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Review

Artificial intelligence applied to conceptual design. A review of its use in architecture

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ABSTRACT

Conceptual architectural design is a complex process that draws on past experience and creativity to generate new designs. The application of artificial intelligence to this process should not be oriented toward finding a solution in a defined search space since the design requirements are not yet well defined in the conceptual stage. Instead, this process should be considered as an exploration of the requirements, as well as of possible solutions to meet those requirements.

This work offers a tour of major research projects that apply artificial intelligence solutions to architectural conceptual design. We examine several approaches, but most of the work focuses on the use of evolutionary computing to perform these tasks. We note a marked increase in the number of papers in recent years, especially since 2015. Most employ evolutionary computing techniques, including cellular automata. Most initial approaches were oriented toward finding innovative and creative forms, while the latest research focuses on optimizing architectural form.

1. Introduction

1.1. Conceptual design

As Song, Ghaboussi, and Kwon have indicated, architecture differs from other arts in that its products are required to be simultaneously aesthetically pleasing, structurally stable, and functional [1]. Determining a building's shape is the principal activity of the architectural design process. It is common for architects to start a design with a disembodied concept and a vague image of its shape which form the basis for proposing a broad set of solutions. The initial form will affect both performance and cost of construction, daylight use, energy consumption, layout configuration, shadow performance, acoustics, functional accessibility, and solar gain, among other features [2]. In this context, the search for shapes becomes one of the key steps in the conceptual design phase, as its results are inputs for the next steps in the design process, in the subsequent construction phase, and throughout the life cycle of the building.

Architectural design is a complicated process that draws on experience and creativity to develop new designs. Therefore, the application of artificial intelligence to this process should not be oriented to finding a solution in a defined search space, since the design requirements are not yet well defined in the conceptual stage. Instead, this process should be considered as an exploration [3] of the requirements, as well as of possible solutions to meet those requirements [4,5]. Many design elements are chosen by considering a wide range of quantifiable and non-quantifiable features simultaneously. Even if a problem allows for numerical formulation, the lack of explicit and standard evaluation criteria makes defining design intentions difficult [6].

1.2. This review

In this work, we will examine the main research projects that applied artificial intelligence solutions to the design of form in architecture. As early as 1987, Soddu [7] created artificial DNA of Italian medieval cities which he used to define the Generative Design approach to Architecture and City Design in his book "Citta' Aleatorie." Since then, various approaches have been developed, such as Yeh's [8], which used an annealed neural network to find solutions to a facility layout problem applied to a hospital building case study in 2006. Wen, Hong, and Xueqiang in 2010 [9], and Rian and Asayama in 2016 [10] used fractal algorithms for the design of architectural forms. In related work,

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Chatzikonstantinou and Sariyildiz investigated self-associated connectionist models in the design of sustainable architectural façades in 2017 [11]. Machine learning approaches are also used in architectural design practice, as in the 2018 example from Tamke, Nicholas, and Zwierzycki [12], although most work in this area concentrates on the use of evolutionary computing and cellular automata to perform such tasks.

Decisions regarding the shape of a building influence its architectural, aesthetic, and structural features as well as its sustainability. Shape affects brightness and heat loss, but also cost and usable area, to name just a few examples. As we will see in this review, there is active work in this area of architecture investigating how to generate complex shapes in an appropriate way for the adjustment and optimization of these parameters. A detailed review of computational optimization techniques implemented for sustainable construction design can be found in Evins' 2013 review [13].

This review began as an investigation into the state-of-art of artificial intelligence applied to architecture. We are particularly interested in the creative capabilities of AI systems, their use in artistic fields for design, and the creation of images with aesthetic value for humans. The methodology used involved several phases: (i) An exhaustive search for literature on the application of artificial intelligence to architecture. This search has been carried out through the scientific portals ScienceDirect, Wiley Online Library, Google Scholar, and ResearchGate. The keywords used were artificial intelligence, cellular automata, evolutionary computing, artificial neural networks, deep learning, and machine learning—each combined with architecture (and variants such as architectural or architectonics) or building design. (ii) Cross-references of these papers were sought (both papers that cite them and those cited by them, up to the third level). (iii) We were immediately overwhelmed by the number of references found, and proceeded by grouping them into three main categories: architectural design, urban planning, and optimization. (iv) We decided to focus in this review on architectural design, and more specifically on research that deals predominantly with form (although some studies also include construction variables) in the conceptual design phase. Research using AI for optimization that is not related to building shape (such as window or shading design and optimization of energy efficiency or thermal comfort) has not been considered in this study.

After a brief introduction to relevant artificial intelligence concepts and methods, we will take a tour of the main research in this field and the results obtained. We decided that an organization of research by topic would be the most interesting, and so created the following groupings: design exploration, morphogenesis, building shape, ceiling form, façade design, layout design and floor plans (see Table 1 in the appendix). Like many classifications, ours is partially subjective, and we are aware that some works could move from section to section without altering the result. To give just one example, Pazos' research [14] has been categorized as morphogenesis, but could also be classified within the subset of façade design. In such cases, we have chosen to include the reference in the category that, in our opinion, best defines the spirit of the research.

1.3. Previous reviews

Previous reviews of the optimization systems used in architecture include that of Evins [13], or the more recent publication by Westerman and Evins on alternative modeling applied to the design of sustainable buildings [15]. Another, by Roman, Bre, Fachinotti, and Lamberts, focused on artificial neural network (ANN)-based metamodels for performance simulation construction [16]. Although all of these reviews include, in one way or another, the conceptual design phase, we have not found any previous publication that extensively addresses the applications of the different artificial intelligence techniques used in the design of architectural form.

2. Artificial intelligence methods

2.1. Evolutionary computation

In the 1950s, Arthur Samuel asked how computers could learn to solve problems without explicit programming to do so, leading to the birth of evolutionary computing. Evolutionary computing has its origins in Darwinian evolutionism and is based on the replication of natural structures, through the simulation of evolution, to generate systems that adapt to their environment in a manner similar to natural selection.

The field of evolutionary computing encompasses four types of algorithms, known generically as evolutionary algorithms: genetic algorithms (GAs) [17], evolutionary strategies [18], evolutionary programming [19], and genetic programming [20]. In the field of design, evolutionary search has been widely used to optimize existing designs [21] based on the realization that algorithms based on evolution are some of the most flexible, efficient, and robust of all known search algorithms [22,23].

Regarding conceptual design, Goldberg [24] presented an idealized framework for conceptual design that is composed of four components: a problem to be solved, someone to solve it, one or more designs and a means to compare them, where the GA is a lower limit in the performance of a human designer using recombinative and selective processes.

In general, the design of an engineering device is governed by numerous objective criteria that conflict, in the sense that improvement in any of the criteria occurs at the expense of one or more of the other criteria (e.g., a decrease in the capital cost of an office building may result in a reduction in revenue potential). This suggests the need to seek conceptual designs that represent the best balance between objective criteria in competition. The relative importance of competing criteria is often unknown, which further suggests the use of optimization to identify a field of conceptual design solutions that can be equally optimal—in the sense that no design is dominated by another feasible design solution for all objective criteria in the solution sector. In the literature, this approach is known as Pareto optimization [25].

The use of computational tools in the generation of architectural designs implies the use of parametric relationships, self-organizing processes, and algorithms to create designs with limited human interaction [14]. Sutherland proposed the creation of a set of rules by means of parametric relationships and algorithms that evolve the original design via manual manipulation of its parameters by the user, leading to results that the designer may not necessarily expect [26]. Dunn added that parametric design makes it possible to define the relationships between elements or groups of elements and to assign values or expressions to organize and control those definitions [27]. Further, Davis indicated that the geometry of a design also changes when the parameters change [28]; that is, a parametric design creates connections and relationships between all design elements, and when one is modified, the others also adapt to the change, usually by automatically changing parameters or related values, as in a system of equations. The disadvantage of this design methodology is the large amount of time consumed in the development of parametric codes. This cost has led the most recent approaches to use generative algorithms, taking full advantage of the computer's analytical potential to address the inherent human limitations [29]. In 2013, Moreno-De-Luca and Carrillo [30] created a compilation of the most common multi-objective optimization techniques applied to structural and architectural design not only as an optimization model, but as an essential piece of a design methodology for creating innovative, high-performance, efficient, creative, and aesthetically pleasing architectural items. The authors proposed the combination of structural, bioclimatic, green building, acoustic, and lighting design considerations into one integrated optimization and morphogenetic procedure. In their opinion, such an approach will lead to holistic design solutions with the best performance and significant cost reductions. Dutta and Sarthak [31] conducted a literature review on the implementation of evolutionary computing approaches for architectural spatial planning, highlighting the usefulness of these methods when the problem is poorly defined, and the range of constraints varies. They noted that evolutionary computing approaches are good at finding a solution that prioritizes certain criteria; somehow, in most cases, rather than the right and perfect solution, the best compromise is sought. Dutta and Sarthak concluded that there is a demand for tools that can assist in space layout planning and optimization, though most such approaches are in research stages and have yet to be incorporated in commercial products.

Generally speaking, conventional genetic algorithms identify the suitability criteria and then automatically search for the optimum solution, while interactive approaches use input from users as subjective evaluation criteria. The development of user-friendly design environments, visual interface, providing parametric variables, skill visualization, and performance feedback have strongly supported the growth of this approach [32]. Finally, Interactive Evolutionary Computing (IEC) is an optimization method based on subjective human assessment that adopts evolutionary computing (EC) in system optimization. It is an EC technique for which a human user replaces the adjustment function [33].

2.2. Artificial neural networks

ANNs consist of neurons and layers which simulate the human brain structure. The layers and neurons enable ANNs to have learning and memory skills which can be trained using algorithms of backward learning. ANNs have been used successfully in analyzing and modeling various types of problems and are a powerful method of optimization. The development of systems that demonstrate self-organization and adaptation in an equivalent, albeit simplified, way to how biological systems work allows their use as search algorithms to find optimal or near-optimal solutions for a variety of problems.

2.3. Fractals

Nature is a source of inspiration for architects and designers designing and utilizing different geometric systems as frames to replicate complex or abstract forms. Fractal geometry allows quick and easy modeling of the complex shapes of many objects and natural phenomena using some simple algorithms and is therefore one of the most appropriate methods for the architectural design of forms inspired by nature. Indeed, Wang et al. argued that fractal architecture can embody the ancient Chinese philosophical idea that “man is an integrated part of nature” [9]. Moreover, fractal models are complex models made up of simple elements connected by simple rules, making them an appropriate choice for industrialized mass production.

2.4. Swarm intelligence

Approaches to swarm intelligence and particle swarm optimization (PSO) are inspired by the behavior of insect swarms. In particular, think of a swarm of bees—they search for pollen in the region of space with the greatest density of flowers because the probability of pollen being present is greater. The same idea was implemented in computing in the form of an algorithm and is now used in different types of optimization and search systems. According to Vehlken [34], the use of techniques such as swarm intelligence and agent-based computer simulation has led current architecture to focus on movement. Vehlken introduced the concept of “futurology in architecture,” related to the large number of different situations that can be analyzed and evaluated, offering a diversity of viewpoints of different desirable futures and allowing for a seamless synthesis of multiple ideas, or feedback from customers or future users during an ongoing design process.

2.5. Cellular automata

Cellular automata (CA) is a mathematical model of a dynamic system composed of a set of cells that acquire different states or values. These states are altered in discrete time units—that is, they can be quantified at regular intervals with integer values. The set of cells thus achieves evolution based on a certain mathematical expression, known as the local transformation rule, that is sensitive to the neighboring cells’ states [35]. One of the advantages of CA is its capacity to achieve a series of properties that arise from the local dynamics through time and not from the beginning. These properties are applied to the whole system. Therefore, it is not easy to analyze the global properties of a CA from its beginning, except using simulation, starting from an initial state or configuration of cells and changing in each instant the states of all of them in a synchronous way. In the field of architectural design, CA are capable of generating patterns or models that cannot be easily anticipated, and can suggest architectural forms. In many cases, the most important thing is the process: using the data generated by a CA, finding a pattern that will serve us, and knowing how to interpret and modify the results for use in architecture. The goal is not those results themselves, but what can be learned and inferred from the generation process.

The patterns generated by CA systems are appreciated in architectural design for their spatial qualities as well as for the often-surprising nature of their results, which allow designers to expand the scope of their imagination [36,37]. Design systems can be explained as a repetition of the process of generating and reducing potential proposals, in which designers alternatively seek inspiration and an analytical evaluation of the generated results. Kicinger et al. [38] wondered whether the advantages of generative representations result, in part, from human designers’ tendency to create design concepts using different heuristics that are gradually applied to individual parts of a building, a process that is at least partially imitated by the use of CA.

3. Studies

As mentioned in the introduction, we have classified studies by their application to different areas of conceptual design: design exploration, morphogenesis, building shape, ceiling form, façade design, layout design, and floor plans. A summary table can be found in the Appendix (Table 1).

3.1. Design exploration

Maher and Poon [39] stressed that the exploratory aspect of design has not been fully addressed, especially during conceptual design, since the assumption that designers have a clear idea of the problem and that the solution is not legitimate. Before starting design synthesis, designers often do not have a complete description of the problem. During conceptual design, they play with ideas to better understand the problem, rather than focusing on finding a solution. Therefore, the authors argued, design is an iterative process of searching for the space of the problem of the design as well as the space of the solution. To do so requires a computer model of exploration that can assist designers. The ability to change objectives, as well as the solution space, over time can be modeled as a co-evolutionary system, suggesting a formal exploration model, such as the interaction between problem space/functional requirements (P), and solution space (S) [39,40]. In exploration, P interacts and evolves over time with S, and the evolution of each space in the other space is guided by the more recent population. The basis of co-evolution is a genetic algorithm in which special attention is given to representing and applying the fitness function so that the definition of the problem can change in response to the current solution space.

Specifically, Maher and Poon proposed a Design Problem Exploration model that could be implemented with a modified genetic algorithm called CoGA1. This approach is novel in its interpretation of the skill function in which the design solution in the same genotype and alternative GA operations in different segments of the genotype allow for the co-evolution of requirements and design solutions. A second approach, called CoGA2, represents the problem of genotyping design in one space and designing solutions in a second space as genotypes. These spaces evolve in response to each other, each providing the fitness function for the other space. These algorithms alter the notion of searching on a fixed target to explore potential targets. The authors wondered whether a solution which meets more criteria is necessarily better than one that meets fewer overall, but *all* of the most relevant criteria. When a threshold value is used to determine a subsequent examination, it is necessary to decide whether the threshold should be a constant, and whether that threshold should evolve. A major problem with both CoGA1 and CoGA2 is that the criteria for suitability change over time, which excludes convergence possibilities. A condition of completion is needed to stop the evolutionary process. If convergence is not a prerequisite for ending the process, we must ask whether time is the only consideration, or whether we should include an objective function, and whether there is a guideline or general criterion indicating that an exploration process should end. A metric would need to be developed to determine a solution's "goodness," or "usefulness." In 1995, Maher and Poon [41] presented a study of this co-evolutionary approach to fitness function and design solution by defining fitness as part of the genotype using the CoGA1 system, testing the design of the reinforced frame panel, and asserting that the results show that interesting solutions arise from genetic cycles and that the design approach is distributed differently. The system does not approach design as an optimization, but as an exploration of the space for design.

Parmee [42,43] used an incorporated design concept in which different forms of evolutionary computing are employed at each stage of a design process and combined with the knowledge and intuition of the designer in the search and exploration process. The author distinguished three stages in the processes of the engineering design: conceptual design, sketch, and detailed design. The first process is a search for possible solutions through an undefined space, using fuzzy objective functions and vague concepts of the final solution structure. The representation of design helps to clarify the subsets that make up the system from the initial design configuration selected in the previous stage, considering quantitative and qualitative criteria. In the detailed design phase, decisions only consider *well-described* quantitative criteria. Parmee argued there are overlaps between the three stages to consider in an integrated design model.

Cvetkovic and Parmee designed a system that works with the designer during the conceptual design phase, prioritizing the designer's interaction and knowledge over precision [44]. The core of the system consists of a module based on genetic algorithms for multi-objective optimization, one for handling dynamic constraints, for handling fuzzy preferences, and the designer's input. The system was applied to a conceptual problem of British Aerospace (BAe) airframe design with 9 variables and 13 outputs. Optimization is a rather small part of the problem; more interesting is the ability to efficiently explore many different variants that the designer can evaluate. To help the designer, the system must be able to sustain the exploration of the design and at the same time suggest the best direction [45]. The authors concluded that, although designed for the BAe problem, the techniques used are generic, and could easily be applied to other conceptual design problems.

Gero and Kazakov [46] distinguished between routine and creative designs and used GA to expand the state space of potential designs as an aid in the conceptual design phase to achieve creative designs. Using Hamming distance as a measure of distance, they used the existing crossover of standard GAs and recast it as an interpolation in a possible design space. Then, through their isomorphic phenotype, they represented the genotype and generalized the interpolation. The result is an interpolation path, which is not necessarily within the space of possible designs defined in the initial problem formulation. Once this generalization is done, extrapolation may be added to the process to produce even more varied models.

Parmee et al. pointed out [47] that the combining flexible interaction and visualization capabilities with evolutionary computing power will provide invaluable support for decision making and knowledge discovery. On that basis, Packham [48] developed in 2003 an interactive visualization and grouping system that uses genetic algorithms, the Interactive and Visualization and Clustering Genetic Algorithm (IVCGA). The system enables the user to interact freely with specific areas of the search space and create new data with more GA runs.

Rafiq [49] applied the IVCGA system in 2005 to the design of an office building, considering architectural, industrial, and heat and ventilation requirements. Each team member can independently assess the suitability of the various alternatives, then overlap of the different solutions to recognize a mutually inclusive region that partially meets the requirements of all design disciplines involved. In 2008 Rafiq and Beck presented [50] a solution that used a version of IVCGA updated by Packham et al. [48,51] to incorporate designer interaction along with its visualization capabilities to show how IVCGA can be utilized in a collaborative multidisciplinary design environment.

Malkawi, Srinivasan, and Choudhary [52] developed a decision support model that uses GA as an evolutionary algorithm and Computational Fluid Dynamics (CFD) [53] as mechanism for assessment. In an attempt to stimulate the designer's creativity, the model is integrated with a visualization module that allows users to interact with and select specific instances as the design evolves. The procedure uses an iterative approach that allows for an automatic evaluation of designs using CFD analysis to maximize various thermal and ventilation criteria while allowing the user to experience the design transformation based on its performance. The process continues, and the designer finally has the opportunity to visualize the evolution of the final set of design alternatives. The automated process has the benefit of not being biased by the vision of the designer, and thus has the potential to create new configurations that might otherwise remain unknown.

Liu, Liu, and Duan presented [54] an approach based on the standard Particle Swarm Optimization (PSO) algorithm along with dynamic niche technology. Liu, Liu, and Duan's approach is also oriented toward the creative conceptual architectural design of ecologically designed homes. Its main concern is to maximize the solar gain in mainland China's northern latitudes, or minimize it in the tropics, while maintaining maximum surface area. All individuals, or particles, make up the search space. An individual in this structure consists of three parts: the total number of buildings in the area, the distribution pattern describing how the buildings are distributed, and information about the buildings. Each building has its own position, height, type, and other dimensions. Buildings' architectural areas are a function of their dimensions.

In 2010, Wen, Hong, and Xueqiang developed a computer-aided method for the design of architectural forms based on a fractal algorithm [9]. The authors stressed that fractals can be used in architecture for aesthetic purposes, and proposed an algorithm that generates fractal dust as the data of unorganized points. They improved the Power Crust algorithm [55] for the surface reconstruction process and applied a KD tree structure [56] in the separation of the inner and outer poles to speed up the search for the nearest neighbor and increase reconstruction efficiency. Despite these advances, the authors indicated that further study was still needed on how to treat sharp edges, sew boundaries, combine swarm and fractal intelligence, perform automatic and interactive assembly, and how to refine current visual software.

In 2015, Mueller and Ochsendorf [57] noted that designers must consider both quantitative performance targets and qualitative requirements in conceptual design. They proposed a computational approach to space exploration design that extends interactive evolutionary algorithms to include designer preferences, allowing them to set the evolutionary parameters of mutation rate and generation size, as well as parent selection, to drive space exploration design. The authors demonstrated the potential of their approach through a numerical parametric study in which they demonstrated that varying mutation rates and generation sizes give the user unprecedented control over the nature of design space exploration, enabling the prioritization of performance, qualitative preferences, diversity, or some desirable combination of those objectives. They also implemented software and a sequence of case studies in which they showed that multiple modes of exploration, including performance prioritization, are possible with their approach, as well as compromises that consider qualitative objectives (Figs. 1 and 2).

Other lines of research have focused on the creation of computer-aided design (CAD) tools through the use of evolutionary techniques. In 2001, Graham, Case, and Wood presented a system that creates objects that initially appear to be random [58], but may be subjected to a user-driven selective breeding program (also guided by predetermined factors, environmental or internal) to provide useful inspiration for the aesthetic and functional characteristics of the products. This resulted in an interactive tool that can help designers during the conceptual phase of aesthetic design, although the authors recognized that it is unrealistic to use the approach to develop a real product, except perhaps a sculpture. DeLanda believes, though, that deliberate design remains a crucial component of aesthetic design, and that these systems will only be useful if virtual evolution can be used to explore a space rich enough to prevent the designer from considering all possibilities in advance. He stated that, "Only if the results have an impact, or at least a surprise, can genetic algorithms be considered useful visualization tools" [59]. Further, he argued that the efficient use of genetic algorithms signifies the deployment of three forms of philosophical thinking first put together by Deleuze [60]—population-based, intensive and topological— establishing the basis for a new conception of the genesis of form.

Broadly, we can say that research focused on design exploration tries, in a general way, to expand the solution space, generating diverse models to help the designer, and does not seek a precise solution. We also find solutions that involve the interaction of the different profiles implicated in the design, creating decision aid models and iterative approaches, using different AI techniques, from GA to PSO, fractals and EA.

3.2. Morphogenesis

A trend in architecture is the construction of buildings inspired by natural forms; thus, as early as 1995, Frazer [61] tried to develop a theoretical basis employing analogies with the evolutionary processes and the morphogenesis of nature. Morphogenesis focuses on the upward logic of finding shape, highlighting performance over appearance [62]. Frazer defines his Reptilian System as a construction set capable of producing a wide range of structures from an initial "seed," a minimal construction that is manipulated through a series of processes and transformations that, if environmentally sensitive, results in forms that are also sensitive to their location. The generalization of this system implies the automatic configuration of the seed from the design requirements on which the solutions evolve (Fig. 3). The quantifiable and specific aspects of the design instructions define the formal criteria that

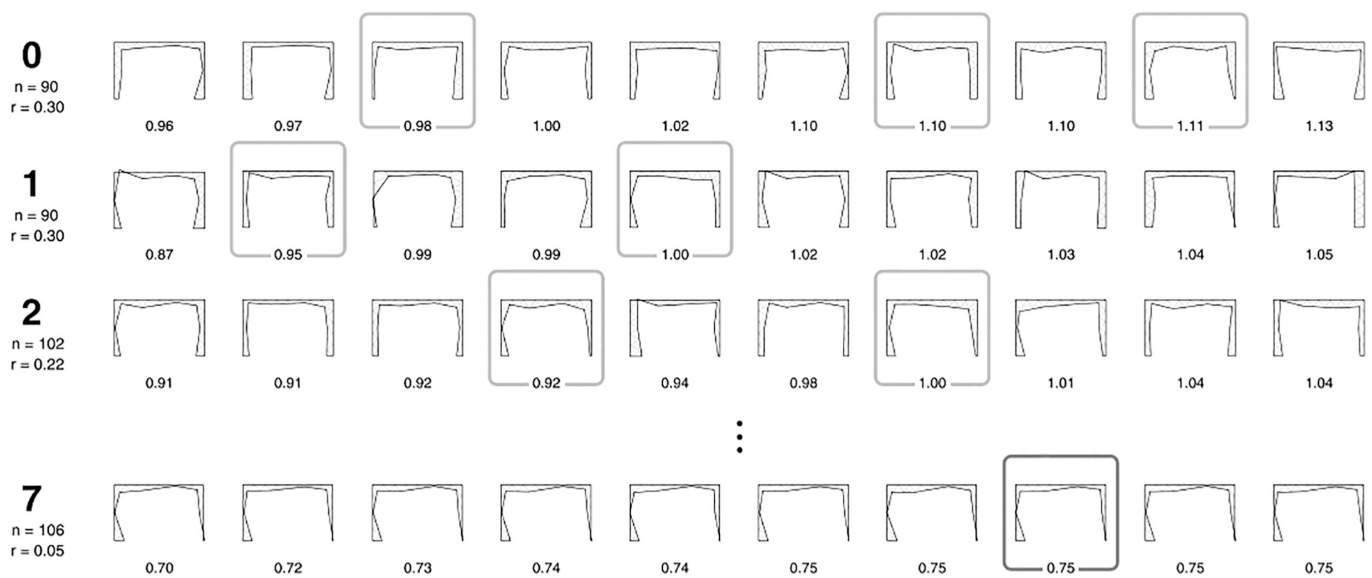

Fig. 1. Excerpt of eight successive generations for a hybrid exploration approach in which designs are selected by the user based on qualitative aesthetic characteristics and quantitative performance. Mueller and Ochsendorf, 2015.

Fig. 2. Two options for the design of the lateral and gravity structural system for an airport terminal: (left) a standard rigid frame and (right) a shaped rigid frame. The shaped frame uses a similar amount of material and creates a more architecturally expressive interior space. Mueller and Ochsendorf, 2015.

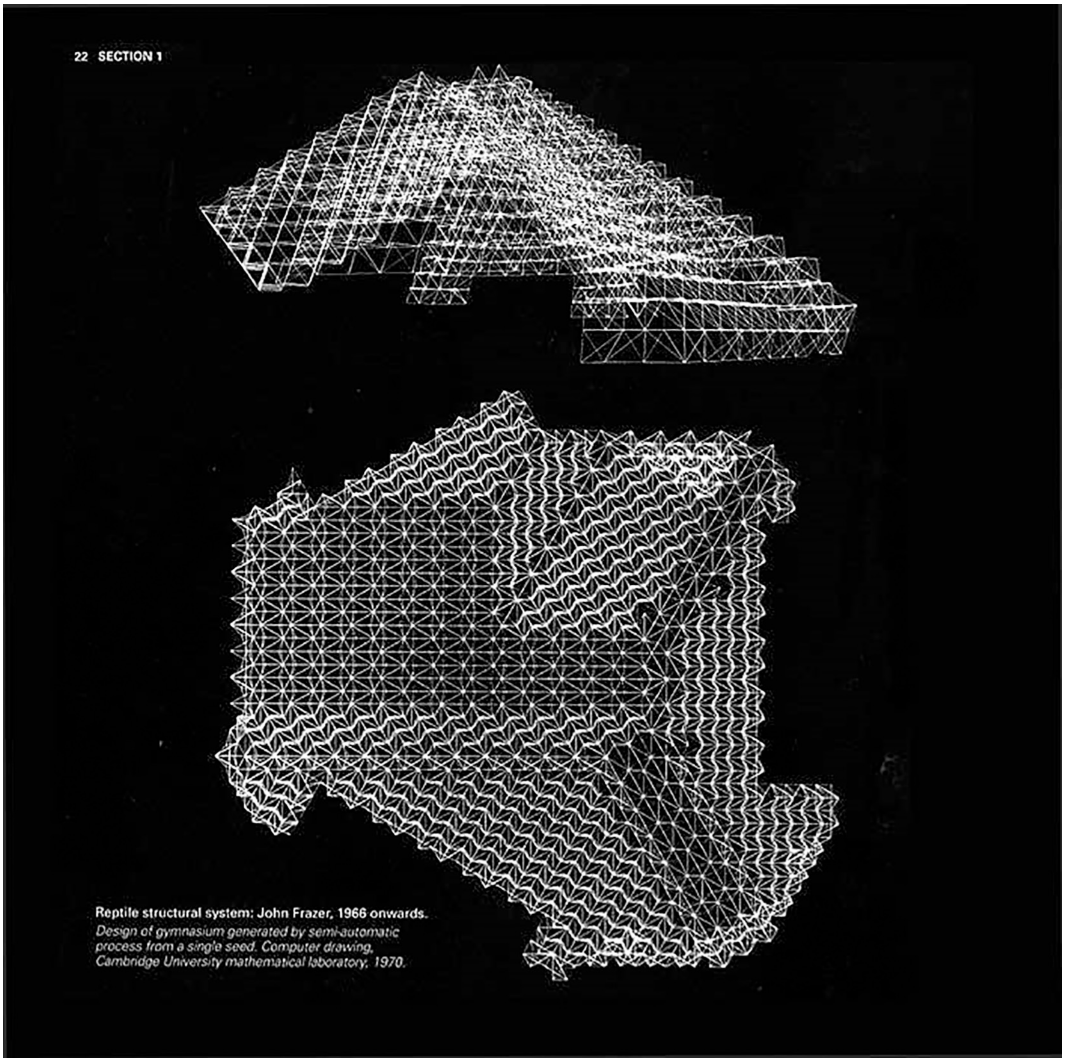

Fig. 3. Example of a design based on John Frazer's Reptile structural system, 1966.

are used as a standard suitability function. Non-quantifiable criteria, such as aesthetic judgments, will be evaluated by the person using the system, thus creating a personal assistant capable of adapting to various criteria, including aesthetic tastes, using previously successful strategies. This concept is similar to that of Negroponte's "Architecture Machine" [63], which proposed a system so personalized that it would be practically unusable by others.

In 1996, Coates et al. [36] presented a series of experiments based on a 3D CA that explored different sets of rules related to several morphological issues. In particular, they suggested a generative mechanism which would allow genetic structure to be accessed in any form and manipulated to increase the possibility of an emerging architectural result. Their aim was to develop a customizable CA engine with the ability to develop shapes within defined CAD environments under a wide range of state change rules, as a basis for a new type of architectural modeling (Fig. 4).

In the same year, Bentley designed an evolutionary system with the ability to evolve solid object designs from purely random beginnings, or from a combination of initial random and user-specified values, guided only by evaluation software during the evolutionary process [64]. Tested with fifteen design tasks, the system can discover solutions and offer conventional and non-conventional designs for all problems presented to it. The less limited the problem, the wider the variety of alternative, even unusual, design solutions that the system evolves, although it should be noted that it cannot accurately represent curved surfaces. The author proposed the improvement of these representations by the addition of non-homogeneous materials or the inclusion of a variable of density and characteristics related to the surface appearance of the designs (such as colors and textures). Bentley noted that the type of real-world design applications best suited for his system will be those that do not have very limited solutions, such as aerodynamic and hydrodynamic shapes. Alternatively, the method could be applied to solve design problems for factories, oil rigs, or shops, using primitives to define individual rooms or walls between rooms. In 1999, Bentley presented [65,66] a prototype design system using a genetic algorithm to develop new conceptual designs without preliminary design input that emphasized the evolution of creative design concepts rather than their optimization. A set of tasks considered "difficult" for a genetic algorithm was tested on the system: the design of optical prisms. Bentley demonstrated that the system can successfully create numerous types of prisms, either by performing the entire design process itself, or by assembling new designs from smaller, pre-developed components.

Some years later, Funes and Pollack presented an evolutionary building system based on Lego pieces as modular components [67]. Instead of incorporating an expert engineering knowledge system into the program, which the authors believed would result in familiar structures, they provided the algorithm with a physical reality model and a purely utilitarian fitness function. Thus, they provided functionality and viability measures and developed the evolutionary system in a not unnecessarily limited environment, to which they added a

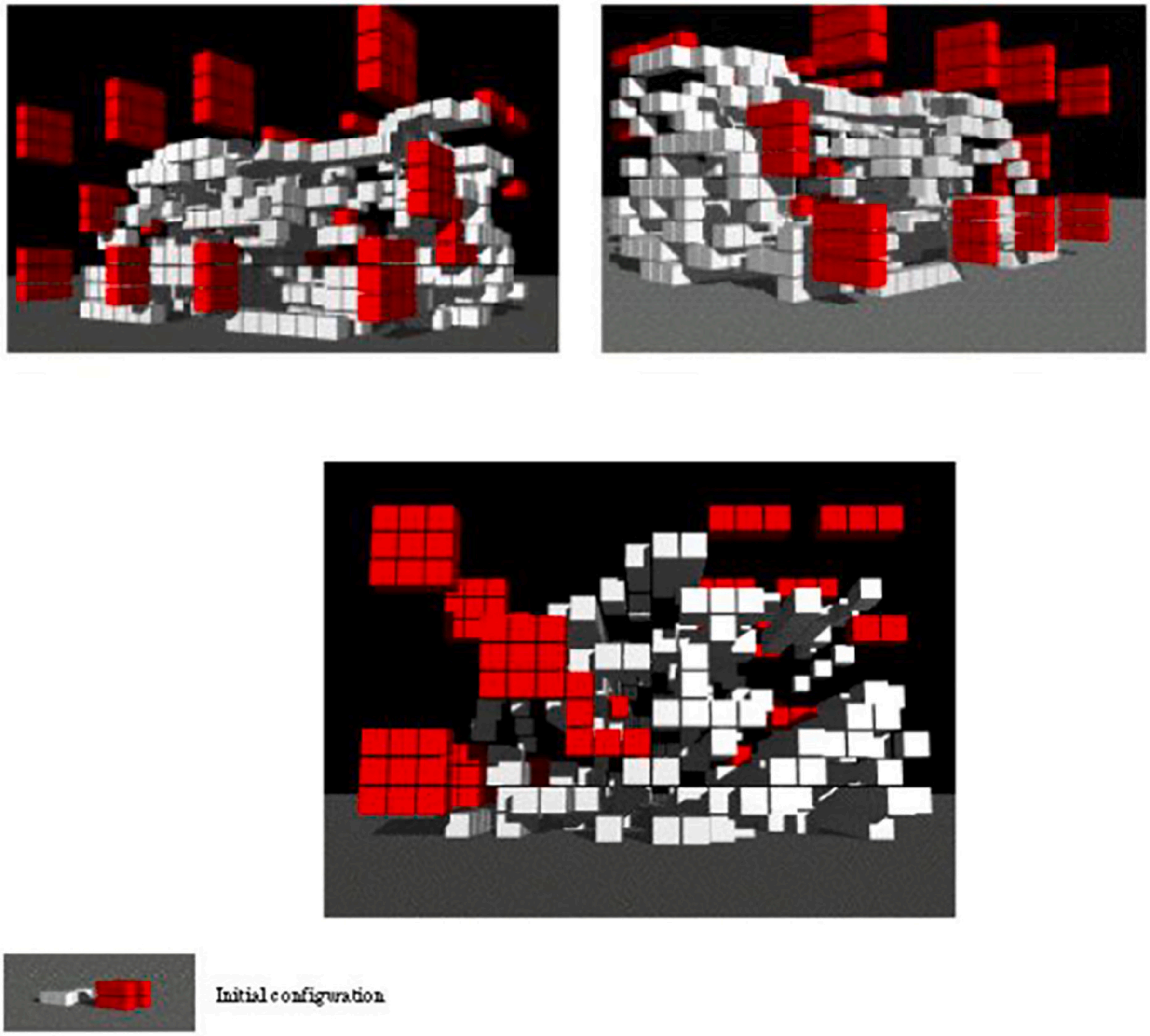

Fig. 4. Multistate automata after ten iterations with counting and voting rules. Coates et al., 1996.

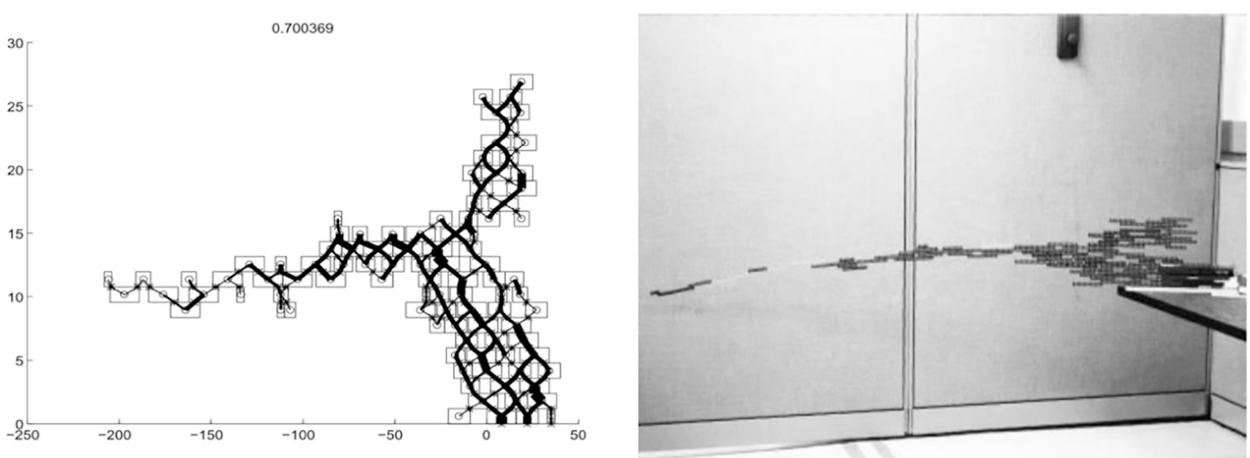

Fig. 5. Scheme evolved for the 'Long Bridge' experiment and the Lego Long Bridge. Funes and Pollack, 1999.

computability requirement to reject overly complex structures. The evolved structures were far from the common knowledge of how to build with bricks, and the authors provided images of the manually assembled designs to confirm that they met the objectives introduced in the proficiency functions (Fig. 5).

In 2002, Krawczyk [68] described the process of generating architectural forms with CA: use raw data from a generative method, find a pattern, and then define methods in interpreting that pattern. According

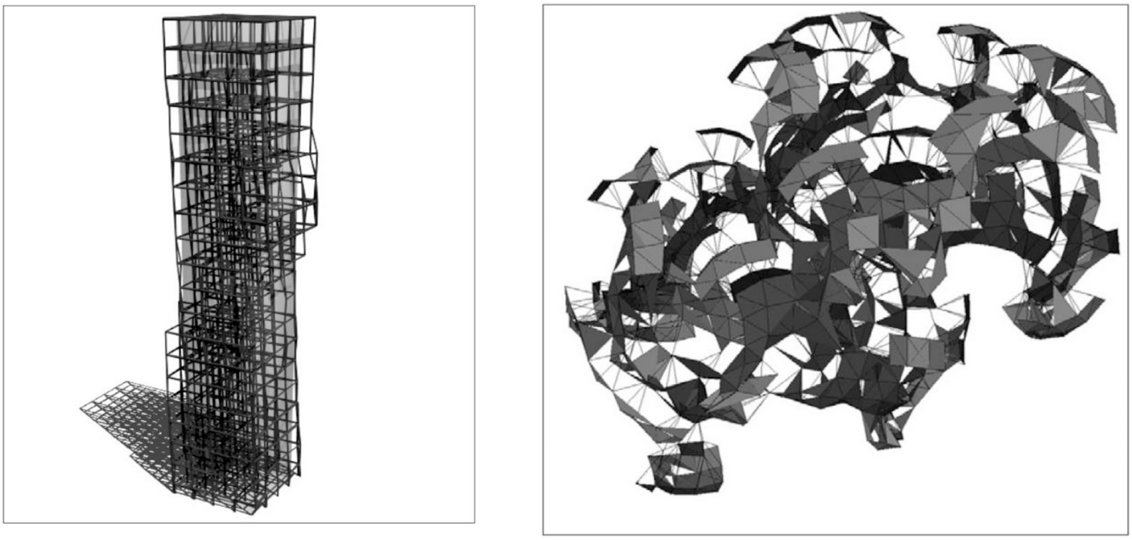

Fig. 6. Tower generated with an architectural design algorithm based on Conway's Game of Life (left) and Structure generated within a landscape using a design algorithm based on Conway's Game of Life (right). Anzalone and Clarke, 2003.

to the author, studying and developing all considerations thus identified forms the basis for a better understanding of the design phase itself, and the final results are not the goal—rather, it is the process that is important.

In the same year, Jackson [69] analyzed the use of genetic programming and the representation of the L-system [70]—created as a method for modeling plant development—within the sphere of generative architectural design, and proposed a model for describing architectural forms as a set of symbiotic relationships. The author presented examples of successful evolution using a single function of fitness.

In 2003, Anzalone and Clarke [71] investigated methods for addressing architectural design and manufacturing using complex adaptive systems. They presented experiments that translated the behavior of a one-dimensional cellular automata system [72] into architectural design, as well as an adaptation of Conway's Game of Life [73] (Fig. 6).

In 2007, Herr and Kvan [74] presented an investigation into the processes of generative architectural design using cellular automated systems with a high level of human engagement. In these processes, different options were explored to modify and expand traditional cellular automata systems to support searches for architectural forms. The authors asked: where does the development of a design promise desirable results from a practical point of view, during which periods of the process and in which functions do cellular automata? In response, they presented a theoretical framework for integrating CA into the design process and implementing a dialog-based model, and evaluated its performance by remodeling an existing project for architectural design. Following Schön's proposal [75], which modeled the design process as a chat between a designer and a particular design situation, the authors relied on the potential to investigate generative dialog-based design processes instead of being fully automated and operating in accordance with predefined rules. However, the responsiveness of a design process, maintaining a constant feedback loop with the designer, is essential in Schön's description of the design process.

Assessment within CA systems is generally based on rules of local interaction which yield emerging results. Making assessment

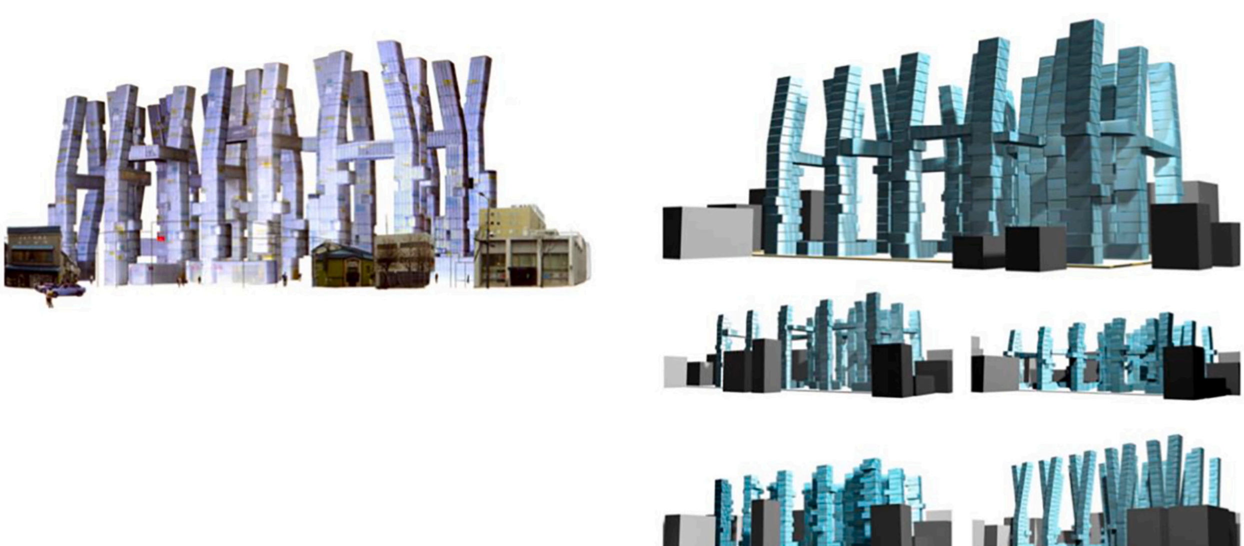

Fig. 7. High-density architecture for Aomori/Japan by Cero9 (left) and Alternative versions of the Cero9 design generated by cellular automatons. Herr and Kvan, 2007.

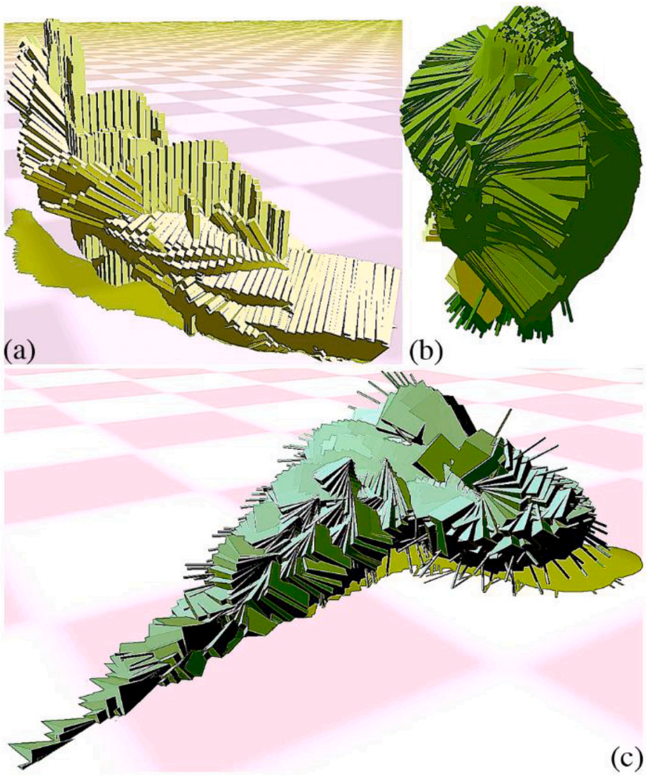

Fig. 8. Examples of evolutionary design of swarms of architectural ideas. Von Mammen, 2008.

mechanisms more flexible, in addition to pre-established local rules, Herr and Kvan proposed that CA be integrated into an interactive design process which involves the designer more closely. The integrated system utilizes CA in its capacity to generate variance and adds the ability of the designer to assess and control overall development. This allows the generative methodology to be controlled and directed according to the evaluation of intermediate outcomes by the designer, rather than at the end of a fully automated generational sequence.

Boden [76] explained in 2004 the potential spaces of the solution as conceptual spaces to a design problem, where the designer navigates through a sequence of decisions until he obtains a suitable result. Effective navigation in design solution spaces requires iteration and the possibility of going back to previous decisions to choose an alternative decision from a previous stage. CA, however, are irreversible systems in the sense that certain states do not allow the reconstruction of previous states. Therefore, a CA system for a dialog-based solution space exploration would require records of its preceding states. Modular software tools seemed to Boden to be the most appropriate, and in the model proposed in the design process, CA support consists of various customizable options that can be adapted through a series of variables to suit the design context.

To show the generative potential of the proposed process in an appropriate design context, Herr and Kvan decided to reshape an architectural design consisting of a group of buildings proposed as a high-density development in northern Japan (see Fig. 7).

Von Mammen and Jacob investigated the applications of evolutionary swarm models and, in 2008, presented an extended swarm grammar model [77,78] to create 3D structures that fit models of architectural ideas. They avoided structural and computational growth by rewarding approximation of a predefined form and rapid computation to guide the evolutionary search. Diversity, productivity, and collaboration are encouraged by counting construction and reproduction events and neighborhood perceptions measurement. The authors concluded that the evolutionary design of swarms of architectural ideas works as a model but that for this technology to be applicable by architects, it must be tailored to their needs. To do so will require stronger construction constraints and an interactive way of promoting the development of compelling designs (Fig. 8).

In 2014, Lin and Gerber [32,79] presented a multidisciplinary design optimization (MDO) framework that they called "Evolutionary Energy Performance Feedback for Design" (EEPFD). It provides information on energy performance as feedback to support early design decision-making, providing rapid iteration with performance feedback through parameterization, automation and multi-target optimization. Yang and Bouchlaghem had already studied the applicability of a multidisciplinary design optimization (MDO) methodology for the design of buildings as early as 2010 [80], developing a collaborative optimization framework based on a Pareto genetic algorithm (PGACO) to sustain interactions among various tasks and coordinate conflicting design goals, though this had been tested only with a mathematical example. In this case, Lin and Gerber presented effective applications of PGACOs for architectural design (Fig. 9) and concluded that the system allows architects to make decisions more smoothly and earlier than other existing approaches.

In 2016, Herr and Ford [81] analyzed the use of adaptation processes in CA as design tools, focusing on the translation of CA's specific characteristics into constraints, opportunities, and adaptations to fit the requirements of architectural design. Among these adjustments and modifications are alterations in CA rules, changes in cell shapes, consideration of the context of the site, adaptation to specific architectural scales, interpretation of results in an abstract way to obtain more architectural options, and, finally, conceptualization of CA systems not

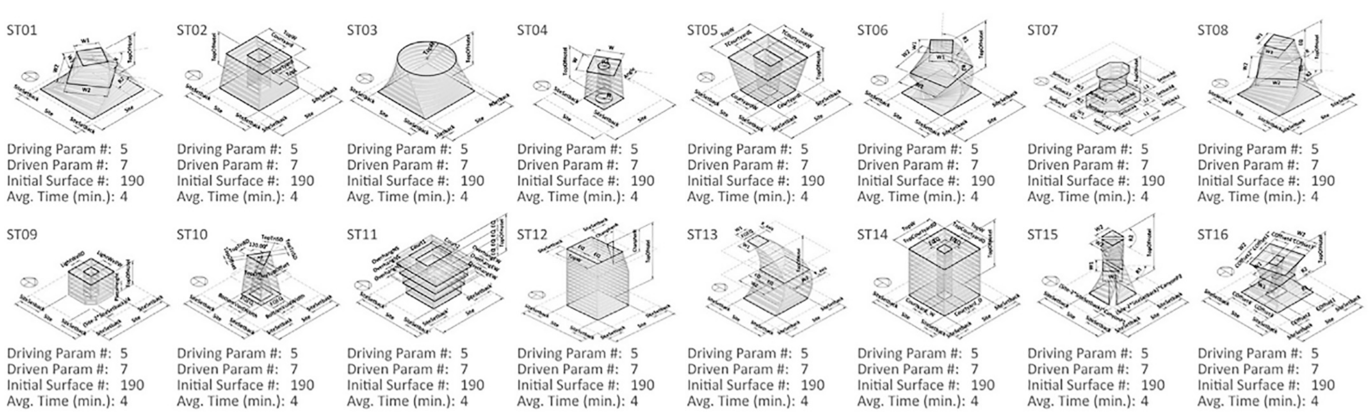

Fig. 9. Illustrated diversity among participants' parameterization/problem formulation for the same design problem. Summary of participants' parametric designs with the comparison of design parameter problem scale, coupling, and geometric complexity. Lin and Gerber, 2014.

Fig. 10. Generating and interpreting architectural results in a conversational generative design process. Herr and Ford, 2016.

as autonomous deterministic systems, but as non-deterministic design tools.

Herr and Ford suggested a case study involving the design of a hotel residence for engineers and scientists working on the European Extremely Large Telescope (E-ELT) located in the Atacama Desert of Chile. Ford responded with an initial methodological proposal to create a CA machine which would adopt architecturally appropriate rules. These rules would generate forms which can then be subjected to detailed architectural examination and intervention (Fig. 10). The designer's role was defined as a shared collaborative and evaluative role alongside the CA system.

Ford sought to focus the generative potential of CA systems, which is not solely predetermined and controlled by the goals of architects, and stressed that the opportunity to achieve results beyond the goals and intentions of architects allows the expansion of their imagination, which will help develop innovative solutions for some design tasks. The surprising elements that appear in CA-based generative processes are generally appreciated. However, at the same time, strong limitations are imposed, since the results often do not respond directly to the task of design. These reviewers believe this can be described as the central challenge of employing CA as generative architectural design tools. Responses to this challenge can be varied, and adapt CA systems or the form in which they are used. These adaptations in the field of research on CA applications to architectural design have not yet been systematically appreciated and addressed, thus preventing continuous learning and exchange between different projects.

Pazos [14] used artificial intelligence techniques to model artificial objects through a morphogenesis process, to make them realistic, creating complexity and diversity to achieve imperfections such as those found in natural objects, and subjected his system to various tests of 3D modeling of complex geometries, including the design of the façade of a skyscraper (Fig. 11).

3.3. Building shape

In 2006, Wang, Rivard, and Zmeureanu [82] proposed a methodology for optimizing the shapes of buildings in the plan using genetic algorithms. Their goal was the design of ecological buildings, with the footprint of a building defined as a simple polygon and the cost of the building's life cycle and its impact on the environment were assessed. The authors presented a case study in which a multi-targeted genetic algorithm optimized the shape of a typical floor of an office building defined by a pentagon (Fig. 12).

Seeking to optimize the shape and characteristics of a building envelope, Tuhus-Dubrow and Krarti [83] developed and applied a simulation-optimization tool in 2010. Their tool combines a genetic algorithm with a simulation engine for building energy to select optimal values for a complete list of building envelope related parameters to

Fig. 11. Tower design resembling the Beekman Tower generated by a GA and rendered in Vray. Pazos, 2017.

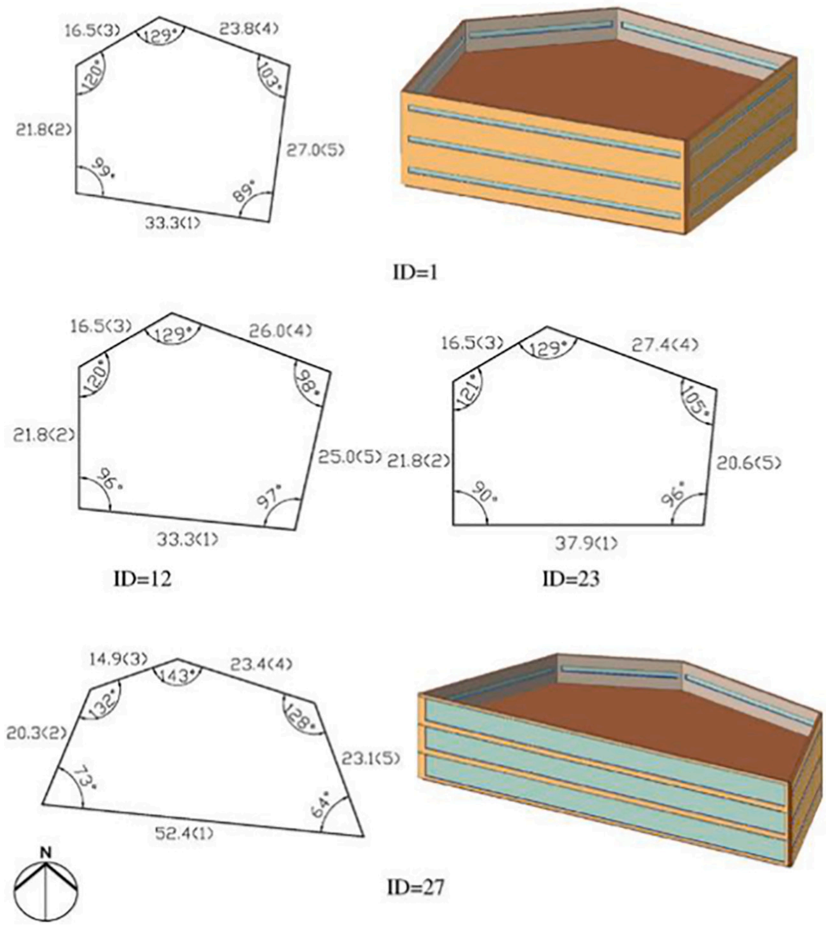

Fig. 12. Building footprints of selected solutions from the global Pareto set. Wang, Rivard and Zmeureanu, 2006.

minimize energy use in residential buildings. As part of the envelope optimization, they investigated different building shapes, including cross, L, T, U, H, trapezoid, and rectangle. The optimization results were applied to a residential building with a Building America Benchmark; the results indicated that the optimal shapes were consistently the rectangle and trapezoid.

Li [84] argued in 2012 that when designers attempt to optimize design problems with the help of a GA, facing the inherent complexities of architectural designs, they must convert specific problems into combinatorial or numerical problems that can be addressed by the GA. Further, the expansion of the search space can be seen as a strong test of the search capacity of the GA.

Li exemplified the optimization of architectural designs aided by the GA with optimization of the modeling for the schematic design of the former Ruins Museum of the South Gate of Yangzhou City. The optimization sought to reduce the number of critical points of the frame, adjusting the relative positions and angles of the textures projected in the unfolded form and the position of the frame apex. The author concluded that, optimization is difficult to achieve for two optimization problems that are embedded in each other. Further, where optimization efficiency is assessed or optimal solution is needed, GAs are not a suitable option, although they can provide architects with diverse and roughly optimal solutions as references. Similar work can be found in the GA method for producing structurally optimal spatial frames triangulated in Delaunay for Papapavlou's dynamic loads [85].

In 2011, Caldas presented GENE-ARCH [86], a generative design system combining Pareto GAs and an energy simulation engine. The system, integrated with a grammar of forms, was applied to the design of Islamic patio houses. The resulting program was able to generate new, more energy-efficient alternative designs, in accordance with the traditional rules captured from the analysis of existing houses.

In 2014, Jin and Jeong proposed a process for optimizing the shape of a free-form building based on GA, using a model to predict the thermal load of the envelope as an objective function [87]. According to the authors, the variation in thermal load characteristics caused by the shape of the building can be quickly predicted and optimized in the initial design phase using the Rhino and Grasshopper software. They tested the proposed process by deriving the optimized form of the construction model for different climatic zones (Fig. 13) and concluded that the effect of GA-based shape optimization on the improvement of free-form building thermal performance was greater in low-latitude regions than in high-latitude regions.

In 2014, Dincer [88] presented a decision support tool that combines the right of choice and standardization in the production of collective housing designs, taking into account user preferences in the early stages of design. The system also includes a "Reflection in Action" protocol and CA. The protocol provides the user/designer with the opportunity to participate in the process using fragmentation and feedback, and also aims to reduce the impact of CA as independent and uncontrolled relationships. This computer model for decision support covers the stages of site and space planning and façade solutions. Dincer experimented with an implementation in the Karabuk-Yenişehir region in Turkey, where sample plans for housing blocks were generated using different parameters: landscape direction, altitude, determination of construction heights for special areas, definition of the area used for socialization, etc. Different placement orientations were collected after each generation (Fig. 14). In the second stage, one of the housing blocks was chosen for space planning, generating several alternatives for each floor using small

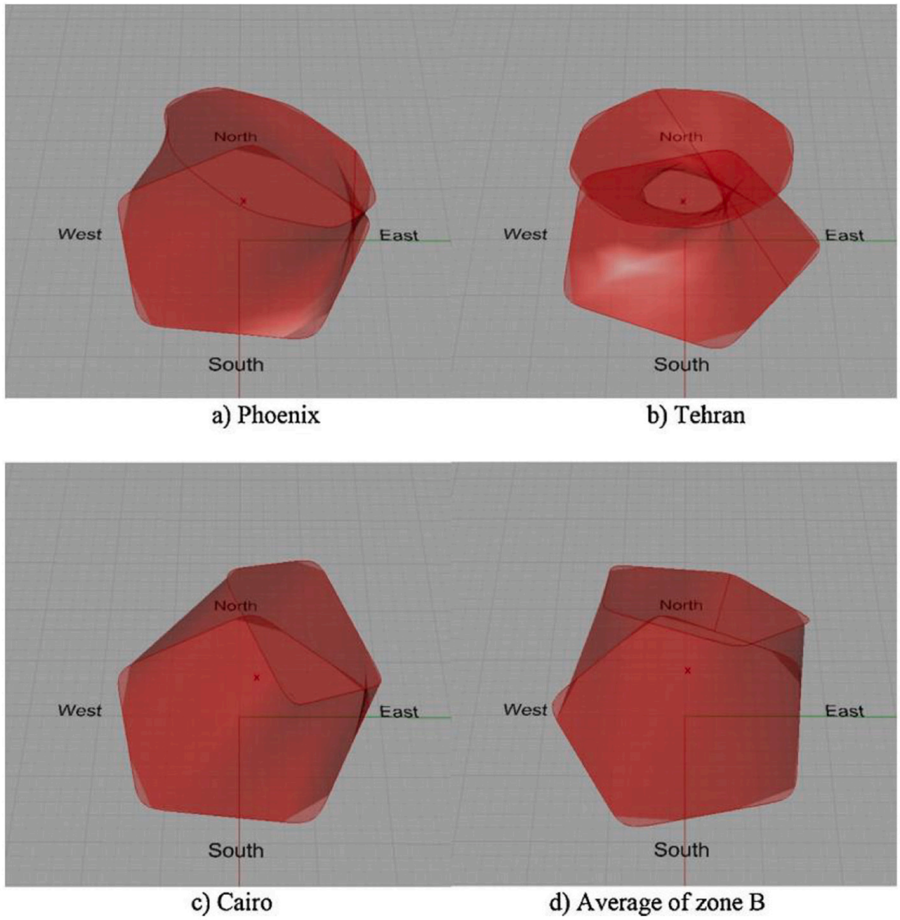

Fig. 13. Optimal shape for climate zone B (Arid): (a) Phoenix, (b) Tehran, (c) Cairo, (d) Average of zone B. Jin, 2014.

changes of parameters, such as the starting direction for the generation and prioritization of the housing types. Finally, samples of the orientation of the façades were generated (Fig. 15). The author reported that the results of design processes are much better and more useful when the mutual relations between the human designer and the generative tools are constructed and positively evaluated.

With a similar objective, in 2015 Araghi and Stouffs [89] presented an investigation into the integration of CAs in the architectural design process, in particular in the design of high-density residential building forms. They addressed accessibility and lighting needs while creating a 3D architectural design for a residential project in the Netherlands (Fig. 16). The mechanism of this generative process contains two steps: first, developing visual descriptions of the architectural requirements, and second, transcribing those descriptions into an algorithmic language and CA rules. In design, CA rules perform analysis and synthesis simultaneously.

Yi and Kim [90] also proposed a method for optimizing access to direct sunlight in a building that allows for varied design possibilities for the layout of high-rise apartment buildings by exploring two models: a non-uniform rational B-spline (NURBS) and a GA model. Korean building codes set the minimum number of hours of direct sunlight that residential buildings should receive, and to meet that requirement, apartment buildings should be separated from neighboring buildings or other structures by certain distances. In Yi and Kim's proposal, an initial random population that sets up the initial design of the apartment building is generated in the NURBS geometry modeling CAD tool. A simulation tool evaluates geometric information (building layout) in the CAD model to determine if each measuring point meets the target (two hours of direct sunlight on the winter solstice). If the geometry fails to meet the target, the next generation is created to change the layout of the building from its original geometry. The simulation tool analyzes this new geometry for changes in the hours of sunlight the building receives, and the result is passed on to the target function. The best building design at this stage will influence the next generation of GA and alternative building designs will be produced until a design solution is found or until a predefined number of generations has been reached. The case studies presented by the authors (see Fig. 17) show that the domain of solutions for the test is large enough to provide multiple viable solutions, although they do not take into account other factors such as the surrounding views or buildings.

In 2016, Ekici, Chatzikonstantinou, Sariyildiz, Tasgetiren, and Pan [91] presented a self-adaptive and multi-target differential evolution algorithm for solving the shape problem found during the conceptual phase in the design of high-rise buildings. Two different optimization algorithms were developed by the authors to achieve Pareto fronts with diversified non-dominated solutions: a Non-Dominated Genetic Classification Algorithm II (NSGA-II) and a self-adaptive Differential Evolution Algorithm (jDE). Their results showed a much more desirable Pareto front is generated by the jDE algorithm.

Konis, Gamas and Kensek proposed a Passive Performance Optimization Framework (PPOF) [92] that can optimize building geometry, orientation, fence configurations, and other building parameters in response to program requirements, site-specific adjacent buildings, and climate-based daylighting and full-building energy use performance metrics. In doing so, it can improve daylight performance, solar control and daylight ventilation strategies in early architectural project design phases. The authors tested the applicability of simulation-based parametric modeling workflow by comparing their results to a reference

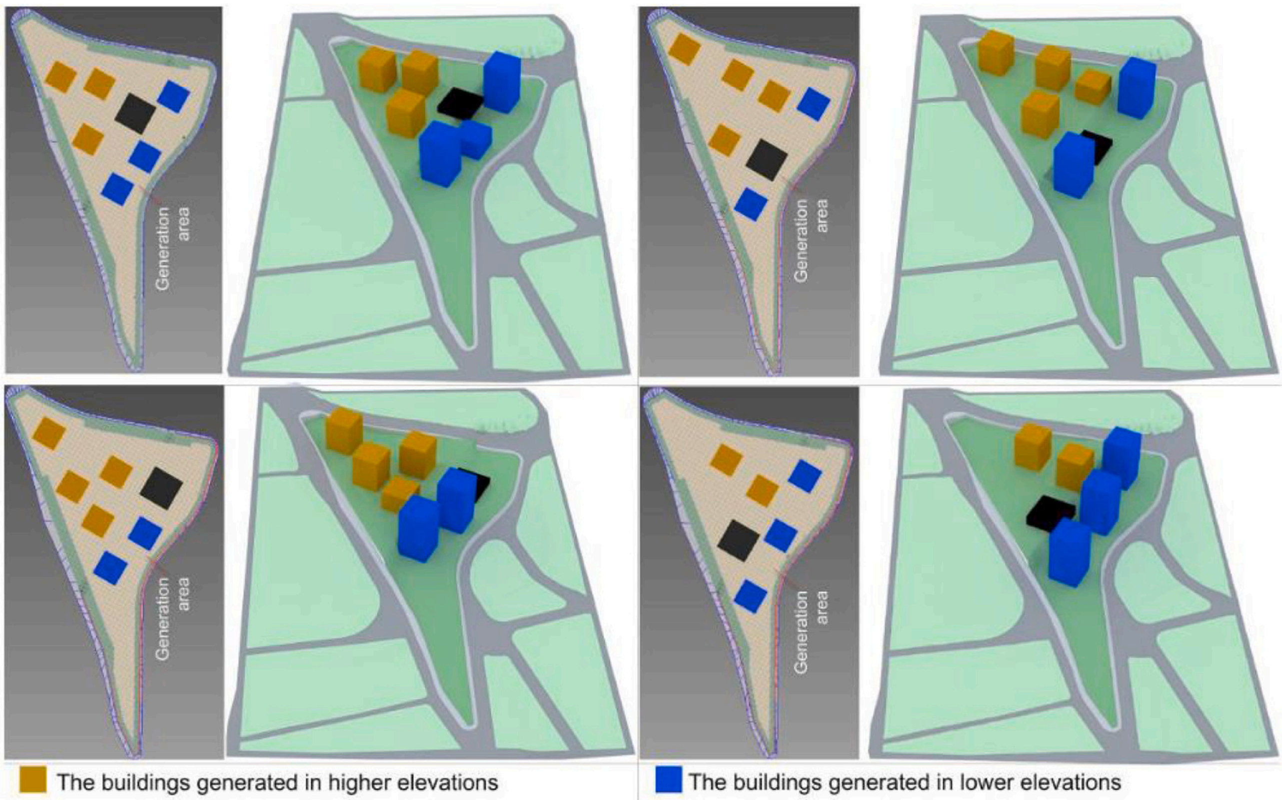

Fig. 14. Site plan implementations for Karabuk-Yenişehir. Dincer, 2014.

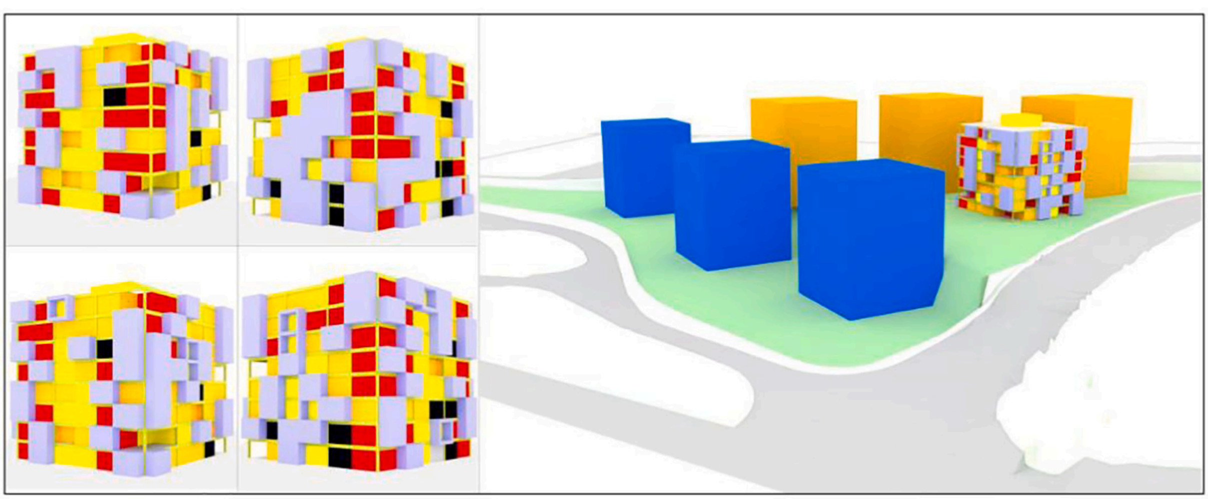

Fig. 15. Views of a chosen block along with its floor plan solutions and facade orientations. Dincer, 2014.

model, ASHRAE 90.1, in four different climates and urban sites (Los Angeles, Helsinki, Mexico City and New York City). They incorporated the actual urban context of each site for testing (Fig. 18). They concluded that PPOF and simulation-based workflow help to make generative modeling more accessible to designers working on regular projects and schedules to create high-performance buildings.

In the same year, Song, Ghaboussi, and Kwon [1] proposed the use of an Implicit Redundant Representation Genetic Algorithm (IRRGA) for an evolutionary architectural design method and applied it to the design of apartment buildings. They suggested a new representation for the design, in which building consists of the number of apartment units and in which each unit is defined by a staircase and an apartment space, so that the size and number of apartment units with staircases are not fixed and may be modified during the design process. The apartment units can be located anywhere in the three-dimensional space in this representation, allowing for greater flexibility during the evolution from a simple base unit to a creative building design. The process of assessing suitability is selectively applied in terms of symmetry, structure, circulation, and façade, and each objective is used as a function of suitability to demonstrate system performance. Each skill function reflects the extent to which an apartment building possesses the characteristics specified. Finally, a multi-target skill function is applied, and the resulting apartment building designs demonstrate their creativity level (Fig. 19).

Zhang, Zhang and Wang [93] designed a free-form construction

Fig. 16. Example of integration of CAs in the design of architecture of high-density buildings: residential project in the Netherlands. Araghi and Stouffs, 2015.

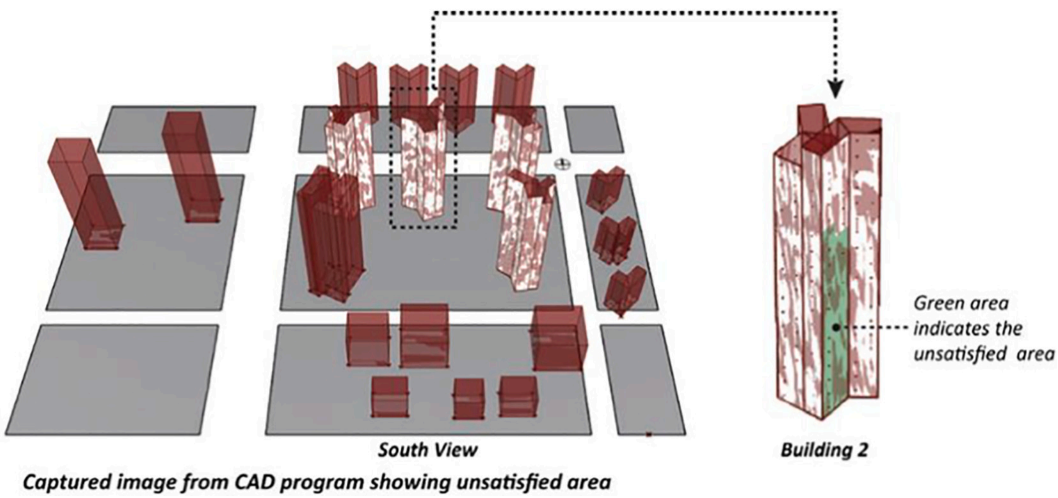

Fig. 17. Image captured from the CAD tool which indicates the unsatisfied area of sunlight access for the base case. Yi and Kim, 2015.

method which receives more solar radiation by optimizing the shape, taking into account the shape coefficient and the space efficiency. Their work provides a method with a "Modeling-Simulation-Optimization" framework, in which parametric modeling with Rhinoceros and Grasshopper is used to build the free-form building model, and optimization of the building shape is processed using a multi-objective genetic algorithm to ensure that three objectives are achieved: maximizing space efficiency, maximizing solar radiation gain, and minimizing the shape coefficient. Finally, a Pareto frontier is created to demonstrate the optimal solutions and help designers make final decisions. Their case study showed that the total solar gain from the optimized free-form building was between 30 and 53% higher than the reference cube-shaped building, and the shape coefficient value was reduced by 15 to 20%, with a decrease in the space efficiency values of less than 5%.

In 2019, Fang and Cho [94] suggested a process that uses parametric design, genetic algorithms and building simulation to explore alternatives to building design automatically, assess daylighting and energy performance simultaneously, and find design options with optimum performance. A case study of a small office building that they optimized for hot, mixed, and cold climates (Miami, Atlanta, and Chicago) tested the applicability and effectiveness of this approach. The authors concluded that design solutions with significant performance improvements can be found with this method, and their results show that the skylight width and length of the analyzed variables are the most important factors for all locations. The authors of this review believe it will be necessary to further expand the optimization objectives and to perform further testing of the process optimization for more complex design projects to confirm its effectiveness more generally.

In the same year, Cubukcuoglu, Ekici, Tasgetiren, and Sariyildiz presented OPTIMUS [95], a self-adaptive differential evolution algorithm with a set of mutation strategies (jEDE) for Grasshopper algorithmic modeling in the Rhinoceros CAD program. The experimental results showed that Optimus (jEDE) outperforms other optimization tools such as Galapagos (genetic algorithm), SilverEye (particle swarm optimization), and Opossum (RbfOpt), achieving better results for 19 of the 20 proposed problems. The authors noted that OPTIMUS can be extended for multi-target optimization problems due to its modular system.

Si, Wang, Yao, Shi, Jin, and Zhou [96] applied the building performance optimization (BPO) method to the conceptual design phase of a newly built tourist complex to improve energy efficiency and indoor thermal comfort, the two design goals of greatest interest to the project's designers. Some variables, such as the shape of the building's eaves, were optimized using an artificial neural network model designed to reduce calculation time. They evaluated the performance of four commonly used multi-objective optimization algorithms—NSGA-II, MOPSO, MOSA, and ES—using the performance assessment criteria proposed to select the best algorithm and parameter values for

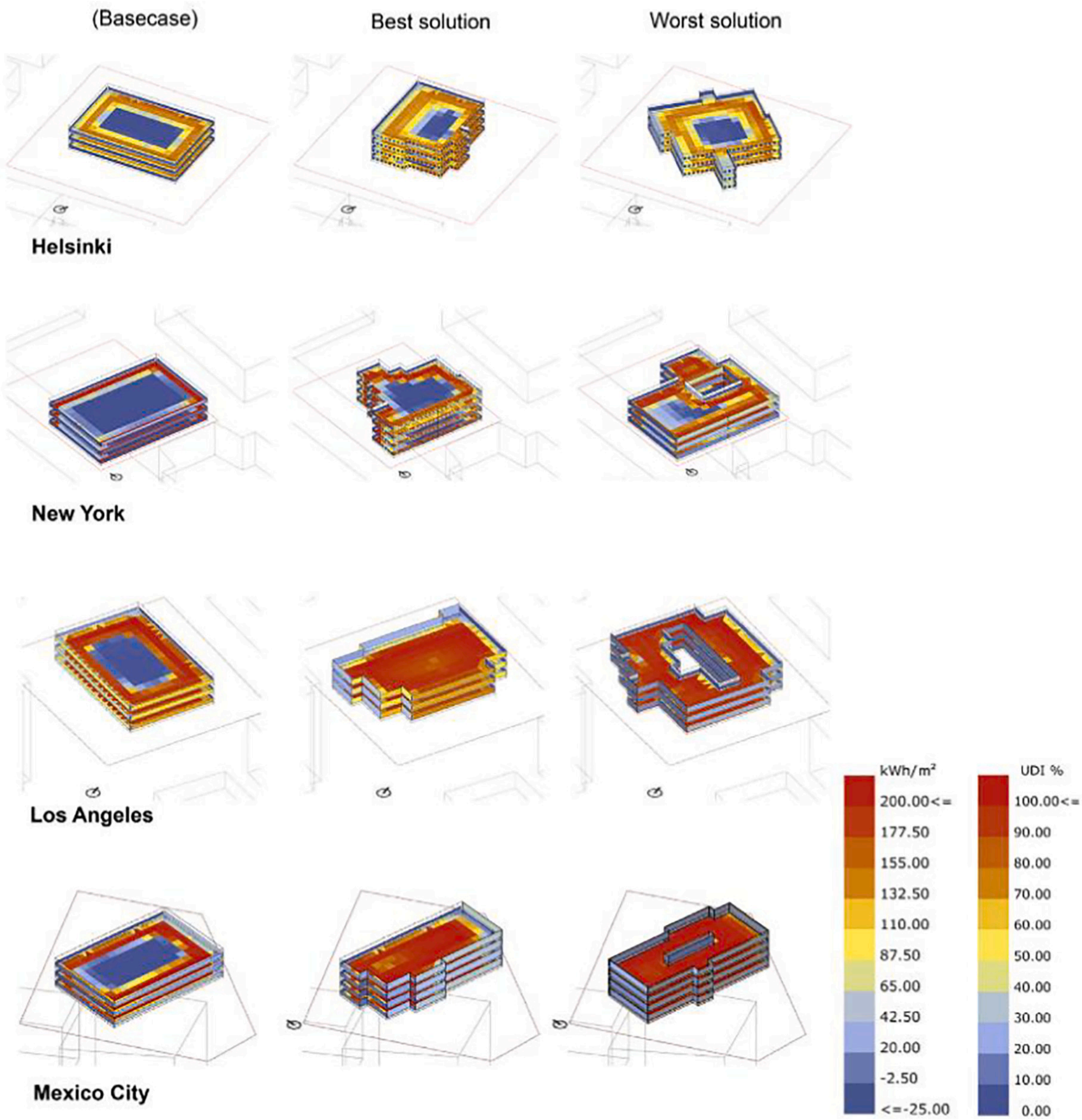

Fig. 18. Parametric building models generated by the PPOF leading to the best (center column) and worst (right column) performance outcomes for each of four climate-based scenarios. The base case model for each scenario is shown in the left column. Konis, 2016.

population size and number of generations. The results indicated that NSGA-II performs better in all aspects assessed. The authors stated that the optimal end solution significantly improves the performance of the building, demonstrating the success of the BPO technique in solving complex construction design problems. They also noted that the results of the algorithm's performance evaluation guide users to select appropriate algorithms and configure parameters according to the most important performance criteria (Fig. 20).

3.4. Ceiling form

In 2007, Pugnale and Sassone [97] described a method for morphogenesis and structural optimization of a reinforced concrete roof based on the application of a genetic algorithm. They performed a case study of the Kakamigahara crematorium in Gifu (Japan), designed by Toyo Ito with Mutsuro Sasaki. The shape of the reinforced concrete roof is free in plan, with a set of support columns placed randomly at ground level. The use of a NURBS (Non-Uniform Rational B-Spline) representation of the roof allows the shape to be modified by changing the position of the control points or by interpolating points, so that the coordinates of these points can be assumed as design variables. The optimization improved the structural behavior about tenfold in 75 generations by selectively modifying the parts of the structure with the worst behavior.

In 2011, Gaspar-Cunha, Loyens and van Hattum [98] tested a computational method of iterative design optimization that combines multi-objective evolutionary algorithms (MOEA) in conjunction with decision-making methodology and critical decision-making interaction (DM) to optimize the "generic" roof structure under natural light conditions, minimizing the surface area, and thus the weight and materials used.

In the same year, Rakha and Nassar [99] investigated the geometry of the ceiling as an element capable of controlling natural light by reflecting and diffusing light in the components and presenting architects with a generic optimization procedure to help generate and find forms of curved and meshed ceilings. The authors found an optimal

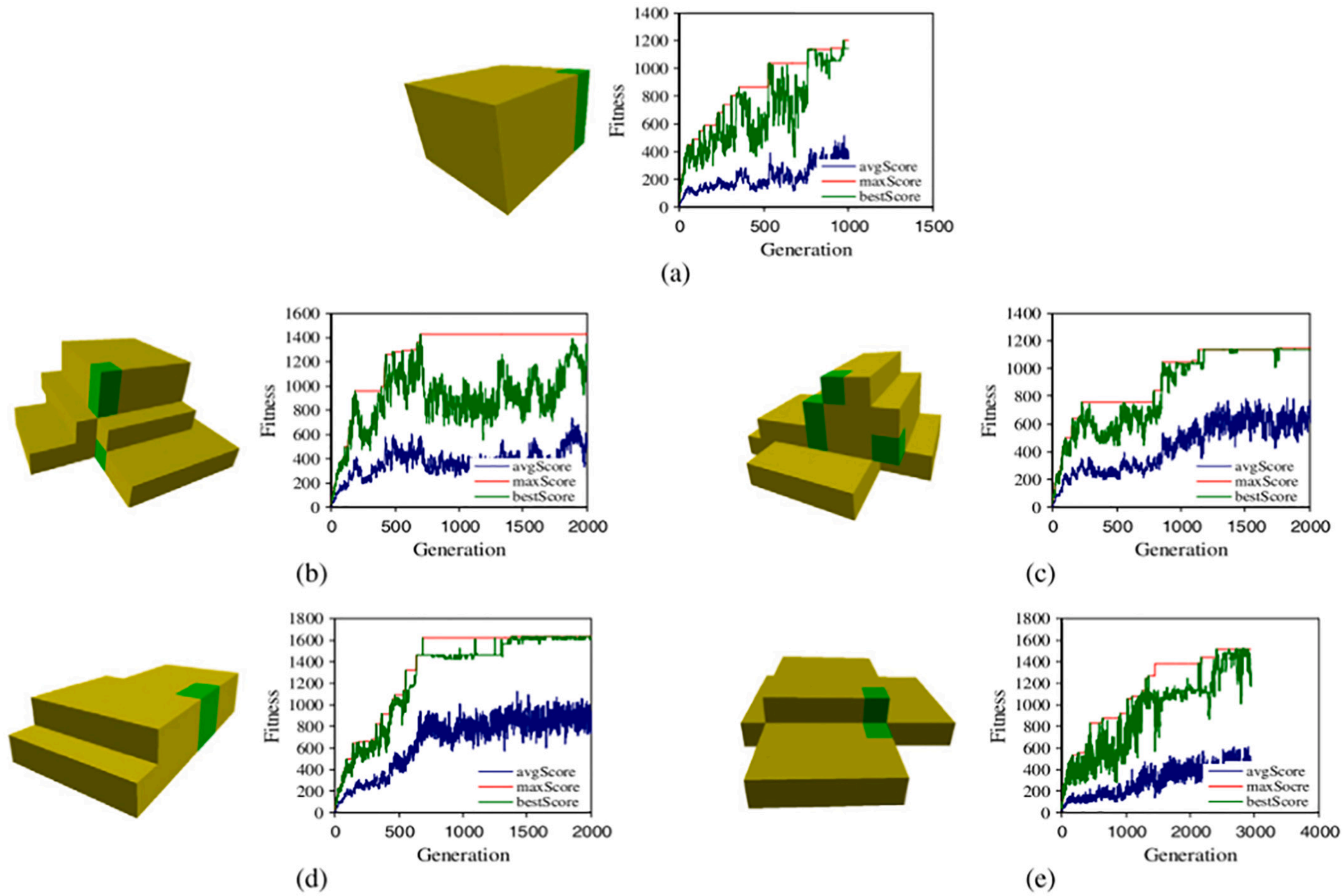

Fig. 19. Diverse solutions after applying the symmetry, structure, cost and connection rule. Song, Ghaboussi and Kwon, 2016.

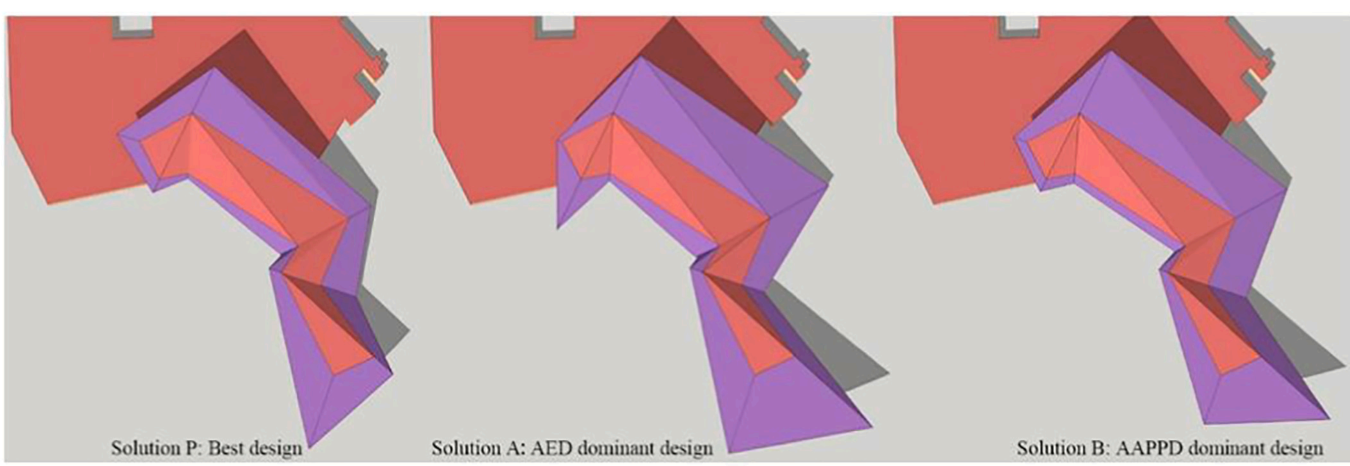

Fig. 20. Shape of the eaves of different design solutions. Si et al., 2019.

ceiling geometry and shape for a case study and noted that the code had demonstrated different new directions for performative fit geometry, providing the architect with a variety of design options and offering a robust and accurate shape-finding method (Fig. 21).

Turrin, von Buelow, and Stouffs [100] investigated in 2011 the benefits derived from the combination of parametric modeling and genetic algorithms to attain a performance-oriented design process and presented a tool they called ParaGen, which allows integration of the evaluation of various performance values in the first stage of the design process. Doing so guides the generation of the alternatives using GA and supports designers in navigating through the alternatives generated and assessment of their performance. The authors presented a specific case study that uses large decks and a method of parameterization enabling the creation of design alternatives that represent the deck geometry, the pattern and densities of its structural tessellation, and, in a second case study, its cladding system (Fig. 22).

In 2016, Zaremba used genetic algorithms [101] to adjust the arches of a roof system that follows a free-form NURBS surface, with double curved glass panels covering the structure. The algorithm adjusts elements to minimize the deviation from the initial curve and maximize

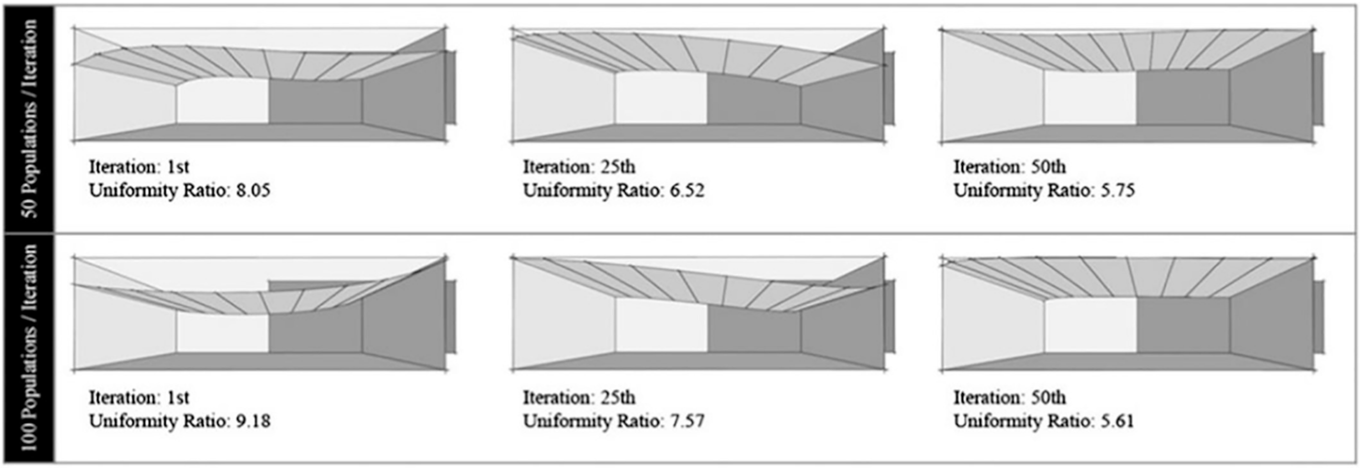

Fig. 21. Examples of ceiling geometry and shapes. Rakha and Nassar, 2011.

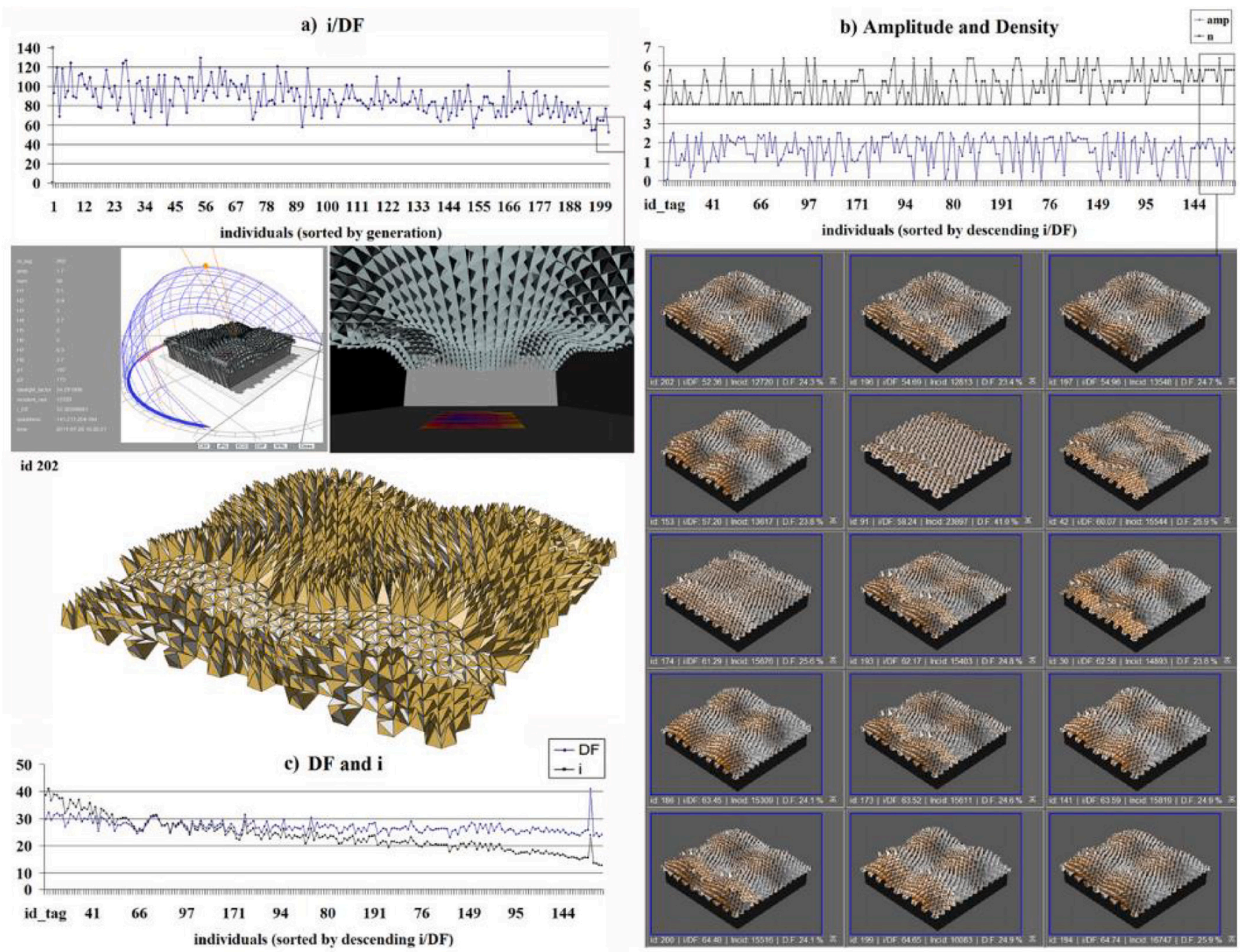

Fig. 22. Examples of results from the ParaGen cycle for summer conditions (with normalized values). Turrin, von Buelow, and Stouffs, 2011.

continuity between arches to provide full design freedom while still ensuring construction is possible.

In 2016, Rian and Asayama [10] used self-similar and random fractals to design a large-scale wrinkled roof structure inspired by a natural terrain's random shape to explore the power of fractal geometry as a framework that can provide new structural forms. The authors explored the relationship between the irregularity factor (fractal dimension) and structural resistance and analyzed the relationship between the roof shape's fractal dimension and its weight. This study's structural analysis confirms the structural feasibility and strength of

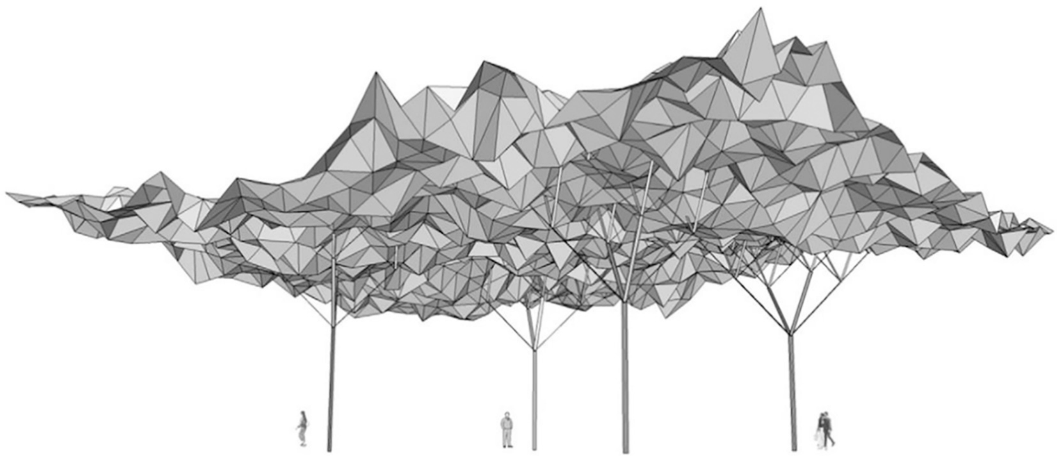

Fig. 23. Wireframe geometric model of the fractal-based canopy structure. Rian, 2016.

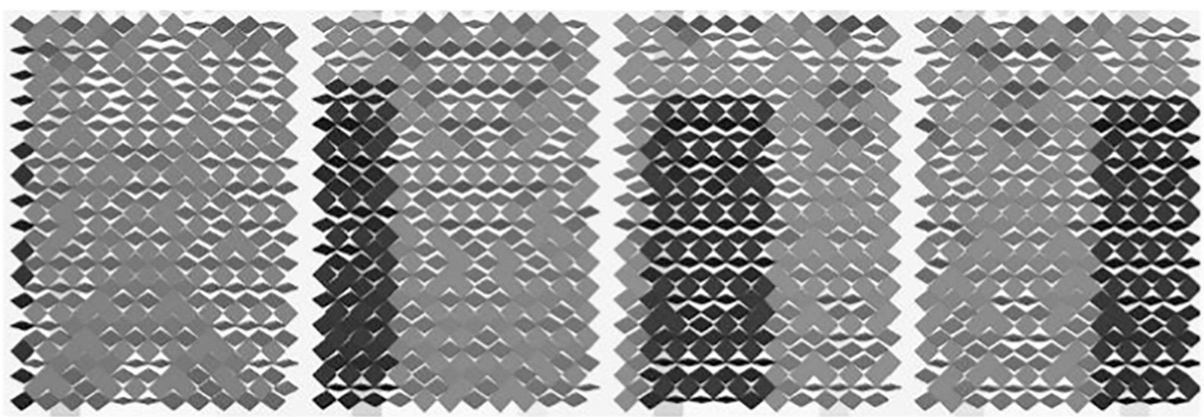

Fig. 24. Seven-state discrete CA implemented on the façade. Screenshots of the program running in Processing 1.0. Skavara, 2009.

such an irregular roof structure, although the authors proposed the implementation of a process of computer optimization based on automatic search algorithms (such as GA) to find the optimal shape of such a structure (Fig. 23). The authors of this review agree with Rian and Asayama that the creative possibilities of using fractals are undeniable, but several questions remain before they can be applied in real design cases, since their structural stability against strong winds has not been studied, nor other practical problems such as water or snow collection in concave areas or the difficulty of cleaning such an irregular structure.

3.5. Façade design

Skavara [102] explored in 2009 the possibilities of controlling a cellular automata's emerging behavior to develop an adaptive, high-performance façade that provides optimal lighting conditions inside a building. To do so, he implemented an artificial neuron network and through a flow of experiments on the control of cellular automata complexity with retro propagation and optimization with genetic algorithms. He trained the façade to handle cellular automata's structural characteristics, to achieve optimum lighting conditions within, to constitute an adaptive and kinetic architectural entity that allowed the system to successfully evolve in its context (Fig. 24). The author argued it is not necessary to reach a compromise between aesthetic merit and pragmatic objectives, and demonstrated that the façade of a building can be trained to improve adaptability to its environment, together with a high aesthetic value (Fig. 25).

In 2010, Gagne and Andersen [103] studied a GA approach that allows performance-based exploration of façade designs. The design of a building's façade has a huge effect on the performance of the interior spaces in daylight, and this method combines an efficient micro-GA algorithm [104,105] with a large number of user inputs, including an original three-dimensional mass model and user-specific performance targets, and assumes the overall shape of the building remains the same while the façade elements may change. The authors presented two case studies that show the performance of the single-objective [106] and multi-objective [107] micro-GA search processes and reflected on the limitations of GA-based approaches. One limitation is the lack of consistency in the final solutions found, owing to the random generation of initial design solutions. This limitation can be addressed to some extent by additional generations, adding extra time to an already long process. Another restriction is the GA's tendency to become "stuck" in a solution that is only a minimum or maximum for the local population. However, the authors of this review agree with Gagne and Anderson that it is not necessary to find an overall optimum to explore performance-based design; it should be sufficient to present the user with a design or set of designs to use as an initial, not a final design (Fig. 26).

In 2017, Chatzikonstantinou and Sariyildiz [11] presented a decision-based support framework for the treatment of design preferences. Their proposed framework is based on self-associated machine learning models which inductively learn the relationships between design features that characterize high-performance designs. The knowledge to be learned is derived through stochastic multi-objective optimization; the model offers a high-performance design solution, in which preferences regarding physical characteristics are also satisfied as

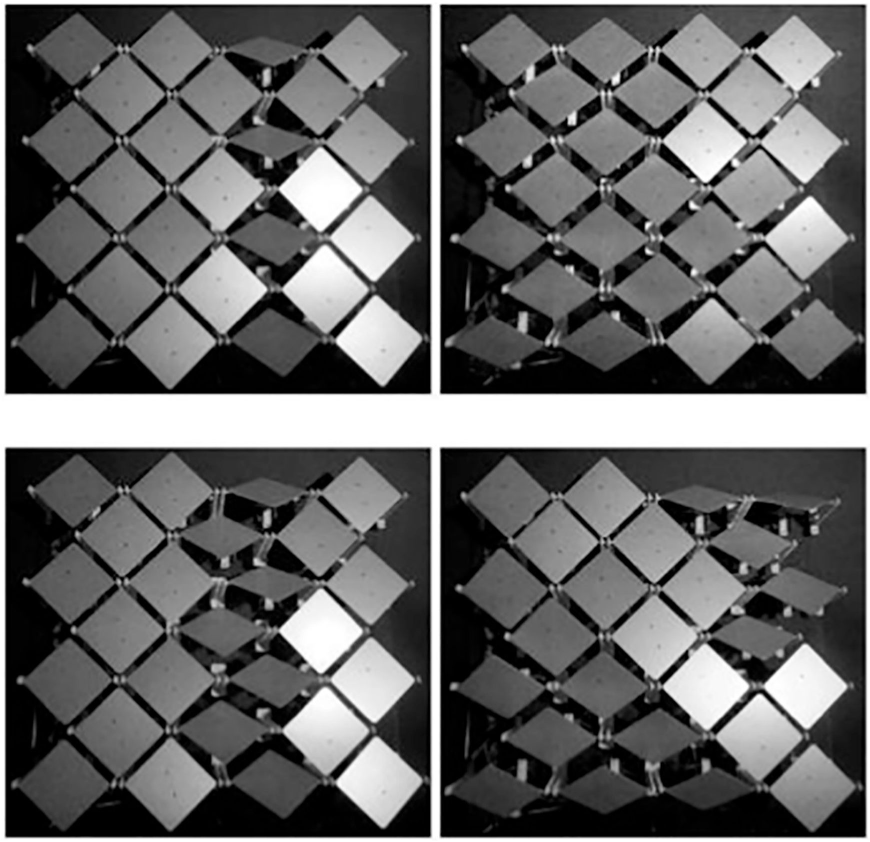

Fig. 25. Physical kinetic model. Skavara, 2009.

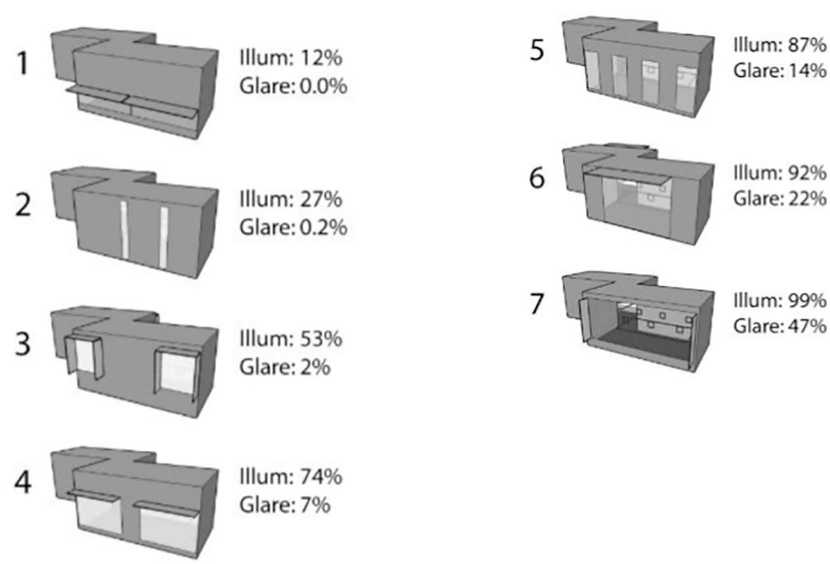

Fig. 26. Seven example designs from the Pareto front with their illumination and glare values. Gagne, 2010.

possible. The authors stressed that decision-makers can focus on addressing the desirable aspects of design with their method, with the certainty that the resulting solutions will be near-optimal. They assessed the proposed method using an application designed for a sustainable façade.

In 2017, Karaman et al. [108] proposed a multi-target optimization implementation for a rectangular façade design for the common space of a healthcare building in Izmir, Turkey. The objective was to improve interior comfort through cost-effective façade design alternatives, maximizing natural light performance, and minimizing construction costs. To do so, they used NSGA-II and the multi-target, self-adaptive differential evolution set (jE_DEMO). The authors stated that both algorithms achieve feasible facade design solutions; NSGA-II converges very quickly and offers better performance in terms of hypervolume calculation, while jE_DEMO presents a broader range of objective results and a greater variety of alternatives to façade design.

In 2019, Agirbas [2] studied the principles of cohesion, alignment and separation from nature, for possible use in architectural design and

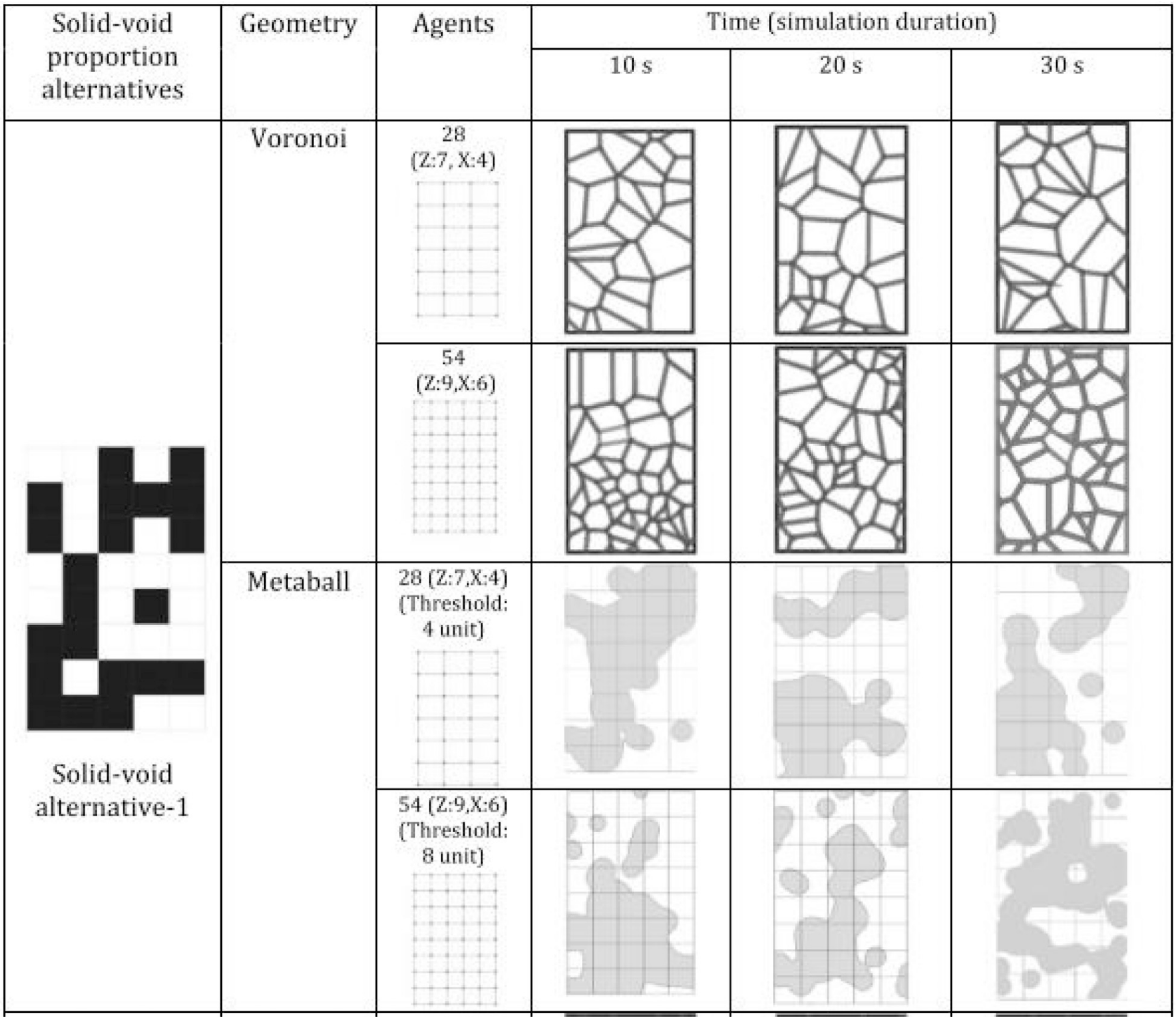

Fig. 27. Façade alternatives produced using swarm intelligence. Agirbas, 2019.

façade construction. In the design process, the author combined the use of (user-defined) morphodynamic and (automated) morphogenetic perspectives; thus, user-defined parameters could be integrated into an automation system based on swarm. The properties of the variations in the façade resulting from this combined approach were evaluated and the results compared based on relative daylight capture (Fig. 27).

3.6. Layout design

The problem with the layout of the facility is to find feasible locations for a set of interrelated objects which satisfy all design requirements. Rafiq, Mathews, and Bullock [109] investigated the use of GA in the design of buildings by extending the previous work of Park and Grierson [25], Grierson and Khajehpour [110] and Sisk et al. [111] to demonstrate the potential of GA-based software. Their approach allows research questions to be addressed from a design engineer 's perspective

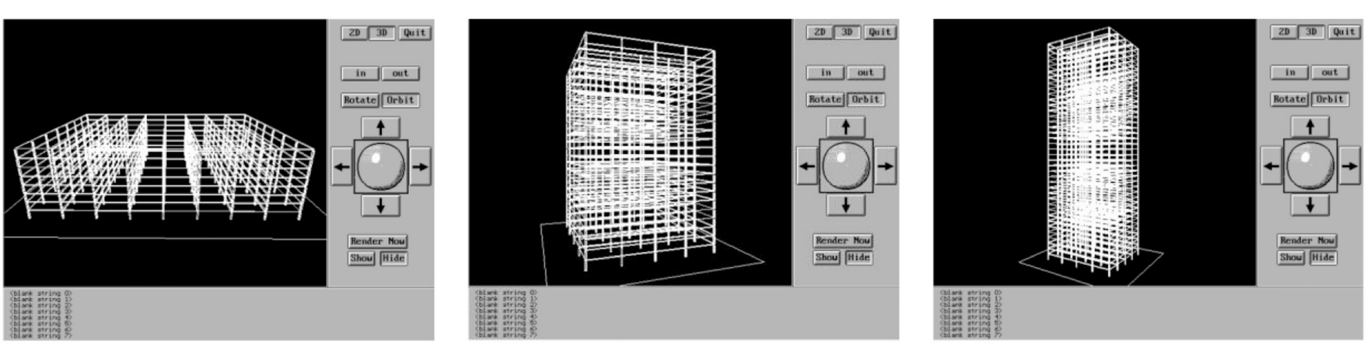

Fig. 28. Visualization of the best concept for land cost variations. Rafiq, Mathews and Bullock, 2003.

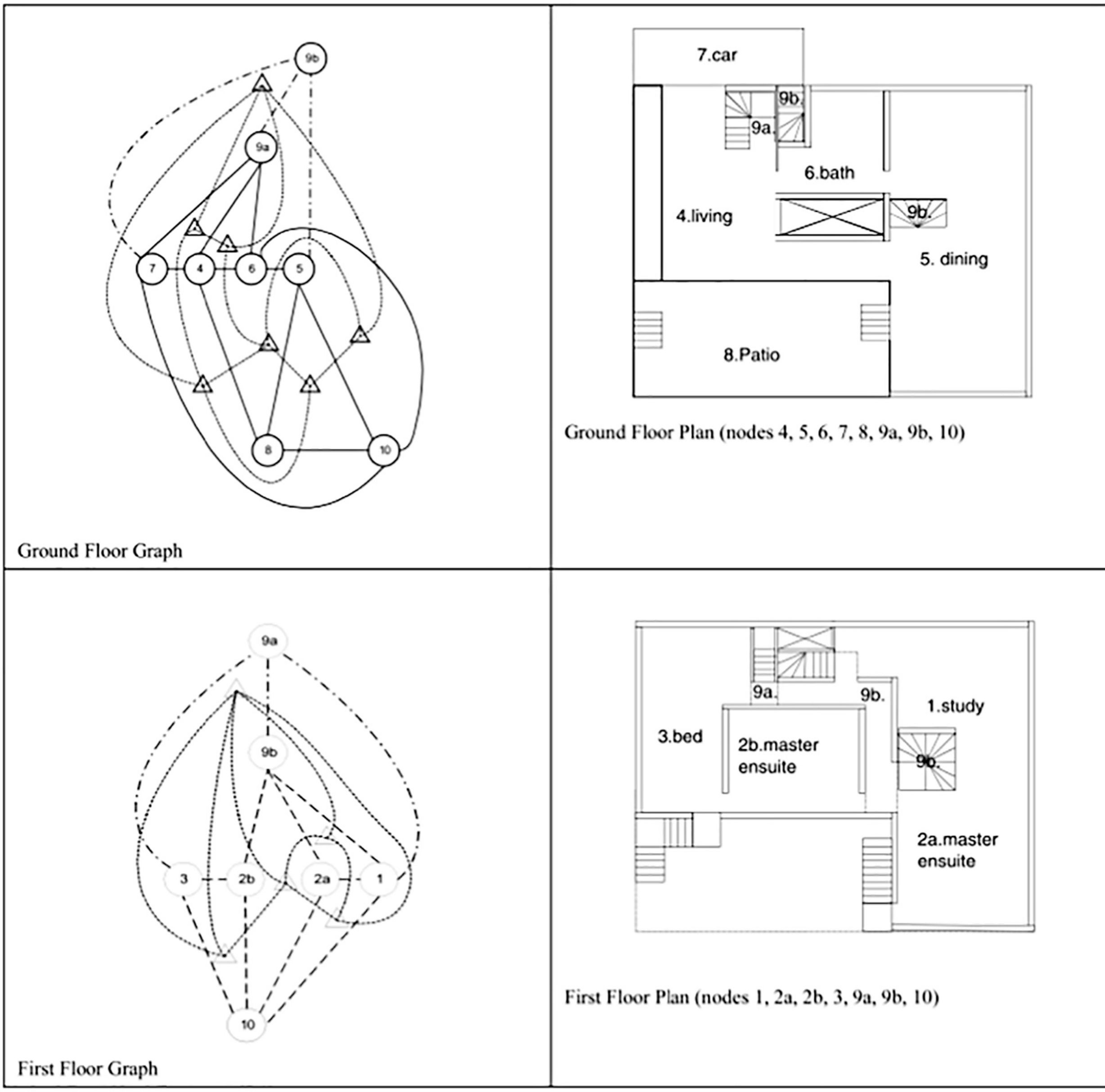

Fig. 29. Examples of optimal architectural space topology generated by experiment with corresponding floor plans. Wong, 2009.

and GA's capacity within a decision support system, capable of considering alternative structural systems in parallel, as long as genes belonging to different design solutions that are incompatible with each other are not mixed. Rafiq, Mathews, and Bullock avoided this problem by using a structured GA applied to the design of medium-height office-type buildings with a rectangular floor plan. The cost functions used to measure the suitability of different design concepts only considered the building's capital cost and expected revenues over its lifetime. The authors concluded that with their system, designs which use different configurations, construction methods and materials can be investigated simultaneously, and that it can also be used for parametric studies of how a change in the value of one design parameter affects the selection of other parameters when searching for an overall optimum design (Fig. 28).

In 2006, Yeh proposed a combination of Hopfield's neural networks (a model representing the problem of design) with annealing simulations (a search algorithm for finding optimal or near-optimal solutions) [8]. A case study of a hospital building with 28 establishments was used to demonstrate the model's efficiency for an architectural distribution problem, and Yeh concluded that it is suitable for the rapid calculation of large distribution problems.

In 2009, Wong and Chan [112] presented the evolutionary system EvoArch, used with a graphical coding scheme. They represented the spatial organization in the form of a labeled graphic, so functions such as kitchens and bedrooms can be represented as nodes and the adjacency between them, such as separation by a wall, can be represented as edges. These graphics are similar to bubble diagrams, from which the dimensions and geometries can be inserted to generate floor plans. The process includes budget and other design constraints in addition to preferred adjacencies. Thus, the resulting graphics that satisfy these constraints will facilitate the next stage of generating the architectural layout plan. The authors utilized EvoArch to design a house with nine functional spaces (Fig. 29).

In 2015, Ugurlu, Chatzikonstantinou, Sariyildiz, and Tasgetiren [113] addressed a layout optimization problem for restaurant architecture. They presented the results of the application of a rapid and unmastered classification GA called NSGA-II [114] and differential evolution (DE) algorithms to identify suitable solutions to this design

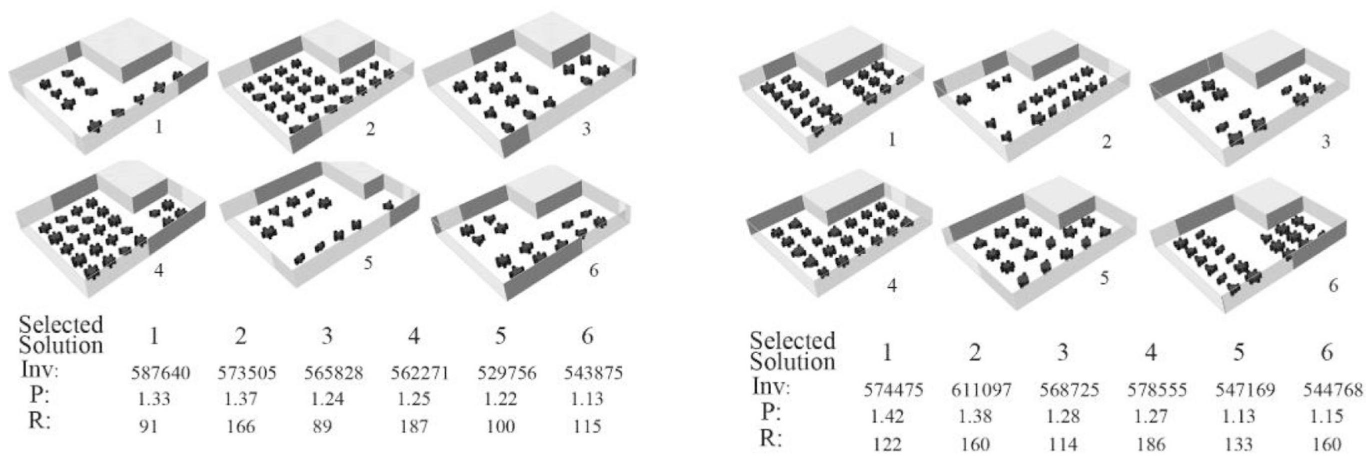

Fig. 30. Cubukcuoglu, 2016.

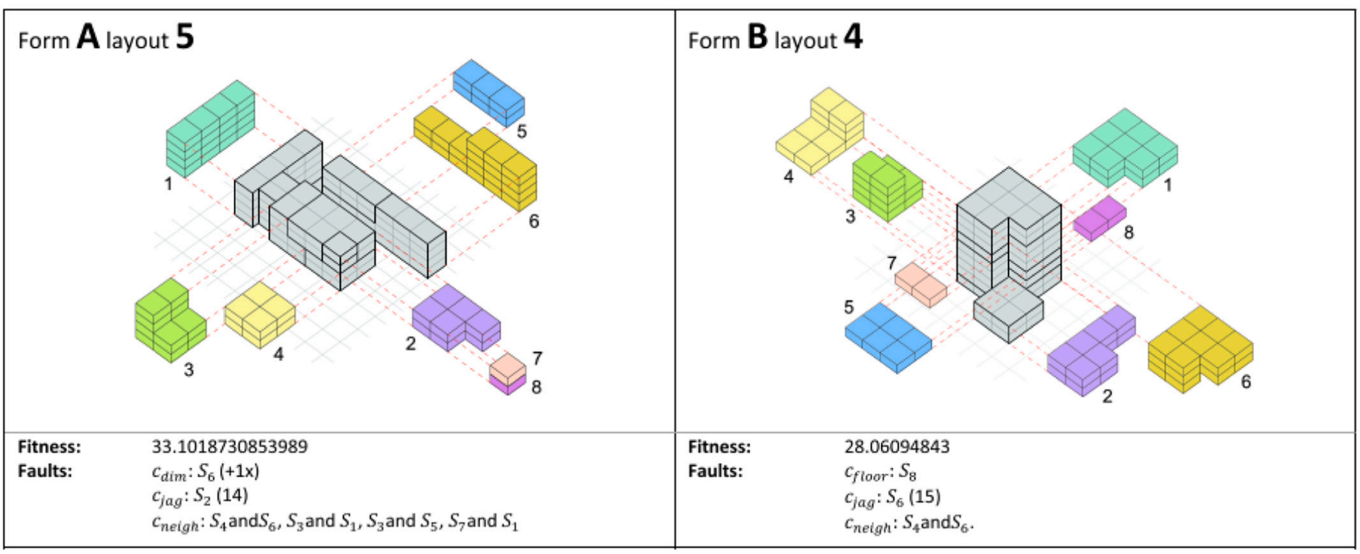

Fig. 31. Examples of AESE tool for the design of a library building, best layout of two forms alternatives. Dino, 2016.

problem. The multi-target problem is how to locate a kitchen and a set of tables to increase profit and decrease investment, using an approach that considers the functional, economic, constructive and architectural aspects of the layout. The authors reported that they achieved plausible design solutions and that the DE algorithm achieves the best performance when calculating hypervolume, as well as promising results when examining a frontal Pareto approach.

The same problem was addressed by Cubukcuoglu, Chatzikonstantinou, Ekici, Sariyildiz, and Tasgetiren [115] in the following year. In this case, a multi-target self-adaptive differential evolution algorithm (jDEMO) inspired by the DEMO algorithm [116] was developed and compared with the NSGA-II genetic algorithm. The authors concluded that the proposed algorithm offered results competitive with the NSGA-II algorithm (Fig. 30).

In 2016, Dino [117] presented a tool called EASE (Evolutionary Architectural Space layout Explorer) to make it easier to optimize the design of 3D spaces. EASE addresses the exploration of architectural design and the need to consider several alternatives in the design of the layout simultaneously, using evolutionary optimization to find a balance between divergent exploration and convergent exploitation. Dino stressed that the designs generated by his system are not intended to be final, but rather serve as design artifacts that provide space for further exploration of the solution. The tool has been tested in the design of a library building, assessing its performance for different construction forms and different parameters of evolutionary algorithms (Fig. 31).

In the same year, De Almeida, Taborda, Santos, Kwiecinski, and Eloy [118] introduced an evolutionary approach that allows modular residential housing to be designed automatically for personalized mass production. Given a set of modular design placement rules, the formal problem can be seen as a two-dimensional issue of placing large objects with fixed dimensions and additional positioning constraints. This formulation outcome in the search for a layout of the floor plan is limited by dimensional and positioning constraints on a size-search space combinatorial. A genetic algorithm strategy for floor plan design automation (G-Shaper) was implemented and exhibited. Once integrated into a suitable graphic interface system, it can help future owners acquire homes at affordable prices that fit their needs. The authors subsequently optimized the system by including, among other improvements, the management of variable room dimensions [119].

In 2017, Guo and Li [120] presented an automated design technique for space allocation, with an approach similar to that previously used by Doulgerakis [121], who developed internal polygon designs representing the boundary of the building. Rooms are created by dividing the original polygon into small parts and division operations were coded using genetic algorithms; although multi-story layouts are addressed, vertical spaces, such as two-story living rooms [122] and stairs

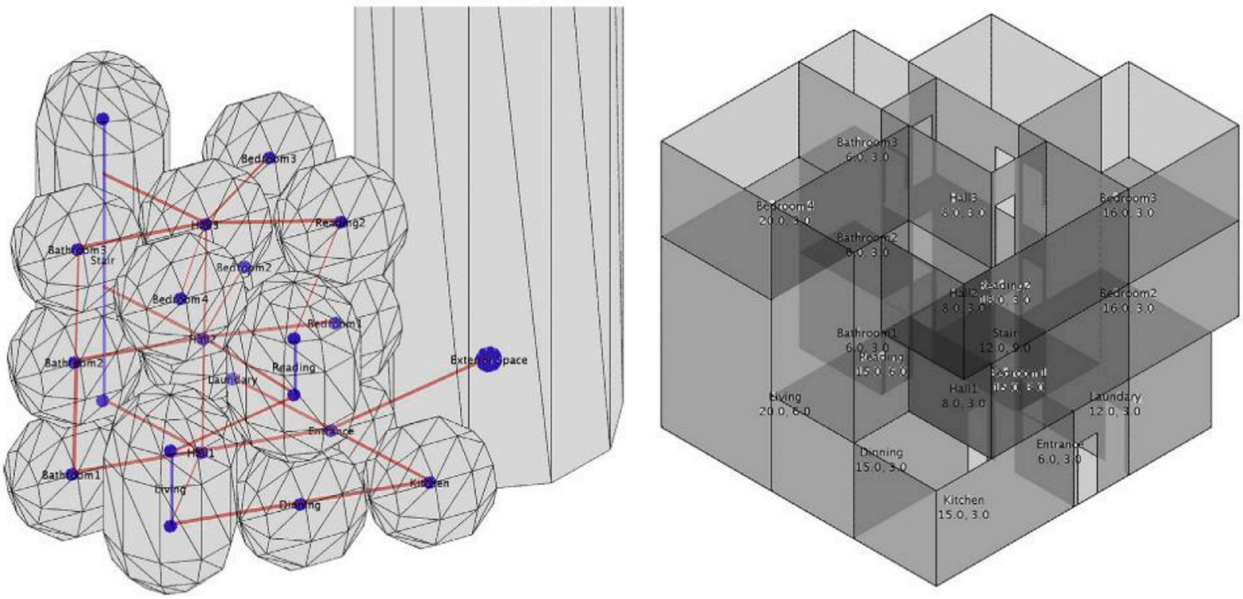

Fig. 32. Left: generated topology relationships of the three-level houses. Blue points and lines show the internal geometries of bubbles, and red lines represent connections between bubbles. Right: optimized grid-based layout. Guo and Li, 2017.

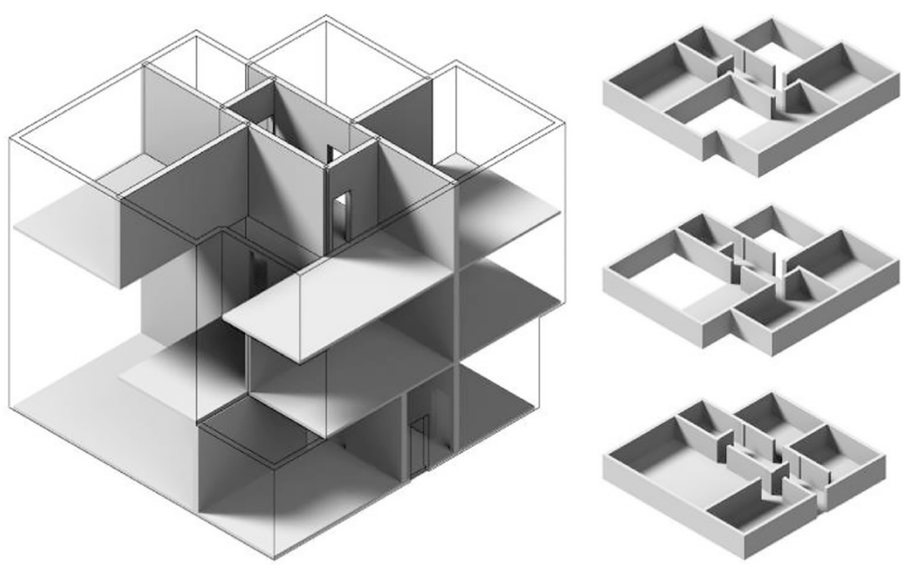

Fig. 33. Spatial layout generated based on the bubble diagram. The left image is rendered without an exterior wall, and the right images are separated into layers. Guo and Li, 2017.

[122,123] were only later addressed by Merrell et al.

The method proposed by Guo and Li combines a multiagent system and progressive process. The multiagent system models the layout as points and lines, reduces the search space, and allows for the optimization of 3D designs (Fig. 32). The model that evolutionary optimization uses is based on a three-dimensional grid system that is easy to implement but limits the space for the solution. Non-orthogonal designs within a grid system are difficult to generate, and curved rooms cannot be achieved in this model (Fig. 33).

In 2018, As, Pal and Basu [124] presented a graphically based automatic learning system to generate a conceptual design. The authors trained deep neural networks to evaluate and score existing designs coded as graphics, decompose them as subgraphs to extract meaningful building blocks, and merge them into new compositions. They also used generative adversarial networks (GAN) to create new designs, not seen in the training set. The system has the disadvantage that, at the moment, no tool automatically converts orthographic drawings into graphics. The authors also indicated that human intervention will be necessary to assess the effectiveness of the AI-generated designs.

3.7. Floor plans

Gero and Schnier [125] worked in 1995 on the adaptation of creative design based on the notion of creativity as “a goal-oriented change of focus in a search process.” They used genetic algorithms and an evolving representation to restructure the search space such that designs similar to the example case are at the center of the search and this approach is the starting point for new design generation. Rosenman and Gero [126], in 1999, worked on the evolution of designs by generating complex and useful genetic structures with a genetic engineering approach applied to architectural plans to overcome the combinational effect of large design spaces by focusing on useful areas of research. Their method starts with

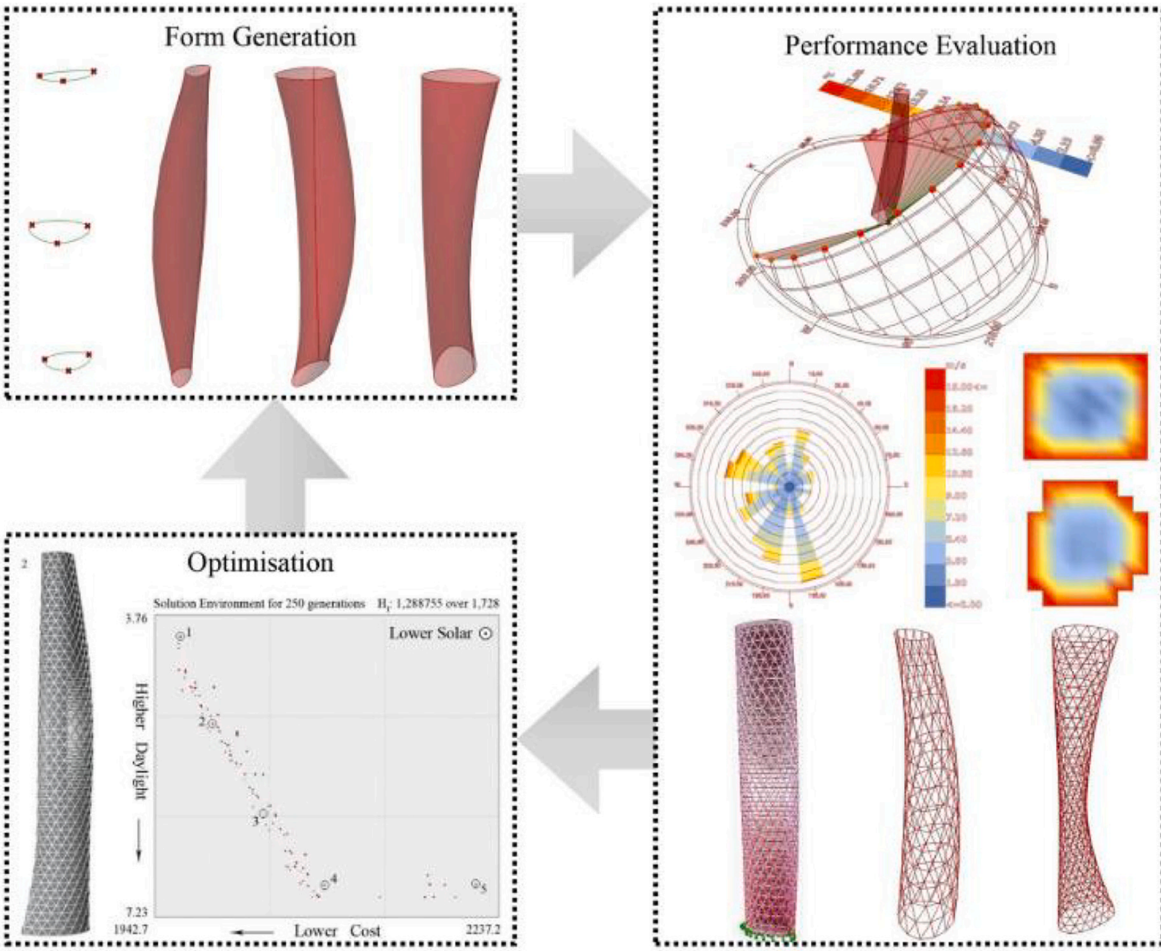

Fig. 34. Performative Computer Architecture (PCA) framework. Ekici, Cubukcuoglu, Turrin and Sariyildizat, 2018.

design spaces defined by low-level basic genes and creates design spaces defined by increasingly complex genetic structures. The low-level basic genes are simple design actions which produce parts of design solutions when executed.

Park and Grierson [25] developed in 1999 a computational procedure for optimal conceptual multi-criteria design of the structural arrangement of buildings subject to specific requirements and specifications. Two objective criteria are used for evaluation of alternative designs: first, minimizing the cost of the construction project by minimizing the function defining the combined costs of the building's structural system and of the land for the work; second, optimizing the flexibility of the use of space, a qualitative criterion given a quantitative form by minimizing the exponential function relating to the tax burden area and the spacing of the columns. Using Pareto's optimization theory, they applied a multi-criteria genetic algorithm to solve the building's conceptual design problem and introduced a variable mutation technique to maintain genetic diversity and speed up the stochastic search for the global optimum and test the system in a building's concept design. The authors concluded that, by providing Pareto curves that define the balance between the various competing objective design criteria, the system is suitable to support a designer's decision making.

In 1999, Rafiq, Bugmann, and Easterbrook [127] developed a GA-based tool for the design of office buildings using an objective functioning neural network. The system is restricted to buildings with a concrete structure and contains the minimum and maximum number of floors, preferred floor height, site dimensions, construction footprint, various grids, loads, and lightness requirements as constraints. The system also calls for inputs of costs for materials, land, and labor. The parameters are the number of floors, their dimensions and the ratio of beam width to depth. They consulted with architects, structural engineers, and quantity surveyors at the start of their work, and used the information they gathered to verify the software's usefulness. Their system delivers a single optimum design, although the user can access information about other options produced by the tool.

In 2001, Miles, Sisk, and Moore [128] developed a decision support system for the conceptual design of commercial office buildings that they call BGRID (full details of BGRID are provided in Sisk's thesis [129]). Previous work [130] had demonstrated the need to support rather than replace the designer in the decision-making process, so the style of the system must be that of a decision support system. It uses a genetic algorithm as a search tool to provide the designer with viable design options, rather than an optimization tool, and incorporates a high level of knowledge about structural design and its constraints. The design process focuses on the floor plan and the determination of column layout based on a wide range of criteria, including lighting requirements, ventilation strategies, limitations introduced by the available dimensions of typical building materials, and structural systems available. The authors noted that the system allows users to quickly explore the design space and consider many options and highlighted that it underwent extensive evaluation to ensure that its shape and characteristics are appropriate and meet the user's chosen domain needs.

In 2002, Von Buelow [131] studied the application of an intelligent genetic engineering tool (IGDT) to explore structures that would otherwise be difficult to assess. The author intended the tool as an aid for designers to meet aesthetic and performance criteria when solving problems, while also offering economic benefits with reduced building weight, although the author indicated tests with external projects and designers would be necessary.

In the same year, Michalek, Choudhary, and Papalambros [132] tested an optimization model for quantifiable architectural design aspects and presented a method for integrating mathematical optimization and subjective decision-making during conceptual design. Their model applies evolutionary algorithms to discrete decision-making and global search. The results of automated optimization of a tiny apartment complex with three independent houses are comparable to those of other methods, and their formulation allows the power of human decision making to be integrated in the process.

Sisk [133] considered that research on computer-aided design is often carried out with little input from designers, and indicated that the techniques developed are not subject to any kind of independent assessment, so such methodologies are therefore lacking in scientific rigor. As an example, he pointed out that the evolutionary computer system applied to the conceptual design of the Khajehpour and Grierson office buildings [134], without any significant industrial involvement. In 2003, he published a research project [133] examining the BGRID evolutionary computing system's application to the design of commercial office buildings. The project involved several designers (two architects, two structural engineers, and a construction service engineer) who provided assessments of the technique, allowing the author to claim that a search engine based on evolutionary computing is an appropriate tool for this type of design problem.

Vertical circulations (stairs and elevators) have been treated as fixed and rigid elements when dealing with the issue of multiple levels in automated architectural design research, which are usually set as constraints at the start of the problem. In 2013, Rodrigues, Gaspar, and Gomes [123] presented a multi-level approach to floor plan design using a hybrid evolutionary technique in which stairways and elevators are parametric objects interacting with other spaces during the search. The authors demonstrated that the algorithm is capable of generating coherent floor plans at several levels in three case studies. The algorithm was tested to deal with large and complex problems—seeing how concurrent vertical circulation objects interact and how multiple levels are stacked within a building boundary. The main advantage of the proposed approach is that it allows stairs and elevators to be part of the evolutionary process and, as a result, the technique expands the region of possible design solutions and increases the number of floor plans from which the architect can choose.

In 2018, Ekici, Cubukcuoglu, Turrin, and Sariyildizat [135] conducted a review of performative computer architecture (PCA) that uses evolutionary and swarm optimization for sustainability, cost, functionality, or structure related goals. This framework consists of three basic phases (as shown in Fig. 34): form generation, performance evaluation, and optimization. The main objective of PCA is to find the geometry that best meets performance-related objectives at the conceptual design stage.

The authors noted that one algorithm can outperform another in solving a particular problem only, since architectural designs are unique problems because of their objectives, schedule of construction, limitations, customer expectations and environmental impacts, different algorithms must be explored and compared to solving the same architectural design problem in order to make more appropriate design decisions. However, the authors of this review have observed that very few studies have compared the application of different swarm and evolutionary computation (SEC) algorithms to the same architectural design problem.

4. Results

From our analysis of the publications cited (see Table 1 in the Appendix) we obtain the following results:

There is a remarkable increase in the number of publications on the topic over time from 2015 onwards, with 85% growth in the last 5 years compared with previous years (see Fig. 35). Most of the articles reviewed have been published in "Automation in Construction," "Energy and Buildings," and "Building and Environment," with residential and office buildings receiving the most research attention.

As for the AI methods used (Figs. 36 and 37), we can see that the vast majority (more than 73%) employ EC. Of the various EC techniques used, GA stands out, with 48 papers (89%), of which 18 use multi-objectives GA.

We found several features that make the way an EC system works and generates new ideas for an architectural object adaptable. The crossover operator allows various potential solutions to be combined whilst the mutation introduces new features. The fact that GAs generate successive generations of solutions from the best results enables a broad

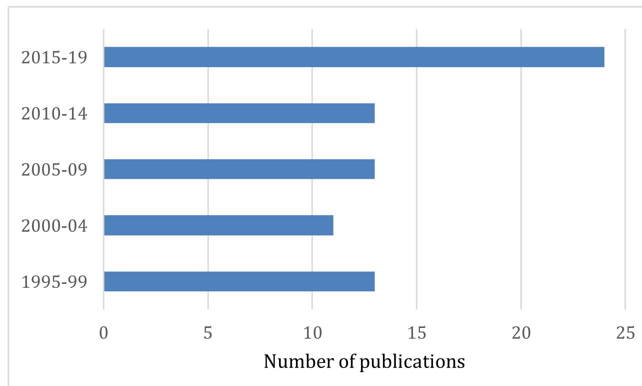

Fig. 35. Studies by date of publication.

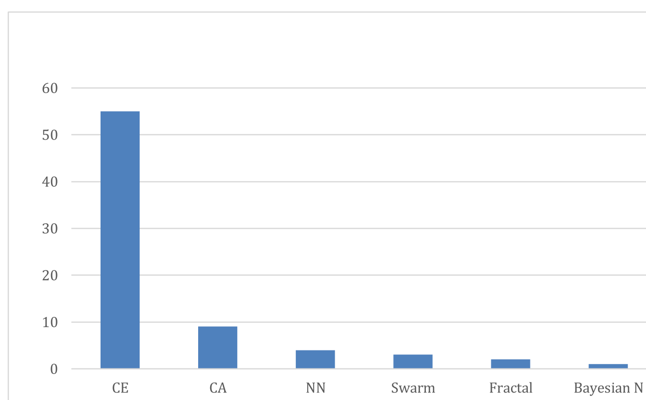

Fig. 36. AI methods used in the analyzed research.

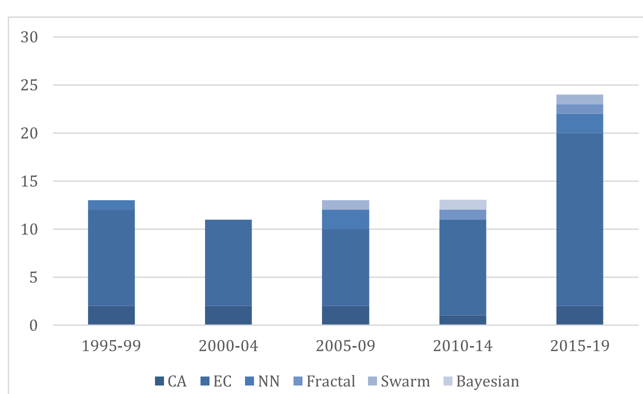

Fig. 37. AI methods used by date of publication.

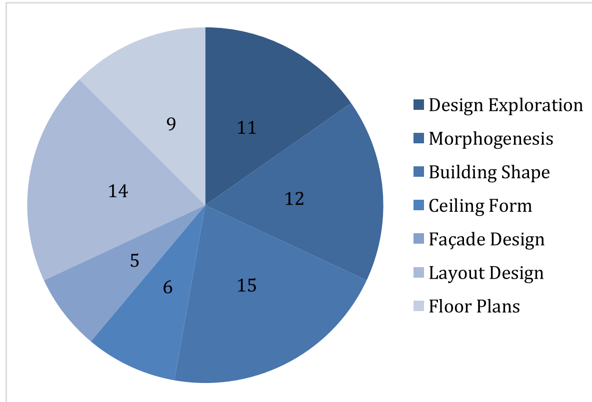

Fig. 38. Topics of research.

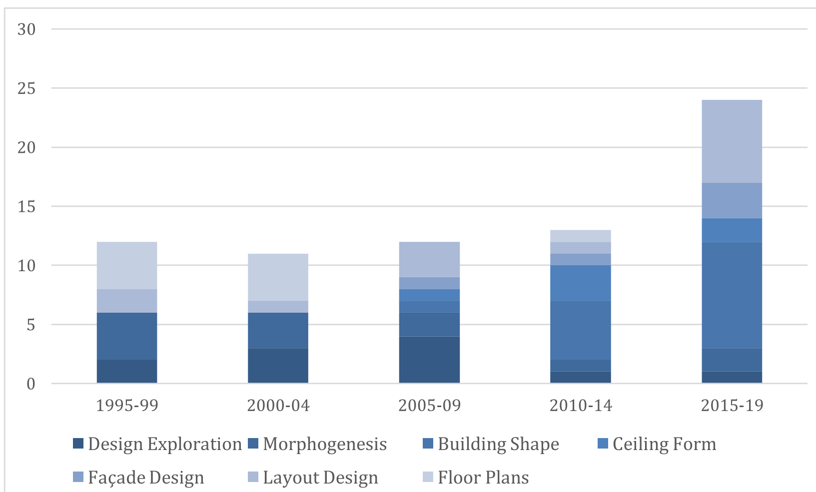

Fig. 39. Topics of research by date of publication.

exploration of the search space while high-quality regions are identified. Finally, these techniques are adapted to multi-target design problems.

CA were mainly employed in early, more exploratory work; the last publication using CA is from 2016. ANN have been little used to date, although we should highlight an example from 2018 of ANN using GAN [124]. It is foreseeable that more publications will appear in coming, years given the growing application of deep learning in other creative fields, such as the arts [136–138].

If we analyze the applications of the research and the topics covered (Fig. 38), we can observe a trend moving from an exploration of design in early years (design exploration, morphogenesis) where inspiration is sought or the generation of complex shapes to an optimization of the shape in recent years—where the goal is not to start from scratch, but to improve a pre-existing design (building shape, layout design, façade design) (Fig. 39).

5. Conclusions

This article provides an overview of the application of state-of-the-art AI techniques to conceptual design problems in architecture. We must highlight the remarkable increase in publications from 2015 onwards. Over the past five years, the number of investigations using AI methods to solve conceptual design problems in architecture has increased by 85%. We also not a trend toward solutions for shape optimization in the latest research. If, at the end of the last century, research was oriented toward the exploration of design and morphogenesis, as an inspiration for the designer through the generation of complex and unexpected shapes, most studies now aim to improve pre-existing designs, and in particular, to optimize their shapes.

As far as AI methods used are concerned, the vast majority of the articles analyzed employ EC methods, and specifically, GA. EC is used to create innovative, creative, efficient, and aesthetically pleasing architectural objects with good performance. EC serves not only as an optimization tool, but as an important component of a design methodology.

GAs can handle large problems easily, because they work with a solution population and provide optimum balance between multiple design criteria, making them an appropriate method for solving problems involving design and optimization. As proposed by Caldas as early as 2003, the use of GA to generate the shape of a building or their façades would benefit from an interface enabling designers to generate initial CAD solutions and view modified GA solutions within the same CAD environment [139]. In this sense, we agree with Ekici, Cubukcuoglu, Turrin, and Sariyildizat in their review of PCA: "A better integration of investigations related to computer science within the architectural domain is missing despite its expected benefits" [135].

Other lines of research apply neural networks, fractal algorithms, or automatic learning approaches to the practice of conceptual architectural design. The creation of IEC solutions can facilitate design customization to meet specific user requirements. Automatic systems based on aesthetic concepts are becoming increasingly popular in related fields (e.g., art and design) [140–143]. And more specifically, aesthetics optimized for an individual or society. We believe that the use of deep learning, especially in combination with ANN, as well as the application of new paradigms in creative systems, such as those presented at the

International Conference on Computational Creativity (ICCC) or the International Conference on Artificial Intelligence in Music, Sound, Art and Design (EvoMUSART*) can open new paths in this area.

Declaration of Competing Interest

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

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Appendix A

Table 1
Summary table of the analyzed research, in chronological order, with information about the main author of the article, the topic addressed, the IA methods used and the reference in the bibliography.

Ref.	Author	Date	Method	Topic
125	Gero	1995	GA	Floor Plans
61	Frazer	1995	CA	Morphogenesis
39,40	Maher	1996	CoGA	Design Exploration
36	Coates	1996	CA	Morphogenesis
64	Bentley	1996	GA	Morphogenesis
44	Cvetkovic	1999	MOGA	Design Exploration
25	Park	1999	MOGA(MGA)	Floor Plans
126	Rosenman	1999	GA	Floor Plans
127	Rafiq	1999	GA + ANN	Floor Plans
110	Grierson	1999	MOGA + ANN	Layout Design
134	Khajehpour	1999	MOGA	Layout Design
67	Funes	1999	GA	Morphogenesis
46	Gero	2000	GA	Design Exploration
58	Graham	2001	GA	Design Exploration
128	Miles	2001	GA (BGRID)	Floor Plans
131	Von Buelow	2002	GA	Floor Plans
132	Michalek	2002	GA + SA	Floor Plans
68	Krawczyk	2002	CA	Morphogenesis
69	Jackson	2002	GP + L-system	Morphogenesis
48	Packham	2003	MOGA (IVCGA)	Design Exploration
133	Sisk	2003	GA (BGRID)	Floor Plans
109	Rafiq	2003	SGA	Layout Design
71	Anzalone	2003	CA	Morphogenesis
49	Rafiq	2005	MOGA (IVCGA)	Design Exploration
52	Malkawi	2005	GA + CFD	Design Exploration
82	Wang	2006	MOGA	Building Shape
8	Yeh	2006	Annealed NN	Layout Design
97	Pugnale	2007	GA	Ceiling Form
54	Liu	2007	PSO	Design Exploration
121	Doulgerakis	2007	MOGA	Layout Design
74	Herr	2007	CA	Morphogenesis
50	Rafiq	2008	MOGA (IVCGA)	Design Exploration
77,78	Von Mammen	2008	PSO	Morphogenesis
102	Skavara	2009	CA + ANN + GA	Façade Design
112	Wong	2009	EA (EvoArch)	Layout Design
83	Tuhus-Dubrow	2010	GA	Building Shape
98	Gaspar-Cunha	2010	MOEA	Ceiling Form
9	Wen	2010	Fractal	Design Exploration
103	Gagne	2010	micro-GA	Façade Design
122	Merrell	2010	Bayesian network	Layout Design
86	Caldas	2011	GA	Building Shape
99	Rakha	2011	GA	Ceiling Form
100	Turrin	2011	GA (ParaGen)	Ceiling Form
84	Li	2012	GA	Building Shape
123	Rodrigues	2013	EP (*EPSAP*)	Floor Plans
87	Jin	2014	GA	Building Shape
88	Dincer	2014	CA	Building Shape
32,79	Lin	2014	MOGA	Morphogenesis
89	Araghi	2015	CA	Building Shape
90	Yi	2015	GA	Building Shape
57	Mueller	2015	IEA	Design Exploration
113	Ugurlu	2015	MOGA (NSGA-II) + DE	Layout Design
1	Song	2016	IRRGA	Building Shape
91	Ekici	2016	MOGA (NSGA-II), EA (jDE)	Building Shape
92	Konis	2016	MOGA	Building Shape
93	Zhang	2016	MOGA	Building Shape
10	Rian	2016	Fractal	Ceiling Form
101	Zaremba	2016	GA	Ceiling Form

(*continued on next page*)

Table 1 (*continued*)

Ref.	Author	Date	Method	Topic
115	Cubukcuoglu	2016	MOGA (jDEMO)	Layout Design
117	Dino	2016	GA (EASE)	Layout Design
81	Herr	2016	CA	Morphogenesis
11	Chatzikonstantinou	2017	Auto-associative NN	Façade Design
108	Karaman	2017	MOGA (jE_DEMO, NSGA-II)	Façade Design
118	De Almeida	2017	GA	Layout Design
120	Guo	2017	GA	Layout Design
14	Pazos	2017	GA, IEC	Morphogenesis
119	Taborda	2018	GA	Layout Design
124	As	2018	DNN, GAN	Layout Design
94	Fang	2019	MOGA	Building Shape
95	Cubukcuoglu	2019	EA (jEDE)	Building Shape
96	Si	2019	MOGA (NSGA-II, MOPSO, MOSA, ES) + ANN	Building Shape
2	Agirbas	2019	Swarm	Façade Design

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