AI-ENHANCED PERFORMATIVE BUILDING DESIGN OPTIMIZATION AND EXPLORATION

A design framework combining computational design optimization and generative AI

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Abstract. When using computational optimization for early-stage architectural design, most optimization applications often produce abstract design geometries with minimal details and information in relation to architectural design, such as design languages and styles. Meanwhile, Generative AI (GAI), including Natural Language Processing (NLP) and Computer Vision (CV), hold great potential to assist designers in efficiently exploring architectural design references, but the generated images are often blamed for having limited relevance to the context and building performance. To address the limitation in computational optimization and leverage the capability of GAI in design exploration, this study proposes a design framework that incorporates Performative/Performance-based Design Optimization (PDO) and GAI programs for early-stage architectural design. A case study is demonstrated by designing a high-rise mixed-use residential tower in Hong Kong. The result shows that the PDO-GAI approach can help designers efficiently proceed with both diverging exploration and converging development.

Keywords. Building Performance, Computational Optimization, Design Exploration, Generative AI, Architectural Style, Façade Language.

1. Introduction

Buildings greatly impact urban environments, and performative/performance-based building design plays a critical role in achieving sustainable urban development. Recently, a number of studies have employed computational optimization to assist in such design tasks to improve environmental and energy performance of the design, such as daylighting, passive heating/cooling, and energy consumption. Computational optimization can automatically generate and evaluate a large number of design variants

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and search for desirable ones with competitive performance using parametric models, performance simulations, and evolutionary algorithms (Li et al., 2020). However, due to the fact that using parametric modeling techniques to generate building design requires a significant degree of design abstraction and simplification, most parametric models developed for computational optimization only generate designs with minimal details and information in relation to architectural design, such as architectural styles and facade languages (Wang, 2022a; Wang et al., 2022). This undermines its integration into architects' design ideation and exploration process.

Regarding architectural design exploration, recent advancements in Generative AI (GAI), including Natural Language Processing (NLP) and Computer Vision (CV) techniques, hold great potential to assist architects in efficiently exploring architectural references with different design styles and languages (Zhu & Luo, 2023). However, solely using GAI is blamed as it can only generate designs with limited relevance to the context and building performance. Most current relevant applications are focused on creating photorealistic rendering images. In contrast, some other recent studies also investigated collaborative applications of different GAIs as a team of design partners in the architectural design process (Cheung & Dall'Asta, 2023), highlighting the potential of GAI in enhancing and strengthening architects' ideation and exploration. This also shows the potential of such applications in more dynamic and abstract design exploration tasks beyond creating appealing architectural images.

Considering the strengths and the weaknesses of computational optimization and GAI, on the one hand, the strength of GAI in rapidly producing architectural images with various styles and languages can be leveraged to address the limitations of the lack of architectural details in conventional computational optimization in performance-based building design. On the other hand, connecting GAI with computational optimization also helps address the issue of the contextualization inherited in GAI. These two aspects reveal a research gap regarding the combination of computational optimization and GAI for early-stage architectural design exploration for both performance and architectural styles and languages.

Departing from this, this study proposes a design framework that incorporates computational optimization with GAI for early-stage architectural design. The framework includes the use of computational optimization to evolve design populations and search for optimized building massing forms ((Wang, 2022b)). Meanwhile, several multimodal AI recognition and generation tools, including Visual-Question-Answering (VQA) AI such as BLIP2, large language model such as GPT, and AI arts generation tools, such as Midjourney and Stable Diffusion, are explored to enhance the design exploration and feedback regarding architectural styles and language. Instead of using them as usual standalone applications, they were experimented with and examined iteratively to conduct design exploration back and forth with the computational optimization tool. Hence, the AI and optimization tools transform from computational tools into design collaborators.

Following this, the main body of the paper describes a design workflow established to integrate computational optimization and GAI for iterative design optimization, ideation, and reflection. At the same time, a case study is presented to demonstrate the proposed workflow and its utility in the architectural design process. The paper concludes by discussing the relevance of this study to the research discourse of computational optimization and GAI while pointing out the future research direction based on the limitations we identified in this study.

2. Method

2.1. DESIGN WORKFLOW

Figure 1 illustrates the overall working system, which mainly consists of two parts: Performance-based Design Optimization (PDO) and GAI program.

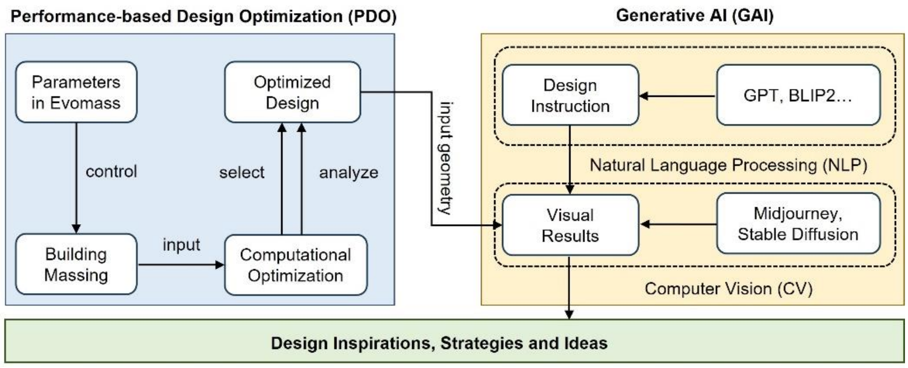

Figure 1. Overall Design Workflow

The workflow starts with the PDO, which can produce several optimized building massing designs through multiple iterations of optimization runs. Subsequently, the GAI process assists in the exploration and visualization of architectural style and design concepts according to the designers' inputs. Finally, designers extract design strategies, ideas, and inspirations related to architectural styles and languages by synthesizing the building massing form with visualized conceptual images, which can guide further design scheme development.

The PDO stage is based on using EvoMass on the Rhino-grasshopper platform (Wang et al., 2020), while EvoMass can also be replaced with other parametric models to achieve similar building massing optimization results. The GAI process involves the use of NLP and CV tools. The NLP tool includes GPT and BLIP2, while CV tools include Midjourney and Stable Diffusion. The application methods and implementation process of EvoMass and related GAI tools are explained in the following demonstration section.

2.2. BUILDING MASSING DESIGN OPTIMIZATION AND EXPLORATION

In the building massing design optimization and exploration stage, EvoMass is used to search for desirable building massing designs with competitive performance. With the use of EvoMass, designers first need to customize it to generate satisfying building massing designs through different user-defined parameters. After the parameter settings are completed, the Steady-State Island Evolutionary Algorithm (SSIEA) embedded in EvoMass is utilized to evolve the design population. The optimization can be driven by various building performance factors such as solar radiation, view, annual sunlight, etc. In Grasshopper, these building performance objectives can be simulated using Ladybug and/or ClimateStudio to measure the performance of the generated designs. With the optimized design, designers need to interpret the formal features revealed by the optimized designs and extract the design implications related to building performance, which can also further inform AI-assisted design exploration.

Moreover, the use of EvoMass also allows for multiple runs of optimization focusing on different performance objectives or using different user-defined parameters to generate building massing designs with different formal characteristics. In this way, the designer can collect more feedback pertinent to different design and performance aspects or iteratively refine the optimization setup and result.

2.3. ARCHITECTURAL LANGUAGE AND STYLE EXPLORATION

In the architectural language and style exploration stage, the NLP tools are first used for textual conversation for design ideation, and it does not necessarily occur after the completion of the PDO stage. The conversation with the NLP tools primarily extends the designer's perception of the design context and understanding of potential design styles into a conversational reflection. Several potential design ideas are fed back to NLP tools such as BLIP2 and GPT to provide further iterative feedback and optimize design guidance instructions.

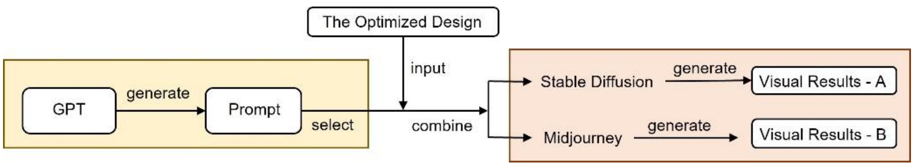

Figure 2. Design Workflow of the GAI Stage

CV tools such as Midjourney and Stable Diffusion are applied based on the optimal solutions obtained from the PDO stage. Combined with the design instructions fed back by NLP tools in the above-mentioned stage and the images of the massing forms provided by PDO, it can provide variations of visual feedback that envision design development possibilities and inspirations. The generated images are the consequences of the iterative process combined with the designer's design intent, performance optimization, and NLP tools' feedback. For example, it could provide variations of sustainable building design based on the input massing model that has considered the site environment in the first place. This workflow integrates site context consideration into GAI, greatly enhancing the practicality of applying GAI to generate controlled and contextualized variations of potential design development.

3. Demonstration

To demonstrate the efficacy of the proposed workflow, a case study is presented, describing the design of a high-rise mixed-use residential tower in Apleichau, Hong Kong, one of the most densely populated islands in the world. Figure 3 demonstrates the location of the selected site, which is alongside Main Street and currently has a

Municipal Building and four old tenement houses that are about to be demolished or renovated. The developer originally intended to renovate the old tenement houses into a "toothpick" building for residential purposes. However, toothpick buildings have the characteristics of obstructed lighting, high thermal radiation, and limited visibility due to their high-density forms, which are not suitable for living.

Figure 3. Site Condition and Surrounding Urban Context

Over recent years, the frequency of extremely high temperatures during Hong Kong's summers has consistently risen, accompanied by a deterioration in the urban heat island effect. Considering these, the proposed design workflow is applied to the case-study with the focus on alleviating the physical environmental challenges of the design of this block, as well as investigating the potential of using building and environmental performance as a driving factor in the design development process.

3.1. PERFORMANCE-BASED DESIGN OPTIMIZATION

In order to optimize the environmental performance of this urban massing design, two optimization objectives were selected: view and summer radiation. To obtain solutions that can simultaneously correspond to the two objectives, a single-objective optimization mode was used, and the two objectives were integrated into one fitness evaluation function using a weight-sum approach. To achieve a solution with more intricate and architectural appealing formal characteristics, the additive algorithm within EvoMass was used for design generation, which produces building massing forms by aggregating multiple sub-volumes within a predefined spatial boundary.

To obtain desirable solutions, three optimization runs were conducted at the PDO stage in this case study. The first and the second optimization runs were conducted in parallel but using different user-defined parameter settings to explore different directions in terms of formal characteristics. The first optimization uses an approach to controlling the overall size of the aggregated volumes, while the second optimization uses a more detailed control of the size of each sub-volume. The differences can be exhibited in the optimization results shown in the first two rows of Figure 4.

The first two rows list five high-performing designs from the first two optimization runs. Regarding the designs from the first optimization run (Group 1), the designs are monolithic and does not coordinate well with the surrounding urban context. In addition, the volumetric configuration in these designs is rather unclear, which makes it difficult to interpret the performance implications related to the building massing form. In contrast, the designs from the second optimization run (Group 2) display interlocking volumes and clear tendencies in terms of volumetric compositions. The slender upper part of the building can reduce solar heat gain while achieving a greater unobstructed view. Additionally, the solid bottom part of the building can make most of the volume within the shadow cast by the surrounding buildings to achieve a greater passive cooling effect. Nevertheless, the bottom part lacks a connection to the surrounding environment.

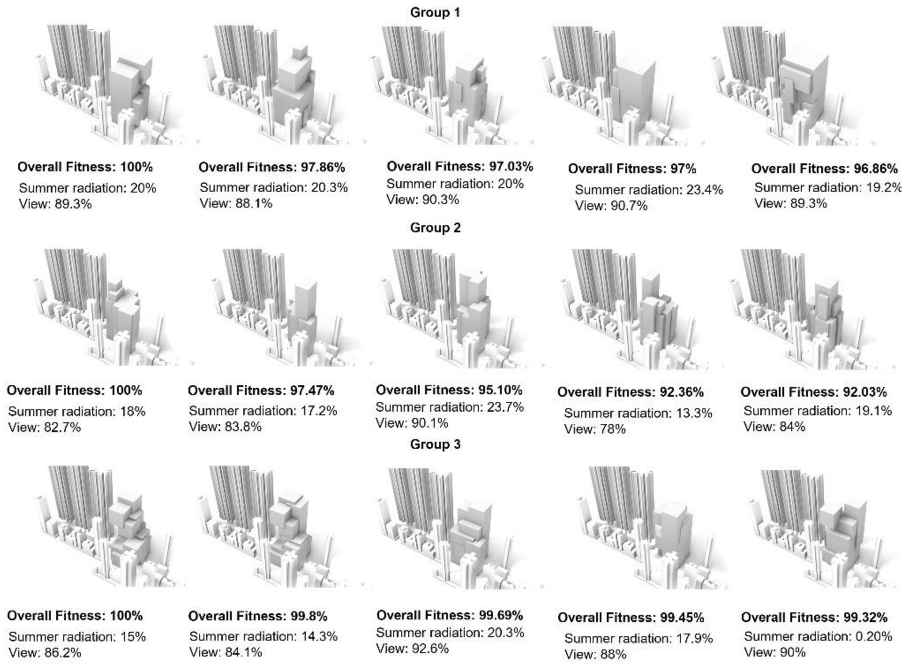

Figure 4. Building Massing and Performance Calculation Results

Based on the issues identified from the first two optimization runs, the third iteration of optimization was conducted, and user-defined parameters were changed to enhance the more even distribution of sub-volumes. The result shows that most optimized designs can overcome the shortcomings in the prior optimized designs. Within these designs, one solution achieving a desirable balance and compromise between performance and building design feasibility was selected (Fig. 5) as the basis for subsequent design exploration using GAI.

As shown in Figure 5, the selected design has multiple cantilevered blocks that enhance the façade surface with an unobstructed view. At the same time, these blocks also self-shade a large proportion of the building façade from excessive solar exposure, which lowers the overall solar radiance received by the building facade surfaces. The above analysis not only can help designers better understand the performance implications of the design strategies revealed by the optimized design, but can also provide hints for the subsequent design exploration using GAI.

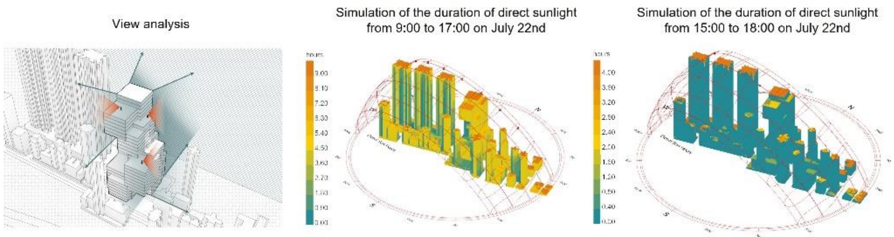

Figure 5. Analysis of the Causes of the Morphological Trend

3.2. ARCHITECTURE LANGUAGE AND STYLE EXPLORATION

In this stage, a large language model, GPT, is first chosen to obtain descriptions in terms of architectural languages and styles, which serves as the input for the architectural image generation in the next step. Since the GPT only receives and produces textual content, a prompt question template is formulated to guide the GPT in generating descriptions that can be interpreted in the image generation step. The prompt question template:

> "According to the design process, provide five sets of prompt words in different directions. Design progress: The current design is optimized according to x and y, hoping to design mixed-use buildings in a densely built city. Next, we want to start deepening the facade of the building, the surrounding landscaping, etc. Please refer to and follow the following format and examples for the prompt words of the AI drawings. Format: Project type + Architecture style + Architects Name + Facade + Rendering Style + View + Environment + Light. Example: museum, modernism, OMA Architecture, glass facade, white light inside, facing the road in downtown Hong Kong, mir rendering, bird's-eye view, natural light."

Prompts generation results from GPT:

- Public office building, Ecological style, Sustainable Architecture Studio, Green facade, Modern rendering style, Urban park landscape, Natural lighting.
- Hotel, Postmodernism, Green Architecture Firm, Adjustable shading devices, Natural ventilation design, Beach landscape, Natural light.
- Apartment building, Ecological style, Sustainable Design Group, Vertical garden facade, Stone exterior, City skyline view, Passive solar energy utilization, Soft lighting.
- Commercial complex, Modernism, Renewable Architects, Glass curtain wall, Green roof garden, City center street view, Natural ventilation, Bright natural light.
- Community center, Futurism, Eco-Friendly Design Studio, Adjustable light control facade, Technological rendering style, Surrounding Park landscape, Optimized lighting, and ventilation.

Finally, the third one is chosen in this demonstration, with a selected style of "Zaha Hadid architects" included manually.

In the next step, the selected optimized solution generated by EvoMass and the prompt obtained from the GPT is used as the input for architectural image generation. In this study, two CV tools, including Midjourney and Stable Diffusion, are used for architectural language and style exploration, which also investigates the differences between these two tools for image generation.

Stable Diffusion implements image generation control through different ControlNet models (Fig. 6), including MLSD (straight line detection), Depth (3D depth detection), and Canny (edge detection). It also integrates the weight of the prompt, mainly divided into 1) "balanced", 2) "the prompt is more important", and 3) "the ControlNet is more important". After experiments and comparison, Stable Diffusion 1.5 and MLSD model were adopted, with two weights, including "balanced" and "the prompt is more important".

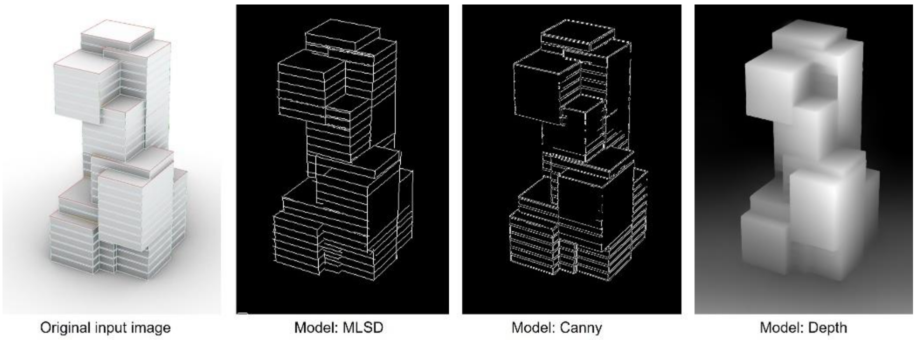

Figure 6. The Original Image and Filtered Images of the ControlNet Models

MLSD model provides precise detection of this building model outline, which is all composed of straight lines. Regarding the ControlNet, the "balanced" mode is able to provide a high consistency of the massing model, and number of floors, while the "the prompt is more important" option creates less-controlled variations such as generating buildings with round corners. Still, the perspective, and overall building height and main gestures of extrusions could be observed. Therefore, these two ControlNet models provide design variations with different consistency depending on how many differences there are from the original model the designers are looking for.

Differing from Stable Diffusion, the control of the generated architectural form of Midjourney shows less relevance to the input images, while the generated design images have significantly more variability. In the design examples illustrated in Figure 7, the v5.2 version of Midjourney is being experimented with three different image weights (0.5, default (1), 2) to compare the design variability of the generated design images. When the image weight was set to 2, the outputs had the greatest similarity with the input image, which is suitable when the massing model is preferred to be developed with little variation. When image weight was set to default (1), it displayed similar results with more creative generation in the context. For the lowest degree of image weight (0.5), it transformed the massing model most creatively with a more photorealistic background generated. Therefore, low image weight is useful when designers look for more creative options. In contrast, high image weight is more suitable for getting controlled variations while trying to keep the form of the original massing model.

Figure 7. Image Generations Based on Optimized Massing Model

4. Discussion and Conclusion

The above demonstration showcases the potential of the integration of computational optimization and GAI in assisting early-stage architectural design exploration. The integration addresses the shortcomings inherited within the two techniques and achieves greater collective utility by synthesizing their strengths for design optimization and exploration.

As shown in the case study, the proposed design workflow allows for a rapid decision-making approach for early-stage design ideation and conceptual development. Although the application solely relying on computational optimization can produce a sizeable number of design options for design space exploration, it is often challenging and overwhelming for designers, especially inexperienced ones, to efficiently evaluate the potential of different design options in other architectural design aspects and select a viable one for subsequent design development. In this regard, the proposed workflow can facilitate designers to quickly visualize the architectural feasibility of the abstract building geometry generated by computational design optimization. At the same time, this approach also extends the utility of GAI for performance-based architectural design by providing more contextualized solutions for the designers.

Despite its potential utility, certain aspects need further improvement and development. First, the design produced by the GAI may contradict the design generated by computational design optimization in terms of design strategies or features associated with building performance. For example, the effectiveness of the self-shading revealed by the computational optimization can be undermined by the large transparent façade surfaces potentially created by the GAI. Thus, the awareness of the performance implications shown in the optimized designs, no matter from human designers or GAI, is a critical step to generate designs more consistent with the optimized design regarding the building performance. Apart from this, the user-friendliness of the design tool and the automation of the design process are also critical future research directions.

To conclude, this paper presents a study investigating the integration of PDO and GAI for early-stage architectural design exploration. The proposed design workflow is established by integrating EvoMass and various GAI tools, and its efficacy is demonstrated through a case-study design. The result shows that the use of the approach allows for rapid and performance-pertinent exploration of building massing and architectural languages and styles. Finally, the relevance of the study is discussed, with limitations and future research directions identified.

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References

Cheung, L. H., & Dall'Asta, J. C. (2023). Exploring a Collaborative and Intuitive Framework for Combined Application of AI Art Generation Tools in Architectural Design Process. In Bertie MullerBertie Muller (Ed.), Proceedings of the AISB Convention 2023 (pp. 122–130).

Li, S., Liu, L., & Peng, C. (2020). 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

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., Chen, K. W., Janssen, P., & Ji, G. (2020). Enabling Optimisation-based Exploration for Building Massing Design - A Coding-free Evolutionary Building Massing Design Toolkit in Rhino-Grasshopper. RE: Anthropocene, Design in the Age of Humans - Proceedings of the 25th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2020, 1, 255–264. https://doi.org/10.52842/conf.caadria.2020.1.255

Wang, L., Zhang, H., Liu, X., & Ji, G. (2022). Exploring the synergy of building massing and façade design through evolutionary optimization. Frontiers of Architectural Research, 11(4), 761–780. https://doi.org/10.1016/j.foar.2022.02.002

Zhu, Q., & Luo, J. (2023). Generative Design Ideation: A Natural Language Generation Approach. In Design Computing and Cognition'22 (pp. 39–50). Springer International Publishing. https://doi.org/10.1007/978-3-031-20418-0_3