs used for the evaluation and optimization of the performance of adaptive facades. In this context, frequently used design parameters, optimization techniques and objective functions, movement typologies, space usage types and location information of the study are listed in tables. A systematic literature review was conducted to perform these analyses. The systematic literature review was conducted based on the PRISMA statement approach and a comprehensive search strategy was applied to maximize the identification of all potentially relevant information. The methodology used in the SLR was appropriate for examining existing research evidence and achieving the study's objectives. This method analyzed studies using leading bibliographic databases (Scopus, Web of Science and EBSCO). The study's inclusion and exclusion criteria were coded and summarized in detail. Although these criteria reduced the possibility of missing relevant studies, there is always the possibility that some appropriate publications may have been overlooked. In addition, the systematic review only includes publications written in English and excludes publications written in other potential languages. In addition, the study outlined the inclusion and exclusion criteria and their justifications in detail. These criteria were related to the aims of the study and were determined without prior knowledge of the studies selected according to the criteria. Thus, possible biases that may occur regarding the studies were avoided and the studies were selected correctly. The stages of identification, screening, eligibility and inclusion were used for each study selected according to the criteria. The data and information obtained from each study were analyzed and summarized appropriately using both text and tables. Moreover, it can be said that these analyses conducted using SLR contributed to the solution of the problem as it identified the gaps in the existing literature and provided practical suggestions. Studies on adaptive façades and their typologies have increased significantly, primarily until 2022. Due to the increasing popularity of the subject, especially in recent years, and the fact that it is a multidisciplinary field, a rapid increase in the number of publications is expected shortly. Therefore, this paper identifies the gaps in existing studies and provides recommendations for future studies. These recommendations cover various research areas and highlight the multidisciplinary nature of optimizing adaptive facades with artificial intelligence algorithms and simulation tools.

CRediT authorship contribution statement

Resul Özlük: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fatih Aydın:** Writing – review & editing, Software, Resources, Investigation, Data curation. **Yusuf Yıldız:** Writing – review & editing, Resources, Project administration, Formal analysis.

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.

References

[1] United Nations Environment Programme (2022), 2022 global status report for buildings and construction: towards a zero-emission, efficient and resilient buildings and construction sector. www.globalabc.org, 2022.

[2] M.S. Gul, S. Patidar, Understanding the energy consumption and occupancy of a multi-purpose academic building, Energy Build. 87 (2015) 155–165, https://doi.org/10.1016/j.enbuild.2014.11.027.

[3] International Energy Agency, Energy Efficiency 2021 (2021). www.iea.org/t&c/.

[4] United Nations Environment Programme (2020), 2020 global status report for buildings and construction: towards a zero-emission, efficient and resilient buildings and construction sector. http://www.un.org/Depts/, 2020.

[5] IEA, GlobalABC/IEA/UNEP (Global Alliance for Buildings and Construction, International Energy Agency, and the United Nations Environment Programme) (2020), GlobalABC Roadmap for Buildings and Construction: towards a zero-emission, efficient and resilient buildings and construction sector, Paris. www.iea.org, 2020.

[6] D. Lee, Y.H. Cho, J.H. Jo, Assessment of control strategy of adaptive façades for heating, cooling, lighting energy conservation and glare prevention, Energy Build. 235 (2021), https://doi.org/10.1016/j.enbuild.2021.110739.

[7] R. Cheng, X. Wang, Y. Zhang, Energy-efficient building envelopes with phase-change materials: new understanding and related research, in: Heat Transfer Engineering, 2014, pp. 970–984, https://doi.org/10.1080/01457632.2013.863674.

[8] S.M. Hosseini, S. Heidari, General morphological analysis of Orosi windows and morpho butterfly wing's principles for improving occupant's daylight performance through interactive kinetic façade, J. Build. Eng. 59 (2022), https://doi.org/10.1016/j.jobe.2022.105027.

[9] A. Tabadkani, A. Roetzel, H.X. Li, A. Tsangrassoulis, A review of automatic control strategies based on simulations for adaptive facades, Build. Environ. 175 (2020), https://doi.org/10.1016/j.buildenv.2020.106801.

[10] S. Soudian, U. Berardi, Development of a performance-based design framework for multifunctional climate-responsive façades, Energy Build. 231 (2021), https://doi.org/10.1016/j.enbuild.2020.110589.

[11] M. Asefi, M. Mitton, S. Currie, A new foldable kinetic architectural system: through an evaluative approach of built examples, case studies: resonant chamber, cheiljedang research center, madina shadi project, Armanshahr Architecture & Urban Development 10 (2017) 1–12.

[12] S. Fattahi Tabasi, S. Banihashemi, Design and mechanism of building responsive skins: state-of-the-art and systematic analysis, Frontiers of Architectural Research 11 (2022) 1151–1176, https://doi.org/10.1016/j.foar.2022.05.006.

[13] J. 'Gaspari, Climate responsive building envelopes. From Facade Shading Systems to Adaptive Shells, 2020. Milano.

[14] B. Kahramanoğlu, N. Çakıcı Alp, Enhancing visual comfort with Miura-ori-based responsive facade model, J. Build. Eng. 69 (2023), https://doi.org/10.1016/j.jobe.2023.106241.

[15] F. Favoino, M. Overend, Q. Jin, The optimal thermo-optical properties and energy saving potential of adaptive glazing technologies, Appl. Energy 156 (2015) 1–15, https://doi.org/10.1016/j.apenergy.2015.05.065.

[16] M. Michael, M. Overend, Closed cavity façade, an innovative energy saving façade, Build. Serv. Eng. Res. Tecnol. 43 (2022) 279–296, https://doi.org/10.1177/01436244221080030.

[17] S. Attia, S. Bilir, T. Safy, C. Struck, R. Loonen, F. Goia, Current trends and future challenges in the performance assessment of adaptive façade systems, Energy Build. 179 (2018) 165–182, https://doi.org/10.1016/j.enbuild.2018.09.017.

[18] S. Attia, S. Bertrand, M. Cuchet, S. Yang, A. Tabadkani, Comparison of thermal energy saving potential and overheating risk of four adaptive façade technologies in office buildings, Sustainability 14 (2022), https://doi.org/10.3390/su14106106.

[19] R. Romano, L. Aelenei, D. Aelenei, E.S. Mazzucchelli, What is an adaptive façade? Analysis of recent terms and definitions from an international perspective, J. Facade Des. Eng. 6 (2018) 65–76, https://doi.org/10.7480/jfde.2018.3.2478.
[20] A. Tabadkani, A. Roetzel, H.X. Li, A. Tsangrassoulis, Design approaches and typologies of adaptive facades: a review, Autom Constr 121 (2021), https://doi.org/10.1016/j.autcon.2020.103450.
[21] H. Altan, I. Ward, J. Mohelnikova, F. Vajkay, An internal assessment of the thermal comfort and daylighting conditions of a naturally ventilated building with an active glazed facade in a temperate climate, Energy Build. 41 (2009) 36–50, https://doi.org/10.1016/j.enbuild.2008.07.009.
[22] H. Elarga, M. De Carli, A. Zarrella, A simplified mathematical model for transient simulation of thermal performance and energy assessment for active facades, Energy Build. 104 (2015) 97–107, https://doi.org/10.1016/j.enbuild.2015.07.007.
[23] K. Fabbri, J. Gaspari, A replicable methodology to evaluate passive façade performance with sma during the architectural design process: a case study application, Energies 14 (2021), https://doi.org/10.3390/en14196231.
[24] T. Srisamranrungruang, K. Hiyama, Balancing of natural ventilation, daylight, thermal effect for a building with double-skin perforated facade (DSPF), Energy Build. 210 (2020), https://doi.org/10.1016/j.enbuild.2020.109765.
[25] W.T. Sheikh, Q. Asghar, Adaptive biomimetic facades: enhancing energy efficiency of highly glazed buildings, Frontiers of Architectural Research 8 (2019) 319–331, https://doi.org/10.1016/j.foar.2019.06.001.
[26] S.M. Hosseini, M. Mohammadi, T. Schröder, O. Guerra-Santin, Bio-inspired interactive kinetic façade: using dynamic transitory-sensitive area to improve multiple occupants' visual comfort, Frontiers of Architectural Research 10 (2021) 821–837, https://doi.org/10.1016/j.foar.2021.07.004.
[27] C.I. Seyrek, B. Widera, A. Woźniczka, Sustainability-related parameters and decision support tools for kinetic green façades, Sustainability 13 (2021), https://doi.org/10.3390/su131810313.
[28] S. Haghighat, H. Sadeh, Parametric design of an automated kinetic building façade using BIM: a case study perspective, J. Build. Eng. 73 (2023), https://doi.org/10.1016/j.jobe.2023.106800.
[29] E. Karakoc, G. Cagdas, Adaptive architecture based on environmental performance: an advanced intelligent façade (Aif) module, Gazi University Journal of Science 34 (2021) 630–650, https://doi.org/10.35378/gujs.725902.
[30] M. Liu, K.B. Wittchen, P.K. Heiselberg, Development of a simplified method for intelligent glazed façade design under different control strategies and verified by building simulation tool BSim, Build. Environ. 74 (2014) 31–38, https://doi.org/10.1016/j.buildenv.2014.01.003.
[31] D.S. Panya, T. Kim, S. Choo, A methodology of interactive motion facades design through parametric strategies, Applied Sciences (Switzerland) 10 (2020), https://doi.org/10.3390/app10041218.
[32] A. Kontadakis, A. Tsangrassoulis, L. Doulos, F. Topalis, An active sunlight redirection system for daylight enhancement beyond the perimeter zone, Build. Environ. 113 (2017) 267–279, https://doi.org/10.1016/j.buildenv.2016.09.029.
[33] N. Heidari Matin, A. Eydgahi, Technologies used in responsive facade systems: a comparative study, Intell. Build. Int. 14 (2022) 54–73, https://doi.org/10.1080/17508975.2019.1577213.
[34] F. Ascione, N. Bianco, T. Iovane, M. Mastellone, G.M. Mauro, The evolution of building energy retrofit via double-skin and responsive façades: a review, Sol. Energy 224 (2021) 703–717, https://doi.org/10.1016/j.solener.2021.06.035.
[35] M. Jafari, A. Alipour, Review of approaches, opportunities, and future directions for improving aerodynamics of tall buildings with smart facades, Sustain. Cities Soc. 72 (2021), https://doi.org/10.1016/j.scs.2021.102979.
[36] G. Barone, A. Zacharopoulos, A. Buonomano, C. Forzano, G.F. Giuzio, J. Mondol, A. Palombo, A. Pugsley, M. Smyth, Concentrating PhotoVoltaic glazing (CoPVG) system: modelling and simulation of smart building façade, Energy 238 (2022), https://doi.org/10.1016/j.energy.2021.121597.
[37] A. Luna-Navarro, G. Lori, D. Callewaert, M. Overend, Semi-automated vs manually controlled dynamic facades: assessment through a field study on multi-domain occupant satisfaction, Energy Build. 286 (2023), https://doi.org/10.1016/j.enbuild.2023.112912.
[38] A. Luna-Navarro, G.R. Hunt, M. Overend, Dynamic façades – an exploratory campaign to assess occupant multi-domain environmental satisfaction and façade interaction, Build. Environ. 211 (2022), https://doi.org/10.1016/j.buildenv.2021.108703.
[39] S.W. Tong, W.P. Goh, X. Huang, C. Jiang, A review of transparent-reflective switchable glass technologies for building facades, Renew. Sustain. Energy Rev. 152 (2021), https://doi.org/10.1016/j.rser.2021.111615.
[40] Y. Zhou, C.M. Herr, A review of advanced façade system technologies to support net-zero carbon high-rise building design in subtropical China, Sustainability 15 (2023), https://doi.org/10.3390/su15042913.
[41] M. Pesenti, G. Masera, F. Fiorito, Exploration of adaptive origami shading concepts through integrated dynamic simulations, J. Architect. Eng. 24 (2018), https://doi.org/10.1061/(asce)ae.1943-5568.0000323.
[42] L. Vercesi, A. Speroni, A.G. Mainini, T. Poli, A novel approach to shape memory alloys applied to passive adaptive shading systems, J. Facade Des. Eng. 8 (2020) 43–64, https://doi.org/10.7480/jfde.2020.1.4700.
[43] J. Yoon, Climate-adaptive facade design with smart materials: evaluation and strategies of thermo-responsive smart material applications for building skins in seoul, in: PLEA 2018 HONG KONG Smart and Healthy within the 2-Degree Limit, 2018, pp. 620–626.
[44] A. Scavée, G. Triantafyllidis, G. Palamas, Bio-mimetic approaches to kinetic facades: a design proposal for a light-responsive facade module, in: IOP Conf Ser Earth Environ Sci, Institute of Physics, 2022, https://doi.org/10.1088/1755-1315/1099/1/012005.
[45] M. Wang, Z. Jia, L. Tao, C. Xiang, Review of dynamic façade typologies, physical performance and control methods: towards smarter and cleaner zero-energy buildings, J. Build. Eng. 98 (2024), https://doi.org/10.1016/j.jobe.2024.111310.
[46] D. Borschewski, M.P. Voigt, S. Albrecht, D. Roth, M. Kreimeyer, P. Leistner, Why are adaptive facades not widely used in practice? Identifying ecological and economical benefits with life cycle assessment, Build. Environ. 232 (2023), https://doi.org/10.1016/j.buildenv.2023.110069.
[47] Y. Wang, Y. Han, Y. Wu, E. Korkina, Z. Zhou, V. Gagarin, An occupant-centric adaptive façade based on real-time and contactless glare and thermal discomfort estimation using deep learning algorithm, Build. Environ. 214 (2022), https://doi.org/10.1016/j.buildenv.2022.108907.
[48] Automated Blind Control Based, (n.d.).
[49] M. Koyaz, A. Ünlü, Human-centred performance criteria for adaptive façade design: based on the results of a user experience survey, Build. Environ. 222 (2022), https://doi.org/10.1016/j.buildenv.2022.109386.
[50] S. Attia, S. Garat, M. Cools, Development and validation of a survey for well-being and interaction assessment by occupants in office buildings with adaptive facades, Build. Environ. 157 (2019) 268–276, https://doi.org/10.1016/j.buildenv.2019.04.054.
[51] E. Anzaniyan, M. Alaghmandan, A. Montaser Koohsari, Design, fabrication and computational simulation of a bio-kinetic façade inspired by the mechanism of the Lupinus Succulentus plant for daylight and energy efficiency, Sci Technol Built Environ 28 (2022) 1456–1471, https://doi.org/10.1080/23744731.2022.2122675.
[52] M. Juaristi, F. Favoino, T. Gómez-Acebo, A. Monge-Barrio, Adaptive opaque façades and their potential to reduce thermal energy use in residential buildings: a simulation-based evaluation, J. Build. Phys. 45 (2022) 675–720, https://doi.org/10.1177/17442591211045418.
[53] S.S. Golzan, M. Pouyanmehr, H. Sadeghi Naeini, Recommended angle of a modular dynamic façade in hot-arid climate: daylighting and energy simulation, Smart and Sustainable Built Environment 12 (2023) 27–37, https://doi.org/10.1108/SASBE-04-2021-0075.
[54] A. Tabadkani, A. Roetzel, H.X. Li, A. Tsangrassoulis, Simulation-based personalized real-time control of adaptive facades in shared office spaces, Autom Constr 138 (2022), https://doi.org/10.1016/j.autcon.2022.104246.
[55] E. Catto Lucchino, G. Gennaro, F. Favoino, F. Goia, Modelling and validation of a single-storey flexible double-skin façade system with a building energy simulation tool, Build. Environ. 226 (2022), https://doi.org/10.1016/j.buildenv.2022.109704.
[56] M. Iommi, The mediterranean smart adaptive wall. An experimental design of a smart and adaptive facade module for the mediterranean climate, Energy Build. 158 (2018) 1450–1460, https://doi.org/10.1016/j.enbuild.2017.11.025.
[57] A. Aksamija, Z. Aksamija, C. Counihan, D. Brown, M. Upadhyaya, Experimental study of operating conditions and integration of thermoelectric materials in facade systems, Front. Energy Res. 7 (2019), https://doi.org/10.3389/fenrg.2019.00006.

[58] C. Bedon, D. Honfi, K.V. Machalická, M. Eliášová, M. Vokáč, M. Kozłowski, T. Wüest, F. Santos, N.W. Portal, Structural characterisation of adaptive facades in Europe - Part II: validity of conventional experimental testing methods and key issues, J. Build. Eng. 25 (2019), https://doi.org/10.1016/j.jobe.2019.100797.

[59] T. Araújo, B. De Andrade, J. Nuno, D. Cabral Beirão, A.J. Vieira De Arruda, C. Cruz, T.A.B.D. Andrade, J.N.D.C. Beirão, A.J.V.D. Arruda, C. Cruz, The adaptive power of ammophila arenaria: biomimetic study, systematic observation, Parametric Design and Experimental Tests with Bimetal (2021), https://doi.org/10.3390/polym.

[60] S. Soudian, U. Berardi, Experimental performance evaluation of a climate-responsive ventilated building façade, J. Build. Eng. 61 (2022), https://doi.org/10.1016/j.jobe.2022.105233.

[61] C.E. Ochoa, I.G. Capeluto, Advice tool for early design stages of intelligent facades based on energy and visual comfort approach, Energy Build. 41 (2009) 480–488, https://doi.org/10.1016/j.enbuild.2008.11.015.

[62] A. Tabadkani, M. Valinejad Shoubi, F. Soflaei, S. Banihashemi, Integrated parametric design of adaptive facades for user's visual comfort, Autom Constr 106 (2019), https://doi.org/10.1016/j.autcon.2019.102857.

[63] H. Özdemir, B.Y. Çakmak, Evaluation of daylight and glare quality of office spaces with flat and dynamic shading system facades in hot arid climate, Journal of Daylighting 9 (2022) 197–208, https://doi.org/10.15627/JD.2022.15.

[64] F. Carlucci, A. Cannavale, F. Fiorito, Electrochromic window integration in adaptive building envelopes in different climates: a genetic optimization of switchable glazing parameters to reduce energy consumptions in office buildings, J Phys Conf Ser (2021), https://doi.org/10.1088/1742-6596/2069/1/012131. IOP Publishing Ltd.

[65] R.P. Khidmat, H. Fukuda, B. Paramita, M.D. Koerniawan, Kustiani, the optimization of louvers shading devices and room orientation under three different sky conditions, Journal of Daylighting 9 (2022) 137–149, https://doi.org/10.15627/jd.2022.11.

[66] A. Alammar, W. Jabi, Predicting cooling energy demands of adaptive facades using artificial neural network, in: Annual Modeling and Simulation Conference (ANNSIM), San Diego, 2022, pp. 656–669, https://doi.org/10.23919/ANNSIM55834.2022.9859413.

[67] K. Hiyama, Y. Omodaka, Operation of climate-adaptive building shells utilizing machine learning under sparse data conditions, J. Build. Eng. 43 (2021), https://doi.org/10.1016/j.jobe.2021.103027.

[68] P. van Esch, J. Stewart Black, Artificial intelligence (AI): revolutionizing digital marketing, Australas. Market J. 29 (2021) 199–203, https://doi.org/10.1177/18393349211037684.

[69] Y. Xu, C.H. Shieh, P. van Esch, I.L. Ling, AI customer service: task complexity, problem-solving ability, and usage intention, Australas. Market J. 28 (2020) 189–199, https://doi.org/10.1016/j.ausmj.2020.03.005.

[70] M.A. Karbasforoushha, M. Khajehzadeh, T. Jearsiripongkul, S. Keawsawasvong, M. Eslami, A comprehensive review of building energy optimization using metaheuristic algorithms, J. Build. Eng. 98 (2024), https://doi.org/10.1016/j.jobe.2024.111377.

[71] Y. Pan, M. Zhu, Y. Lv, Y. Yang, Y. Liang, R. Yin, Y. Yang, X. Jia, X. Wang, F. Zeng, S. Huang, D. Hou, L. Xu, R. Yin, X. Yuan, Building energy simulation and its application for building performance optimization: a review of methods, tools, and case studies, Advances in Applied Energy 10 (2023), https://doi.org/10.1016/j.adapen.2023.100135.

[72] A. Ravikumar, Deepthi, A study from the perspective of nature-inspired metaheuristic optimization algorithms, in: Proceedings of the the 2012 IEEEWICACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology, 2015.

[73] S. Mirjalili, J. Song Dong, A.S. Sadiq, H. Faris, Genetic algorithm: theory, literature review, and application in image reconstruction, in: Studies in Computational Intelligence, Springer Verlag, 2020, pp. 69–85, https://doi.org/10.1007/978-3-030-12127-3_5.

[74] B. Alhijawi, A. Awajan, Genetic algorithms: theory, genetic operators, solutions, and applications, Evol Intell (2023), https://doi.org/10.1007/s12065-023-00822-6.

[75] S. Katoch, S.S. Chauhan, V. Kumar, A review on genetic algorithm: past, present, and future, Multimed Tools Appl 80 (2021) 8091–8126, https://doi.org/10.1007/s11042-020-10139-6.

[76] M.J. Ko, Analysis and optimization design of a solar water heating system based on life cycle cost using a genetic algorithm, Energies 8 (2015) 11380–11403, https://doi.org/10.3390/en81011380.

[77] C. Yu, X. Xue, K. Shi, R. Wang, L. Zhang, M. Shao, Optimization of wavy fin-and-elliptical tube heat exchanger using CFD, multi-objective genetic algorithm and radical basis function, Energy Sci. Eng. 9 (2021) 1359–1372, https://doi.org/10.1002/ese3.897.

[78] M.T.M. Emmerich, A.H. Deutz, A tutorial on multiobjective optimization: fundamentals and evolutionary methods, Nat. Comput. 17 (2018) 585–609, https://doi.org/10.1007/s11047-018-9685-y.

[79] E. Bonamente, C. Brunelli, F. Castellani, A. Garinei, L. Biondi, M. Marconi, E. Piccioni, A life-cycle approach for multi-objective optimisation in building design: methodology and application to a case study, Civil Engineering and Environmental, Systems 35 (2018) 158–179, https://doi.org/10.1080/10286608.2019.1576646.

[80] A. Vukadinović, J. Radosavljević, A. Đorđević, M. Protić, N. Petrović, Multi-objective optimization of energy performance for a detached residential building with a sunspace using the NSGA-II genetic algorithm, Sol. Energy 224 (2021) 1426–1444, https://doi.org/10.1016/j.solener.2021.06.082.

[81] L. Magnier, F. Haghighat, Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network, Build. Environ. 45 (2010) 739–746, https://doi.org/10.1016/j.buildenv.2009.08.016.

[82] C. Liu, L. Wu, W. Xiao, G. Li, D. Xu, J. Guo, W. Li, An improved heuristic mechanism ant colony optimization algorithm for solving path planning, Knowl Based Syst 271 (2023), https://doi.org/10.1016/j.knosys.2023.110540.

[83] I. Kucukkoc, Z. Li, A.D. Karaoglan, D.Z. Zhang, Balancing of mixed-model two-sided assembly lines with underground workstations: a mathematical model and ant colony optimization algorithm, Int. J. Prod. Econ. 205 (2018) 228–243, https://doi.org/10.1016/j.ijpe.2018.08.009.

[84] F.A. Khan, K. Ullah, A. ur Rahman, S. Anwar, Energy optimization in smart urban buildings using bio-inspired ant colony optimization, Soft Comput. 27 (2023) 973–989, https://doi.org/10.1007/s00500-022-07537-3.

[85] A.G. Gad, Particle swarm optimization algorithm and its applications: a systematic review, Arch. Comput. Methods Eng. 29 (2022) 2531–2561, https://doi.org/10.1007/s11831-021-09694-4.

[86] S. Lu, R. Wang, S. Zheng, Passive optimization design based on particle swarm optimization in rural buildings of the hot summer and warm winter zone of China, Sustainability 9 (2017), https://doi.org/10.3390/su9122288.

[87] E. Henrichs, V. Lesch, M. Straesser, S. Kounev, C. Krupitzer, A literature review on optimization techniques for adaptation planning in adaptive systems: state of the art and research directions, Inf Softw Technol 149 (2022), https://doi.org/10.1016/j.infsof.2022.106940.

[88] Y. Zhu, G.H. Huang, Y.P. Li, L. He, X.X. Zhang, An interval full-infinite mixed-integer programming method for planning municipal energy systems - a case study of Beijing, Appl. Energy 88 (2011) 2846–2862, https://doi.org/10.1016/j.apenergy.2011.01.058.

[89] L. Shen, Y. Han, Optimizing the modular adaptive façade control strategy in open office space using integer programming and surrogate modelling, Energy Build. 254 (2022), https://doi.org/10.1016/j.enbuild.2021.111546.

[90] V. Kumtepeli, Y. Zhao, M. Naumann, A. Tripathi, Y. Wang, A. Jossen, H. Hesse, Design and analysis of an aging-aware energy management system for islanded grids using mixed-integer quadratic programming, Int. J. Energy Res. 43 (2019) 4127–4147, https://doi.org/10.1002/er.4512.

[91] M. Killian, M. Zauner, M. Kozek, Comprehensive smart home energy management system using mixed-integer quadratic-programming, Appl. Energy 222 (2018) 662–672, https://doi.org/10.1016/j.apenergy.2018.03.179.

[92] A.W.A. Hammad, K. Figueiredo, A.C. Rosa, E. Vazquez, A. Haddad, Enhancing the passive design of buildings: a mixed integer non-linear programming approach for the selection of building materials and construction building systems, Energy Rep. 7 (2021) 8162–8175, https://doi.org/10.1016/j.egyr.2021.04.063.

[93] P.A. Fokaides, A. Panayidou, C. Hadjichristos, M.C. Phocas, Application of non-linear programming to optimize buildings' solar exposure, J. Build. Eng. 11 (2017) 127–133, https://doi.org/10.1016/j.jobe.2017.04.007.

[94] O. F.Y, A. J.E.T, A. O, H.J. O, O. O, A. J, Supervised machine learning algorithms: classification and comparison, Int. J. Comput. Trends Technol. 48 (2017) 128–138, https://doi.org/10.14445/22312803/IJCTT-V48P126.

[95] H.W. lan, F. Eibe, M. A. Hall, Data Mining Practical Machine Learning Tools and Techniques, n.d.
[96] H. Hosamo, M.H. Hosamo, H.K. Nielsen, P.R. Svennevig, K. Svidt, Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA, Adv. Build. Energy Res. 17 (2023) 125–171, https://doi.org/10.1080/17512549.2022.2136240.
[97] M. Baghoolizadeh, M. Rostamzadeh-Renani, S.A.H.H. Dehkordi, R. Rostamzadeh-Renani, D. Toghraie, A prediction model for CO2 concentration and multi-objective optimization of CO2 concentration and annual electricity consumption cost in residential buildings using ANN and GA, J. Clean. Prod. 379 (2022), https://doi.org/10.1016/j.jclepro.2022.134753.
[98] G. Salvalai, Y. Zhu, M.M. Sesana, From building energy modeling to urban building energy modeling: a review of recent research trend and simulation tools, Energy Build. 319 (2024), https://doi.org/10.1016/j.enbuild.2024.114500.
[99] H. Liu, Z. Du, T. Xue, T. Jiang, An integrated artificial intelligence-driven approach to multi-criteria optimization of building energy efficiency and occupants' comfort: a case study, J. Build. Eng. (2025) 111944, https://doi.org/10.1016/j.jobe.2025.111944.
[100] T. Xuan Nghiem, T.X. Nghiem, MLE+: a Matlab-EnergyPlus Co-simulation Interface, (n.d.). https://doi.org/10.13140/RG.2.1.1127.0880.
[101] EnergyPlus. https://energyplus.net/, 2024. (Accessed 7 January 2024).
[102] N. Fumo, P. Mago, R. Luck, Methodology to estimate building energy consumption using EnergyPlus Benchmark Models, Energy Build. 42 (2010) 2331–2337, https://doi.org/10.1016/j.enbuild.2010.07.027.
[103] D. Mazzeo, N. Matera, C. Cornaro, G. Oliveti, P. Romagnoni, L. De Santoli, EnergyPlus, IDA ICE and TRNSYS predictive simulation accuracy for building thermal behaviour evaluation by using an experimental campaign in solar test boxes with and without a PCM module, Energy Build. 212 (2020), https://doi.org/10.1016/j.enbuild.2020.109812.
[104] M. Wetter, K. Benne, H. Tummescheit, C. Winther, Spawn: coupling Modelica Buildings Library and EnergyPlus to enable new energy system and control applications, J Build Perform Simul 17 (2024) 274–292, https://doi.org/10.1080/19401493.2023.2266414.
[105] R. Zhang, K.P. Lam, S. chune Yao, Y. Zhang, Coupled EnergyPlus and computational fluid dynamics simulation for natural ventilation, Build. Environ. 68 (2013) 100–113, https://doi.org/10.1016/j.buildenv.2013.04.002.
[106] Y. Chen, L. Gu, J. Zhang, EnergyPlus and CHAMPS-Multizone co-simulation for energy and indoor air quality analysis, Build Simul 8 (2015) 371–380, https://doi.org/10.1007/s12273-015-0211-1.
[107] Trnsys. https://www.trnsys.com/index.html, 2024. (Accessed 7 January 2024).
[108] M. Webb, L. Aye, R. Green, Simulation of a biomimetic façade using TRNSYS, Appl. Energy 213 (2018) 670–694, https://doi.org/10.1016/j.apenergy.2017.08.115.
[109] E. Asadi, M.G. da Silva, C.H. Antunes, L. Dias, A multi-objective optimization model for building retrofit strategies using TRNSYS simulations, GenOpt and MATLAB, Build. Environ. 56 (2012) 370–378, https://doi.org/10.1016/j.buildenv.2012.04.005.
[110] S. Lu, X. Tang, L. Ji, D. Tu, Research on energy-saving optimization for the performance parameters of rural-building shape and envelope by trnsys-genopt in hot summer and cold winter zone of China, Sustainability 9 (2017), https://doi.org/10.3390/su9020294.
[111] Y. Zhang, I. Korolija, Performing Complex Parametric Simulations with jEPlus, 2010.
[112] A.J. Mettrick, Z. Ma, Integrating phase change materials in buildings for heating and cooling demand reduction – a global study, Case Stud. Therm. Eng. 63 (2024), https://doi.org/10.1016/j.csite.2024.105337.
[113] N. Amani, Sustainable construction of green school building using energy simulation analysis and modeling, Hybrid Advances 6 (2024) 100236, https://doi.org/10.1016/j.hybadv.2024.100236.
[114] F. Del Ama Gonzalo, B. Moreno Santamaría, M.J. Montero Burgos, Assessment of building energy simulation tools to predict heating and cooling energy consumption at early design stages, Sustainability 15 (2023), https://doi.org/10.3390/su15031920.
[115] L. Zhang, Simulation analysis of built environment based on design builder software, in: Applied Mechanics and Materials, Trans Tech Publications Ltd, 2014, pp. 3134–3137, https://doi.org/10.4028/www.scientific.net/AMM.580-583.3134.
[116] E. Weaver, N. Long, K. Fleming, M. Schott, K. Benne, E. Hale, Rapid application development with OpenStudio: preprint. http://www.osti.gov/bridge, 2012.
[117] N. Yu, Y. Jiang, L. Luo, S. Lee, A. Jallow, D. Wu, J.I. Messner, R.M. Leicht, J. Yen, Integrating BIMserver and OpenStudio for energy efficient building. https://doi.org/10.1061/9780784413029.065, 2013.
[118] J. Hu, Z. Wang, W. Chen, A study on automatic form optimization procedures of building performance design based on "ladybug+Honeybee,", in: IOP Conf Ser Earth Environ Sci, Institute of Physics Publishing, 2020 https://doi.org/10.1088/1755-1315/531/1/012020.
[119] Ladybug tools. https://www.ladybug.tools/honeybee.html, 2024. (Accessed 10 January 2024).
[120] P. de Wilde, Building performance simulation in the brave new world of artificial intelligence and digital twins: a systematic review, Energy Build. 292 (2023), https://doi.org/10.1016/j.enbuild.2023.113171.
[121] C. Lu, S. Li, Z. Lu, Building energy prediction using artificial neural networks: a literature survey, Energy Build. 262 (2022), https://doi.org/10.1016/j.enbuild.2021.111718.
[122] B. Mahesh, Machine learning algorithms-A review, Int. J. Sci. Res. (2018), https://doi.org/10.21275/ART20203995.
[123] H. Liu, X. Liao, B. Du, The applications of nature-inspired meta-heuristic algorithms for decreasing the energy consumption of software-defined networks: a comprehensive and systematic literature review, Sustainable Computing: Informatics and Systems 39 (2023), https://doi.org/10.1016/j.suscom.2023.100895.
[124] H. Khajavi, A. Rastgoo, Improving the prediction of heating energy consumed at residential buildings using a combination of support vector regression and meta-heuristic algorithms, Energy 272 (2023), https://doi.org/10.1016/j.energy.2023.127069.
[125] H. Dasi, Z. Ying, B. Yang, Predicting the consumed heating energy at residential buildings using a combination of categorical boosting (CatBoost) and Meta heuristics algorithms, J. Build. Eng. 71 (2023), https://doi.org/10.1016/j.jobe.2023.106584.
[126] B. Chegari, M. Tabaa, E. Simeu, F. Moutaouakkil, H. Medromi, Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms, Energy Build. 239 (2021), https://doi.org/10.1016/j.enbuild.2021.110839.
[127] H. Yi, M.J. Kim, Y. Kim, S.S. Kim, K.I. Lee, Rapid simulation of optimally responsive façade during schematic design phases: use of a new hybrid metaheuristic algorithm, Sustainability 11 (2019), https://doi.org/10.3390/su11092681.
[128] B. Zeng, L. Gao, X. Li, Whale swarm algorithm for function optimization, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 2017, pp. 624–639, https://doi.org/10.1007/978-3-319-63309-1_55.
[129] M. Jahannoush, S. Arabi Nowdeh, Optimal designing and management of a stand-alone hybrid energy system using meta-heuristic improved sine–cosine algorithm for Recreational Center, case study for Iran country, Applied Soft Computing Journal 96 (2020), https://doi.org/10.1016/j.asoc.2020.106611.
[130] C. Deb, A. Schlueter, Review of data-driven energy modelling techniques for building retrofit, Renew. Sustain. Energy Rev. 144 (2021), https://doi.org/10.1016/j.rser.2021.110990.
[131] A. Chakrabarty, E. Maddalena, H. Qiao, C. Laughman, Scalable Bayesian optimization for model calibration: case study on coupled building and HVAC dynamics, Energy Build. 253 (2021), https://doi.org/10.1016/j.enbuild.2021.111460.
[132] B. Ekici, O.F.S.F. Turkcan, M. Turrin, I.S. Sariyildiz, M.F. Tasgetiren, Optimising high-rise buildings for self-sufficiency in energy consumption and food production using artificial intelligence: case of europoint complex in rotterdam, Energies 15 (2022), https://doi.org/10.3390/en15020660.
[133] A.E.I. Brownlee, J.A. Wright, Constrained, mixed-integer and multi-objective optimisation of building designs by NSGA-II with fitness approximation, Applied Soft Computing Journal 33 (2015) 114–126, https://doi.org/10.1016/j.asoc.2015.04.010.
[134] Q. Tang, J. Dang, Y. Cui, X. Wang, J. Jia, Machine learning-based fast seismic risk assessment of building structures, J. Earthq. Eng. 26 (2022) 8041–8062, https://doi.org/10.1080/13632469.2021.1987354.
[135] S. Gupta, H. Abderazek, B.S. Yıldız, A.R. Yildiz, S. Mirjalili, S.M. Sait, Comparison of metaheuristic optimization algorithms for solving constrained mechanical design optimization problems, Expert Syst. Appl. 183 (2021), https://doi.org/10.1016/j.eswa.2021.115351.
[136] D. Chakraborty, H. Elzarka, Advanced machine learning techniques for building performance simulation: a comparative analysis, J Build Perform Simul 12 (2019) 193–207, https://doi.org/10.1080/19401493.2018.1498538.

[137] V. Nasteski, An overview of the supervised machine learning methods, HORIZONS.B 4 (2017) 51–62, https://doi.org/10.20544/horizons.b.04.1.17.p05.
[138] Y. Boutahri, A. Tilioua, Machine learning-based predictive model for thermal comfort and energy optimization in smart buildings, Results in Engineering 22 (2024), https://doi.org/10.1016/j.rineng.2024.102148.
[139] M. Zorn, N. Catunda, L. Claus, N. Kobylinska, M. Frey, T. Wortmann, Replacing energy simulations with surrogate models for design space exploration, Bauphysik 44 (2022) 311–316, https://doi.org/10.1002/bapi.202200034.
[140] P. De Wilde, C. Martinez-Ortiz, D. Pearson, I. Beynon, M. Beck, N. Barlow, Building simulation approaches for the training of automated data analysis tools in building energy management, Adv. Eng. Inform. 27 (2013) 457–465, https://doi.org/10.1016/j.aei.2013.05.001.
[141] S. Attia, R. Lioure, Q. Declaude, Future trends and main concepts of adaptive facade systems, Energy Sci. Eng. 8 (2020) 3255–3272, https://doi.org/10.1002/ese3.725.
[142] X. Zhang, H. Zhang, Y. Wang, X. Shi, Adaptive façades: review of designs, performance evaluation, and control systems, Buildings 12 (2022), https://doi.org/10.3390/buildings12122112.
[143] M. Koyaz, A. Prieto, A. Ünlü, U. Knaack, Towards a human centred approach for adaptive façades an overview of user experiences in work environments, J. Facade Des. Eng. 10 (2022) 29–54, https://doi.org/10.47982/jfde.2022.1.02.
[144] A. Tabadkani, A. Roetzel, H.X. Li, A. Tsangrassoulis, A review of occupant-centric control strategies for adaptive facades, Autom Constr 122 (2021), https://doi.org/10.1016/j.autcon.2020.103464.
[145] M.P. Voigt, K. Chwalek, D. Roth, M. Kreimeyer, L. Blandini, The integrated design process of adaptive façades – a comprehensive perspective, J. Build. Eng. 67 (2023), https://doi.org/10.1016/j.jobe.2023.106043.
[146] R. El-Dabaa, S. Abdelmohsen, Hygroscopy and adaptive architectural façades: an overview, Wood Sci. Technol. 57 (2023) 557–582, https://doi.org/10.1007/s00226-023-01464-8.
[147] D. Khraisat, D. Qashmar, O. Alomari, Exploring the impact of kinetic façade environmental control systems in the development of sustainable design: a systematic literature review, Civil Engineering and Architecture 11 (2023) 268–278, https://doi.org/10.13189/cea.2023.110122.
[148] X. Liu, C. Shen, J. Wang, C. Zhang, Y. Shuai, Static and dynamic regulations of photovoltaic double skin facades towards building sustainability: a review, Renew. Sustain. Energy Rev. 183 (2023), https://doi.org/10.1016/j.rser.2023.113458.
[149] S. Habibi, O.P. Valladares, D.M. Peña, Sustainability performance by ten representative intelligent Façade technologies: a systematic review, Sustain. Energy Technol. Assessments 52 (2022), https://doi.org/10.1016/j.seta.2022.102001.
[150] S.M. Hosseini, M. Mohammadi, A. Rosemann, T. Schröder, J. Lichtenberg, A morphological approach for kinetic façade design process to improve visual and thermal comfort: review, Build. Environ. 153 (2019) 186–204, https://doi.org/10.1016/j.buildenv.2019.02.040.
[151] R.C.G.M. Loonen, F. Favoino, J.L.M. Hensen, M. Overend, Review of current status, requirements and opportunities for building performance simulation of adaptive facades, J Build Perform Simul 10 (2017) 205–223, https://doi.org/10.1080/19401493.2016.1152303.
[152] A. Shafaghat, A. Keyvanfar, Dynamic façades design typologies, technologies, measurement techniques, and physical performances across thermal, optical, ventilation, and electricity generation outlooks, Renew. Sustain. Energy Rev. 167 (2022), https://doi.org/10.1016/j.rser.2022.112647.
[153] A.M.A. Faragalla, S. Asadi, Biomimetic design for adaptive building façades: a paradigm shift towards environmentally conscious architecture, Energies 15 (2022), https://doi.org/10.3390/en15155390.
[154] D. Andreeva, D. Nemova, E. Kotov, Multi-Skin adaptive ventilated facade: a review, Energies 15 (2022), https://doi.org/10.3390/en15093447.
[155] N. Heidari Matin, A. Eydgahi, Factors affecting the design and development of responsive facades: a historical evolution, Intell. Build. Int. 12 (2020) 257–270, https://doi.org/10.1080/17508975.2018.1562414.
[156] C. Bedon, D. Honfi, K.V. Machalická, M. Eliášová, M. Vokáč, M. Kozłowski, T. Wüest, F. Santos, N.W. Portal, Structural characterisation of adaptive facades in Europe – Part I: insight on classification rules, performance metrics and design methods, J. Build. Eng. 25 (2019), https://doi.org/10.1016/j.jobe.2019.02.013.
[157] W. Mengist, T. Soromessa, G. Legese, Method for conducting systematic literature review and meta-analysis for environmental science research, Sci. Total Environ. 702 (2020), https://doi.org/10.1016/j.scitotenv.2019.134581.
[158] M. Pacheco, P. Moura, C. Silva, A systematic review of syngas bioconversion to value-added products from 2012 to 2022, Energies 16 (2023), https://doi.org/10.3390/en16073241.
[159] M. Michael, F. Favoino, Q. Jin, A. Luna-Navarro, M. Overend, A systematic review and classification of glazing technologies for building façades, Energies 16 (2023), https://doi.org/10.3390/en16145357.
[160] X. Wang, G. Wang, T. Chen, Z. Zeng, C.K. Heng, Low-carbon city and its future research trends: a bibliometric analysis and systematic review, Sustain. Cities Soc. 90 (2023), https://doi.org/10.1016/j.scs.2022.104381.
[161] N. De Bellis, Bibliometrics and Citation Analysis : from the Science Citation Index to Cybermetrics, Scarecrow Press, 2009.
[162] N. Varshabi, S.A. Selçuk, G.M. Avinç, Biomimicry for energy-efficient building design: a bibliometric analysis, Biomimetics 7 (2022), https://doi.org/10.3390/biomimetics7010021.
[163] B. Marco-Lajara, J. Martínez-Falcó, E. Sánchez-García, L.A. Millan-Tudela, Analyzing the role of renewable energy in meeting the sustainable development goals: a bibliometric analysis, Energies 16 (2023), https://doi.org/10.3390/en16073137.
[164] N.J. van Eck, L. Waltman, Software survey: VOSviewer, a computer program for bibliometric mapping, Scientometrics 84 (2010) 523–538, https://doi.org/10.1007/s11192-009-0146-3.
[165] S. Wen, X. Hu, G. Hua, P. Xue, D. Lai, A genetic-algorithm-based framework for assessing the performance of shading strategies, in: Building Simulation Conference Proceedings, International Building Performance Simulation Association, 2023, pp. 138–145, https://doi.org/10.26868/25222708.2023.1141.
[166] J. Liu, G. Bi, G. Gao, L. Zhao, Optimal design method for photovoltaic shading devices (PVSDs) by combining geometric optimization and adaptive control model, J. Build. Eng. 69 (2023), https://doi.org/10.1016/j.jobe.2023.106101.
[167] A. Tabadkani, A. Nikkhah Dehnavi, F. Mostafavi, H.G. Naeini, Targeting modular adaptive façade personalization in a shared office space using fuzzy logic and genetic optimization, J. Build. Eng. 69 (2023), https://doi.org/10.1016/j.jobe.2023.106118.
[168] E. Catto Lucchino, F. Goia, Multi-domain model-based control of an adaptive façade based on a flexible double skin system, Energy Build. 285 (2023), https://doi.org/10.1016/j.enbuild.2023.112881.
[169] N. Biloria, M. Makki, N. Abdollahzadeh, Multi-performative façade systems: the case of real-time adaptive BIPV shading systems to enhance energy generation potential and visual comfort, Front Built Environ 9 (2023), https://doi.org/10.3389/fbuil.2023.1119696.
[170] S. Wen, X. Hu, G. Hua, P. Xue, D. Lai, Comparing the performance of four shading strategies based on a multi-objective genetic algorithm: a case study in a university library, J. Build. Eng. 63 (2023), https://doi.org/10.1016/j.jobe.2022.105532.
[171] Y. Xue, W. Liu, A study on the optimization of atrium daylight and energy performance through skylight and shading design in commercial buildings in cold zones, Buildings 13 (2023), https://doi.org/10.3390/buildings13010228.
[172] J. Gaspari, K. Fabbri, Exploring the effects of climate-adaptive building shells: an applicative time-saving algorithm on a case study in bologna, Italy, Energies 15 (2022), https://doi.org/10.3390/en15218168.
[173] L. Shi, S. Pouramini, Adaptive façade for building energy efficiency improvement by arithmetical optimization algorithm, Concurr. Comput. (2022), https://doi.org/10.1002/cpe.7152.
[174] S. Besbas, F. Nocera, N. Zemmouri, M.A. Khadraoui, A. Besbas, Parametric-based multi-objective optimization workflow: daylight and energy performance study of hospital building in Algeria, Sustainability 14 (2022), https://doi.org/10.3390/su141912652.
[175] L. Bande, H. Hamad, D. Alqahtani, N. Alnahdi, A. Ghunaim, F. Fikry, O. Alkhatib, Design of innovative parametric/dynamic façade integrated in the library extension building on UAEU campus, Buildings 12 (2022), https://doi.org/10.3390/buildings12081101.
[176] L.E. Hinkle, J. Wang, N.C. Brown, Quantifying potential dynamic façade energy savings in early design using constrained optimization, Build. Environ. 221 (2022), https://doi.org/10.1016/j.buildenv.2022.109265.
[177] S.O. Sadegh, E. Gasparri, A. Brambilla, A. Globa, Kinetic facades: an evolutionary-based performance evaluation framework, J. Build. Eng. 53 (2022), https://doi.org/10.1016/j.jobe.2022.104408.

[178] N.H. Matin, A. Eydgahi, A. Gharipour, P. Matin, A novel framework for optimizing indoor illuminance and discovering association of involved variables, Buildings 12 (2022), https://doi.org/10.3390/buildings12070878.
[179] Z. Zeng, G. Augenbroe, J. Chen, Realization of bi-level optimization of adaptive building envelope with a finite-difference model featuring short execution time and versatility, Energy 243 (2022), https://doi.org/10.1016/j.energy.2021.122778.
[180] M. Valitabar, A. GhaffarianHoseini, A. GhaffarianHoseini, S. Attia, Advanced control strategy to maximize view and control discomforting glare: a complex adaptive façade, Architect. Eng. Des. Manag. 18 (2022) 829–849, https://doi.org/10.1080/17452007.2022.2032576.
[181] R.A. Mangkuto, M.D. Koerniawan, S.R. Apriliyanthi, I.H. Lubis, Atthaillah, J.L.M. Hensen, B. Paramita, Design optimisation of fixed and adaptive shading devices on four façade orientations of a high-rise office building in the tropics, Buildings 12 (2022), https://doi.org/10.3390/buildings12010025.
[182] N. Heidari Matin, A. Eydgahi, A data-driven optimized daylight pattern for responsive facades design, Intell. Build. Int. 14 (2022) 363–374, https://doi.org/10.1080/17508975.2021.1872478.
[183] S. Sankaewthong, T. Horanont, K. Miyata, J. Karnjana, C. Busayarat, H. Xie, Using a biomimicry approach in the design of a kinetic façade to regulate the amount of daylight entering a working space, Buildings 12 (2022), https://doi.org/10.3390/buildings12122089.
[184] D.M. Le, D.Y. Park, J. Baek, P. Karunyasopon, S. Chang, Multi-criteria decision making for adaptive façade optimal design in varied climates: energy, daylight, occupants' comfort, and outdoor view analysis, Build. Environ. 223 (2022), https://doi.org/10.1016/j.buildenv.2022.109479.
[185] S. Wang, Q. Zhang, P. Liu, R. Liang, Z. Fu, A parameterized design method for building a shading system based on climate adaptability, Atmosphere 13 (2022), https://doi.org/10.3390/atmos13081244.
[186] M. Brzezicki, P. Regucki, J. Kasperski, Optimization of useful daylight illuminance for vertical shading fins covered by photovoltaic panels for a case study of an office room in the city of Wroclaw, Poland, Buildings 11 (2021), https://doi.org/10.3390/buildings11120637.
[187] A. Tabadkani, A. Roetzel, H. Xian Li, A. Tsangrassoulis, S. Attia, Analysis of the impact of automatic shading control scenarios on occupant's comfort and energy load, Appl. Energy 294 (2021), https://doi.org/10.1016/j.apenergy.2021.116904.
[188] L. Le-Thanh, T. Le-Duc, H. Ngo-Minh, Q.H. Nguyen, H. Nguyen-Xuan, Optimal design of an Origami-inspired kinetic façade by balancing composite motion optimization for improving daylight performance and energy efficiency, Energy 219 (2021), https://doi.org/10.1016/j.energy.2020.119557.
[189] M. Ishac, W. Nadim, Standardization of optimization methodology of daylighting and shading strategy: a case study of an architectural design studio–the German University in Cairo, Egypt, J Build Perform Simul 14 (2021) 52–77, https://doi.org/10.1080/19401493.2020.1846618.
[190] R.A. Rizi, A. Eltaweel, A user detective adaptive facade towards improving visual and thermal comfort, J. Build. Eng. 33 (2021), https://doi.org/10.1016/j.jobe.2020.101554.
[191] J. Zhu, A data-driven method to minimize sensor use for dynamic shading control, J Phys Conf Ser (2021), https://doi.org/10.1088/1742-6596/1904/1/012014. IOP Publishing Ltd.
[192] R. Hammoud, K. El Khoury, R.Z. Daou, On the possibility of using simple weather forecast in the adaptation of building envelopes for energy efficiency, in: 2021 IEEE 3rd International Multidisciplinary Conference on Engineering Technology, IMCET 2021, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 179–183, https://doi.org/10.1109/IMCET53404.2021.9665544.
[193] E. Sorooshnia, M. Rashidi, P. Rahnamayiezekavat, F. Rezaei, B. Samali, Optimum external shading system for counterbalancing glare probability and daylight illuminance in Sydney's residential buildings, Eng. Construct. Architect. Manag. 30 (2023) 296–320, https://doi.org/10.1108/ECAM-03-2021-0191.
[194] R.P. Khidmat, H. Fukuda, Kustiani, Parametric study of expanded metal shading toward Daylight Glare Possibility (DGP) optimization, in: IOP Conf Ser Earth Environ Sci, IOP Publishing Ltd, 2021, https://doi.org/10.1088/1755-1315/881/1/012019.
[195] H. Bazazzadeh, B. Świt-Jankowska, N. Fazeli, A. Nadolny, B.S.A. Najar, S.S.H. Safaei, M. Mahdavinejad, Efficient shading device as an important part of daylightophil architecture; a designerly framework of high-performance architecture for an office building in Tehran, Energies 14 (2021), https://doi.org/10.3390/en14248272.
[196] A.A.S. Bahdad, S.F.S. Fadzil, H.O. Onubi, S.A. BenLasod, Sensitivity analysis linked to multi-objective optimization for adjustments of light-shelves design parameters in response to visual comfort and thermal energy performance, J. Build. Eng. 44 (2021), https://doi.org/10.1016/j.jobe.2021.102996.
[197] H. Kim, M.J. Clayton, A multi-objective optimization approach for climate-adaptive building envelope design using parametric behavior maps, Build. Environ. 185 (2020), https://doi.org/10.1016/j.buildenv.2020.107292.
[198] A. Tabadkani, A. Tsangrassoulis, A. Roetzel, H.X. Li, Innovative control approaches to assess energy implications of adaptive facades based on simulation using EnergyPlus, Sol. Energy 206 (2020) 256–268, https://doi.org/10.1016/j.solener.2020.05.087.
[199] Z. Luo, C. Sun, Q. Dong, A daylight-linked shading strategy for automated blinds based on model-based control and Radial Basis Function (RBF) optimization, Build. Environ. 177 (2020), https://doi.org/10.1016/j.buildenv.2020.106854.
[200] X. Shi, T. Abel, L. Wang, Influence of two motion types on solar transmittance and daylight performance of dynamic façades, Sol. Energy 201 (2020) 561–580, https://doi.org/10.1016/j.solener.2020.03.017.
[201] D.K. Bui, T.N. Nguyen, A. Ghazlan, N.T. Ngo, T.D. Ngo, Enhancing building energy efficiency by adaptive façade: a computational optimization approach, Appl. Energy 265 (2020), https://doi.org/10.1016/j.apenergy.2020.114797.
[202] T. Mendis, Z. Huang, S. Xu, W. Zhang, Economic potential analysis of photovoltaic integrated shading strategies on commercial building facades in urban blocks: a case study of Colombo, Sri Lanka, Energy 194 (2020), https://doi.org/10.1016/j.energy.2020.116908.
[203] S.M. Hosseini, M. Mohammadi, T. Schröder, O. Guerra-Santin, Integrating interactive kinetic façade design with colored glass to improve daylight performance based on occupants' position, J. Build. Eng. 31 (2020), https://doi.org/10.1016/j.jobe.2020.101404.
[204] A.G. Kheybari, S. Hoffmann, Exploring the potential of dynamic façade systems: an exterior shading system versus a switchable window, Bauphysik 42 (2020) 277–288, https://doi.org/10.1002/bapi.202000034.
[205] H. Kim, M.J. Clayton, Parametric behavior maps: a method for evaluating the energy performance of climate-adaptive building envelopes, Energy Build. 219 (2020), https://doi.org/10.1016/j.enbuild.2020.110020.
[206] A.A.S. Bahdad, S.F.S. Fadzil, N. Taib, Optimization of daylight performance based on controllable light-shelf parameters using genetic algorithms in the tropical climate of Malaysia, Journal of Daylighting 7 (2020) 122–136, https://doi.org/10.15627/jd.2020.10.
[207] R. Sharston, Advanced daylight admission systems using auxetic structures in Florida, USA, in: UrbSys 2019 - Proceedings of the 1st ACM International Workshop on Urban Building Energy Sensing, Controls, Big Data Analysis, and Visualization, Part of BuildSys 2019, Association for Computing Machinery, Inc, 2019, pp. 6–13, https://doi.org/10.1145/3363459.3363538.
[208] J.M. Han, D. Park, Seasonal optimization of a dynamic thermo-optical ETFE façade system, in: Building Simulation Conference Proceedings, International Building Performance Simulation Association, 2019, pp. 4887–4893, https://doi.org/10.26868/25222708.2019.210642.
[209] A.L. Navarro, J.D.B. Cadena, F. Favoino, M. Donato, T. Poli, M. Perino, M. Overend, Occupant-centred control strategies for adaptive facades: a preliminary study of the impact of shortwave solar radiation on thermal comfort, in: Building Simulation Conference Proceedings, International Building Performance Simulation Association, 2019, pp. 4910–4917, https://doi.org/10.26868/25222708.2019.211013.
[210] H.J. Kim, C.S. Yang, H.J. Moon, A study on multi-objective parametric design tool for surround-type movable shading device, Sustainability 11 (2019), https://doi.org/10.3390/su11247096.
[211] S.Y. Chen, Enhancing validity of green building information modeling with artificial-neural-network-supervised learning —taking construction of adaptive building envelope based on daylight simulation as an example, Sensor. Mater. 31 (2019) 1831–1845, https://doi.org/10.18494/SAM.2019.2147.
[212] A. Tabadkani, S. Banihashemi, M.R. Hosseini, Daylighting and visual comfort of oriental sun responsive skins: a parametric analysis, Build Simul 11 (2018) 663–676, https://doi.org/10.1007/s12273-018-0433-0.
[213] E.S. Mazzucchelli, M. Alston, M. Brzezicki, L. Doniacovo, Study of a BIPV adaptive system: combining timber and photovoltaic technologies, J. Facade Des. Eng. 6 (2018) 149–162, https://doi.org/10.7480/jfde.2018.3.2602.
[214] L. Giovannini, V. Serra, V.R.M. Lo Verso, A. Pellegrino, M. Zinzi, C.R.C. Enea, F. Favoino, A Novel Methodology to Optimize Visual Comfort and Energy Performance for Transparent Adaptive Façades, 2018.

[215] M. Ayoub, Integrating illuminance and energy evaluations of cellular automata controlled dynamic shading system using new hourly-based metrics, Sol. Energy 170 (2018) 336–351, https://doi.org/10.1016/j.solener.2018.05.041.
[216] R. Shan, L. Junghans, "Adaptive radiation" optimization for climate adaptive building facade design strategy, Build Simul 11 (2018) 269–279, https://doi.org/10.1007/s12273-017-0406-8.
[217] F. Favoino, Q. Jin, M. Overend, Design and control optimisation of adaptive insulation systems for office buildings. Part 1: adaptive technologies and simulation framework, Energy 127 (2017) 301–309, https://doi.org/10.1016/j.energy.2017.03.083.
[218] A.P. Biju, C. Sarkar, R. Venkatesha Prasad, Poster: an energy-harvesting facade optimization system for built environments, in: BuildSys 2017 - Proceedings of the 4th ACM International Conference on Systems for Energy-Efficient Built Environments, Association for Computing Machinery, Inc, 2017, https://doi.org/10.1145/3137133.3141442.
[219] M. Werner, R. Pfluger, D. Geisler-Moroder, W. Feist, Analysis of worldwide performance of façade systems, in: Building Simulation Conference Proceedings, International Building Performance Simulation Association, 2017, pp. 864–873, https://doi.org/10.26868/25222708.2017.267.
[220] J. Xiong, A. Tzempelikos, Model-based shading and lighting controls considering visual comfort and energy use, Sol. Energy 134 (2016) 416–428, https://doi.org/10.1016/j.solener.2016.04.026.
[221] A.H.A. Mahmoud, Y. Elghazi, Parametric-based designs for kinetic facades to optimize daylight performance: comparing rotation and translation kinetic motion for hexagonal facade patterns, Sol. Energy 126 (2016) 111–127, https://doi.org/10.1016/j.solener.2015.12.039.
[222] K.S. Lee, K.J. Han, J.W. Lee, Feasibility study on parametric optimization of daylighting in building shading design, Sustainability 8 (2016), https://doi.org/10.3390/su8121220.
[223] R. Velasco, R. Hernández, N. Marrugo, C. Díaz, Notes on the design process of a responsive sun-shading system: a case study of designer and user explorations supported by computational tools, in: Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM, Cambridge University Press, 2015, pp. 483–502, https://doi.org/10.1017/S0890060415000463.
[224] V. Garg, A. Mittal, R. Patni, A. Rathish, A. Bhatia, P. Haves, WinOpt-An Early Stage Design Tool for Optimizing Window Parameters Cool Roof Implications on Thermal Adaptation in Built Environment View project PhD: Modeling of Displacement Ventilation and Chilled Ceiling Systems using Nodal Models View project, n.d. https://www.researchgate.net/publication/301671998.
[225] F. Favoino, Q. Jin, M. Overend, Towards an ideal adaptive glazed façade for office buildings, in: Energy Procedia, Elsevier Ltd, 2014, pp. 289–298, https://doi.org/10.1016/j.egypro.2014.12.390.
[226] C. Kasinalis, R.C.G.M. Loonen, D. Cóstola, J.L.M. Hensen, Framework for assessing the performance potential of seasonally adaptable facades using multi-objective optimization, Energy Build. 79 (2014) 106–113, https://doi.org/10.1016/j.enbuild.2014.04.045.
[227] J. Kim, Adaptive façade design for the daylighting performance in an office building: the investigation of an opening design strategy with cellular automata, Int. J. Low Carbon Technol. 10 (2013) 313–320, https://doi.org/10.1093/ijlct/ctt015.
[228] K. Sharaidin, J. Burry, F. Salim, Integration of Digital Simulation Tools with Parametric Designs to Evaluate Kinetic Façades for Daylight Performance, n.d.
[229] A. Eltaweel, Y. Su, Parametric design and daylighting: a literature review, Renew. Sustain. Energy Rev. 73 (2017) 1086–1103, https://doi.org/10.1016/j.rser.2017.02.011.
[230] M. Thirunavukkarasu, Y. Sawle, H. Lala, A comprehensive review on optimization of hybrid renewable energy systems using various optimization techniques, Renew. Sustain. Energy Rev. 176 (2023), https://doi.org/10.1016/j.rser.2023.113192.
[231] N. Hashempour, R. Taherkhani, M. Mahdikhani, Energy performance optimization of existing buildings: a literature review, Sustain. Cities Soc. 54 (2020), https://doi.org/10.1016/j.scs.2019.101967.
[232] V. Machairas, A. Tsangrassoulis, K. Axarli, Algorithms for optimization of building design: a review, Renew. Sustain. Energy Rev. 31 (2014) 101–112, https://doi.org/10.1016/j.rser.2013.11.036.
[233] Z. He, G.G. Yen, Many-objective evolutionary algorithms based on coordinated selection strategy, IEEE Trans. Evol. Comput. 21 (2017) 220–233, https://doi.org/10.1109/TEVC.2016.2598687.
[234] A. Mohammad, O. Saleh, R.A. Abdeen, Occurrences algorithm for string searching based on brute-force algorithm, J. Comput. Sci. 2 (2006) 82–85, https://doi.org/10.3844/jcssp.2006.82.85.
[235] Z. Xing, Z. Zhang, J. Guo, Y. Qin, L. Jia, Rail train operation energy-saving optimization based on improved brute-force search, Appl. Energy 330 (2023), https://doi.org/10.1016/j.apenergy.2022.120345.
[236] M. Magni, F. Ochs, S. de Vries, A. Maccarini, F. Sigg, Detailed cross comparison of building energy simulation tools results using a reference office building as a case study, Energy Build. 250 (2021), https://doi.org/10.1016/j.enbuild.2021.111260.
[237] RADSITE. https://www.radiance-online.org/archived/radsite/radiance/desktop.html, 2024. (Accessed 10 January 2024).
[238] ClimateStudio. https://www.solemma.com/climatestudio, 2024. (Accessed 10 January 2024).
[239] J. Sousa, Energy Simulation Software for Buildings: Review and Comparison, n.d.