Simplified Methods for Generative Design That Combine Evaluation Techniques for Automated Conceptual Building Design

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Abstract: Smart design and construction have emerged as pivotal forces in the construction industry. Numerous studies have been conducted in the realm of design optimization, using artificial intelligence data-driven approaches and optimization theories. This increase in research has sparked interest in generative design, a process that automatically generates algorithm-based design alternatives, thereby reducing human effort and time by a significant margin. The objective of this study was to explore the potential of generative design to boost productivity within architectural practices and reduce redundant and unnecessary tasks for an aging construction workforce. Specifically, it illustrates the process of selecting superior alternatives by generating various three-dimensional layouts, using a generative design methodology. This occurs during the creation of a building layout concept with subsequent partial evaluations. The methodology of this study was mainly divided into four stages: objective setting, design algorithm development, the establishment of evaluation methodology, and the comparison of the results’ values. The findings of this study confirmed that the design algorithm and evaluation methodology form a single loop, generating a multitude of design alternatives that satisfy the algorithm designer’s evaluation criteria.

Keywords: design automation; visual programming; artificial intelligence; computer-aided design; computer-aided engineering

1. Introduction

Artificial intelligence (AI) has become an integral part of the construction industry, sparking a recent increase in related research in the field. Numerous studies are currently underway that focus on construction optimization, drawing on the principles of AI, data, and optimization theories. They are subdivided into numerous specialized fields, including topology optimization, computer-aided engineering (CAE), simulations, and generative design [1,2]. However, these studies have gradually evolved into research centered on generative design, a concept in which AI autonomously creates design alternatives, a process that is time-consuming for humans. Generative design, in essence, is a technology that creates a variety of optimal designs that match the design objectives, constraint classifications, and their respective levels, specified by the designer or engineer [3,4]. Generative design is a technology-driven process that uses algorithmic or rule-based systems to generate design outputs. In the construction domain, this approach provides more efficient, innovative, and customized solutions [5,6].

In 2020, the construction industry encountered a severe crisis due to decreasing productivity and an aging workforce [7]. Consequently, a number of solutions were proposed. First, from a technological standpoint, construction automation initiatives...
exploiting the possibilities of the Fourth Industrial Revolution and AI were implemented. In particular, fundamental research was conducted in the field of design automation. Second, from an economic perspective, progress was made in increasing productivity in construction by creating a national-level research foundation for the advancement of construction software. Finally, from a societal perspective, efforts have been made to replace low-value, repetitive tasks with automated solutions to address the problems of an aging workforce and the avoidance of construction employment.

In addition, the intersection of AI with various domains has the potential to reduce conventional theories and redefine innovation. For example, AlphaGo, an AI program developed by Google DeepMind for the Go game, broke new ground in 2016 as the first AI program to defeat a professional Go player [8]. This victory was a result of the AI’s game-changing strategy, which significantly challenged conventional Go theories, prompted efforts to debunk them, shattered preconceptions, and prompted a comprehensive reevaluation of human Go strategies. Similarly, if AI-driven design automation techniques are cultivated in the construction industry, they have the potential to transform existing frameworks and significantly increase productivity in construction [9].

Generative design approaches are not only gaining traction in building and architectural practices, but they also represent a significant scientific contribution to these fields, as shown by the increasing research literature [1,2]. This research addresses a critical gap by developing a sophisticated algorithm that generates numerous design alternatives, taking into account a comprehensive set of conditions—design, regulatory, and evaluative—early in the design phase. The novelty and scientific contribution of this work lies in its holistic exploration of generative design’s ability to boost productivity in the construction industry and reduce the repetitive, non-essential tasks that burden the aging workforce. We present an approach that begins with an exhaustive review of the existing literature, leading to a systematic categorization of generative design methods based on our extensive analysis. Moreover, this study breaks new ground by applying a generative design framework to the architectural design process, aiming to yield a varied portfolio of layout options and to evaluate a subset of them to identify optimal solutions. Our research delivers pivotal insights into the evolution of AI and AI-assisted design automation, spotlighting the advancements in generative design within the construction industry. The findings from this study are poised to guide and catalyze subsequent research in this evolving domain, underscoring our work’s scientific contribution to the community.

2. Literature Review

In this study, we examined international research trends using the Web of Science as our search engine. We examined and categorized 35 studies pertinent to conceptual generative design, as outlined in Table 1.

Generative design can be broadly categorized into three sections. The first category pertains to algorithm development, where different algorithms are applied to generative design, and ongoing efforts are made to merge algorithms from different areas or improve existing ones.

The second category is the domain used for preliminary feasibility assessments. This area of research examines the many requirements of the construction planning stage and develops with the designs accordingly.

The third category entails the development of a wide range of alternatives. Research in this area seeks to input design conditions during the conceptual design phase and rapidly generate a variety of alternatives.
### Table 1. Literature review results of papers based on subcategories.

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2.1. Evolution of the Algorithm

The application of algorithms is vital for realizing generative designs. Advances in these algorithms have enabled designers to showcase superior results in their generative...
designs. Numerous studies have been undertaken to further refine algorithms, and a myriad of methodologies have been formulated. In this section, we present algorithms from four distinct domains.

Using a grid-based cellular system, Sung and Jeong [42] introduced a methodology for automating the positioning of buildings on a site. This method surpassed the constraints of conventional multivariate optimization or agent-based packing approaches, which do not typically provide real-time calculation results. Notably, users were no longer required to make speculative assumptions about the outcomes and could instantly access automated building layouts. In contrast to multivariate optimization or agent-based packing techniques, this methodology bypassed expensive and prolonged calculations, providing users with immediate results. This expedites the design process, allowing for the exploration of multiple design alternatives in minimal time.

Ghannad and Lee [39] proposed an innovative framework based on coupled generative adversarial networks (CoGANs) for the automated generation of modular housing designs. By using CoGANs, an extension of generative adversarial networks (GANs) in machine learning, this strategy provides both time and cost savings, ensuring that the design project adheres to its limited budget while still meeting all the essential requirements.

As et al. [25] studied and presented a graphics-centric automatic learning system to conceptualize initial design ideas. This system integrates deep neural networks (DNNs), a subtype of deep learning models, with GANs from machine learning. Initially, DNNs, trained using data that translate designs into graphical forms, generate key building components from extant designs that are then combined to form novel configurations. Then, with GANs at the helm, a new design is formed that goes beyond the training dataset of the DNNs, thus addressing the limitations of DNNs, which are restricted to their training sets.

Lastly, AlOmani and El-Rayes [32] developed a novel method that automates the genesis of thematic architectural layout designs by drawing inspiration from natural images. This procedure begins with image processing, using a combination of algorithms: a thresholding algorithm and an area and boundary extraction algorithm. The design is then optimized to ensure maximum alignment with the designer’s specifications, functions, and operational performance.

2.2. Preliminary Feasibility Assessments

During the construction planning process, designers conduct a preliminary feasibility study to ensure consistent compliance with various regulatory conditions and determine the extent of the fulfillment of requirements. This assessment must be repeated for every design modification, requiring significant time and effort from the designers. The goal is the optimal execution of an architectural plan that satisfies the maximum number of requirements while complying with various regulatory requirements. Thus, by automating labor-intensive tasks and exploring design alternatives with optimal performance, unnecessary time and financial expenditures can be avoided.

Fang and Cho [28] have presented a process for identifying design alternatives that excel in daylight and energy performance. This method relies on building simulations and the application of a genetic algorithm to design variations stemming from a parametric design. This emphasizes improving the design solution by automatically identifying building design alternatives and optimizing daylight and energy efficiency for these choices.

Zaraza et al. [44] developed a generative design tool geared towards curtailing embodied emissions (EE) during the conceptual phase of high-rise residential structures. This tool takes into account the industry-standard design objectives and constraints. In summary, a new geometric system is introduced. The proposed GenGHG system is groundbreaking in the creation and evaluation of design alternatives. Remarkably, the design alternatives generated using this system manifested a 7% reduction in EE, in contrast to the non-optimal alternative solutions.
Guo et al. [37] put forth a semantic method to automate the automatic compliance checking (ACC) process for building projects. The ACC procedure retrieves rule terms and logical associations from regulatory documents via natural language processing (NLP), checks semantic similarities, and matches the extracted terms with BIM data keywords (either concepts or attributes). Subsequent SPARQL queries were autonomously constructed, based on the logical relationships between the BIM keywords, to ultimately verify regulation compliance.

2.3. Generating a Multitude of Alternatives

Algorithms and tools capable of generating multiple alternatives play a pivotal role in the conceptual design phase, enabling designers to explore a wide range of options. This streamlines the process for designers, allowing them to pinpoint optimal design alternatives more efficiently than with conventional methods.

Zhang et al. [35] devised a parametric generation algorithm tailored to the automated generation of design blueprints for performance-centric urban dwellings in China. This algorithm is particularly suitable for the energy-efficient design of residential buildings during the preliminary design stages of eco-friendly housing. It empowers designers to sift through a multitude of design alternatives that are in alignment with design specifications.

Dino [16] unveiled a tool named the Evolutionary Architectural Space (EASE). This tool streamlines the optimization of 3D spatial designs. By employing evolutionary optimization, EASE strikes a balance between wide-ranging and focused applications. It addresses the challenge of concurrently evaluating numerous alternatives during the conceptualization and arrangement of architectural designs.

Araghi and Stouffs [12] melded generative design with conventional design techniques to cater to design mandates in the creation of 3D architectural forms for a residential commission in the Netherlands. The authors leveraged Cellular Automata (CA) as an instrumental tool to address the design prerequisites. Through the manual manipulation of the CA rules by users, this tool offers an array of design variations that cater to the accessibility and natural light demands of high-density residential structures.

Gradišar et al. [45] outline the framework of generative design, followed by its practical application in a case study that focuses on devising an efficient shading solution. They then showcase the outcomes and conduct a comparative analysis with conventional methodologies. This approach is relevant to both designers and software developers, who are expected to further advance this method in their work.

3. Method

In this study, we used Autodesk’s Revit and Dynamo software to generate alternatives using generative design methods during the planning and initial design stages of buildings. Dynamo is a visual coding platform primarily used in conjunction with Revit. In contrast to conventional programming languages, Dynamo is characterized by the use of visual elements that allow users unfamiliar with programming languages to write algorithms that computers can understand. In this study, we developed a methodology to identify the problems associated with generative design techniques when using this software and created numerous three-dimensional layout design alternatives. Finally, a representative design was selected from many design alternatives based on specific evaluation criteria.

3.1. Generative Design Procedure

Generative design is a fascinating and powerful approach to building design that uses computer algorithms and artificial intelligence (AI) to develop innovative and efficient solutions. This represents a paradigm shift in the design process, resulting in a collaboration between designers and algorithms that consequently yields more optimized and creative results. To establish design automation using the simplest algorithm possible, we initially employed a checkerboard-like grid, populating the design at random intervals. Moreover, we categorized the essential components of design automation into three groups: the
design conditions, regulatory conditions, and evaluative conditions. We then developed individual algorithms for each category and an integrated algorithm that encompasses all three. The following is an expanded description of the three design phases.

- **Phase 1: Identifying Challenges and Setting Levels Based on Attribute Types**

  The first phase focused on understanding the problem at hand and identifying the challenges that needed to be addressed. These may include spatial constraints, structural requirements, material usage, cost limitations, and environmental impacts. Each of these attribute types is then assigned specific “levels”. These levels could represent different potential values or states that the attribute can take on, and they serve to define the range of possibilities that will be explored during the generative design process.

- **Phase 2: Generation of Distinct Topology-Optimized Designs**

  Once the challenges and attribute levels are identified, the generative design process begins generating a variety of design solutions. These designs are “topology-optimized”, meaning they are generated with the optimal layout or “topology” of the material, accounting for the predefined constraints from Phase 1. The generation of the designs is based on an “amalgamation of problem definitions”, meaning all of the attribute types and levels defined in Phase 1 are considered when generating a wide variety of possible solutions.

- **Phase 3: Evaluation and Selection of Standout Designs**

  In the final phase, the generated designs are evaluated against predefined criteria. These may include how well they address the challenges identified in Phase 1, as well as other factors such as aesthetic appeal, practicality, and feasibility. The optimal designs are selected for further development and implementation. It should be noted that generative design is an iterative process. The results from Phase 3 could lead to adjustments in Phases 1 and 2 as new challenges are identified, different levels are set, and changes occur in the generation or evaluation criteria. This cycle was repeated until a satisfactory solution was obtained.

The methodology of this study is primarily divided into three stages. First is “Goal Setting”, where we define the objectives and desired outcomes of the study. In the second stage, the “Design Algorithm Development” stage, we developed algorithms that can be used for generative design. The third stage is “Evaluation Methodology Establishment”, where we determine how we will evaluate the results.

### 3.2. Dynamo Script Overview and Implementation

Dynamo is a visual programming tool that allows designers to explore parametric conceptual designs and automate tasks. The structure of a Dynamo script consists of seven steps, as shown in Figure 1.

- **Step 1–3: Preparatory Tasks for Fundamental Design Automation**

  The first three steps involve establishing the problem and defining the parameters and constraints for the generative design process. These preparatory steps lay the foundation for the design automation process by defining what is and is not allowed in the final design process.

- **Step 4–5: Randomized Design Generation**

  Steps four and five involve the generation of design solutions. Algorithms have been used to create a variety of possible designs. The “randomness” suggests that these algorithms use some sort of stochastic (random) process to explore a broad range of possible designs. In this process, the parameters defined in the first three steps can be randomly varied to generate tens of thousands of unique design solutions.
1. land form formation
2. Formation of true north sunlight
3. 2m setback from road corner intersection and extraction of buildable area
4. Spatial shaping and random placement
5. Substitute the number of floors and floor heights and create a mass excluding the true north sunlight area
6. Output extraction [number of masses, building area, site area, building-to-land ratio, floor area ratio, building-to-land ratio, total floor area, etc.]
7. Extract environmental performance output using north-south and east-west length

Figure 1. Dynamo script overview, https://github.com/onehojoe/Design-Automation-sample (accessed on 20 November 2023).

- Step 6–7: Design Evaluation

The sixth and final step consisted of evaluating the designs generated in steps four and five. An evaluation methodology was introduced into the algorithm that allows each design to be evaluated against predefined criteria. Various metrics such as performance, efficiency, and feasibility can be considered. The objective is to determine which designs best meet the desired objectives.

3.2.1. Set the Site Area

To determine the shape of the land parcel, three main steps were performed, as shown in Figure 2.

- Define the Dimensions: First, the dimensions of the site were defined. In this case, both the width and length of the site were set at 20 m. This provides a fundamental understanding of the space in which we are working.
- Setting Building Limit Lines and Site Boundary Lines: After setting the dimensions, it is crucial to establish the building limit lines and site boundary lines. These lines are important because they denote where construction is allowed and not allowed on the property. They help protect the site from overdevelopment and ensure safe spaces between buildings and site boundaries.
- Extract the Site Area: Finally, to obtain a clear idea of the total area of the site, the boundary of the site is extracted as the surface. This is achieved by plotting the perimeter of the site on a flat plane and calculating the enclosed area. This provides the total usable area for construction, landscaping, parking, and other uses.

3.2.2. Setting the Slant Line Restriction for Daylight

The slant line restriction for daylight is a design rule used in Korea to ensure that buildings receive an adequate amount of daylight [46]. According to this rule, the height of a building must be controlled according to its distance from the boundary of an adjacent site in the north.
To follow the slant line restriction for daylight rule, a portion of a building that is 9 m or less in height must be at least 1.5 m away from the adjacent site’s boundary. For parts of a building exceeding 9 m in height, the distance from the adjacent site’s boundary should be at least half the height of that particular part of the building. Mathematical calculations must be performed to implement the slant line restriction for daylight rule. In these calculations, the corresponding points are connected to other points based on a specific formula, as shown in Figure 3. Based on these values, the final corresponding position can be determined. Next, a plane is created by establishing a point that forms a diagonal line proportional to the height of the building. Once this is completed, the shape of the building is finalized by eliminating any overlapping parts. This ensures that the design adheres to the slant line restriction for daylight rule and promotes maximum daylight exposure.

Figure 2. Visual programming of the determination of the site area.

Figure 3. Visual programming of setting the slant line restriction for daylight.
3.2.3. Road Intersection Spacing

This scenario assumes that a building site, with four corners, has some of its corners near a road, reducing the potential buildable area due to intersections, as shown in Figure 4. The study in this article assumes that this hypothetical site has two intersections adjacent to the road. These two intersections were considered in the calculations. In addition, because of the existence of the road itself and the turning radius of the road, the study assumes that a 2 m buffer space around each intersection is non-buildable. This non-buildable buffer further reduces the potential area that can be used for construction. Thus, the buildable area on the site is calculated by considering the proximity to roads, intersections, and a non-buildable buffer space around the intersections.

![Figure 4. Visual programming of road intersection spacing.](image)

3.2.4. Spatial Shaping and Randomization

The process of space formation on the plane, created through the site and building boundary lines, consists of three major steps, as shown in Figure 5.

![Figure 5. Visual programming of spatial shaping and randomization.](image)
• Creating the Grid

In the first step, a grid was created on a 2D plane. This grid consisted of 441 points arranged in a $21 \times 21$ matrix. These points are said to be “transparent”, suggesting that they do not in themselves define a space or structure, but rather serve as potential anchor points for the spatial structures that will be created in the following steps.

• Random Point Selection

In the second step, an algorithm was used to randomly select four points from the grid created in the previous phase. This randomness introduces a degree of variability and unpredictability into the design process, allowing for a wide range of possible spatial configurations.

• Square Formation and Combination

In the third and final step, a square was created for each of the four points selected in the previous phase. These squares can vary in size from 1000 mm to 10,000 mm. The squares were then combined to create a unified space. This combination arranges or connects the squares to create a coherent spatial structure. The result of this process is a 2D spatial arrangement, an alternate layout, or a design based on the selection and combination of squares. Because the process involves random selection, it can generate a wide variety of potential spatial arrangements, thereby providing multiple design alternatives for a given site.

3.2.5. Input of the Number of Floors and the Floor Height, and the Generation of Mass Excluding the True North Sunlight Area

During the building design process, two critical parameters come into play: the number of floors and the height of each floor, commonly referred to as the “floor height”. The input of these values yields a predictive model that reflects the anticipated shape and size of an actual building. This results in a primary building mass, often without accounting for the direction of sunlight and the influence of true north. By defining the height of each floor and determining the total number of floors, the 3D model of the resulting building, particularly its surface and solid components, were adjusted or shifted in the Z-axis direction. This determines the overall height and form of the building, as shown in Figure 6.

Figure 6. Visual programming of the number of floors and the floor height, as well as the generated mass.
For certain experiments or tests in the design phase, the number of floors was restricted to eight to reduce the number of variables. This limitation offers a more comprehensive understanding of the ramifications of the other influencing factors. When specific sections of a building design are omitted due to the influence of sunlight, the resultant shapes of the surface and solid components are analyzed meticulously. For visual differentiation, these components are assigned distinct colors and levels of transparency using a geometric color node. This visualization strategy provides a clearer insight into the different design segments and their respective influences.

### 3.2.6. Extracting the General Performance Output

In this method the values of the shared outputs are extracted during the design automation process, as shown in Figure 7. This method can be used to determine parameters such as the number of buildings, building area, site area, total floor area, building-to-land ratio, and floor area ratio. These general output values were derived using the calculation formulas fundamental to the architecture.

#### Figure 7. Visual programming of the general performance output.

- **Number of buildings**: the total number of distinct structures within a designated area or plot.
- **Building area**: This represents the footprint of the building on the land, typically measured in square meters or square feet. This provides information on how much of the land is directly under the buildings.
- **Site area**: The total area of the land or plot on which the building or buildings are situated. This includes building footprints, open spaces, gardens, driveways, and other elements within the boundaries.
- **Total floor area**: The sum of the floor areas of the building across all levels. This typically includes corridors, stairwells, and possible areas such as balconies, depending on the specific definition used.
- **Building-to-land ratio (BLR or site coverage)**: This is calculated by dividing the building area by the site area. This ratio provides information on the extent to which a site is occupied by its building footprint. For instance, a BLR of 0.5 or 50% means that half of the site is covered by buildings.
- **Floor area ratio (FAR) or floor space index (FSI)**: This is calculated by dividing the total floor area by the site area. The FAR provides a measure of site density. A higher FAR...
indicates more built-up space relative to the plot size. Urban planners often use these values to control and limit the amount of construction in a given area.

For an automated design process, these values can be automatically extracted using computer-aided design tools and building information modeling (BIM) software. These tools can be programmed to calculate metrics based on the design data input, enabling architects and designers to instantly evaluate different design alternatives based on these quantitative measures. These metrics are crucial in the field of generative design, where numerous design alternatives are generated. They facilitate the rapid filtering and ranking of the generated designs based on the desired criteria, ensuring that the final chosen design aligns with the project’s goals and constraints.

3.2.7. Extraction of the Environmental Performance Output Using North–South and East–West Lengths

The algorithm shown in Figure 8 was developed to understand the impact of a building’s façade on its environmental performance. In particular, buildings with many south-facing façades can benefit from environmental advantages such as lower heating costs due to their increased absorption of solar heat.

### Algorithm Coding

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<td>Extract north-south and east-west lengths</td>
<td>Extract the length of the north-south and east-west sides of a generated mass</td>
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### Sample output

- **Extract environmental performance output**
- **Apply the concept that more southern exposure is good for a building**
- **Extract Sum value of Length by dividing by North, South, and East**
- **Calculate environmental performance with extract values**

**Figure 8.** Visual programming of environmental performance output.

To concretely implement this algorithm, the following steps should be considered:

- The extraction of the building’s façade: first, extract the outline of the building from its 3D model.
- Determine the directionality of the façade: calculate the vector or normal vector of each façade to determine its directionality.
- Classify the façade as north–south or east–west: Based on the calculated directionality, each façade is classified as either north–south or east–west. To do this, compare the angle between the directionality of each façade and the standard directions of north–south or east–west.
- Calculate the length of the facade: compute the length of the classified façade.
- Calculate the total length: sum the total length of the facades classified as north–south and east–west.
The data extracted in this way can be used to evaluate the environmental performance of a building. In particular, buildings with larger south-facing façades can utilize solar heat more effectively. Therefore, this information can be used to improve the energy efficiency of buildings.

4. Results and Discussion

4.1. 3D Implementation of Generative Design Alternatives

Based on the design automation algorithm, random result values were output for the design concept alternatives, as shown in Figure 9.

![Figure 9. Multiple alternative outputs.](image)

One of the main criteria used to filter the output of the algorithm was the building-to-land ratio, for which acceptable results ranged from 40–60%. Another important condition was the floor area ratio, which was set at 400%. When these conditions are met, the algorithm can generate hundreds or thousands of design alternatives. Interestingly, some of the numerous alternatives generated closely resemble the results produced by human designers and architects. These results share design characteristics with the 3D models created by professionals during the conceptual design phase for a typical site. This observation suggests that a design automation algorithm can be an effective tool in the early stages of architectural design. It can generate a diverse range of viable design alternatives that are consistent with fundamental architectural principles and professional design esthetics.

4.2. Creation of Design Alternatives Based on Variations in the Building Coverage Ratio

Second, an algorithm for calculating the building coverage ratio is added. When alternatives with a low coverage ratio and alternatives with a high coverage ratio are listed, they appear as shown in Figure 10. The coverage ratio is the area occupied by a building compared to the area of the site. By including this value in the algorithm, the difference in design as a function of building density can be recognized. In other words, it can be seen that the alternatives with a low building-to-land ratio have a relatively unvaried shape. In contrast, it can be seen that alternatives with a high coverage ratio are created with diversified forms such as “L”-, “U”-, and “T”-shaped alternatives. This approach allows architects and designers to create a spectrum of design alternatives, from more minimal, open layouts to denser, complex alternatives. By recognizing and understanding these differences, architects and designers can make more informed decisions when it comes to selecting the most appropriate design solution for a particular site or project.
4.3. Creation of Design Alternatives Based on Variations in the Horizontal and Vertical Ratios

Third, we tested the addition of another criterion to the generative design algorithm, namely the horizontal and vertical lengths of the building. By determining the sum of these lengths in each direction and expressing them as a ratio, this criterion can help distinguish buildings that are elongated in the north–south direction from those that extend in the east–west direction. Figure 11 shows the results for high and low aspect ratios, and illustrates how this attribute can affect the building orientation and form. When a building is elongated in the east–west direction, more of its facades face south. This orientation can be advantageous, particularly in terms of sustainability, as it maximizes the exposure to solar radiation (a key factor for passive solar heating) and encourages the formation of wind paths in the north–south direction for natural ventilation. Alternatively, a building elongated in the north–south direction has more elevations facing east and west. These directions receive relatively less solar radiation than the southern direction, which may affect the energy efficiency of the building. This approach can provide insights into the impact of building orientation on energy efficiency and environmental comfort, enabling architects and designers to make more informed decisions regarding building layouts and forms.

![Figure 10](image1.png)

**Figure 10.** Multiple alternative outputs based on the building coverage ratio.

4.4. Creation of Design Alternatives Based on Variations in the Number of Masses

In this final step, the design results are examined based on the variance of the number of masses, as shown in Figure 12. The term “masses” alludes to distinct volumetric elements of the building. Thus, each square in a four-point grid is defined as a separate mass. The algorithm recognizes them as single entities when they share an area. In other words, if
a square does not overlap, it is considered a unique mass or building. Designs with a high number of masses take the form of four buildings with no shared or overlapping squares. This configuration implied that each of the four randomly selected points from the 441-point grid generated their own separate building. From an environmental impact perspective, as the number of masses (i.e., distinct buildings) increases, the orientation of the building becomes less significant. This may be because each mass can align independently of environmental factors, such as the sun and wind, without the constraints that might apply to a single, larger building. This also suggests that a higher number of masses allows for the creation of more diverse and innovative results as each mass can take on a unique form and layout. This approach provides us with an opportunity to explore a wide range of design alternatives and may yield unexpected and novel solutions.

Figure 12. Multiple alternative outputs based on the number of masses.

5. Conclusions

In this study, generative design techniques were investigated, particularly in the context of conceptual phases in the construction and design fields. The main results can be summarized as follows:

- The application of generative design in the conceptual design stage—in this study, generative design techniques were applied in the conceptual design stage using a three-step method:
  
  Step 1. Attribute classification and definition of the methodology for the definition of the problem: this step includes the identification of the problem, the setting of the parameters, and the definition of the methodology used in the generative design process. 
  
  Step 2. Layout design generation: this is where the design alternatives are created. 
  
  Step 3. Evaluation criteria and representative design selection: the generated designs were evaluated against predefined criteria, and the most suitable designs were chosen for further development. 

- The selection of the optimal alternatives—detailed minimum and maximum values for the aforementioned three conditions were selected. Based on the results, a layout design plan with optimal alternatives was created. This means that the best design was chosen considering all three criteria: the effective use of the land, the proportionality of the building dimensions, and the number of building masses or units. 

This study highlights the powerful role that generative design plays in assisting architects and designers in the conceptual stages by generating a multitude of viable design alternatives, and by selecting the optimal design quickly and efficiently. In this way a large number of alternatives can be generated during both the conceptual and detailed design stages. In addition, the application of diverse evaluation techniques will lead
to the development of more systematic generative design techniques that can be used through platforms.

This study is subject to certain limitations. Initially, to simplify the algorithm’s application, a modestly sized 20 m × 20 m plot was selected, and the construction space was confined to a uniform square ranging from 1000 mm to 10,000 mm. Crucial aspects typically considered in actual layout design—such as the site’s external conditions, the internal functions of the building, circulation plans, and functional arrangements—were omitted. Further research is necessary to integrate these elements into the generative design algorithm to overcome these limitations. Additionally, the current model only accommodates the creation of square shapes aligned with the grid, thus precluding the possibility of diagonal configurations on the site. Enhancing the algorithm to allow for a wider variety of shapes, including diagonally-aligned ones, could yield more versatile design options. Another area for improvement involves refining the evaluation criteria to produce outcomes more attuned to the designers’ objectives. Moreover, while the current algorithm can generate an infinite array of designs, applying a threshold within a specific evaluation framework would allow for the selection of designs that meet or exceed certain standards. Researchers have the flexibility to employ any combination of the three proposed evaluation methods to pinpoint the most suitable design alternative. However, the current setup does not support the extraction of result values for statistical analysis, which is a gap that future studies might aim to fill.

Nonetheless, the algorithm developed in this study was meticulously designed by categorizing the design, legal, and evaluative conditions in a manner that not only streamlined its use but also encouraged its further adaptation by the research community. By making the original source code publicly available, we invite modifications, enhancements, or the refinement of the set conditions, thereby fostering continuous innovation based on our foundational work. Moreover, the potential benefits and implications of this work for the community are substantial. It paves the way for architects and designers to harness increasingly complex variables and sophisticated computational methods. This, in turn, enhances their creative capabilities, optimizes compliance with legal standards, and enriches the evaluative processes, leading to more efficient and impactful design outcomes. Overall, our study illuminates the dynamic nature of generative design—a field that is rapidly advancing and becoming an indispensable tool in the architectural and design industries, with far-reaching implications for productivity, sustainability, and the advancement of the built environment.

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