Univerza *v Ljubljani*
Fakulteta *za gradbeništvo in geodezijo*

MINJA RADENKOVIĆ

EXPLORING THE POTENTIAL OF GENERATIVE DESIGN FOR CONCEPT DESIGN DEVELOPMENT IN ARCHITECTURE

OCENA UPORABNOSTI GENERATIVNEGA NAČRTOVANJA ZA RAZVOJ KONCEPTUALNIH MODELOV V ARHITEKTURI

BIM A+ European Master in Building Information Modelling

Master thesis No.:

Supervisor:
Assist. Prof. Matevž Dolenc, Ph.D.

Co-supervisor:
Assist. Luka Gradišar

Ljubljana, 2023

Co-funded by the Erasmus+ Programme of the European Union

ERRATA

Page	Line	Error	Correction

»This page is intentionally blank. «

BIBLIOGRAFSKO – DOKUMENTACIJSKA STRAN IN IZVLEČEK

UDK: 004.925.8:72-028.7(043.3)

Avtor: Minja Radenković

Mentor: doc. dr. Matevž Dolenc

Somentor: asist. Luka Gradišar

Naslov: Ocena uporabnosti generativnega načrtovanja za razvoj konceptualnih modelov v arhitekturi

Tip dokumenta: Magistrsko delo

Obseg in oprema: 57 str., 50 sl., 6 pregl.

Ključne besede: generativno načrtovanje, optimizacija, računsko načrtovanje, parametrično modeliranje, konceptualni razvoj, arhitektura, BIM

Izvleček:

V arhitekturni, inženirski in gradbeni industriji (AEC) so zgodnje faze razvoja projekta izredno pomembne, saj določajo potek rezultatov načrtovanja. Ker industrija sprejema tehnološki napredek, se vključevanje pristopov generativnega načrtovanja kaže kot obetavna pot za novo opredelitev postopka načrtovanja. Generativno načrtovanje pomeni spremembo paradigme, saj avtomatizira generiranje številnih alternativnih možnosti načrtovanja in omogoča na podatkih temelječe vrednotenje, ki spodbuja inovacije, racionalizira procese in izboljšuje sprejemanje odločitev.

Ta študija se poglablja v transformativni potencial generativnega oblikovanja v začetnih fazah arhitekturnih projektov. Zgodnji razvoj projekta zahteva občutljivo ravnovesje med domiselnimi oblikovalskimi koncepti in pragmatičnimi premisleki, ki vključujejo izvedljivost, trajnost in stroškovno učinkovitost. Ta raziskava z natančnim preučevanjem raziskuje, kako generativno načrtovanje izpolnjuje te zahteve in utira pot razvoju uveljavljenih praks. Poudarja ključno vlogo generativnega oblikovanja pri preoblikovanju arhitekturnih inovacij in usklajevanju postopkov oblikovanja s sodobnimi industrijskimi trendi.

»This page is intentionally blank. «

BIBLIOGRAPHIC– DOKUMENTALISTIC INFORMATION AND ABSTRACT

UDC: 004.925.8:72-028.7(043.3)

Author: Minja Radenković

Supervisor: Assist. Prof. Matevž Dolenc, Ph.D.

Cosupervisor: Assist. Luka Gradišar

Title: Exploring the potential of generative design for concept design development in architecture

Document type: Master thesis

Scope and tools: 57 p., 50 fig., 6 tab.

Keywords: generative design, optimization, computational design, parametric modeling, concept development, architecture, BIM

Abstract:

In the Architecture, Engineering, and Construction (AEC) industry, the early stages of project development hold paramount importance, shaping the trajectory of design outcomes. As the industry embraces technological advancements, integrating generative design approaches emerges as a promising avenue for redefining the design process. The generative design signifies a paradigm shift by automating the generation of numerous design alternatives, enabling data-driven evaluations that drive innovation, streamline processes, and enhance decision-making.

This study delves into the transformative potential of generative design within the initial phases of architectural projects. Early project development demands a delicate balance between imaginative design concepts and pragmatic considerations encompassing feasibility, sustainability, and cost-effectiveness. Through rigorous investigation, this research explores how generative design addresses these imperatives, paving the way for the evolution of established practices. It underscores the pivotal role of generative design in reshaping architectural innovation and aligning design processes with contemporary industry trends.

»This page is intentionally blank. «

ACKNOWLEDGEMENTS

I am immensely grateful for the funding provided by the Erasmus Mundus scholarship, which made this work possible.

I extend my heartfelt thanks to my co-supervisor, Luka Gradišar, whose introduction to this inspiring topic and unwavering support allowed me the freedom to develop it, and to my supervisor, Prof. Matevž Dolenc, who has been a true mentor throughout this journey. Their guidance, extensive expertise, patient support, detailed feedback, and unwavering motivation were invaluable at every step.

Special thanks to Eliana Nigro and Riccardo Piazzai for their generous contribution of industry insights, which greatly enriched the case study within this study.

To all the professors and assistants of the BIM A+ Master course, I extend my gratitude for imparting knowledge, tools, and their wealth of experience during the first semester.

I am indebted to my colleagues and friends, the BIM A+ Master students, for their friendship and shared experiences.

Last but certainly not least, I want to express my deep appreciation to my family for their unwavering and unconditional support throughout this journey.

»This page is intentionally blank. «

TABLE OF CONTENTS

INDEX OF FIGURES AND TABLES

LIST OF ABBREVIATIONS

2D	Bidimensional
3D	Tridimensional: 3D modelling
AEC	Architecture, Engineering, and Construction
AI	Artificial intelligence
BIM	Building Information Modeling
CAD	Computer-aided design
EA	Evolutionary algorithm
GA	Genetic algorithm
GD	Generative Design
GH	Grasshopper
IFC	Industry Foundation Classes
MOO	Multi-objective optimization
NSGA-II	Nondominated sorting genetic algorithm
OS	Objective space
PF	Pareto Front
SWOT	Strengths, Weaknesses, Opportunities and Threats

1 INTRODUCTION

The early stages of project development are essential in the Architecture, Engineering, and Construction (AEC) industry. These earliest phases chart a design's trajectory and significantly impact its ultimate success. Nonetheless, traditional approaches in the AEC industry have often struggled with the challenge of limited opportunities for physical prototyping, necessitating the reliance on virtual simulations for testing and validation. (Ramanauskas, 2020; Royal Institute of British Architects, 2020)

In an era distinguished by technological developments, the introduction of generative design appears to be a transformative answer.

The emergence of generative design has brought an alternative solution to the forefront as a paradigm change that can potentially revolutionize the AEC design process (BuHamdan et al., 2021). By harnessing the power of computational algorithms and evolutionary principles, generative design empowers architects, engineers, and designers to generate many design options swiftly and systematically. This approach accelerates the design process and broadens the horizon for problem-solving. As a result, it encourages innovation, streamlines operations, and improves decision-making across the industry. (Janssen et al., 2002; Rutten, 2010)

This study investigates the possibilities of generative design in the early stages of architectural projects. At the start of a project, a harmonious blend of creative ideation and pragmatic concerns, including feasibility, sustainability, and cost-effectiveness, is required. The investigation digs into how generative design, as a disruptive force, responds to these imperatives, changing established techniques and establishing a new path in architectural innovation. Through in-depth analysis and investigation, the transformative ability of generative design is demonstrated as a motivation for change in concept design development in architecture.

1.1 Problem Statement and Research Objectives

Three problem areas have been identified:

1. **Design Exploration Efficiency:** Due to time constraints, traditional design techniques may limit the design possibilities considered. Potential lies in how generative design techniques can help architects produce and assess design solutions more quickly, allowing for a more thorough study of multiple possibilities.
2. **Optimal Design Solution**: Traditional design methodologies may fail to balance multiple design goals successfully. The research looks into how generative design can address several criteria simultaneously, resulting in more optimal and well-balanced design solutions.

3. **Collaboration and Iteration:** Collaboration and iterative design refinement can be complex, especially with the traditional design approaches. This study looks into the potential of generative design to improve collaboration among interdisciplinary teams and stakeholders, allowing for quick design revisions and promoting a more inclusive decision-making process.

1.2 Methodology and Objective

The study takes a multidimensional approach, combining a literature analysis with insights from industry experts. This convergence of theoretical and practical knowledge provides a comprehensive view of the current environment of generative design within the concept design development in architecture, demonstrating its revolutionary potential in real-world workflows.

In addition, a case study also serves as tangible proof of generative design's prowess in optimizing project models. This study focuses on the critical early stages of a project, emphasizing its relevance when it counts the most. The primary goal of this study is to bridge the gap that frequently occurs between theory and practice. By doing so, it hopes to increase our understanding of how generative design may be effectively utilized throughout the early stages of architectural concept development, thus meaningfully contributing to the evolution of design processes in architecture.

1.3 Structure of the research

This research's subsequent sections are organized as follows:

- Section 2 is focused on the literature review, providing an overview of current knowledge on generative design and its applications;
- Section 3 highlights the research methodology;
- Section 4 focuses on the case study that shows the implementation of generative design;
- Section 5 presents the results and their implications, analyzing how they fit with industry trends and recommending future research options;
- Section 6 concludes by reflecting on the implications of the findings.

Iterative approaches are used to create a framework for the investigation. It is an ongoing process of learning, refining, and applying generative design through a case study to enhance creativity, efficiency, and innovation in concept design development in architecture.

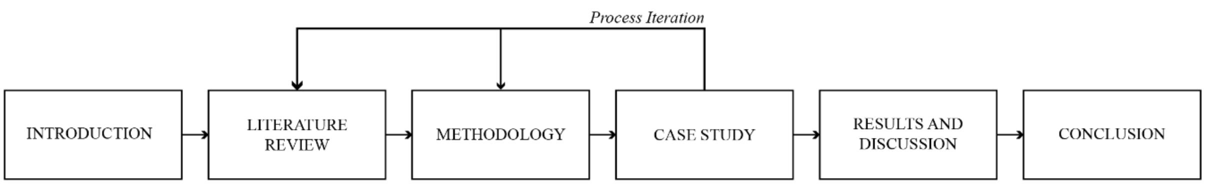

Figure 1: Research Proposal Workflow with Process Iteration.

2 LITERATURE REVIEW

2.1 Historical Overview

Generative design is a design methodology that uses computer algorithms and evolutionary principles to generate many designs based on specified restrictions and requirements.(Janssen et al., 2002) The concept of generative design dates back to the early 1970s when the first design algorithms emulating nature were created. (Barbieri & Muzzupappa, 2022) Mathematicians' efforts to mimic the beauty, symmetry, and order of natural patterns inspired the development of generative systems, leading to the invention of algorithms that allow computers to copy nature's creations. (BuHamdan et al., 2021)

However, generative design did not gain popularity in academic studies until the beginning of the twenty-first century, particularly in architecture. Several factors contributed to the advancement of generative design, including technological advancements, interdisciplinary collaboration, industry recognition, and the development of specialized software. These factors all contributed to the emergence and adoption of generative design in both academic and professional practice. (Barbieri & Muzzupappa, 2022)

2.2 Understanding Generative Design

To better understand how the process of designing can be effectively restructured, it is necessary to delve into the process of designing. This exploration helps us understand how different tools and methods offered by computers align with design processes and how they can be combined.

2.2.1 Design and Design Strategies

"The human designer, like other animals, is capable of producing outputs in which he has confidence, and which often succeed, without his being able to say how these outputs were obtained." (Jones, 1970)

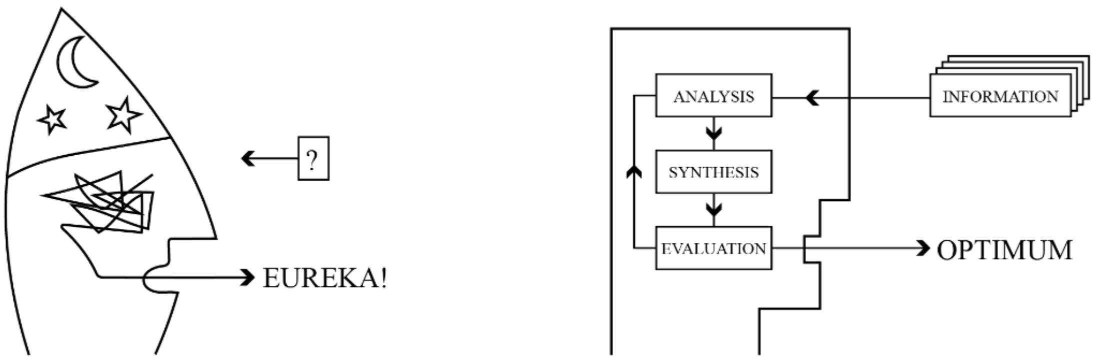

Figure 2: Designer as a magician and as a computer, based on drawings by Jones (1970).

In his work "The State of the Art in Design Methods," Jones (1970) makes an analogy: a designer as a magician. The primary idea is to describe how designers use their skills to create an output when facing a problem but often need help articulating how they arrived at that solution. An alternative model takes a more rational view of designing: operating in an iterative sequence. This approach involves analyzing information about the problem, formulating rules for creating solution candidates, and evaluating them until an optimal solution is reached. Furthermore, in his work "The Sciences of the Artificial," Simon (1970) states that by understanding the design problems and the complexities involved, we can effectively employ computational methods to support and enhance the design process.

The design space is often restricted by our assumptions about the design and the limitations of the tools available for creating. Within this design space, we strive to navigate toward the solution space, and due to time constraints, we aim to reach the solution space as efficiently as possible. Design strategies are developed to guide us through the design process and help us explore and generate solutions within the given constraints, providing a framework for making informed decisions and optimizing the path toward finding suitable solutions. (König & Schneider, 2020)

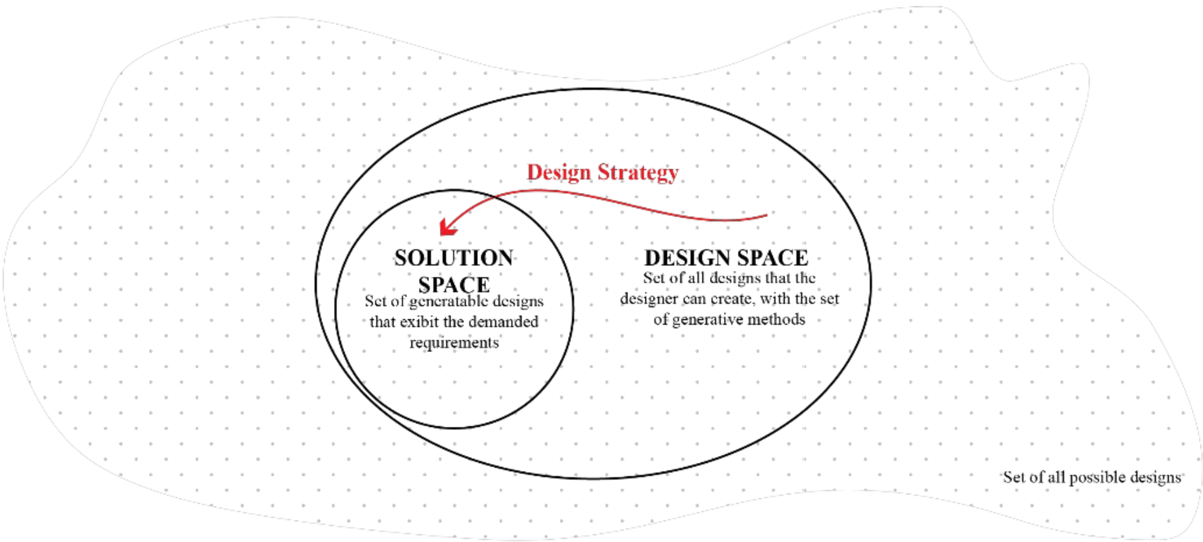

Figure 3: Design Space and Solution Space Relationship with Design Strategies, based on König and Schneider (2020).

The algorithmic approach is a design strategy defining a set of functions or performance criteria the object should fulfill, which serve as guidelines. By systematically analyzing the desired functions and their relationships, one can develop a step-by-step process for generating the form that best meets those functions. (Kazemi et al., 2015)

In order to incorporate requirements into the algorithm, it is necessary to include conditional »if« statements that check for specific conditions, which could be a problem when numerous possible cases may need to be covered. In an iterative sequence, one part of the sequence involves an algorithm that generates a range of variants, and the second part of the sequence involves evaluating the generated variants against the desired functions or performance criteria. The process then repeats itself, iterating through the generate-test cycle until a satisfactory solution is found. (König & Schneider, 2020)

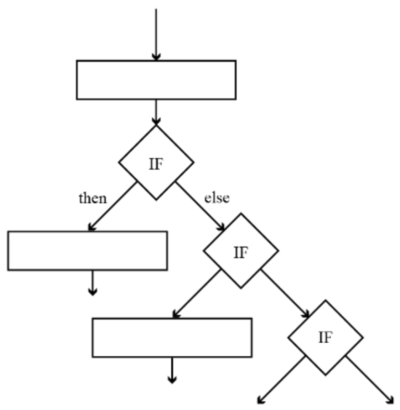

Figure 4: Comparison of Linear and Iterative Sequence.

Automation of the design process involves developing algorithms and computational systems that can perform the tasks of generation and evaluation. By automating the design process, designers can benefit from the efficiency and speed of computational tools to explore a vast solution space and generate numerous design alternatives. The automated search process helps identify promising solutions, helping with the decision-making process.

2.2.2 Generative Design Model

Generative design is a design approach that uses computational algorithms and evolutionary principles to generate and explore alternative design proposals. This method allows designers to break free from conventional wisdom and design fixation, enabling them to explore many possible solutions for a design problem. Generative design tools are considered active as they become integral to the manual and cognitive design processes. (Janssen et al., 2002)

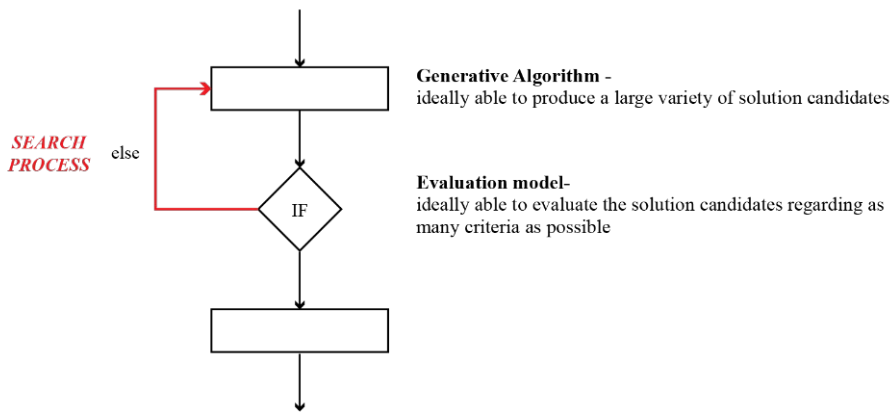

Figure 5: Generative Model as an Iterative Sequence, based on König and Schneider (2020).

In his work "A Practical Generative Design Method," Krish (2011) offers a sound generative design strategy. This model uses algorithmic design tools and parametric modeling to generate and investigate a range of design choices. To effectively direct the generative process, the author underlines the significance of identifying design objectives, constraints, and parameters. The proposed approach is centered on iterative refinement, in which numerous design iterations are produced and assessed according to predetermined criteria. The advantages of generative design, some of them being improved design exploration, quicker decision-making, and the potential for more creative solutions, are emphasized by Krish.

2.2.3 Multi-objective Optimization

Finding the best solutions frequently involves optimization because it leads to good results faster. Optimization algorithms can search the design space and identify the most promising solutions based on the evaluation criteria, leading to more informed and optimized decision-making.

One often encounters multi-objective optimization problems in a design with multiple competing objectives. In such problems, the goal is to find a set of optimal solutions, known as Pareto-optimal solutions, where no single solution can be better without additional information. Classical optimization methods often involve converting multi-objective optimization problems into single-objective optimization problems, which can be inadequate and may not capture the full range of optimal solutions. (Deb et al., 2002)

2.2.4 Evolutionary Strategies

When the design process becomes time-consuming, it may be necessary to employ »shortcuts« to accelerate the search for a solution. Heuristics are strategies that guide the search process by providing hints, clues, or approximate measures of progress toward the goal. In the design context, designers can focus on existing strategies, avoiding exhaustive exploration of every possibility by leveraging heuristics**.** Heuristics can take various forms, depending on the design problem and the specific context. They can be derived from prior experience, expert knowledge, or domain-specific rules. (König & Schneider, 2020)

An excellent example of a computation-based heuristic search is the evolutionary strategy, which mimics biological evolution and operates based on the principle of "survival of the fittest." Evolutionary optimization draws inspiration from natural processes, aiming to integrate it into our design thinking and computational processes to generate innovative designs. (Bentley & Corne, 2002)

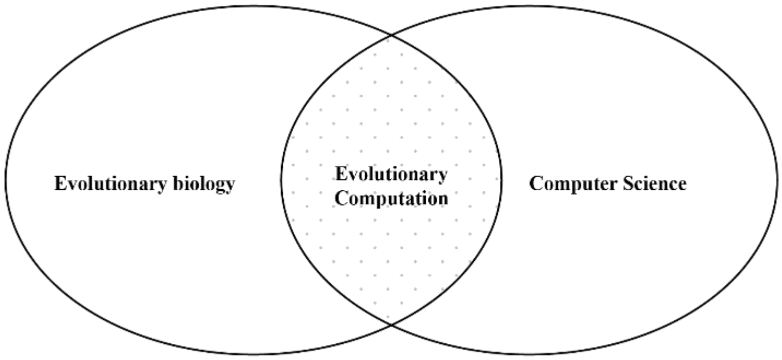

Figure 6: Foundations of Evolutionary Computation: Computer Science and Evolutionary Biology, based on the drawings from Bentley and Corne (2002).

In the essay "Evolutionary Design Systems and Generative Processes" by Janssen, Frazer, and Ming-xi (Janssen et al., 2002), the authors review how generative design processes can benefit from evolutionary computation approaches motivated by biological evolution. The authors highlight the capacity of generative processes to explore a broad range of design ideas along with their iterative and adaptive character. The article advances knowledge of how generative processes can be improved through evolutionary design systems and how this might motivate creative and practical design solutions.

All evolutionary processes follow a structured framework:

1. **Random Variant Generation**: The first step involves randomly generating variants representing different design alternatives. In the design context, this can be achieved by randomly defining the parameters of a parametric model.

2. **Evaluation**: Each variant is evaluated based on predefined criteria, assessing the fitness of the variant. In the design context, it means measuring how well a design solution meets objectives.

3. **Selection**: Variants with the worst performance are eliminated from the pool. Variants exhibiting better performance are selected to form the next generation of solutions. **Alternatively, manual selection can be employed. However, it can be time-consuming; thus, automating the selection process using computational performance measures is more common.*

4. **Variation**: The selected variants undergo slight modifications, introducing variability and diversity within the design space, aiming to explore new possibilities and potentially improve the solutions.

5. **Evaluation (Again)**: The modified variants are re-evaluated, following the same performance criteria. This step allows for the comparison and assessment of the new solutions.

6. **Iteration**: Steps 3 to 5 are repeated iteratively.

7. **Termination**: The evolutionary process continues until a termination condition is met, such as reaching a satisfactory fitness level or a specific number of iterations.

By following this structured framework, we can effectively navigate the design space, iteratively refining solutions and ultimately arriving at designs that meet our objectives. Automating selection and using termination conditions help streamline the process, making it more efficient and effective in finding optimal solutions.

The evolutionary process starts with random solutions, progressively narrowing to goal-specific outcomes through iterations after evaluating many factors: goal values, algorithm settings, number of mutations, and length of the generation period runs.

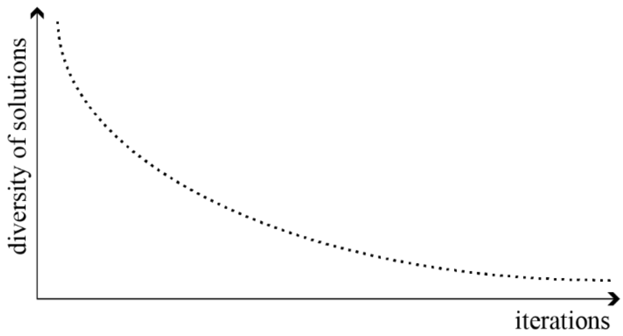

Figure 7: Diversity of Solutions vs. Iterations.

2.3 Generative Design in the AEC Industry

Generative design has become an increasingly used method in the Architecture, Engineering, and Construction (AEC) industry as it can generate unique and complex design solutions based on specific design needs. This approach allows designers to explore various design alternatives and select the best choice depending on their needs and project resources. In the AEC industry, generative design has been used in various ways, with integration with Building Information Modeling (BIM) technology becoming increasingly popular.

In their research titled "Generative Design in Building Information Modelling (BIM): Approaches and Requirements,"(Ma et al., 2021) the authors examine how generative design methodologies might be integrated into the BIM framework. They draw attention to the advantages of generative design, including enhanced design exploration, optimization, and automation. The paper also discusses the technological prerequisites and factors for applying generative design in BIM, such as data interoperability, computational performance, and user interface design. Finally, the authors stress the importance of cooperation and interdisciplinary integration for generative design to be successfully included in BIM methods.

2.4 Generative Design in Architecture

In architectural practice, generative design can generate novel and efficient solutions to various design difficulties. These examples demonstrate the adaptability of generative design, which frequently bridges numerous categories to create holistic solutions to architectural difficulties. This adaptability highlights the ability to transcend traditional boundaries and contribute to numerous aspects of architectural practice.

Object Typology

Generative design is employed across various object typologies in architectural practice. For instance, the study by Mukkavaara and Sandberg (2020) showcases its application to a residential block, highlighting how generative design can yield innovative solutions tailored to specific typologies. Moreover, Smorzhenkov and Ignatova's (2021) exploration of generative design's role in residential buildings demonstrates its adaptability to typological contexts. Pibal, Khoss, and Kovacic's (2022) work addresses challenges related to modular design, standardization, flexibility, and efficiency in residential building projects. On the other hand, Rohrmann's (2019) study on office buildings further exemplifies how generative design can be effectively integrated into the design process of different typologies, such as office buildings.

Project Phases

The generative design demonstrates its versatility across various project phases, although this study primarily centers on the concept design stage due to its significance in shaping the entire design trajectory. As Rohrmann's (2019) study shows, generative design streamlines projects' early design stages, emphasizing its potential to enhance decision-making from project inception. Similarly, Chang and Shih's (2018) research emphasizes the multi-disciplinary communication benefits of generative modeling in the early stages of architectural design, impacting decision-making and project progress.

Design Objectives

Generative design aligns with various design objectives. Li and Lachmayer's (2018) study, which focuses on modeling creative designs, showcases how generative algorithms can aid in pushing the boundaries of creative design. Furthermore, the study by Mukkavaara and Sandberg (2020) emphasizes generative design's potential to generate context-sensitive architectural proposals that meet design criteria. Similarly, Gradišar, Klinc, Turk, and Dolenc's (2022) work exemplifies the symbiotic relationship between designers and algorithms, contributing to both the implementation within projects and the advancement of generative design's potential. In the case of a contextual adaptation, the study showcases how generative design methodologies can be integrated into various stages of project development, ensuring contextually relevant and innovative architectural solutions.

Material and Fabrication Optimization

Incorporating generative design for material and fabrication optimization is another promising application. Pibal, Khoss, and Kovacic's (2022) study delves into modular design challenges and how generative algorithms contribute to the efficient design, visualization, and analysis of building components.

2.5 Research Gap, Aim, Motivation

Generative design research already conducted in architecture shows limitations in its application and a lack of comprehensive integration. This shortcoming affects generative design's practical application in actual architectural projects and precludes a complete examination of its potential across various design phases.

By performing a thorough analysis of the application of generative design in the development of architectural concepts, this study aims to fill these gaps. In order to better comprehend generative design's usefulness in a larger design context, the study attempts to shed light on its consequences for later project phases.

This study seeks to close these gaps by thoroughly analyzing the use of generative design in creating architectural conceptions and contributing to more informed and effective decision-making processes, thus reshaping architectural design practices and elevating design quality to new heights.

3 METHODOLOGY

3.1 Problem

The study addresses the challenge architects face when embarking on projects with both creative and pragmatic goals, starting with a blank page. Architects are entrusted with concept design, essential to project development, since it establishes the project's original direction, vision, guiding principles, and aesthetics, thus directing the following design, development, and construction phases.

Concept design is significant for various reasons:

- **Vision and Direction:** Concept gives the project a distinct vision and direction, bringing stakeholders together around the project's objectives, aims, and overall design intent;
- **Innovation and Creativity:** Concepts are investigated during this stage, pushing the boundaries of design and developing original solutions to design problems;
- **Cost and Time Savings:** A clearly defined concept design aids in the early detection of possible problems, avoiding the need for expensive design adjustments at a later stage;
- **Stakeholder Engagement**: Effective communication with customers, end users, and other stakeholders is made possible by concept design, ensuring that their requirements and goals are taken into account immediately;
- **Risk reduction:** Concept design helps reduce risks related to later design and construction stages by addressing design limits and anticipating future problems.

Concept design corresponds to Stage 2 of the RIBA (Royal Institute of British Architects, 2020) stages, when the initial design concepts are expanded to form a cohesive concept. The project's spatial relationships, materials, shapes, and aesthetics are defined in this phase. Budgetary and functional needs are also taken into account. A project is successfully guided through the concept design stage, detailed design stage, construction stage, and beyond.

Figure 8: RIBA plan of work (Royal Institute of British Architects, 2020).

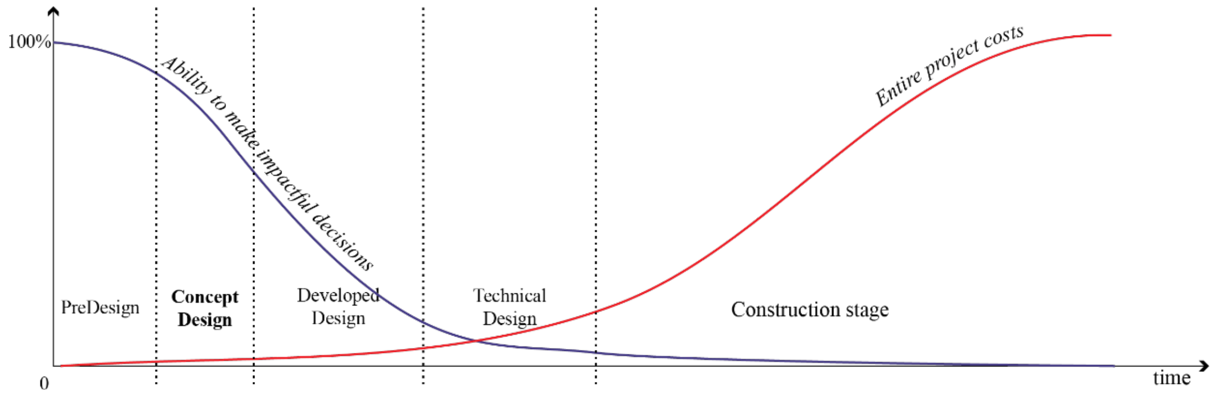

Figure 9: Impactful Decision Ability vs. Project Cost, adapted from Ramanauskas (2020).

Furthermore, collaboration across the AEC industry is currently fragmented, mainly due to several challenges:

- **Diverse Tool Ecosystem:** Different software tools are used, complicating data sharing and integration, potentially causing compatibility issues.
- **Cross-Company Workflows:** Multi-organization collaboration lacks streamlined data filtering and management, risking data inconsistencies.
- **Project Complexity:** Growing project complexity leads to fragmented data updates, causing information gaps and inefficiencies.

The application of generative design is predominantly limited to the initial stages of a project, encompassing a few early steps. However, significant potential exists for its expansion, fostering a more comprehensive integration of generative design.

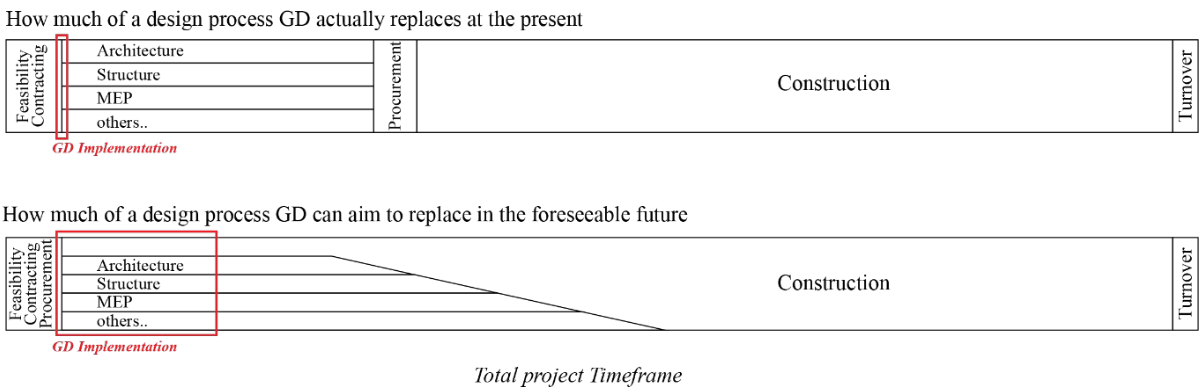

Figure 10: Generative Design Application: Present vs. Future, adapted from Ramanauskas (2020).

3.2 Case Study

This paper adopts a test project as a primary methodological approach to investigate and explore the potential of generative design in concept design development. The project provides a controlled and focused research environment, enabling systematic examination of specific design parameters and considerations.

While a complex case study would include real-world data and variables, using an illustrative case study allows for variable modification and controlled experimentation, isolating and emphasizing generative design's impact on design results, which would be difficult to do in a complicated real-world case study. Furthermore, it increases generalizability by allowing us to investigate a greater range of design scenarios and generate insights that can be applied to various real-world design contexts.

3.3 Generative Design Framework

A simple framework has been developed within this project's scope to investigate the possibilities. The following section will go into the complexities of this framework, outlining its general workflow, components, and integration with software tools to provide a better understanding of its application and outcomes.

3.3.1 Workflow

The GD process workflow is the foundation for methodically investigating its possibilities, and it has three major stages:

1. **Problem definition:** Project objectives and constraints are transformed into mathematical formulations and design requirements; these act as guides for following creative processes.

2. **Design space exploration:** Multiple design choices are generated using computer techniques such as evolutionary processes; evolutionary operators navigate the evolution of design solutions, constantly optimizing them against predefined objectives.

3. **Evaluation and refinement:** The fitness of created designs is assessed using multi-objective assessments that compare them to various criteria. Pareto front analysis helps find optimal or near-optimal solutions, while visualization tools help comprehend trade-offs and design details.

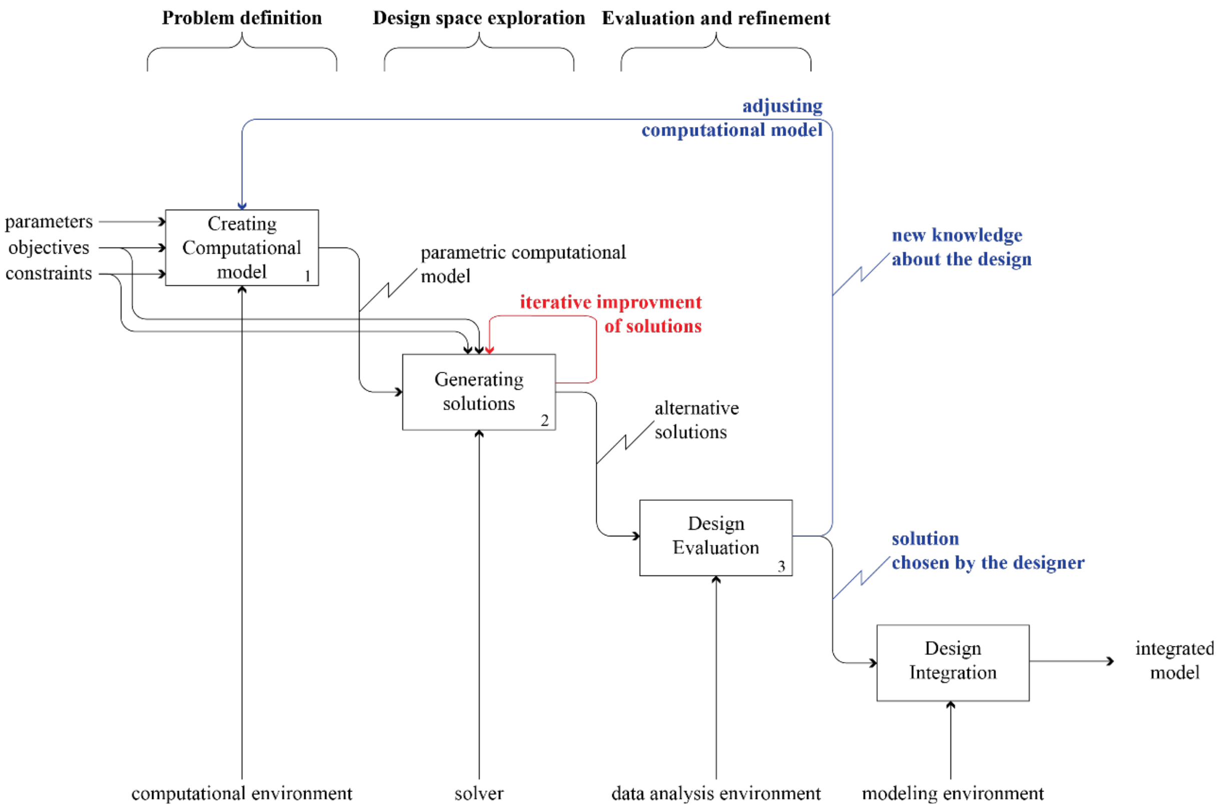

Figure 11: IDEF0 diagram of the Generative Design Process, adapted from Gradišar et al. (2022).

3.3.2 Components

The generative design framework comprises several vital components, forming the foundation for a methodical exploration of its possibilities.

Design Objectives

The design objectives are goals that define directions for a good design. Unfortunately, design problems often possess characteristics that make the task complex and challenging. Some problems include vaguely defined design goals, subjective criteria that are difficult to quantify, contradictory criteria, and unknown relationships between criteria (many-to-many connections).

Some criteria can be subjective to the human decision-maker, such as aesthetics or comfort, or objective, such as profit or the number of daylight hours inside the building. Once the design goals have been determined, they must be coupled with quantitatively measurable indicators, allowing the designs to be objectively compared.

Examples: cost efficiency (construction, materials, maintenance, lifecycle), regulatory compliance, sustainability, functionality, space use, energy efficiency, daylighting, acoustics, thermal comfort

These examples depict the multifaceted nature of architectural design goals and the factors designers must consider while making significant project settings.

Input Parameters and Constraints

Input parameters and constraints act as a navigational compass, leading the study of design options. Input parameters cover various factors determining the design space, from geometrical dimensions to material qualities. On the other hand, constraints are the boundaries that limit this space, signifying real-world restrictions and practical requirements.

These variables and limitations define the spectrum of design iteration possibilities, providing a framework for the generative algorithm to develop and assess solutions. The precise calibration of input parameters and restrictions is critical, as they shape the evolution of designs and influence the outcome's alignment with stated objectives. Parameters and constraints should be quantitatively measurable to ensure precise evaluation and effective optimization.

Examples: number of floors, setback requirements, building dimensions, level height, floor area ratio, total floor area, unit mix, green space area, amenities area, accessibility, material selection

A variety of these examples show how input parameters and constraints can be adjusted to correspond with particular design categories, enabling consideration of various design options while staying in line with the objectives and limitations of the project.

Computational model

In creating the computational model, inputs are the initial design parameters and data provided to define the model. Outputs are the results and representations the computational model generates based on those inputs. Constraints are the limitations and requirements that must be satisfied during the model's execution.

The computational model creation process is guided by parameters alongside constraints. Objectives are formulated through computational design, becoming values that steer and evaluate the generative design process.

Algorithmic Logic

The generative design process is driven by algorithmic logic, which enables the transformation of input parameters and constraints into various helpful design solutions. Fundamentally, the generative algorithm follows the rules, protocols, and frameworks that guide the algorithm as it manipulates and mixes design aspects to improve the solutions and align them with the desired goals. Algorithmic logic covers everything from creating initial design configurations to systematically changing parameters using mathematical equations, conditional logic, and evolutionary algorithms. It balances exploration and exploitation, encouraging the algorithm to test fresh concepts while optimizing for desired results concurrently.

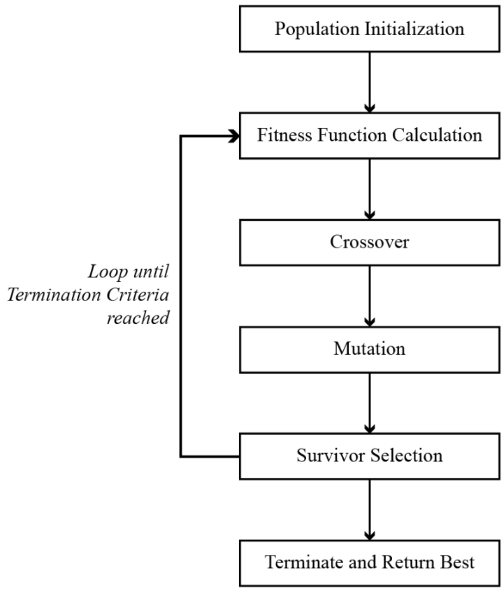

Figure 12: Basic model of Genetic Algorithm, adapted from König and Schneider (2020).

Selection, crossover, and mutation are genetic operators that imitate the principles of biological evolution, systematically improving and diversifying the pool of design possibilities. Understanding these operators is crucial to evolutionary optimization models:

1. **Selection:** The selection mechanism involves several methods to determine which solutions are chosen to reproduce and influence the quality of the next generation. In the context of fitness landscapes, the selection focuses on solutions that are close in design quality, fitness values, or design parameters, ensuring that offspring are derived from similar regions in the landscape.

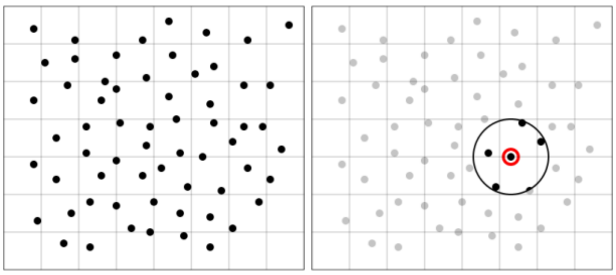

Figure 13: Selection Operator – Coupling: Visual Explanation, based on Rutten (2010).

2. **Crossover:** A common approach to combining genetic information from parents to create offspring is taking half from the mother and half from the father. There are numerous other ways to combine the parental genes. However, the fundamental principle is for offspring to inherit genetic information from both parents, resulting in a new generation with a combination of traits from the previous generation.

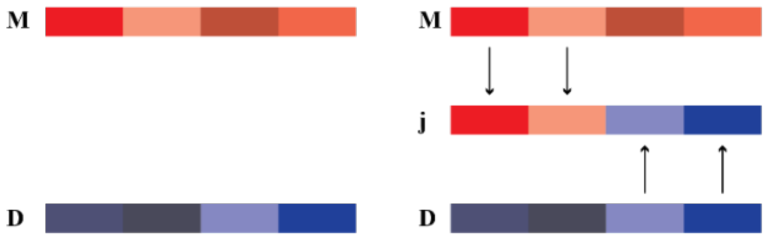

Figure 14: Crossover Operator: Visual Explanation, based on the drawings of Rutten (2010).

3. **Mutation:** The mutation operator is a relatively simple operator that introduces random changes to design parameters. It randomly selects a parameter and modifies its value to introduce diversity and explore new regions of the solution space.

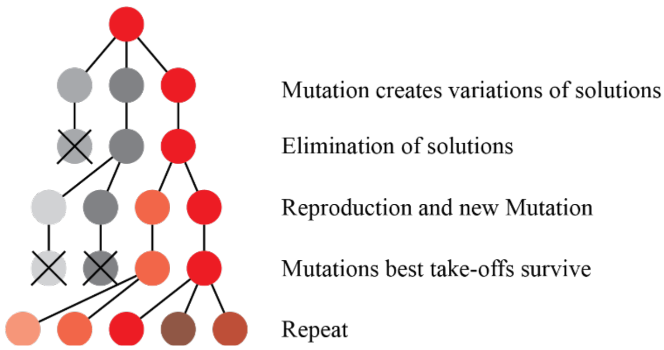

Figure 15: Mutation Operator: A Visual Explanation, redrawn from Rohrmann (2019).

The chosen **Non-dominated Sorting Genetic Algorithm II (NSGA-II)** is an example of algorithmic logic and functions, and it serves as a guiding force that orchestrates the search for design solutions. NSGA-II is a multi-objective evolutionary optimization method that uses natural selection techniques to generate a population of potential designs that evolve across generations. The method uses a Pareto-based ranking system to classify designs according to their dominance in several objectives, facilitating the discovery of a diverse group of optimal or near-optimal solutions. (Deb, 2001; Deb et al., 2002)

Exploration and Exploitation

Exploration (diversification) refers to the range of design options that the algorithm wants to investigate in the design space. The algorithm explores unknown ground by producing solutions, preventing design staleness, and encouraging new concept development.

On the other hand, exploration (convergence) embodies the algorithm's dynamic search for optimal or nearly ideal solutions by methodically identifying viable design options. The algorithm incorporates controlled randomness through evolutionary operators like mutation and crossover.

Thus, exploration sparks innovation, and design problem-solving is improved via exploration. A rich design ecology that combines originality, performance, and viability can be fostered by balancing these factors, creating a positive feedback loop.

Iterative Exploration

The exploration entails progressively creating, evaluating, and refining design solutions to achieve desired outcomes. The generative algorithm generates a wide range of design options, which are then evaluated concerning predetermined goals. With the help of this evaluation, the algorithm adapts its strategy to produce more effective results in subsequent cycles by considering each iteration's successes and failures. The design is pushed toward more excellent fitness and alignment with project goals by the revisions made in response to the learnings from one iteration.

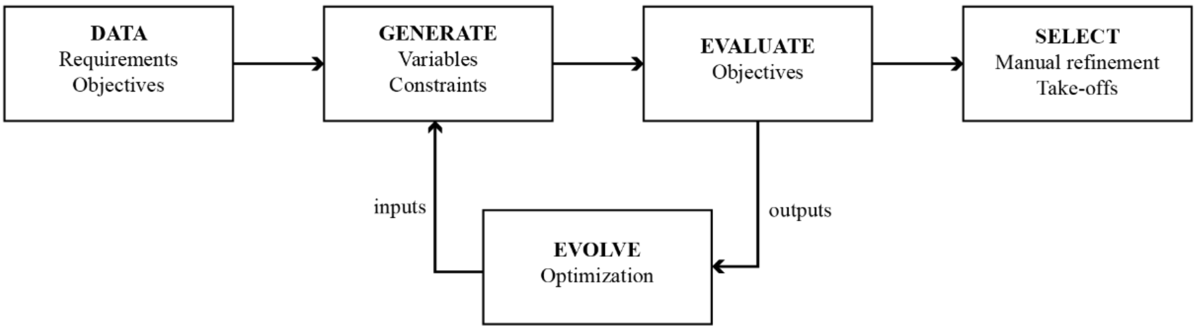

Figure 16: Iterative Exploration: Generate, Evaluate, Evolve, based on (Nagy & Villaggi, 2020).

Fitness Evaluation

The crucial assessment mechanism in the generative design process is fitness evaluation, which measures how well each design solution corresponds with the desired goals. It entails applying predetermined criteria to each created design. Design solutions are then given fitness ratings through a methodical review procedure that indicates how well they performed regarding these criteria. These ratings help the algorithm determine which options are most likely to produce the intended results. The fitness evaluation process guides the algorithm's decision-making, which chooses which solutions are kept, improved upon, or dropped in the following rounds.

The fitness landscape is a metaphor to help explain and visualize the relationships between genotype and fitness. The goal is to ascend the peaks of the fitness landscape by manipulating parameters., where optimal solutions reside.

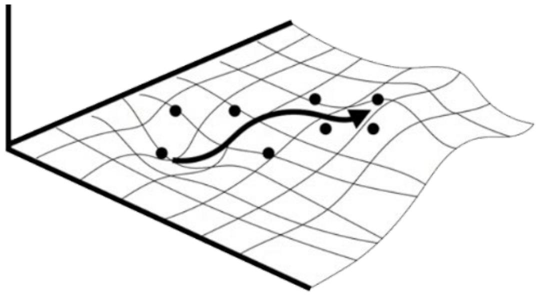

Figure 17: Visualization of Fitness Function and Landscape, based on Rutten (2010).

Pareto Front Analysis

A critical method in generative design is Pareto front analysis, which makes it possible to visualize and evaluate several competing goals simultaneously. This approach asserts that enhancements in one area frequently result in trade-offs in other areas and focuses on finding solutions that represent the best compromise between competing design goals.

In a visual representation of solutions, each dot on the Pareto front represents a design approach that strikes a particular balance between the goals. These solutions are significant as optimal options because no other solution outperforms them in all criteria.

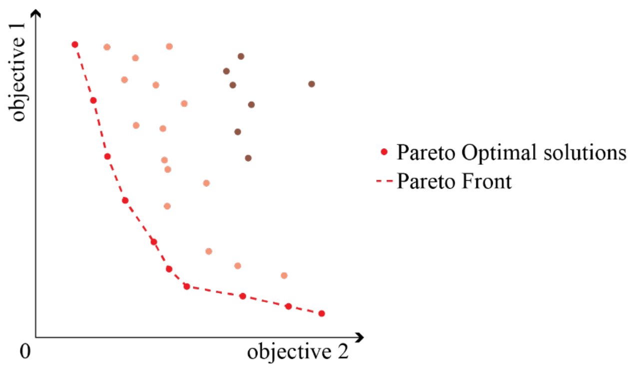

Figure 18: 2D example of Pareto front and Pareto-optimal solutions.

Pareto front analysis aids designers identify trade-offs and making decisions about solutions that align with project priorities by assisting them understand the alternatives in the design environment. It supports knowledgeable design decisions by showing the range of potential alternatives, ensuring that the final design is well-informed, balanced, and reflective of the project's complicated objectives. (Deb, 2001)

Objective Space Analysis

The 'Objective Space' (OS) and 'Pareto Front' (PF) complement each other and should be used together.

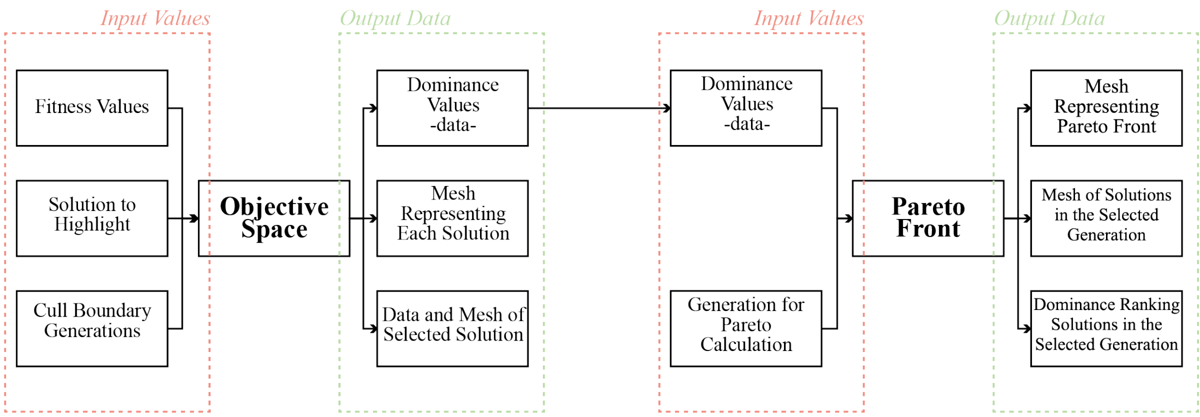

Figure 19: Correlation between Objective Space and Pareto Front, Wallacei Primer (Makki et al., 2019).

The Objective space component remaps the simulation's fitness values and assigns a unique axis to each objective:

- Objectives 1–3 are displayed on the X, Y, and Z axes;
- Objective 4 is expressed by color (Green to Red, best fit to worst fit);
- Objective 5 is represented by the scale of the cubes in the objective space (big to small, best fit to worst fit).

It is possible to highlight specific solutions in the objective space by picking the solution based on its generation and population size.

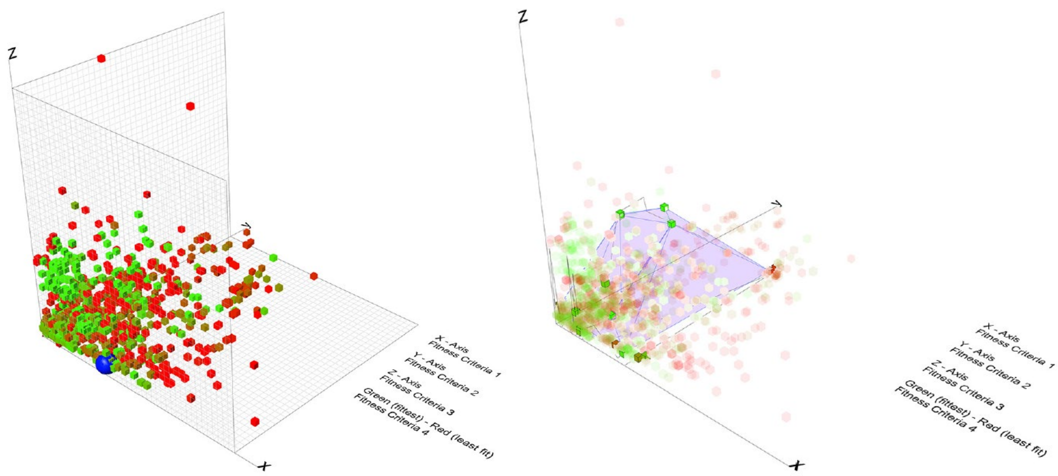

Figure 20: 3D Visualization of Objective Space and Pareto Front, from Wallacei Primer (Makki et al., 2019).

The Pareto Front component computes the non-dominance value for any given generation in the population and draws the Pareto Front for that generation, visually represented by a 3D mesh.

Design Space Visualization

A crucial component of generative design is design space visualization, which makes it easier to explore and comprehend the vast array of design options inside a specific parameter and variable framework. It requires producing graphical representations that show the distribution and interactions among various design options, frequently in interactive 2D or 3D plots.

The Parallel Coordinates Plot, Clustering, and Diamond Fitness Chart are some Design Space Visualization tools used to highlight trends, correlations between parameters, and the impact of factors on the final design. These tools aid in identifying areas of interest and comprehending complicated interactions within the design space. However, these tools are not exhaustive; other visualization methods can also help capture subtle differences in data patterns, support designers in making educated decisions, and explore the full potential of the generative design process.

Parallel Coordinates Plot

This plot displays all input and output variables for each design solution side-by-side, enabling a comprehensive understanding of the relationships between variables and design outcomes. By adding boundaries to the variables, we can narrow the design solutions to a smaller sample, facilitating individual examination and visual comparison of designs.

The parallel coordinates plot is an effective tool for understanding design variations, identifying patterns, and making informed decisions during the design evaluation.

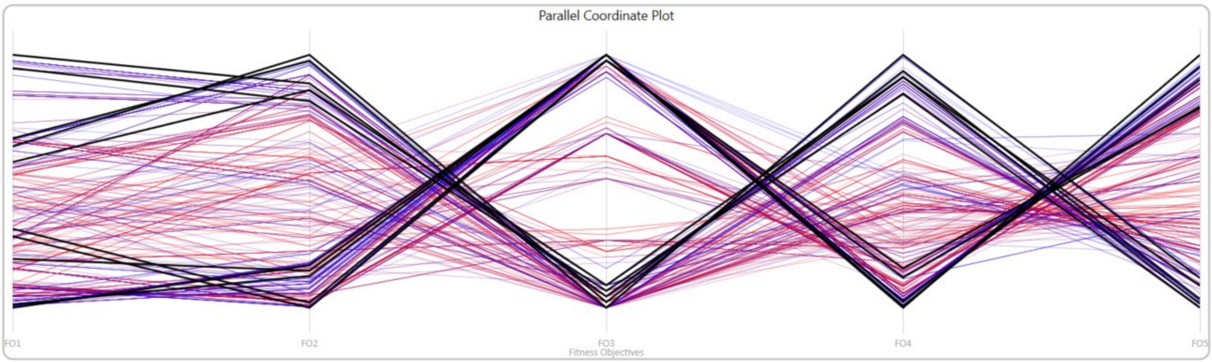

Figure 21: Parallel Coordinate Plot with Highlighted Pareto Front Solutions.

Clustering – K-means

Clustering, mainly through the k-means algorithm, arranges similar data elements based on defined features. In k-means, data points are grouped into a set number of clusters, determined by the nearest mean to each point. This technique results in unveiling patterns within generated design solutions. Clustering solutions can discern emerging design trends according to specific design parameters or performance metrics, aiding in categorizing solutions and exploring variable interactions shaping design outcomes. (Kaushik et al., 2014; Makki et al., 2019)

Clustering and k-means facilitate the identification of shared attributes among designs – like floor sizes, facade layouts, or energy performance, providing insights into interrelated design aspects and their collective influence on overall performance. Such strategies synthesize data, enhance visualization, and extract valuable insights from optimization results. In k-means, the central solution is the cluster's center or centroid. It encapsulates the cluster's collective characteristics and guides data point assignments to minimize the distance between points and centroids. The central solution embodies the "average" features of the cluster's data points, serving as a reference for grouping similar data points.

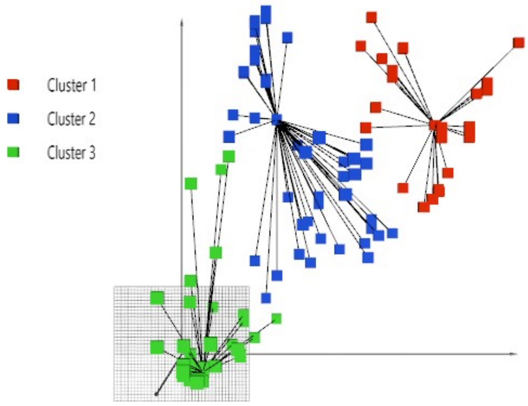

Figure 22: Visualization of K-means Clustering.

Diamond Fitness Chart

The Diamond Fitness chart examines the fitness values of a single solution rather than the population-wide analysis used in earlier components. The goal is to let the user understand how a single solution performs by comparing fitness values and rankings for each fitness target.

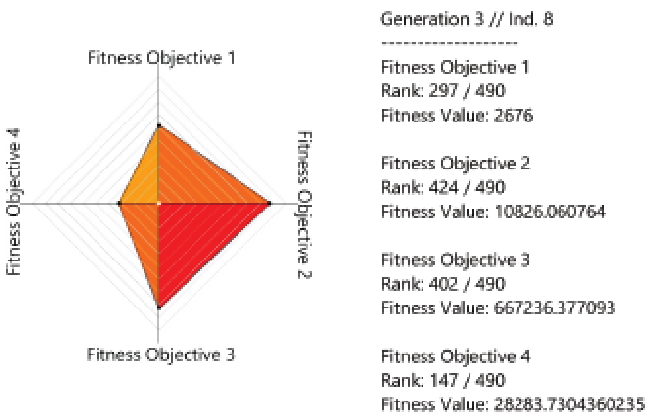

Figure 23: Diamond Fitness Chart Visualization, from Wallacei Primer (Makki et al., 2019).

Selecting Optimal Design Solutions

In an evolutionary optimization study, the final design entails selecting the best-performing solution that fits the design objectives and constraints to the greatest extent possible. This final design represents the optimal or near-optimal solution within the researched design space. There are several ways to choose the design:

- **Termination Criteria:** Establish termination criteria that govern when the optimization process should be terminated: a set number of generations, a certain level of convergence, or when the improvement in fitness values becomes insignificant.
- **Best Solution Tracking:** Throughout the optimization process, identify the best solution. This one will have the highest fitness value among all the created solutions.
- **Final Assessment:** Once the optimization process has been completed, assess the fitness value of the best solution discovered. This fitness rating quantifies the solution's ability to meet the design objectives and restrictions.
- **Comparison with Thresholds:** For each design objective, compare the fitness value of the best solution to specified acceptable thresholds. The solution is judged practical and optimal if the fitness value reaches or exceeds certain thresholds.
- **Trade-offs:** Consider the trade-offs between competing agendas. If the optimization process takes into account many objectives, no one solution is likely optimal for all objectives at the same time. In such instances, approaches such as Pareto front analysis can identify a set of Pareto-optimal solutions representing various trade-offs.
- **Expert Opinion:** Expert opinion may be necessary to decide in some circumstances. If the fitness functions cannot adequately capture subjective aspects, interacting with domain experts can provide significant insights.
- **Validation and Sensitivity Analysis:** Validation and sensitivity analysis ensure the final design is robust and operates well in various situations and conditions.
- **Iterative Refinement:** Depending on the complexity of the problem and available time/resources, many optimization iterations might be run with varied settings or objectives to refine the final design further.

The final design should be chosen after thoroughly examining the fitness values, design objectives, and constraints. It is critical to analyze both quantitative and qualitative indicators to verify that the chosen design not only performs effectively but also aligns with the overall goals and requirements of the project.

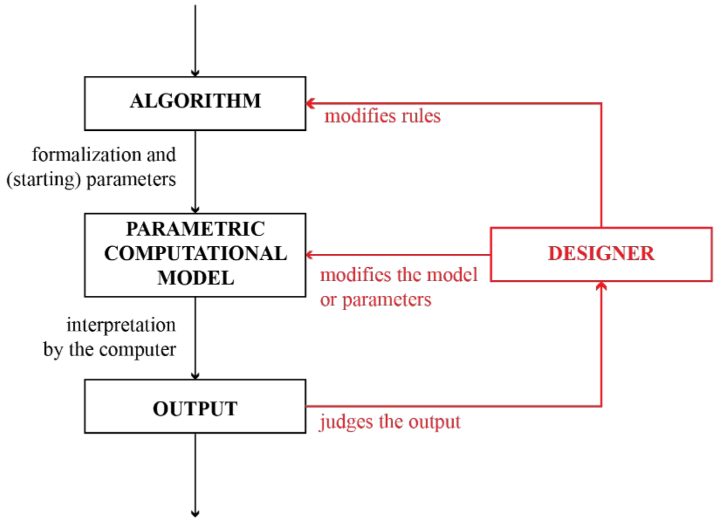

Figure 24: Designer's Role in the Generative Design Process, based on Bohnacker et al. (2019).

While generative design produces a wealth of data and potential solutions, the ultimate decision-making usually resides with the designer. Despite the insights and options the generative process provides, the designer's expertise, creativity, and subjective judgment play a critical role in selecting the final design. This human input is essential for considering nuanced factors, such as contextual relevance, aesthetic preferences, and project-specific considerations, that the computational algorithms may not fully capture. Thus, generative design augments the designer's capabilities rather than replacing their pivotal role in shaping the ultimate design outcome.

3.3.3 Integration with Software Tools

Grasshopper, integrated with Rhinoceros, is a widely adopted algorithmic modeling tool in architecture, while Dynamo, part of Autodesk's Revit, is another option. The study initially contemplated between Dynamo and Revit versus Grasshopper and Rhinoceros. Dynamo's integration with Revit initially seemed appealing, given Revit's focus on building models. However, Grasshopper was chosen to explore broader design possibilities, particularly in geometric manipulation.

It is crucial to emphasize that while this study uses specific software, the underlying principles apply to other software.

Grasshopper and Rhino

The rise of Grasshopper in the generative design community, combined with expert input on current practices, drove the selection of **Grasshopper and Rhinoceros 7** as the study's primary software. This choice fosters flexibility, innovation, and expanded design exploration beyond conventional BIM-centric approaches.

Grasshopper uses graphical nodes instead of text commands, allowing architects to create parametric models through visual, code-free algorithms. This approach streamlines parametric design by connecting nodes within a definition, enabling the exploration of the entire solution space and performance evaluation for each solution. Visual programming enables a more accessible and efficient way of working with parametric design.

Grasshopper offers built-in node libraries, and users can expand its capabilities in three ways:

- Install Additional Libraries: Utilize the package manager to download and add nodes developed by other users, expanding the toolbox.
- Create Custom Nodes: Combine multiple nodes into clusters for repetitive tasks, streamlining design and enhancing reusability.
- Run External Scripts: Execute textual scripts, with Python being a prominent choice, to further extend Grasshopper's functionality.

Specialized plugins like Honeybee or Kangaroo can be integrated into Grasshopper for specific analyses. Honeybee and LadyBug facilitate environmental simulations (e.g., energy efficiency, daylighting), while Kangaroo enables dynamic simulations (e.g., structural behavior, physics-based modeling). These plugins enhance the study's comprehensiveness and provide valuable insights into generative design from various perspectives.

Wallacei X

Wallacei is an evolutionary multi-objective optimization and analytics engine that seamlessly integrates with Rhino and Grasshopper, extending their capabilities for generative design. Wallacei X's principal evolutionary algorithm is the NSGA-II algorithm, while the clustering algorithm is the K-means approach. Wallacei efficiently explores the design space, seeking optimal or near-optimal solutions considering multiple objectives and constraints. (Makki et al., 2019)

Revit

Revit was chosen for its popularity as BIM software in the AEC industry and strong user support. This decision was driven by its seamless compatibility with Grasshopper via RhinoInside.

RhinoInside

By combining the strengths of Revit's BIM capabilities with Grasshopper's flexibility and advanced modeling features, designers can take advantage of a powerful and well-rounded toolset for conceptual design exploration and development. This integration enables smooth data exchange between the two platforms, facilitating a more efficient and collaborative generative design process.

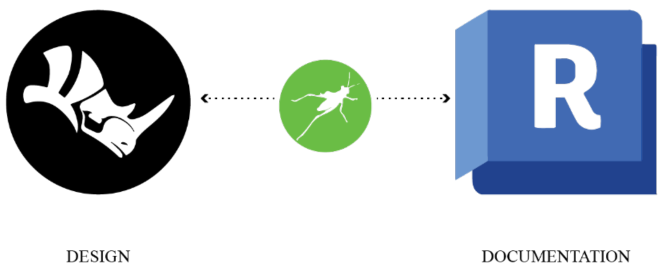

Figure 25: Design to Documentation Workflow: Rhino to Revit.

3.4 Generative Design Integrated Framework

Combining the workflow, components, and software tools produces a unified and methodical approach to generative design. The workflow describes the steps that must be taken to progress from the initial design objectives to the final evaluation of design choices. Components are essential in this workflow because they represent the building pieces that shape the design process as a whole. Software tools provide the essential platforms for properly performing these components. This integrated framework serves as the generative design process's backbone.

1. **Problem Formulation**

Computational Model with Variables, Constraints, and Objectives: The initial groundwork for the generative design process is laid. This stage involves identifying the project's objectives, constraints, and parameters to guide the subsequent computational exploration. Parameters are the adjustable variables that will be manipulated during the generative design process. Design goals and constraints are defined, ranging from functional requirements to aesthetic preferences.

2. **Design space exploration**

Selection of Generative Algorithms: The selection of generative algorithms is critical as each algorithm has a unique behavior adapted to various design issues.

Generating Design Solutions: With given parameters and variables, the generative algorithm begins the development of design alternatives. The method iteratively generates solutions by altering variables and gradually refining designs to line with preset objectives.

3. **Evaluation and refinement**

Design Evaluation: The designs created are evaluated against performance criteria. Generated designs are ranked based on their fitness against evaluation criteria using multi-objective optimization. Pareto front analysis identifies designs that optimally balance objectives, which serve as benchmarks against which other alternatives can be measured.

Iterative Enhancement and Refinement: Iterations are essential to the generative design process. Each iteration kickstarts an evolutionary path toward even better design solutions.

Visualization and Analysis: Design variations are clarified using visualization tools, which aids comprehension and analysis of the data.

Decision-Making: Data collected serves for informed decision-making after being presented with various design possibilities.

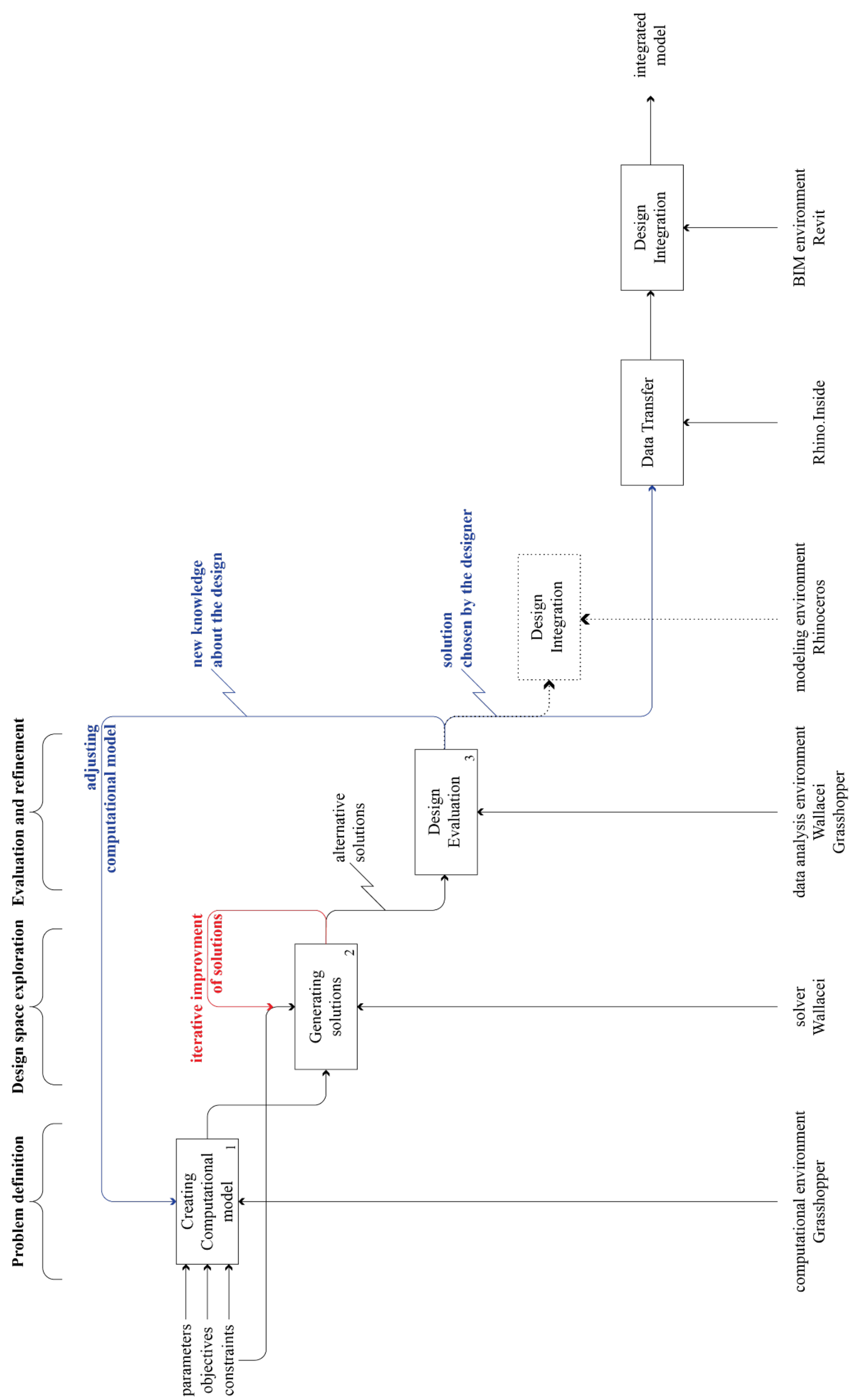

Figure 26: IDEF0 diagram of Generative Process, based on Gradišar et al. (2022).

4 CASE STUDY

This integrated generative design framework is put into practical use through an illustrative case study replicating a simplified architectural context.

In architectural terms, the context comprises three key elements: the site, representing the physical location; restrictions encompassing regulations and limitations; and requirements, encompassing functional and design criteria. Architects can creatively navigate these confines within this architectural scenario, employing parameters as guiding principles and objectives as goals to craft innovative designs. Here, the site's physical characteristics and regulatory constraints define a boundary for architects to exercise creativity. This case study serves as a simplified demonstration.

Standardized buildings have predetermined design variables and constraints that dictate the building's general shape, size, and layout. These attributes make them ideal for parametric modeling and generative design. These variables offer users control over various building design elements and can be adjusted to achieve a broad spectrum of architectural variations.

The workflow, encompassing the selection of input parameters, specification of design objectives, formulation of algorithmic logic, and evaluation of design options, is systematically executed using the chosen software tools. This configuration is tailored to the parameters, objectives, and constraints outlined for the case study, operating without specific real-world requirements, underscoring the framework's adaptability and flexibility in accommodating diverse design scenarios.

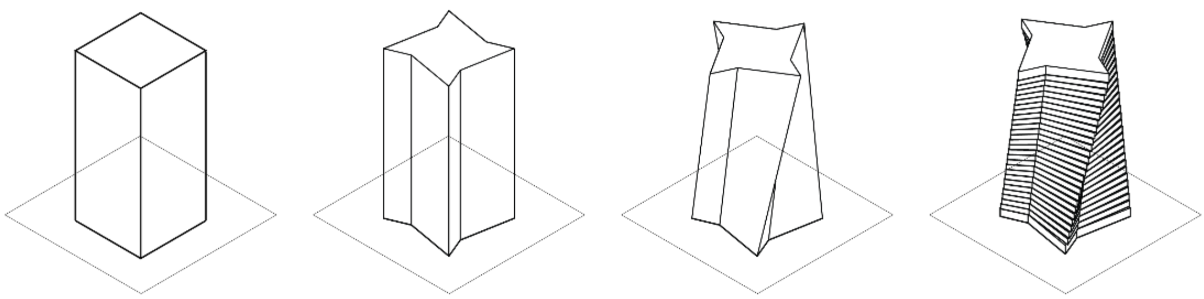

Figure 27: Visual Representation of Case Study Workflow Steps.

4.1 Problem definition

4.1.1 Design objectives

This study's objectives were chosen to ensure ease of verification and evaluation, with many criteria suitable for a more straightforward analysis of the results.

Objectives are as follows:

Soil sealing
Indicator: Ground Floor Area – footprint
Objective: Minimize - the smaller the GF, the less invasive soil sealing
Aesthetics
Indicator: Roof Area
Objective: Minimize - preserve visually pleasing proportions, avoiding disproportionate aesthetics
Cost
Indicator: Façade Area
Objective: Minimize – The smaller the area, the lesser the construction and operational costs
Profit
Indicator: Total Floor Area
Objective: Maximize – the more area, the more sellable/rentable area, thus more profit
Energy usage
Indicator: Form Factor (surface to volume ratio)
Objective: Minimize – the smaller the Form Factor, the less energy usage

Table 1: Summary of Objectives Used in the Study.

4.1.2 Input Parameters and Constraints

The parameters and constraints were chosen to accommodate various design options while remaining simple for efficient time management and extensive analysis.

This study's parameters include geometric features and material and performance criteria. Geometric parameters encompass aspects including building footprint, height, and façade articulation. Spatial configurations include floor plans and basic room layouts, contributing to the design's functional quality. Materials were considered for cost-effectiveness and combined with performance criteria.

4.1.3 Computational model

In summary of the preceding chapters, the study's constraints, parameters, and objectives are as follows:

CONSTRAINTS
The bounding box of the building: Volume_X, Volume_Y, Volume_Z
PARAMETERS
Ground Floor Height
Typical Floor Height
Vertex Location for transformation of the L0
Vertex Movement for the transformation of the L0
Vertex Location for the transformation of the Ln
Vertex Movement for the transformation of the Ln
Vertex Rotation
OBJECTIVES
Soil sealing – Minimize Ground Floor Area
Aesthetics – Minimize Roof Area
Cost – Minimize Facade Area
Profit – Maximize Total Floor Area
Energy consumption – Minimize Form Factor

Table 2: Summary of Constraints, Parameters, and Objectives Used in the Study.

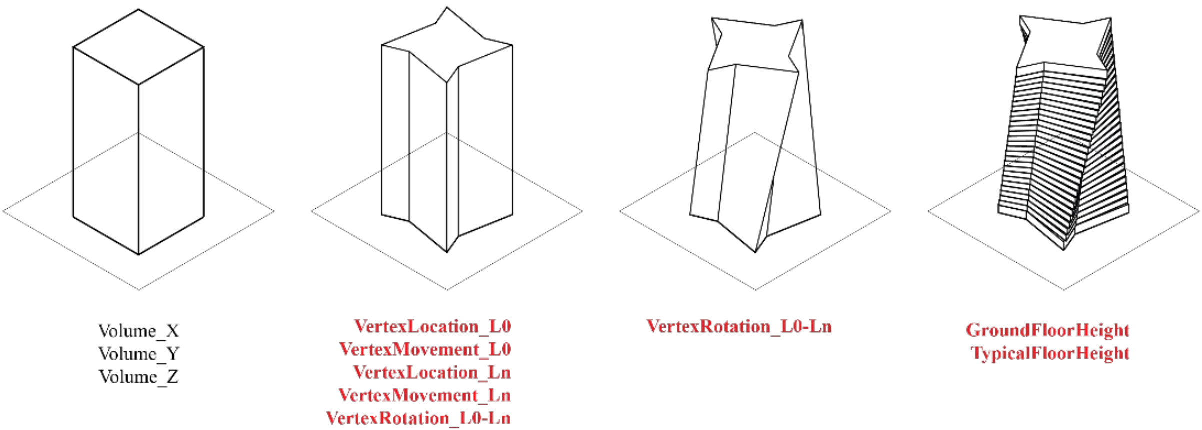

Figure 28: Visual Representation of Case Study Workflow with Constraints and Parameters.

A computational model is constructed using Grasshopper and serves as the design generator, producing many design options. The graphical interface of GH vividly depicts complicated data relationships, parameters, and design objectives, allowing designers to grasp and manage computational models. This visual clarity allows for dynamic design exploration and real-time modifications. IDEF0 simplifies and visually communicates complex GH definitions, improving comprehension and management.

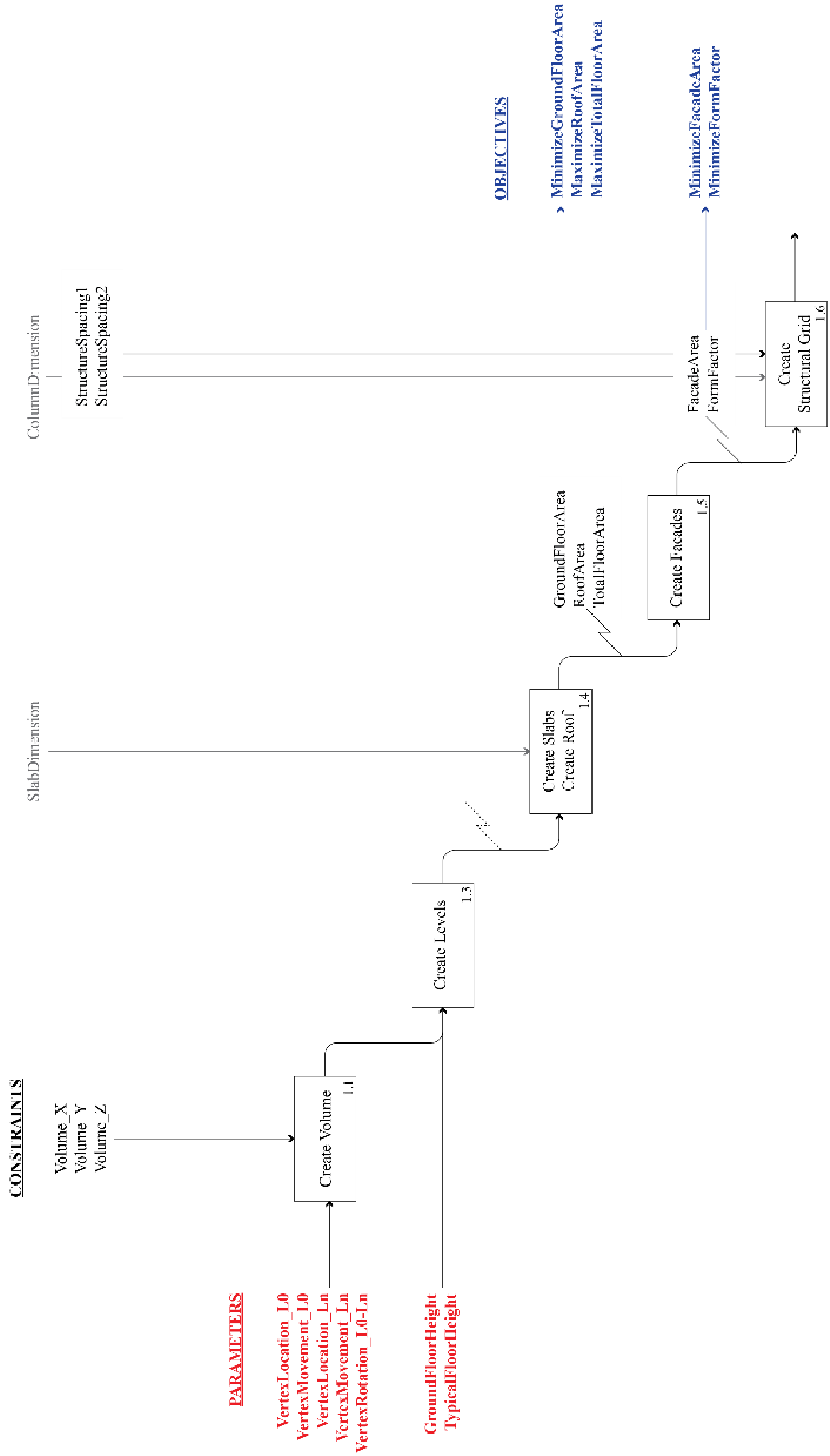

Figure 29: IDEF0 Diagram: Activity 1 - Creating Computational Model.

Create Volume

In the GH workflow for generating simple geometry, the process begins by defining the primary volume of the building. The volume can be easily adjusted in size and proportions using inputs such as sliders to suit the project requirements.

By limiting the number of sliders, the study can avoid unnecessary complexities and facilitate a clearer understanding of the design space.

CONSTRAINTS: *Volume X, Volume Y, Volume Z*

PARAMETERS: *Vertex Location L0, Vertex Location Ln, Vertex movement L0, Vertex Movement Ln, Vertex Rotation*

Create Levels

Level planes are introduced to establish distinct vertical divisions within the building. The floor-to-floor height is incorporated as a variable range to introduce greater diversity in the generated solutions, with specific differences applied between the ground floor and the typical floors.

PARAMETERS: *Ground Floor Height, Typical Floor Height*

Create Ground Floor, Typical Floors, Roof

After defining the Levels, the Floors can be extracted from the initial volume. In this process, it is recommended to avoid using a contour function but instead employ a Brep|Plane, ensuring a more accurate and controlled representation of the building's horizontal divisions, enabling precise adjustments, and avoiding potential inaccuracies that might arise from contour functions.

Create Facades

By intersecting the generated volume with the Level planes, the workflow produces lines representing the boundaries of all the floors. Subsequently, the facade design can be accomplished through a straightforward extrusion process guided by predefined floor-to-floor heights. The workflow efficiently generates a well-defined building envelope by using this simple extrusion technique.

Create Structural Grid

A structural grid is established in an 8x8m pattern. Due to the object's rotation, floors are initially overlapped to ensure comprehensive grid coverage. The core is generated by selecting the central grid module. While the object's rotation might alter proportions, this is not a primary focus of the study. Additionally, walls are established as basic placeholders, achieved through extrusions of the structural grid. Given the study's emphasis on more broad design exploration, these elements are represented in a simplified manner, serving as reference lines for potential future modeling in BIM software.

4.2 Design space exploration

In the design space exploration, the design parameters act as inputs and are considered genes in the optimization. Similarly, objectives act as inputs and are considered fitness objectives in the optimization. Outputs are the design alternatives and their properties generated by altering these inputs, while constraints ensure alignment with predefined criteria.

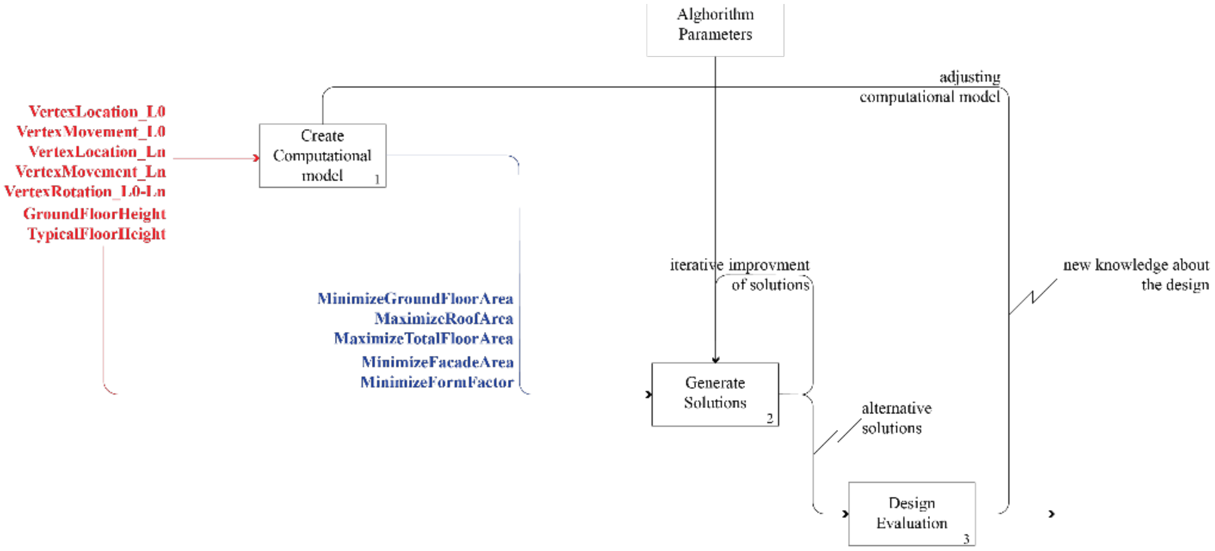

Figure 30 IDEF0: Diagram: Activity 2 - Design Space Exploration (Parameters and Objectives as Inputs, Algorithm Parameters as Constraints).

The primary focus now shifts to generating and iteratively refining solutions. The computational model evolves alongside the design process, incorporating revised parameters, constraints, and objectives, thus promoting dynamic learning, advancing awareness of the design space, and fostering novel approaches.

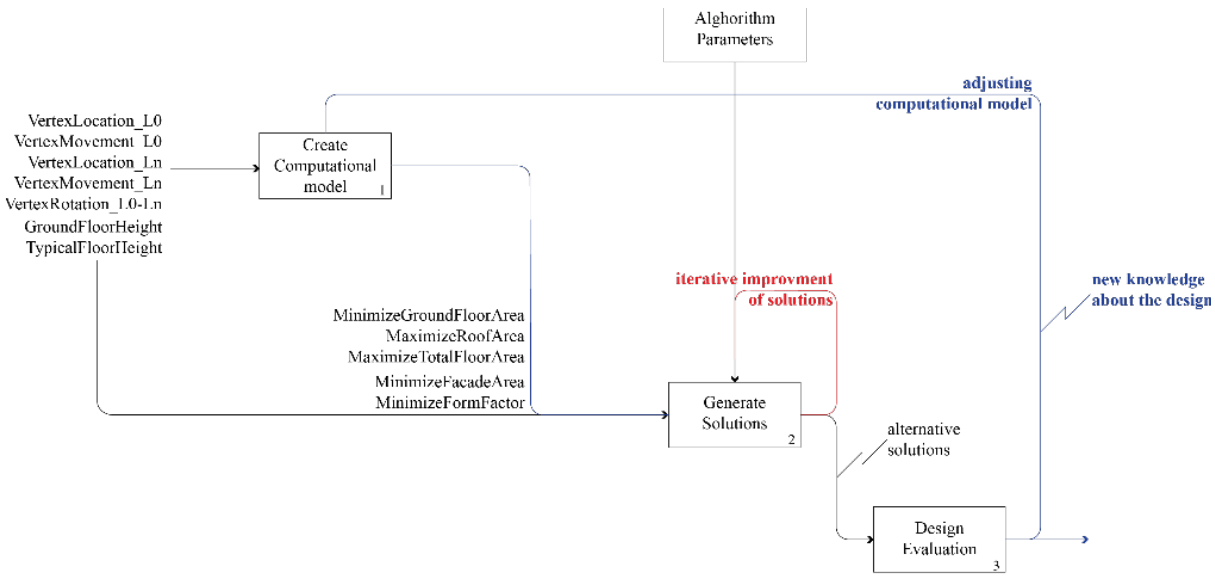

Figure 31: IDEF0 Diagram: Activity 2 - Design Space Exploration (Iterative Generative Design).

The continuous adaptation and refinement of the model epitomize generative design, aiming to explore diverse possibilities and progressively enhance design outcomes through ongoing knowledge generation.

Before employing Wallacei to generate solutions, input values should be defined.

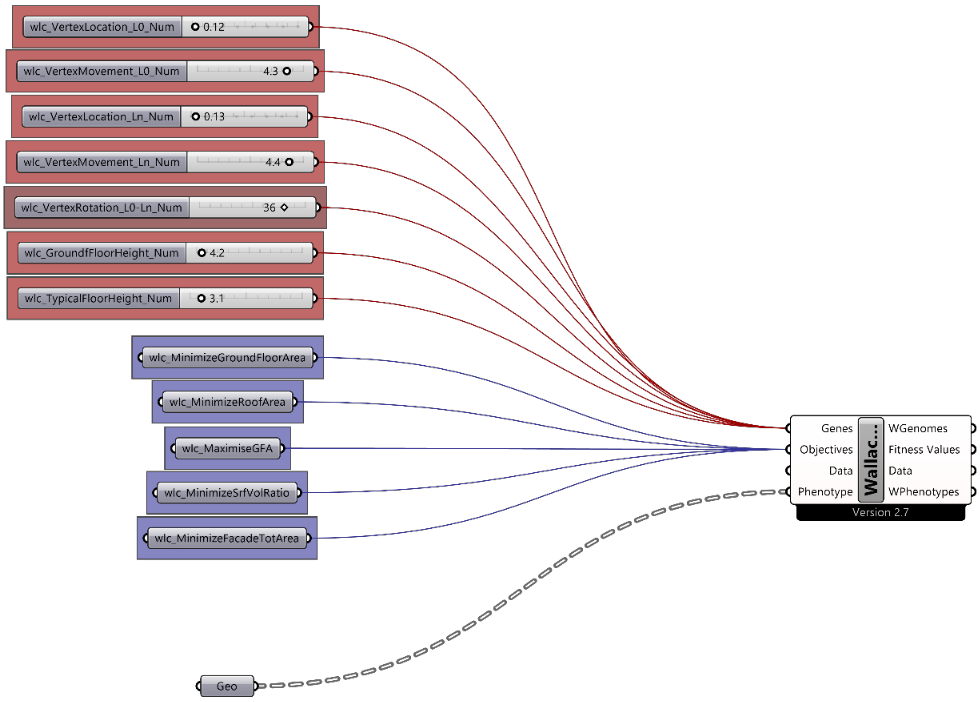

Figure 32: Wallacei X Component: Inputs.

1. **Genes** are made up of sliders, whereas genepools could be used for more random exploration.

In this case, genes are represented by previously chosen parameters and are defined as sliders that include each gene's range and potential values. Choosing the proper range impacts the design solutions regarding feasibility, objective relevance, iteration speed, and the number of possible combinations.

PARAMETERS	***Boundaries***
Ground Floor Height	*4.0-8.0*
Typical Floor Height	3.0-4.0
Vertex Location for transformation of the L0	*0.1-0.8*
Vertex Movement for the transformation of the L0	0.5-5.0
Vertex Location for the transformation of the Ln	*0.1-0.8*
Vertex Movement for the transformation of the Ln	0.5-5.0
Vertex Rotation	*0-45*

Table 3: Summary of Genes (Parameters) and its Boundaries Used in the Study.

2. **Fitness Objectives** are values with a 'number' component.

In the case of Wallacei, the algorithm is programmed to minimize any objective related to it. Similarly, to transform it from a minimization objective to a maximization objective, the inverse function - 1/f(x) is used.

OBJECTIVES
Soil sealing – Minimize Ground Floor Area
Aesthetics – Minimize Roof Area
Cost – Minimize Facade Area
Profit – Maximize Total Floor Area
Energy consumption – Minimize Form Factor

Table 4: Summary of Fitness Objectives (Objectives) Used in the Study.

3. **Data** contains any data to be saved and used in every solution in the population (recommended to be numerical). In this case study, data was not used.
4. **Phenotypes** are data to be exported using the solver. Any data type is acceptable (Breps, Meshes, Numbers.) This case contains all geometry defined and relevant to the study (Level surfaces, Facade Breps, Structural Grid Cruves, Core Breps, and Wall Breps).

4.2.1 Algorithm

Algorithm parameters have been set by default within Wallacei X, with the default values recommended for NSGA-II explorations:

- **Crossover Probability**: the proportion of solutions from one generation that will reproduce in the following generation;
- **Mutation Probability**: the proportion of mutations that occur during a generation;
- **Crossover and Mutation Distribution Index:** A higher index value improves the possibility of having children close to the parent solutions; a lower value allows for selecting children distant from the parent solutions.

It is up to the designer to choose the Generation Size (the number of individuals in each generation) and Generation Count (the number of generations in the simulation) for each specific simulation.

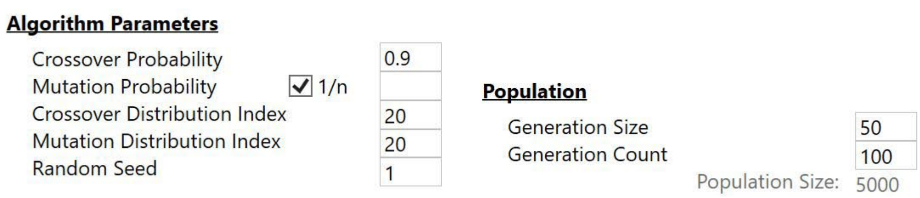

Figure 33: Algorithm and Population Parameters Used in the study.

Simulation Parameters are then summarized and show us valuable data. Considering the search space, simulation typically takes some time to complete, so lowering the number of parameters to do rougher but faster simulations could be used to attain faster results.

This study created a complex parametric model with seven parameters, each having a specific number of variable values. Collectively, these parameters resulted in a total of 332 parameter variables. This extensive set of variables contributed to the vast search space, which consisted of 2.2e11 (220 billion, or precisely 221 292 519 976) possible combinations.

Simulation Parameters	
No. of Genes (Sliders)	7
No. of Values (Slider Values)	332
No. of Fitness Objectives	5
Size of Search Space	2.2e11

Figure 34: Summary of Simulation Parameters Used in the Study.

If the challenge included a lot of design parameters and objectives, the ideal way would be to split it down into smaller groups and address them one at a time

4.2.2 Generating Solutions

The generator produces various design alternatives by running the simulation, each with a fitness score. It is recommended to run the generator multiple times to review and evaluate the outcomes thoroughly and to refine the model if needed. The process is iterative, meaning we gain valuable insights into the computational model's behavior by analyzing the generated solutions.

The iterative process involved fine-tuning the computational model by determining the optimal number of parameters and variables within those parameters and addressing constraints and correlations between them. The aim was to create a functional and logical model aligned with the project's objectives and constraints.

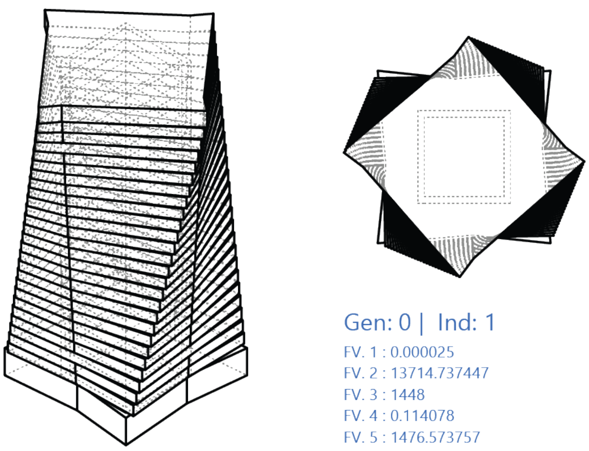

Figure 35: Zoomed-In Solution with Extracted Data.

Figure 36: Visualization of Generated Solutions (Top View).

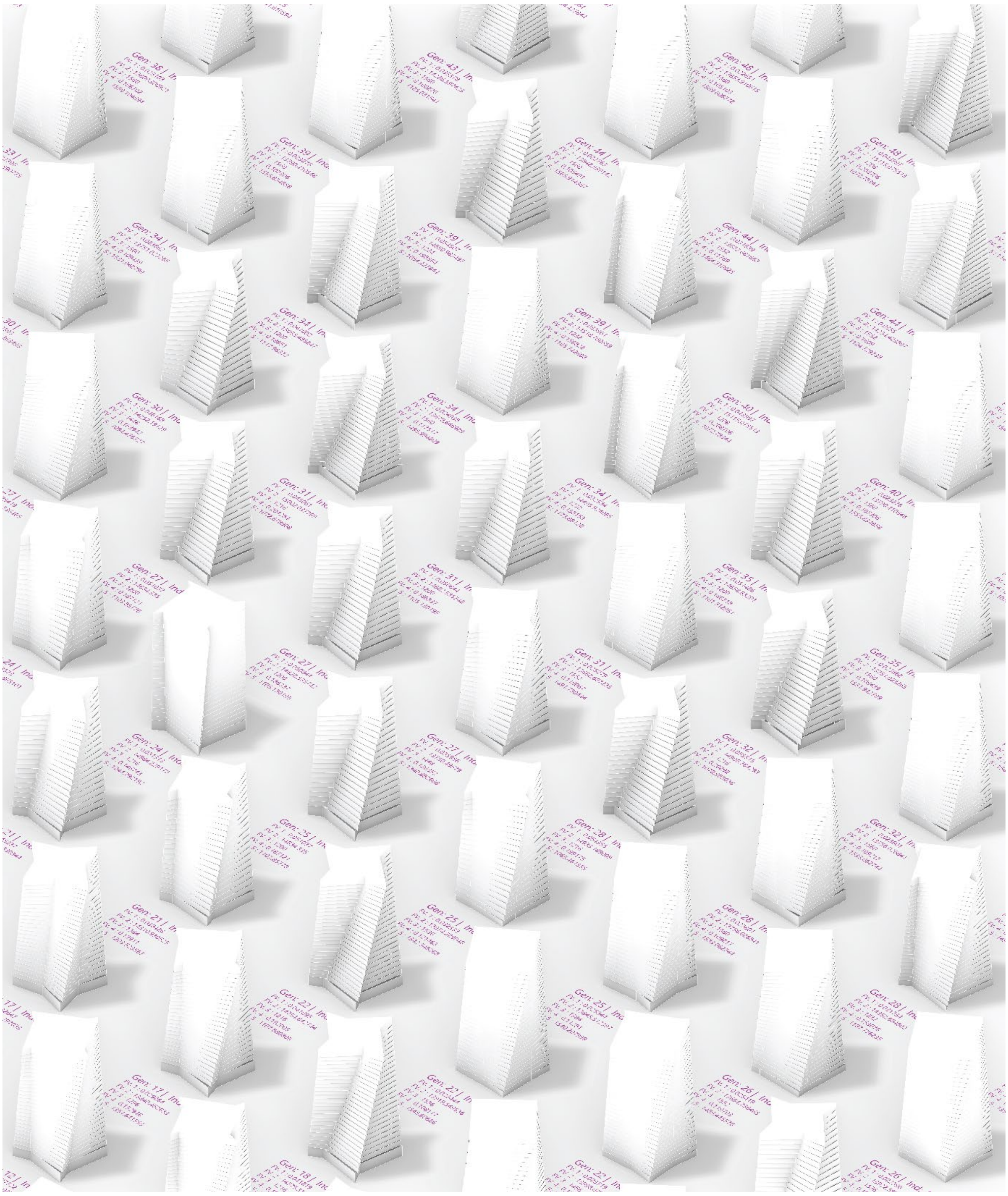

Figure 37: Visualization of Generated Solutions (3D View).

4.3 Evaluation and refinement

The generated design solutions are analyzed through two perspectives: direct evaluation within Wallacei X and enhanced insights provided by Wallacei Analytics. While Wallacei X focuses on individual solution assessment using predefined criteria, Wallacei Analytics offers a broader view, facilitating the exploration of relationships between objectives and constraints across the entire solution set.

Adjustments and enhancements to the model improved its performance until it arrived at an optimal solution for the design problem. This iterative approach allows fine-tuning of the model, addressing problems, and optimizing the design solutions, ultimately achieving a more robust and effective design process.

Finally, the simulation involved 50 generations, each generating ten solutions, thus 500 solutions in total. Among these, 128 solutions were identified as Pareto-optimal solutions, allowing trade-offs between competing design objectives to be identified.

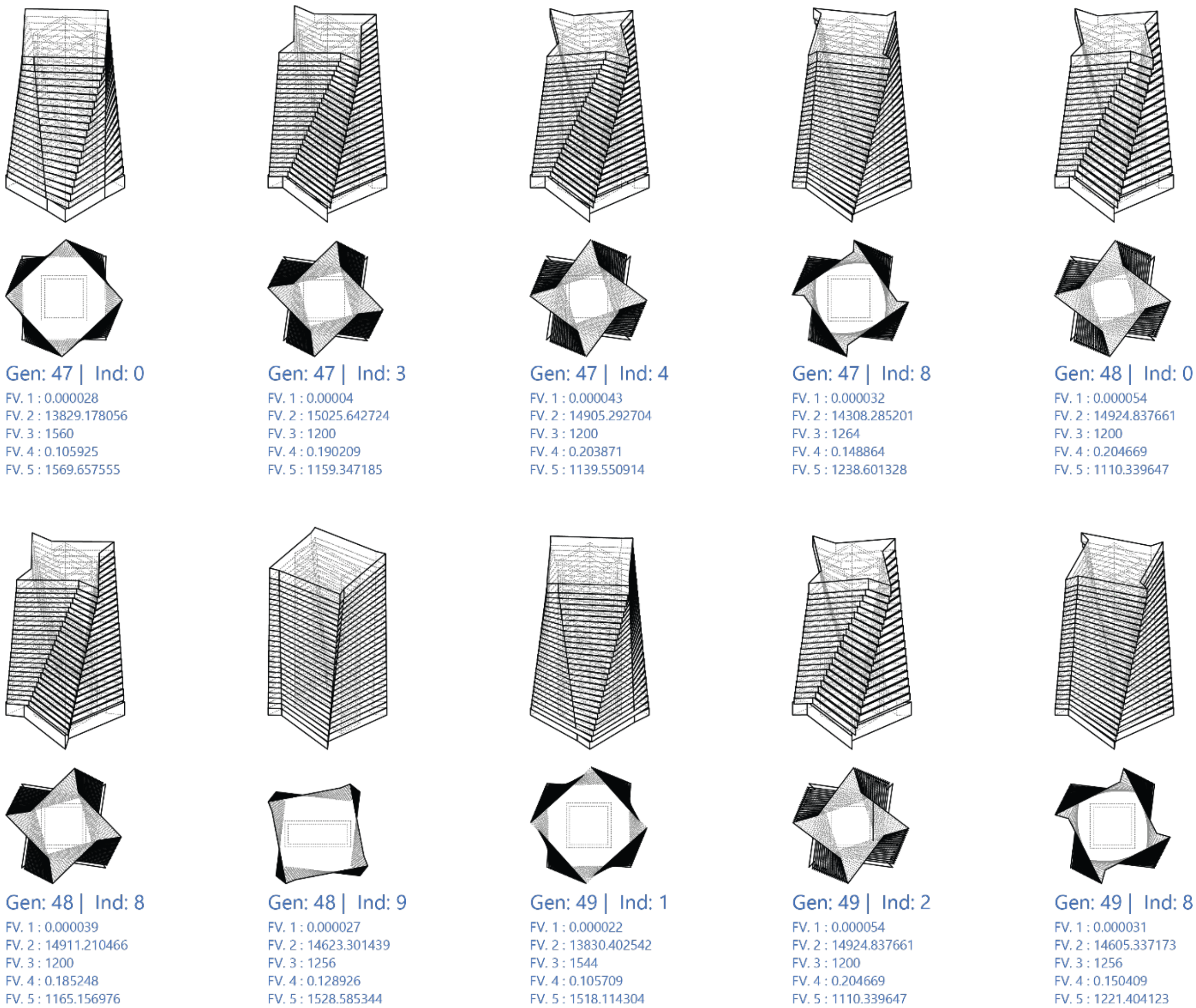

Figure 38: Visualization of 10 Pareto-optimal Design Solutions from the Latest Generations.

4.3.1 Design analysis

Objective space and Pareto Front

A deliberate decision was made to limit the number of objectives to five to improve the analysis and grasp the correlations between them more effectively. This option allows for a more understandable display in a 3D coordinate system and the addition of color and size of markers as an additional dimension in the Pareto front representation. Given the difficulty of seeing more than three elements in a typical XYZ system, color and size give a unique solution to retaining comprehensibility while transmitting critical data.

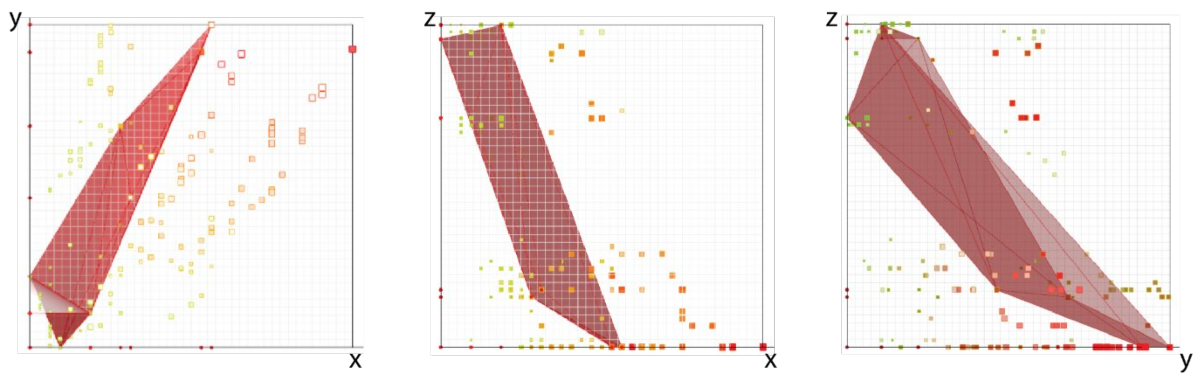

Figure 39: Visualization of Objective Space and Pareto Front of the Last Generation.

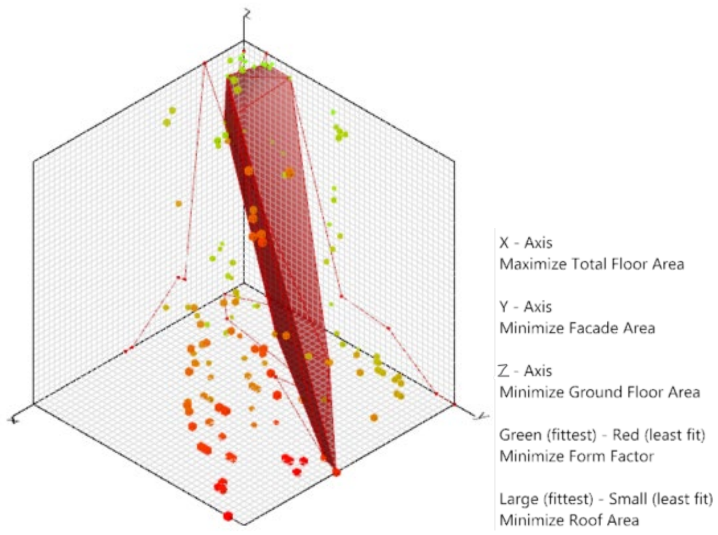

Figure 40: 3D Pareto Front of the Last Generation.

Furthermore, when incorporating more objectives becomes necessary, a strategic strategy entails breaking the study into many parts. Each phase would concentrate on a subset of carefully chosen objectives that are known to influence one another significantly. This staged method retains the lucidity of the analysis and provides a greater knowledge of the subtle interactions between factors, improving the study's overall efficacy.

Parallel Coordinate Front

The relationship between the objectives is essentially a trade-off.

When optimizing overall floor size, the facade, ground floor, and roof area will likely grow to accommodate the bigger internal space. Minimizing the facade, ground floor, and roof space, on the other hand, would result in a reduction in overall floor area. Another influencing aspect is the form factor; a lower form factor often suggests a more compact building with less outer surface area relative to its inner volume. As a result, striking a balance between these parameters is critical for optimizing the design for both functional interior space and economic resource consumption.

The addition of the cost factor deepens the relationship between these metrics. Minimizing the facade, ground floor, and roof areas may be prioritized when evaluating costs to save construction expenses. However, this could result in a reduction in the overall floor area. Balancing cost efficiency and usable space necessitates carefully evaluating how these characteristics interact. Because of the smaller external surface area, a lower form factor may contribute to lower material and construction costs.

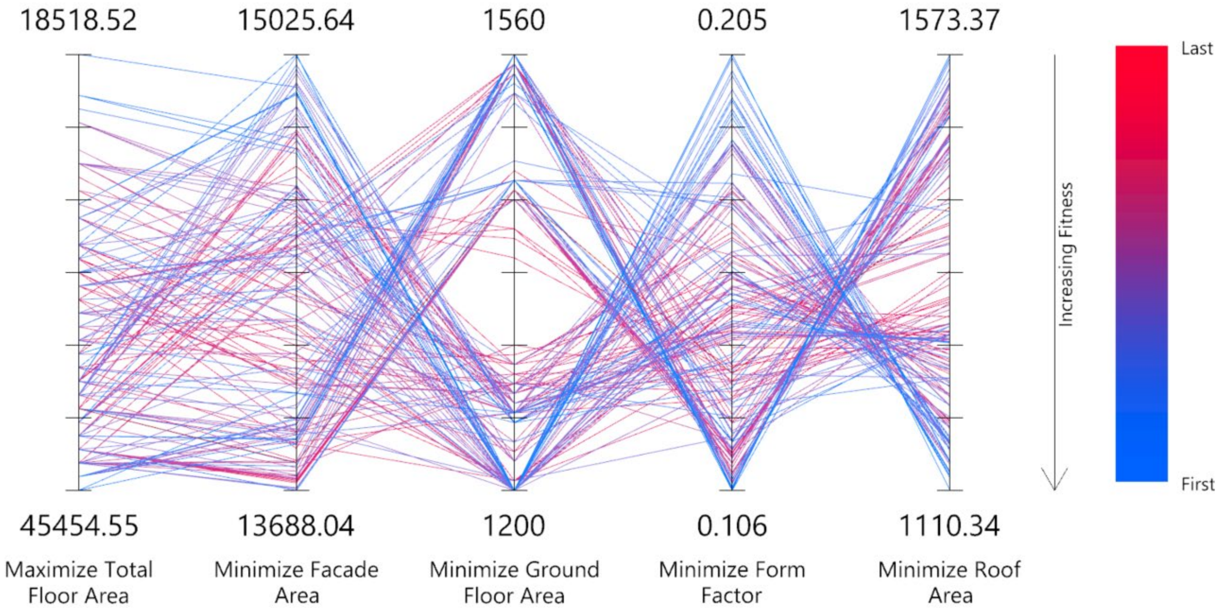

Figure 41: Parallel Coordinate Plot of Objective Correlations.

Without subjective preferences informing the search, the decision was made to utilize clustering as the following analytical approach.

Clustering

This study employed k-means clustering to group the Pareto solutions into distinct clusters to provide a more structured and interpretable representation of the solution space. As in this case, the Pareto solutions can be numerous and diverse, making it challenging to analyze each solution individually. By applying k-means clustering, the Pareto solutions were grouped into three distinct clusters.

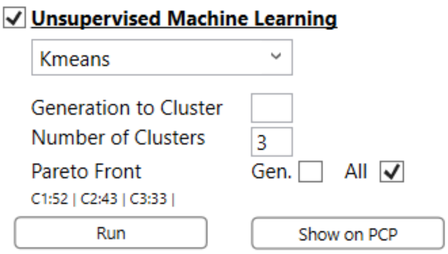

Figure 42: Clustering Settings Used in the Study.

Clusters are categorized into three groups: the first compromises 51 solutions, the second 43, and the third 33 solutions. Central solutions were identified within each cluster: C1-G49i8, C2-0i1, and C3-G30i8. These central solutions serve as representative points, encapsulating the distinctive features and attributes of the solutions within their respective clusters. This clustering process effectively narrowed the initial pool of 128 solutions into three representative solutions.

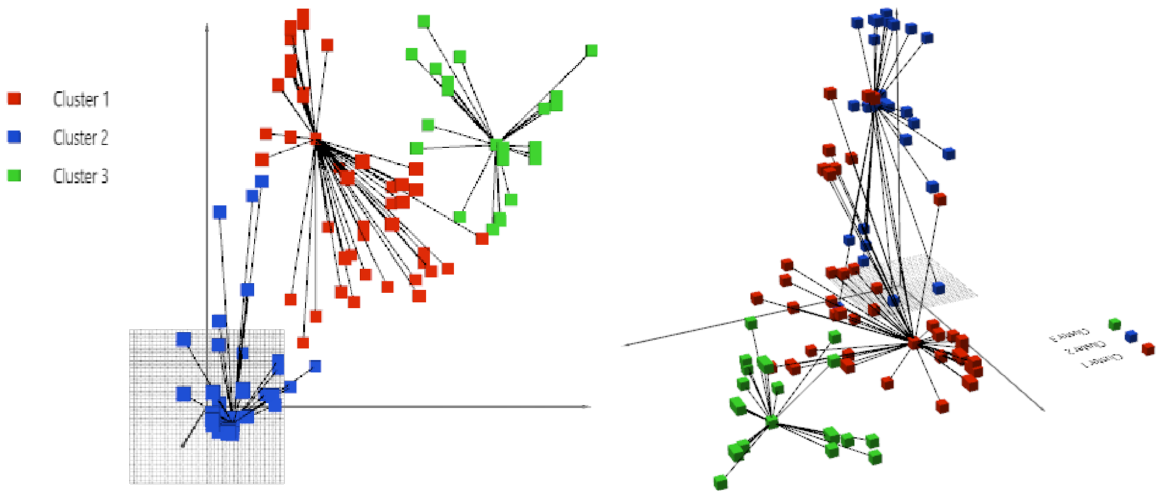

Figure 43: Clustering of Pareto Front Solutions.

Because k-means clustering uses random cluster center initialization, the cluster outputs differ slightly between runs. Nonetheless, it is preferred due to its quickness and effectiveness in categorizing based on performance similarities. Despite its initial uncertainty, k-means is frequently employed for rapid and exploratory research, providing valuable insights into data trends.

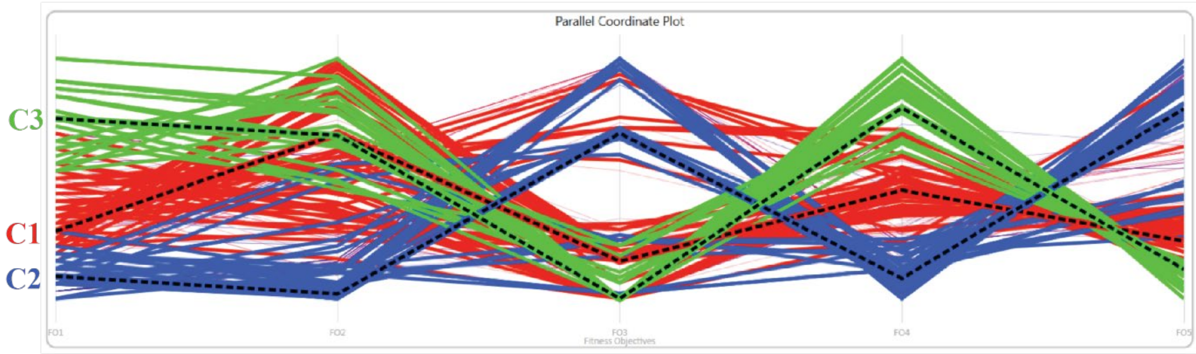

Figure 44: Clustering of Pareto Front Solutions Visualized in Parallel Coordinate Plot with Central Solutions Highlighted.

C1: C1 strives to balance interior space utilization and aesthetic considerations. It focuses a modest emphasis on optimizing the overall floor area while also considering variables such as the visual appeal of the facade, the efficiency of the ground level, and the building's form. While these issues are considered, decreasing the roof area is given a lower priority.

C2: C2 focuses on the efficiency of the ground floor and roof design. It seeks to improve efficiency in these areas and may choose a design that effectively uses the ground level while keeping the roof design simple. Furthermore, it has a less compact form when compared to other clusters.

C3: C3 focuses heavily on optimizing interior space within the building. It prioritizes roomy interiors while simultaneously considering the facade's attractiveness. It also aims to develop a more compact and efficient building shape. The reduction of roof area is not a significant concern for this cluster.

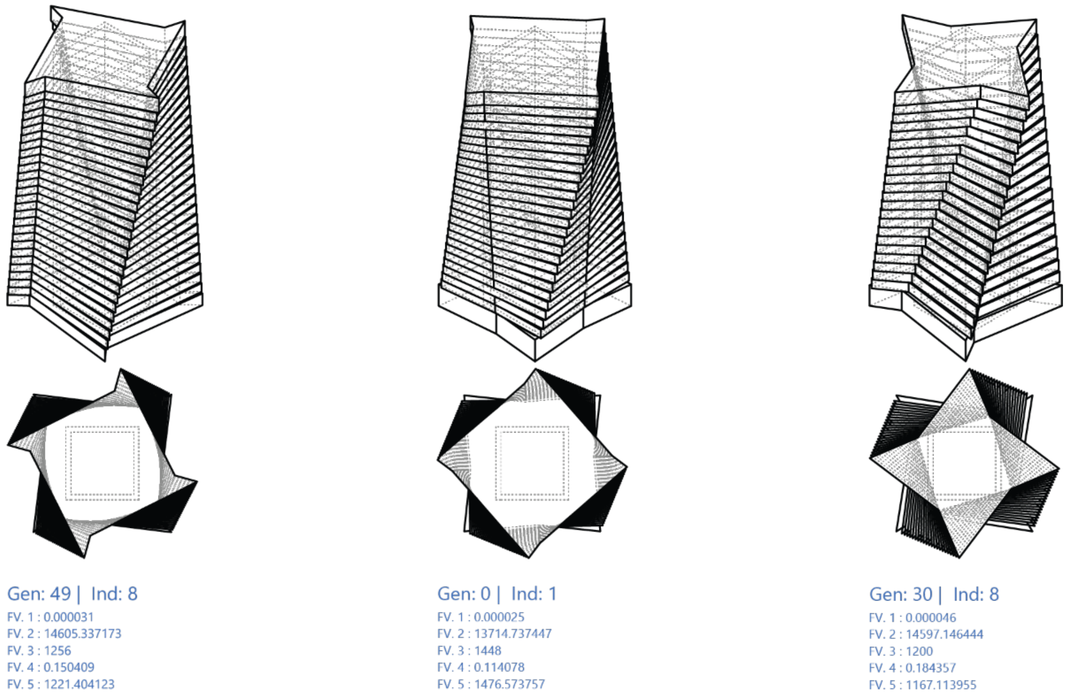

Figure 45: Central Solutions Within Each Cluster: C1-G49i8, C2-0i1, and C3-G30i8.

4.3.2 Selecting Optimal Design Solutions

When the three representative solutions are examined, it is evident that C1 has a significant advantage regarding balanced results. This balance is visible on the parallel coordinate diagram, demonstrating that numerous design considerations were carefully considered. While C1 appears to be a well-rounded option, it is crucial to note that the best cluster selection depends on the project's objectives and priorities. Each cluster has unique characteristics, and the choice should be based on the project's specific requirements and goals.

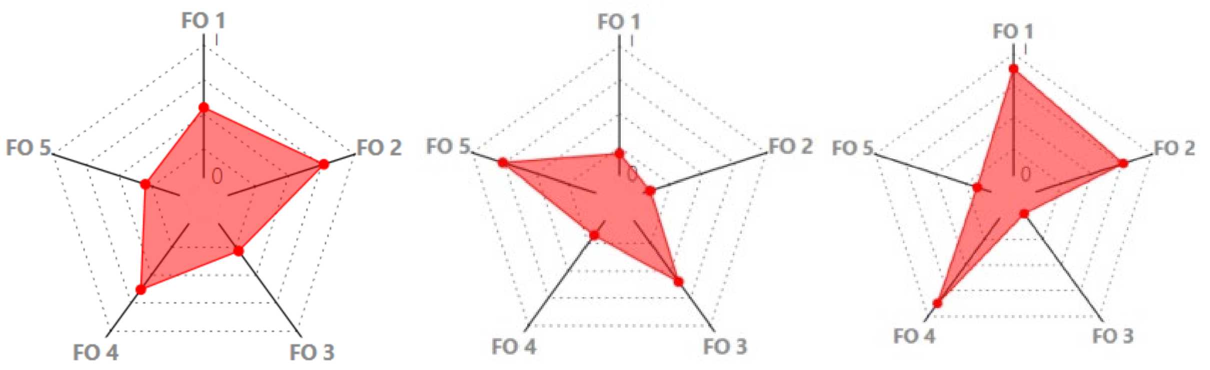

Figure 46: Comparison of Diamond Fitness Charts for Central Solutions.

The selected solution in the Diamond Fitness Chart analysis demonstrates a balanced objectives distribution. None of the objectives fall into the extreme ranks; instead, they are continuously near the middle of the set of 500 solutions. This balanced distribution implies that the chosen solutions take a well-rounded approach to design priorities, with no single goal being overly prioritized or ignored. This balance in objective rankings implies that the chosen solutions thoroughly study design possibilities, contributing to a more holistic grasp of the design space.

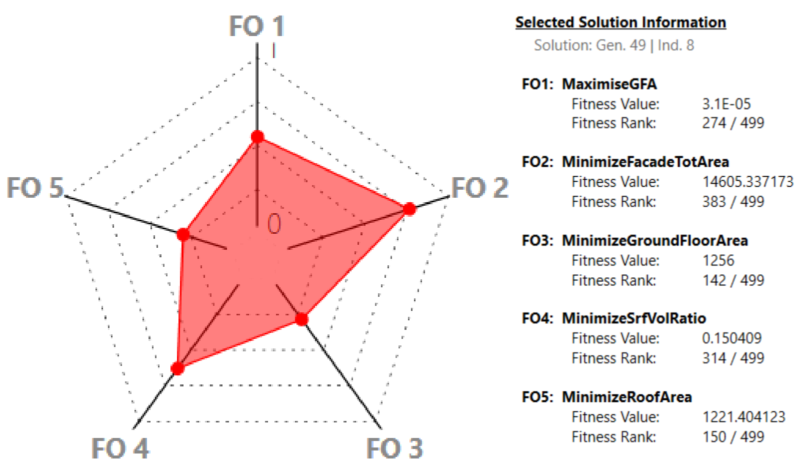

Figure 47: Selected Solution G49i8 with Objective Values.

While examining objectives alone can provide valuable insights into design priorities, it may lack the depth obtained by considering the underlying characteristics. Incorporating objectives and parameters into the analysis provides a more comprehensive view, allowing for more informed design decisions and a deeper study of trade-offs. The limits imposed by the current use of the Wallacei plugin are principally responsible for the limitation inhibiting the simultaneous investigation of parameters alongside the objectives of this study. However, it is worth mentioning that this constraint may be overcome by experimenting with different strategies or tools.

4.4 Design Integration

Transferring data to other BIM tools like Revit is common in the transition from concept design in Rhinoceros to later design stages and construction documentation. This transfer optimizes the design and documentation process by leveraging the capabilities of each software, seamlessly integrating parametric modeling from Rhinoceros with Revit's BIM functionalities.

While data transfer is typical, it is vital to know that there may be issues with geometry compatibility, file formats, and data loss. Using plugins for interoperability, such as Rhino.Inside or IFC (Industry Foundation Classes) file formats can help alleviate these issues and promote a more seamless transition between the two software systems.

4.4.1 Rhino.Inside

The workflow for transferring Grasshopper geometry to Revit through the RhinoInside plugin simplifies the design-to-documentation process, bridging Grasshopper's parametric modeling and Revit's BIM environment. A foundational understanding of Revit elements is critical for this integration. It streamlines the initial exploration stage using basic elements like points and curves, enabling faster concept iteration and exploration while aligning with Revit's BIM capabilities.

Based on this study, simplified mapping of Rhino geometry elements to corresponding Revit elements includes linking levels to points, floors and roofs to boundary curves, facades to base curves, and walls, beams, and columns to curves.

This mapping is a simplified overview, and the process requires additional steps, such as assigning Levels, Family Types, and other element-specific inputs to accurately transfer and adapt geometry while maintaining design accuracy and adherence to BIM standards. It should be noted that this is not the only approach for achieving such mapping; in actuality, numerous methodologies are available.

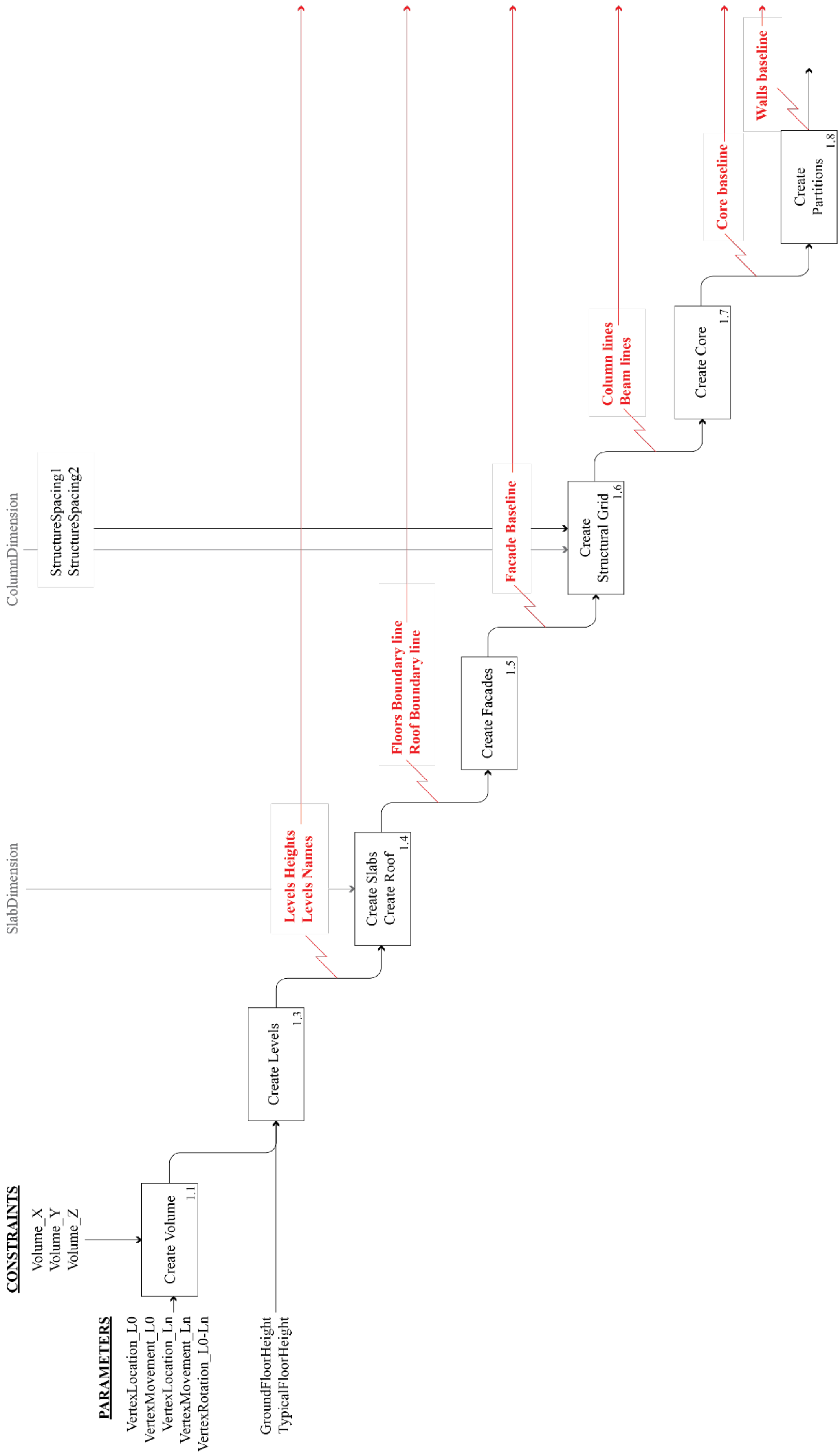

Figure 48: IDEF0 Diagram of Action 1: Outputs for Data Transfer.

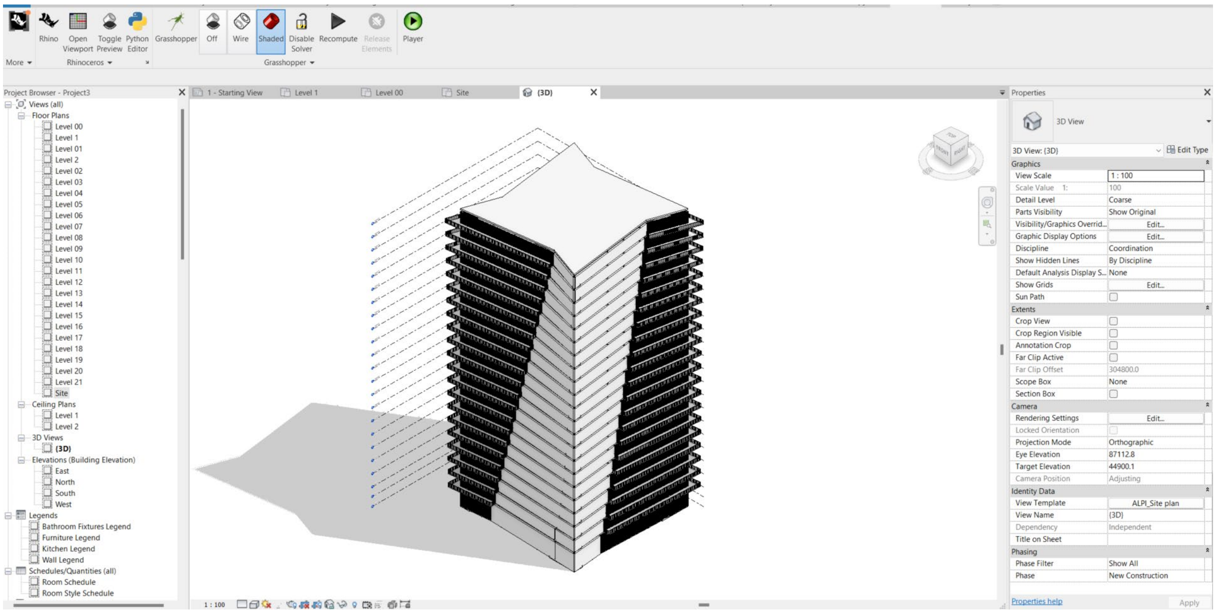

Figure 49: Study Model Preview in Revit.

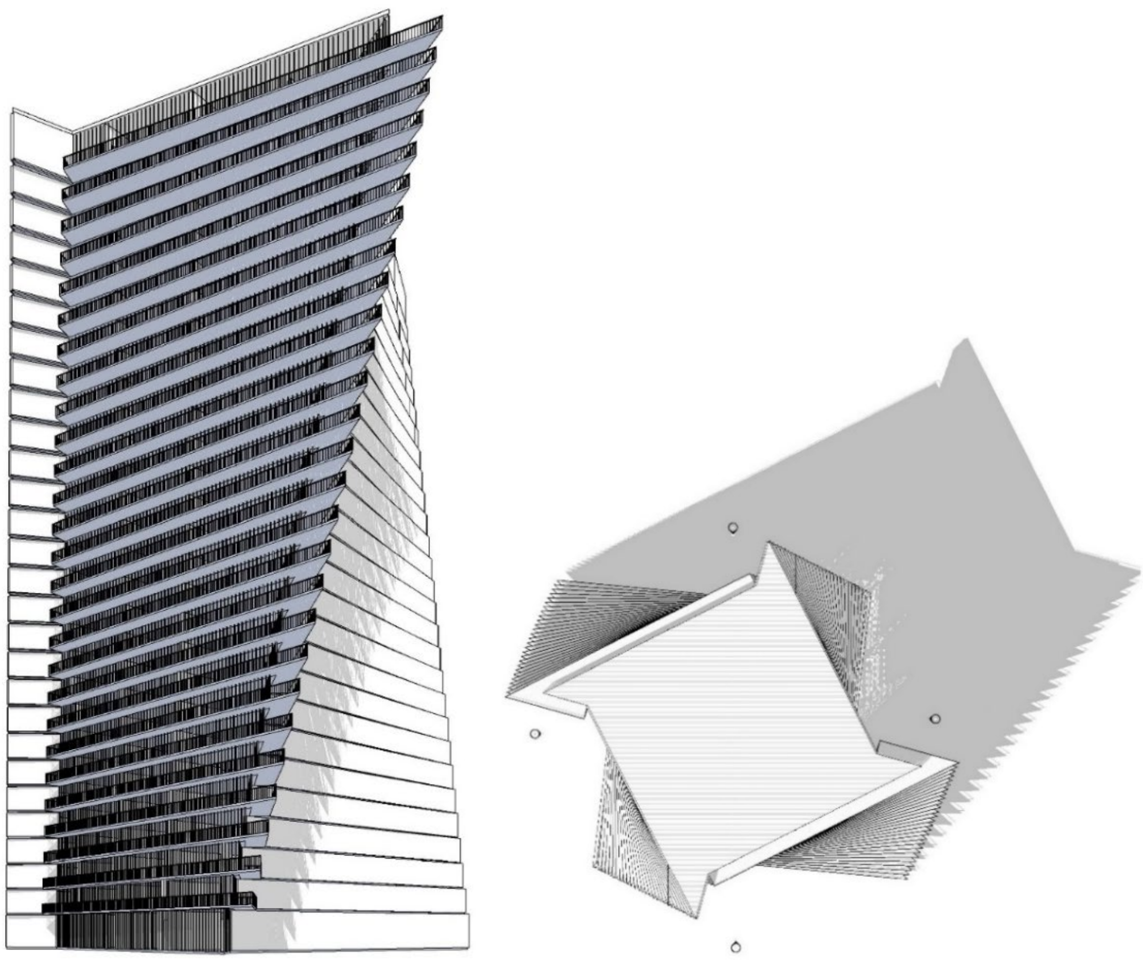

Figure 50: Perspective and Top View of the Study Model.

4.5 Expanding Possibilities and Iterative Evolution

With this test running without problems, it is possible to introduce more design variables and more objectives to the parametric model, allowing for greater complexity and a broader range of design possibilities.

A logical progression would involve incorporating more factors other than geometric ones into the analysis, such as material choices, spatial arrangements, energy efficiency, and environmental considerations, which could significantly influence the design's sustainability and comfort. By evaluating the effects of various parameter combinations on energy usage, indoor comfort, and environmental impact, designers can make more informed decisions, prioritizing both cost-effectiveness and ecological soundness. This expanded research would offer a comprehensive view of the design's performance, enabling a more holistic approach to optimization.

The iterative nature of the generative design process ensures that the model continues to evolve, providing designers with more comprehensive and diverse design solutions. This iterative expansion and refinement generate innovative and optimized architectural concepts, fostering creativity and exploration in the early stages of the design process.

5 RESULTS AND DISCUSSION

5.1 Comparison with Traditional Design Approach

This visual representation highlights the fundamental differences in the design process, where GD leverages automation and iterative exploration to enhance efficiency and creativity:

TRADITIONAL DESIGN APPROACH	***GENERATIVE DESIGN APPROACH***
Conceptualization & Ideas	*Input Parameters & Constraints*
Sketches & Manual Planning	*Algorithmic Logic & Computational Modeling*
Manual Iterative Refinement	*Iterative Exploration & Optimization*
Final Design	*Evaluation of Design Solutions*

Table 5: Traditional Design Approach vs. Generative Design Approach Comparison.

A more in-depth comparison between the Generative Design and Traditional Design approach is structured around previously identified problem areas:

1. **Design Exploration Efficiency:** Generative design significantly enhances exploration efficiency by rapidly generating many design solutions addressing various factors and constraints. This approach allows for a broader range of design options to be explored quickly, which is often impractical with traditional, time-consuming, one-at-a-time manual methods.
2. **Optimal Design Solution:** Generative design, guided by predefined criteria and optimization algorithms, is characterized by examining a larger set of design solutions that may be optimal or near-optimal. This methodical approach strives to find the best answers within defined limits. In contrast, traditional design relies on the designer's intuition and expertise, which can introduce human biases and potentially lead to suboptimal outcomes. The data-driven nature of generative design enhances the likelihood of discovering solutions that align more closely with project objectives and constraints.
3. **Collaboration and Iteration:** Generative design fosters collaboration and stakeholder engagement throughout the design process by enabling feedback on parameters, constraints, and objectives. Its iterative nature facilitates the rapid exploration of diverse design possibilities and the ability to refine parameters to achieve enhanced results. In contrast, traditional design methods may lead to linear workflows, constraining opportunities for collaboration and iteration.

5.2 Generative Design and Human Creativity

The intriguing subject of whether generative design can replace human function in design arises. The answer is now negative. The designer's skill is still critical in building computer models, analyzing data, and making final design decisions. The optimum road forward is the merger of human creativity and modern technology, where generative design augments designers' abilities, particularly in automating activities like data analysis and repetitive task analysis.

The study also acknowledges the intrinsic complexity of design processes, emphasizing the iterative nature required for excellent results. In this context, generative design allows architects to specify challenges, use generative algorithms to generate several design alternatives, and then choose refined solutions or continue design development. This repeating loop emphasizes the generative design's adaptive and dynamic character.

5.3 Generative Design Integration in Practice

This analysis of the architecture industry's obstacles to adopting and fully integrating generative design methodologies, which includes insights from interviews with industry professionals, offers light on the limitations that prevent generative design from being widely implemented in practice:

- **Deficits in Education**: Architectural education often lacks proper training in generative design tools and concepts.
- **Lack of Knowledge and Expertise**: There is a widespread lack of understanding of generative design complexities and practical applications.
- **Time-Intensive Process:** Creating effective generative design models can be time-consuming, conflicting with the fast-paced nature of architectural projects.
- **Emphasis on Expediency:** The industry's focus on quick solutions can hinder the development of optimal design solutions.
- **Resistance to Change:** Shifting to generative design requires a mental shift and is met with skepticism.

While generative design offers promise for architectural processes, collaborative efforts are needed to overcome these challenges. Bridging knowledge gaps, providing relevant education, and fostering an innovative culture are crucial steps toward realizing generative design's full potential in the architectural field.

5.4 SWOT Analysis

Generative design in architecture presents a multifaceted landscape of advantages, encompassing rapid design exploration, heightened creative potential, objective-driven design optimization, task automation, and enhanced synergy with Building Information Modeling (BIM) for early-stage, constructible solutions.

Nonetheless, this innovative approach grapples with several challenges rooted in the nascent stage of development within the field. These encompass limitations when accommodating diverse design requisites through standard models, underscoring the pressing need for more robust frameworks and tools capable of seamlessly integrating production constraints and encapsulating design knowledge. Additionally, there is the challenge of time-consuming computational model building, a necessary step that can potentially deter architects from harnessing generative design's full potential despite its significant time savings in other aspects of the design process. It is also crucial to acknowledge that the outcomes of generative design studies may significantly hinge upon the designer's expertise, potentially constraining the emergence of genuinely innovative solutions.

Furthermore, generative design introduces both opportunities and risks into architectural practice. Excessive reliance on generative design tools could stifle critical thinking and originality, emphasizing the importance of balanced utilization. The quality of generative design solutions remains intricately linked to the precision and comprehensiveness of input data, signifying room for refinement in data handling. While generative design offers substantial benefits across a spectrum of architectural projects, it is imperative to recognize its limitations as a foundation for informed decision-making. Misinterpreting generative design outputs can potentially lead to suboptimal design choices and implementation challenges, underscoring the significance of risk awareness in its application.

S	W
◦ Efficient design exploration ◦ Enhanced creativity ◦ Objective-based optimization ◦ Task automation ◦ Improved BIM integration	◦ Underdeveloped field ◦ Limited adaptability ◦ Time-consuming model building ◦ Designer-dependent outcomes ◦ Potential overreliance
◦ Balanced utilization ◦ Data handling enhancement ◦ Wide applicability ◦ Knowledge capture	◦ Overreliance risks ◦ Data quality concerns ◦ Misinterpretation risks ◦ Resistance to change
O	**T**

Table 6: SWOT Analysis.

5.5 Limitations and Future Research Directions

While the study illuminates the promising characteristics of generative design, certain limitations should be considered:

- **Complex Design Requirements:** As generative algorithms become more intricate, defining precise criteria and evaluating designs can become challenging.
- **Algorithmic Complexity and Input Quality:** Design quality relies on accurate computational models, requiring validation and verification.
- **Algorithm Constraints:** Relying on fixed algorithms may hinder innovation, especially in complex architectural projects.

On the other hand, exploring future research and development in the field, various attractive directions emerge that could further enhance the potential of this revolutionary technique, such as:

- **Machine Learning Integration:** Enhancing generative algorithms with machine learning can enable adaptability and continuous improvement.
- **Incorporating Real-World Constraints:** Considering practical constraints like construction methods and sustainability can enhance design viability.
- **Sustainability:** Harmonizing generative design with sustainability principles can lead to environmentally and socially beneficial solutions.

The study notes challenges in defining design needs, potential stagnation from predetermined algorithms, and limited application to complex projects as limits of generative design. However, these limits provide avenues for further research. Researchers could look at refining algorithms for various issues, integrating machine learning, considering real-world restrictions, and harmonizing generative design with sustainability principles. These directions promise to improve generative design capabilities as the discipline progresses.

6 CONCLUSION

Generative design has emerged as a transformative approach in architecture, addressing key aspects of design exploration efficiency, optimal design solutions, collaboration, and iteration. This study draws insights from extensive research, highlighting generative design's theoretical and practical foundations and its transformative potential within architecture.

The case study demonstrated the adaptability and applicability of generative design in the context of architectural concept design development through a straightforward yet demonstrative project. This study highlights the ability of generative design to accelerate the design workflow, optimize architectural conceptualization, and cultivate inventive ideas firmly grounded in practical considerations. Generative design successfully overcomes the limits associated with traditional approaches by generating various design alternatives. Utilizing data-driven criteria and optimization algorithms increases the likelihood of multiple optimal or nearly optimal solutions, thereby reducing the impact of human biases commonly observed in traditional design approaches. Moreover, the iterative structure promotes cooperation and enables the swift exploration of creative ideas, presenting a distinct break from the sequential workflows typically observed in traditional design methodologies.

While this study primarily focused on examining the problems of design exploration efficiency, optimal design solutions, collaboration, and iteration, it is essential to acknowledge that generative design faces various challenges in the field. These include deficits in education, a lack of expertise, the time-intensive nature of computational modeling, a bias towards expediency, and resistance to change.

In conclusion, generative design signifies a harmonious blend of automation and human ingenuity, fostering creativity and collaboration. Addressing challenges like machine learning and data consistency will amplify its impact, marking a significant stride toward the future of creative innovation in architecture. Bridging theoretical potential with practical implementation is vital for successful generative design integration into architectural practice. While challenges exist, they offer avenues for further research, such as refining algorithms, integrating machine learning, considering real-world constraints, and aligning generative design with sustainability principles. These directions promise to enhance generative design's capabilities as it evolves.

7 REFERENCE LIST

Barbieri, L., & Muzzupappa, M. (2022). Performance-Driven Engineering Design Approaches Based on Generative Design and Topology Optimization Tools: A Comparative Study. *Applied Sciences*. https://api.semanticscholar.org/CorpusID:246990492

Bentley, P. J., & Corne, D. W. (2002). An introduction to Creative Evolutionary Systems. In *Creative Evolutionary Systems* (pp. 1–75). Elsevier. https://doi.org/10.1016/b978-155860673-9/50035-5

Bohnacker, H., Groß, B., Laub, J., & Lazzeroni, C. (2019). *Generative Design - Visualize, Program, and Create with Processing*. Princeton Architectural Press.

BuHamdan, S., Alwisy, A., & Bouferguene, A. (2021). Generative systems in the architecture, engineering and construction industry: A systematic review and analysis. In *International Journal of Architectural Computing* (Vol. 19, Issue 3, pp. 226–249). SAGE Publications Inc. https://doi.org/10.1177/1478077120934126

Deb, K. (2001). *Multi-objective Optimization Using Evolutionary Algorithms*. John Wiley & Sons. http://books.google.de/books?id=OSTn4GSy2uQC

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A Fast and Elitist Multi-objective Genetic Algorithm: NSGA-II. In *IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION* (Vol. 6, Issue 2).

Feng Chang, Y., & Guan Shih, S. (2018). *Exploring Multi-Disciplinary Communication Based on Generative Modeling at the Early Architectural Design Stage*. https://doi.org/10.20944/preprints201806.0230.v1

Gradišar, L., Klinc, R., Turk, Ž., & Dolenc, M. (2022). Generative Design Methodology and Framework Exploiting Designer-Algorithm Synergies. *Buildings*, *12*(12). https://doi.org/10.3390/buildings12122194

Janssen, P., Frazer, J., & Ming-xi, T. (2002). Evolutionary Design Systems and Generative Processes. In *Applied Intelligence* (Vol. 16).

Jones, J. C. (1970). *The State of the Art in Design Methods*.

Kaushik, M., Mathur, B., & Mathur, M. B. (2014). *Comparative Study of K-Means and Hierarchical Clustering Techniques Object Oriented System View project Comparative Study of K-Means and Hierarchical Clustering Techniques*. https://www.researchgate.net/publication/293061584

Kazemi, M., Borjian, B., & Architecture, M. A. (2015). Algorithmic Approach Functions in Digital Architecture and its Effect on Architectural Design Process. *European Online Journal of Natural and Social Sciences*. www.european-science.com

König, R., & Schneider, S. (2020). *Evolutionary Design Methods :: EDM Open*. Bauhaus-Universität Weimar, Chairs of Computational Architecture and Computer Science in Architecture. https://otp.uni-weimar.de/courses/evolutionary-design-methods-edm-open-2/

Krish, S. (2011). A practical generative design method. *CAD Computer Aided Design*, *43*(1), 88–100. https://doi.org/10.1016/j.cad.2010.09.009

Li, H., & Lachmayer, R. (2018). Generative Design Approach for Modeling Creative Designs. *IOP Conference Series: Materials Science and Engineering*, *408*(1). https://doi.org/10.1088/1757-899X/408/1/012035

Ma, W., Wang, X., Wang, J., Xiang, X., & Sun, J. (2021). Generative design in building information modelling (Bim): Approaches and requirements. In *Sensors* (Vol. 21, Issue 16). MDPI AG. https://doi.org/10.3390/s21165439

Makki, M., Showkatbakhsh, M., & Song, Y. (2019). *Wallacei Primer 2.0*. https://www.wallacei.com/.

Mukkavaara, J., & Sandberg, M. (2020). Architectural design exploration using generative design: Framework development and case study of a residential block. *Buildings*, *10*(11), 1–17. https://doi.org/10.3390/buildings10110201

Nagy, D., & Villaggi, L. (2020). Generative Design for Architectural Space Planning. In *Autodesk University*. https://www.autodesk.com/autodesk-university/class/Generative-Design-Architectural-Space-Planning-Case-Autodesk-University-2017-Layout-2017

Pibal, S. S., Khoss, K., & Kovacic, I. (2022). Framework of an algorithm-aided BIM approach for modular residential building information models. *International Journal of Architectural Computing*, *20*(4), 777–800. https://doi.org/10.1177/14780771221138320

Ramanauskas, R. (2020). Thoughts on the future of Generative Design in AEC from an engineering perspective. *Invoke SHIFT*. https://www.invokeshift.com/thoughts-on-the-future-of-generative-design-in-aec-from-an-engineering-perspective/

Rohrmann, J. (2019). *Design Optimization in Early Project Stages A Generative Design Approach to Project Development* [Technical University of Munich]. https://publications.cms.bgu.tum.de/theses/2019_Rohrmann_Vilgertshofer.pdf

Royal Institute of British Architects. (2020). *RIBA Plan of Work*. https://www.architecture.com/knowledge-and-resources/resources-landing-page/riba-plan-of-work

Rutten, D. (2010). *Evolutionary Principles applied to Problem Solving*. https://www.grasshopper3d.com/profiles/blogs/evolutionary-principles

Simon, H. A. (1970). *The Sciences of the Artificial*. The MIT Press. https://mitpress.mit.edu/9780262690232/the-sciences-of-the-artificial/

Smorzhenkov, N., & Ignatova, E. (2021). The use of generative design for the architectural solutions synthesis in the typical construction of residential buildings. *E3S Web of Conferences*, *281*. https://doi.org/10.1051/e3sconf/202128104008