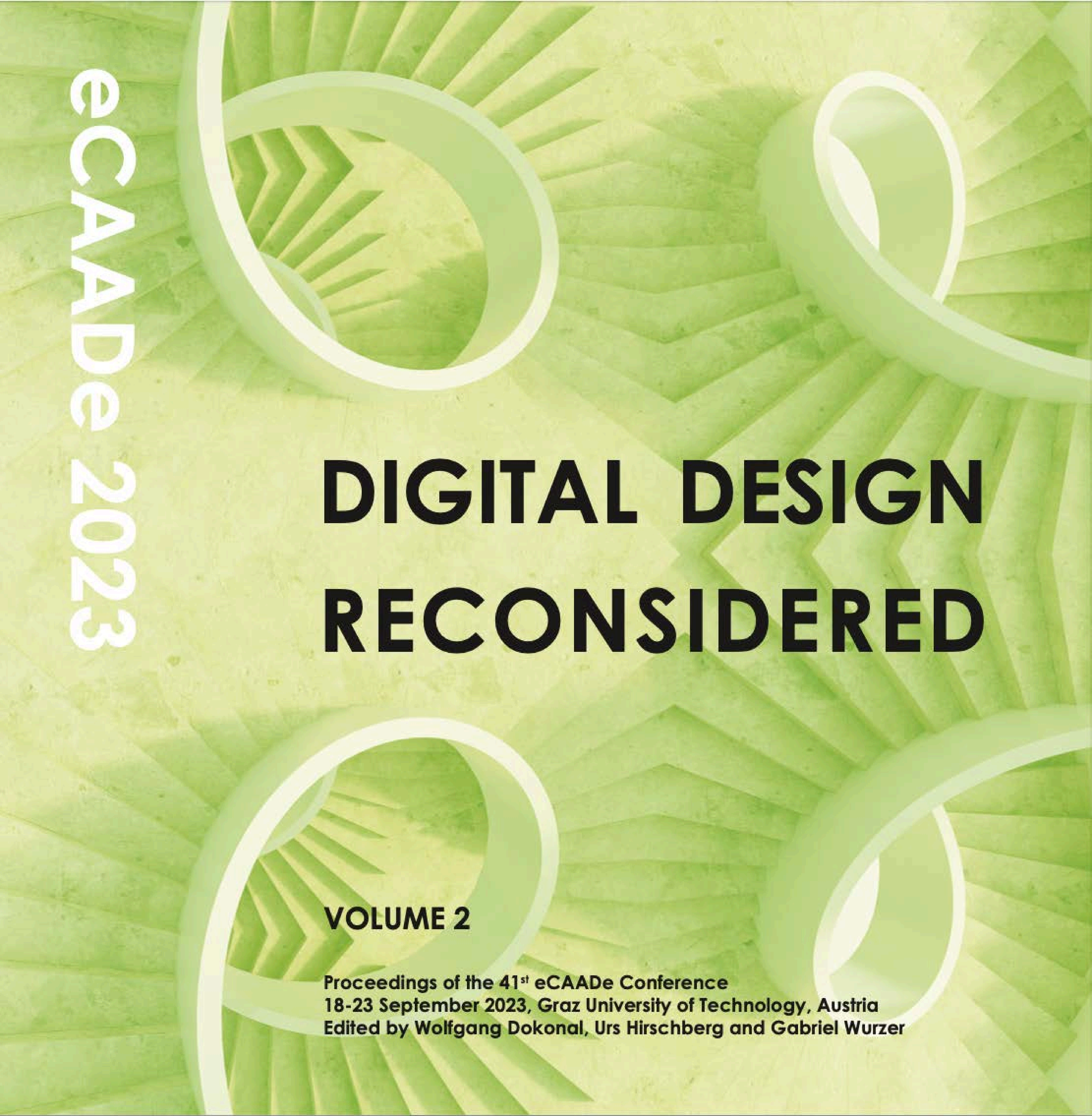

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Edited by
Wolfgang Dokonal
Urs Hirschberg
Gabriel Wurzer

Editors
Wolfgang Dokonal[1], Urs Hirschberg[1], Gabriel Wurzer[2]
[1]Graz University of Technology, Faculty of Architecture
[2]Vienna University of Technology Wien, Institute of Architectural Sciences, Digital Architecture and Planning

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Rethinking Architectural Design Process using Integrated Parametric Design and Machine Learning Principles

Alexis Andreou[1], Odysseas Kontovourkis [1], Solon Solomou[2], Andreas Savvides [1]
[1] University of Cyprus [2]Manchester Metropolitan University
[1]{andreou.alexis| kontovourkis.odysseas|savvides.andreas.1}@ucy.ac.cy
[2]S.Solomou@mmu.ac.uk

Artificial Intelligence (AI) has the potential to process vast amounts of subjective and conflicting information in architecture. However, it has mostly been used as a tool for managing information rather than as a means of enhancing the creative design process. This work proposes an innovative way to enhance the architectural design process by incorporating Machine Learning (ML), a type of Artificial Intelligence (AI), into a parametric architectural design process. ML would act as a mediator between the architects' inputs and the end-users' needs. The objective of this work is to explore how Machine Learning (ML) can be utilized to visualize creative designs by transforming information from one form to another - for instance, from text to image or image to 3D architectural shapes. Additionally, the aim is to develop a process that can generate comprehensive conceptual shapes through a request in the form of an image and/or text. The suggested method essentially involves the following steps: Model creation, Revisualization, Performance evaluation. By utilizing this process, end-users can participate in the design process without negatively affecting the quality of the final product. However, the focus of this approach is not to create a final, fully-realized product, but rather to utilize abstraction and processing to generate a more understandable outcome. In the future, the algorithm will be improved and customized to produce more relevant and specific results, depending on the preferences of end-users and the input of architects.

Keywords: *End-users, Architects, Mass Personalization, Visual Programming, Neural Network Algorithm.*

INTRODUCTION

The internet has facilitated an abundance of global information, which has presented both opportunities and challenges for individuals, businesses, and society. While it has enabled greater access to knowledge and information, driving innovation and progress, there are also concerns regarding data privacy, information overload (Day et al. 2009), and effectively managing the sheer volume of available information (Froudist-Walsh et al. 2017). Therefore, in accordance with Industry 4.0 (i-SCOOP, n.d.) and Society 5.0 (Cabinet Office of Japan, n.d.), different forms of AI among other technologies, are the key enabling technology for further technology development and information handling.

In recent years, the advancement of AI techniques, particularly Deep Learning (DL), has played a significant role in the field of computer vision. This has led to the development of 3D reconstruction/generation techniques working on different types of input formats, e.g., text, image. Although generative models have demonstrated remarkable successes in generating realistic high-resolution images (Karras et al. 2018), this level of success has yet to been equally replicated in the 3D domain.

In architecture, AI can be used to optimize various processes, from processing massive data on a large scale up to synthetic process evolving or for processing large amount of subjective and conflicting information. Not as a mere additional design tool, but as a revolutionary way of communication between design environment, architect, and final user, acting as a countermeasure to immense amount of available information (parameters) as mentioned earlier. Additionally, considering a concept such as "machine hallucinations" as mentioned in book by (Leach, 2021), introduction of AI as a creative partner may challenge traditional design approaches; nonetheless, allowing the architects to push the boundaries of creativity and explore uncharted design territories, leading to innovative and exciting architectural solutions.

Currently, related works on the implementation of AI in computer vision or architectural design focuses on two broad categories: accurate reconstruction (3D) or abstract representation (2D, 3D).

3D reconstruction is the process of creating a precise three-dimensional model or representation of an object from a set of 2D images, point clouds, or other data sources. Occupancy Networks paper (Mescheder et al. 2018; Niemeyer et al. 2019) has investigated the implicit representation of continuous 3D shapes as level sets by optimizing deep networks that map XYZ coordinates to signed distance functions or occupancy fields. However, these models are limited by their requirement for access to ground truth 3D geometry, manually created or typically obtained from synthetic 3D shape datasets such as ShapeNet (Chang et al. 2015). Therefore, there’s a need to find models that work only on images.

Neural Radiance Fields (NeRF) (Mildenhall et al. 2020; Zhang et al. 2020) is considered the most recent and advanced research paper which follows this criterion. NeRF is a state-of-the-art machine learning model that uses a neural network to generate high-quality 3D scene renderings from a set of input images. NeRF has shown impressive results on a wide range of scenes, including complex outdoor environments and indoor scenes with complex lighting and material properties. However, the authors indicate that the model is computationally expensive and time-consuming.

Abstract representation involves the creation of a simplified or stylized version of an object or concept that emphasizes its essential features and characteristics while omitting or reducing less important details. In the studies by (Parker, 2016; Parker and Johnson, 2016) the use of semi-autonomous algorithms is discussed, specifically the Scale-Invariant-Feature-Transform (SIFT) algorithm, in processing large datasets of architectural images to generate new design outputs. SIFT workflows involve identifying and abstracting key architectural characteristics into geometric compositions and assigning codified key points, which are then processed to produce dynamic vector-flow-fields that can be optimized for specific performance criteria. However, the authors acknowledge that SIFT algorithms are dependent on existing input images, and any "novelty" produced through them is based on relations to those inputs. Nonetheless, SIFT algorithms can produce novelty by intentionally augmenting the data input, resulting in digitally curated images through an internal and autonomous interpretation of data. Overall, the paper suggests that SIFT algorithms can be a valuable tool for architects and designers to generate new design possibilities and explore the potential of large datasets of architectural images.

Zhang and Blasetti (2020) proposes a method for style transfer of 3D architectural forms using a machine learning approach. The authors use a generative adversarial network (GAN) to learn the mapping between a set of input 3D shapes and a target style. They introduce a new dataset of 3D shapes with diverse styles to train and evaluate their model and discuss the challenge of maintaining spatial continuity and relationships in the generated 3D model. Additionally, the paper presents results from applying several state-of-the-art GANs for style transfer, resulting in a new 3D form combining the original and target styles. Overall, the paper demonstrates the potential of using machine learning techniques for architectural design and provides insights into the specific challenges and considerations involved in 3D style transfer.

Lastly, ArchiGAN (Chaillou, 2019) as symbiosis between statistical approach and conceptual generation, is a tool designed to generate architectural plans based on a set of constraints and preferences provided by the user. ArchiGAN consists of two neural networks, a generator and a discriminator, which are trained simultaneously to produce realistic and diverse architectural plans. The generator produces plans based on the user's input, while the discriminator evaluates the realism and feasibility of the plans. ArchiGAN has shown promising results in generating diverse and realistic plans that meet the user's constraints and preferences, making it a useful tool for architects and designers.

Previous research indicates that AI has potential in architecture, primarily for managing information rather than a direct part of the creative design process. In order to challenge this and incorporate AI as a significant part of the creative process, was concluded that the most appropriate implementation is within a multi-level system, where the architect is the subject, with a subsystem where the subject is the user. However, to create such a system, the input of many subjects (architects) is required. Therefore, instead of this scenario, we propose to build a flexible model based on the basic principles of learning models for its subsequent improvements and extensions by its users.

In addition to the advancements in design generation, by considering the environmental impact from the early stages of design, architects can contribute to a more sustainable and resilient built environment, addressing the urgent need for sustainable practices in the face of global challenges such as climate change. Therefore, the key point for this concept realization is the construction of a parametric model based on several implemented architectural tools and performance metrics, with the principle that any input should lead to an acceptable output with its ability to extend the range of variations, by adapting to the individual needs of the final user. Nevertheless, due to constraints at all levels of realization, the task of this work is to construct a simplified model with a focus on the ability to reproduce these principles.

METHODOLOGY

Based on existing generative models' capabilities and structural models, this work aims to explore how machine learning (ML) can be used to generate visual creative outcomes by transferring information from one form to another - for instance, from text to image (Reed et al. 2016) or image to 3D architectural shapes (Wu et al. 2017). To accomplish this, ML will be integrated as a form of AI into a parametric architectural design process, acting as a mediator between architects and end-users. The proposed method (as illustrated in Figure 1) fundamentally consists of the following steps:

1. Model creation: Refers to a process that encompasses the formation of domain, spatial division, and final shape construction.
2. Revisualization: A process that involves the generation of external elements.
3. Performance evaluation: The part of the computational process dealing with the extraction and valuation of generated data.

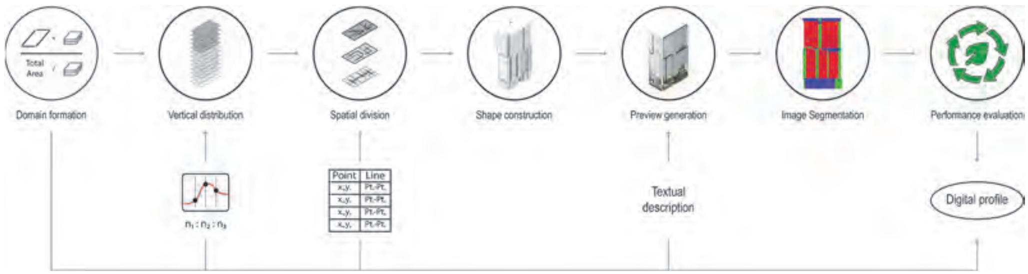


Figure 1:
Pipeline process illustration

The main concept behind the process is based on the idea that any design exists and can be expressed by a certain sequence of actions. Hence, it is proposed to use step by step transition between dimensions keeping their connectivity in order to inform each particular component if required, no matter of its dimensionality, while providing options (e.g., functional distribution, inner space arrangement, outer shell look and overall approximate efficiency) at each stage of dimensionality change.

The entire process of model creation (Figure 2) takes place within the Grasshopper environment (Grasshopper, 2021), of Rhinoceros software (Rhino, 2020) and begins with the formation of a domain using a limited set of inputs such as plot (specific outline or total area), number of floors and their height.

The spatial division process incorporates the "Magnetizing Floor Plan Generator" (MFPG) plug-in (Magnetizing Floor Plan Generator, 2019) because of its intuitive workflow via analog of the traditional "bubble diagram" and ability to generate complex connectivity relationships between spaces. Additionally, the process of image extraction is facilitated through the "Human" plug-in (Human, 2018). As it is reasonable to achieve connectivity with images instead of vector-based geometries or even ready to go plans at the particular phase in order to achieve greater flexibility, while keeping generated surfaces as crucial source for subsequent performance evaluation.

Then, the shape creation process occurs using the "Monolith" plug-in (Monolith, 2017), which is used to combine those images of generated plans into a general 3D shape in accordance with manually determined proportions (if there is more than one floor plan type).

Once the optimal shape is defined, the output images of it are used as an input in the portable version of Stable Diffusion (Stable Diffusion, 2022) via depth2img model (Stability AI, 2022) for their revisualization as the most effective way to achieve the appropriate variability of outcomes, while maintaining the tolerable coherence between images within generation attempts. Additionally, an extension "stable-diffusion-webui-depthmap-script" (Depthmap, 2022) is used as an extra composition "preserve" component, also capable of exporting images with transparent background (a significant factor for further processing in Grasshopper).

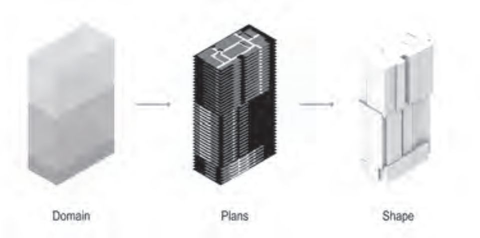


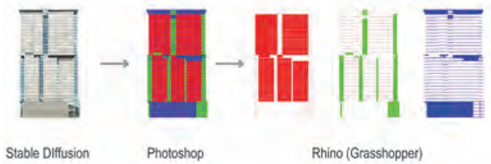
Figure 2:
Formation process

It is worth noting that within this study only 'manual creation' and 'extraction from reference image' (CLIP, 2023) have been used for prompt production.

Finally, the process of performance evaluation is based on the fact that different types of performance analysis such as energy efficiency, CO2 emission etc. do not require the input of a fully developed 3D model. Rather, simplified surfaces that represent its topology serve as the needed parameters to run the analysis (Manfren et al. 2020). Hence, the particular part involves extraction of values from previously generated images and usage of input/obtained data as necessary source of data for calculating.

The process of images digitization (value extraction) requires some image segmentation technique, which is a manageable task for models such as PSPNet (Zhao et al. 2017). However, this is a complex, time-consuming task requiring some technical knowledge in the field. Therefore, this part will not be featured in the proposed process, images edited in Photoshop (Photoshop, n.d.) are used instead (Figure 3).

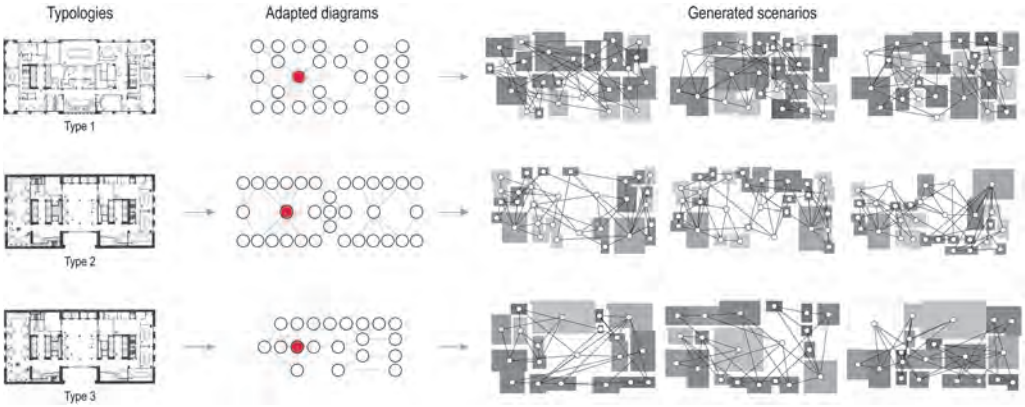
Figure 3:
Color
Segmentation



After that, the processed images are used as input in part of Grasshopper algorithm responding for "color sorting" as a source of the Window-to-Wall Ratio (WWR). It is important to note that the algorithm is based on absolute RGB values of colors (Red(R) – 255,0,0; Green(G) – 0,255,0; Blue(B) – 0,0,255; Magenta(M) – 255,0,255; Cyan(C) – 0,255,255; Yellow(Y) – 255,255,0), which means that the number of individual groups is limited to 6. In our case, only RGB are used, where: R - Solid Wall, G - glazing, B - anything else that is neither one nor the other.

The final aspect of the proposed design process includes an evaluation of generated results through a performance analysis that calculates both embodied carbon and operational energy needs for the design. This is achieved through the use of a grasshopper script developed as part of a master's thesis by the CPU Atelier of Manchester School of Architecture. It incorporates both an embodied carbon and energy performance building material database that the final output draws from, to analyse its environmental impact as well as potential energy generation capability if it incorporated solar panels. This enables more informed choices by the designer/user that include a sustainability dimension geared at reducing the negative impact of the building on the environment.

Figure 4:
Spatial transition



While the provided algorithm offers a broad range of performance metrics, this study focuses primarily on specific parameters such as:

- Original energy use & Average AFTER passive energy use
- Average original CO2 & Total embodied emission of building materials (kg/CO2)
- Average Original Cost & Total cost of building materials

CASE STUDY RESULTS

To demonstrate the capability of generating variability, it was decided to employ an existing building as a source of values and a benchmark for subsequent comparisons. Thus, the “AT&T” building designed by Philip Johnson (Banham, 2017) was selected as the reference building due to accessibility of information and simple form to showcase the ability of the tool.

After a manual redrawing of basic lines in order to calculate (approximately) each space area and general outline parameters, the outline was estimated as 60m*30m (1800m^2) and each area was rounded to the closest absolute value.

Model creation

To begin with, the outcome of domain formation process provides necessary base for both 2D and 3D development in the form of a ‘curve’ and a ‘box’ respectively. As mentioned earlier, the main idea is to develop understandable, yet minimal for evaluation outcomes. Hence, it was prioritized to achieve connectivity across dimensions instead of influencing each one of them.

Regarding spatial division, the output gained from this step essentially provides a set of surfaces approximately corresponding to input area values and the overall relationship diagram.

Additionally, corridor’s area wasn’t included in the generation process, autogenerated areas with width 1m/2m are used instead. Thus, after generation of 3 scenarios for each type (Figure 4), new plans have the following total area:

- Type 1: 1729m^2, 1747m^2, 1738m^2
- Type 2: 1557m^2, 1610m^2, 1591m^2
- Type 3: 1820m^2, 1839m^2, 1871m^2

Afterwards, a set of 3D shapes is generated with the help of a small cluster of components that provide every possible combination among generated plans (e.g., 1,1,1; 1,1,2; 1,1,3; … 3,3,3) in proportion manually defined via graph (Bezier) component. Some samples are illustrated in Figure 5. Meanwhile, the final outcomes used for subsequent processing are typically the views of shape (Front, Right, Left, Back).

Figure 5: Samples of gained combinations

Revisualization

Subsequently, following the previously described depth2img approach, the texture-less shape undergoes a transformation to align with the provided prompt, acquiring the corresponding characteristics. However, it is important to acknowledge that not everything included in the prompt will be generated as expected or may not be generated at all due to limited data availability in the database, especially considering image distortion of realistic buildings. Furthermore, the quality of the prompt itself is crucial, as it adheres to specific structural rules and incorporates various symbols that serve distinct purposes. Therefore, we utilized a prompt derived from the image of "Prince Plaza" by OMA (OMA, n.d.) and generated using the aforementioned 'CLIP interrogator' model.

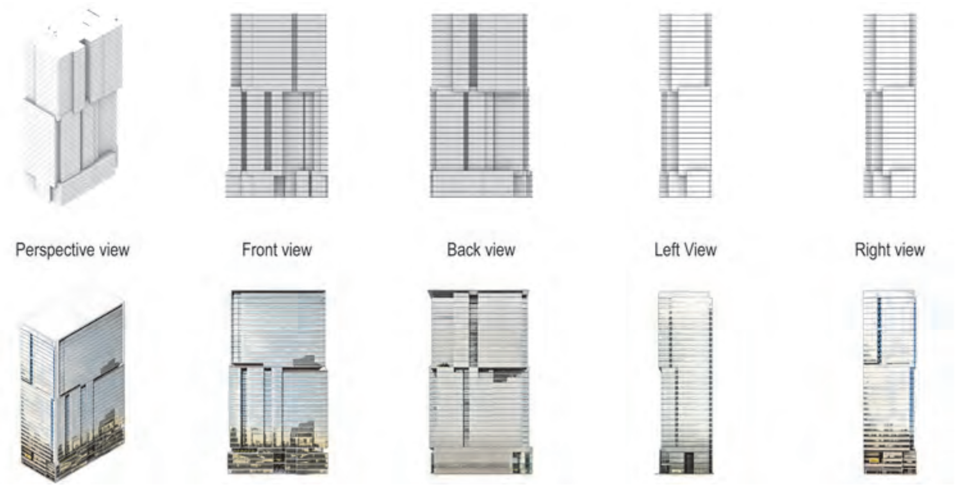
- Prompt: *a tall office building with façade panels!!, cinematic 4 k, hangzhou, symmetry!! solid cube of light, modern glass building, award-winning details", huge office, pure gold pillars, beijing, dark library, perforated metal, hive.*
- Negative prompt (Manually created): *(deformed, distorted, disfigured:1.3), poorly drawn, ugly, disgusting, blurry*
- Additional prompt in form of a "Style": *((intricate details)), hdr, ((intricate details, hyperdetailed))*
- Features such as --xformers and SD VAE (vae-ft-mse-840000-ema-pruned.skpt) were also used.

Some of the representative results may be observed in Figure 6.

Performance evaluation

Lastly, once the generated images are edited to absolute RGB colors, their digitization and further use of values take place back in the Grasshopper environment. The outcome of the digitization process is typically a single number that represents combined proportions of glazing to everything else from all views, in our case the value '55.863' was gained (Estimated value of 20 was applied for original). Therefore, Figure 7 displays the outcomes that were generated based on the acquired data, showcasing the potential of the tool in allowing users to make informed decisions that go beyond visual form to the function and performance of the artifact.

Figure 6:
Generated results



CONCLUSIONS

In this paper, a simplified version was introduced, that combines different types of generative and optimization tools to provide an informed choice from acceptable options for the end user. The workflow focuses on parameter-based boundary construction for further holistic evaluation. The approach is based on the unique ability of generative models to produce different variations using the same input values. Nonetheless, potential limitations and challenges of the proposed method are recognized as follows.

In considering the structural system, achieving substantial connectivity between levels seems to be one of the major challenges that requires additional computational techniques to provide solutions without limiting the overall process and variability of outcomes.

Although the MFPG allows the operation with a generally recognized and intuitive architectural tool like a bubble diagram, it is not able to qualitatively perform an input connection between spaces. This occurs due to the standardization of the 'Max Adjusted Distance' input value, which should be calculated separately for every particular connection, necessitating a better approach for a spatial division that addresses an architectural program.

Aspects of aesthetics and coherency of generated results are also questionable. This is mainly a technical issue arising from a limited diversity of datasets and the fact that ML-based tools are still evolving. Consequently, as datasets become more diverse and as tools are augmented, results are bound to be markedly improved. This might be a manageable issue with the help of hypernetworks (Andrew, 2023) or embedding (Gal et al. 2022). Meanwhile, extensions such as ContolNet (Zhang and Agrawala, 2023) in combination with Posex (2023) demonstrate incredible results in control and multiview connectivity of the human figure.

Type	Case	Energy use	Passive energy use	Average CO2	Total emmision of materials (kg/C02)	Average cost	Cost of materials
1	Original	7267.02	6645.75	6831.00	4.764e+7	1940.29	261.23
	1	5925.27	4500.79	5569.75	1.0683e+8	1582.04	372.89
	2	6918.75	4709.63	6503.62	1.5801e+8	1847.30	435.64
	3	6487.94	4644.67	6098.66	2.35e+8	1732.28	550.28
2	Original	6152.34	5752.34	5783.20	4.764e+7	1642.67	261.23
	1	5746.18	4462.38	5401.41	1.3998e+8	1534.23	445.25
	2	5825.48	4498.76	5475.95	1.8562e+8	1555.40	498.93
	3	5789.62	4505.53	5442.24	1.6114e+8	1545.82	463.61
3	Original	6912.18	6362.48	6497.45	4.764e+7	1845.55	261.23
	1	7068.49	4841.27	6644.38	1.2436e+8	1887.28	359.94
	2	7458.71	4851.25	7011.18	1.0966e+8	1991.47	353.58
	3	7362.91	4876.23	6921.14	1.3293e+8	1965.89	374.75

Figure 7:
Table of results

Moreover, this approach necessitates supplementary optimization procedures for each generative method to enhance connectivity and accuracy of outcomes. This may occur through an adaptation of a systemic perspective and holistic systems approach that examines how different components and scales are interconnected and influence each other, allowing architects and designers to make more informed creative decisions in alignment with environmental and user requirements.

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