1. Introduction

1.1 STATE OF THE ART

Current research in generative AI in architecture can be divided into the following categories: (1) 2D generative models based on images or vector graphics (floor plans), (2) 2,5D generative models based on images that have been "threedimensionalised" in post. (3) 3D generative models based on point clouds, voxel or mesh geometries.

(1) 2D image generation has been successfully been used the longest, due to its great accessability in generaliyability towards architecture. In addition it also offers a almost seamless integration into the contemporary workflow of architectural design, requiring a minimal of postprocessing before the result is fully usable (i.e. a quick visualisation of a design idea only needs to be edited in photoshop to shouw the designer's idea to be ready to be shown). No special research for the architectural domain was necessary, but architects can use models like DALL-E (QUOTE) and Stable Diffusion (QUOTE). Only some big offices like Zaha Hadid Architects (quote) and Coop Himmelblau (Quote) developped their own models being able to further control the output. (2) We define here 2,5D generative models as any AI model that generates 3D models, but is trained on any basis of 2D input. That includes Campo...

(3)

While there already is architectural research about graphs and graph neural networks in architecture (Alymani et al., 2022), it mostly focuses on classification tasks rather than generative ones. Alymani et al. use the dual graph representation for classification tasks with graph machine learning and already show promising results. The trend can also be seen in other research on generative architecture lately. Zhong et al. (2023) use graph representation learning in combination with a recursive neural network to generate 3D massing models of architecture, while other research uses layout graphs to generate 2D floorplans (Hu et al., 2020). In both cases, the results are far from perfect and not completely generalizable. Yet being based on graph representations, the models seem to be more capable of generating logical architectures than models built upon pixel- or voxel data (del Campo, 2022; Koh, 2020), where although the generated architectures are 3D and partially look stunning, they seem to still need manual or parametric postprocessing to represent a real-world building design.

1.2 FOLLOW UP RESEARCH

Here we present an extended and improved version of spatial generation with a graph autoencoder presented originally in Bauscher et al. (2024). The original paper presents a generative AI system the outputs new spatial configurations of architectural elements in three dimensions. The graph based autoencoder can read 3D buildings as training input and does not rely on any sort of conversion between 2D images or plans and a desired three-dimensional output in post. While this new approach shows high potential and is well rooted in the modern idea of the architectural design process, it also still has its weak points and open questions:

1. The used dataset consists of only four original buildings, that are each augmented a hundred times parametrically. As Aroyo et al. (2021) argue data might be the most important factor in successfully performing AI systems, and the slight geometrical augmentation of only 4 buildings is not ideal for training.
2. The conversion from 3D model to graph shows huge impact on the generated outputs and might not be perfectly suited for the task.

While these points offer room for improvement

1. State of the Art

idually remodeled parametrically in Grasshopper inside Rhino. That gave the opportunity to