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ARTIFICIAL INTELLIGENCE–BASED 3D MODEL GENERATION FOR ARCHITECTURAL DESIGN: A REVIEW OF CURRENT APPROACHES

https://doi.org/10.5281/zenodo.17934870

Zafar Matniyazov
Jurat Tajibaev
Samidullo Elmurodov
Nizomjon Buronov
Zilola Rakhmatillaeva
[1]*Tashkent University of Architecture and Civil Engineering*
[2]*Alfraganus University*

ABSTRACT: *The advancement of deep learning methods and generative artificial intelligence opens new opportunities for the automated generation of three-dimensional building models. Contemporary research aims to generate entire buildings—from massing to facades and floor plans—utilizing technologies such as GANs, diffusion models, transformers, and LLMs, as well as 3D neural networks (VoxelNet, 3D-GAN) and rule-based systems (shape grammars). This review examines key approaches and tools, including their integration with platforms like Rhino/Grasshopper, Revit, Blender, and others. Emphasis is placed on technical aspects (form generation, parameterization, automation, variability), while ethical and legal issues remain outside the scope of this study. The paper presents method comparisons (including a comparative table) and discusses the limitations and prospects for the further development of architectural 3D model generation.*

KEYWORDS: *artificial intelligence, generative models, 3D architectural design, GAN, diffusion models, transformers, Rhino, Grasshopper, Revit.*

INTRODUCTION

Generative design, a well-established paradigm in architecture, has begun to undergo significant transformation with the advent of AI methods. As early as the 20th century, architects employed rule-based systems (pattern language, shape grammars, expert systems) for the automated generation of forms [1]. With the advancement of computational methods in the 1990s, evolutionary computation algorithms and cellular automata emerged. However, with the recent boom in deep learning and the emergence of powerful neural network-based generative models, interest in design automation has surged [1]. The task of generating complete 3D building masses, including the building envelope, internal layouts, and facades, is particularly relevant. A volumetric building model is

Latin American Journal of Education
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more complex than a standard object (such as a chair or a car), requiring the consideration of functional and contextual constraints. Various studies propose generating buildings via 3D generative networks (e.g., 3D-GANs and their variants), diffusion models, transformers/LLMs, as well as combined methods. This review is structured according to the types of approaches, tools, method comparisons, limitations, and future prospects. Current English-language research (indexed in Scopus/Web of Science/Elsevier/Springer) describing specific algorithms and their application in architecture was utilized in the preparation of this paper.

CLASSIFICATION OF APPROACHES

Generative Neural Networks (GANs, VAEs, Diffusion Models)

GANs (Generative Adversarial Networks) represent one of the first successful approaches to 3D generation. The classic 3D-GAN by Wu et al. (2017) allows for obtaining 3D objects from a random latent vector [2]. Specialized GAN architectures have been developed specifically for architecture. For instance, Building-GAN (Chang et al., 2021) generates a multi-layered 3D building form based on a functional program graph (representing multiple room types) [3]. Instead of a dense 3D grid, the authors introduce a compact "voxel graph" representation and train the GAN generator alongside a graph neural network. The results demonstrate the generation of realistic building volumes, surpassing previous methods [3]. Another example is 3DBuildingGAN (Mueller et al., 2024), focused on single-story residential houses. The authors utilized a dataset of 3D house models and developed a GAN with a modified architecture (Wasserstein loss with gradient penalty, LeakyReLU, RMSProp) [4]. The model yields highly detailed house geometries, comparable in form to the training data, with minimal output noise [4].

Beyond GANs, Diffusion Models are gaining popularity. They learn to "decode" noise into data by gradually denoising it. Recently, several studies have emerged adapting diffusion to 3D geometry. Thus, Sebestyen et al. (2023) proposed a prototype for generating conceptual building forms using a 3D diffusion network [8]. They constructed a dataset using parametric design (Grasshopper) to overcome the scarcity of 3D data, presented an architecture based on volumetric density grids, and demonstrated the viability of this approach [8]. Diffusion models are capable of providing smooth quality control and creatively combining styles, but require large volumes of data and computation. In a recent application, authors merged LLMs and diffusion to output architectural visualizations considering lighting parameters [5].

TRANSFORMERS AND LLMS

Transformers and Large Language Models (LLMs) are also finding applications in building design. Although

Latin American Journal of Education
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originally developed for text processing, their self-attention architecture allows for context expansion. In architecture, LLMs can be used to generate text descriptions or prompts, which are subsequently converted into models or plans. For example, Li et al. (2024) integrated GPT-4 and Stable Diffusion into a design pipeline: first, parametric massing models (Grasshopper) are configured; then, facade schemes are selected based on lighting; finally, text prompts (architectural term categories) are generated by GPT-4 and passed to Stable Diffusion to obtain 2D visualizations of the architectural design [5].

This approach combines the power of LLMs (creating semantic queries) and generative visual models. Meanwhile, the 3D geometry itself is generated by auxiliary modules. One key prospect is the implementation of "text-to-3D" models within CAD/BIM environments to form plans and facades inside software like Revit, ArchiCAD, or Rhino/Grasshopper based on descriptions [1]. This would allow, for example, generating building frameworks via text queries directly within the architect's tools.

3D Deep Networks (VoxelNet, DeepSDF, etc.)

A significant category comprises neural networks operating directly on 3D data: VoxelNet, DeepSDF, PointNet, and others. These models generate objects in volumetric representation (voxels), as meshes, or as implicit fields. VoxelNet (known for 3D object detection) and similar 3D convolutional networks can generate architectural volumes in the form of a volumetric matrix. DeepSDF (Park et al., 2019) learns to represent 3D models via a Signed Distance Field (SDF), which can be utilized to generate smooth forms given suitable data.

In the architectural domain, Zuan et al. (2023) compared voxel and SDF representations, finding that voxelization preserves key building features (sharp corners) better than the smoothed SDF representation [6], although it may suffer in resolution and precision. Their network learns to map buildings into a latent space and back. One limitation is that training datasets of 3D building objects are significantly inferior in volume and diversity to datasets like ShapeNet, which affects generation quality. Furthermore, if input data is presented as point clouds, the result loses edge sharpness [6]. Nevertheless, these models allow for the study of architectural form diversity based on big data statistics regarding buildings.

Point Cloud Generation

Some approaches are beginning to work with building point clouds derived, for example, from LiDAR scanners. Diffusion networks and autoencoders are employed to create new point clouds in a given style. Although there are few direct examples of generating buildings from point cloud noise, point-cloud GAN methodologies and diffusers (analogous to [9]) promise to yield 3D forms while preserving detail. However, their application in architecture is complicated

Latin American Journal of Education
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by the fact that a point cloud per se does not contain building semantics; subsequent post-processing (semantic segmentation, skeleton extraction) is required. Hybrid solutions can generate intermediate point clouds, which are then reconstructed into surfaces via third-party CAD tools.

Rule-Based Systems (Shape Grammar, Algorithmic Design)

Alongside learning-based methods, there exist "hard" algorithmic approaches—algorithmic and parametric design, and shape grammars. Such systems are based on rules and constructive algorithms rather than statistics. For example, formal shape grammars (G. Stiny et al., 1970s–1980s) describe how elementary shapes are transformed into architectural plans according to rules [1]. These methods do not rely on training, but they can define spatial constraints (adaptive layout, modulated patterns). Modern architectural CAD software, such as Grasshopper for Rhino or Dynamo for Revit, actively employs algorithmic design: visual components or plugins (e.g., LunchBox, Owl) are used to define rules for generating facades, layouts, or three-dimensional forms. Although difficult to classify as AI in the narrow sense, combining parametric rules with optimization (genetic algorithms) or ML modules allows for the automated generation and selection of design variants. Thus, modern practice views the generation of architectural forms as a combination of template rules and machine learning methods [1].

Tools and Frameworks

The integration of AI algorithms into architectural tools represents a significant trend. The Rhino/Grasshopper platform is among the most widely used; it serves as a visual programming environment where TensorFlow or PyTorch models can be invoked via Python plugins. For instance, Li et al. implemented their massing generation algorithm (Grasshopper) and daylighting analysis directly within the Rhino interface [5].

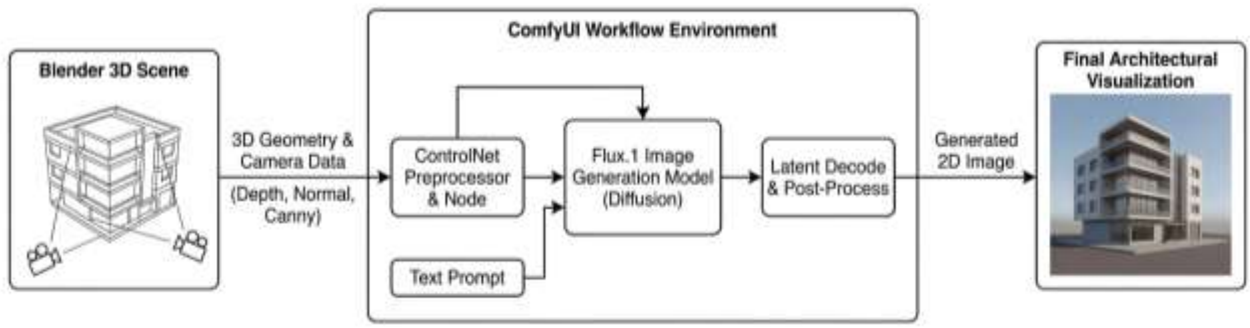

Fig. 1. Example of an architectural design generation pipeline: a 3D scene in Blender is utilized to control the image generation model (Flux.1), implemented via ComfyUI and interacting with ControlNet (adapted from NVIDIA materials).

Latin American Journal of Education
www.lajoe.org

Through the Rhino.Inside plugin, such a core can interact with Revit/Dynamo, enabling data transfer between Grasshopper and BIM (converting meshes into editable walls, slabs, etc.) [1].

Beyond Rhino, Revit and ArchiCAD are widely used—these BIM platforms feature built-in generative design tools (e.g., Autodesk Generative Design). In Revit, scripts (Python/Dynamo) can be configured to generate layouts or facades. Research exists where neural networks directly output results into Revit, thereby constructing "BIM-ready" models with preserved element semantics [1].

Blender and Unity are utilized for visualization and prototyping. Blender allows for the creation of 3D scenes and camera control, acting as an intermediary for text-to-image models (see Figure 1). For instance, an NVIDIA special project demonstrates how a scene can be modeled in Blender and subsequently used with Stable Diffusion (FLUX.1) to generate high-quality architectural visualization images [7]. Unity is frequently employed for virtual walkthroughs of architectural prototypes; while it allows for the integration of AI modules for interactive environment generation, native built-in AI tools are limited.

Beyond CAD software, key tools include ML frameworks (PyTorch, TensorFlow) and development environments. Architects can utilize open libraries—for example, CityEngine (Procedural CGA grammars) is applied to generate urban street plans and buildings based on rule sets, while Blender and specialized plugins enable the invocation of diffusion models. Frameworks such as ControlNet and ComfyUI simplify the management of the generation process. In general, professional pipelines require the integration of multiple software applications via APIs and scripts [1][5].

Comparative Analysis of 3D Generation Methods

The table below describes the primary approaches to generating 3D building models.

Approach / Method	**Data Representation**	**Output Type**	**Tools**	**Advantages**	**Limitations**
3D-GAN (Wu et al., 2017)	Voxels (3D grid)	3D object	PyTorch; ShapeNet	Proven GAN architecture; diverse shape generation	Low resolution; needs large datasets
Building-GAN (Chang et al., 2021)	Voxel + graph	Multilayer building form	Custom GNN + 3D generator	Includes space program graph; multilayered	Needs functional graph input; lacks façade

Latin American Journal of Education
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Approach / Method	Data Representation	Output Type	Tools	Advantages	Limitations
				output	details
3DBuildingGAN (Mueller et al., 2024)	Voxelized models (houses)	3D house geometry	WGAN-GP; Grasshopper	High-res output for houses; minimal noise	Domain-specific (houses only); no room semantics
3D Diffusion (Sebestyen et al., 2023)	Voxel / density fields	Conceptual architectural forms	3D Diffusion + Grasshopper	Smooth generation, style blending, concept flexibility	Computationally heavy; requires custom 3D dataset
LLM + Generation (Li et al., 2024)	Text prompt (semantic)	2D render / conceptual 3D	GPT-4 + Stable Diffusion	Text-driven control; architectural style guidance	No direct 3D output; needs CAD/BIM conversion
Shape grammar / rule-based	Geometric rules / parametric	Plans, façades, 3D forms	Rhino, Grasshopper, Dynamo	Full control over rules and spatial layout	No novelty without rule definition; rule setup is complex
Point clouds + ML	Point cloud (raw 3D scan)	Detailed 3D model	PyTorch, PointNet, Diffusion	High surface detail from scanned geometry	No semantic structure; post-processing required

The presented table summarizes the strengths and weaknesses of the discussed approaches. The classic 3D-GAN is effective for prototyping but lacks detail preservation. Specialized GANs (Building-GAN, 3DBuildingGAN) are tailored for architecture, accounting for room programs or specific building typologies [3][4]. 3D diffusion models show promise regarding quality; however, they necessitate the creation of architectural 3D datasets (e.g., via parametric generators) [8]. Integration with text (LLMs) simplifies creative control but currently yields only conceptual images rather than ready-to-

Latin American Journal of Education
www.lajoe.org

use CAD models [5]. Rule-based systems excel in controlling generated geometry but fail to generate non-trivial novel forms without ML augmentation. Point clouds offer accurate scans but require reconstruction algorithms and semantic analysis.

Limitations and Prospects

Despite rapid progress, significant limitations persist. First, data scarcity: large and diverse datasets of 3D building models for training are lacking (see discussion by Zhuang et al.) [6]. Architectural datasets are typically small and stylistically homogeneous; this constrains the space of possible generations and leads to structural repetition. Second, morphological complexity: buildings combine numerous elements (walls, roofs, windows) and parameters (functions, regulations). Contemporary networks are not yet capable of accounting for all these interrelationships. For instance, the model by Zhuang et al., trained on points, "poorly preserves clear building edges" [6]. Furthermore, there is no straightforward method to embed building codes or engineering calculations directly into a neural network.

Third, integration into the workflow. As reviews indicate, most generative methods yield graphics or meshes requiring manual refinement in CAD/BIM [1]. True readiness ("tier 2") is achieved when results are immediately imported into Revit/Grasshopper as editable objects [1]. Until this generation is realized, "bridges" (scripts, plugins) are necessary, which still require the architect's involvement. From a performance standpoint, scalability presents another challenge: generating highly detailed models (millions of voxels or thousands of polygons) demands substantial GPU power and training time.

Nevertheless, the prospects are encouraging. Large models are developing rapidly: text-to-3D (DreamFusion, SDFusion, etc.) and 3D-visual language models already exist.

Hybrid systems are emerging that combine parameters (e.g., programmable variables in Grasshopper) with AI generation (so-called "design machines"). Diffusion models, such as Stable Diffusion 3D, promise more realistic building forms. The use of simulations (solar, wind) within the generation cycle is expanding, rendering AI projects not only stylistic but also technically sound. In the future, full integration of AI models into CAD/BIM is anticipated: for example, a "text-to-plan" module directly within Revit, accounting for semantics and relationships. This aligns with the trend: "Generative modules will be embedded into major CAD/BIM systems (Revit, ArchiCAD, Rhino) for the automated creation of plans and facades" [1]. A crucial direction remains the development of standardized interfaces (data exchange protocols) and the expansion of architectural metadata within neural networks (introducing concepts of rooms, slabs, and columns

Latin American Journal of Education
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into the latent space).

Conclusion

Modern artificial intelligence methods are already capable of significantly assisting architects during the conceptual design phase by automatically generating architectural masses and even preliminary plans. GAN architectures and 3D networks yield rough building volumes with specified properties [3][4], while diffusion models demonstrate a new level of quality in visual imagery [8]. The integration with CAD/BIM tools (Rhino/Grasshopper, Revit, Blender) is gradually transforming the design workflow: the output of generative algorithms is becoming accessible within the architect's familiar interface [5][1].

Nevertheless, current solutions primarily function as "ideation assistants" rather than full replacements for the designer: they propose form variants but require human oversight and refinement. Bridging this gap will be facilitated by further research into hybrid approaches (combining AI and rule-based systems), large-scale architectural datasets, and the standardization of "AI → CAD/BIM" processes. This constitutes part of the prospect of "intelligent architectural design," where creative functions are augmented by algorithms trained on multi-million-item archives of forms and scenarios.

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