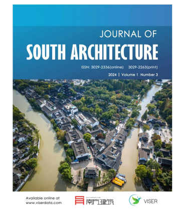
Contents lists available at Viser

Journal of South Architecture

http://www.viserdata.com/journal/jsa



Research on the Architectural Generative Design Practices Driven by Optimization Algorithms

ZHU Shuyan[1], MA Chenlong[2], XIANG Ke[3]

Author Affiliations 1&2 Doctor, Engineer; 3 Associate Professor, Corresponding Author, Email: kee53@126.com; 1&3 School of Architecture, South China University of Technology, Guangzhou 510641, China; 2 Architectural Design and Research Institute Co., Ltd., South China University of Technology, Guangzhou 510641, China; 1&2&3 State Key Laboratory of Subtropical Building and Urban Science, South China University of Technology, Guangzhou 510641, China

ABSTRACT: The development of technology will eventually lead to industry transformation. By studying the relevant contents of the optimization algorithm and its application cases, the present study aims to provide future architectural design practice methods and create more possibilities. This paper sorts the optimization algorithm's development and the historical evolution of its application in architectural design. Simultaneously, the algorithm- based generative design platform and its corresponding plug-in have been generalized. Based on the analysis of two specific cases, this paper proposes the concept and process of building designs driven by an optimization algorithm. Under the background of transforming architectural practice towards "digitalization" in the new century, the general process of building generative designs driven by the optimization algorithm is summarized from different perspectives. These include the selection of design platform, determination of optimization goals for different design stages, and iterative process of algorithm optimization. Then, the development prospects of the optimization algorithm and its potential impact on architects are discussed.

KEY WORDS: optimization algorithm; generative design; building performance; design practice

Introduction

At the beginning of 2020, the winning proposal for the Shanghai Alibaba Group Headquarters, designed by Norman Foster and his team (Foster+Partners)[1], garnered significant attention from architects. This interest was not solely due to the design itself, but also because the design concept prominently featured the use of "Genetic Algorithms."

"Genetic Algorithms" (GA) are well-known in academic circles, but in architectural practice—particularly bid proposals, the project using it as a design philosophy and finally winning the bid remains rare. The case underscores the growing impact of technological advancements on architecture. Over the past half-century, architectural design practices have undergone remarkable evolution and transformation under computer aid: Transitioning from hand-drawing with tools to 2D computer drafting in the 1980s, then to 3D modeling in the 1990s, and to Building Information Modeling (BIM) technologies emerging in the early 21st century. Recently, artificial intelligence and optimization algorithms have become prominent research topics in the field of architecture (Figure 1) [2]. These

[The format of citation in this article]
ZHU Shuyan, MA Chenlong, XIANG Ke. Research on the Architectural Generative Design Practices Driven by Optimization Algorithms [J]. Journal of South Architecture, 2024(3): 14-25.

• **Fund Projects**: This research was funded by the Guangdong Provincial Natural Science Foundation General Project (Grant No. 2024A1515012576); the State Key Laboratory of Subtropical Building and Urban Science, South China University of Technology (Grant No. 2022ZB11).
Document Identification Code A **DOI** 10.33142/jsa.v1i3.13922 **Article number** 1000-0232(2024)03-002-12

five stages reflect the evolving focus and perspectives of designers in different periods, and they are not independent or sequential; rather, they often overlap in practice.

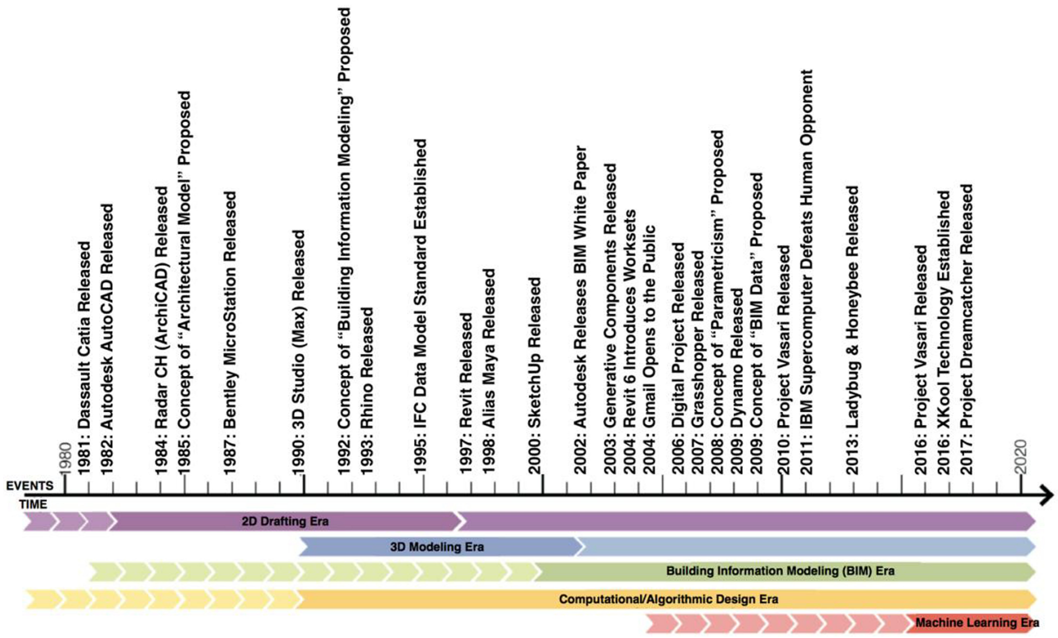


Figure 1 The history of computer-aided architectural design: Five eras

1 Optimization algorithms and their design platforms

An algorithm is a computational process used to solve problems within a finite number of steps. It involves methods such as deduction, induction, abstraction, generalization, and structured logic. An algorithm systematically proposes logical principles and develops a solution that can universally address problems. The strategy of an algorithm lies in its ability to search for repetitive patterns, universal principles, interchangeable modules, and inductive links, while its advantages include inferring new knowledge and extending human cognitive limits [3]. For propositions with unknown, vague, or uncertain outcomes, algorithms can be the optimal choice for seeking potential solutions. Problems solvable by algorithms include P problems (Polynomial Problems) and NP[1)] problems. NP problems are characterized by uncertain computational processes that cannot be strictly defined by mathematical equations, resulting in a vast "solution space." Most problems in architecture are NP problems [4], making optimization algorithms the best approach for addressing them. In engineering practice, optimization algorithms typically refer to "metaheuristic algorithms," which are inspired by random processes in nature, such as biological evolution, swarm intelligence, and immune mechanisms. These algorithms are designed to escape local optima and reliably search the solution space[5].

1.1 History and development of optimization algorithms

Algorithms have historically accompanied the development of disciplines such as mathematics and physics, with their interaction with machines tracing back to the establishment of computer science in the 1950s. With the improvement of computational capabilities and growing pursuit of enhanced performance in the field of engineering , various optimization algorithms have emerged, developed, and spread from computer laboratories to numerous engineering practice fields.

Notable optimization algorithms in engineering include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Immune Algorithms (IA), General Pattern Search (GPS), Coordinate Search, and Hooke-Jeeves (HJ) Algorithms. These algorithms are used to optimize design parameters in engineering practice. When combined with certain physical simulation processes, they create hybrid algorithms, which are widely applied in the field of building energy [6,7]. Most optimization algorithms derive from mathematical descriptions of natural phenomena or physical processes, relying on these descriptions to find optimal performance results within a vast "solution space." Consequently, different optimization algorithms exhibit varying characteristics for specific engineering problems, and no single optimization algorithm performs optimally for all problems. Christoph Waibel and colleagues have investigated optimization issues related to building energy consumption by comparing various optimization algorithms in terms of search speed and robustness. Their findings reveal that the choice of hyperparameters for different optimization algorithms significantly affects the convergence speed of the optimization process. Without considering prediction speed, Genetic Algorithms and Particle Swarm Optimization consistently yield relatively optimal results across different problems [8].

The Genetic Algorithm (GA), previously mentioned, was proposed by John Holland and his colleagues at the University of Michigan in the 1960s [9]. Inspired by Darwin's theory of evolution, GA is an optimization method based on genetic principles and natural selection. Compared to other optimization algorithms, GA offers a more intuitive physical interpretation and has seen widespread application in engineering due to the development of numerous robust algorithmic tools. GA is suitable for nonlinear, discontinuous problems and is characterized by features such as the use of stochastic operators, handling of large parameter spaces, open-source availability, simultaneous processing of discrete and continuous parameters, and multi-objective optimization using Pareto fronts [10].

1.2 Optimization algorithms and architectural design

The relationship between computers and architectural design dates back to the 1960s and 1970s, when Nicholas Negroponte established computer models that transcended clear-cut divisions in the design process and advocated for a closer relationship between computers and designers [11]. It is noteworthy that in the early stages of 2D CAD, 3D modeling, and even BIM, computers primarily assisted with drafting and drawing, with limited involvement in design optimization [12]. It was not until the advent of Generative Components software in 2003 [13] and the Grasshopper parametric software in 2007 that parametric design and algorithmic design were truly accepted and promoted, with the latter becoming a widely used tool for architectural parametric design [14].

It is important to clarify that "parametric" and "algorithmic" design are often conflated, with some perceiving them as identical or overlapping concepts. However, "parameters," "algorithms," and "results" are all integral components of architectural parametric models [15], with "algorithms" specifically describing the computational methods and generative logic from "parameters" to "results." Additionally, the concept of "Generative Design" complements these two design concepts by focusing on process and outcomes, while parametric and algorithmic design emphasize data and methods. The exploration of generative design by Christiano Sodu has catalyzed a shift in architectural design from a "result-oriented" approach to a "process-oriented" one [16].

Entering the 21st century, architects face a doubling of information quantity and increasing complexity. Optimization algorithms such as GA can serve as both form-generating tools and design optimization tools, offering effective means to address design issues related to form, structure, performance, and facade. Recent applications of optimization algorithms in architectural practice have concentrated on aspects such as energy consumption, structural performance, and daylighting, with simulations and iterations used to achieve optimal building performance. Recent academic research focuses on optimization for structural performance [17-20], building energy consumption and lifecycle costs [21-24], daylighting efficiency [25], integrated energy and daylighting optimization [26, 27], and multi-objective optimization incorporating energy, daylighting, and structural costs [28]. A recent review study by Berk Ekici et al. [29] provides a comprehensive summary of the literature on two representative optimization algorithms, genetic algorithms and particle swarm optimization, within the context of building performance optimization. It is noteworthy that this review also highlights that various variants of PSO and GA are among the most widely applied optimization algorithms in the field of building performance optimization, but as noted by Thomas Wortmann, the extent of application of different optimization algorithms does not directly reflect the quality of their performance. Instead, it is more influenced by researchers' preferences and the constraints of design platforms regarding the ease or difficulty of integrating different algorithms [30].

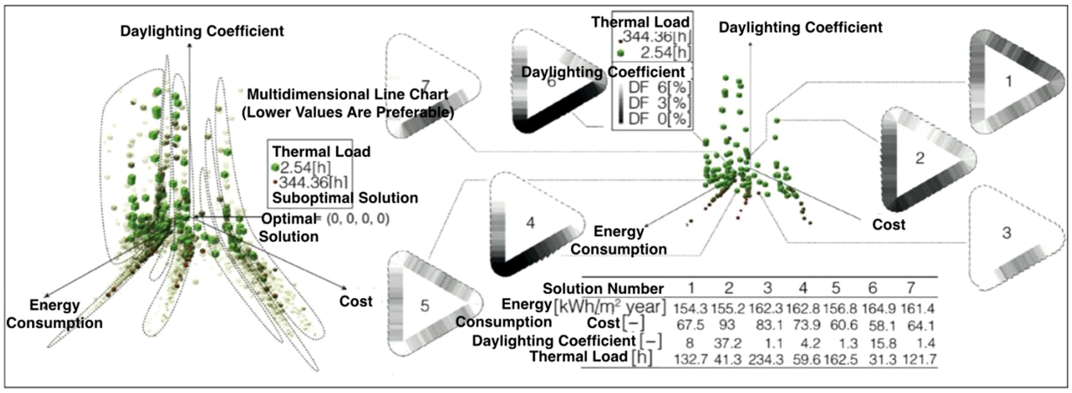


Figure 2 Multi-objective performance optimization algorithm model for an office building design

Table 1 Algorithm-based design platforms (grasshopper & dynamo) and their corresponding plugins

Intervention methods	Design platforms	Plugins	Algorithm descriptions
Built-in plugin approach	Grasshopper	Octopus	SPEA2 and HypE algorithms are applicable to single-objective ormulti-objective optimization tasks within algorithm-based design platforms (such as Grasshopper and Dynamo) and their corresponding plugin tasks.
		Wallacei	Utilizes the NSGA-II algorithm with enhanced custom visualization capabilities.
		Optimus	Developed by TU Delft, this adaptive differential evolution algorithm features a set of mutation strategies (jEDE).
		Silvereye	Based on the Particle Swarm Optimization algorithm, it is suitable for single-objective optimization and can achieve superiorperformance results compared to genetic algorithms in certain optimization problems.
		Opossum	Based on surrogate model concepts, it addresses single-objective optimization problems with rapid early convergence, making it suitable for obtaininghigh-quality solutions with small sample sizes.
		Goat	Introduces gradient-based mathematical optimization algorithms, which provide more stable optimal performance values compared to heuristic methods but are prone to local optima and require integration with global optimization algorithms.
		Nelder-Mead Opt	Utilizes the Nelder-Mead algorithm (Simplex method), a classic non-heuristic mathematical optimization technique that is susceptible to local optima.
	Optimo	Evo	Performs single-objective optimization based on the classic GA algorithm.
		Optimo	Enables both single-objective and multi-objective optimization based on the NSGA-II algorithm.
External interface approach	Grasshopper	FrOG	An open-source optimization framework based on C# ,with limited built-in algorithms, requiring the development of optimization algorithms in C# to interface with its visualization environment.
	Python/C# API Integration	mode FRONTIER	A mature optimization software that includes a variety of built-insingle-objective and multi-objective optimization algorithms.
		MATLAB	Implements optimization algorithms through MATLAB programming.

Building performance does not exhibit a simple trade-off relationship during the design process; optimizing individual element does not necessarily lead to a globally optimal solution. For example (Figure 2), researchers from the Technical University of Denmark analyzed the facade window design of an office building by BIG Architects using the SPEA2 algorithm within GA. They obtained optimal solutions and globally non-dominated solutions for various building performance parameters, such as energy consumption, daylighting coefficients, and costs, associated with serrated windows under different thermal property settings. These results are intended to assist designers in adjusting and optimizing window designs [31]. This algorithmic model met local energy-saving design standards with high precision and rapid computation speed, providing a convenient basis for timely decision-making in the early stages of design.

1.3 Generative design platforms based on optimization algorithms

The application and proliferation of optimizationalgorithms in architectural design have closely followed the emergence of "parametric" design platforms within modeling software. Notably, the Grasshopper platform, developed by Robert McNeel & Associates and based on Rhino software, and the Dynamo platform, developed by Autodesk and based on Revit software, are among the most prominent. Optimization algorithms within these design platforms can be integrated into the architectural design process via built-in plugins or external interfaces. Utilizing various algorithmic tools allows for iterative computation to achieve optimal solutions under single or multiple objectives, thereby providing technical support for architects' design thinking and creative processes and enabling the exploration of greater possibilities.

Integration via Built-in Plugins: In Grasshopper, the Octopus plugin, based on ETH Zurich's SPEA2 and HypE algorithms, is suitable for single or multi-objective optimization tasks. Other notable plugins include Wallacei[32], Optimus [33], Silvereye [34], Opossum [35], Goat [36], and NELDER-MEAD OPTIMISATION[37]. In contrast, the Dynamo platform features fewer optimization plugins, such as Evo [38] and the Optimo [39] developed by the Texas A&M University team. Dynamo's optimization capabilities often require designers to link external optimization programs using its built-in programming interfaces.

Integration via External Interfaces: Both Grasshopper and Dynamo come with Python/C# programming interfaces. By using the MATLAB API, numerical parameters from the design platforms can be imported in real-time into MATLAB, where various optimization algorithms can be introduced through programming languages. Additionally, modeFRONTIER, a specialized performance optimization tool, uses its API for data conversion and serves as a core process control, invoking various single and multi-objective optimization algorithms for performance optimization and visualization. Thomas Wortmann's open-source plugin, FrOG, can interface flexibly with custom optimization algorithms, though this requires a proficient background in C# programming.

Table 1 lists the generative design platforms based on these two integration methods, detailing the various optimization algorithms and plugins used in architectural design.

2 Generative design practice based on optimization algorithms

2.1 Foster + Partners and the Alibaba Headquarters

Foster+Partners is one of the most renowned architectural firms globally, established in 1967. Norman Foster, a prominent figure of high-tech architecture, pioneered "sustainable" design methods in the 1970s, focusing on green and energy-efficient design as core elements of sustainability. His approach involves considering environmental friendliness and energy-saving technologies in architectural solutions [40]. Additionally, the firm actively organized research and development teams to integrate comprehensive design processes through techniques such as computer data analysis, thereby pushing technological control in design to its limits.

2.1.1 The Specialist Modelling Group (SMG)

The Specialist Modelling Group (SMG) within Foster +Partners was established by Hugh Whitehead in 1997, focusing on finding more energy-efficient architectural forms through computer-aided design [41]. The team comprises architects skilled in digital technology and has grown to include experts from fields such as mathematics, industrial design, mechanical engineering, computational physics, manufacturing, and acoustics. Over the next decade, SMG's development focused on two main areas: computational geometry and construction-related issues, and environmental analysis and simulation[42]. They have utilized various algorithms for design optimization and generative design across hundreds of projects, with notable examples including the London City Hall, Swiss Re Headquarters, and Beijing Capital International Airport Terminal 3.

2.1.2 The design of Alibaba Headquarters

The continuous development of specialized teams like SMG, combined with over fifty years of practice and technical accumulation, has enabled Foster + Partners to adeptly handle parameters, algorithms, and related design methods. Therefore, in the Shanghai Alibaba Headquarters design competition (Figure 3), the proposal emphasized the use of a unique architectural form guided by an innovative design process, utilizing genetic algorithms to achieve the optimal solution.

Figure 3 Renderings for the competition of Shanghai Alibaba Headquarters design

The application of algorithmic generative design in this project focused primarily on the following four aspects[1, 43]:

(1) The modular unit assembly and construction approach is employed, utilizing "genetic algorithms" to optimize the design of modules, resulting in a "pixelated" volumetric arrangement. Subsequently, modules are mass-produced off-site to reduce waste and ensure construction quality and efficiency.

(2) Algorithms are used to enhance the design's responsiveness to environmental conditions. For example, the central open public space is designed to provide optimal comfort throughout the year, shielding users from cold winter winds and intense summer sunlight.

(3) Through calculations, the integration of indoor and outdoor spaces and the maximization of external scenic views are significantly enhanced. A key feature of this design is the intention to increase the building's transparency, allowing the public to gain insight into Alibaba's world while enabling employees to enjoy views of the surrounding waterfront.

(4) The design is optimized according to the functional requirements of different areas to achieve the most suitable layout. For example, customized workspaces are designed for various departments within Alibaba, integratingconsiderations such as furniture arrangement and natural light, thereby enhancing user work efficiency.

2.2 The Design of MaRS Office

The MaRS Office project, a three-story building with an approximate total area of 5600 m, was developed by Autodesk in Toronto, Canada. The design vision was to create a dynamic and highly functional innovative workspace.

During the design of the three-story interior layout—covering conference rooms, social spaces, special areas, and equipment—the design team first gathered real demands from over 250 employees, who are often overlooked. The team then established six distinct objective parameters for algorithmic generation and evaluation of the office space [44], including:

Parameter 1: Space Preference—Distances from each employee to their preferred interaction spaces and related facilities.

Parameter 2: Work Style—Assessing whether the lighting or visual elements of work areas match the preferences of users.

Parameter 3: Activity Level—Identifying potential high-activity areas based on the geometric characteristics of the room (Buzz[45]).

Parameter 4: Productivity—Controlling desk density to minimize visual and noise distractions.

Parameter 5: Daylighting—Total number of natural daylight hours throughout the year.

Parameter 6: External Views—Proportion of windows offering unobstructed views from desks, corridors, and other workspaces.

2.2.1 Model generation

Based on a homogeneous office space plan, the logic for further design generation was defined. Initially, a floorplan contour and standard column grid were established from the design layout. Areas requiring optimization were delineated, with axes, boundaries, and capture points set for seven different work team zones. Changes in capture points could automatically trigger boundary modifications. One edge of each zone was automatically designated for meeting rooms, while other areas were arranged with employee workstations. Various combinations of capture points and boundaries generated a range of design options for selection by the designers, as illustrated in Figure 4.

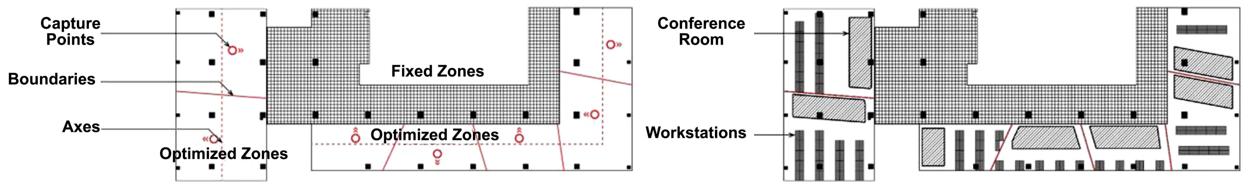


Figure 4 Plan of the generated model and schematic diagrams of various elements

2.2.2 Parameter evaluation

After establishing the basic model generation system, the design teamemployed a Multi-Objective Genetic Algorithm (MOGA) to evaluate different design options. The evaluation results obtained from the calculation of input values across different scenarios and the corresponding variations in the six target parameters, providing real-time feedback on design plans, as illustrated in Figure 5.

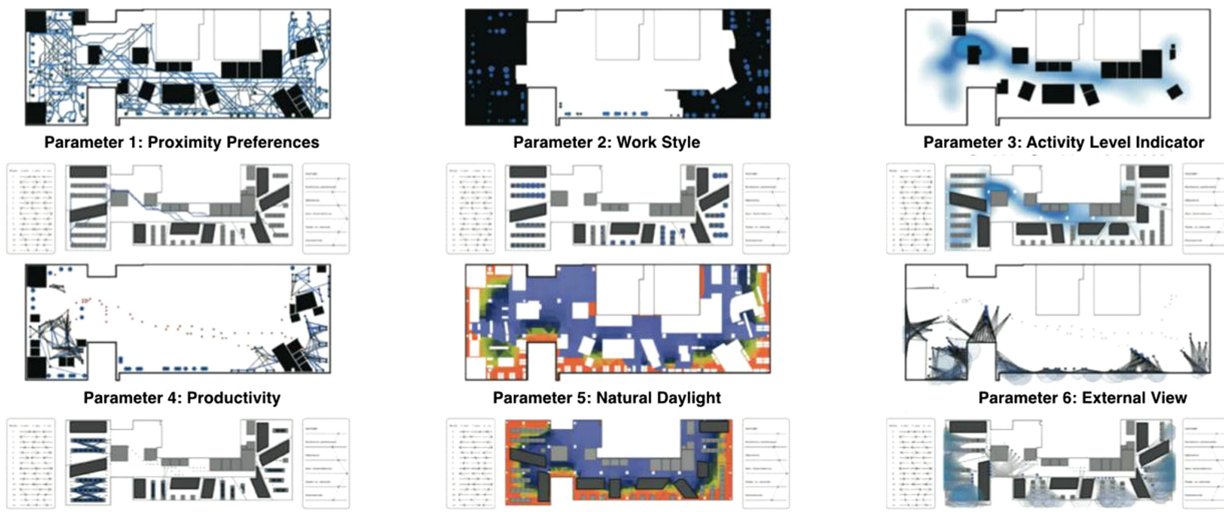


Figure 5 Real-time simulation analysis diagrams corresponding to evaluation parameters

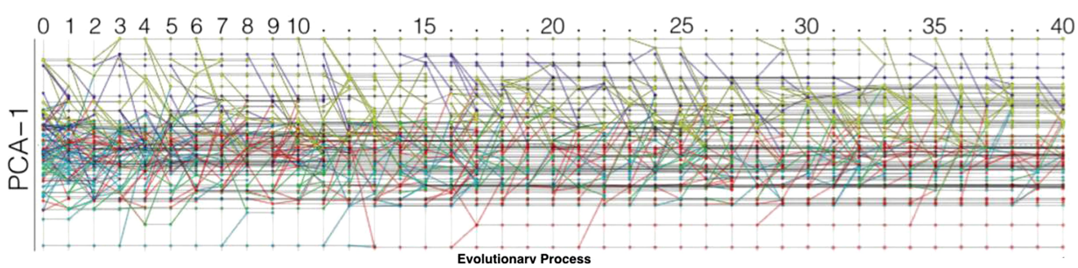


Figure 6 Real-time feedback diagrams of different iteration counts during scheme evolution

2.2.3 Solution evolution

For this project, the genetic algorithm was configured with a crossover rate of 95% and a mutation rate of 0.2%. The process involved 100 designs per generation, with a total of 100 generations, resulting in 10000 generated designs. Figure 6 depicts the evolution process, with each point representing a design solution, each column indicating a generation, and different colors denoting various parameter characteristics. The x-axis shows the number of generations, and the fine black lines connecting the points illustrate the direct transfer of designs to the next generation.

2.2.4 Data analysis

Following the evolutionary process, the performance of different design solutions was analyzed and filtered. The MOGA approach yielded a Pareto-optimal set that satisfied all performance criteria, narrowing down the design options. As shown in Figure 7, the design identified as #3251 was selected based on its superior performance in a radar chart evaluating six parameters, with relatively balanced scores across parameters. Figure 8 presents the final plan corresponding to design #3251, categorized into four functional spaces: basic office (blue), team meetings (green), equipment (red), and support services (orange), addressing users' primary needs and preferences.

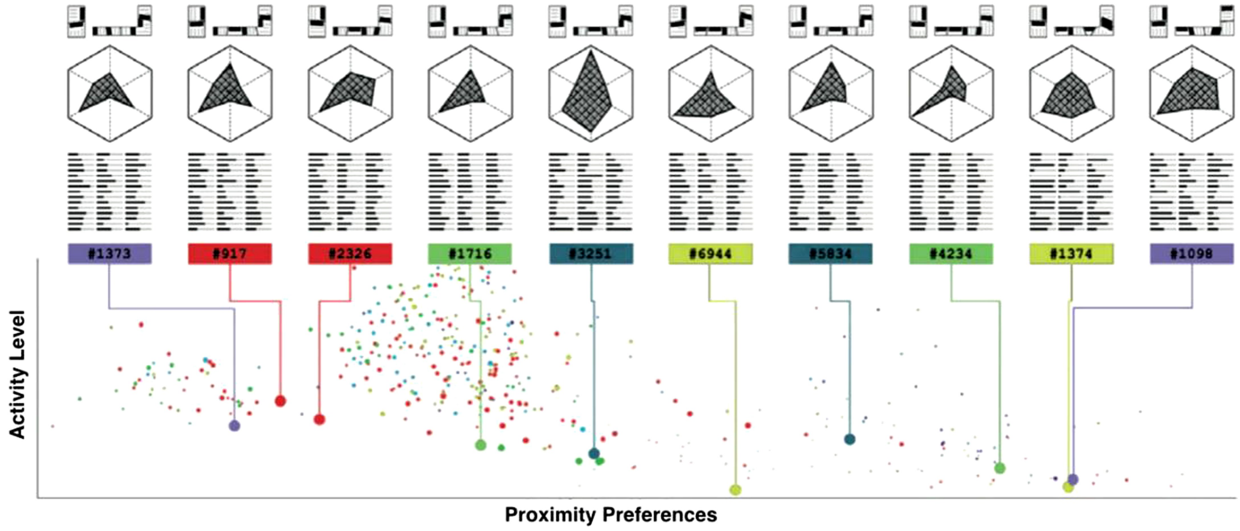


Figure 7 Scheme groupings and selected optimal solutions after data analysis

2.2.5 Summary

The complete design process of this project highlights several advantages of algorithm-driven generative design: first, it truly realizes "human-computer collaboration" in design; second, it evolves solutions by establishing goals, constraints, and geometric systems rather than producing a final form directly; third, it explores thousands of options to find optimal solutions for predefined parameters; fourth, it enables data exchange, creating possibilities for innovative designs; and fifth, it allows for iterative reuse of algorithms and evolution processes, offering valuable references for future project planning and design.

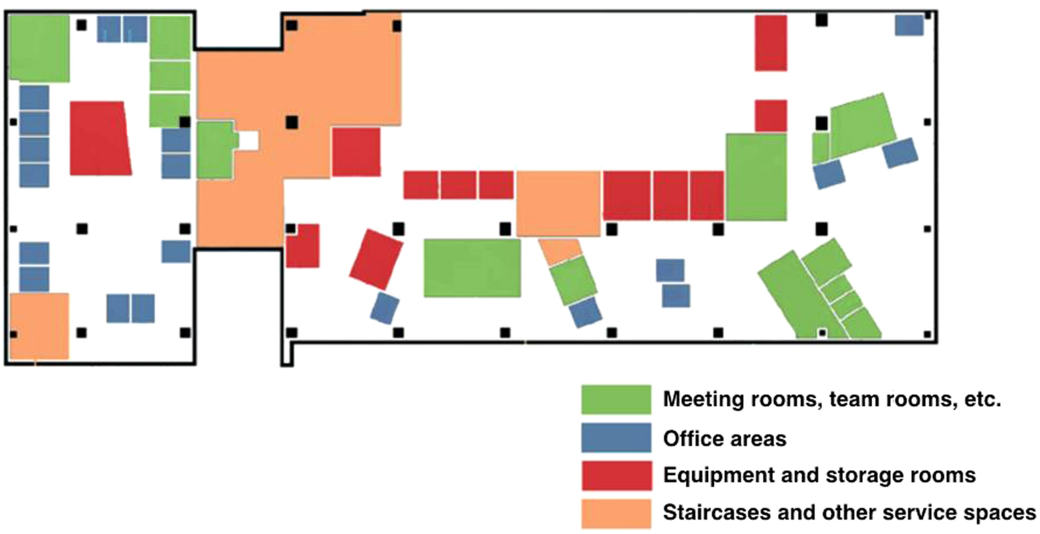


Figure 8 Floor plan of the corresponding generated scheme after optimization calculations

2.3 Other relevant projects

In recent years, generative design practices driven by optimization algorithms can be categorized into five main types, distinguished by the specific optimization goals addressed for different architectural contexts, as summarized in Table 2.

Table 2 Statistical overview of algorithm-driven generative design practices based on different optimization objectives

Optimization objectives	Application phase	Algorithm type	Representative case studies	Illustrations
Floor plan layout	Planning and design: Volume design and interior detailing	Genetic algorithm	Las Vegas Convention Center [46] (2017 Exhibition hall layout)	
Structural form	Volume design during construction phase	Particle swarm algorithm	Japan's "Meditation Forest" Crematorium [47] (Roof structure optimization)	
Morphological envelope	Performance in the latter construction phase of volume design	Unknown	Dubai Future Museum (Facade material assembly)	
Building performance	Planning and design: Volume design during construction phase	Genetic algorithm	Nanhai Museum (Hainan, China) [48] (Facade shading design and optimization)	
Other (e.g., 3D printing, virtual simulation)	Post-construction performance of volume design	Unknown	Kazakhstan National Pantheon (3D printing of model)	

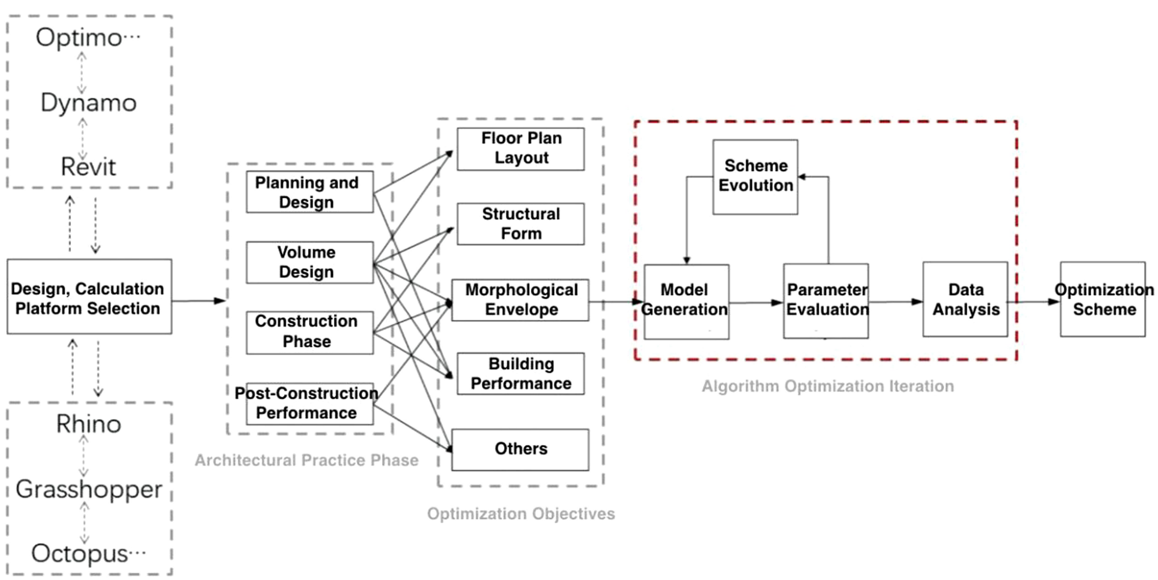


Figure 9 General workflow of optimization algorithm-driven generative design practice

3 General process of optimization algorithm-driven generative design

The concept of "optimization algorithms" is closely related to contemporary architectural practices and has been increasingly applied and developed in the field. Based on the analysis of related concepts and case studies, a typical process for algorithm-driven generative design in architecture includes several key stages: design, selection of computational platforms; determination of optimization goals for different stages of architectural practice, and the iterative process of algorithm optimization, leading to an optimized solution, as shown in Figure 9.

The selection of design and computational platforms is primarily based on commonly used platforms such as-Revit and Rhino (refer to Section 1.3). Optimization goals and stages of architectural practice can be referenced from the cases in Table 2, where designers select goals based on desired outcomes for the project. The iterative process of algorithm optimization involves four main steps detailed in the MaRS Office case (refer to Section 2.2). Through a series of filtering, evolution, analysis, and evaluation processes, a relatively optimal solution is achieved, representing the designer's desired outcome.

Conclusion and outlook

Technological advancements invariably drive industry transformation, and emerging terminologies in architectural practice such as "digitalization," "sustainability," "industrialization," "information technology," and "intelligence" are closely linked to the evolution of computer software. In the 21st century, architects are tasked not only with addressing the form and spatial aspects of buildings but also with focusing on their inherent performance and external impacts. Optimization algorithms provide a valuable pathway and method for architects to obtain a more comprehensive understanding of buildings through relatively scientific approaches.

Undoubtedly, the widespread application of optimization algorithms across all steps of design practice presents significant challenges. Nevertheless, these algorithms are highly beneficial for specific aspects of current design practices and for research into future comprehensive design methodologies. With changing lifestyles and increasing attention to spatial quality, architectural design must meet more complex functional demands and pursue innovative forms, resulting in greater design complexity. Algorithm-driven generative design allows architects to explore a broader range of problem-solving possibilities through computation. Moreover, algorithms, devoid of human intuition or biases, help architects overcome subjective judgments in traditional design processes, leading to novel and high-performance design solutions. As David Benjamin, the technical lead for the MaRS office project, states, "Ideally, an algorithm-based automated process can make design decisions more inclusive. Computation assists designers in making better trade-offs, not by removing subjective judgment but by enabling them to avoid relying on vague concepts to explain why one design is effective and another is not" [49].

Algorithmic design does not imply that the role of architects will be replaced. Architects must contextualize and simplify relevant design issues, ensuring alignment with their design concepts and visions. Thus, the translation between design solutions and algorithmic data, the inclusion and exclusion of effective evaluation or optimization parameters, and the balancing of rational indicators with humanistic factors are crucial. In the human-computer interaction of architects and optimization algorithms, architects' decision-making remains pivotal, demanding elevated comprehensive skills and presenting ongoing challenges [50].

Figure and table sources

Figure 1: Prepared by the author based on reference [2].
Figure 2: Prepared by the author based on reference [31].
Figure 3: Foster+Partners official website.
Figures 4-8: Redrawn by the author based on project video materials from ARCHITECT website.
Figure 9: Prepared by the author.
Tables 1 and 2: Prepared by the author, with images sourced from the web and references [46-48].

Notes

1)NP: The term stands for Non-deterministic Polynomial, which denotes problems that can be verified to a correct solution within polynomial time. Problems classified as P (polynomial) are those solvable by polynomial-time algorithms; NP problems are those for which it is unknown if a polynomial-time algorithm exists but can be verified to a correct solution within polynomial time.

References

[1] Press Release: Foster + Partners Wins Competition to Design Alibaba's New Offices in Shanghai[EB/OL]. Foster and Partners,

Jan 8,2020.

[2] PAULWINTOUR. A Brief History of Computation[EB/OL]. June 8,2018.

[3] KOSTAS T.Algorithmic D: A Paradigm Shift in Architecture? Architecture in the Network Society,22nd eCAADe Conference Proceedings, Denmark,15-18 September 2004:201-207.

[4] LI B.Algorithm Makes the Techniques of Digital Design Return to Essence[J].Architectural Journal,2017(5):1-5.

[5] FRED G, GARY A K.Handbook of Metaheuristics [M]. DOI: https://doi.org/10.1007/b101874.

[6] MACHAIRAS V, TSANGRASSOULIS A, AXARLI K.2014.- Algorithms for Optimization of Building Design: A Review[J].Renewable and Sustainable Energy Reviews, 2014(31): 101-112.

[7] NGUYEN A T,REITER S, RIGO P.2014.A Review on Simulation-based Optimization Methods Applied to Building Performance Analysis[J].Applied Energy,2014(113):1043-1058.

[8] CHRISTOPH W. Building Energy Optimization: An Extensive Benchmark of Global Search Algorithms[J]. Energy & Buildings, 2019(187):218-240.

[9] MELANIE M. An Introduction to Genetic Algorithms[J]. MIT Press, 1996(3):3.

[10] WANG W M,RIVARD H,ZMEUREAN R.2005.An object- oriented framework for simulation based green building design optimization with genetic algorithms[J].Advanced Engineering Informatics, 2005(19): 5-23.

[11] THEODORA V.Computer of a Thousand Faces: an Topomerizations of the Computer in Design (1965-1975) [J].Dosya 29 Computational Design, 2012(11): 27.

[12] WUJEC T. The Future of Making[M]. Melcher Media, London, 2017,20:88.

[13] Morphosis, Generative Components Software[EB/OL], https://www.architecturalrecord.com/articles/12260- generative components-software.

[14] SAKAMOTO T. From Control to Design: Parametric/ Algorithmic Architecture[M]. Actar-D, 2008.

[15] DAVID S. Design Modeling Terminology[J].Proving Ground, 2018,13: 3.

[16] SUN C, HAN Y S, REN H. A Study on Architectural Computational Design Oriented Towards Artificial Intelligence [J]. Architectural Journal, 2018(9):98.

[17] PAN W,TURRIN M,LOUTER C, et al. Integrating Multi- functional Space and Long-span Structure in the Early Design Stage of Indoor Sports Arenas by Using Parametric Modelling and Multi-objective Optimization[J]. Journal of Building Engineering, 2019,22(1):464-485.

[18] VEENENDAAL D. Design and Form Finding of Flexibly Formed Concrete Shell Structures[J].Thesis TMS,2017(24190).

[19] BROWN N, OCHSENDORF J, MUELLER C, et al. Early-stage Integration of Architectural and Structural Performance in a Parametric Multi-objective Design Tool[J]. Structures and Architecture - Proceedings of the 3rd International Conference on Structures and Architecture, ICSA 2016, 2016: 1103-1111.

[20] TSERANIDIS S. Approximation Algorithms for Rapid Evaluation and Optimization of Architectural and Civil Structures[D]. 2015.MIT.

[21] JAVANROODI K, NIK V M, MAHDAVINEJAD M. A Novel Design-based Optimization Framework for Enhancing the Energy Efficiency of High-rise Office Buildings in Urban Areas[J]. Sustainable Cities and Society, 2019, 49(5): 101597.

[22] HAMDY M, NGUYEN A T, HENSEN J L M. A Performance Comparison of Multi-objective Optimization Algorithms for Solving Nearly-zero-energy-building Design Problems[J]. Energy and Buildings,2016,121(3): 57-71.

[23] SHARIF S A, HAMMAD A. Simulation-Based Multi- Objective Optimization of institutional building renovation considering energy consumption, Life- Cycle Cost and Life-Cycle Assessment [J]. Journal of Building Engineering, 2019, 21(2018): 429-445.

[24] JIN J T,JEONG J W. Optimization of a Free-form Building Shape to Minimize External Thermal Load Using Genetic Algorithm [J]. Energy and Buildings, 2014, 85: 473-482.

[25] LEE J,BOUBEKRI M,LIANG F. Impact of Building Design Parameters on Daylighting Metrics Using an Analysis, Prediction, and Optimization Approach Based on Statistical Learning Technique[J].Sustainability (Switzerland), 2019,11(5).

[26] ZHANG A,BOKEL R,VAN DEN DOBBELSTEEN A, et al. Optimization of Thermal and Daylight Performance of School Buildings Based on a Multi-objective Genetic Algorithm in the Cold Climate of China[J]. Energy and Buildings, 2017, 139: 371-384.

[27] KIRIMTAT A, KREJCAR O,EKICI B, et al. Multi-objective Energy and Daylight Optimization of Amorphous Shading Devices in Buildings[J].Solar Energy, 2019,185(2018): 100-111.

[28] YANG D, REN S, TURRIN M, et al. Multi-disciplinary and Multi-objective Optimization Problem Re-formulation in Computational Design Exploration: A case of Conceptual Sports Building Design[J]. Automation in Construction, 2018, 92(4): 242-269.

[29] EKICI B, CUBUKCUOGLU C, TURRIN M, et al. Performative Computational Architecture Using Swarm and Evolutionary Optimisation: A Review[J]. Building and Environment, 2019, 147:

356-371.

[30] WORTMANN T. Efficient , Visual , and Interactive Architectural Design Optimization with Model-based Methods[D]. 2018(7): 324.

[31] NEGENDAHL K, NIELSEN T R. Building Energy Optimization in the Early Design Stages: A Simplified Method[J]. Energy and Buildings, 2015, 105:95-96.

[32] https://www.wallacei.com/

[33] CEMRE E, BERK T, MEHMET S. OPTIMUS: Self-Adaptive Differential Evolution with Ensemble of Mutation Strategies for Grasshopper Algorithmic Modeling[J/OL]. Algorithms.12.141. 10.3390/a12070141.

[34] CICHOCKA J M , MIGALSKA A, BROWNE W N, Rodriguez E. (2017) SILVEREYE - The Implementation of Particle Swarm Optimization Algorithm in a Design Optimization Tool[C]. In: Computer-Aided Architectural Design. Future Trajectories. CAADFutures 2017.Communications in Computer and Information Science, vol 724. Springer, Singapore .

[35] WORTMANN T. Opossum: Introducing and Evaluating a Model-based Optimization Tool for Grasshopper[C]. CAADRIA 2017.

[36] https://www.rechenraum.com/en/goat.html.

[37] https://www.food4rhino.com/app/nelder-mead- optimisation-eoc.

[38] https://dynamopackages.com/.

[39] Mohammad R. Optimo-Optimization Algorithm for Dynamo[EB/OL].November 18, 2014. https://dynamobim.org/optimo/.

[40] PENG L X, NORMAN F. Dialogue with Norman Foster[J]. UED, 2015(12):1.

[41] HUGH W,XAVIER D K, IRENE G,TUBA K. Interview with the Specialist Modelling Group(SMG):The Dynamic Coordination of Distributed Intelligence at Foster and Partners[M].Distributed Intelligence in Design，2011(3):232.

[42] XAVIER DE K. Recent Development at Foster＋Partners' Specialist Modelling Group[J].Architectural Design,2013,12:22-27.

[43] LIZZIE C. Foster＋Partners reveals visuals for gridded Alibaba Shanghai offices[EB/OL].08 January 2020. https://www.dezeen.com/2020/01/08/foster-partners- alibaba-shanghai-headquarters-architecture/.

[44] DANIL N, DAMON L. Project Discover: An Application of Generative Design for Architectural Space Planning[J]. SIMAUD, No.7 May 2017:6.

[45] NAGY D.The Buzz Metric: A Graph-based Method for Quantifying Productive Congestion in Generative Space Planning for Architecture[J]. TAD Volume 1 Issue 2, October 2017：64-73.

[46] NAGY D. Beyond Heuristics：A Novel Design Space Model for Generative Space Planning in Architecture[C].ACADIA 2017, Cambridge, MA 2-4 November, 2017: 436-445.

[47] JUDYTA M. SILVEREYE-The Implementation of Particle Swarm Optimization Algorithm in a Design Optimization Tool [C].CAAD Futures 2017,18 June 2017：151-169.

[48] MA C L, ZHU S Y, XIANG K. A Digital Cooperative Facade Optimization and Detailed Design of Cultural Architecture: A Case Study of Nanhai Museum[J]. Huazhong Architecture, 2018 (3)：35-38.

[49] KATIE G.The Polymath: David Benjamin Is Expanding The Definition of Architecture[EB/OL]. Architect magazine, January 12, 2018.

[50] HU W B, GAO N, WI C C, et al. Simulation Technique used for Architectural Design: Application and Innovation of a Building Simulation Technique at Architectural Design & Research Institute of SCUT Co., LTD.[J].South Architecture,2019(5)：86-90.