FORMAL VARIATION EXPLORATION FOR PERFORMANCE-BASED BUILDING MASSING DESIGN OPTIMIZATION

TONG SHAO[1], LIKAI WANG[2] and GUOHUA JI[3]
[1,3]Nanjing University.
[2]Xi'an Jiaotong-Liverpool University.
[1]mg20360016@smail.nju.edu.cn, 0000-0002-5646-3376
[2]wang.likai@outlook.com, 0000-0003-4054-649X
[3]jgh@nju.edu.com, 0000-0003-3237-1263

Abstract. Due to the requirement of design abstraction and simplification for early-stage building design optimization tasks, most applications of performance-based building design optimization are based on the designs generated using orthogonal and cubical geometries, which allows for simpler geometrical operations and sufficient design variability and differentiation in terms of geometrical configuration. However, these applications are only able to produce coarse solutions with room for improvement. In order to address this issue, this study proposes a method focusing on the formal variation in performance-based building massing design optimization to produce more detailed and precise solutions. In this study, two formal variation algorithms are developed using a volume-based and a boundary-based approach, which can modify the input orthogonal geometries produced by EvoMass, a design tool for building massing optimization and exploration. To demonstrate the efficacy of the proposed approach, a case study is presented, which shows that the use of the two formal variation algorithms can further improve the design performance and also allow designers to extract more accurate information related to the design strategies and performative design implications.

Keywords. Design Optimization, Formal Variation, Performance-based Design, Design Exploration, Parametric Design, EvoMass

1. Introduction

With the increasing attention to energy consumption, performance-based building design has become an important topic for researchers and designers. It is widely accepted that early-stage design optimization and exploration play an important role in enhancing overall building performance (Li et al., 2020a, 2020b). Among various factors, building massing forms are one of the most critical factors determining the design performance of buildings. In order to improve the efficiency of performance-based building massing form finding, computational design optimization has been widely applied to relevant research and applications (Wang, 2022b; Wang, Janssen, et al., 2023). A computational design optimization framework typically consists of three

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 1, 333-342.

components: a parametric model for design generation (design generative models), performance simulators for design evaluation, and an optimization algorithm for design evolution. Among these three components, the design generative model defines the design space for the optimization search and has a decisive impact on the information revealed by the optimization result (Wang, 2022a). Two typical approaches have been often adopted in existing studies and applications to build up design generative models.

The first approach focuses on the topological variation, which often creates building massing forms using voxels or cubical geometry. By varying the topological configuration of the building form, this approach can create design variants with significant differentiations, which can further reflect different design strategies or typologies, such as courtyards, self-shading, and solar envelopes (De Luca, 2017; Huang et al., 2015). The optimization incorporating this design generative approach is typically aimed at producing design variants that can convey abstract information related to overarching design strategies or typologies. Moreover, using such voxel and cubical volumes also facilitates geometrical operations for complex topological configurations, such as alignment and gridding, which can ensure the feasibility and rationality of the generated design to be maintained. Nevertheless, this approach is only able to produce abstract but coarse design solutions as the design variation is mostly at the building configuration and topological levels, and as a result, the optimized design often requires further refinement to exploit its performance potential.

The second approach focuses on the design manipulation of relatively subtle and detailed geometrical variations, and it often adopts operations such as twisted, slant, and taper (Chen et al., 2019). This approach can overcome the limitation inherited in the first approach and can produce more precise and detailed design solutions that are capable of harnessing greater performance potential. However, as the overall building configuration and typology remain fixed, using this approach often creates a confined design space for the optimization process to explore. As a result, solely using this approach makes it difficult to help architects achieve a systematic design exploration of different building typologies.

1.1. PAPER OVERVIEW

The above discussion highlights the advantages and disadvantages of the two design generative approaches frequently adopted in performance-based building design optimization. It is evident that these two approaches can complement each other and address the limitations inherent in each approach. In light of this, this study aims to incorporate these two approaches for performance-based building design, aiming to explore how their integration can further enhance the efficacy of computational design optimization during early-stage building design and streamline the process of design exploration and optimization. Herein, this study primarily focuses on a second-phase building massing design optimization workflow based on the design generated by a Rhino-Grasshopper plugin, called EvoMass (Wang, Luo, et al., 2023) with the use of two formal variation algorithms to further diversify the optimized design produced by EvoMass.

EvoMass is a design tool that generates and optimizes building massing based on cubical volumes. Nevertheless, it also holds the limitation mentioned above and is only able to produce coarse solutions for designers. As a result, two formal variation algorithms are developed respectively using a volume-based and a boundary-based approach to introduce additional formal variability to the optimized design. The details of the implementation of the two developed algorithms are elaborated in the next section, with a case study demonstrating the utility of the proposed workflow afterward. Finally, the paper concludes by discussing the relevance of the study as well as the limitations and future research directions.

2. Method

This section describes the workflow that incorporates EvoMass with the two developed formal variation algorithms for building massing design generation and optimization as well as the details of the algorithm implementation.

2.1. WORKFLOW

The proposed second-phase design optimization process is based on the optimization result produced by EvoMass. As mentioned above, EvoMass is a design tool aimed at generating and optimizing building massing designs for various environmental performance objectives. It contains two generative models that create building volumes based on the subtractive and additive principles (Wang, 2022b). Due to operations such as gridding and surface alignment, all the elements used in EvoMass are cubical, and as a result, all generated building geometries are orthogonal. While the optimized design produced by EvoMass can help designers identify promising design typologies and strategies related to energy-saving or passive design (Wang, Luo, et al., 2023), the cubical geometry still leaves great room for further performance improvement (Wang et al., 2019; WANG et al., 2019). To this end, designers often need to manually refine and develop the optimized design to exploit the performance potential, which could be time-consuming and laborious.

Considering the generative approach and the orthogonal building geometry produced by EvoMass, the proposed second-phase optimization connects the optimized design produced by EvoMass with two formal variation algorithms, each corresponding to one of the two generative models. The two algorithms can provide additional formal variations to the optimized design and enhance design performance by refining the building massing form. When using these two algorithms, an optimized design produced by EvoMass is first employed as the input for the corresponding formal variation algorithm. Subsequently, a second-phase optimization process is executed to further enhance the performance of the design through subordinate formal variations. This sequential design workflow enables designers to conduct secondary optimization and provides them with more precise and accurate solutions.

2.2. VARIATION ALGORITHMS

The two variation algorithms: *Volume-Based Algorithm* (VBA) and *Boundary-Based Algorithm* (BBA), correspond to the design produced by the two generative models in EvoMass. In addition, the two algorithms provide a set of user-defined parameters for designers to tailor the generated design, including mass selection, range of control points, displacement distances, etc. (Fig. 1).

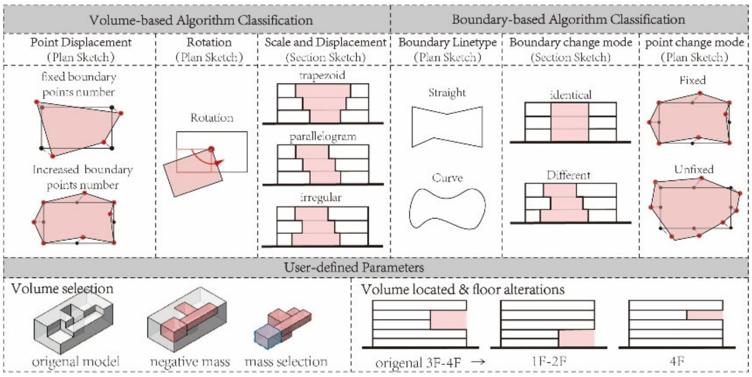

Figure 1 Overview of the Two Formal Variation Algorithms

2.2.1. Volume-Based Algorithm

Figure 2 illustrates the operational workflow of using VBA, which is designed to be connected with the design generated by the subtractive model in EvoMass. First, the negative volume of the subtracted void needs to be extracted, and the selected negative volume is then connected to the algorithm. There are three variation strategies provided for VBA, including 1) Control Point Displacement, 2) Scale and Rotation, and 3) Scale and Displacement. Finally, the varied design can be integrated with an evolutionary optimization for performance-based design optimization. The three strategies are elaborated as follows.

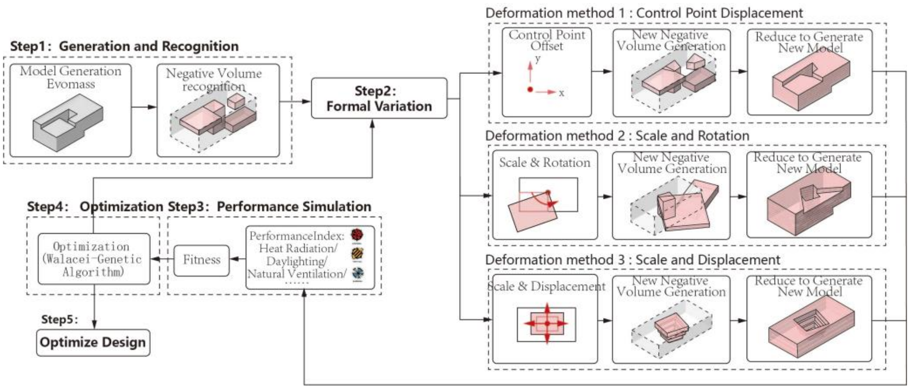

Figure 2 Formal Variation Operations of VBA

Regarding the control point displacement strategy, this strategy alters the geometry by varying the control point position of the selected negative volume (Figure 3). The displacement direction is determined by the position of each control point. The control point at the corner of the exterior building massing boundary is fixed. Displacements alongside the boundary surface are only applied to the control point on the exterior building massing boundary. Free displacements are applied to control points within the exterior building massing boundary. The example of the original geometries produced by EvoMass and the varied geometries are illustrated in Figure 4.

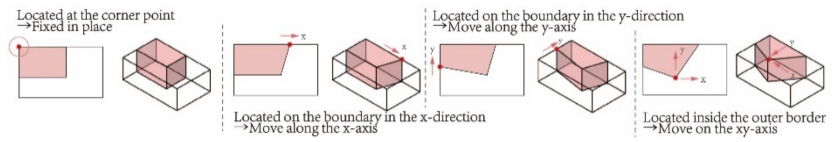

Figure3 Control point displacement strategies

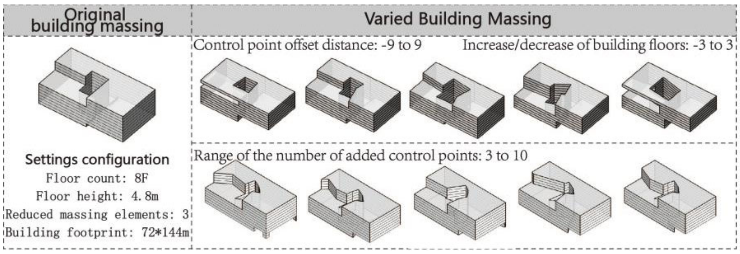

Figure 4 Random Sampling Designs Generated Using the Control Point Displacement Mode

Regarding the scale and rotation strategies, the selected negative volume is scaled and rotated, and the scaling and rotation center is determined according to the relationship between the negative volume and the input building massing exterior boundary (Fig. 5). This strategy can increase the design variability, while the change of the floor area is also relatively controllable. Designers can specify the scaling ratio, the range of rotation angles, and the range of affected floors. Figure 6 demonstrates a group of reshaped designs with the degree of variations controlled by different scaling ratios, ranges of rotation angles, and ranges of affected floors.

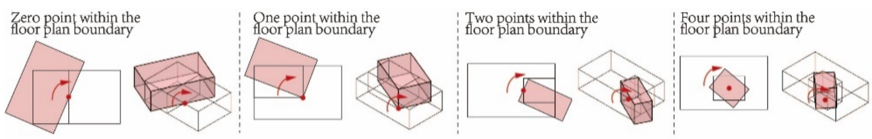

Figure 5. Rotation Center Selection Approach

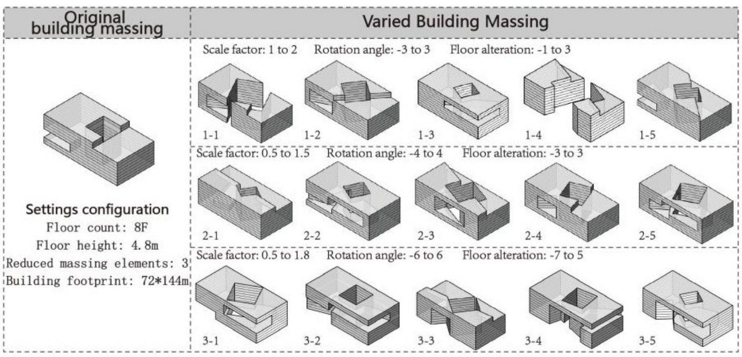

Figure 6. Random Sampling Designs Generated Using the Scale & Rotation Mode

Regarding the scale and displacement strategy, this strategy modifies the building form by scaling and moving the negative volume, and the variation is also applied to the vertical direction based on approaches including rectangular, trapezoidal, irregular, and parallelogram (Fig. 7). Likewise, designers can configure this strategy through parameters such as displacement distance, scaling ratio, and vertical alternation modes. Figure 8 demonstrates the effects of this strategy. As shown, significant change in the building massing form can be observed, and architectural features such as terraces can be clearly identified.

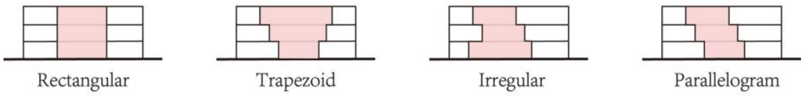

Figure 7. Vertical Variation Modes

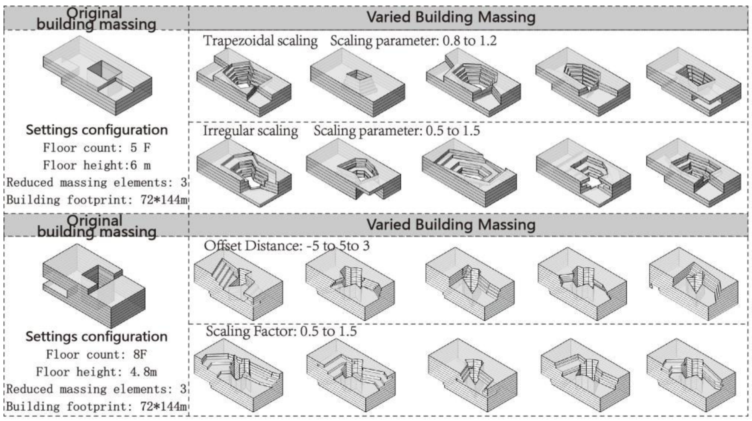

Figure 8. Random Sampling Designs Generated Using the Scale and Displacement Mode

2.2.2. Boundary-Based Algorithm

BBA (Boundary-Based Algorithm) contains a series of steps primarily to handle the building massing generated by the additive model in EvoMass, which, unlikely the design generated by the subtractive model, the sub-volume constituting the final aggregated volume is difficult to separate and extract. As a result, to address this issue, BBA alters the building form using the floor plan boundary of each floor level. BBA first creates a boundary polyline for each floor level, based on which a set of control points are created according to a user-defined interval. The position of these control points is then varied by the algorithm to change the shape of the boundary of each floor level. The use of boundary polylines also enhances the algorithm's generalizability, rendering it applicable to designs generated by the subtractive model as well.

The workflow of BBA is illustrated in Figure 9. In BBA, a set of user-defined parameters is provided to tailor the generated design, which includes the interval distances of the control point, boundary point adjustability mode, and the vertical consistency of the boundary variation (Fig. 10). Figure 11 demonstrates a set of example designs generated using BBA based on the additive models. As shown, BBA can generate buildings with curvilinear shapes. At the same time, using inconsistent vertical variation mode can produce architectural forms with fluidity.

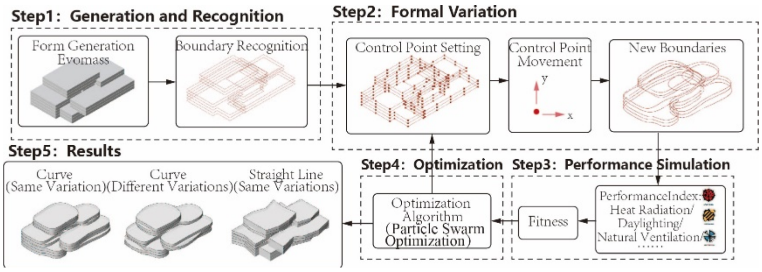

Figure 9 Formal Variation Operations of BBA

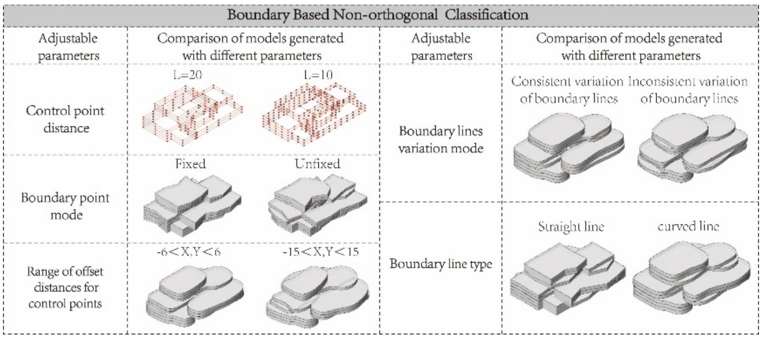

Figure 10 User-defined Parameters in BBA

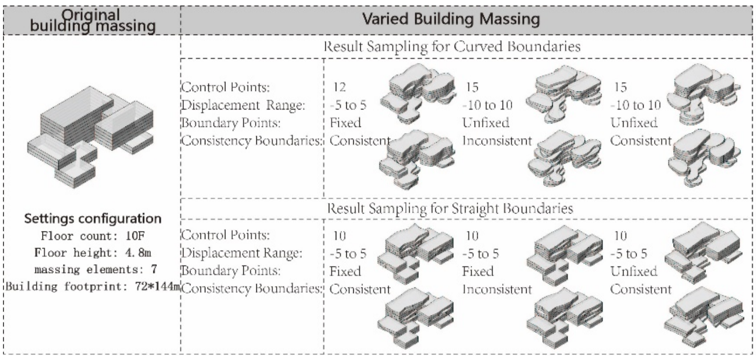

Figure 11 Random Sampling Designs Generated Using BBA

3. CASE STUDY

To demonstrate the effectiveness of proposed formal variation algorithms in performance-based building design tasks, a case-study design is conducted, which describes a teaching complex building in Nanjing, Jiangsu. The existing building is first deformed and then optimized. The total area of the building is 11,000 square meters, 7 floors with 3.5 meters height for each floor. The site, surrounded by multi-story buildings, has complex shading conditions, posing significant challenges for architects to balance various performance indicators using conventional methods.

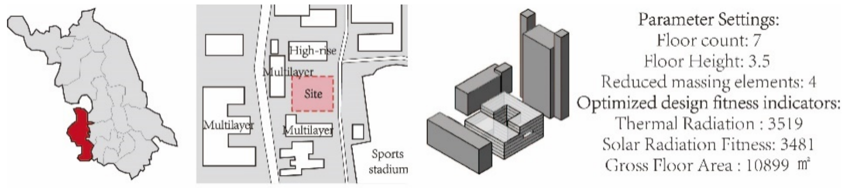

Figure 12 Site Condition and an Optimized Form Generated by EvoMass

Nanjing is characterized by a hot-summer-and-cold-winter climate, which stresses the importance of balancing solar radiation in both seasons, e.g. minimizing summer solar radiation and maximizing winter solar radiation. Thus, the optimization objective is defined as minimizing the difference between the received solar radiance between summers and winters, which ensures that the optimized design either has lower solar heat gain in summer or higher solar heat gain in winter.

The design presented in Figure 12 shows an optimized design produced by EvoMass, which is used for further formal variation. Featuring a central atrium, the selected optimized design contains a stepping terrace on the south side and a cantilevered block on the west side for self-shading. This design can obtain a summer-winter radiation difference of 3481 kWh. On this basis, the formal variation optimization was performed, aiming at refining the facade orientation, atrium size, and self-shading positions of the original design.

In test one, the genetic algorithm in Wallacei was employed. With solar radiation differences (SRD) used as the optimization objective, factors, including the gross floor area (GFA) and the number of floors, are also integrated into the objective function. The optimization produces 800 iterations of design generations and evaluations (8 generations, 100 individuals per generation, 0.9 crossover rate). The scale and rotation mode of the VBA was selected. The top-ranking optimized design, as well as those results on the Pareto curve, are summarized in the upper part of Figure 13.

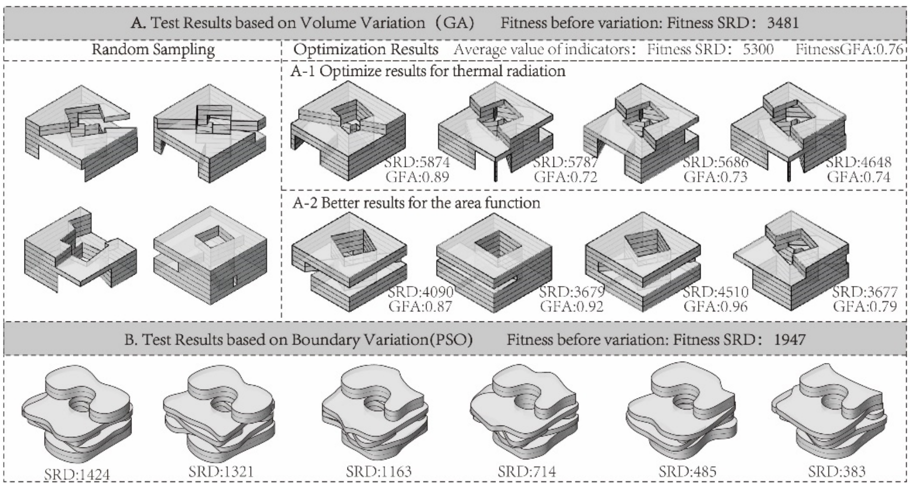

Figure 13 Test Results (SRD: solar radiance)

Overall, the optimized building forms in this test perform better than those originally produced by EvoMass. The optimized designs are characterized by a setback volume with internal corridors (A-1). Large self-shading blocks can be also identified among those designs that can better satisfy the GFA and floor number objectives (A-2). Further comparisons between optimization results and random samplings reveal that the optimized courtyard typically has a 30° clockwise rotation towards the north-south axis, and has a smaller self-shading area on the west side.

In test two, a Particle Swarm Optimization (PSO) algorithm is used, which is specifically designed for minimizing a single objective function. Currently, there is no available plugin having a PSO in Grasshopper, and therefore, the PSO algorithm was imported using Python through Jupyter Notebook to Rhino-Grasshopper. In the second test, with the use of PSO, BBA was used to modify the optimized design, and the optimized results in the lower part of Figure 13 present a significant performance improvement compared to the original design.

In comparison, VBA is able to achieve more substantial design variation by varying the orientation or cross-sectional shape of the negative void, which has a greater impact on performance improvement. In contrast, BBA is more focused on detailed formal variation and is more suitable for design refinement after the design solution has been primarily determined.

4. DISCUSSION AND CONLUSION

This paper investigates formal variation approaches for early-stage building massing design exploration, which is aimed to provide more detailed and precise solutions based on the input abstract design created using orthogonal geometric operations. Two formal variation algorithms are developed on the basis of Evomass, which can be widely adopted in various application scenarios such as courtyards, facades, and self-shading designs. The case study shows that with the use of the second-phase optimization incorporated with the selected optimized design and the two algorithms, the design performance can be further enhanced. In addition, designers can also extract more pertinent information from the refined design solution. Moreover, the two formal variation algorithms also include different geometrical variation modes, which provides greater flexibility for designers to conduct the design exploration using different variation algorithms and variation modes.

While it is possible to integrate the formal variation within the original optimization process based on the orthogonal geometry, one critical issue of using this approach is that there will be a large number of parameters required to control the building massing and the formal variation. This will further cause the failure of the optimization due to the huge design space for the optimization search. In contrast, the proposed second-phase optimization approach can avoid this issue, and at the same time, it also allows the designer to be more involved in the design process, as they can select different solutions for the secondary optimization.

To conclude, the paper presents a study focusing on the optimization for early-stage building design exploration, which is aimed to overcome the limitation inherited in the simplified geometric operation and generation that are often adopted in the initial design stage. The two developed algorithms for formal variations allow designers to further exploit the performance potential of the selected design solution. At the same time, it also helps designers identify more precise and detailed design implications related to the building performance. The case study shows the efficacy of the proposed algorithms, in which the design performance can be further improved by using the second-phase optimization. Regarding future research, more user-friendly and integrated tools are needed to enhance its applicability for a wider range of users. Furthermore, incorporating general formal variation algorithms that extend beyond the geometric aspects generated by EvoMass would contribute to enhancing the proposed approach's generalizability in diverse design scenarios.

References

Chen, K. W., Choo, T. S., & Norford, L. (2019). Enabling Algorithm-Assisted Architectural Design Exploration for Computational Design Novices. Computer-Aided Design & Applications, 16(2), 269–288. https://doi.org/https://doi.org/10.14733/cadaps.2019.269-288

De Luca, F. (2017). From Envelope to Layout - Buildings Massing and Layout Generation for Solar Access in Urban Environments. Proceedings of the International Conference on Education and Research in Computer Aided Architectural Design in Europe, 2, 431–440. https://doi.org/10.52842/conf.ecaade.2017.2.431

Huang, Y. S., Chang, W. S., & Shih, S. G. (2015). Building Massing Optimization in the Conceptual Design Phase. Computer-Aided Design and Applications, 12(3), 344–354. https://doi.org/10.1080/16864360.2014.981465

Li, S., Liu, L., & Peng, C. (2020a). A Review of Performance-Oriented Architectural Design and Optimization in the Context of Sustainability: Dividends and Challenges. Sustainability, 12(4), 1427. https://doi.org/10.3390/su12041427

Li, S., Liu, L., & Peng, C. (2020b). Energy strategy pattern for climate responsive architecture: workflow in the early stages of design. Architectural Science Review, 63(6), 494–506. https://doi.org/10.1080/00038628.2020.1724071

Wang, L. (2022a). Understanding the Span of Design Spaces. In D. Gerber, E. Pantazis, B. Bogosian, A. Nahmad, & C. Miltiadis (Eds.), CAAD Futures 2021: Computer-Aided Architectural Design. Design Imperatives: The Future is Now (Vol. 1465, pp. 288–297). Springer Singapore. https://doi.org/10.1007/978-981-19-1280-1_18

Wang, L. (2022b). Optimization-aided design: two approaches for reflective exploration of design search space. International Journal of Architectural Computing, 20(4), 758–776. https://doi.org/10.1177/14780771221134958

Wang, L., Janssen, P., Bui, T. D. P., & Chen, K. W. (2023). COMPARING DESIGN STRATEGIES - A system for optimization-based design exploration. HUMAN-CENTRIC, Proceedings of the 28th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), 1, 221–230.

Wang, L., Janssen, P., & Ji, G. (2019). Reshaping Design Search Spaces for Efficient Computational Design Optimization in Architecture. 10th International Conference on Computational Creativity, 100–107.

WANG, L., Janssen, P., & Ji, G. (2019). Progressive Modelling for Parametric Design Optimization - An Example of How Parametric Design Optimization Can Support Reflection. In T. F. M. Haeusler, M. A. Schnabel (Ed.), Intelligent and Informed - Proceedings of the 24th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2019 (Vol. 1, pp. 383–392). https://doi.org/10.52842/conf.caadria.2019.1.383

Wang, L., Luo, T., Shao, T., & Ji, G. (2023). Reverse passive strategy exploration for building massing design-An optimization-aided approach. International Journal of Architectural Computing, 21(3), 445–461. https://doi.org/10.1177/14780771231177514