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## A review

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**DOI**
10.1016/j.buildenv.2018.10.023

**Publication date**
2019

**Document Version**
Final published version

**Published in**
Building and Environment

Building and Environment 147 (2019) 356–371

Contents lists available at ScienceDirect

Building and Environment

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

# Performative computational architecture using swarm and evolutionary optimisation: A review

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ARTICLE INFO

*Keywords:*
Performance-based design
Building design
Architectural design
Computational optimisation
Swarm intelligence
Evolutionary algorithm

ABSTRACT

This study presents a systematic review and summary of performative computational architecture using swarm and evolutionary optimisation. The taxonomy for one hundred types of studies is presented herein that includes different sub-categories of performative computational architecture, such as sustainability, cost, functionality, and structure. Specifically, energy, daylight, solar radiation, environmental impact, thermal comfort, life-cycle cost, initial and global costs, energy use cost, space allocation, logistics, structural assessment, and holistic design approaches, are investigated by considering their corresponding performance aspects. The main findings, including optimisation and all the types of parameters, are presented by focussing on different aspects of buildings. In addition, usage of form-finding parameters of all reviewed studies and the distributions for each performance objectives are also presented. Moreover, usage of swarm and evolutionary optimisation algorithms in reviewed studies is summarised. Trends in publications, published years, problem scales, and building functions, are examined. Finally, future prospects are highlighted by focussing on different aspects of performative computational architecture in accordance to the evidence collected based on the review process.

## 1. Introduction

Architectural design is a complex task. One of the most important reasons for its complexity is that multiple objectives affect the overall performance of the designed object [1]. In many cases, these objectives conflict with each other. In addition, each design is a unique task based on the problem, objectives, building program, constraints, client expectations, and the surrounding impacts owing to the built environment. For this reason, there are many "design-related parameters" to cope with the design process. Moreover, architectural design is a critical mission. Architects are responsible for creating living environments not only for human beings but also for all living creatures. Therefore, in the design process, the decisions require increased awareness for the anticipated consequences.

Conversely, design is an iterative process [2]. During this phase, the architect employs many design methods, such as sketching and physical as well as digital modelling, in order to feature the invention and revision cycles simultaneously. During this process, many criteria are considered, which correspond to the many requirements the final design is expected to satisfy. Such criteria regard several fields, from structural safety to climatic comfort, from energy efficiency to real estate values, etc. The ultimate goal is the identification of a design solution that satisfies at best many different (and sometime conflicting) objectives. Most of these objectives are highly affected by the decisions taken during the early design phase.

Performance-based design (PBD) has become a vital approach to satisfy many objectives. Kolarevic [3] underlined the importance of PBD as a guiding design principle. Among several possible approaches, this study focuses on a specific framework, which was presented by Sariyildiz [4] in order to support the design process. The presented framework is called performative computational architecture (PCA). This framework consists of three main phases as illustrated in Fig. 1. These are form generation, performance evaluation, and optimisation. Therefore, the main purpose of PCA is to investigate the most desirable geometry that satisfies performance-related goals in the conceptual design stage. In this study, journal articles associated with PCA are reviewed. Section 1.1 highlights the focus based on the relevant search of journal articles in the literature. Section 1.2 presents review articles

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https://doi.org/10.1016/j.buildenv.2018.10.023
Received 23 May 2018; Received in revised form 11 October 2018; Accepted 11 October 2018
Available online 15 October 2018
0360-1323/ 

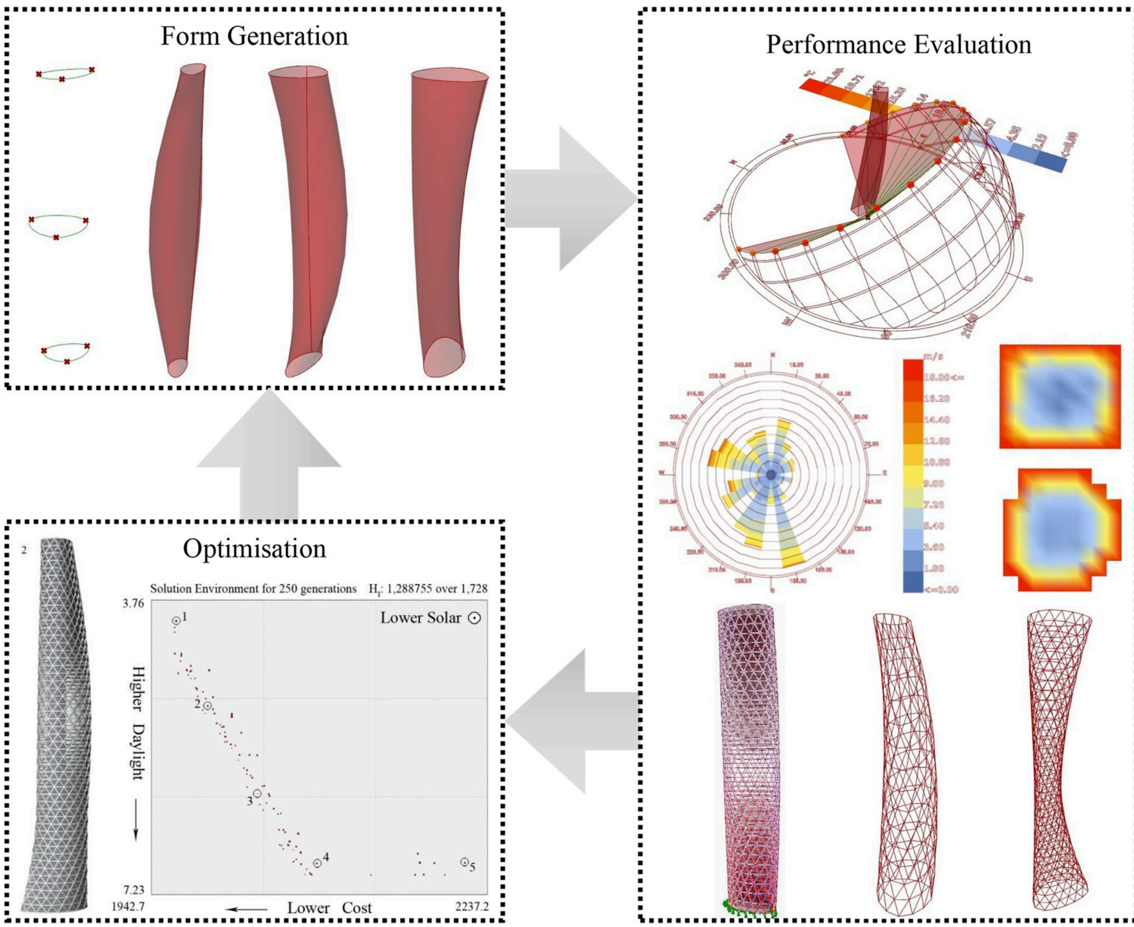


**Fig. 1.** PCA framework [4].

that have similar focus, and underlines the differences with this study.

### 1.1. Focus of this review

This review focuses on studies that match the PCA framework. Dealing with different geometric configurations as design alternatives (obtained from computational processes for form generation) is crucial to this focus. Optimising the designs by means of geometric variations in the early design stages is essential in architectural design. This clearly differentiates the use of optimisation in architectural design from the use of optimisation in engineering. In this sense, the architectural shape is mostly used as a set of specific boundaries within which a search for good engineering solutions is conducted. The shape is not typically modified as is done during the architectural explorations in PCA. As such, this review considers only the studies in which architectural geometric variations are (also) included (and it is not concerned with purely engineering optimisation).

Moreover, this review is concerned only with specific optimisation methods. It focuses on swarm and evolutionary computation (SEC). There are two reasons for this choice. First of all, direct search methods require expensive computational time to handle many parameters in the optimisation problem [5,6]. Secondly, metaheuristics can suggest near-optimal solutions with many design parameters within a reasonable time [7]. Swarm intelligence (SI) and evolutionary computation (EC) are two powerful optimisation methods in metaheuristics. SI uses intelligent multi-agent systems inspired by the behaviour of social swarms [8]. Conversely, EC uses procedures inspired by the biological evolution of the Darwinian theory [9].

Numerous publications were analysed within a broad spectrum of thematic areas by considering the PCA framework and SEC. To identify relevant studies, keywords such as "building design", "architectural design", "evolutionary algorithm", "evolutionary computation", "swarm intelligence", and "swarm optimisation" were used. During this search, Science Direct, Scopus, and Thomson Reuters, were employed as databases. To investigate the field in-depth, there was no time limitation. The final cut-off date for published studies was 26 August 2018. This broad search led to the collection of a relevant number of publications. From this collection, a subset of journal articles was selected according to the defined criteria. These studies:

- Include all three phases of PCA (form generation, performance evaluation, and optimisation)
- Explicitly deal with architectural form-finding (on real and/or hypothetical architectural designs)
- Include optimisation processes based on swarm and/or evolutionary computation
- Must be published as journal (not conference) articles (because most conference studies lack fundamental information)
- Could consider any performance criteria (there was no selection based on specific performance criteria)

An initial analysis of the selected sub-set, led to the identification of additional criteria that were followed to review the selected papers, as follows:

- Most building design problems could be analysed by categorising them in accordance to the layout, skin, and overall building shape
- Most holistic approaches obviously integrate several design decision steps that have to be analysed by taking this integration into account

### 1.2. Focus of previous review articles

Several reviews have been published by other authors during the past few decades. Some of them share a similar approach with this review, but in their searches/evaluations they have not included the recent decades and/or have focussed only on some of the three phases of PCA. Some of them focussed on the categorisation and performance of optimisation algorithms. Most of them focus only on specific building performance criteria. All of them include relevant information and different perspectives. In an early study in 1980, Radford and Gero [10] discussed simulation, generation, and optimisation methods for supporting architectural design decisions. Touloupaki and Theodosiou [11] presented a recent review on the combined use of parametric modelling, performance simulations, and optimisation algorithms. Based on several examples, their review provides valuable highlights on the potentials and limitations of the current state-of-art. However, it does not include a systematic analysis of trends, nor of used design variables and objectives. Negendahl [12] focussed on building performance simulations. In turn, Machairas, Tsangrassoulis, and Axarli [6], reviewed optimisation algorithms for building design by considering tools, objectives, and performance assessments. In another study, Nguyen, Reiter, and Rigo [13], overviewed simulation-based optimisation methods for building performance analyses based on the discussion of the major challenges. Concerning the building envelope, Huang and Niu [5] reviewed numerous studies to compare popular optimisation algorithms. When the focus is on specific performance domains, subjects such as the efficient spatial planning, energy efficiency, daylight, etc. may constitute relevant examples. Concerning the layout configuration, Dutta and Sarthak [14] compared applications of EC for architectural space planning. For sustainable building design, Evins [15] reviewed the application of computational optimisation by considering different research branches. In another study, Attia, Hamdy, O'Brien, and Carlucci [16], investigated potential challenges and opportunities for the integration of optimisation tools in net-zero energy buildings (NZEBs). Shi, Fonseca, and Schlueter [17], reviewed simulation-based design generation and optimisation in order to discuss their applications on energy-driven urban design at the district scale. Cui, Geng, Zhu, and Han [18], reviewed multi-objective optimisation applications for environmental protection fields (such as optimisation for energy saving and for emission, and cost reductions). Based on users surveys and literature reviews, Tian, Zhang, Jin, Zhou, Si, and Shi [19], focussed on the application of building energy simulations and optimisations for passive building designs. Kheiri [20] highlighted the potentials of different optimisation methods to shape energy-efficient architectural building geometries and envelopes. Shi, Tian, Chen, Si, and Jin [21], focussed on energy performance by analysing several optimisation methods, including the types of algorithms, the design objectives and variables, and the energy simulation engines. Eltaweel and Yuehong [22] focussed on the parametric design for daylight and solar radiation. In contrast to prior reviews, the review presented herein focuses on form generation and on performance evaluation and optimisation by offering a systematic analysis and categorisation of design variables and design objectives, without being confined to specific performance criteria.

## 2. Performative computational architecture and review taxonomy

This section presents the three phases of PCA in depth. As previously mentioned, the first phase is form-finding, which corresponds to the form generation in this iterative process. The second phase is performance evaluation, which focuses on objectives that are desired to be satisfied in form-finding. The final phase is optimisation, which uses search method to identify satisfactory design alternatives in a systematic way. The three phases are iteratively looped. Section 2.1 introduces the form-finding phase of PCA. Section 2.2 explains the role of performance evaluation in this framework. Section 2.3 focuses on SI and EC as part of the optimisation phase of PCA. Finally, Section 2.4 introduces PCA taxonomy.

### 2.1. Form-finding

Early examples of form-finding studies have focussed on structure, especially for shell designs. Antoni Gaudi is accepted as one of the pioneer architects of this field, based on his work on hanging-chain models [23]. Therefore, form finding is defined as a forward process controlled by parameters to discover an optimal geometry of a structure that is in static equilibrium subject to a specific design loading scheme [24]. From the standpoint of structural form-finding, several definitions can be found in addition to those described in Refs. [25,26].

In this study, the notion of form finding is beyond the structural performances alone, and is defined as *the architectural design exploration aiming to satisfy predetermined building performance aspects via computational optimisation in order to provide sufficient information to the decision makers.* This includes performance aspects other than structural performance. For the sake of clarity, the shape of the building affects many performances, such as energy consumption, daylight usage, layout configuration, functional accessibility, shading performance, solar gain, acoustics, and others. In this context, form-finding corresponds to one of the most crucial steps in the conceptual design process. The reason is attributed to the fact that this step comprises the decisions on the determination of the mass and shape of the overall form of the design. Therefore, form-finding outputs are inputs for all subsequent steps in the design process, in the subsequent construction phase, and throughout the building's life-cycle.

### 2.2. Performance evaluation

With the recent developments in digital technology, the predictions and numeric assessments of performance aspects can be integrated into the architectural design process in order to investigate how well the design eventually meets the requirements. This regards all the design phases, and it is especially important in the conceptual stage. Despite the importance of the decisions taken in the early phase, current practice lacks numeric assessments in the conceptual design phase.

Broadbent [27] pointed out that the amount of a priori knowledge available at the beginning of each design process highly depends on the design case, and is quite limited when innovation is involved in the process. Hubka and Eder [28] emphasised that the design has traditionally been conducted using intuition, know-how, and judgment. This highlights the need for measuring and numerically assessing the capacity of the design in satisfying the various requirements and supporting the exploration of design alternatives by means of multidisciplinary measurable performance values as guiding criteria.

Turrin [29] emphasised that geometry has an enormous impact on the realisation of performance-related goals. Owing to the number of parameters, many design alternatives exist in the search space [30]. For this reason, discovering feasible and desirable design solutions is a complicated task during the performance evaluation phase. To support this process, computational optimisation techniques have proven to be relevant. In fact, owing to the size of the solution space, a systematic performance assessment by the designer for each desirable design solution is generally impossible owing to time and other restrictions. Furthermore, a systematic exploration of the solution space that aimed at selecting a subset of solutions is challenging when is simply left to the intuition of the designer.

### 2.3. Swarm and evolutionary computation for optimisation

In the domain of architectural design, metaheuristics constitute one of the most extensively used optimisation methods, and corresponds to the third phase of PCA [6,15,31]. These search algorithms are capable of dealing with continuous and discrete parameters in large parameter

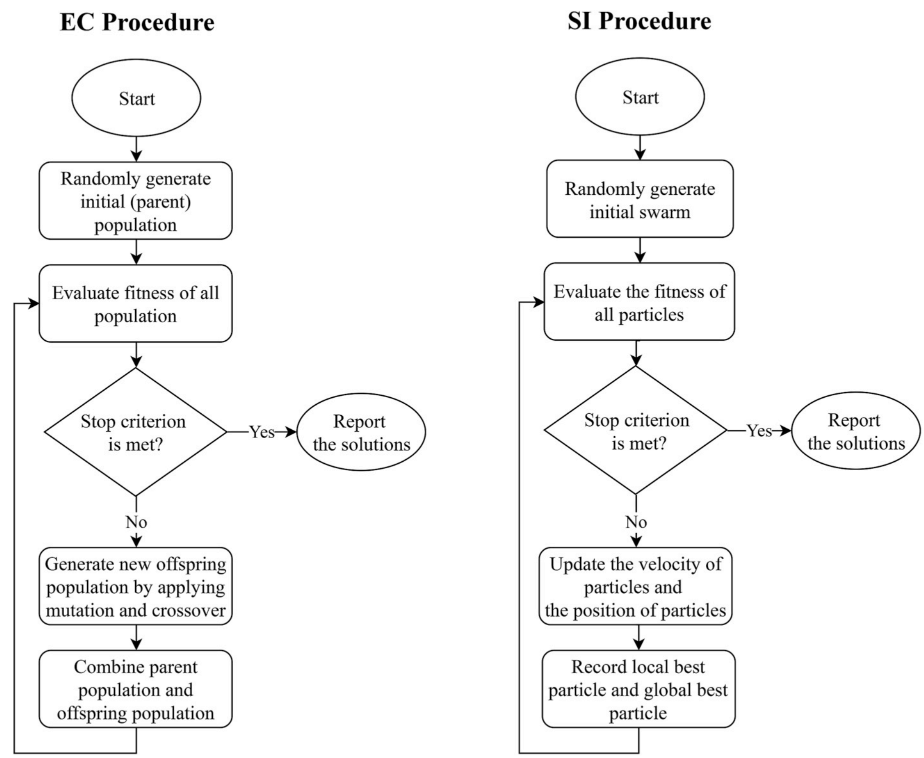


**Fig. 2.** EC and SI procedures.

spaces, and they also avoid local minima and maxima. Moreover, when compared to other direct search methods, metaheuristics are capable in presenting near-optimal results in a reasonable time [7].

SI and EC are based on different search strategies inspired by nature. In the EC procedure, individuals with decision variables in $D$ dimensions are encoded into chromosomes to obtain an initial population. At each generation, pair(s) of individuals from the population are chosen and mated. These individuals are then crossed over to generate new solutions referred to as offspring or children. Some individuals are mutated to escape from local minima and maxima. Ultimately, the offspring population is combined with the parent population to select new individuals for the next generation. The genetic algorithm (GA) proposed by Holland and Goldberg [32], and the differential evolution (DE) presented by Storn and Price [33], can be used in EC.

On the other hand, SI focuses on the interactions of individuals with each other and their environment. For this reason, SI uses societies, such as ants, wasps, termites, bees, schools of fish, flocks of birds, and herds of land animals. An SI algorithm typically consists of many individuals. Simple behavioural rules direct the interactions among the individuals in $D$ dimensions. As a result of the overall behaviour of the swarm system, there are consequences to the self-organising group behaviour. Particle swarm optimisation (PSO) founded by Eberhart and Kennedy [34], ant colony optimisation (ACO) suggested by Dorigo, Birattari, and Stutzle [35], can also be used in SI. As an example, procedures of generic EC and SI are illustrated in Fig. 2.

### 2.4. Review taxonomy

One hundred journal articles relevant to the focus of this review were identified. In order to investigate these papers systematically, a PCA taxonomy was defined as shown in Fig. 3. The main categories of this taxonomy were sustainability, cost, functionality, and structure. In

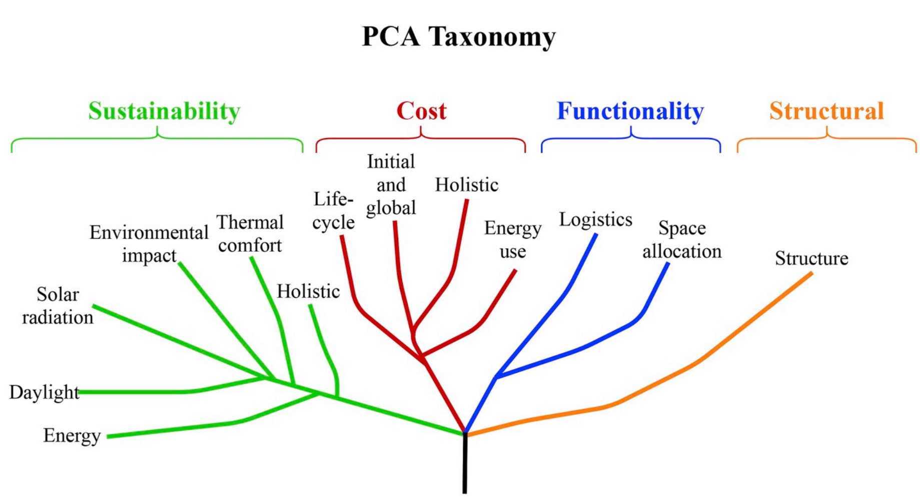


**Fig. 3.** Taxonomy.

addition, several sub-categories were also determined according to performance objectives as shown in Fig. 3. In the following chapters, each sub-category is explained in detail.

## 3. Sustainability

### 3.1. Energy

As an early example that focussed on the skin of the building, Caldas and Norford [36] minimised the annual energy consumption for office buildings using GA-based design tools. Afterwards, Caldas, Norford, and Rocha [37] minimised the annual energy consumption with GA for a school building. Wetter and Wright [38] used the discrete armijo gradient (DAG), GA, coordinate search (CS), Hooke-Jeeves (HJ), Nelder-Mead (NM), PSO with HJ, and other variants of PSO, to minimise the annual energy consumption for an office building. Lee [39] combined GA and computational fluid dynamics (CFD) to minimise energy supplied by HVAC for heating and cooling in office buildings. More recently, Bucking, Zmeureanu, and Athienitis [40], minimised the net annual energy consumption for a net-zero energy house design using modified EA and PSO. Ramallo-González and Coley [41] minimised the heating and cooling demands of residential building a using covariance matrix adaptation (CMA), evolution strategy (ES), sequential assessment (SA), and the canonical form of the GA. As one of the early examples of multi-objective optimisation, Naboni, Malcangi, Zhang, and Barzon [42], used the non-dominated sorting genetic algorithm II (NSGA-II) to minimise heating, cooling, and lighting demands for a residential building. Méndez Echenagucia, Capozzoli, Cascone, and Sassone [43], also used NSGA-II to minimise the energy need for heating, cooling, and lighting in office buildings. Xu, Kim, Hong, and Koo [44] examined the trade-offs between cooling and heating loads using NSGA-II for envelope design of an office building. Wright and Alajmi [45] minimised the building's energy consumption using the GA for the building envelope design of an office building. Delgarm, Sajadi, Kowsary, and Delgarm [46], minimised the annual cooling, heating, and lighting electricity consumptions using single and multi-objective approaches using PSO. In turn, Delgarm, Sajadi, Delgarm, and Kowsary [47], minimised the annual cooling and lighting electricity consumptions considering two different optimisations using single objective GA and NSGA-II. Si, Tian, Jin, Zhou, Tang, and Shi [48] minimised the annual energy consumption using the HJ, multi-objective genetic algorithm II (MOGA-II), and the multi-objective PSO (MOPSO) for an office building envelope. Li, Pan, Xue, Jiang, and Mao [49], used MOPSO and artificial neural networks (ANN) to minimise the energy consumption for residential buildings. Bre and Fachinotti [50] used NSGA-II to examine trade-offs between heating and cooling demands for residential buildings, as well. Bamdad, Cholette, Guan, and Bell [51], minimised the annual energy consumption of commercial buildings using several optimisation algorithms, such as ACO, NM, and hybrid PSO variants. Chen and Yang [52] minimised the heating, cooling, and lighting energy demands of high-rise residential buildings using NSGA-II for formulating the bi-objective and three objective optimisation problems. Recently, Bamdad, Cholette, Guan, and Bell [53], minimised the energy use by considering low, base, and high simulation scenarios for office buildings using ant colony optimisation algorithm for mixed variables (ACOMV), and proposed a modified ACOMV.

By focussing on building shapes, Caldas [54] optimised the energy consumption, energy use intensity, thermal, and daylight performances, and the initial cost of materials using GA and Pareto GA in office and school buildings. Lin and Gerber [55] presented evolutionary energy performance feedback for a design (EEPFD) approach using multi-disciplinary design optimisation (MDDO). Related to this work, Lin and Gerber [56] minimised the energy use and maximised the spatial programming compliance score with the net present value for several building cases using MOGA. Another recent work of Gerber and Lin [57] included additional qualitative data driven by human designers, and discussed the importance of EEPFD in the conceptual phase. Recently, Li, Chen, Lin, and Zhu [58], minimised the total energy consumption by focussing on the heating, cooling, and lighting demands of a school building that employed GA. Moreover, Bizjak, Žalik, Štumberger, and Lukač [59], first minimised the heating and cooling loads, and then maximised the heat gain using single-objective DE for residential building.

Apart from these, several other studies also included the energy aspects, but these studies are discussed in other sections. Futrell, Ozelkan, and Brentrup [60], Negendahl and Nielsen [61], Chen, Janssen, and Schlueter [62], and Chatzikonstantinou and Sariyildiz [63] evaluated and explained the effects of daylight. Yi [64] presented the impacts of solar radiation. Azari, Garshasbi, Amini, Rashed-Ali, and Mohammadi [65], stated the environmental impact. Magnier and Haghighat [66], Kasinalis, Loonen, Cóstola, and Hensen [67], Yu, Li, Jia, Zhang, and Wang [68], Zhang, Bokel, van den Dobbelsteen, Sun, Huang, and Zhang [69], Lin, Zhou, Yang, and Li [70], and Gou, Nik, Scartezzini, Zhao, and Li [71], investigated thermal comfort. Dhariwal and Banerjee [72], and Harkouss, Fardoun, and Biwole [73], analysed the life-cycle cost. Znouda, Ghrab-Morcos, and Hadj-Alouane [74], Talbourdet, Michel, Andrieux, Millet, Mankibi, and Vinot [75], Wright, Brownlee, Mourshed, and Wang [76], Brownlee and Wright [77], Yang, Lin, Lin, and Tsai [78], Rafiq and Rustell [79], and Chang and Shih [80], presented evaluations on the initial and global costs. Michalek, Choudhary, and Papalambros [81], and Baušys and Pankrašovaité [82] studied energy use cost. Finally, Menges [83] and Yang, Ren, Turrin, Sariyildiz, and Sun [84] discussed structure.

### 3.2. Daylight

In an early study that focussed on the skin of the building during daylight, Turrin, von Buelow, and Stouffs [85] maximised the daylight factor and minimised the solar incidence and structural weight of a parametric long-span roof using GA. Rakha and Nassar [86] minimised the daylight uniformity ratio for gallery building using GA. Gagne and Andersen [87] also utilised GA for maximising non-conflicting illuminance goals. Conversely, authors also applied multi-objective micro-GA for maximising illuminance and minimising glare objectives. Futrell, Ozelkan, and Brentrup [60], employed PSO using the construction coefficient and the HJ algorithm, while they maximised the pi scores from hourly illuminance outcomes, and minimised the thermal performance based on the sum of annual hourly energy consumption for envelope design. Negendahl and Nielsen [61] optimised daylight performance, capital cost, building energy use, and thermal requirements for a folding façade design using the strength Pareto evolutionary algorithm 2 (SPEA-2). Futrell, Ozelkan, and Brentrup [88], utilised several algorithms, such as NM, HJ, and variants of PSO to maximise the daylight performance for a classroom. Chen, Yang, and Sun [89], used NSGA-II to minimise the daylight and thermal discomfort times. Recently, Chatzikonstantinou and Sariyildiz [63] minimised the trade-off between the energy consumption and artificial light dependence for an office building using NSGA-II. In order to characterise alternatives with good performance, authors presented an auto-associative machine learning framework.

From the viewpoint of building shape, Chen, Janssen, and Schlueter [62], maximised daylight and minimised the cooling energy consumption using NSGA-II of a parametric building. In addition to these, several studies considered daylight as a performance aspect as well. Caldas [54] presented details on energy considerations. Zhang, Bokel, van den Dobbelsteen, Sun, Huang, and Zhang [69], explained aspects of thermal comfort. Chang and Shih [80] discussed initial and global costs. Su and Yan [90] stated and evaluated logistics. Finally, Yang, Ren, Turrin, Sariyildiz, and Sun [84], considered and analysed the structure.

### 3.3. Solar radiation

Based on the skin of the building, Bizjak, Žalik, and Lukač [91], used a self-adaptive differential evolution (DE) algorithm to maximise solar irradiation. For the sake of the shape of the building, Liu, Liu, and Duan [92], performed PSO to minimise the solar gain and maximise the area of the residential buildings in an urban setting. Oliveira Panão, Gonçalves, and Ferrão [93], also used GA for maximising the absorption of solar radiation in the winter season and minimise it during the summer in urban forms. Kämpf and Robinson [94] maximised the solar energy potential using two different algorithms, namely CMA-ES, and the hybrid differential evolution (HDE), by focussing on three different cases. In comparison, Kämpf, Montavon, Bunyesc, Bolliger, and Robinson [95], minimised irradiation offset by thermal losses, while they maximised building volumes using MOEA. Yi [64] used MOEA for solar radiation and energy consumption in high-rise office buildings. Zhang, Zhang, and Wang [96], used GA to maximise the total radiation as a function of the shape efficiency, and to minimise the shape coefficient for a community centre. More recently, Vermeulen, Merino, Knopf-Lenoir, Villon, and Beckers [97], maximised solar radiation in an urban context using EA for winter, equinox, and summer times.

From the viewpoint of the layout, António, Monteiro, and Afonso [98], also maximised energy received per building in an urban context by considering different building amounts using GA. Yi and Kim [99] minimised the solar radiation of a set of residential blocks using GA. In another study, Vermeulen, Knopf-Lenoir, Villon, and Beckers [100], maximised the solar energy received by each building using an evolutionary algorithm (EA) for high-rise buildings.

In addition to these, several studies were associated with solar radiation but are explained in other sections. Turrin, von Buelow, and Stouffs [85], considered daylight. Menges [83] explained the environmental impact, whereas other cases considered structure.

### 3.4. Environmental impact

Wang, Zmeureanu, and Rivard [101], focussed on the building's skin to minimise life-cycle costs and life-cycle environmental impacts using MOGA. Rapone and Saro [102] minimised carbon emissions for a single office zone using PSO considering different cities. More recently, Azari, Garshasbi, Amini, Rashed-Ali, and Mohammadi [65], utilised NSGA-II for minimising the environmental life-cycle impact and operational energy use for set objectives. Additionally, authors also utilised GA for a single objective environmental life-cycle impact optimisation problem with ANN.

With regard to the shape of the building, Wang, Rivard, and Zmeureanu [103], used MOGA to examine the trade-offs between the life-cycle cost and life-cycle environmental impact for a green building design. Following this, Wang, Rivard, and Zmeureanu [104], addressed a similar problem using MOGA to minimise the life-cycle environmental impact and life-cycle cost. Menges [83] optimised environmental criteria, such as block ventilation, covered outside space, outer solar radiation, unit ventilation, solar radiation per unit, circulation, and unit count. More recently, Huang, Chang, and Shih [105], minimised the building shadow area in an urban setting as an environmental impact form, and maximised the building floor area to reach a satisfactory building mass using GA. McKinstray, Lim, Tanyimboh, Phan, Sha, and Brownlee [106], minimised the carbon impact and embodied carbon of a frame portal building using MOEA.

There are other publications that considered environmental impact objectives, as well. Li, Pan, Xue, Jiang, and Mao [49], referred to in Section 3.5 considered on thermal comfort. Karatas and El-Rayes [107], Liu, Meng, and Tam [108], and Hester, Gregory, Ulm, and Kirchain [109], discussed life-cycle cost, as outlined in Section 4.1.

### 3.5. Thermal comfort

All the reviewed publications in this section focussed on the building's skin. As an early example, Magnier and Haghighat [66] used simulation-based ANN with NSGA-II to minimise the average absolute thermal comfort and annual energy consumption. Kasinalis, Loonen, Cóstola, and Hensen [67], also used NSGA-II to examine the trade-offs between the thermal discomfort and annual primary energy consumption for seasonally adaptable façade designs in office buildings. Yu, Li, Jia, Zhang, and Wang [68], optimised the annual energy consumption and the percentage of thermal discomfort hours with the use of NSGA-II in residential cases. Furthermore, Li, Pan, Xue, Jiang, and Mao [49], used NSGA-II, MOPSO, MOGA, and multi-objective DE (MODE), to optimise the total percentage of cumulative time with discomfort, life-cycle cost and carbon dioxide equivalence for residential cases. Zhang, Bokel, van den Dobbelsteen, Sun, Huang, and Zhang [69], optimised a school model using SPEA-2 in order to minimise the energy use and summer discomfort time, while maximising useful daylight illuminance (UDI). Lin, Zhou, Yang, and Li [70], also maximised thermal comfort and minimised energy consumption using MOGA with multi-linear regression (MLR) and ANN. Sghiouri, Mezrhab, Karkri, and Naji [110], minimised discomfort hours using NSGA-II in residential buildings. Gou, Nik, Scartezzini, Zhao, and Li [71] maximised the annual indoor thermal comfort and minimised building energy demand using NSGA-II and ANN for residential buildings. Chen, Yang, and Sun [89], also considered the thermal comfort performance objective, but their findings are presented in the daylight section.

### 3.6. Holistic sustainability

Finally, holistic approaches are discussed which considered several steps to reach a sustainable design. In an early study on the building's skin, Ercan and Elias-Ozkan [111] focussed on the atrium design. In the first stage, authors minimised solar irradiation of the building using GA. In the second stage, they focussed on the façade shading device to minimise the standard deviation of the daylight factor and annual solar irradiation. Recently, Ferrara, Sirombo, and Fabrizio [112], optimised a single-zone classroom model using PSO and focussed on different cities with various orientations. In the first step, authors minimised the total energy demand. Thereafter, they maximised thermal and visual comfort.

Based on the building shape, Youssef, Zhai, and Reffat [113], optimised the energy consumption of office buildings using GA in two steps. First, authors optimised the shape of the building using shape grammar design rules. Secondly, they optimised the façade design for the integration of photovoltaic panels.

For the sake of the building layout, Sleiman, Hempel, Traversari, and Bruinenberg [114], firstly focussed on the layout configuration aspects using EA. Subsequently, authors considered two major performance objectives, namely, the energy performance and life-cycle cost for a healthcare facility. Similarly, Dino and Üçoluk [115] synthesised the building's space layout performance with energy and daylight aspects. In the first step, authors optimised the unique fitness function by considering several layout aspects using EA. Thereafter, they used NSGA-II for daylight autonomy and total energy.

## 4. Cost

### 4.1. Life-cycle cost

By focussing on the building's skin, Tuhus-Dubrow and Krarti [116] minimised the life-cycle cost using GA, PSO, and sequential search (SS) algorithms for five different climates. Conversely, Bichiou and Krarti [117] minimised life-cycle cost using GA, PSO, and SS. Using a different approach, Gengembre, Ladevie, Fudym, and Thuillier [118], used PSO with Kriging metamodeling for the minimisation of the life-cycle cost.

 

**Table 1**
Overview of form-finding parameters, performance objectives and topic for each reviewed paper.

| | | | Form-finding parameters | | | | | | | | | | | | | | | | | Performance objectives | | | | | | | | | | | | | Topic | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Adjacency matrix | Number of buildings | Building's shape | Ceiling design | Façade design | Floor height | Light shelf | Orientation | Roof's shape | Roof's structure | Shading | Space dimensions | Space location | 2D / 3D grid matrix | Window dimensions | Window location | Window-to-wall ratio | Energy | Daylight | Solar radiation | Environmental impact | Thermal comfort | Holistic sustainability | Life-cycle cost | Initial and global costs | Energy use cost | Holistic cost | Space allocation | Logistics | Structure | Building skin | Building shape | Building layout |
| Ref. | Author(s) | Year | x1 | x2 | x3 | x4 | x5 | x6 | x7 | x8 | x9 | x10 | x11 | x12 | x13 | x14 | x15 | x16 | x17 | y1 | y2 | y3 | y4 | y5 | y6 | y7 | y8 | y9 | y10 | y11 | y12 | y13 | z1 | z2 | z3 |
| [121] | Gero and Kazakov | 1998 | | | | | | | | | | | | | x | | | | | | | | | | | | • | | | | • | | | | □ |
| [128] | Jo and Gero | 1998 | | | | | | | | | | | | | x | | | | | | | | | | | | | | | | • | | | | □ |
| [36] | Caldas and Norford | 2002 | | | | | | | | | | | | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [81] | Michalek et al. | 2002 | x | | | | | | | | | | | x | x | | x | | | • | | | | | | | | • | | | | | | | □ |
| [37] | Caldas et al. | 2003 | | | | | | | | | x | | x | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [123] | Khajehpour and Grierson | 2003 | | | x | | | | | | | | | | | | | | x | | | | | | | | | | • | | | | | □ | |
| [38] | Wetter and Wright | 2004 | | | | | | | | x | | | x | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [82] | Baušys and Pankrašovaitė | 2005 | | | | | | | | | | | | x | | | | | | • | | | | | | | | • | | | | | | | □ |
| [101] | Wang et al. | 2005 | | | | | | | | x | | | | | | | | | x | | | | • | | | • | | | | | | | □ | | |
| [103] | Wang et al. | 2005 | | | x | | | | | x | | | x | | | | | | x | | | | • | | | • | | | | | | | | □ | |
| [104] | Wang et al. | 2006 | | | x | | | | | | | | x | | | | | | x | | | | • | | | • | | | | | | | | □ | |
| [39] | Lee | 2007 | | | | | | | | | | | | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [92] | Liu et al. | 2007 | | x | x | | | x | | | | | | | x | | | | | | | • | | | | | | | | | | | | □ | |
| [74] | Znouda et al. | 2007 | | | | | x | | | | | | x | | | | | | x | • | | | | | | | • | | | | | | □ | | |
| [54] | Caldas | 2008 | | | | | x | x | | | x | | x | x | | | x | | | • | • | | | | | | • | | | | | | | □ | |
| [93] | Oliveira Panão et al. | 2008 | | x | x | | | | | x | | | | | | | | | | | | • | | | | | | | | | | | | □ | |
| [129] | Wong and Chan | 2009 | x | | | | | | | | | | | | | | | | | | | | | | | | | | | | • | | | | □ |
| [94] | Kampf and Robinson | 2010 | | | x | | | | | x | | | | | | x | | | | | | • | | | | | | | | | | | | □ | |
| [95] | Kampf et al. | 2010 | | | x | | | | | x | | | | | | | | | | | | • | | | | | | | | | | | | □ | |
| [66] | Magnier and Haghighat | 2010 | | | | | | | | | | | | | | | | | x | • | | | | • | | | | | | | | | □ | | |
| [116] | Tuhus-Dubrow and Krarti | 2010 | | | x | | | | | | | | x | | | | | | | | | | | | | • | | | | | | | □ | | |
| [117] | Bichiou and Krarti | 2011 | | | x | | | | | x | | | x | | | | | | x | | | | | | | • | | | | | | | □ | | |
| [86] | Rakha and Nassar | 2011 | | | | x | | | | | | | | | | | | | | | • | | | | | | | | | | | | □ | | |
| [85] | Turrin et al. | 2011 | | | | | | | | | x | x | x | | | | | | | | • | • | | | | | | | | | | • | □ | | |
| [87] | Gagne and Andersen | 2012 | | | | | x | | | | | | x | | | | | x | x | | • | | | | | | | | | | | | □ | | |
| [118] | Gengembre et al. | 2012 | | | | | | | | | | | x | | | | | | x | | | | | | | • | | | | | | | □ | | |
| [134] | Li | 2012 | | | | | | | | | | x | | | | | | | | | | | | | | | | | | | | • | □ | | |
| [83] | Menges | 2012 | | | | | x | | | | | x | | | | | | | | • | | • | • | | | | | | | | | • | | □ | |
| [102] | Rapone and Saro | 2012 | | | | | | | | | | | x | | | | | | x | | | | • | | | | | | | | | | □ | | |
| [40] | Bucking et al. | 2013 | | | | | x | | | x | x | | x | | | | | | x | • | | | | | | | | | | | | | □ | | |
| [130] | Güleç Özer and Şener | 2013 | x | | | | | | | | | | | x | x | | | | | | | | | | | | | | | | • | | | | □ |
| [107] | Karatas and El-Rayes | 2013 | | | | | | | | | | | | | x | | | x | x | | | | • | | | • | | | | | | | □ | | |
| [124] | Rodrigues et al. | 2013 | x | | | | | | | | | | | x | x | | x | | | | | | | | | | | | | • | | | | | □ |
| [125] | Rodrigues et al. | 2013 | x | | | | | | | | | | | x | x | | x | | | | | | | | | | | | | • | | | | | □ |
| [75] | Talbourdet et al. | 2013 | | | | | | | | x | | | x | | | | | | x | • | | | | | | | • | | | | | | □ | | |
| [98] | Antonio et al. | 2014 | | x | | | x | | | | | | | | x | x | | | | | | • | | | | | | | | | | | | | □ |
| [57] | Gerber and Lin | 2014 | | | x | | | | | | | | | | | | | | | • | | | | | | • | | | | | | | | □ | |
| [119] | Karatas and El-Rayes | 2014 | | | | | | | | | | | | | x | | | x | x | | | | | | | • | | | | | | | □ | | |
| [67] | Kasinalis et al. | 2014 | | | | | | | | | | | | | | | | | x | • | | | | • | | | | | | | | | □ | | |
| [56] | Lin and Gerber | 2014 | | | x | | | | | | | | | | | | | | | • | | | | | | • | | | | | | | | □ | |
| [55] | Lin and Gerber | 2014 | | | x | | | | | | | | | | | | | | | • | | | | | | • | | | | | | | | □ | |
| [79] | Rafiq and Rustell | 2014 | | | x | | | | | | | | | | | | | | x | • | | | | | | | • | | | | | | | □ | |
| [41] | Ramallo-González and Coley | 2014 | | | | | | | | | | | x | x | | | | | x | • | | | | | | | | | | | | | □ | | |
| [76] | Wright et al. | 2014 | | | | | | | | | | | x | | | | | | | • | | | | | | | • | | | | | | □ | | |
| [64] | Yi | 2014 | | | x | | | | | | | | | x | | | | | | • | | • | | | | | | | | | | | | □ | |
| [91] | Bizjak et al. | 2015 | | | | | | | | x | x | | | | | | | | | | | • | | | | | | | | | | | □ | | |
| [77] | Brownlee and Wright | 2015 | | | | | | | | x | | | | | | | | | x | • | | | | | | | • | | | | | | □ | | |
| [80] | Chang and Shih | 2015 | | | x | | | | | x | | | | | | | | | x | • | • | | | | | | • | | | | | | | □ | |
| [111] | Ercan and Elias-Ozkan | 2015 | | | | | x | | | | | | x | | | | | | | | | | | | • | | | | | | | | □ | | |
| [122] | Evins | 2015 | | | | | | | | | | | x | | | | x | | | | | | | | | | | | • | | | | □ | | |
| [60] | Futrell et al. | 2015 | | | | x | | | x | | | | x | | | | x | | | • | • | | | | | | | | | | | | □ | | |
| [88] | Futrell et al. | 2015 | | | | x | | | | | | | x | | | | | | x | | • | | | | | | | | | | | | □ | | |
| [105] | Huang et al. | 2015 | | | x | | | | | | | | | | | x | | | | | | | • | | | | | | | | | | | □ | |
| [108] | Liu et al. | 2015 | | | | | | | | x | | | x | | | | | | x | | | | • | | | • | | | | | | | □ | | |
| [106] | McKinstray et al. | 2015 | | | | | | | | | x | | | | | | | | x | | | | • | | | | | | | | | | | □ | |
| [43] | Méndez Echenagucia et al. | 2015 | | | | | | | | | | | | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [42] | Naboni et al. | 2015 | | | | | | | | x | | | x | | | | | | x | • | | | | | | | | | | | | | □ | | |
| [61] | Negendahl and Nielsen | 2015 | | | | | x | | | | | | | | | | | | | • | • | | | | | | • | | | | | | □ | | |
| [90] | Su and Yan | 2015 | | | | | | | | x | | | | x | x | | x | | | | • | | | | | | | | | | • | | | | □ |
| [100] | Vermeulen et al. | 2015 | | | x | | | | | | | | | | | | | | | | | • | | | | | | | | | | | | | □ |
| [44] | Xu et al. | 2015 | | | | x | | | | x | | | | | | | | | x | • | | | | | | | | | | | | | □ | | |
| [99] | Yi and Kim | 2015 | | | x | | | | | | | | | | | | | | | | | • | | | | | | | | | | | | | □ |
| [68] | Yu et al. | 2015 | | | | | | | | x | | | | | | | | | x | • | | | | • | | | | | | | | | □ | | |
| [65] | Azari et al. | 2016 | | | | | | | | | | | | | | | | | x | • | | | • | | | | | | | | | | □ | | |
| [89] | Chen et al. | 2016 | | | | | | | | x | | | x | | | | | | | | • | | | • | | | | | | | | | □ | | |
| [132] | Cubukcuoglu et al. | 2016 | | | | | | | | | | | | x | x | | | | | | | | | | | | | | | | • | | | | □ |
| [46] | Delgarm et al. | 2016 | | | | | | | | x | | | x | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [47] | Delgarm et al. | 2016 | | | | | | | | x | | | x | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [131] | Dino | 2016 | | | | | | | | | | | | | | x | | | | | | | | | | | | | | | • | | | | □ |
| [120] | Ferrara et al. | 2016 | | | | | | | | | | | | | | | x | | | | | | | | | • | | | | | | | □ | | |
| [48] | Si et al. | 2016 | | | | | | | | x | | | | | | | | x | | • | | | | | | | | | | | | | □ | | |
| [126] | Song et al. | 2016 | | | x | | | | | | | | | x | x | | | | | | | | | | | | | | | • | | | | | □ |
| [45] | Wright and Alajmi | 2016 | | | | | x | | | | | | | | | | | | | • | | | | | | | | | | | | | □ | | |
| [127] | Yazici | 2016 | | | | | | | | | | | | | | x | | | | | | | | | | | | | | • | | | | | □ |
| [96] | Zhang et al. | 2016 | | | | | x | | | | | | | | | | | | | | | • | | | | | | | | | | | | □ | |
| [133] | Bahrehmand et al. | 2017 | x | | | | | | | | | | | | x | | | | | | | | | | | | | | | | • | | | | □ |
| [51] | Bamdad et al. | 2017 | | | | | | | | x | | | x | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [50] | Bre and Fachinotti | 2017 | | | | | | | | x | | | x | | | | x | | | • | | | | | | | | | | | | | □ | | |
| [63] | Chatzikonstantinou and Sariyildiz | 2017 | | | | | | | | | | | x | | | | x | | | • | • | | | | | | | | | | | | □ | | |
| [52] | Chen and Yang | 2017 | | | | | | | | x | | | x | | | | | | | • | | | | | | | | | | | | | □ | | |
| [72] | Dhariwal and Banerjee | 2017 | | | | | | | | | | | | | | | | | x | • | | | | | | • | | | | | | | □ | | |
| [115] | Dino and Üçoluk | 2017 | | | | | | | | | | | | | | x | | | x | | | | | | • | | | | | | | | □ | | □ |
| [135] | Elshaer et al. | 2017 | | | x | | | | | | | | | | | | | | | | | | | | | | | | | | | • | | □ | |
| [49] | Li et al. | 2017 | | | | | | | | x | | | | | | | x | | x | • | | | • | • | | • | | | | | | | □ | | |
| [114] | Sleiman et al. | 2017 | | | | | | | | | | | | | x | | | | x | | | | | | • | | | | | | | | □ | | □ |
| [78] | Yang et al. | 2017 | | | | | | | | | | | x | | | | x | | | • | | | | | | | • | | | | | | □ | | |
| [69] | Zhang et al. | 2017 | | | | | | | | x | | | x | x | | | | | x | • | • | | | • | | | | | | | | | □ | | |
| [53] | Bamdad et al. | 2018 | | | | | | | | | | | x | | | | | | | • | | | | | | | | | | | | | □ | | |
| [59] | Bizjak et al. | 2018 | | | x | | | | | x | | | | | | | | | x | • | | | | | | | | | | | | | | □ | |
| [62] | Chen et al. | 2018 | | | x | | | | | | | | | | | | | | x | • | • | | | | | | | | | | | | | □ | |
| [112] | Ferrara et al. | 2018 | | | | | | | | | | | x | | | | x | | | | | | | | • | | | | | | | | □ | | |
| [71] | Gou et al. | 2018 | | | | | | | | x | | | x | | | | | | x | • | | | | • | | | | | | | | | □ | | |
| [73] | Harkouss et al. | 2018 | | | | | | | | | | | | | | | x | | | • | | | | | | • | | | | | | | □ | | |
| [109] | Hester et al. | 2018 | | | | | | | | | | | | | | | | | x | | | | • | | | • | | | | | | | □ | | |
| [58] | Li et al. | 2018 | | | x | | | | | | | | | x | | | | | x | • | | | | | | | | | | | | | | □ | |
| [70] | Lin et al. | 2018 | | | | | | | | | | | | | | | | | x | • | | | | • | | | | | | | | | □ | | |
| [110] | Sghiouri et al. | 2018 | | | | | | | | | | | x | | | | | | | | | | | • | | | | | | | | | □ | | |
| [97] | Vermeulen et al. | 2018 | | | x | | | | | | | | | | | x | | | | | | • | | | | | | | | | | | | □ | |
| [84] | Yang et al. | 2018 | | | | | | | | | x | x | x | | | | | | | • | • | | | | | | | | | | | • | □ | | |
| [113] | Youssef et al. | 2018 | | | x | | x | | | | | | | | | | | | | | | | | | • | | | | | | | | □ | □ | |

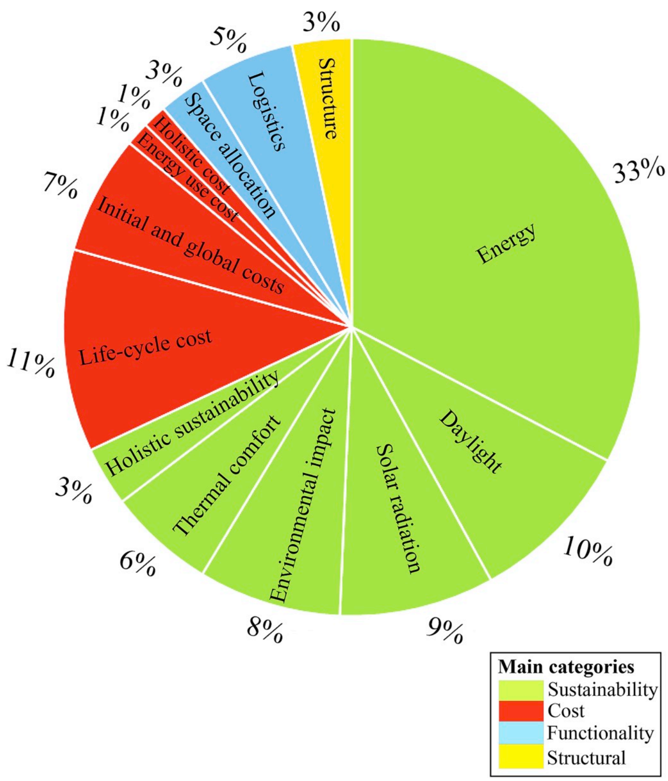


**Fig. 4.** Distribution of sub-categories.

In comparison to previous studies, Karatas and El-Rayes [107] considered the minimisation of both the life-cycle cost and operational environmental cost, and the maximisation of social quality of life using MOGA for a single-family house. Afterwards, Karatas and El-Rayes [119] used MOGA to minimise the life-cycle cost and maximise social quality. In another multi-objective optimisation approach, Liu, Meng, and Tam [108], minimised the life-cycle cost and life-cycle carbon emissions using MOPSO. Ferrara, Fabrizio, Virgone, and Filippi [120], minimised the global cost over the life-cycle using PSO for a single-family house. Dhariwal and Banerjee [72] proposed an approach using fractional factorial design and response surface methods to optimise the life-cycle cost. To validate the proposed approach, authors minimised the incremental life-cycle cost using GA and minimised the both life-cycle cost and energy use intensity using NSGA-II. More recently, Hester, Gregory, Ulm, and Kirchain [109], minimised the life-cycle cost and life-cycle impact in order to explore the building's design space by comparing GA results, sequential specifications, and unguided specification algorithms. Harkouss, Fardoun, and Biwole [73] minimised an auxiliary electric heater with a pump, thermal demands for cooling and heating, exports, and life-cycle costs using NSGA-II for NZEBs.

In addition to these studies, several publications included the life-cycle cost as well. However, these studies are mentioned in other sections. Lin and Gerber [55], Lin and Gerber [56], and Gerber and Lin [57], explained and discussed energy considerations. Wang, Zmeureanu, and Rivard [101], Wang, Rivard, and Zmeureanu [103], and Wang, Rivard, and Zmeureanu [104], are referred to in the environmental impact section. Finally, Li, Pan, Xue, Jiang, and Mao [49], are cited in the thermal comfort section.

### *4.2. Initial and global costs*

In consideration of the skin of the building, Znouda, Ghrab-Morcos, and Hadj-Alouane [74] used GA to minimise the global monetary cost for four different economic scenarios based on gas and electricity. For the investigation of trade-offs between the minimisation of the construction cost and energy need objectives, Talbourdet, Michel, Andrieux, Millet, Mankibi, and Vinot [75], used NSGA-II for an office building. Wright, Brownlee, Mourshed, and Wang [76], also optimised a commercial building in order to minimise the energy use and capital cost objectives using NSGA-II by considering several optimisation experiments. For the same trade-off, Brownlee and Wright [77] also used NSGA-II but with surrogate models based on radial basis functions (RBFs). More recently, Yang, Lin, Lin, and Tsai [78], used NSGA-II in three different analyses approaches. The first approach minimised both the envelope construction cost and energy performance. The second approach minimised the objectives that were considered in the first analysis and maximised the window opening rate. The third analysis focussed on the same objective functions used in the second analysis scheme but for different climatic zones in Taiwan.

For the sake of the building shape, Chang and Shih [80] integrated dynamic programming and GA to minimise the construction cost with the energy cost, and maximised the area of visual view with daylight illumination, for a residential building. Rafiq and Rustell [79] minimised the structural cost, energy loss, and area loss objectives, using interactive visualisation clustering GA in the case of a commercial building.

In an early study that focussed on building's layout, Gero and Kazakov [121] minimised the layout cost based on travel distances and space relations using GA for office and hospital building cases. Apart from these, Caldas [54] and Negendahl and Nielsen [61] considered the initial and global costs, respectively, but they are mentioned and referred to in the energy and daylight sections.

### *4.3. Energy use cost*

In this part, there are only two studies that focussed on the building layout. Michalek, Choudhary, and Papalambros [81], minimised the heating cost, cooling cost, lighting cost, wasted space, hall size, and access way size, using GA and simulated annealing (SA) for residential buildings. Baušys and Pankrašovaité [82] minimised the heating cost, lighting cost, wasted space, doorways, and hallways using improved GA in the case of a residential building.

### *4.4. Holistic cost*

In consideration of the building skin, Evins [122] proposed a multi-level optimisation framework by dividing the design and operation of a building into three phases: building, plant, and operational levels. For the building and plant levels, the author used NSGA-II to minimise the annual carbon emissions and initial capital cost. At the operational level, a mixed integer programming approach was used to minimise the annual running costs.

For the sake of the building shape, Khajehpour and Grierson [123] integrated EC and colour filtering in a high-rise office building. In particular, the first step of the study applied optimisation techniques to minimise the capital, and operating costs, and to maximise the income revenue using a multi-criteria genetic algorithm (MCGA). The second step focussed on the determination of profit and safety potentials using colour filtering.

## 5. Functionality

### *5.1. Space allocation*

As an early example for a building layout, Rodrigues, Gaspar, and Gomes [124], presented an optimisation framework. Authors considered adjacency, space overlap, opening overlap, and orientation, floor dimensions, compactness, and overflow using a hybrid evolutionary technique and ES with a stochastic hill climbing (SHC). To validate the proposed method, the authors applied the framework used to a residential layout problem [125]. As another example of residential

**Table 2**
Overview of optimisation methods and list of all parameters.

Related with form-finding parameters (red)
Non-related with form-finding parameters (blue)

| Performance objectives | SEC methods used in PCA problems: Layout | Skin | Shape | All used parameters |
|---|---|---|---|---|
| Energy | EC | EC & SI | EC | Window dimension, WWR, shading and ceiling design, building and roof shape, orientation, space dimension and location, light shelf, floor height, set points, temperature, construction and glazing properties, photovoltaic system, infiltration rate, solar absorptance, HVAC system and control variables. |
| Daylight | EC | EC & SI | EC | Window dimension, WWR, shading and ceiling design, façade-roof-building shape, orientation, space dimension and location, light shelf, floor height, roof structure, window locations, construction and glazing properties, infiltration rate, HVAC system and control variables. |
| Solar radiation | EC | EC | EC & SI | WWR, shading design, façade-roof-building shape, orientation, space dimension and location, roof structure, building urban layout, floor height. |
| Environmental impact | | EC & SI | EC & SI | Window dimension, WWR, shading design, building shape, orientation, set points, construction and glazing properties, building structure, air leakage, heat generator. |
| Thermal comfort | | EC & SI | | Window dimension, WWR, shading design, building shape, orientation, set points, temperature, construction and glazing properties, solar absorptance, start-stop delays, relative humidity, airflow rate. |
| Holistic sustainability | EC & SI | EC | | WWR, shading design, façade and building shape, construction and glazing properties, space location, photovoltaic design, 2D/3D grid matrix for layout |
| Life-cycle cost | | EC & SI | EC & SI | Window dimension, WWR, shading design, building shape, orientation, set points, construction and glazing properties, infiltration rate, HVAC system and control variables, humidity, ventilation, photovoltaic design, air leakage, heat generator. |
| Initial and global cost | EC | EC | EC | Window dimension, WWR, façade and shading design, building and roof shapes, orientation, space dimesion and location, floor count and height, construction and glazing properties, HVAC system. |
| Energy use cost | EC | | | Window dimension, space dimesion and location |
| Holistic cost | | EC | EC | WWR, shading design, structural and floor system, construction and glazing properties, renewables, plant and storage |
| Space allocation | EC | | | Building shape, space dimesion and location, geometric transformation, grid subdivision. |
| Logistics | EC | | | Window dimension, orientation, space dimension and location, facility assignment, adjacency matrix and preference, space properties, voxel matrix, window-door-entrance placement. |
| Structure | | EC | EC | Building and façade shape, roof structure, geometric transformation. |

layout, Song, Ghaboussi, and Kwon [126], used implicit redundant representation GA and simple GA for maximising symmetry, structural safety, stair connectivity, and façade exposure. More recently, Yazici [127] minimised the total built area in urban layouts using the EA and parametric design environment.

### 5.2. Logistics

As a manifestation of early work conducted in this area, Jo and Gero [128] optimised the interactions between interrelated spaces and the travel cost between the space elements with GA in an office layout case. More recently, Wong and Chan [129] optimised the adjacency preference matrix, adjacency limitations caused by physical and budget constraints, range of relative ratios between spaces, and the number of functions that can contribute acceptable designs using EA for a residential building. Focussing on health campuses, Güleç Özer and Şener [130] used GA to find an optimal route of users in functionally complex buildings. Related to the healthcare facility, Su and Yan [90] optimised a nursing unit layout by maximising daylight illuminance and by minimising travel distances of nurses using GA. Dino [131] used EA to optimise unique fitness functions based on size, absolute dimension, compactness, jaggedness, convexity of space, as well as the façade, floor, neighbourhood, and separation criteria. The author focussed on a three-dimensional library building layout problem to implement the developed method. Cubukcuoglu, Chatzikonstantinou, Tasgetiren, Sariyildiz, and Pan [132], maximised accessibility, visibility, and wind protection objectives by proposing a multi-objective harmony search (MOHS) algorithm for an urban context. Authors also compared the results of MOHS with the self-adaptive differential evolution multi-objective (jDEMO) algorithm. More recently, Bahrehmand, Batard, Marques, Evans, and Blat [133] optimised the overflow quality, topological quality, spatial quality, and user rating, with the use of an

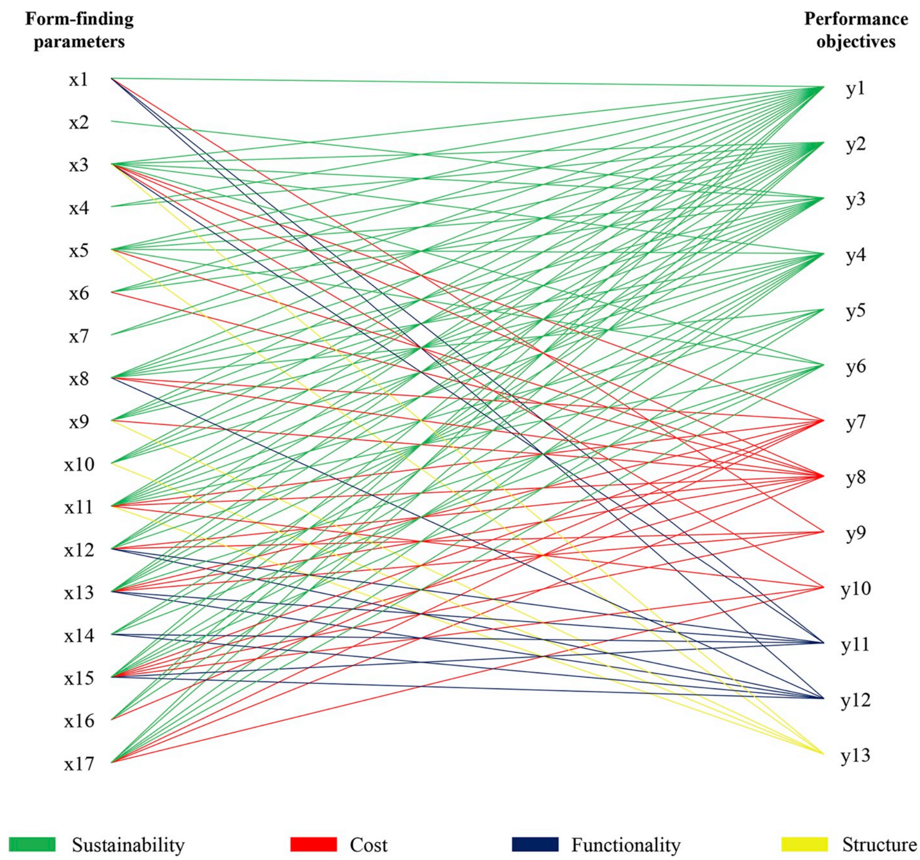


**Fig. 5.** Relationship between form-finding parameters and performance objectives.

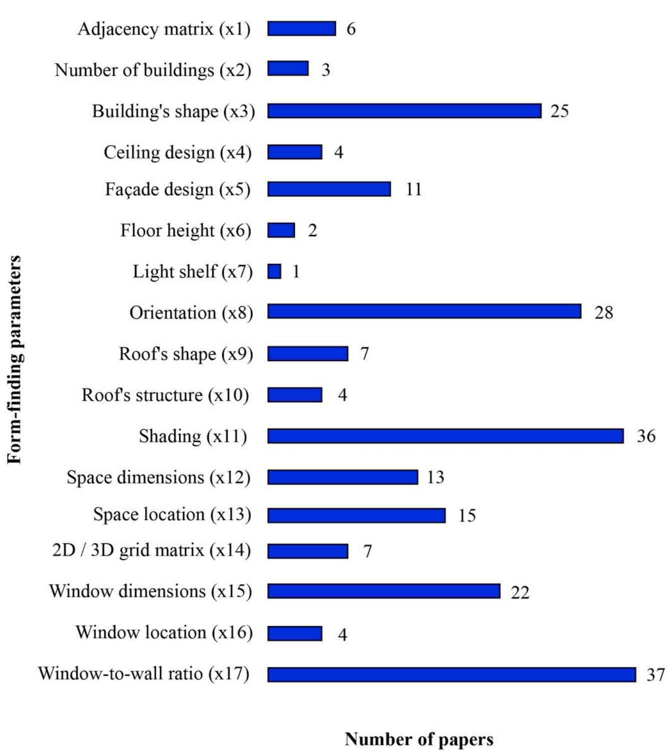


**Fig. 6.** Total number of form-finding parameters.

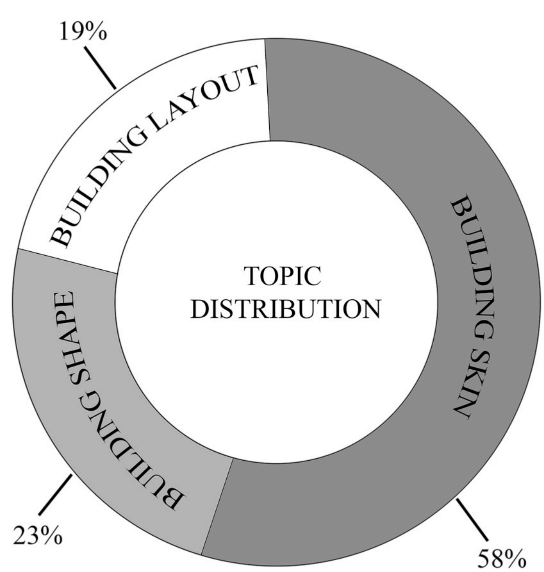


**Fig. 7.** Distribution of building optimisation topics.

interactive EA in the case of a museum building. Gero and Kazakov [121] was also related to the logistics aspect but was mentioned in initial and global costs.

## 6. Structure

By focussing on the building's skin, Turrin, von Buelow, and Stouffs [85], used GA to minimise the weight of the dome design with an acceptable deformation for a semi-spherical structure. Authors combined the structural performance with the architectural form-finding process. In another study, Li [134] minimised discontinuous edges on the façade of a museum design using a GA-based split edge algorithm and an SS-based split edge algorithm. More recently, Yang, Ren, Turrin, Sariyildiz,

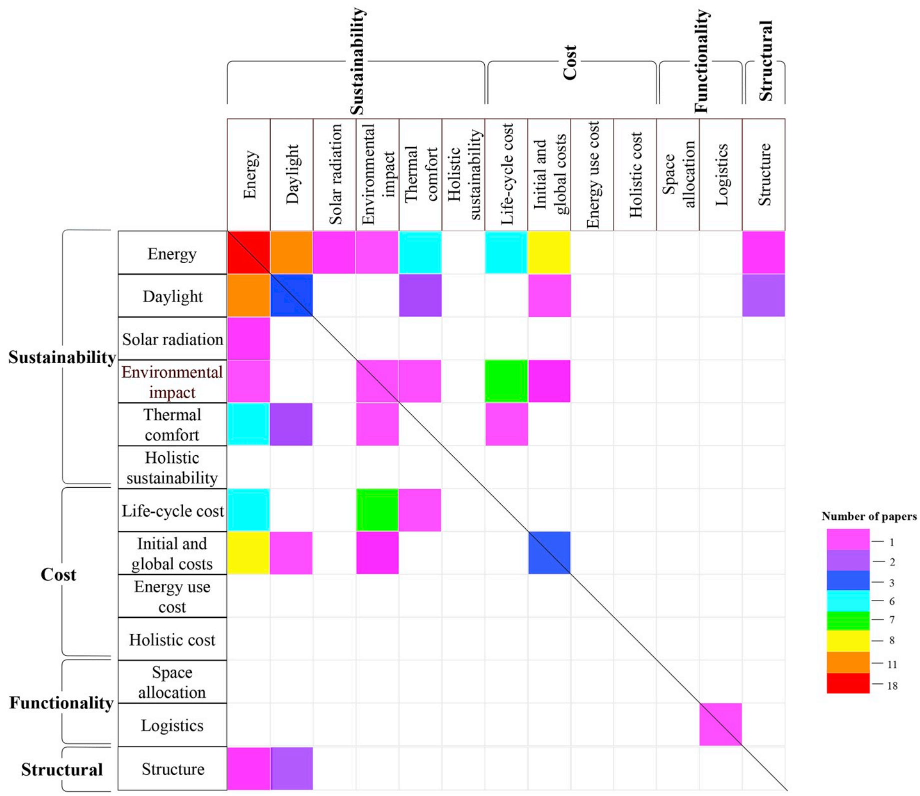


**Fig. 8.** Matrix showing the use of conflicting objectives.

and Sun [84] optimised the roof of the sports building in order to maximise UDI, and minimise energy use and structural mass using NSGA-II.

For the sake of the building shape, Menges [83] used EA to optimise the morphologic criteria, such as the floor area, envelope heights, envelope slope, unobstructed view axes, incident solar radiation, and interior thermal loading. More recently, Elshaer, Bitsuamlak, and El Damatty [135], used ANN to minimise the mean drag coefficient for the first case and minimised the standard deviation of the lift coefficient for the second case using GA in high-rise buildings.

## 7. Review results

To highlight the correspondence between architectural geometry and performance, the form-finding parameters, and their corresponding performance objective(s) with respect to the building were presented in Table 1. To sum up, the distribution of each sub-category within the total number of performance objectives presented in the one hundred reviewed papers considered herein are shown in Fig. 4. All decision variables (both related and non-related with form finding), and SEC methods used for each performance objective, are presented in Table 2. In relation to Table 1, the relationship between form-finding parameters used for each performance objectives in reviewed papers are listed in Fig. 5, and the total usage amount of form-finding parameters, such as window-to-wall ratio (WWR), and orientation, are shown in Fig. 6. The total usage of building topics are also listed in Fig. 7. All trade-offs between each performance objective used in bi-objective, three objective, and many objective optimisation problems are illustrated in Fig. 8. Finally, other relevant information, which is not mentioned above, is summarised in Fig. 9. Since different methods are used in some papers, some graphs are presented as pie charts. This also includes the distribution of objectivity (where the term “many objectives” indicates a minimum of four objectives [136]).

Evaluating of these results allows the extraction of some information as follows:

- From the viewpoint of the main categories, Fig. 4 shows that sustainability was the most studied topic. The least studied category was structure
- From the viewpoint of the sub-categories, energy was the most dominant performance objective among all reviewed papers as it can be observed in Fig. 4, while little attention was attributed to holistic and energy use costs. The efforts on other sub-categories were almost equally distributed
- As in Table 2, EC was the major optimisation method used in reviewed papers
- As shown in Table 2, energy and daylight related papers considered a broader range of parameters than other performance topics. In addition to form-finding related parameters, non-related form-finding parameters played a crucial role in energy, daylight, environmental impact, thermal comfort, life-cycle cost, initial and global costs, and holistic cost considerations
- From the viewpoint of form-finding parameters illustrated in Fig. 6, WWR (x17), shading (x11), orientation (x8), window dimensions (x15), and building's shape (x3), were mostly used. Conversely, number of buildings (x2), ceiling design (x4), floor height (x6), light shelf (x7), roof's structure (x10), and window location (x16), were the least used form-finding parameters
- By matching the information of Fig. 6 and Table 1, the relationship between mostly used form-finding parameters and the corresponding building topic was investigated in detail. The window-to-wall ratio (x17) was used 28 times in relation to the building's skin from a total of 37 cases. The remaining cases were related to building's shape. The window dimensions (x15) was used 17 times (out of 22 cases in total) in relation to building's skin. Moreover, in one occasion (from a total of 22 times) it was used in relation to the

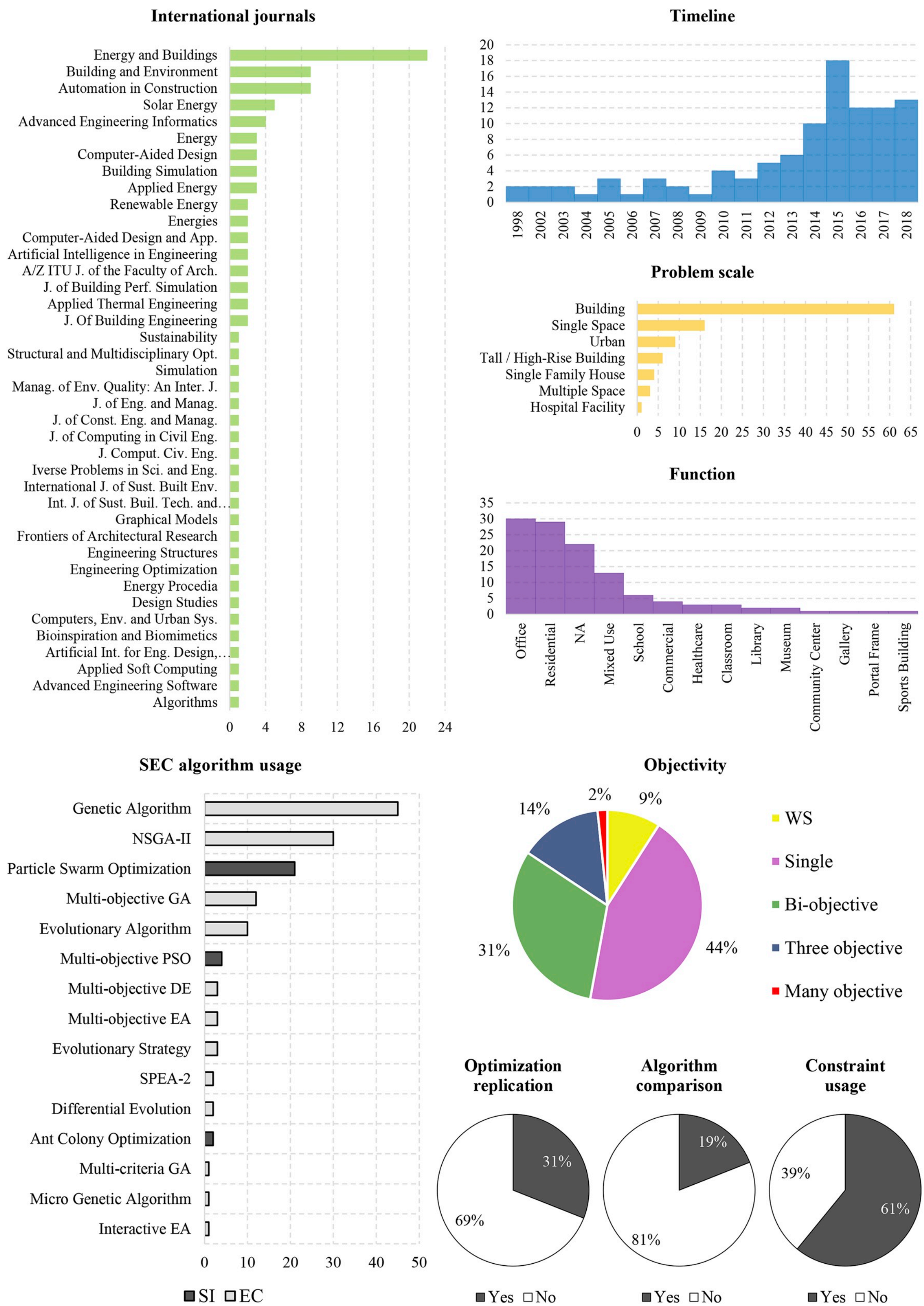


**Fig. 9.** Current trends.

building's shape, whereas in four occasions (out of 22 total cases) it was used in the building's layout. Shading (x11) was used 33 times (out of 36 cases in total) in relation to the building's skin. In addition, shading was studied in relation to the building's shape in the remaining cases. Orientation (x8) was used 22 times (out of 28 in total) in relation to the building's skin whereas in a building layout it was used in one case (out of 22 times). The rest of the times it was studied in relation to the building's shape. Finally, building's shape (x3) was used two times (from a total of 25 cases) in relation to the use of the building's skin. Furthermore, in 20 out of 25 times it was used in the building's shape whereas in three cases (out of 25 times) it was used in a building layout

- As shown in Fig. 7, the major building topic was the building's skin. Studies on the building layout and building shape were almost equally distributed
- As shown in Fig. 8, combinations of objectives in regard to sustainability were dominant. In contrast, the second most dominant combination was between sustainability and cost. Among the subcategories, combinations of these objectives that related to either energy or energy and daylight were the most common trade-offs. Trade-offs between functionality and sustainability were obviously neglected in multi-objective approaches, though they were only considered in weighted sum approaches, e.g. in Ref. [90]. Furthermore, the trade-offs between functionality and cost were neglected both in the multi-objective and in weighted sum approaches
- As shown in Fig. 9, the number of published papers increased significantly in the last five years. Most of the reviewed papers were published in "Energy and Buildings", "Building and Environment", and "Automation in Construction". The most studied problem scale was the building and the functions that received maximum attention were offices and residences
- Single-objective and bi-objective optimisation problems were mostly considered, second to weighted summation (WS) and three objective optimisation problems. Many objective optimisation problems have rarely been considered. Most of the reviewed studies used constraints in the formulation of the optimisation problem
- In approximately one third of the published studies, optimisation replications were considered (e.g. different initial populations were used for each of the runs described within one publication). In addition, comparisons of the optimisation results using several SEC algorithms were also very limited
- GA was mostly used for single objective optimisation, whereas NSGA-II was mostly used for multi-objective optimisation problems

## 8. Conclusions

This study provides a systematic review of PCA using SEC. The topic has been in the agenda of architects and engineers during the past few decades. Based on evidence presented in the results, conclusions were drawn in relation to form-finding parameters, performance objective, and optimisation, as summarised below.

Conclusions on form-finding parameters:

- All reviewed publications dealt with the architectural design (this is because they all included form-finding as explained in the introduction of this study). Nevertheless, some of these publications placed more emphasis on architectural concerns (and therefore include parameters that have great impact on architectural design, such building's shape (x3)). These publications are also the ones that focussed their conclusions on the building design. Other reviewed publications placed more emphasis on engineering concerns (such as the window-to-wall ratio (x17)). Several of these publications are also the ones that focus their conclusions on aspects related to computer science (such as algorithmic comparisons). A better integration of investigations related to computer science within the architectural domain is missing despite its expected benefits
- Form-finding parameters, such as window-to-wall ratio (x17) and shading (x11) can enhance the sustainability performances. However, these parameters should be more representative compared to the window ratio or shading dimensions by including more design concerns
- Based on the sustainability objective in building layout problems [81,90], authors tended to use window dimensions (x15) instead of the window-to-wall ratio (x17). One reason is the fact that the window dimension parameters are more controllable in relation to variations in the layout
- Aspects that are usually delegated to shading (x11) (such as the control of solar gain for thermal comfort, control of the amount of daylight for visual comfort and prevention of glare) can be also improved by layout optimisation. Currently, this potential is not exploited given the lack of works that use shading parameters (x11) in the layout topic
- Orientation (x8) is one of the most crucial parameters used to improve sustainability and functionality performances of the building. From this point-of-view, it is remarkable that the orientation (x8) parameter has been rarely investigated in relation to the building layout. Currently, potentials are not exploited when the orientation parameter (x8) is incorporated in layout problems
- There is no doubt that the façade design affects the sustainability related performance objectives. In the reviewed publications, orientation parameters (x8) are mostly used in building skin problems. However, orientation can also be controlled by the variations of the building shape (e.g. twisted building)
- Among the least used parameters, the light shelf (x7) has only been used in only one study thus far [60]. In order to improve the sustainability performance of existing buildings, the light shelf related parameters can play an important role

Conclusions on performance objectives:

- Only three studies [61,73,84] solved many objective optimisation problems that involved all four objectives. Considering the necessity of satisfying many aspects of the design process, many objective optimisation algorithms could be used. When doing so, the selection of the optimisation algorithm is crucial, since some of these are not convenient for use in many objective optimisation problems. In the literature there are some novel and recent techniques, which can be found in Ref. [136]
- There were only three holistic approaches [113–115] that focussed on different building topics as part of the same optimisation problem, such as the skin and layout. These approaches presented promising potentials, while they integrated different performance objectives and minimised the design complexity. These approaches can be considered, especially in research studies that are focussed on integrated design approaches for high-performance buildings
- Owing to the expensive computation time, the number of large-scale building studies, such as tall buildings and hospitals, was limited. Objective functions based on ANN can be an effective solution

Conclusions on optimisation:

- There are several methods to handle more than one objective in the multi-objective optimisation problem. One of them is the weighted summation approach which appears to be relevant and used in many of the reviewed documents. It combines different objectives by assigning some weights to each objective in order to convert the problem to a single-objective optimisation problem. However, defining these weights is a very difficult task (especially if this needs to be done at the beginning of the process, such as the case of weighted summation). Conversely, Pareto-optimality approaches in multi-objective problems (e.g. bi-objective or three objective problems) allow the identification of the final decision at the end of the optimisation process
- Owing to the formulation of optimisation problem, the final design decision can consider and eventually incorporate the results of the optimisation in different ways. From the standpoint of single-objective problem, the result of the optimisation process can be used as the final design decision. The reason is that in this approach there is only one fitness function to be either minimised or maximised. From the standpoint of weighted summation problem, the final design decision depends on the weights that are defined for each fitness function. Even if there is only one result at the end of this

optimisation process, the weights (defined by the decision maker) may affect the result. From the standpoint of multi-objective problem, further investigation is required after the optimisation. The reason is that the Pareto-front suggests many alternatives as result. Owing to the non-domination, each alternative has either advantage or disadvantage for each objective function based on where the alternative is selected from the Pareto-front. Considering multi-objective optimisation may support the investigation of relationship among objectives and decision variables. In reviewed documents, there are several methods explicitly used to support the decision-making process in the multi-objective domain (e.g. weighted summation approach to pick the closest solution to the utopic point in Refs. [46,47], clustering to categorise solutions in Pareto-front using self-organising maps in Ref. [84], and auto-associative connectionist model for threating preferences in Ref. [63]). A further consideration is valid for all types of optimisation and relates to the complexity of architectural design. Regardless how many objectives it can include, the optimisation tackles only a limited range of design requirements. Many other requirements and qualities expected from the design are not included in the optimisation. The optimisation results may have to be assessed and further elaborated also based on these additional criteria

- According to the "No Free Lunch (NFL)" theorem [137], there is no global metaheuristics optimisation algorithm that is capable of discovering the best results for all real-world or benchmark problems. In other words, one algorithm can outperform another algorithm only in terms of the solution to a specific problem. Architectural designs are unique problems owing to objectives, building program, constraints, client expectations, and the surrounding impacts of the built environment. Therefore, one must explore and compare different algorithms for solving the same architectural design problem in order to eventually provide more adequate design decisions. However, in the literature, it is observed that very few studies have compared different SEC algorithms for the same architectural design problem
- Only one study [97] explicitly considered equality constraints, which are very important in architecture (e.g. in order to match the design with strict municipality regulations). The use of equality constraint causes is associated with a more challenging optimisation process while searching for feasible design solutions. For this reason, only specialised constraint handling methods can cope with equality constraint problems [138]
- Many objective optimisation problems are challenging in terms of observing the final set of solutions in the search space since they integrate at least four objectives at the same time. Different visualisation methods should be considered in order to facilitate the design choice

Given the tremendous effort expended on research on this topic, the relevance of the PCA framework is confirmed by the conducted review of the one hundred articles considered and referenced in this study. Nevertheless, the itemised points listed above clearly indicate the directions in which further efforts are needed.

## Declarations of interest

None.

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