

Performance-based Design

From *form making* to *form finding*

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Abstract

Architecture, since its inception, has been through a constant process of diversifying its means of representation, which deeply impacts how designers view the discipline and manage the design process. The notion that, in Architecture, form should follow function, has been one of the core principles introduced in the 20th century. Rejecting ornaments that do not benefit the construction in any way is part of a broader pragmatic approach to building forms. Beauty and aesthetics were no longer the prime concern of architects, and notions such as thermal comfort and harnessing daylight became increasingly important.

With expanding computational power and the development of analysis software, complex mathematical formulas, based on physics principles, are embedded into the software and can be easily applied to models of buildings. This allows for the creation of optimization workflows that not only test the efficiency of a completed building, but can aid in defining the optimal design solution. Thus, this brings on a shift from *form making* to *form finding*. Using computational tools provide an ample range of solutions that can be easily changed and tested for efficiency, while a manual approach would take considerable added amounts of effort and time, even sacrificing accuracy. These tools favour the creation of multiple models, facilitating the process of seeking the best characteristics that amount to a better performing building in a particular environment.

This thesis intends to develop a combination of parametric design, analysis tools and optimization algorithms in order to find an optimal design solution, based on a specific architectural design as a conceptual basis. That is to say, an initial design will be shaped according to variables that impact building performance the most. Without jeopardizing the design intent, it is possible to reach a novel and contemporary version of the *form follows function* principle ¹: *form follows performance*.

¹Louis Sullivan, The tall office building artistically considered, 1896

Resumo

Arquitetura, desde a sua génesis, tem atravessado um processo constante de diversificação dos seus meios de representação, alterando o modo como arquitetos vêm a disciplina e gerem o processo projetual. A noção de que, em Arquitetura, a forma deve seguir a função, tem sido um dos princípios fundamentais introduzido no século XX. A rejeição de ornamentos, quando estes não benificiam a construção de todo, integra uma abordagem pragmática alargada ao desenho de edifícios. Beleza e estética deixaram de ser a preocupação principal dos arquitetos, e noções como conforto termal e capturar luz natural tornaram-se progressivamente importantes.

Com a expansão do poder computacional e do desenvolvimento de softwares de análise, fórmulas matemáticas complexas, baseadas em princípios físicos, são embebidas no software de modo a serem facilmente aplicáveis a edifícios. Isto permite a criação de workflows para optimização que não testam apenas edifícios construídos, mas podem ajudar a definir a solução óptima do design do edifício. Assim sendo, isto precipita uma mudança de *desenhar a forma* para *encontrar a forma*. A utilização de ferramentas computacionais providencia um amplo leque de soluções que podem ser facilmente testadas para maior eficiência, enquanto uma abordagem manual iria tomar consideravelmente mais esforço e tempo, sacrificando mesmo o rigor nos cálculos. Estas ferramentas privilegiam a criação de múltiplos modelos, facilitando o process de procura das melhores características que se traduzem numa melhor performance do edifício num ambiente específico.

Esta tese pretende desenvolver uma combinação de design paramétrico, ferramentas de análise e algoritmos de optimização de modo a encontrar a melhor solução projetual, com base num conceito inicial previamente desenvolvido. Ou seja, o projeto base será explorado de acordo com as variáveis com maior impacto na performance do edifício. Sem sacrificar as intenções iniciais, é possível chegar a uma versão nova e contemporânea do princípio *forma advém da função*²: *forma advém da performance*.

²Louis Sullivan, The tall office building artistically considered, 1896

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Abbreviations and Glossary of Terms

Abbreviations

UDI - Useful Daylight Illuminance

NSGA - Non-dominated Sorting Genetic Algorithm

VOC - Volatile Organic Compounds

ACR - Air Change Rate

HVAC - Heating, Ventilation, and Air Conditioning

Glossary of Terms

Algorithm - A step-by-step description of a process that solves a given problem.

Program - An unambiguous, well-defined, formal description of an algorithm. An algorithm written in a way that the computer understands, i.e. in a programming language, with specific and rigorous instructions that tell the computer which steps to perform.

Programming - The act of translating algorithms into programs, using a programming language.

Parametric Design - Parametric Design is a design approach based on algorithmic way of thinking that exploits associative geometry to describe relationships and dependencies between objects.

Parameters/Variables - A property of a program that, for different values, produces different results.

Optimization - The search for the best possible solution, called the optimal solution, from a set of different options, according to certain criteria.

Design Space - The universe of all possible solutions for a design problem.

Meta-Model - A model of the model or the model that generates all the possible iterations of a design. A model used for optimization.

Performance-based Design - A building that aims to meet specific performance levels in regards to environmental impact, structural performance, and energy consumption, amongst others.

"Civilization is the process of setting man free from men." - The Fountainhead, Ayn Rand

Chapter 1

Algorithmic Thinking and Architecture

1.1 Introduction

Since the invention of the profession, architecture has been through transformations that have changed the way architects work [8]. With the creation and spread of Computer-Aided Design (CAD) tools, new and more complex architectural shapes can be achieved (figure 1.1) [9]. However, manually exploring and manipulating complex shapes with these tools remains an exhausting, time-consuming process. Parametric tools were created to help mitigate this issue.

Parametric Design is a design approach based on algorithmic thinking that exploits associative geometry to describe relationships between objects, creating a dependencies between them [10]. Defined by a set of rules and encoded variables called parameters, a parametric model is able to instantiate a wide range of possible iterations of a design solution through the exploration of its parameters values. [11]. For example, a parametric model of a tree could be based on a subdivision process where each new branch has half of the size of the previous one, and each branch produces two new branches. The parametric model would accept as parameters the length of the initial branch and a value n , representing the number of subdivisions of the tree. By exploring different values for parameter n , a wide variety of results can be achieved: if $n=0$, the tree would only produce the trunk; if $n=1$, the trunk would have two branches; if $n=2$, there would be two new branches coming from each of the previous ones, and so on (figure 1.2).

Parametric tools enable the creation of parametric architectural models, exploiting the flexibility of Parametric Design. It allows the fast exploration of shapes that can be changed and manipulated, according to the designer's preferences (figure 1.3).

Another important development brought by digital technology is the creation and spread of analysis tools. With

¹source:<https://www.ice.org.uk/news/knowledge/may-2016/zaha-hadid-pushing-the-engineering-envelope>



Figure 1.1: Nanjing Youth Cultural Center, Zaha Hadid architects. ¹

the growing demand for sustainable building, it has become crucial for designers to take sustainability issues and building performance into account during the development of their designs [12]. For clarification, a sustainable building is a building that is highly efficient in terms of resource use (such as energy, water, and materials). For that reason, analysis tools have become important tools for the design process: they facilitate performance analyses by executing the necessary calculations and allow architects to make more informed decisions regarding building performance. There are various types of tools for different types of analysis that can be used to evaluate a design, being Radiance for daylight analysis and EnergyPlus for thermal calculations just a few examples.

By combining analysis tools with the flexibility of parametric tools, better performing buildings can be achieved

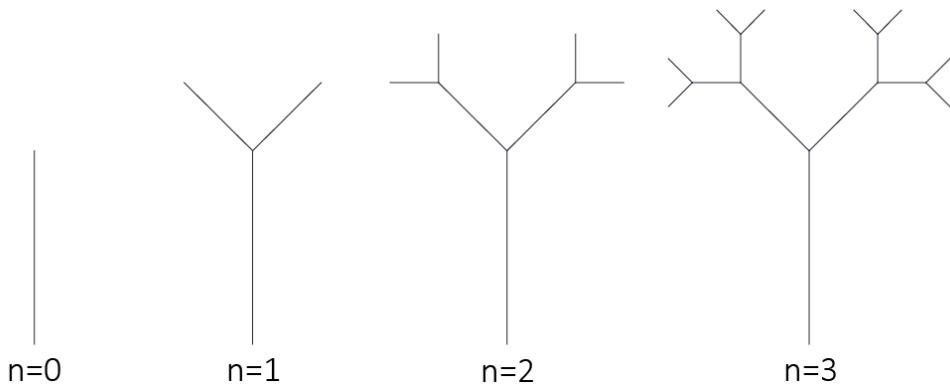


Figure 1.2: Example of a parametric design.

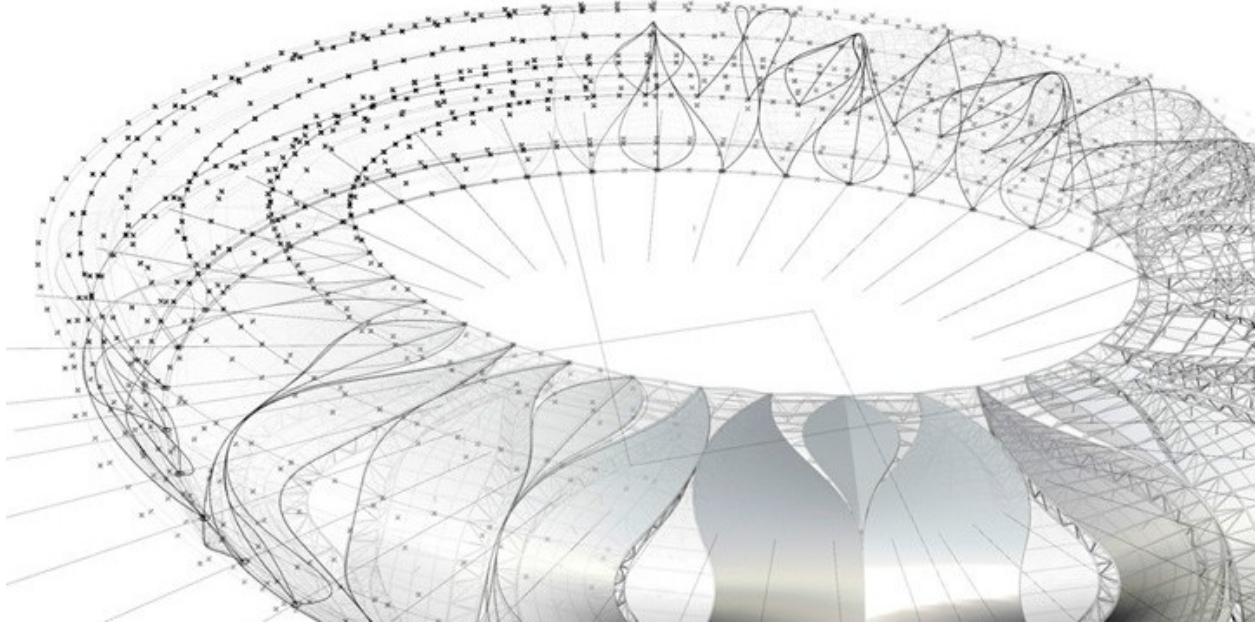


Figure 1.3: Example of a building designed parametrically (Hangzhou Tennis Center).

[13]. Parametric tools can significantly reduce the amount of time that designers spend manually modifying their designs. Thus, more design alternatives can be tested and compared in order to find architectural solutions with better performances.

Nevertheless, both manual and parametric processes require the designer to identify design trends that result in improvements. Design trends can be understood as the typical range of values for certain specific parameters that will result in improvements in the design, according to certain criteria. Considering a simple example, while trying to improve natural lighting inside a building, bigger openings will result in more natural daylight. Therefore, the design trend to improve natural lighting is to increase the size of the openings. However, depending on the design and the considered criteria, identifying these design trends might not be a trivial process and might lead to combinations of parameters that are not obvious.

This process might be facilitated through the use of optimization processes. Optimization can be defined as the search for the best possible solution, called the optimal solution, from a set of different options, according to certain criteria. During an optimization process, the architect is aided by an algorithm of his/hers choice to find the optimal solution for a certain design, according to the given parameters and optimization goals (e.g. improving building performance). This algorithm produces different designs, compares them with the designs that were previously produced, selects and retains the designs that achieved best results, according to the optimization goals.

When performing an analysis, performance criteria may be established for that analysis. Identifying which design, or design trends, will be optimal to satisfy a certain performance becomes more difficult when working with more than one type of analysis. This is particularly the case when the criteria have an inverse relationship. For example, if the objectives are to reduce the heat gains but at the same time increase the natural lighting of a building, these two criteria would have an inverse relationship. This is because if more natural light enters a building, then there is an increase in heat gains due to increased solar radiation. Imagining that there is a parametric feature in the design that allows the size of the building's openings to be changed, the optimal opening size would be a balance between the increased natural light and the heat gained.

To do an optimization process manually, it would require several iterations of analysis of design variations, trying to understand the relationship between the parameters and the different criteria. Once these relationships are understood, it would be necessary to find the optimal values of the parameters. It is important to note that there might not be a single optimal value, but rather a set of optimal values. For this reason, after the optimal values are found, they need to be compared and their trade-offs understood.

To make this process as fast and as smooth as possible, it is ideal to have an optimization tool that can simultaneously produce, analyse, and rank different designs according to their performance. This process would produce the best comparison of design trade-offs and their corresponding parameters. The optimization process would not require the designer to manually change each design. It would automatically vary the values of the parameters and find the best design solution, which results in reduced time and effort for the entire design process.

This approach requires the designer to be aware of not only the conceptual and aesthetic premises of the design, but also which factors influence the performance of the various criteria that require analysis. The result of this approach is Performance-based Design [14]. Performance-based Design, as the name suggests, is when a building aims to meet specific performance levels in regards to environmental impact, structural performance, and energy consumption, amongst others. Designing according to these demands is what results in *form finding* over the traditional process of *form making* [13]. This means that the performance will influence the final shape of the design because we are searching for the best performing shape.

1.2 Research Purposes

The research purpose of this thesis is to test different approaches to an optimization process of a building, in terms of natural lighting performance. This will be done firstly through a parametric model, that is manually iterated and each solution is simulated through an analysis software; and secondly by combining parametric tools with an optimization algorithm, in order to automate the process. These processes inform the user about the possible design options and support the choice of an optimal design. This research process is also a reflection

on new ways to explore the potentialities and forms of architectural design. By automating the process as much as possible, this thesis will show that the user can save significant amounts of time and effort for finding the design alternatives that perform best without sacrificing the design intent. In order to evaluate this thesis, we will consider a case study of an office building in Shanghai for the exploration of optimization processes, as will be described below.

Two different approaches were utilized when developing this case study: (1) iterating the parametric model manually and (2) automating the iteration of the model to search for the best solution using an algorithm. By doing this, it will be possible to:

1. Test the proposed methodology.
2. Compare the solutions achieved by these two different approaches in terms of performance.
3. Understand if there is a reduction of effort and an increased benefit in using these methods.

1.3 Methodology

Through literature review, we obtained an overview of the work that has been developed regarding optimization applied to architectural design. The literature review phase allowed us to understand the present state of the art in regards to whether optimization processes are advantageous or not when trying to find design options. The literature review revealed that optimization is gaining popularity within the architecture world, as it is becoming a common practice in some top architectural firms, such as Foster and Partners, Herzog and de Meuron, and Cox Architects. As section 2.7 will demonstrate, there is a broad range of criteria that different authors and offices use to optimize for their buildings. These criteria include energy efficiency, daylight optimization, wind exposure, and structural performance. Furthermore, with the increasing geometrical complexity of contemporary building shapes, the optimization of both construction and structural aspects is becoming essential.

After the literature review phase, we hypothesize that **using automated optimization methods is less time-consuming than manual changes to a parametric model method, and achieves better performance results when designing a building**. It should also be able to generate and analyse more design solutions, in a shorter amount of time, and give priority to the ones that meet to desired criteria and performance.

This hypothesis describes a workflow that starts by creating a parametric model, that is then tested in the selected analysis tool. However, each iteration of the parametric model has to be tested individually, so it would be advantageous to automate this process. In order to do this, the parametric model needs to be reworked as a meta-model. This is a model of every design solution that the parametric model can potentially be, simultaneously.

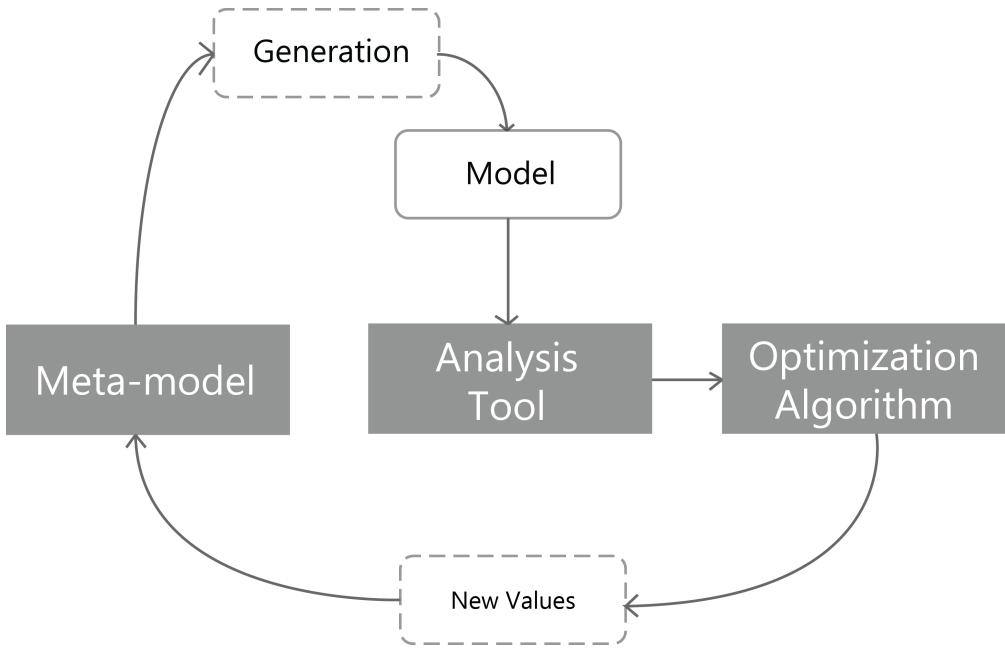


Figure 1.4: Optimization work flow.

Therefore, the meta-model is built for optimization, in order to automate the way the parameters work with the model. This generates different versions of the 3D model of the design, which are then analysed by the analysis tool. Then, the optimization algorithm receives the resulting designs and ranks them according to the pre-established objectives. According to the type of algorithm used, it may or may not produce the next values for the parameters, considering the results of the previous ones. The algorithm introduces the new values to the meta-model and the cycle restarts. This process is illustrated in figure 1.4 .

After comparing multiple designs through the analysis tool, the optimization algorithm retains the best values and uses the meta-model to generate the final solution as illustrated in figure 1.5.

Before the existence of software tools that allow these workflows, engineers created formulas and metrics that allowed them to calculate the performance regarding various aspects of a building. Looking at these formulas and metrics is a fundamental step of the research as it gives us a deep understanding of how analysis software works and enables us to be more critical of the results. In section 2.3, several formulas were studied, as for how they can influence the design process according to performance.

The next step is selecting a case study to be used in evaluating this hypothesis - we selected an office building in Shanghai which required a new façade design that would achieve the best natural lighting performance. This criteria was chosen due to the fact that it is a working environment, so in order to be functional, natural lighting is essential. Therefore, Useful Daylight Illuminance (UDI) was the chosen metric as a basic principle for creating a more comfortable work environment. UDI can be defined as the range of illuminance across a work plane

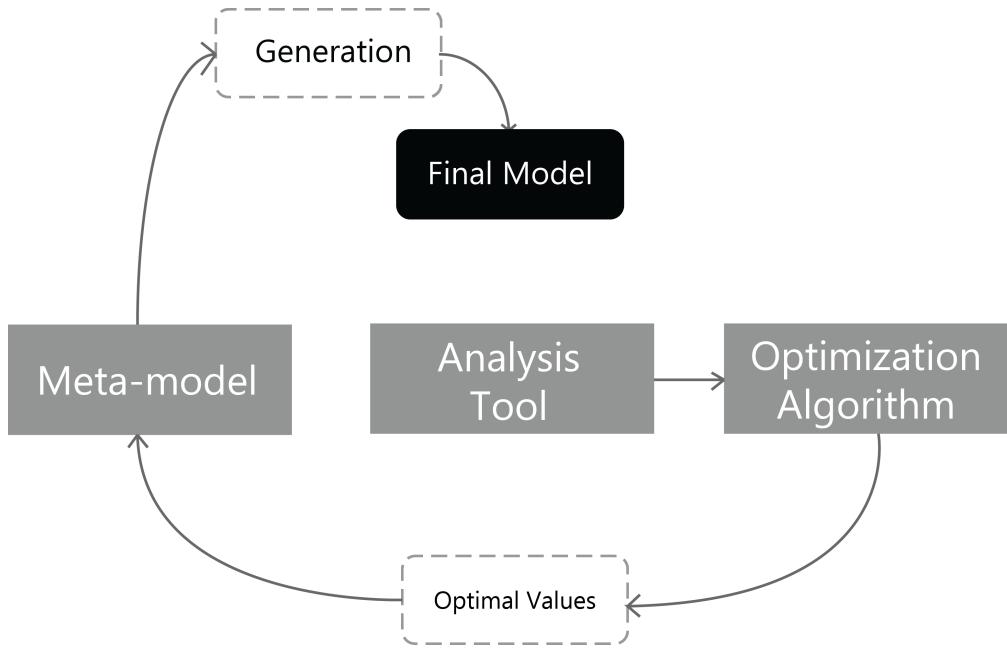


Figure 1.5: Optimization work flow.

considered useful by occupants, measured within an annual timeframe [15].

To ensure that the optimal solution, reached during the optimization process, is buildable, the parametric model rationalizes the geometry and allows the user to set a limited number of different construction elements. It is also vital to ensure that an obtained optimal UDI value does not compromise thermal comfort and, consequently energy efficiency, due to overloading the cooling system. Thus, the possible solutions should also be tested for optimal Solar Radiation values.

The selection of software for analysis was critical to obtain the most reliable results. For this, our literature review was essential for choosing the software that provided the most accurate information for building performance, namely daylight analysis [16][17] [18] [15] [19] [20].

1.4 Structure

This thesis is divided into four main parts:

2. Background

The **Background** chapter is divided into eight sections:

2.1. Architecture Throughout History - This section contains a brief overview of how the evolving means of representation influenced this discipline and how architects regard it;

2.2. Importance of Parametric Design - A section that addresses how Parametric Design works and the

importance of parametric tools for architecture;

2.3. *Building Performance* - This section explains the formulas and software that architects and engineers use to calculate the performance of their buildings;

2.4. *Performance-Based Design* - This section explains Performance-based Design and how it works;

2.5. *From Parametric Model to Meta-Model* - A section that makes a distinction between the parametric model and the meta-model;

2.6. *Optimization* - This section gives a more detailed explanation on optimization processes and how they work;

2.7. *Related Work* - This section explores both theoretical and built work done in the area of optimization;

3. Performance-Based design

The **Performance-Based design** chapter is divided into five sections, three of which focus on the different performance criteria analysed:

3.1. *Introduction* - This section introduces the second part of this thesis as well as the analyses performed;

3.2. *Case Study: Office Building in Shanghai* - In this section, the case study is introduced and explained;

3.3. *Reducing the Number of Types of Elements* - This section focuses on the constructability of the case study.

The purpose of this study is to optimize construction costs and reduce the risk of mistakes during construction by reducing the number of different types of elements that compose the façade;

3.4. *Enhancing the Lighting Performance (UDI)* - This section is about enhancing the lighting performance of the case study building. This is achieved by first manually experimenting with the parametric model and, secondly, by using optimization processes to optimize the lighting performance of the case study;

3.5. *Regulating Solar Radiation* - This section addresses solar radiation, in order regulate the temperature inside the case study building;

4. Discussion

The fourth and final chapter of this thesis, **Conclusion**, is divided into the following three sections:

4.1. *Evaluation* - This section discusses the results of the previous chapter and evaluates if an optimization approach is advantageous or not, when compared to a manual parametric approach. This section also addresses the trade-offs between the different analyses in order to try to manually identify the design trends;

4.2. *Final Considerations* - This section presents our final considerations and contributions and reflects upon the importance of this research;

4.3. *Future Work* - This final section introduces future experiments to be done for the optimization of the case study and proposes potential topics of research.

Chapter 2

Background

"Here are my rules: what can be done with one substance must never be done with another. No two materials are alike. No two sites on earth are alike. (...) The purpose, the site, the material determine the shape. Nothing can be reasonable or beautiful unless it is made by one central idea, and the idea sets every detail. A building is alive, like a man. Its integrity is to follow its own truth, its one single theme, and to serve its own single purpose. A man doesn't borrow pieces of his body. A building doesn't borrow hunks of its soul. Its maker gives it the soul and every wall, window and stairway to express it." - The Fountainhead, Ayn Rand

2.1 Architecture Throughout History

The need to have means of representation in architecture was originated in the Renaissance period, when architecture developed as an intellectual profession that was distinctly separate from craftsmanship. The social consequences of this change for the information flow (from mouth to mouth to written knowledge) were that only those who could read, namely the most wealthy and intellectual layers of society, were the ones that could be allowed to practice the profession.

In order to study and develop buildings, architects started using technical drawings, plans, elevations, and sections as their primary means of representation [8]. The production and manipulation of these drawings and models turned into the very core of what being an architect represented as well as the profession's main activity [21].

Architecture went from a craftsmanship to a intellectual activity, and it could be argued that architecture is presently going through another transition phase. With the transition of architecture to a digital environment, and the implicit change of support, the process of architectural thinking and the way architects work is evolving yet again [14].

Software applications are built upon the accumulated knowledge of mankind. This means that an architect can benefit from the very specific knowledge of other disciplines without fully understanding those disciplines, only needing to master the medium or tool interface. This might represent a turning point for architects, which have to be more aware of these tools but do not need to have expertise that otherwise would have taken years to acquire. Nevertheless, a base knowledge about these subjects is needed in order to be critical of the results.

Unlike during the previous periods, these tools are becoming increasingly more accessible to anyone and are not strictly confined to a particular group. Nevertheless, despite these tools being more easily accessible, exploring design options is still a demotivating and exhausting process, hence the importance in developing Parametric design options.

2.2 Importance of Parametric Design

When working with CAD tools, a simple change in a 3D model might need to be propagated through its entirety, which often requires the model to be rebuilt. The tedious, time-consuming nature of this process can be disruptive for the design process, discouraging further changes and the exploration of design alternatives as the project evolves.

The use of parametric tools can help mitigate this issue. A parametric design works by using declared parameters to generate a form [22]. By experimenting with these parameters, a wide range of possible alternatives can be generated without the need to redo the model, or parts of the model. Thus, by parametrizing parts or elements of a model, changes and the exploration of alternatives can become effortless.

According to Woodbury (2010), author of *Elements of Parametric Design*, there are three distinguishable types of “thinking” that can be applied to Parametric Design: thinking with abstraction, thinking mathematically, and thinking algorithmically. The abstraction process is what allows the parametric model to produce several design alternatives for the intended design. Mathematical thinking is directly related to the parameterization process, whereby the parameters need to be chosen. As for thinking algorithmically, it is related to the steps or rules the design can handle: remove, modify, repeat, amongst others [11].

Although parametric tools allow the architect to change the design at any stage [21], it is important to mention that both the algorithmic and mathematical thinking of the project should take into account any analysis or optimizations to be done in the future. That is because the parameters of the design need to be chosen according to what needs to be evaluated or optimized. If the wrong parameters are selected, the parametric model is of no use [21]. For example, if we intend to optimize the structural behavior of a building, we should parametrize the elements relative to its structural performance. If we parameterize an element such as the building’s windows, its variations will not improve the building’s structural behavior.

2.3 Building Performance

Since long, engineers and architects have developed formulas and methods to evaluate the performance of buildings. These formulas not only evaluate structural performance, but also thermal performance, humidity, and acoustics, among others. The calculations required by these formulas are very extensive and most of them need additional information contained in auxiliary documents, such as materials' thermal coefficients and reflectance, regional climate, schedules, and others.

These calculations are now embedded in software analysis tools that, by reading geometry, with the addition of materials and location, save a considerable amount of time when analysing the building's performance.

In order to provide a better understanding of the analysis tools, some of the most commonly used formulas to evaluate building performance will be explained in the next section along their scientific meaning.

2.3.1 Manual Calculations

Formulas and calculations to estimate building behaviour have been for a long time a discipline integrated into building engineering and architecture. For example, formula 2.1 calculates the thermal energy loss according to the building's material:

$$Q_{cond} = \sum_{k=1}^{NumEle} U_{Ek} \cdot A_k \cdot (\theta_i - \theta_o) \quad (2.1)$$

Where:

Q_{cond} = Energy loss

U_{Ek} = Coefficient of thermal transmission ($W/m^2\text{°}C$)

A_k = Area of the surface (m^2)

θ_i = inside temperature ($^{\circ}\text{C}$)

θ_o = outside temperature ($^{\circ}\text{C}$)

$NumEle$ = Number of elements

The following subsections will explain the formulas used to evaluate the different performance criteria, namely: thermal efficiency/comfort, visual comfort, acoustic comfort, indoor air quality, and cost.

Thermal

Thermal comfort is one of the most documented and tested feature concerning a building's performance. It is one of the most important concerns regarding the well-being of a person inside the building. Thermal comfort is

Season	Clothing insulation (clo)	Activity level (met)	Optimum Operative Temp. (°C)	Operative Temperature Range
Winter	1	1.2	22	20-24
Summer	0.5	1.2	24.5	23-26

Table 2.1: Recommended temperatures for occupants for sedentary activity based on ISO 7730-18984. [7]

a theme that has been approached from a trade-off perspective with energy efficiency [23]. However, optimizing the building during the design process allows for cooling/warming cost savings. A good design in terms of passive building implies less usage of HVAC systems. This not only uses less energy, but also has advantages when considering the health of the users. The incorrect planning and use of HVAC systems has been proven to be detrimental to human health and reducing their use has economic, environmental, and health benefits [24].

The temperatures that fulfil human comfort are a very debated theme [25]. Although there is a general disagreement on the temperature values, there is an agreement that this is a highly contextual situation [25]. Moreover, thermal comfort is dependent on other secondary variables such as moisture content, rate of ventilation, and thermal insulation.

When considering the average comfort temperatures, there are some other variables that should be taken into account. These variables include the season, the respective typical clothing insulation, and the activity level as described in table 2.1.

It is important to mention that thermal comfort is highly dependent on the humidity level. Not all temperatures feel comfortable with the same humidity levels and vice-versa (figure 2.1).

Thermal comfort is a very complex theme, with many variables that should be taken into account. Location, orientation, coefficient of thermal transmission of both the walls and openings, are variables that have a great influence in the results.

Different locations have different climates and weather. The required data for this calculation are the average temperatures for each hour, of each day, for every month of the year. The reason for this is that the trajectory of the sun, relative to the earth, is different every day of the year. Therefore, there are different temperatures to be considered. It is very important to make sure, even in a scenario where HVAC systems are being taken into account, that you have the necessary information about the most extreme temperatures in a given location. This is so the systems can keep up with these temperatures.

The orientation is another important factor since different orientations have different relative positions to the solar azimuth. The solar azimuth can be understood as the angle of the sun along the horizon, with zero degrees corresponding to North, and increasing in a clockwise fashion. The fact that the sun has a specific route in the

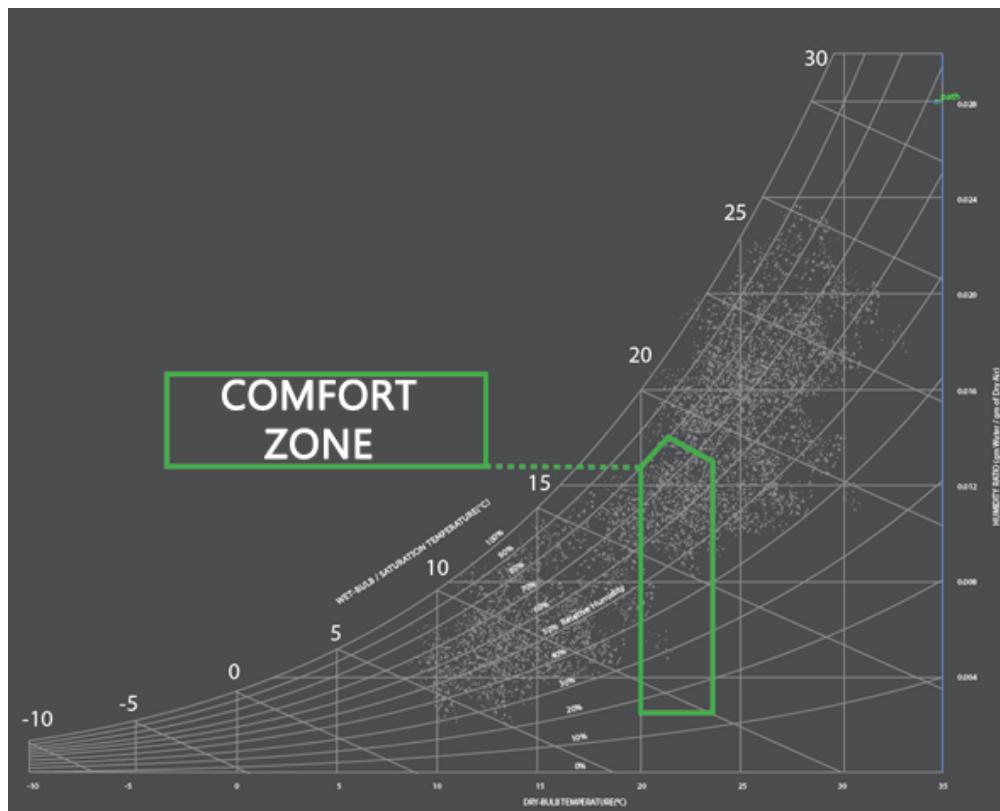


Figure 2.1: Psychometric Chart; Source: California Energy Code

sky means that different orientations are differently exposed to its solar radiation.

When speaking of buildings, it is also important to consider the materials. The coefficient of thermal transmission is a characteristic of the material; materials with higher coefficients have worse insulation than materials with lower coefficients. For our purposes, the importance of the coefficient of thermal transmission is that it can be used to compute the gain or loss of thermal energy by transmission. Nevertheless, it is important to mention that a coefficient of thermal transmission should only be considered bad or good in the context of a specific climate.

The final result will be given by the balance of all the heat losses and gains for each hour, which will be identified as heating or cooling needs. The thermal balance between the heat losses and gains is given by equation 2.2:

$$Energy\ Balance = Q_{solar} + Q_{trans} + Q_{int} \quad (2.2)$$

Where:

Q_{solar} = Gains by solar radiation

Q_{trans} = Losses or gains by thermal transmission

Q_{int} = Internal gains

When values of Q_{trans} are negative they represent a heat loss, and when positive they represent a heat gain. If the balance is negative, it will be translated into heating needs. If the balance is positive, it will be translated into cooling needs. Equation 2.3 is the heat gained by solar radiation. This should be calculated for each one of the orientations of the building.

$$Q_{solar} = \cos \frac{\phi_s - S_a}{180 \cdot \pi} \cdot \sin \frac{\theta_s}{180 \cdot \pi} \cdot SHGC \cdot A_w \cdot \left(\frac{A_o \cdot 100}{A_w} \right) \quad (2.3)$$

Where: Q_{solar} = Heat gains by radiation

ϕ_s = Solar azimuth angle

S_a = Surface azimuth

θ_s = Solar elevation angle

$SHGC$ = Solar heat gain coefficient

A_w = Area of the windows

A_o = Area of the outside walls

Equation 2.4 is the formula that represents the energy loss:

$$Q_{trans} = \sum_{k=1}^{NumEle} U_{Ek} \cdot A_k \cdot (\theta_i - \theta_o) \quad (2.4)$$

Where:

Q_{trans} = Energy loss

U_{Ek} = Coefficient of thermal transmission ($W/m^2\circ C$)

A_k = Area of the surface (m^2)

θ_i = inside temperature ($^\circ C$)

θ_o = outside temperature ($^\circ C$)

$NumEle$ = Number of elements

The internal gains Q_{int} include the sources of heat placed in a building (excluding active heating systems). It includes the dissipated heat from lighting, electric plugs (used as a proxy for electronic equipment), and the heat associated with the metabolism of the occupants.

It can be translated by equation 2.5.

Internal load	values
Electrical plug loads	50 (Kw/m^2)
Lighting loads	5 (Kw/m^2)
Occupancy	10 (m^2/pp)

Table 2.2: Standard values for the internal gains (Source: ASHRAE handbook: Fundamentals (2001) and Code for lighting (2002)).

$$Q_{int} = q_i \cdot A_f \cdot 0.720 \quad (2.5)$$

Where:

Q_{int} = internal energy gains

q_i = Sum of internal gains through occupancy and electrical devices (W/m^2)

A_f = Area of the floor

Some standard values for occupancy-related heat are represented in table 2.2. This energy gain should only be taken into account within working hours.

After the hourly Energy Balance is calculated, the annual energy cost is obtained by summing up all of the hourly heating/cooling needs. By varying orientations and materials (and therefore the thermal transmission coefficients), different heating/cooling values can be generated.

Visual Comfort

Lighting conditions have proven to have a significant role in human comfort and work productivity [7] [26]. The visual criteria considers factors such as the light level and the glare. Different activities require different lighting levels (figure 2.9).

Glare can be defined as the interference of the brightness of a light source on the visual perception. There are two main types of glare: discomfort and disability glare. Discomfort glare provokes discomfort but does not disable the ability to see information. Disability glare reduces or impairs the ability to see information [27].

Concerning the lighting comfort illuminance, there are two main approaches: one where a single optimal value, usually referred to as "daylight factor", is considered (figure 2.2) [1]; whereas the second approach takes an interval of values into consideration.

The daylight factor method does not consider scenarios involving overcast skies nor does it consider the path of the sun. This means that the building's orientation becomes irrelevant. When considering an entire building,

it is not realistic to assume that it will have the same overall illuminance value. A more appropriate approach would be to consider intervals of daylight instead of a single value.

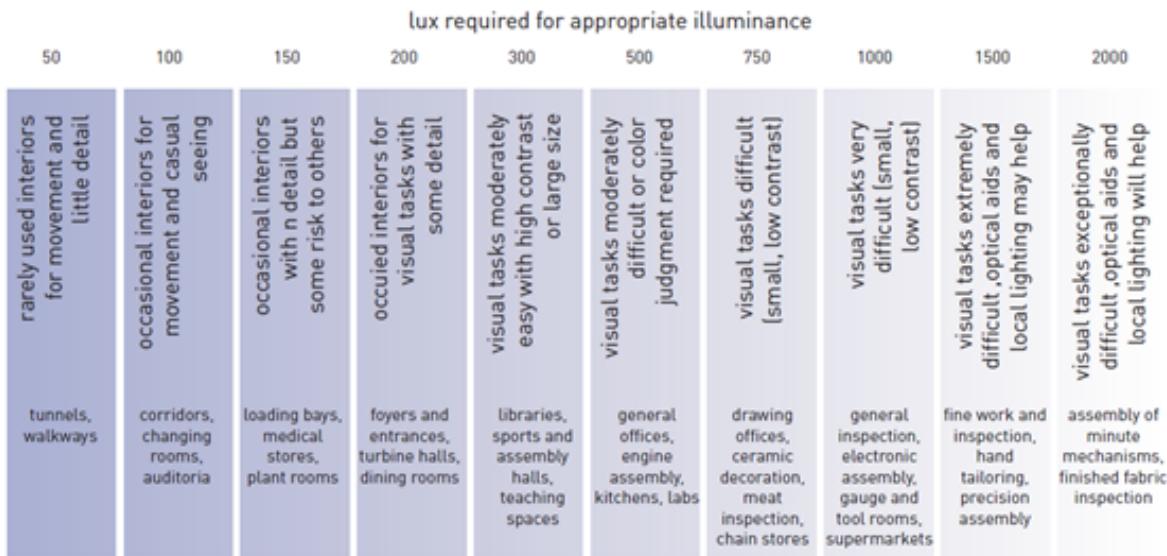


Figure 2.2: Lux required for appropriate iluminance. [1]

According to the building's morphology and function, if the illuminance is too low, it will impair discernment of the visual environment and the performance of visual tasks. Conversely, illuminance levels that are too high will cause visual discomfort, and may cause thermal discomfort as well. Illuminance levels within the range of values considered comfortable is called the Useful Daylight Illuminance (UDI) [17].

There are numerous research papers addressing the ideal illuminance, and they generally conclude that 500 lux is the ideal value [28] [17] [15] [20]. Nevertheless, there is a large interval that can also be considered as satisfactory for performing visual tasks [28] [17].

While still a considerable number, fewer studies have been completed regarding the range of values that can be considered as comfortable. In a survey of the occupants' preferences and behaviours, conducted by Nabil and Mardaljevic, the authors concluded that, between 100 and 2000 lux (table 2.3), it is still possible to fulfil office tasks without major impairments [17].

Illuminance analysis is important as it allows buildings to be designed with daylight as its main source of light. This means that these buildings require less artificial lighting, and thus consuming less energy.

Acoustic Comfort

Acoustic comfort is a context-dependent variable: the decibel level that is suitable for sleeping is not the same as the decibel level considered adequate for domestic work. According to this logic, different functions require

Table 2.3: Lux values and comfort

<100 lux	100-500 lux	500-2000 lux	>2000 lux
Insufficient to either be the sole source of illumination or to contribute significantly to artificial lighting	Effective either as the sole source of illumination or in conjunction with artificial lighting	Often perceived as either desirable or at least tolerable	Likely to produce visual or thermal discomfort

different suitable acoustic characteristics. In figure 2.3, we can find the adequate reverberation times for different building functions. For clarification, reverberation time is the time necessary for a signal to drop by 60 dB.

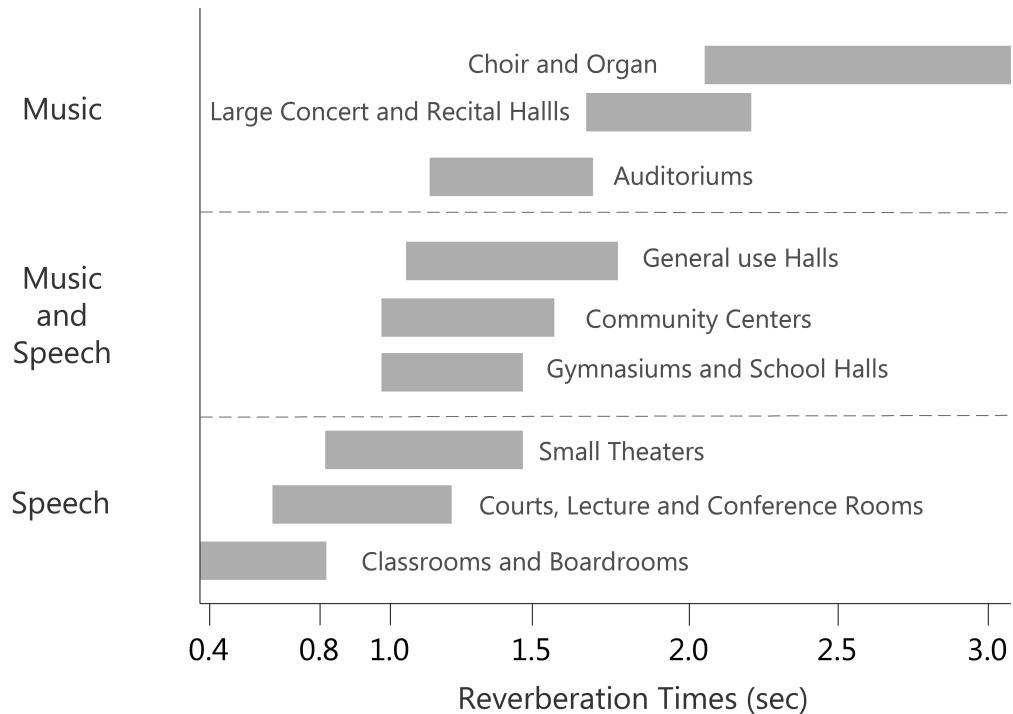


Figure 2.3: Adequate reverberation times for specific functions; (Source: Melfoam Acoustics)

The formula that relates the building material used, area, and reverberation time is:

$$RT_{60} = \frac{24\ln 10^1}{C_{20}} \cdot \frac{V}{S_a} \approx 0.1611 sm^{-1} \frac{V}{S_a} \quad (2.6)$$

Where:

RT_{60} = time required for a direct sound decay of 60 dB

C_{20} = Speed of sound in the room (for 20 degree Celsius)

V = Volume of the room (m^3)

Source	Particles	Formaldehydes	Organic gas	Asbestos	
Building materials and soil		X	X	X	
Heating Systems	X	X			
Smoke	X		X		
Human Presence	X				
Source	Radon	Carbon ide	Monox- ide	Carbon Diox- ide	Nitrogen Dioxide
Building materials and soil	X				
Heating Systems			X		X
Smoke		X			X
Human Presence	X			X	

Table 2.4: Pollutants present in buildings

S = Total surface area of the room (m^2)

S_a = Total absorption in sabins

sm = Seconds by meter

Indoor Air Quality

Building materials emit pollutants that impact the air quality inside a building. From a passive point of view, these pollutants can be reduced not only by considering the material but also by improving the ventilation inside the building. Humans are also responsible for the presence of pollutants (CO₂ production through breathing), which further reinforces the need for proper ventilation (table 2.4).

For the indoor air quality, the Volatile Organic Compounds (VOC) emissions of the building materials, as well as the volume of the room and the air exchange rate must be taken into consideration. The Total VOC's value is given by the equation:

$$TVOC = TVOC(material) \cdot \frac{T_{rs}}{T_{rv} \cdot ACR} \quad (2.7)$$

Where:

$TVOC_{material}$ = Total VOC concentration in the material

T_{rs} = Total room surface

T_{rv} = Total room volume

ACR = Air Exchange Rate

For clarification, the Air Change Rate (ACR) represents how many times the total volume of air of the room was substituted by a new volume.

Finally, it is important to mention that ventilation also has a role on thermal comfort.

Cost and Construction Predictability

Nowadays, the use of parametric tools in architectural design is increasing. These tools not only allow the designer to rapidly make design changes and explore alternatives, but they also enable the creation of new and more complex shapes. These tools allowed architecture to achieve results that could not have been achieved using conventional design methods [9].

The exploration of these new complex shapes have brought forth new challenges when it comes to transferring the project to real life, as they are more likely to have increased construction costs and risks when compared with conventional projects [29].

After the architectural design phase, adapting the building to reality can have devastating consequences to the design intent and can cause over-budget situations [29]. The advantage of being aware of these setbacks during the design phase is that choices that influence building costs can be made in advance and the increased costs of non-conventional shapes can be reduced, while maintaining the design intent.

2.3.2 Software Analysis Tools

Over the past years, analysis tools have increased their accuracy and have become more frequently used. These analysis tools include a wide diversity of types of analysis: they may be connected with the building thermal efficiency, the lighting conditions, the structural performance, cost, amongst others. Over the years, these tools have been helping designers make more efficient and sustainable designs, by informing them about the design's performance. Using that information, architects can provide the changes that they think will improve the design and evaluate it anew.

There are several tools for the different types of analysis. However, being the objective of the second part of this work to optimize the lighting conditions of a case study, we will only present tools related to daylight analysis. Thus, in the following sections, we present some of the best and most popular tools used for daylight analysis in architecture.

Ecotect and Lightning Analysis

Originally developed by Square One Research as an independent tool, Ecotect Analysis became one of the most commonly used analysis tools in the building industry [30], providing various types of analysis to evaluate and

simulate building performance, including energy and daylight analyses.

In 2008, Ecotect Analysis was acquired by Autodesk which later discontinued this tool as an independent analysis tool and integrated its features into the Lighting Analysis plug-in for Revit. This plug-in is able to perform daylighting and electric lighting analyses, while exposing the analysis results directly on the Revit model.

Radiance

Radiance [31] is a suite of tools originally developed by Greg Ward that allows users to evaluate and predict buildings' lightning conditions and visual quality. This software takes into account a big variety of design characteristics for daylight calculations, such as scene geometry, materials, luminaires, time, date, and sky conditions. The outputs of these calculations include spectral radiance (i.e. luminance + colour), irradiance (illuminance + colour) and glare indices. These results can be visualized through different representations: colour images (see figure 2.4), numerical values and contour plots.

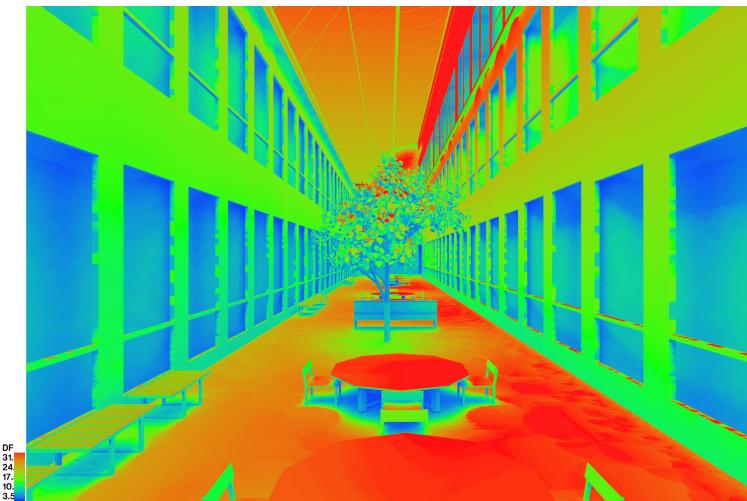


Figure 2.4: Image produced by Radiance.¹

EnergyPlus

Founded by the U.S. Department of Energy's Building Technologies Office, EnergyPlus [32] is an analysis tool that simulates and estimates buildings' energy consumption, taking into account HVAC systems, radiant, and convective effects. It also conducts illuminance and glare evaluations to report visual comfort and drive lighting controls.

EnergyPlus itself is console-based and lacks a friendly graphical user interface. For that reason, several plug-ins and graphical interfaces have been developed, taking full advantage of EnergyPlus' features but providing a friendly

¹source:<https://www.iesve.com/software/ve-for-engineers/module/RadianceIES/465>

work environment for architects. The **OpenStudio** plug-in for SketchUp (see figure 2.5) and **DesignBuilder** interface are just a few examples. OpenStudio also uses Radiance for advanced daylight analysis.

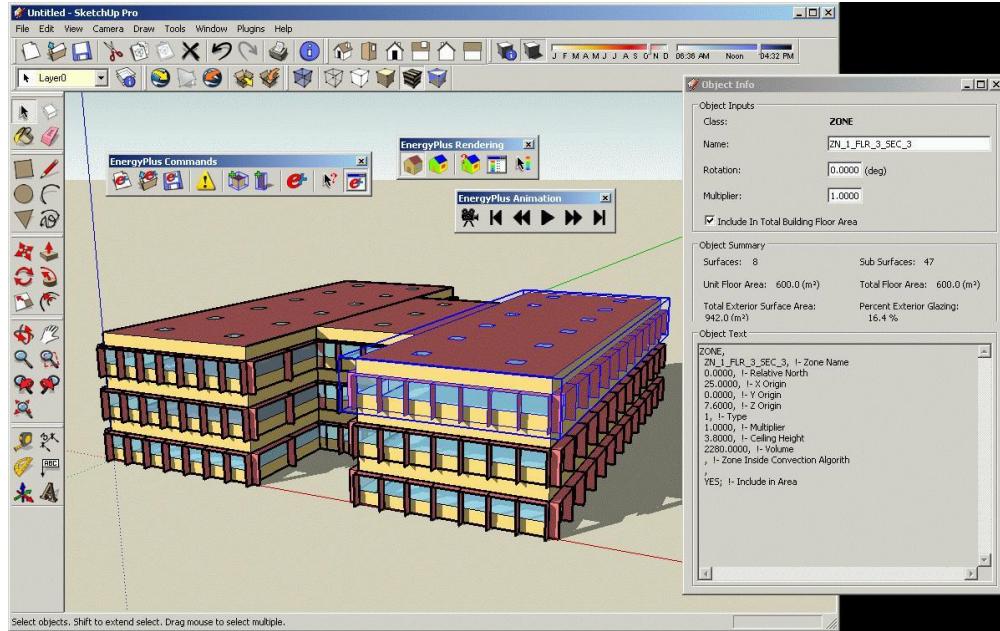


Figure 2.5: Energy Analysis by EnergyPlus.²

Daysim

Daysim [33] is a Radiance-based daylighting analysis software that models the annual amount of daylight in and around buildings. Simulation outputs range from climate-based daylighting metrics such as daylight autonomy and Useful Daylight Illuminance to annual glare and electric lighting energy use. Daysim also generates hourly schedules for occupancy, electric lighting loads and shading device status which can be directly coupled with thermal simulation engines such as EnergyPlus, eQuest and TRNSYS.

Like EnergyPlus, Daysim also has several plug-ins and interfaces that make this tool easier to use and more accessible to architects, being the Su2ds plug-in for SketchUp just one example.

DIVA

DIVA [34] is a plug-in for Rhinoceros that was initially developed by the Graduate School of Design at Harvard University. This plug-in uses Energy Plus as well as both Radiance and Daysim to perform energy and daylighting analysis, respectively [18], providing a friendly, easy-to-use environment within Rhinoceros for architects to work with these tools.

²source:<http://energyplus.software.informer.com/screenshot/299680/>

DIVA is able to perform a wide range of environmental performance evaluations, including Radiation Maps, Climate-Based Daylighting Metrics, Annual and Individual Time Step Glare Analysis, LEED and CHPS Daylighting Compliance.

Overview

Two important factors to consider when using analysis tools is (1) ease of use for architects, and (2) integration with architectural software [35]. While more powerful and accurate, tools such as Radiance, Daysim and Energy-Plus lack a friendly work environment for architects to work with, making them difficult to use. To mitigate this, several plug-ins and graphical user interfaces have been developed, taking advantage of these tools' capabilities while providing a more intuitive work environment.

These tools should also be closely integrated with architectural software so that models can more easily be linked with the analysis tool. By doing this, a lot of time and effort in the input of information can be saved, allowing evaluations to run more smoothly and efficiently.

Of all the presented tools, Radiance is the one that produces the most accurate and realistic analysis result [18] [35]. However, by itself, it is a complex tool to use and might require a plug-in to both facilitate the use of this tool and integrate it into architectural software for a smoother analysis process. DIVA, with its direct connection to Rhinoceros, presents a more appropriate, user-friendly alternative. DIVA also uses both Radiance and Daysim to perform daylight analysis, thus taking advantage of the analysis capabilities of these tools while offering a friendlier work environment.

2.4 Performance-Based Design

By using analysis tools, and changing the design of a project according to the results of those analyses, we are shaping the model based on its performance. This means that the final design is somewhat influenced by how the building performs. That is the essence of Performance-based Design.

Performance-based Design is, as described by Kolaveric (2005), the difference between *form making* and *form finding* [13]. Parametric tools can be used to achieve a particular shape through digital means, but when combined with environmental or structural analysis tools, it is the results of these evaluations that will determine the final shape.

In current practices, it is the human designer that manually adapts the geometry of the model according to the results of the evaluation. In order to achieve a performance-based design, instead of analysing the performance of a design, manually modifying it, and running the evaluation again to check for improvements, the modifications to the model could be executed by the analysis tools directly informing the model on what changes should be

made to improve the design's performance. To achieve this workflow, it is necessary to implement optimization processes [14].

This iterative process of evaluation and adaptation to form a building with better performative characteristics could be likened to Darwin's theory of Natural Selection. In fact, this is not an unusual concept for Architecture as there is always the presence of a Darwinistic factor when designing a project: in the conceptual phase of the project, there is a set of ideas, in which the ones that are best suited to the project evolve into something more tangible, whereas the ones which do not adapt will perish and be forgotten. When using programming tools, we can think of the code as DNA, where the variation of a parameter or gene produces a new building or species iteration. When facing these iterations with environmental factors, only the best-performing ones can survive and reproduce, passing on the characteristics that make them fit, and producing another generation (figure 2.6).

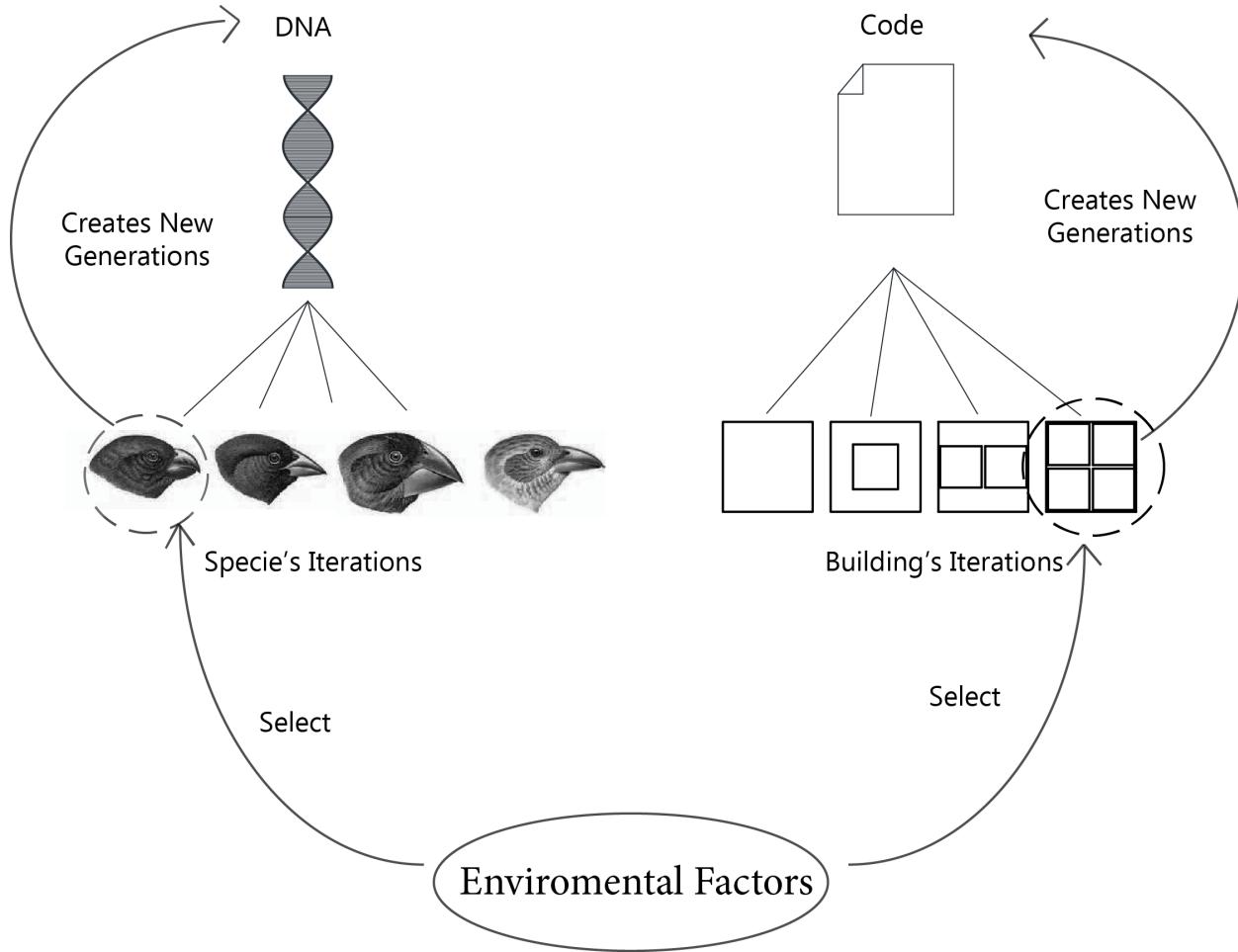


Figure 2.6: Comparison between natural selection and Performance-based Design

Along the whole design process, this Darwinism is a reality [36]. With the implementation of Performance-based design, the architectural process is one step closer to almost achieving a literal meaning in the Darwin

analogy. Performance-based design, not only presupposes that the environment shapes a building, but also the use of optimization tools that frequently employ genetic algorithms to sort the buildings' iterations. To make this process happen, the parametric model is no longer directly changed by the user; it is a broader model that shows all of the alternatives that the design can potentially be.

2.5 From Parametric Model to Meta-model

A parametric model built for optimization is fundamentally different, on both a conceptual and functional level, from a parametric model that has to be manually changed by the user. A model built for optimization encompasses every design solution that the parametric model can potentially be, simultaneously. As such, it should no longer be referred to as a parametric model but as a meta-model [36]. This is because the parameters do not have a fixed value, so they have any value or none at the same time. The model produced by the meta-model is only defined when new values are introduced by the optimization algorithm.

The prefix “meta” implies that it becomes a “model of the model” or an array of options that will lead to the final solution. This terminology also reflects the distance gained from the model, meaning that the user no longer has to interact with the model directly while the optimal solution is being found. Instead of interacting directly with the parametric model, the changes are automated on the meta-model through an optimization process. The different variations are tested and sorted by an optimization algorithm, a complex process that relies on different mathematical approaches, described in the following section.

2.6 Optimization

Optimization can be defined, from a mathematical, computational, and operations research point of view, as the best option from a set of different solutions according to certain criteria/criterion. The most common methods to find an optimum were calculus-based and were proposed by Nemat and Lagrange. In contrast, Newton and Gauss proposed iterative methods.

As an example, a simple optimization problem could be finding the maximum point of a paraboloid: $z = f(x, y) = -(x^2 + y^2) + 4$.

To find the maximum point, one possible approach could be by inputting various values, and keep the highest z-value as the optimum. In this case, the global optimum is at $(x, y, z) = (0, 0, 4)$, as shown in figure 2.7.

For an optimization to be possible, a parametric model (or a future meta-model) needs to be built. The reason for this is that the parametric model can process different ranges of values or information, and re-shape

³source:<https://commons.wikimedia.org/wiki/File:Maxparaboloid.svg>

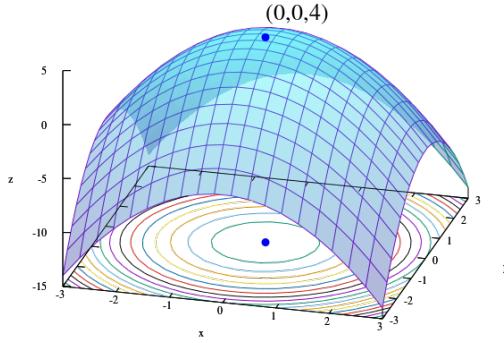


Figure 2.7: Paraboloid Maximum.³

the model according to it. In the traditional use of parametric models, a user will insert the desired values or information directly and observe the results it produces in the 3D model. On the other hand, using an optimization process, the input of information as well as the interpretation and evaluation of the results can be automated by an algorithm.

Towards a better understanding of the optimization process, it is important to understand its components. Nevertheless, the vocabulary associated with the optimization components is not very well defined in the literature, so to create a better understanding of the next sections, this is how these components will be defined:

Fixed Inputs. Fixed inputs is all the information about the model that is not changed and does not vary during the optimization process. For example, a building's location can be a fixed input.

Variable Inputs. This is all the information in the model that contains an element or elements that vary, within the constraints of the input.

Independent Variables. As the name suggests, these are the parts of the design that can be changed. Different values for the variables of the design produce different design results.

Dependent Variables. These are variables that are not directly modified, but they vary because they are linked to the independent variables.

Constraints. The constraints express the boundaries of values intended. These boundaries are commonly established to avoid results that do not have a connection to reality or that do not follow certain standards. By

establishing these boundaries, there are certain designs that are automatically excluded from the optimization process.

Objectives. The objectives are what is intended to be optimized. Usually, these objectives are translated into *objective functions*. These *objective functions* are a mathematical approach formula where each one of the different values will produce different results that the user intends to minimize, maximize, or have within a certain range, etc. After the values are produced, the software will evaluate and rank how close they are to the objectives.

Outputs. The outputs are linked to the objectives. The outputs are the information produced by the optimization that will be compared to the objectives' goals.

Inputs can be seen as the information the whole system needs to take in. The difference between fixed and variable inputs is that the fixed input do not change during the optimization process, while the variable inputs contain parameters that can vary. Variables are the parameters that are changing.

The relationship between the parametric model and the optimization process is considerably simple: the optimization software runs with different ranges of values that produce different versions of the building, evaluates them, and uses the results to adjust the parameters of the parametric model for further improvement. This process is repeated until an optimal solution(s) is found or the time limit imposed by the user for the evaluation is reached.

The set of all possible solutions for a particular design is called design space. One iteration of a certain design corresponds to one solution of the design space. These solutions exist regardless of the ability of the user to reach them or not. This means that by making iterations of a design, the user is not creating more solutions. Instead, the user is finding options that already exist in an abstract sense. Figure 2.8 illustrates the idea of design space: the design space is represented by the set of squares, being the darker squares the solutions found. The circles represent all the solutions the design space cannot support since the chosen variables will not allow this shape. Important distinction because it is through the variables or parameters that the architect defines the shapes he or she is comfortable with.

The design space of a certain design can be infinite or finite. The design space is infinite if the chosen variables are continuous or the variables, and finite if the variables are discontinuous (figure 2.9).

The type and dimensions of the solutions are restricted to the number of variables selected and by the constraints imposed. Nevertheless, a continuous design space has infinite solutions regardless of the number of variables, so it means that a continuous design space with two variables, for example, is larger than a discontinuous design space of four. The number of variables, in visual terms, affects the morphology and the graphic variety of solutions of the design that can be obtained.

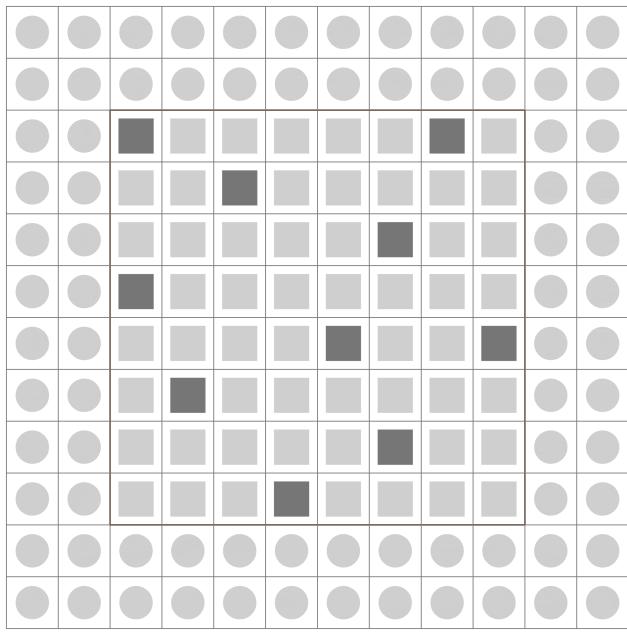


Figure 2.8: Design Spaces.

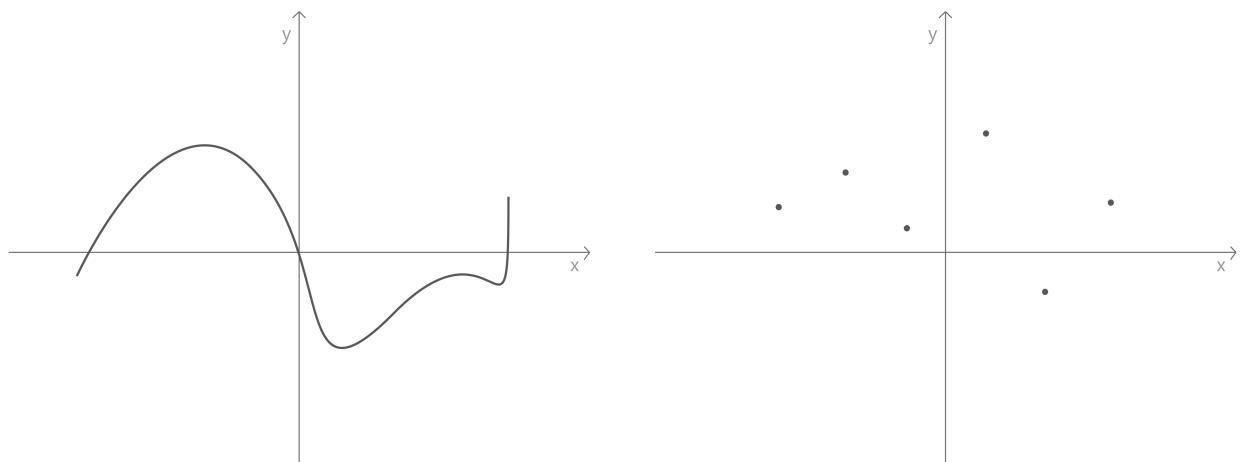


Figure 2.9: Continuous function on the left, discontinuous function on the right.

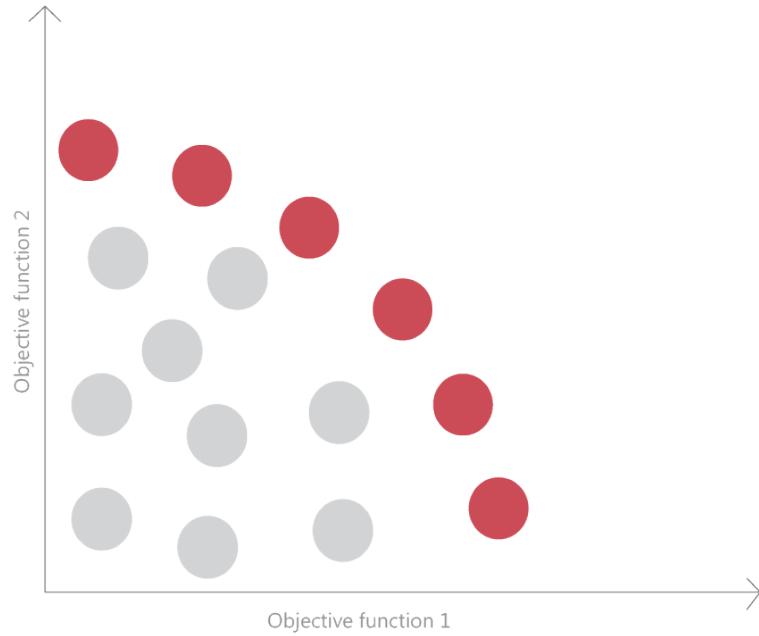


Figure 2.10: Pareto front.

Finding the optimum value of a function can be a relatively linear process, when speaking of a simple single objective function or even two, but it is not the case if there are more. If the case is that we intend to optimize more than two functions, both the methodologies to find the optimum(s) and to visualize the information are relatively different. When an optimization has more than one objective, it is called multi-objective optimization.

2.6.1 Multi-Objective Optimization and Optimization Algorithms

Multi-objective optimization (or multi-criteria optimization) is an optimization in which more than one objective function is being optimized simultaneously. Multi-objective optimization is mostly used in the fields of engineering and economics, to analyze the trade-offs between performance and cost [37] [38].

The most significant difference between a single criteria optimization and multi-objective optimization towards decision making is that, in most cases, there is not a *best solution*, but a set of best possible solutions according to the different criteria. To understand the relationship between these solutions, it is necessary to visualize them through a Pareto Front.

Pareto Front

Named after the Italian engineer and economist Vilfredo Pareto, the Pareto front represents a situation in which it is impossible to generate a better solution for one of a set of objective functions, without making it worse for another objective function of that same set of objectives functions (figure 2.10).

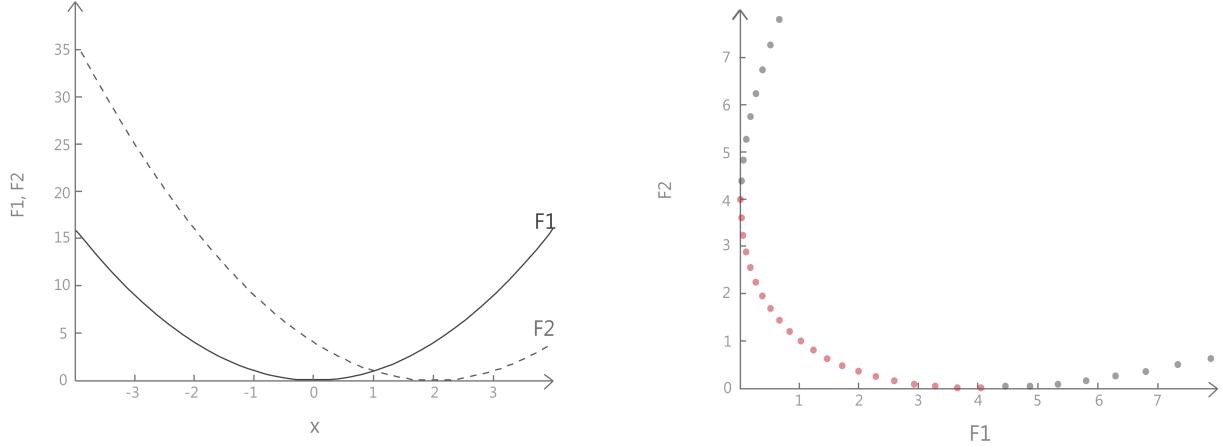


Figure 2.11: In red the Pareto front of the minimized functions.

Let us consider functions $F1$ and $F2$ as the two objective functions:

$$F1 = x^2 \quad (2.8)$$

$$F2 = (x - 2)^2 \quad (2.9)$$

The objective of the optimization would be to minimize the values of both functions. The optimal solution for $F1$ is $x = 0$, with the result of $y = 0$. Nevertheless, if this value is to be applied to $F2$ the result would be 4. Thus, $x = 0$ is only an optimal value for function $F1$. On the other hand, if the optimization is being done only for $F2$, the optimal value would be $x = 2$, with $y = 0$ as a result. Again, this value is only optimal for $F2$ but not for $F1$. In figure 2.11, on the left, the plot of the two functions is described. When minimizing the two functions, the optimal values belong to the interval $0 \leq x \leq 2$. That is the interval of values between which there is no better solution in the set. The values belonging to that interval are represented in the red color on the right plot in figure 2.11. It is visible that some of the solutions are more optimal for function $F1$ and others for function $F2$. This usually corresponds to the part of the process where the user makes a choice. Usually, these choices are based on the relative importance that $F1$ and $F2$ have. This kind of plot is commonly referred to as "trade-offs" for that reason.

Monte Carlo Algorithm

Monte Carlo Algorithm is a randomized sorting algorithm, generally using in single objective optimization. This algorithm's search mechanism consists in generating a random value for the parameters and comparing the result

with the previous value [39]. It was named after the Principality of Monaco at Monte Carlo since Monte Carlo is well-known around the world as an icon of gambling, which many times has a random nature.

When using this algorithm, the probability of obtaining a wrong or not optimal result decreases when the number of samples increases[39]. In case we are doing an optimization of a finite number of options, in case we generate the results for all of them, the probability of finding the optimal solution is one. In case of an infinite design space this algorithm guarantees variety on the sampling results, since it does not follow gradients or tendencies, when opposed to the genetic algorithm.

Focusing in the particular case of design optimization, this is the same to say that if the design space is finite, the more design options we produce, the more likely it is that we found the optimal solution. When having an infinite design space it is impossible to know if the solution found by the algorithm is the optimal one, but the more solutions we produced, the closer we are to find it. Considering an infinite design space, and considering the fact that we do not have infinite time to search thorough infinite solutions, there needs to be an established method to interrupt the search. This can be either setting a limit of design options produced during the optimization, establishing a minimum or maximum threshold value or setting a time limit.

Genetic Algorithms

To go through an optimization process, an algorithm is necessary to select and sort the iterations. With the increased complexity of the optimization, more complex algorithms are needed. A simple algorithm that tests every option within the design space and saves the best solution, could eventually find the optimal or set of optimal solutions. Nevertheless, considering the computational power and therefore the time it takes to test each one of the iterations of a certain project, using an algorithm like this could reveal itself useless. For that motive, more complex algorithms have been developed: instead of scanning through the entire design space (all possible design solutions), these algorithms try to identify trends that correspond to the best design options. This way, the search time is reduced.

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is considered to be the most suitable algorithm for multi-objective optimization [40]. To lead to a better understanding of the genetic algorithm NSGA-II, a brief explanation of natural selection is necessary.

Natural Selection

The process of natural selection occurs when within certain environmental conditions the fittest individuals of a population can live and pass on their genes, therefore the characteristics that make them adapt to the environment, while other individuals perish, not passing on their genetic heritage (figure 2.12).

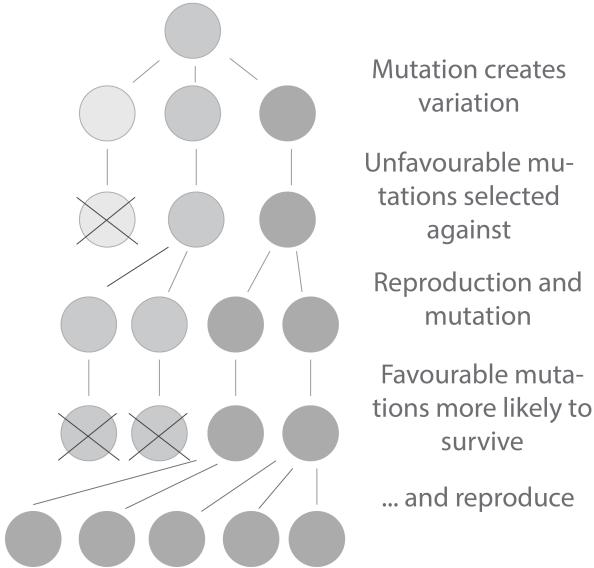


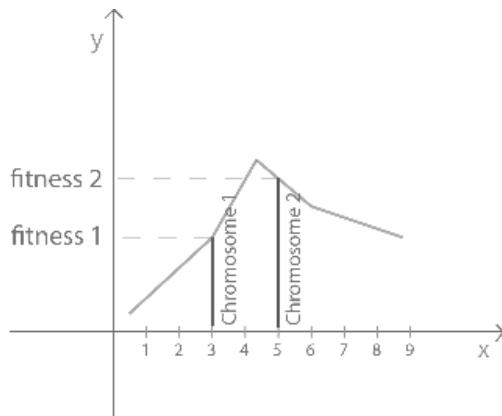
Figure 2.12: Natural Selection. [2]

It is also important to mention genetic mutations: in nature, there are sometimes alterations in the DNA that causes a difference in the morphology of the species. These mutations, in nature, are 70% harmful and 30% neutral or weakly beneficial [41]. When the individuals with these mutations are subjected to natural selection, the ones with harmful mutations tend to perish, the neutral ones tend to reproduce and the ones with beneficial mutations tend to live longer, therefore reproducing more. In a harsh environment or an environment that had radical changes, only the specimens with beneficial mutations tend to reproduce and pass on these alterations to their descendants. The characteristics of the parents are passed on by the chromosomal crossover. The chromosomal crossover takes place when homologous chromosomes exchange segments of their DNA information. This process is called genetic recombination.

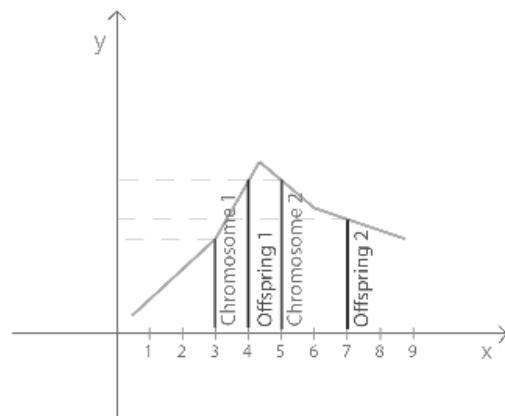
Chromosomal Crossover and Genetic Algorithms

In the genetic algorithms, the crossover process is inspired by the chromosomal crossover. There are many crossover types that are used in a genetic algorithm. Figure 2.13 illustrates two of them: the chromosomes 1 and 2 can be perceived as the parents, whose information will be exchanged. In the first table, we show a binary representation of a one-point crossover and, in the second table, of a middle point cross-over.

In a genetic algorithm, the first generation of the population is usually randomly generated, and the fitness of every individual ranked. The criteria for fitness are given by the objective functions. The closest an individual is to the objective functions' values that are considered optimal, the closest to fitness it is. After the first population is generated, their characteristics are crossed-over and the individuals ranked. These selected ranked individuals



Chromosome 1	0	0	1	1
Chromosome 2	0	1	0	1



Chromosome 1	0	0	1	1
Chromosome 2	0	1	0	1
Offspring 2	0	1	1	1

Chromosome 1	3
Chromosome 2	5

Chromosome 1	3
Chromosome 2	5
Offspring 1	4

Figure 2.13: Chromosomal crossover: one point crossover and middle point cross-over. [3]

will again reproduce and the next generation is ranked. This process happens repeatedly until the population limit (that may be defined by the user) is reached or an optimal solution is reached.

NSGA

Nondominated Sorting Genetic Algorithm (NSGA) is a well-known algorithm used to solve multi-objective optimizations. A nondominated sorting is the ability of the algorithm to rank the generated solutions and maintain a sub-population with the characteristics that are considered to be beneficial for the optimization [40]. As an example of a nondominated sorting, two functions F_1 and F_2 will be considered. The objective is to minimize the values of those functions. Considering 4 solutions as set $A = \{(2, 5), (1, 6), (5, 9), (2, 3)\}$, the different solutions will be compared to find out if they will be dominated by others or not, and be placed in their respective fronts according to their rank. Front 1 will be the solution (2,3), front 2 (2,5), front 3 (1,6) and finally, in front 4, (5,9).

The difference between NSGA and ‘simpler’ genetic algorithms is that, while others are used for a single objective function, NSGA generates a set of solutions. This set of optimal solutions is designated Pareto front. Nevertheless, this algorithm had some criticism due its excessive computational complexity, lack of elitism, and the need to specify a sharing parameter. For clarification, elitism means copying a proportion of the fittest solutions, unchanged, into the next generation. The sharing parameter is usually used to ensure the diversity of the population, but it is required to be specified, which creates a need to find another way to ensure diversity. In NSGA, the complexity can be given by MN^3 (where M is the number of objectives and N the population). This excessive complexity makes the computational process slow. The lack of elitism of NSGA caused both a slower process, when it comes to finding the optimal solution, and the loss of optimal solutions along the way.

Nondominated Sorting Genetic Algorithm II (NSGA-II) is another algorithm used for multi-objective optimization and it can be seen as a correction of the limitations of NSGA.

When running an optimization, this algorithm generates two sets of population with a number N of elements. In figure 2.14, the two populations are represented by P_t and Q_t . R_t refers to the sum of P_t and Q_t . This population is sorted and ranked according to the optimal values in the objective functions. F_1 refers to the best solutions in the combined population. When F_1 is inferior to N, all individuals of F_1 will be chosen for the next population. The next higher ranked solutions will fill the population of P_{t+1} (F_2 and F_3) and this process will continue until no more solutions can be filled in. P_{t+1} has a new population sized N that will be used again for selection, crossover, and mutation, to create the new population and restart the loop process. The crowding comparison system allows this process to keep diversity. The crowding distance is the average distance or density of generated solutions on the neighborhood [4].

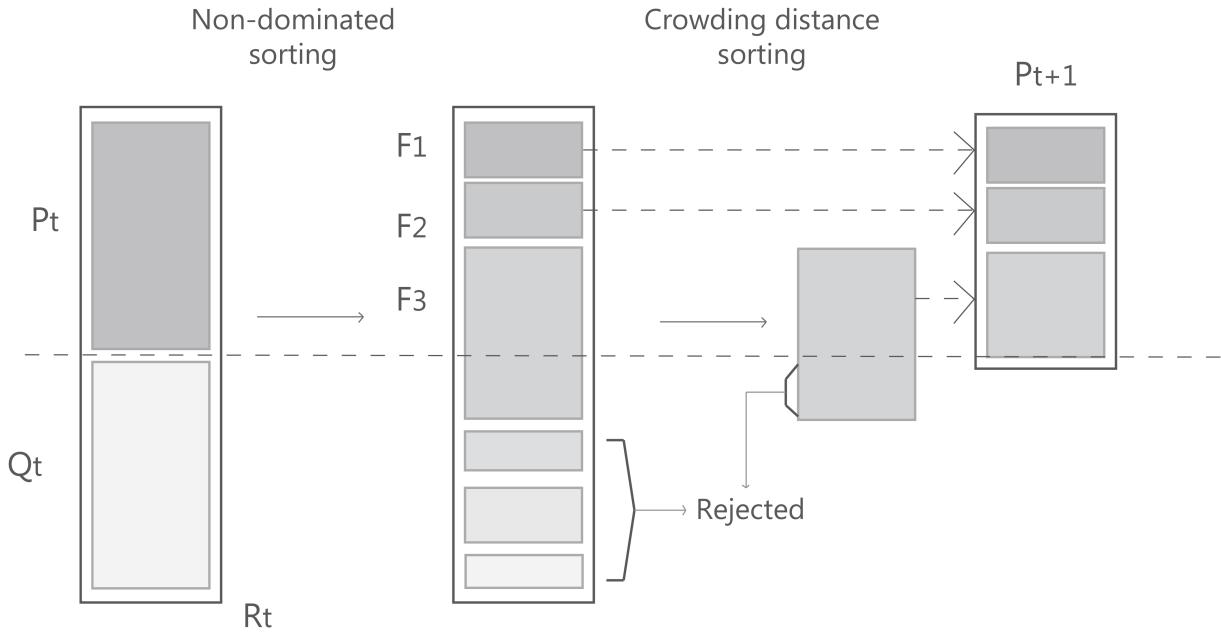


Figure 2.14: NSGA-II process.^[4]

2.7 Related Work

2.7.1 Research Work

Building optimization processes are not new: Hyoungsub (2015) studies the optimization of the façade of the Al Bahr Towers according to energy performance [42]; Ramzi Quarghi (2014), with the purpose of optimizing various performance criteria of a building, changes the shape of a building to the best behavior [43].

Most of the previous work done in this area stands on the idea that the knowledge required to take the design process forward is very difficult to coordinate and chain, in order to favor all the disciplines of the design [44].

Using parametric models and the adequate objectives, variables and constraints, it is possible to optimize a building's performance. There is a vast collection of work done in this area, but most of them use a very simplified version of the buildings, as will be described below.

In the paper “Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design” (2015) [45], Wei Yun tries to achieve thermal comfort and lower energy consumption of a typical Chongqing building through optimization processes. For this optimization, the considered variables are divided into two types: building design and envelope design. The building design variables considered were: layout plans, orientation, shape coefficient, floor area, stories and window-wall ratios for the west, east, north and south orientations. Concerning the envelope design, the chosen variables were: wall heat transfer coefficient and inertia

index, roof heat transfer coefficient and inertia index and window heat transfer coefficient. These variables were constrained to only vary between specific intervals of values. The selected objective functions are both energy consumption and thermal comfort. As a result of the optimization, Wei Yun is given a set of results with different variable values. The changes included in the design space have some architectural translation, but a very simplistic one in the sense that no complex geometry is involved.

Ramzi Ouarghi [43] (2014) optimizes a building shape using a neural network and a genetic algorithm. The optimization problems he considers are energy cost and construction cost. Both the footprint area and the volume of the building are pre-selected, and the footprint is always assumed to be a rectangle. Again, the achieved shapes have poor architectural relevance.

Forest Flager [46] (2012) tries a simple model of multi-criteria optimization. The case study was done in a single classroom building with windows on two opposite façades and a steel frame structure. The variables that were taken into account were the structural integrity, energy consumption, daylight, initial capital and life cycle costs. The objectives were to both minimize the capital cost of the steel frame and the life-cycle cost of the building's operation. As for constraints, the structural members should meet the requirements for strength, daylight performance, and the floor area.

The case study developed by Flager does not have a very noticeable degree of practical relevance since the only thing that is manipulated in the model are the dimensions of the "classroom". Nevertheless, this process shows how it is possible to apply a multi-criteria optimization process in a building, and the inherent benefits of doing so.

2.7.2 Built Work

Before delving into several built projects that have been subjected to optimization processes during the design stage, it is also important to mention examples where the application of optimization tools could have made a difference in the project.

An example of this is the Taichung Metropolitan Opera House, from the architect Toyo Ito (figure 2.15). The geometry of the building is inspired on a Voronoi tessellation, where a horizontal grid is stacked and shifted from floor to floor (figure 2.16). This kind of metric creates a complex geometry. These complex geometries can be well supported in a digital format, but they do not necessarily fit the limitations of construction [47]. This complexity resulted in a series of complications that made the project go over budget and caused major delays in the construction. The reason for this was connected to the concrete's plastic limitations [48]. If an analysis that considered the plasticity of concrete and of the steel frames that support it had been executed to adjust the



Figure 2.15: Metropolitan Opera House.⁴

curves of the design, it is possible that some budget and time would have been spared.

There are many examples of projects that indeed benefited from optimization processes. This section describes some of the most significant ones.

Hyoungsub [42] did an optimization study on the Al Bahr Towers in Abu Dhabi (figure 2.17). The objective of the referred optimization is to make the kinetic façade of the building more efficient as a shading element. To achieve this result, Hyoungsub first studied a more simplistic form of shading device and tried to adapt it to the Al Bahr Towers' façade. This work provides an important study on optimization processes with an aesthetical component.

One of the most relevant examples of cost oriented optimization is the Museo Soumaya, in Mexico City. The Museum was projected by the Mexican architect Fernando Romero (figure 2.18).

The building's design consists on a curved façade that is filled with hexagonal pieces. It is important to mention that the design team for this project requested that the projected curvature of the façade would not be changed: the hexagons had to adapt to the curvature. As a geometry problem, this can be easily overcome by using conformal mapping: a 2D drawing of the hexagonal part is wrapped over the curved surface. This means a certain level of deformation on both the angles and the sizes of the hexagons. These deformations produce new versions of these hexagons, making thousands of pieces with different dimensions [5].

⁴source:<http://www.oistat.org>

⁵source:<http://www.phaidon.com>

⁶source:<http://inhabitat.com/>

⁷source:<http://www.theonlinecentral.com>

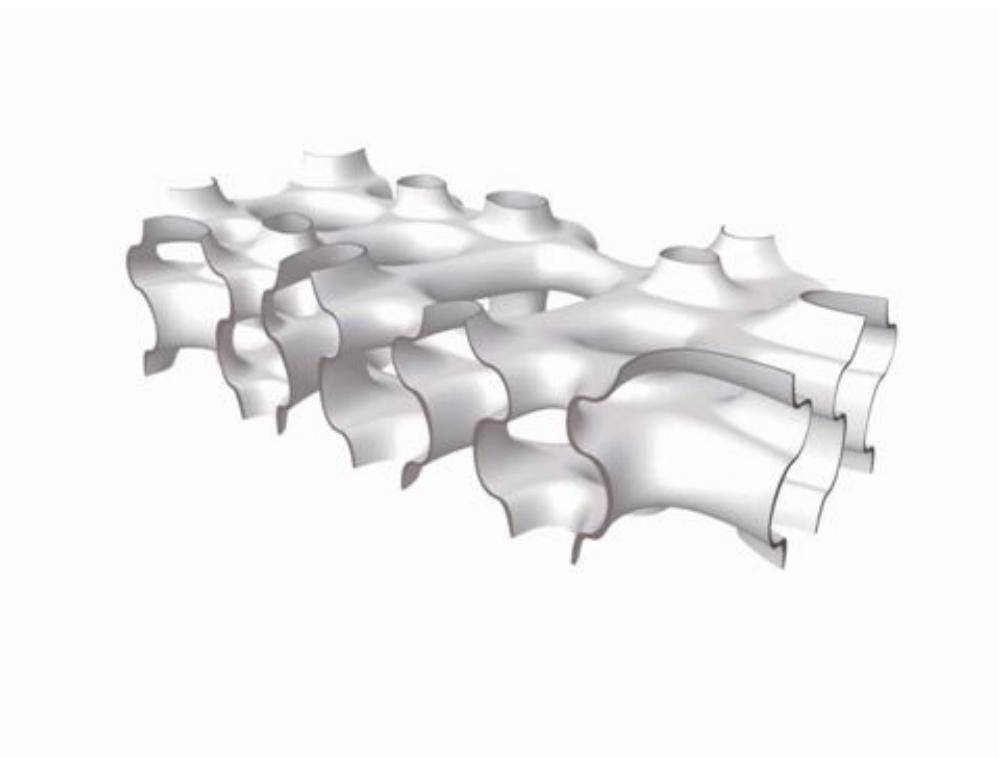


Figure 2.16: Metropolitan Opera House diagram.⁵

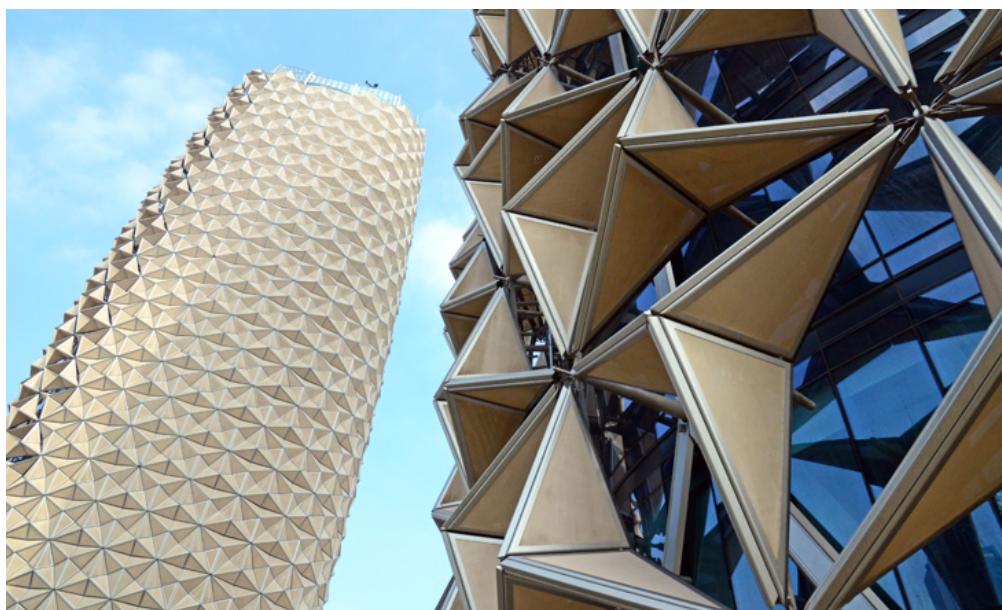


Figure 2.17: Al Bahr Towers, Abu Dhabi.⁶



Figure 2.18: Museo Soumaya.⁷

This situation would be problematic for two reasons: it is not realistic to think that it would be possible to mount the panels over the façade on-site, in the right place, and by unskilled labour; in terms of budget it would require thousands of molds, some of which would probably only be used to make a single piece. Furthermore, the client of this project required, as a personal request, that there could only be either 7 or 24 different kinds of panels. It is important to mention that the differences between the visual intention and the actual panels should not be perceptible to the human eye.

The kinds and respective dimensions of the panels were obtained by using k-means clustering analysis. K-means clustering analysis is a method to group big sets of data. The k-means specifically tries to group a n number of data in k number of groups, according to similarity [49]. This analysis ran and weighted 21 parameters, with the area of the panel being a key one, over the population (figure 2.19). By omitting some of these attributes, different results were obtained, mainly on the result of the panels fragmentation.

When confronted with different options, the decision was made based on the trade-offs between the geometrical and aesthetical implications [5].

The firm Foster and Partners has also done some work in this area, namely in their project British Museum Great Court Roof (figure 2.20) [50]. This project consists of a rooftop that covers the courtyard of the British Museum. This courtyard is 73 by 97 m and has, at the center, a 44 m diameter reading room.

The shape of the rooftop is based on a complex curved mathematical surface (figure 2.21). This surface was intended to be materialized into a triangular truss of steel members. These steel members would be welded in

⁸source:<http://www.modernarchitecturelondon.com/photos/bm-greatcourt-04.jpg>

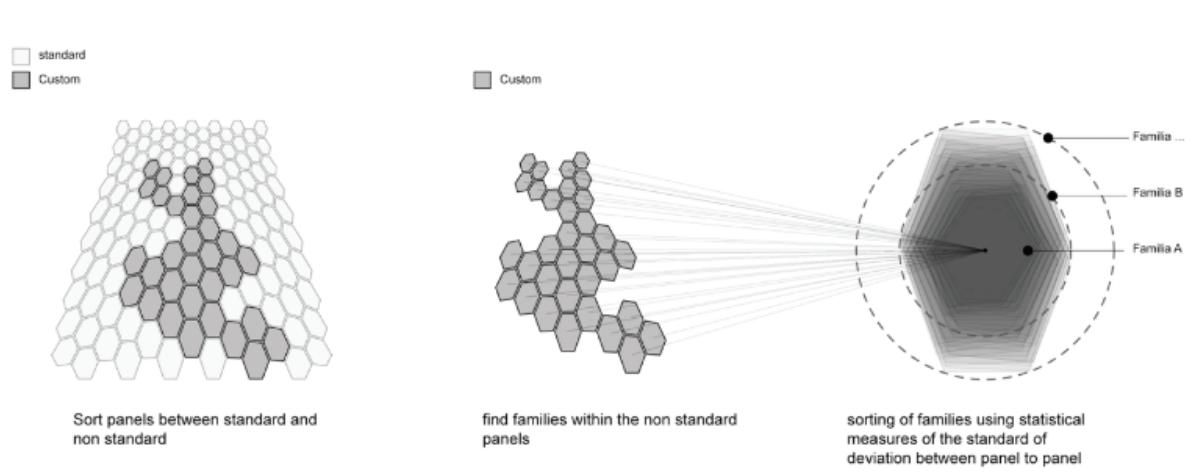


Figure 2.19: Different families of panels. [5]



Figure 2.20: British Museum Great Court.⁸

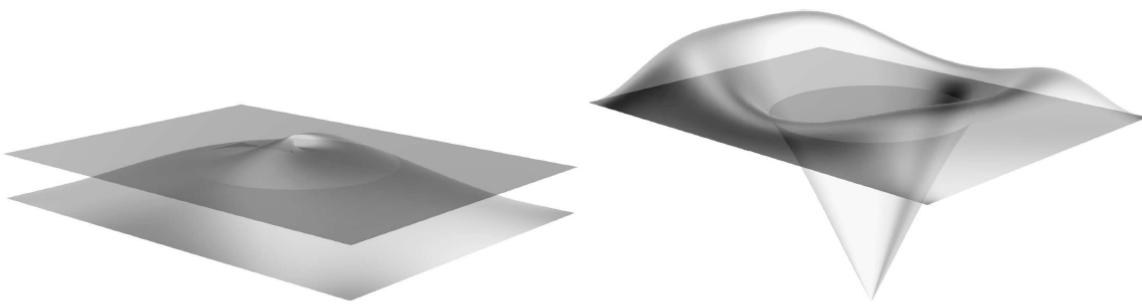


Figure 2.21: Mathematical surface of the roof. [6]

node pieces and covered by glass panels. To materialize this design, these nodes were laid on the surface and the surface was divided into triangles, according to the nodes' positions. Every time the nodes were positioned, a new grid was formed and, therefore, a new triangulated surface.

The most critical points of this design were the corners because that is where the beams meet. To make the rooftop structurally possible, more constraints were added to the corners.

Like in any parametric design process, a lot of solutions were unsatisfactory according to the aesthetic requirements of the firm Foster and Partners. After a structural grid was chosen from the produced iterations, there were further alterations to eliminate undesired effects: the chosen structural grid had some discontinuities in the diagonal direction. These discontinuities were overcome by a *relaxation* process. The relaxation process consisted on manipulating the positions and tensions in the truss's nodes, controlling the maximum glass size [6].

As these examples show, utilising optimization processes are indeed advantageous to the design process. These tools open many new possible ventures into architectural practices, namely allowing for more cost effective buildings.

Chapter 3

Performance-Based Design

"Now take a human body. Why wouldn't you like to see a human body with a curling tail with a crest of ostrich feathers at the end? And with ears shaped like acanthus leaves? It would be ornamental, you know, instead of the stark, bare ugliness we have now. Well, why don't you like the idea? Because it would be useless and pointless. Because the beauty of the human body is that it hasn't a single muscle which doesn't serve its purpose; that there's not a line wasted; that every detail of it fits one idea, the idea of a man and the life of a man. Will you tell me why, when it comes to a building, you don't want it to look as if it had any sense or purpose, you want to choke it with trimmings, you want to sacrifice its purpose to its envelope—not knowing even why you want that kind of an envelope? You want it to look like a hybrid beast produced by crossing the bastards of ten different species until you get a creature without guts, without heart or brain, a creature all pelt, tail, claws and feathers? Why? You must tell me, because I've never been able to understand it." - The Fountainhead, Ayn Rand

3.1 Introduction

As mentioned in previous chapters, architectural design practices have been evolving according to new ways of development and representation. In particular, combining analysis and parametric tools has allowed architects to create progressing iterations of different design options, in pursuit of better performance. By adding optimization tools to this process, solutions with improved performance can be achieved. The parametric model, while relevant for the beginning stages of analysis, has to be redesigned as a meta-model in order to allow the use of these optimization tools.

Optimization processes not only provide a way to improve a building's performance regarding energy, lighting, and structural behaviour, but also a new way to find and explore new design shapes. The initial design degree of flexibility is determined while creating the meta-model: it is the architect's decision as to how extensively the

building can be re-shaped. This process relies on experimenting with parameter's values and establishing a value range on the parametric model, from which they can vary within for the creation of the meta-model. Thus, there are two main approaches for design using optimization tools. With the first approach, there is a very clear set of rules for the building, where the building's parametric elements and their variations create different versions of the same shape. Whereas the second approach uses more open-ended parameters with very high degrees of flexibility, where there is even the possibility of certain shapes having unexpected outcomes.

Architecture Firms more technologically driven, such as Foster and Partners, are eagerly adopting Optimization and incorporating it into a wide variety of projects. Many other firms already combine the use of analysis and parametric tools. The combination of analysis tools, parametric design, and optimization methods allows designers to reach better solutions, in less time and with less effort. The optimization process is able to generate several iterations of the parametric model, and rank them according to their performance.

In this chapter, a parametric model of a new façade proposal for an office building in Shanghai was developed, with the intent of optimizing the lighting conditions. The best metric to ascertain this would be the Useful Daylight Illuminance (UDI). This value was calculated through two different approaches: by manually changing the parameters in the parametric model, and through an optimization process to find an optimal value. For the parametric model, the UDI values were calculated for four design options. For the optimization process, a meta-model was created from the parametric model, sorting out a wider range of design options.

The façade model was created using the parametric tool Rosetta [51]. Rosetta was selected due to its portability, allowing the generation of models in different CAD and BIM environments, including SketchUp, Rhino and Revit, using the same code. Since analysis tools are generally associated to specific CAD or BIM environments, this portability allowed us to easily experiment with different analysis tools, including OpenStudio, DIVA, and Lightning Analysis. During the early stages of this research, this feature was crucial for helping us understand how different analysis tools worked and performed in order to guide our choice of an analysis tool for our experiments. Ultimately, DIVA was selected for our parametric-based analysis due to its easy-to-use interface, close integration with the Rhino environment and use of both Radiance and Daysim to perform lighting analysis.

Another key reason for selecting Rosetta in the development of our case study was the direct connection that was recently introduced between this tool and the daylight analysis tools used by DIVA, i.e. Radiance and Daysim, allowing the model to be analysed without errors or loss of information during the algorithmic-based analysis. This direct connection enables the automated optimization process to occur more smoothly and efficiently.

In order to ensure the constructibility of the project, the façade design also underwent a cost optimization in order to reduce the number of different types of elements that composed the façade. By doing this, fabrication costs as well as the risk of mistakes during the construction phase can be significantly reduced.

Finally, to make sure that the optimal UDI value found would not compromise thermal comfort inside the

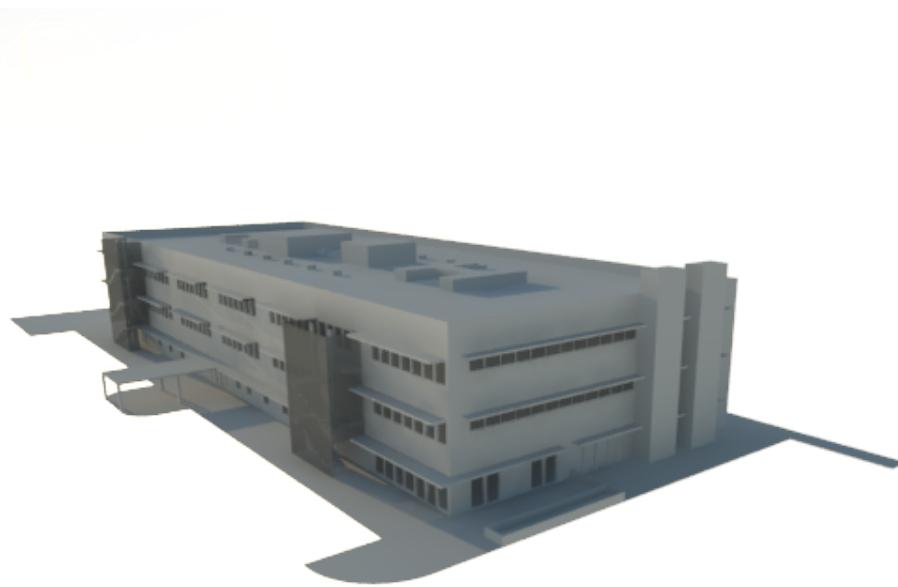


Figure 3.1: East view render of the original building.

building, the parametric model also underwent a solar radiation analysis, to ensure that the UDI values produced an acceptable heat gain range.

3.2 Case Study: Office Building in Shanghai

The case study designed to test our optimization process was a proposed addition to the project for a three-floor office building under development by Walt Disney Incorporated. The first floor of the pre-existing building contains offices of varying size, canteen, a coffee shop, restrooms and several service areas. Both the second and third floors are mainly occupied by an open office space, while also containing a few conference rooms and pantries. The building dimensions are 99.6 by 33.6 meters with a total height of 13.5, 4.33 meters per floor. For intellectual property reasons regarding the Walt Disney Corporation, technical drawings and photos of the existing building cannot be displayed in this document. Instead, figure 3.1 and 3.2 show two renders of the existing building that we were authorized to show.

The building can be accessed through a main entrance door, and alternatively via four sets of exterior stairs, each connecting every floor. As for inner circulation, there is a staircase and elevator in the centre of the building.

Although the building was concluded, it was severely lacking in aesthetic appeal, comfort and overall ambiance. Although it was necessary to improve the interior natural lighting conditions, it was vital to make sure that the

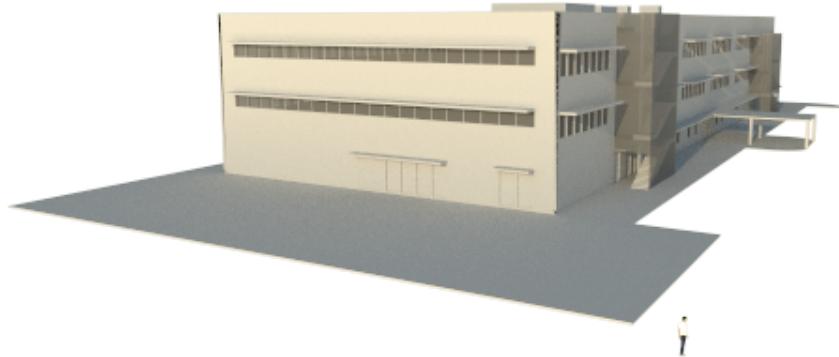


Figure 3.2: West view render of the original building.

resulting design would not compromise the temperature inside the building from excessive solar heating, and consequently the energy consumption for the cooling system. Therefore, we proposed a design for a new façade that would look into tackling these issues.

Design

Since the case study is located in China, the concept for this building's façade was inspired by the dougong, which is one of the most fundamental structural elements in Chinese traditional architecture (figure 3.3). The similarities between elements of a traditional Chinese building (figure 3.4) and a classic European one are easily discernible. In both buildings, there is a platform, columns, and the Chinese toukung can be considered the equivalent to an architrave.

The dougong rests on top of the column and supports the building's roof (figure 3.5). It is possible to draw a parallel between a dougong and a chapter (architectonic element) from ancient greek architecture. The chapter's design varies according to the architectural order: Doric, Ionic, and Corinthian. The process is similar with the dougong, where the number of elements increases according to hierarchy. The fundamental difference between a chapter and a dougong is that the latter is an important structural element in the building. Since the walls are

¹source:<https://en.wikipedia.org/wiki/Dougong>

²source:<https://en.wikipedia.org/wiki/Chinesearchitecture>



Figure 3.3: Dougong.¹

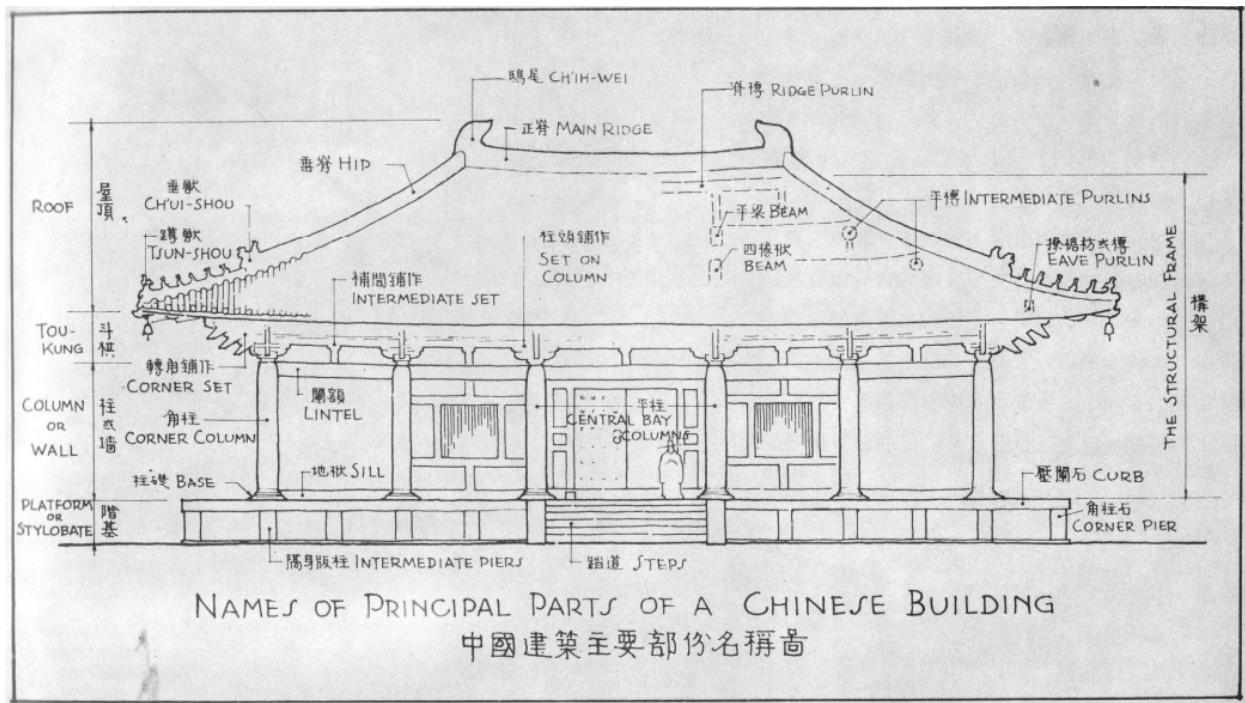


Figure 3.4: Elements in a traditional chinese building.²

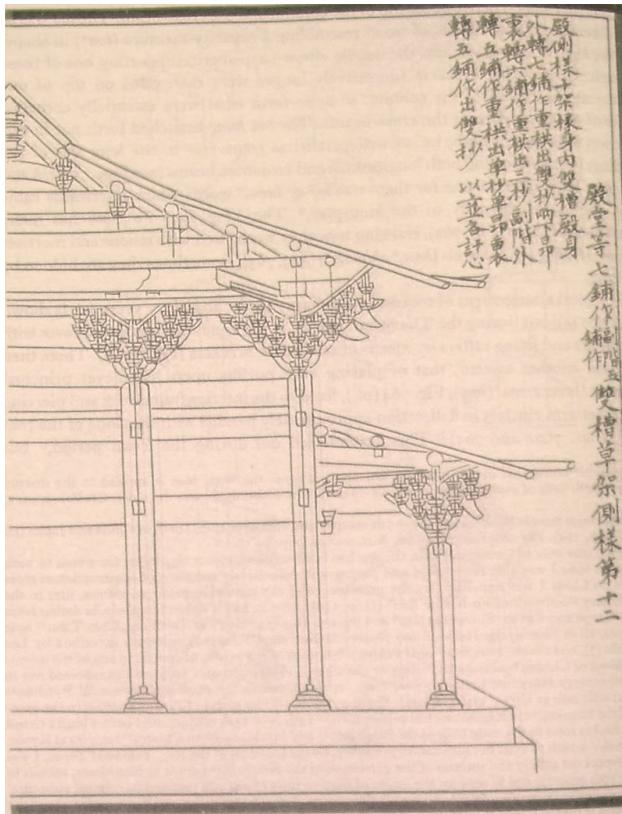


Figure 3.5: Dougong and column.³

frequently built with fragile materials, and therefore are not load bearing, the dougong is a structurally significant element.

A dougong is constructed using a set of interlocking wooden brackets. These sets are formed using a block, on top of a column, and using it as the base for bow-shaped brackets that will support either a beam or another bracket above it. The dougong's purpose is to support the horizontal beams' load, by transferring it to a wider area, and consequently more columns. This element, and the stacking logic behind its structural qualities, was the inspiration for the façade shape (figure 3.6).

The initial design steps for this façade consisted in sketching and re-interpreting the dougong as an architectural and structural element, as shown in figure 3.7. It was also necessary to assess, in a very pragmatic way, the impact that this element would have on the shading within a building. This resulted in the dougong being re-interpreted as a interlock of rectangular elements, weaved together. This weaving of exterior shade devices reduces glare and contributes to a more even diffusion of sunlight [52].

The adopted design for the new façade is a stack of two elements, joined at the edge, with variable dimensions and angle. By stacking these elements for the entire height of the building, a module is formed. From a top

³source:https://en.wikipedia.org/wiki/Chinese_architecture

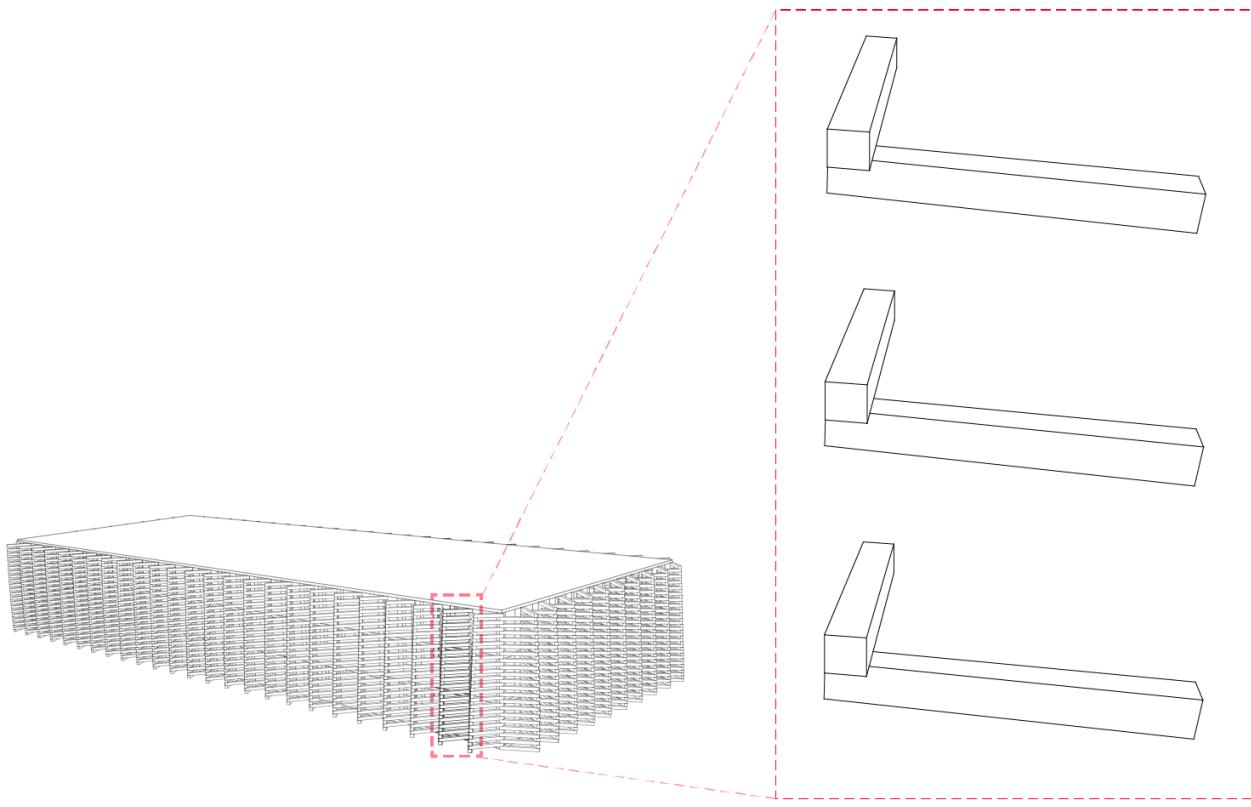


Figure 3.6: Stacking logic and façade.

view, each set of two bars are shaped as a triangle, and each module describes, on its section, a smooth repetitive curvature along the façade, describing an oscillatory design. This movement can be seen in the building section, represented in figure 3.8.

However, if every stack was exactly alike, the design could be perceived as monotonous. In order to enliven the façade, each stack describes its own curvature along the height of the building and the same logic was applied to the variation in plan. This evolution can be seen in (figure 3.9). Each module is composed using the same principle, but each one of them has the maximum wave amplitude at different points. By doing this, the façade will have a more three-dimensional aspect. This was done in order to create dynamic notions of movement and visual flair to be attained while walking past the building. However, it is necessary to understand how these design choices affect the natural lighting conditions.

Due to the complexity of this design, it would be a painstaking process to model it through a manual approach. For each amplitude, or number of waves, each and every element would have to be calculated. By making a parametric model of this design, not only is it easier to model the façade using a mathematical approach to define the waves, but it is also easier to visualize several iterations of this design, by varying the defining parameters. Therefore, it also becomes easier to analyse and compare different design solutions in order to ascertain if the design is capable of providing good natural light conditions without retaining too much heat.



Figure 3.7: Conceptual sketches.

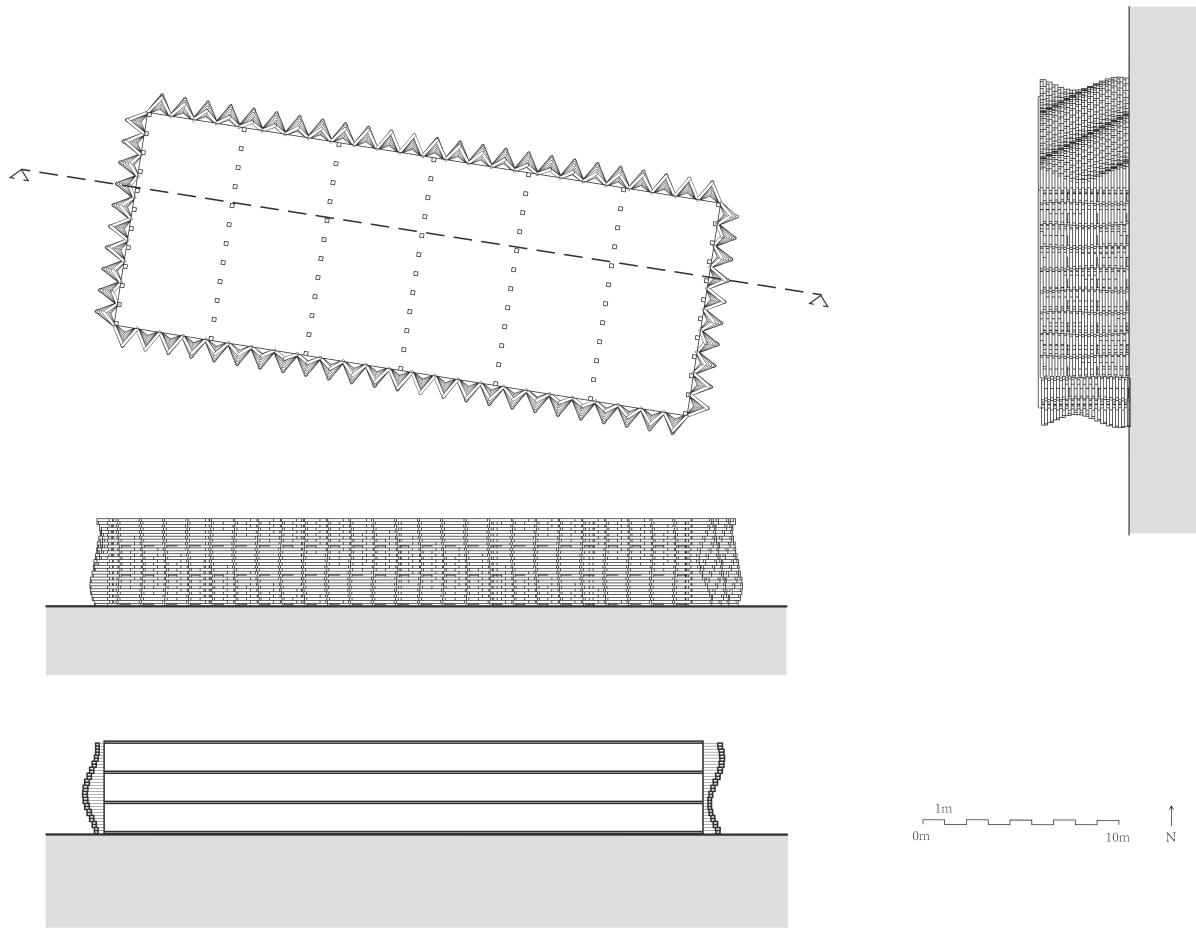


Figure 3.8: Plan and elevations of the façade design.

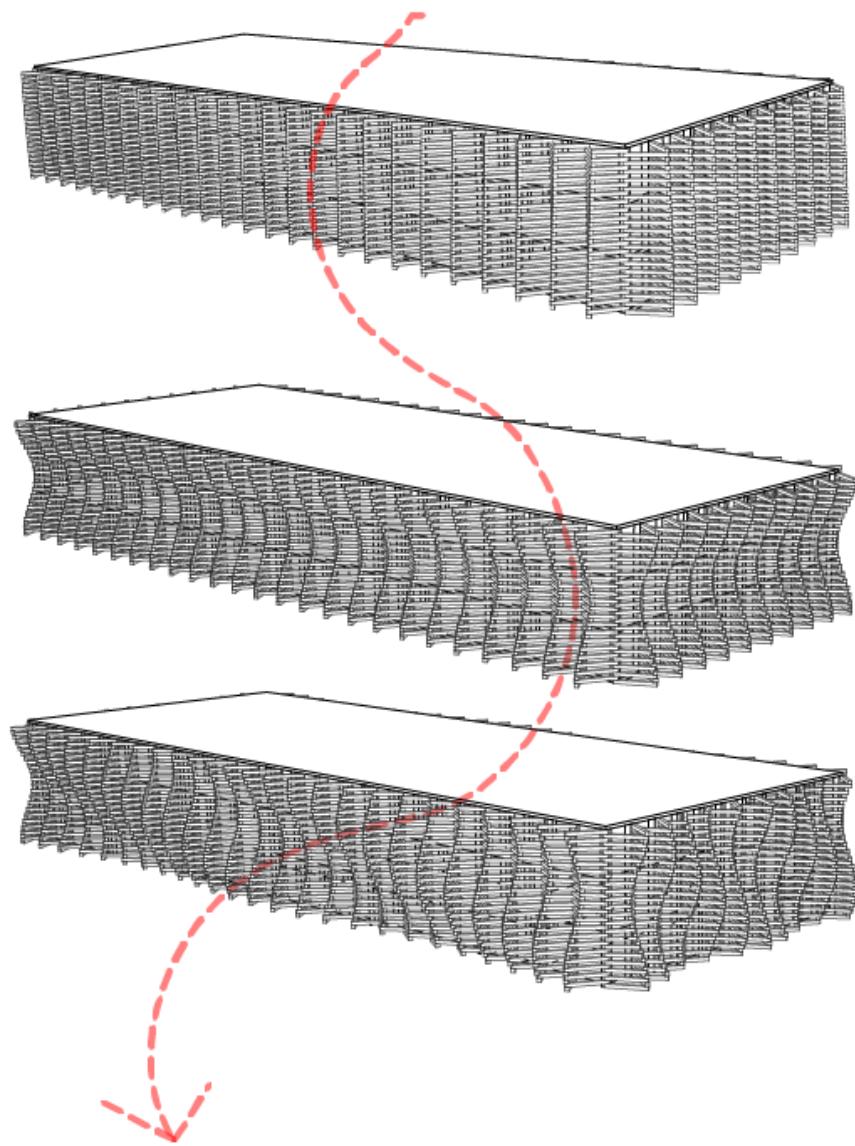


Figure 3.9: Evolution of the parametric model.

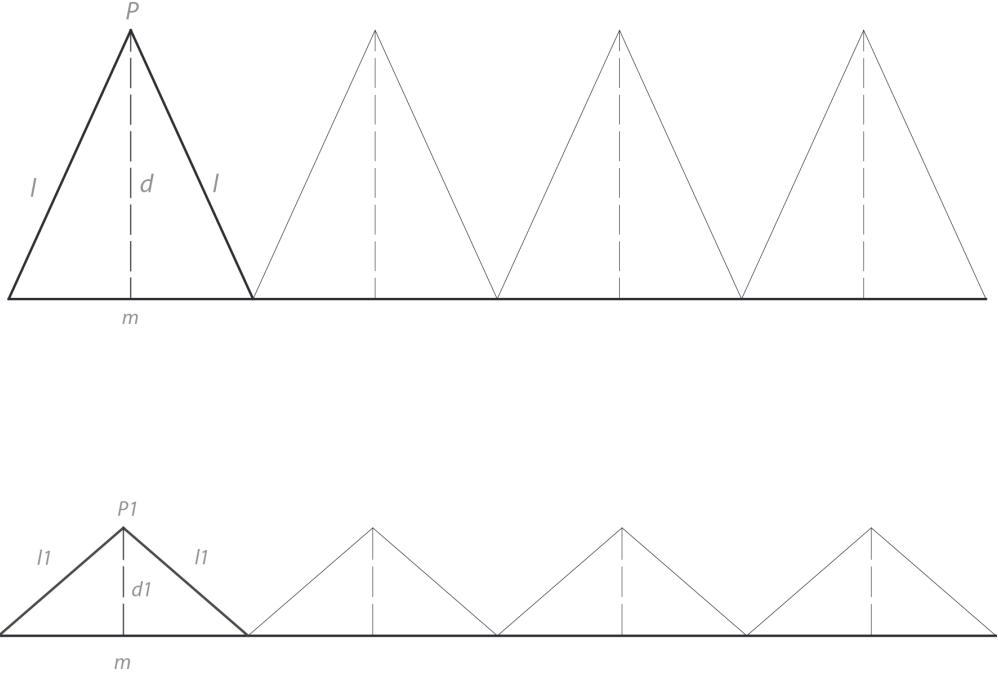


Figure 3.10: Trigonometric relationship between elements.

Parametrization

In order to build a parametric model for the façade, mathematical formulas were used to describe the oscillatory movement of the elements and control the relations that they establish. Therefore, this phase required a thorough understanding of the conceptual portion of the project in order to establish how the parameters should associate and vary. After defining the design, it became clear how this design could be parametrized and which factors should vary. Ultimately, the relevant parameters became the elements' length l and the distance from their joint to the edge of the building d (see figure 3.10).

The variation of the distance d between the edge of the building m and the furthest edge of the stacks P is given by the formula:

$$d = \cos(\text{height}) \quad (3.1)$$

This formula assures that the distance d , and therefore the disposition of the elements along the stack, varies according to a wavy shape along the entire height of the building.

After the distance is settled, it is necessary to calculate l , the length of a given element:

$$l^2 = d^2 + (m/2)^2 \quad (3.2)$$

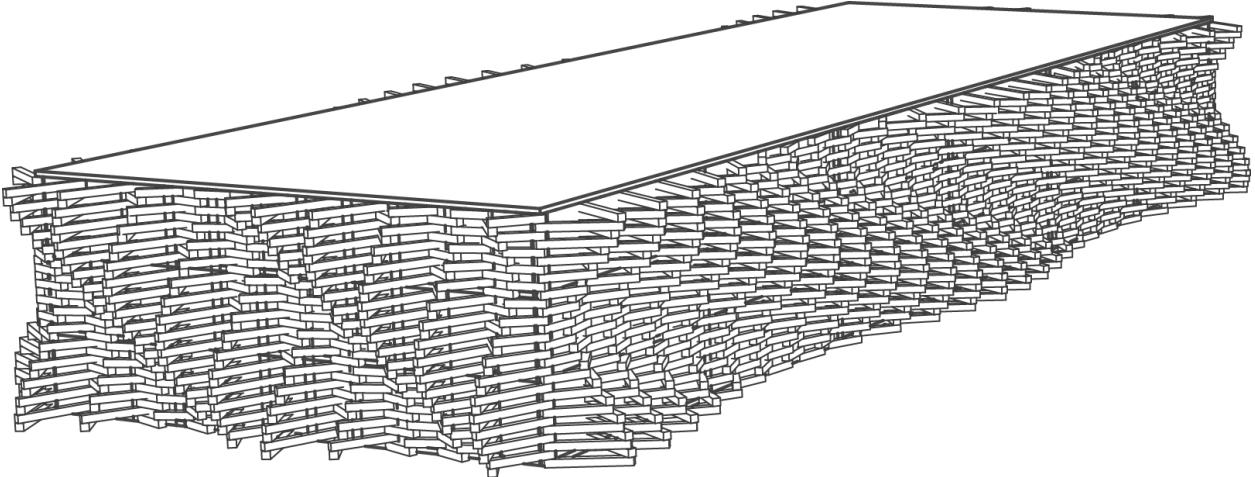


Figure 3.11: Final Design Scheme

$$l = \sqrt{d^2 + (m/2)^2} \quad (3.3)$$

For distance d , the point P , the intersection between the two lines, will have as coordinates $P(m/2, d)$.

$$d_1^2 = l_1^2 - (m/2)^2 \quad (3.4)$$

$$d_1 = \sqrt{l_1^2 - (m/2)^2} \quad (3.5)$$

Having d_1 calculated, the point P_1 coordinates will be $P_1 = (m/2, d_1)$.

It is important to mention that, for simplification purposes, the façade does not take into consideration the openings for doors, and other elements, which are necessary for the building to function normally.

With the parametrization process completed, the resulting façade design can be visualized in figure 3.11.

Given the wavy shape of the façade, the length of the elements varies along the building, resulting in several different types of elements, each with different lengths. This situation could potentially cause several complications during construction and have a devastating impact on fabrication costs. Thus, the following section will attempt to reduce the number of elements with different lengths, without compromising the design intent.

It is important to mention that we did not try to build the model for this building manually due to being too difficult, if not impossible. Moreover, using a manual approach to change the model would require almost a complete rebuilt, making the parametric approach ideal.

3.3 Reducing the Number of Types of Elements

The original design has 346 types of bars, and each one of them has to be placed in a particular order and position. It is not reasonable to assume that, on a construction site, these bars could be set by unqualified labour in the right order and place. However, it would be reasonable to assume that, with fewer modular sizes, the risk of mistakes during the construction process would be reduced.

It is important to mention that sometimes a building needs to go through considerable changes in order to adapt to a limited geometrical model so that it can be translated into a practical construction method. When these changes are not carefully planned during the design stage they can have severe effects on the design intent as well as the construction budget, as described in section [2.7](#). Therefore, before testing different amplitudes for the cosine wave and their effect on Lighting Performance and Solar Radiation, it is necessary to come to a number of types of elements that would allow this design to be built. Otherwise, the optimization process for the lighting performance might point towards a solution that is not possible to build due to the high number of different elements.

In order to reduce the number of façade elements, we developed a script that makes the smallest possible adjustment to each generated bar so that its length is one of a pre-selected set of acceptable lengths. This script accepts a minimum and maximum value for the size of the bars as well as a variation increment. This increment is variable so that bigger increments mean less variety of bar lengths available. Using this script, the length of each bar is compared to the bar sizes generated by the chosen increment in order to determine which size the length is closer to. Each bar is then adjusted to one the closest match. In the end, the script returns the generated bar sizes as well as how many bars were adjusted to each size.

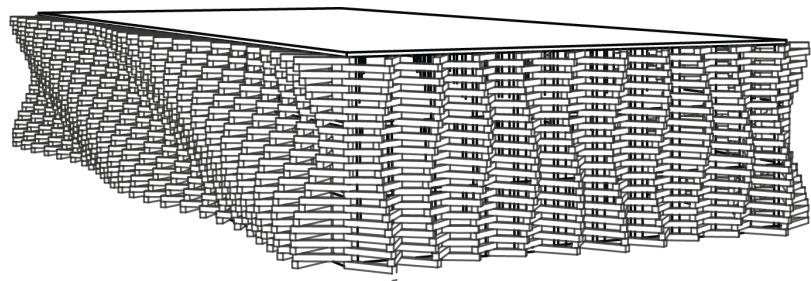
By simply changing the increment size, it is possible to visualize the impact on the design, but also generate a different number of bar sizes and compute how many bars fit into each size.

Figure [3.12](#) illustrates what can be described as a discretization process, where it is very notorious how the design is progressively discretized by the bars adjustment. By increasing the increment, the fewer number of different bar sizes there are, thus reducing the number of different types of elements. At the same time, being that the design describes a curve in section, the larger the increment to adjust the bars is, the wider gap there is between the geometrical design and the adapted design: ultimately, the curve starts to form noticeable steps. At this point, resolving this problem becomes a matter of trade-off between the number of different bar sizes and the design intent.

This discretization process can go even further: changing the amplitude of the wave has a deep impact on the number of types of bars contained in the design. This factor is of utmost importance, since the following optimization process will rely on changing the amplitude values in order to optimize the design.

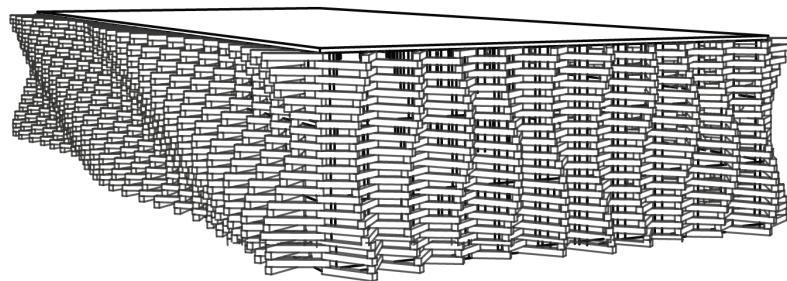
Increment: 100 mm

16 types of beams



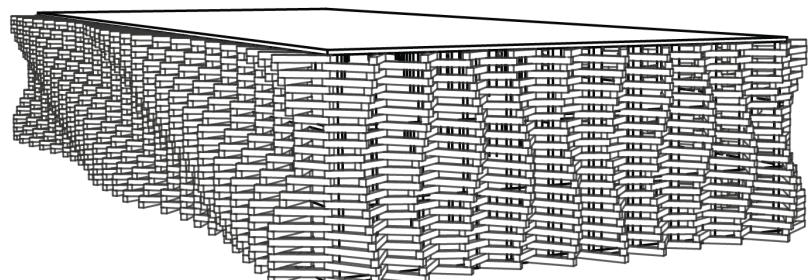
Increment: 200 mm

8 types of beams



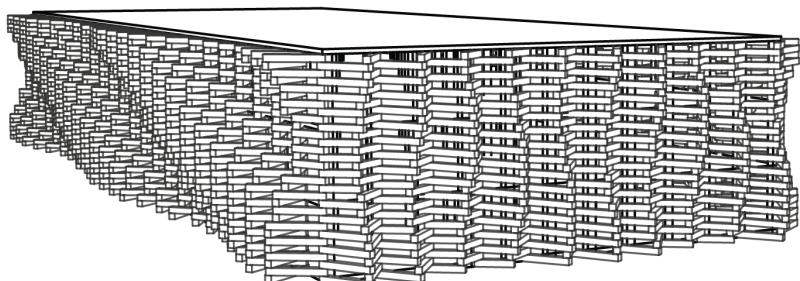
Increment: 300 mm

6 types of beams



Increment: 400 mm

4 types of beams



Increment: 500 mm

3 types of beams

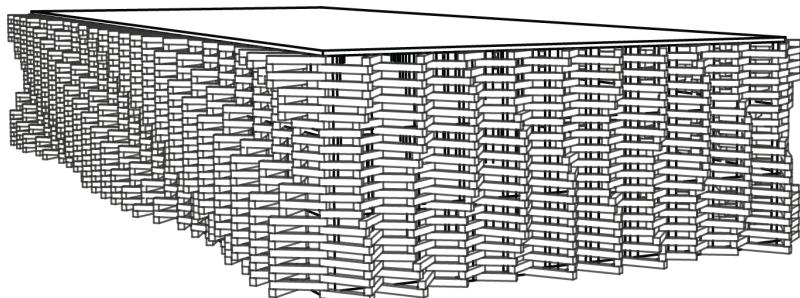


Figure 3.12: Discretization.

By looking at the discretization results, it is possible to see that, as far as 8 different types of bars, it is possible to maintain the design intent while reducing fabrication costs resulting from the variety of different bar sizes. This would also make the construction process easier, while reducing the risk of mistakes.

Having established a fixed number of different bar types, we can proceed to the optimization process regarding the daylight performance with the expectation that the resulting design will not be compromised by over-budget issues.

3.4 Enhancing the Daylight Performance (UDI)

To evaluate daylight performance in the proposed design, the considered metric is the Useful Daylight Illuminance (UDI). As mentioned previously, UDI is the range of illuminance across a work plane considered useful by occupants, measured within an annual time frame [15]. The reason behind this choice is because the case study is an office building, and this metric considers useful values of light to perform work.

In order to find the façade design that provides the best lighting performance, it is necessary to generate many variations of the building in order to assess and compare the results. Consequently, in order for an optimization process to be possible, the simulations could never be set up in a way that one single iteration of the building would take hours to evaluate. If each iteration takes hours or days, it means that the optimization would need to run for weeks before getting any meaningful number of iterations.

Firstly, we established four design solutions, from the original parametric model, that will be tested individually through the selected analysis tool, in order to compare the UDI values. Afterwards, the meta-model, which also originated from the parametric model, will be tested through an optimization algorithm. This process will test a new approach, called Algorithmic-based Analysis, which automates the process and delivers more reliable results while reducing the time needed for the simulations.

The algorithm used in this process, which will be explained in detail, will search for the optimal UDI values for the amplitude, which was the variable tested in the manual approach. Moreover, the algorithm we will also use materials for the façade, in terms of their UDI value.

3.4.1 Manual Changes to the Parametric Model

Before explaining the evaluations that were performed for the parametric model, it is useful to understand how DIVA for Rhino, our chosen analysis tool to perform the parametric-based analysis, works.

There are four necessary steps to complete a manual evaluation when using DIVA, each utilizing a different menu in DIVA's graphical interface: (1) submitting the location, (2) setting the analysis nodes, (3) assigning the materials, and (4) inserting the metrics (see figure 3.13).

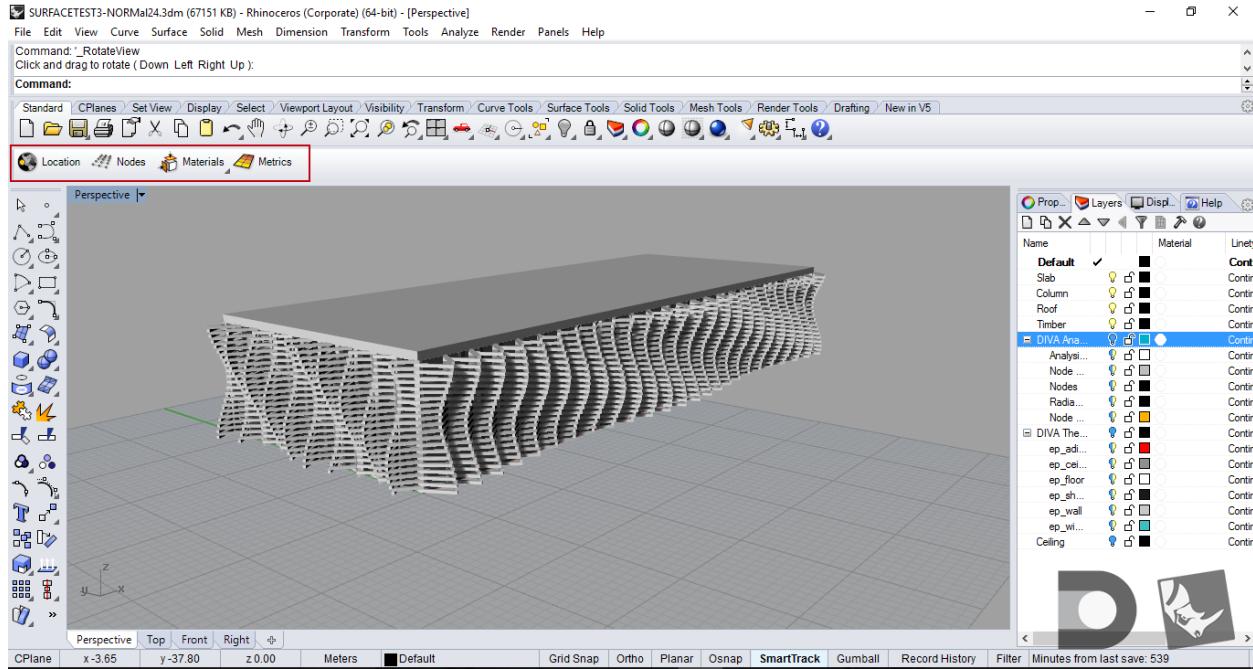


Figure 3.13: Menus on DIVA for rhino.

On the **Location** menu, we input a weather file for the building's location, in this case a file for Shanghai was used. This weather file contains the geographical coordinates of the building's location. This data allows DIVA to consider the appropriate temperature data as well as the correct sun's trajectory, over the course of one year.

The light-sensors are set on the **Nodes** menu. These measure the light intensity on a specified surface, and display it according to the selected type of evaluation. In order to define the nodes, firstly, it is necessary to select the planar surface that will be divided for analysis. In this case, the surface will be each one of the floors that compose the building. The second request is the height of the nodes. The relevance of the height is connected to the function of the building. In this case, as it is an office building, the ideal height is the plane level of an average work desk: 0.8 meters.

As for the **Materials** menu, it is possible to assign materials to the project's different layers. Therefore, it is crucial to appropriately set the layers, according to the constructive elements, so that the simulation can be done correctly. The materials are suggested according to their constructive role, and their coefficient of reflectance is considered in the simulation.

Finally, the **Metrics** menu includes several simulations related to thermal performance, lighting levels, and glare. The simulation done was the "daylight grid-based climate-based". Being "grid-based" means that the simulation result will be presented as a colour-coded grid above the floor. This colour code corresponds to the percentage of time that a certain area is within the desired lux interval. As for the occupancy schedule, it is once more taken into account that it is an office, so the expected work schedule would be from 9 am to 5 pm during

weekdays.

Taking these four steps into account, our case study was evaluated regarding its UDI values. The results of the simulations show the percentage of time, measured within an annual time frame and the established occupancy schedule, in which nodes are 50% of the time within the UDI range between 100 and 2000 lux. Thus, in order to improve the building's lighting performance, the goal of the simulations performed was to maximize the percentage time in which nodes are within the established UDI range. To do this, several variations of the design were generated, evaluated and compared in order to find the iteration with the best UDI results. The solutions tested were 500, 1000, 1500, and 2000, which are non-dimensional values for the wave amplitude.

The parametric alteration considered for these variations was the *amplitude* of the wave, i.e. varying the distance between the edges of the building and the furthest edge of the façade design. In this particular case, the goal was to understand whether alterations in the wave amplitude would impact the UDI values. The hypothesis was that increasing the wave amplitude would improve the UDI values.

When performing DIVA evaluations, the ideal distance between the nodes is considered to be 0.4 m [17]. At the same time, it is advisable that they stay no more than 90 cm from each other, for accuracy reasons [17]. However, due to the size of the building, these node distances would create over 5000 nodes. When this happens, the DIVA plug-in cautions that a simulation with 5000 nodes might take hours, or even days, to be executed, which is particularly problematic when several simulations are needed. To speed-up the simulation, it is necessary to reduce the total number of nodes, which means that we need to increase the node distance.

In order to test if increasing the node distance would compromise the results, it was first studied how this distance affects the results. In Figure 3.14, it is possible to compare the percentage of nodes that are between 100 and 2000 lux at more than 50% of the time, for different node distances. The graph shows that for the variation of a node distance from 0.4 meters to 2m, the UDI percentage varies only between 79% and 85%, an acceptable margin, considering the dramatic reduction in the simulation time that the larger node separation allows. Despite the possible error in the UDI evaluation that results from increasing the node distance, by running all simulations using the exact same node distance, we get a consistent evaluation that allows us to compare designs. Thus, by increasing the node distances, we were able to speed up the simulations without significantly affecting the results. In the end, the distance between nodes used for this case study was 2 meters.

The results of the simulations performed for the four considered design solutions can be seen in figure 3.15, which shows that the optimal design for the best UDI value, of 80%, is the one with the amplitude value of 2000.

Using a parametric approach, generating variations of the design becomes effortless. Nevertheless, setting up the simulation, making sure all the steps have the same values, and finally, the simulation itself, is a very time-consuming process. It also requires that whoever is running the operation to be periodically checking when the parametric model is generated and the simulation is over. Each iteration, including generating the model,

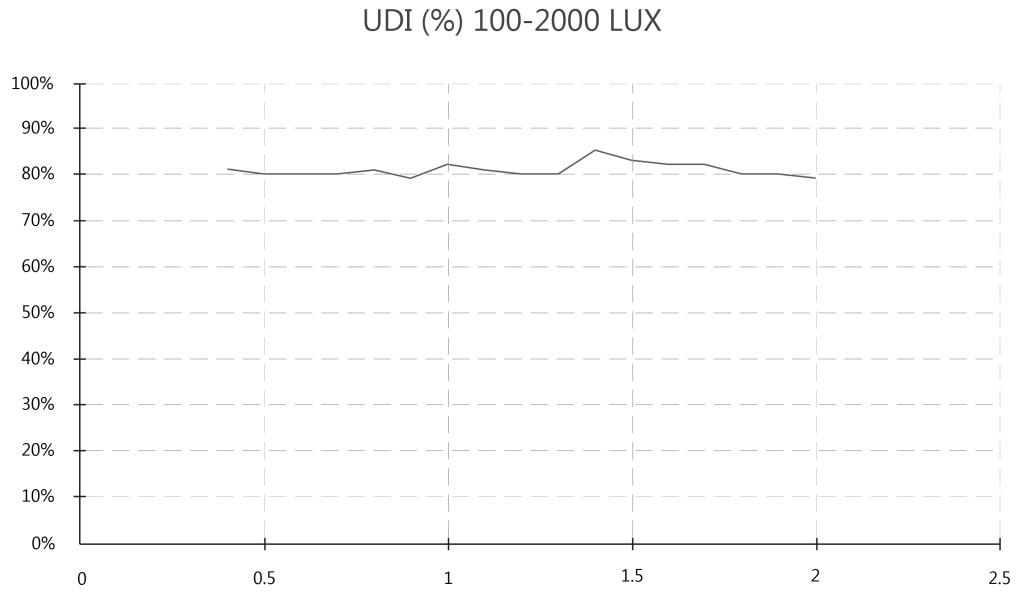


Figure 3.14: Percentage of UDI and distance between nodes (m).

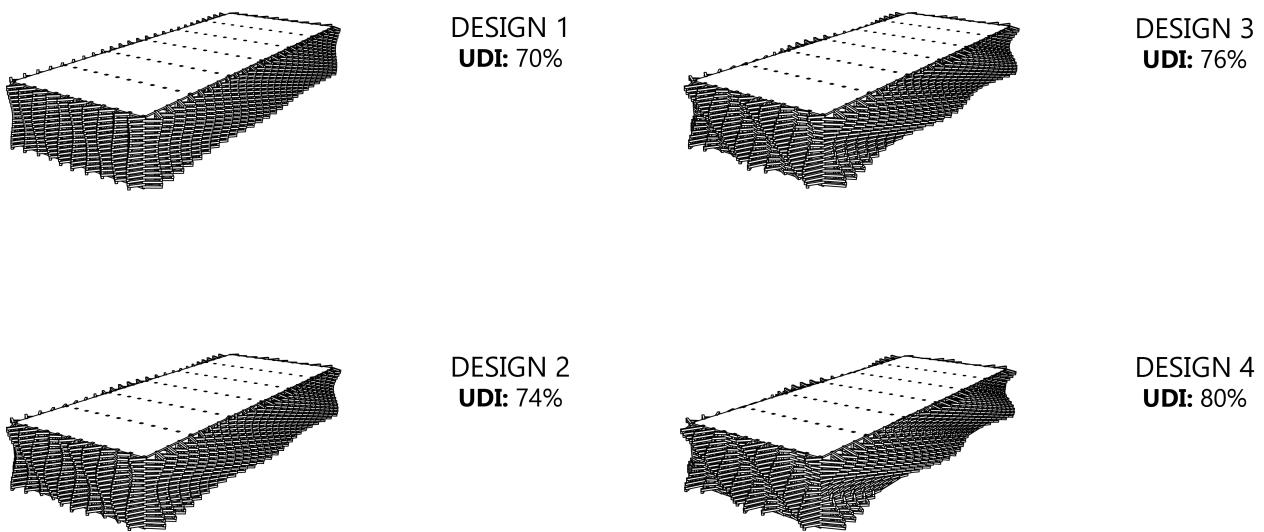


Figure 3.15: Four building versions and respective UDI's.

setting up the simulation and obtaining the results takes about 2 and a half hours for lighting analysis.

Still, when compared to a manual approach, using a parametric model represents a very significant improvement in the time it takes to generate a solution, and in the quality of the solutions produced. This is because introducing changes to the model using parametric tools is quicker and effortless when compared with manually changing a 3D model. It also allows users to quickly understand which parameters have an influence in the building's performance, and the ones that do not impact it at all. This is commonly understood as identifying the design trends according to performance, which are useful during the optimization process to narrow down the design space. The design space is the set of every possible solution for that design, and by selecting the relevant parameters as variables for the façade optimization, it becomes easier to generate only the models that produce the best results for the intended feature.

3.4.2 Algorithmic-Based Analysis

During the early stages of this research, when experimenting with different analysis tools and performing various types of simulations, we quickly realized that there are often many exportation errors when transferring the model built in a CAD or BIM environment to the various analysis software. These exportation errors occurred due to the various formats that different programs require. Furthermore, the 3D models built for design purposes frequently contain far more detail than required for analysis. This means that, in some cases, the architect needs to rebuild a simplified version of the model, containing only the relevant information for analysis. Both the exportation errors, and the use of simplified versions of a model can make the analysis results unreliable. As a result, building a new model or correcting errors becomes necessary, which is time-consuming.

DIVA for Rhino already represents an improvement in terms of interoperability: DIVA is already embedded in Rhino, which means that DIVA internally handles the details related to exporting the model file to a different format for evaluation, thus reducing the risk of exportation errors.

Figure 3.16 shows an example of how the data flow works in DIVA. First, the user builds a 3D model in Rhino. DIVA reads the model and sends the necessary information to Radiance where the simulations are run (1). The results are then communicated back to DIVA which uses the Rhino model to show them (2). Despite this improvement, DIVA still often requires the model to be simplified for analysis, or otherwise the simulation may not be executed properly.

In addition, as explained previously, performing manual simulations, even when using a parametric model, is a repetitive and time-consuming process due to (1) having to repeatedly set up the simulations, using the same steps and values, and (2) the time needed for the model to be generated and for the evaluation to run. For an optimization process, this becomes even more problematic due to the large number of iterations that need to be

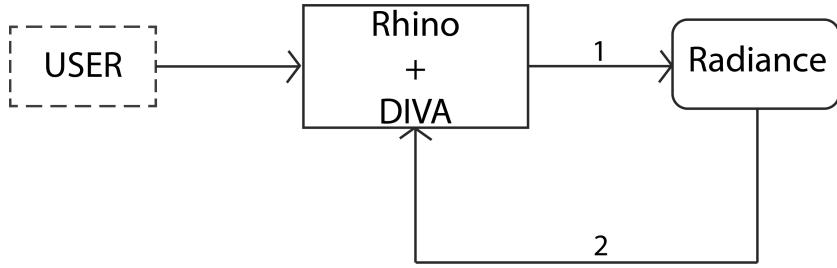


Figure 3.16: DIVA's data flow

tested in order to have a large enough sampling to find an optimal solution. To address these problems, a new analysis back-end was created for Rosetta, connecting directly to Radiance and Daysim to automate the analysis process, making it more reliable, and reducing the time needed for simulations.

Using Rosetta's analysis back-end, the model is set to only generate the information relevant for the simulation. This means that, despite sharing the same source code, the model given to the simulation tool is a different version from the one produced in a visualization back-end. In other words, the tool that generates the model, i.e. Rosetta, is always the same, but different back-ends can be chosen according to what the user wishes to do with the model. If the user wants to see the model that is being developed, they can visualize it in one of the various CAD and BIM applications supported by Rosetta, and the generated model will contain all the information supported by the chosen back-end. On the other hand, if the user wishes to run simulations in the model, using the analysis back-end, the model produced will be tailored for analysis, containing only the required information and/or simplifications that the user would normally have to do manually.

Figure 3.17 illustrates the data flow introduced by this new back-end: the user models his design parametrically in Rosetta with no concerns regarding the analysis tools' requirements and then (1) Rosetta sends to the simulator only the necessary information for the analysis to be performed. After the simulation is concluded, the analysis results are retrieved (2) and the results can either (3) be displayed in the 3D modelling back-ends, e.g., Rhino or AutoCAD, or (4) exported for further processing, for example, in Excel.

When using this analysis back-end, the analysis results themselves have no visualization unless a platform (e.g. Rhino, AutoCAD or Excel) is chosen to visualize them. The reason for this is because the publication of these results into a visualization format uses a significant amount of computer power which slows the analysis process down. For an optimization process, where several simulations need to be executed, this would cause the optimization to take an excessive amount of time to run. Moreover, the optimization algorithm does not actually need the results to be published to be able to use them, it only needs the results themselves. Therefore, by skipping the publication of the results into a visualization format as well as reducing the analysis model to only

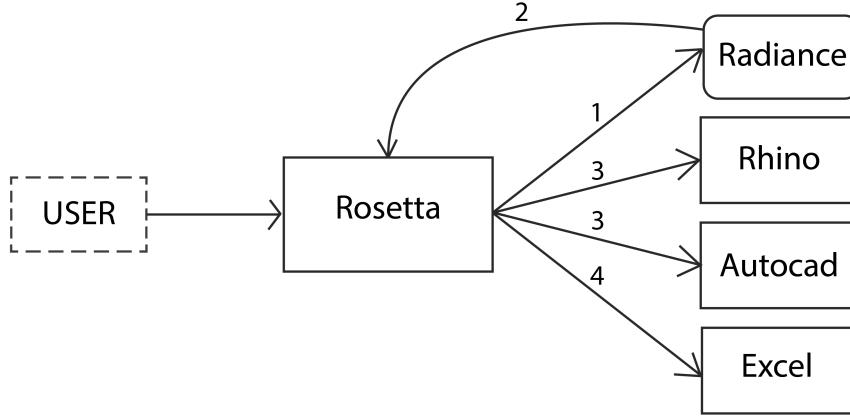


Figure 3.17: New backend's data flow

the relevant information needed for simulation, the optimization process can be significantly speeded up. When the optimization is concluded, the user can then choose to visualize the results as well as the obtained design by publishing them in the desired platform.

With this tool, most of the process of analysing and ranking of design solutions happens at an *algorithmic level*, only showing the results when an optimal solution is found or the optimization is stopped. We call this approach **Algorithmic-Based Analysis** and we claim that this method reduces the loss of information or misinterpretation of the model, making the results more trustworthy. To confirm this hypothesis, this method was used in the optimization process. Based on the results of the previous section, we were able to find the relevant parameters and reduce the design space, establishing a baseline for the optimal UDI values. The objective is to find similar or better results, through a more efficient and less time-consuming method.

Using this approach, we seek to find the optimal UDI values for the façade design, using the previously developed parametric model as the starting point for the optimization process. Using Rosetta's analysis back-end, the model's information, in terms of level of complexity and type of data, are produced according to what the analysis requires. Since the optimization process is automated, the user does not have to re-build the analysis model every time a new variation is tested, since the changes directly translate into the analysis tool's needs.

In the following sections, we present two optimizations executed using this method of analysis to optimize the UDI values of the façade design.

3.4.3 UDI Optimization through Amplitude Changes

The goal of this optimization is to explore the amplitude of the façade's wave in order to find the best possible solution for the building's lighting performance, measured through the UDI.

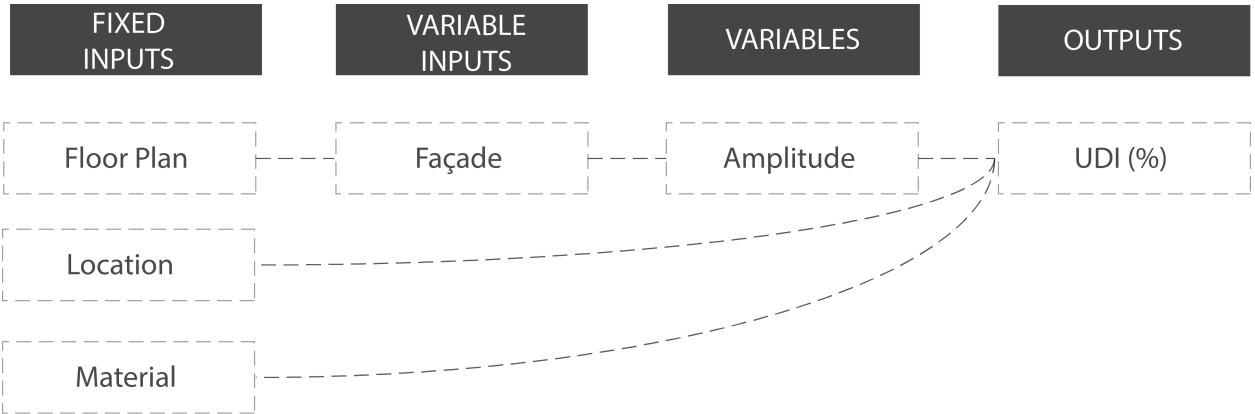


Figure 3.18: Data flow.

Framework

As mentioned in section 2.6, the components needed for optimization are fixed or variable inputs, independent or dependent variables, objectives/outputs, and constraints. The inputs comprise the information that Radiance must receive to produce the outputs. For the presented case study, the fixed input information consists of the building's location (Shanghai), façade material (we used a generic material provided by Radiance), and the building's floor plan. These fixed inputs differ from the variable inputs in the sense that neither of these things will change during the optimization process. The variable input considers the façade, in which the independent variable used, i.e. the parameter we wish to optimize, is the amplitude of the façade's wave, and there are no dependent variables. The objective/output is to reach the highest possible UDI percentage value, while the only constraint is that the values of the variable should stay between 500 and 2000. These constraint values are non-dimensional and correspond to the limits considered aesthetically acceptable. The workflow resulting from this optimization is schemed in Figure 3.18.

Meta-Model

As previously explained, a meta-model is a parametric model built for optimization. As the prefix "meta" suggests, it is a model of the model, meaning that it represents all that the building can potentially be.

To build the meta-model, it is necessary to automate the way in which the parameters vary - mechanizing the optimization process requires doing the same to the analysis process. The Rosetta back-end already automatically sets up the analysis model and its simulation, as described previously. This automation process results in the general geometry of the building being simplified to only the elements that affect the simulation. In the original parametric model, the geometry was associated with architectural elements (slabs, beams, columns, etc). By removing unnecessary information for the analysis, the architectural model turns into the analysis model. When

running the simulation, this information is simplified into geometrical surfaces, resulting in a more abstract version of the building. This abstract version is advantageous because it needs less computational power, resulting in a faster generation of the model.

For this phase, the meta-model was built from the parametric model used in the previous sections. This meta-model accepts a variation of wave amplitude. This variation will create a series of different versions of the building that will be evaluated by the analysis software. Defining boundaries for the variable is important since these limits correspond to the limits of variation of the design that the designer finds acceptable. This process reduces the design space, which results in a faster search time.

Algorithm

In an optimization process, there is generally a range of variation that is accepted for each parameter. The combination of parameters creates a multi-dimensional Cartesian space. The product of the number of values each parameter takes gives us the size of the design space. For this optimization the only parameter considered was the amplitude of the wave of the façade.

The algorithm used in this optimization is the Monte Carlo Algorithm, mentioned in the section 2.6.1. The reason behind this choice is because it is the most adequate algorithm for a single objective optimization. This algorithm searches through the design space by evaluating solutions randomly generated within a specified interval. This range should be defined by the architect, therefore representing the set of values between which the designer feels comfortable iterating his design. Once these limits are set, the algorithm will search through the values, strictly contained within the interval, and rank the solutions found according to optimal performance.

This algorithm tests different amplitude values and retains a value only if it has a better performance than the previous ones. In other words, the new iteration has a better performance if the new value is higher than the previous one. This algorithm generates random amplitude values, and within the interval of 500 and 2000. These limits were imposed since the aesthetics of values beyond that interval do not correspond to the design intent. We gave a time limit of two days for the algorithm to search for the best performing version of the building.

Optimization

Once the algorithm is running and finding design iterations, the optimization process starts. While this process takes place there is no need for interaction between the model and the architect, since the process is fully automated. In case the design space is finite, the architect can wait for all options to be generated. In case it is infinite, the designer can either set a time limit for the search and stop it, set threshold values within which the optimization should stop or impose a limit of generated designs. For this optimization we set a time limit of

Table 3.1: Iterations, amplitudes and respective UDI values.

Iteration Number	Amplitude	UDI
0 (of 270)	1415	78%
2 (of 270)	1616	80%
13 (of 270)	1868	81%
49 (of 270)	1776	82%

two days. In Figure 3.19, we can see the scatter plot of several of the obtained solutions. Each dot in the scatter plot represents a different version of the building. Looking at these results, it is evident that the UDI values and the amplitude do not have a linear relationship. This means these results would be impossible to predict using a mathematical function, accentuating the need for the analysis.

The optimal amplitude value found for the façade design by the implemented algorithm is 1776, with a UDI of 82%, corresponding to the 49th iteration of the building. This solution can be visualized in the scatter plot on the right 3.19.

Table 3.1 shows the best four optimal values obtained and their respective iteration number.

3.4.4 UDI Optimization through Material Changes

For this optimization, we decided to test different materials for the façade elements in order to understand the impact that these materials have on the UDI and find the one that offers the best results. Each different building material has distinct characteristics which affect how the material behaves in the presence of light. The major characteristics relevant for a lighting analysis are (1) the three values of the RGB channels (red, green, and blue) which define the colour of the material, (2) the specularity, and (3) the roughness. The specularity is a mirror-like reflection of light, a value commonly used in computer graphics and ray tracing for rendering and analysis [53]. The roughness represents the material's texture.

Framework

Concerning the data flow for this optimization, we can once more divide it into fixed inputs, variable inputs, variables, and outputs. For this simulation, we used the same optimization components as the previous optimization but, in this case, the materials are not a fixed input but the variable that we wish to change. On the other hand, the amplitude of the wave is no longer a variable but a fixed input. In this optimization, there are no constraints as the design space is already limited to only seven chosen materials that we wish to test: translucent plastic, sheet metal, white enamel paint, gray paint, white paint, light wood, and dark wood. The data flow for this optimization is illustrated in Figure 3.20.

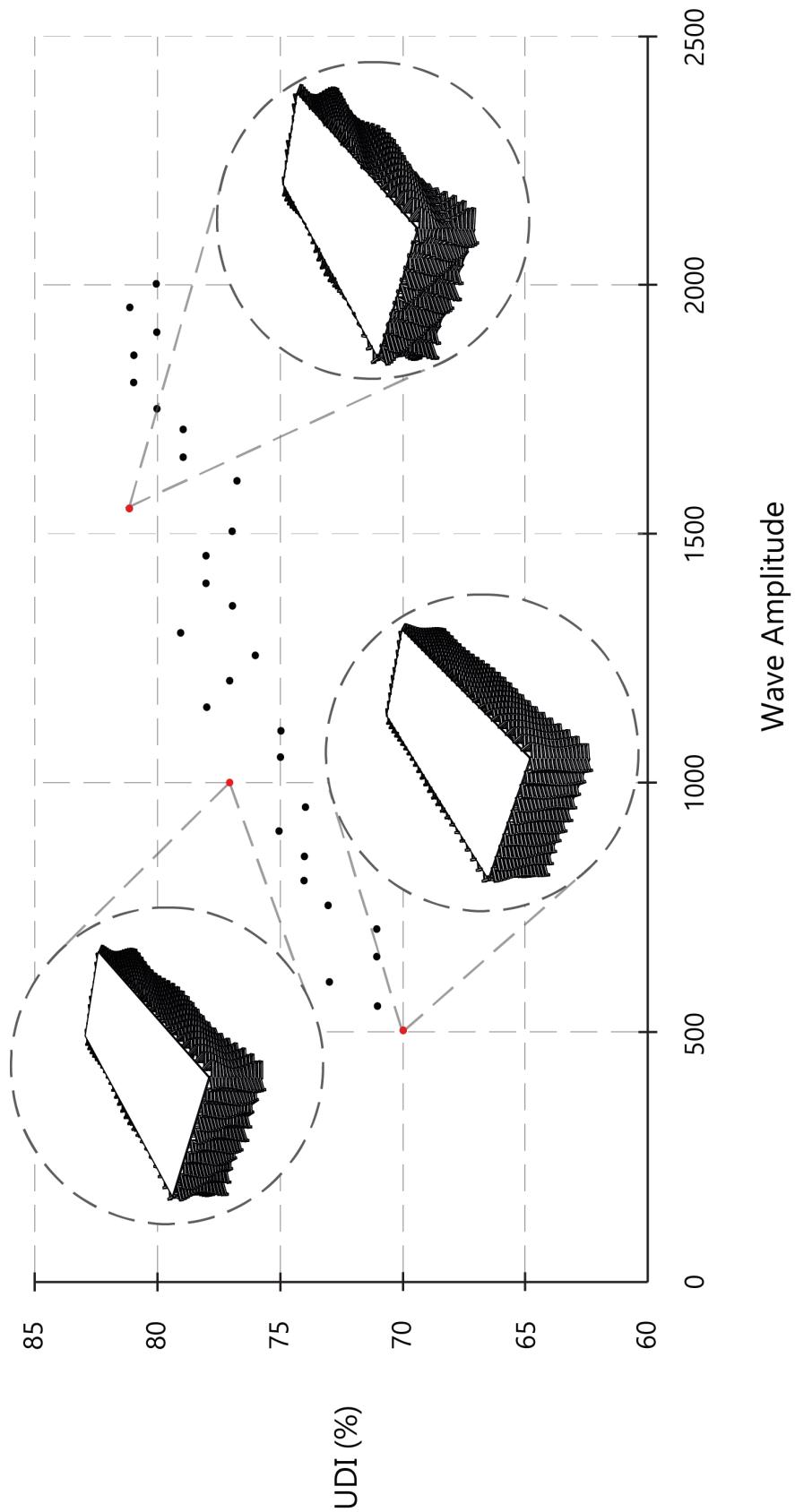


Figure 3.19: Scatter plot and corresponding designs. The optimal design solution corresponds to the one on the right.

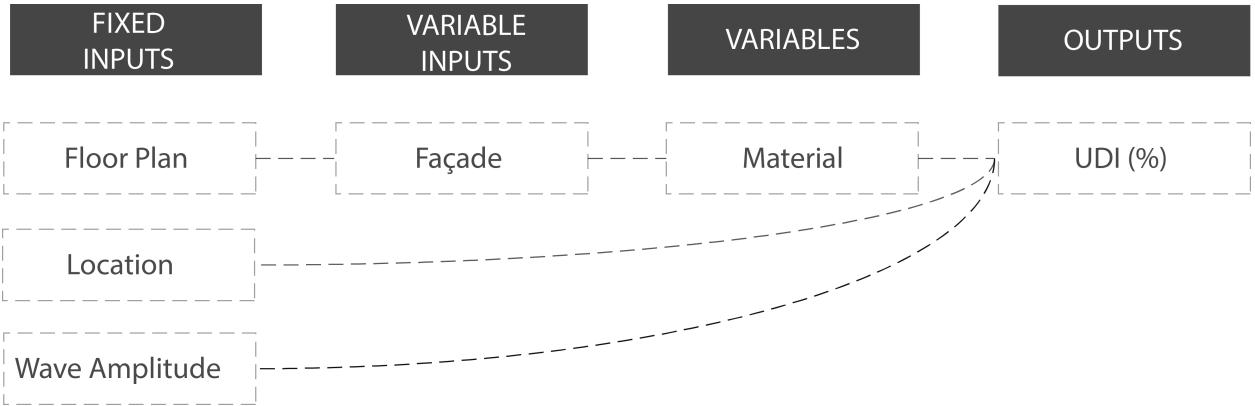


Figure 3.20: Data-Flow for Material Optimization

Meta-Model

For this optimization, the meta-model is the same as the one used for the previous optimization, with the difference that this time the materials are the ones changing. These materials and respective characteristics are embedded in Radiance. Each of the seven materials mentioned above will be applied to the façade and the respective UDI values analysed and ranked.

Algorithm

The algorithm used for this optimization is the same as the one used in the previous optimization.

Optimization

During the optimization process, the materials are applied to the building's façade and the UDI value is calculated. Every time a version of the building with a new material is produced, the algorithm compares it with the previous one and ranks it. Since this is an optimization with a very small design space (7 design solutions), the optimal result is insured to be found within 7 iterations. Nevertheless, this is an important exercise, in case the designer wants to try more options. In figure 3.21, we can see the optimization results obtained. The materials from 1 to 7 are white enamel paint, grey paint, white paint, light wood, dark wood, generic translucent plastic and metal sheet. The material that increases the UDI inside the building is the metal sheet with the UDI value of 82% (see table 3.2).

The design solutions according to the selected materials and respective UDI values can be visualized in figure 3.22.

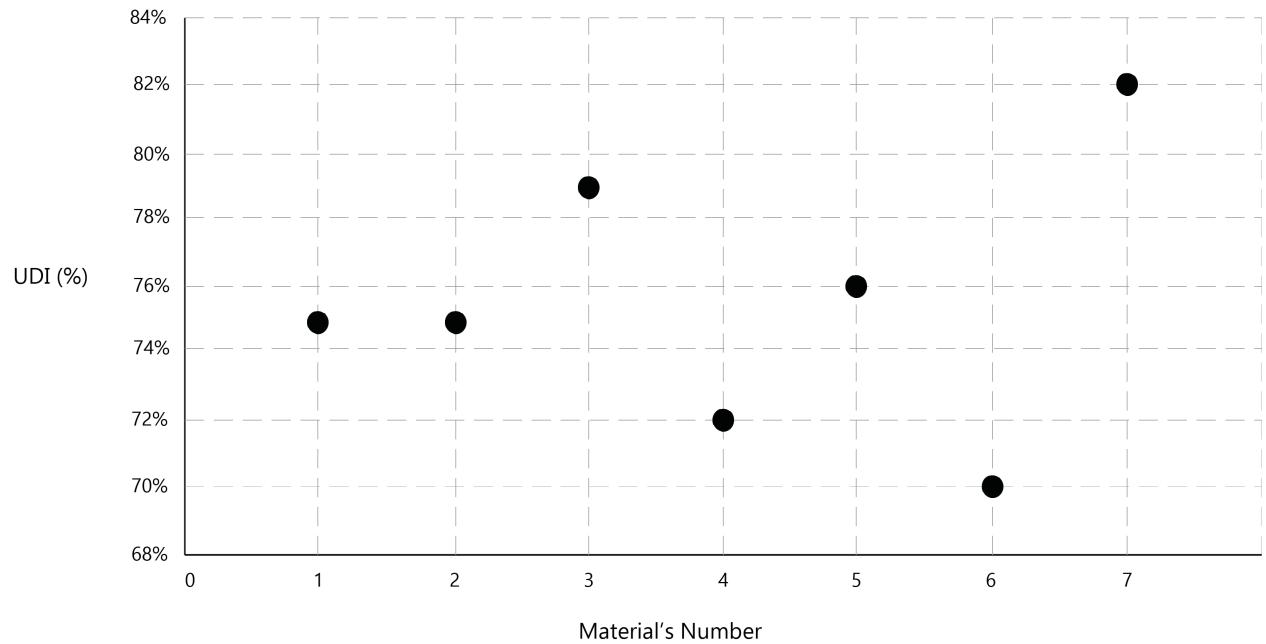


Figure 3.21: Materials and respective UDI values

Table 3.2: Materials and respective UDI values

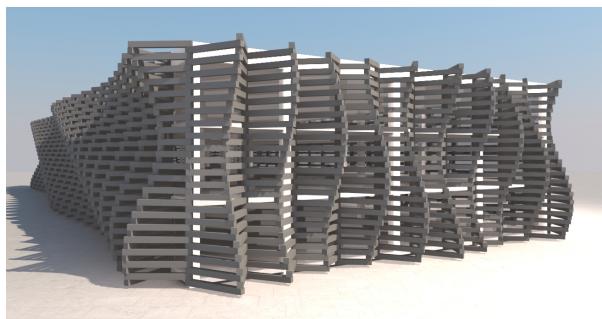
- | | |
|------------------------|-----|
| 1. White Enamel Paint | 75% |
| 2. Gray Paint | 75% |
| 3. White Paint | 79% |
| 4. Light Wood | 72% |
| 5. Dark Wood | 76% |
| 6. Translucent Plastic | 78% |
| 7. Metal Sheet | 82% |



White Enamel Paint: UDI 75%



Dark Wood: UDI 76%



Grey Paint: UDI 75%



Translucent Plastic: UDI 78%



White Paint: UDI 79%



Metal Sheet: UDI 82%



Light Wood: UDI 72%

Figure 3.22: Renders showing the materials and respective UDI values

3.5 Regulating Solar Radiation

After obtaining the optimal UDI values, it is necessary to verify whether these result in excessive amounts of solar radiation. Since heat can be transferred by radiation, the temperature inside the building would not be suitable during the summer. If this happens, in order to achieve comfortable working conditions, the cooling system would have to work excessively, spending a lot of energy in the process. However, if the building is overly shaded by the façade, the office would be compromised in terms of natural light coming in. So even though it is important to lower the amount of radiation coming in, the UDI cannot be compromised by this action. Therefore, the solar radiation was to be regulated to acceptable values instead of finding the lowest possible value.

The DIVA plug-in for Rhino provides a visualization based on a radiation grid that informs the user about how much heat by solar radiation is entering the building. There are two different methods to obtain this grid: Cumulative Sky Method and Daysim-based Hourly Method. The Cumulative Sky Method will be the one considered for this research, since it is less time-consuming in computational terms and the losses of accuracy are not considerable [54]. The Daysim-based Hourly Method, besides the cumulative radiation map, produces an hourly result file, which is not vital for this process.

Keeping in mind that the UDI is a relevant factor to the optimization process, it would be expected that better lighting performance means more radiation coming in. However, the goal is still to reduce the radiation load as much as possible, in order to lower the HVAC energy demands inside the building. Because these two variables are inversely proportional, in order to find an *equilibrium* it is necessary to view their relationship in a way that makes the trade-off between the two clear.

For the radiation evaluation, only the hottest two months in Shanghai, i.e. July and August, were considered as the worst case scenario for high temperatures (figure 3.23). The hours considered were between 5 a.m. and 6 p.m., since those are the hours during which there is the highest values for solar irradiation.⁴

A parametric model can significantly reduces the time necessary for each evaluation, since a radiation simulation takes about 12 minutes to completion using the current hardware. Thus, it represents a vast improvement in the design space search, both timewise and qualitywise.

Intuitively, one could say that the radiation value grows with the amplitude value: if there is more light, there is more heat. This because solar radiation transfers heat, so we can associate a strong lighting level to more heat. Nonetheless, simulation results show that this is not necessarily the case, as the figure 3.24 shows. The four designs show a steadily increasing UDI, but the radiation values do not vary consistently nor does it have a direct correlation. It appears that there is no consistent pattern that can be identified with the number of simulations done. However, it is easy to consider the trade-off between these two values, since the best UDI percentage (80%)

⁴<http://www.timeanddate.com/sun/china/shanghai>

⁵source:<https://www.travelchinaguide.com/climate/shanghai.htm>

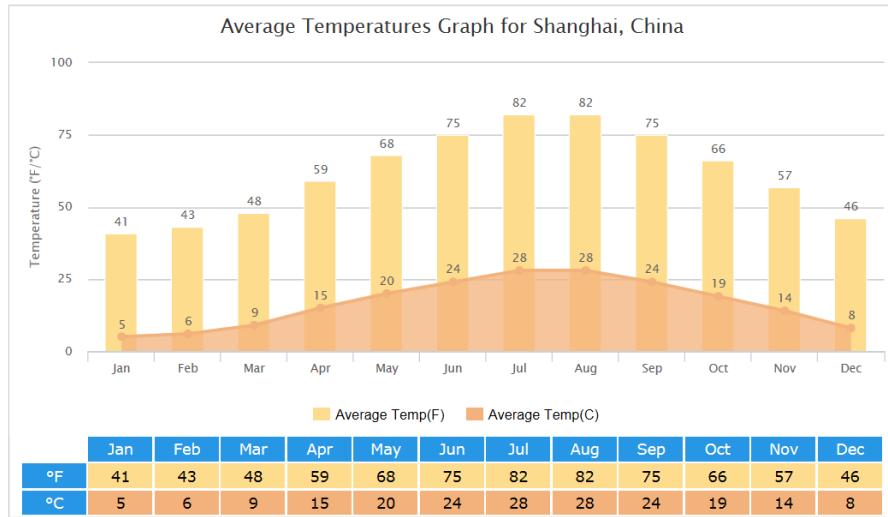


Figure 3.23: Average temperatures in Shanghai.⁵

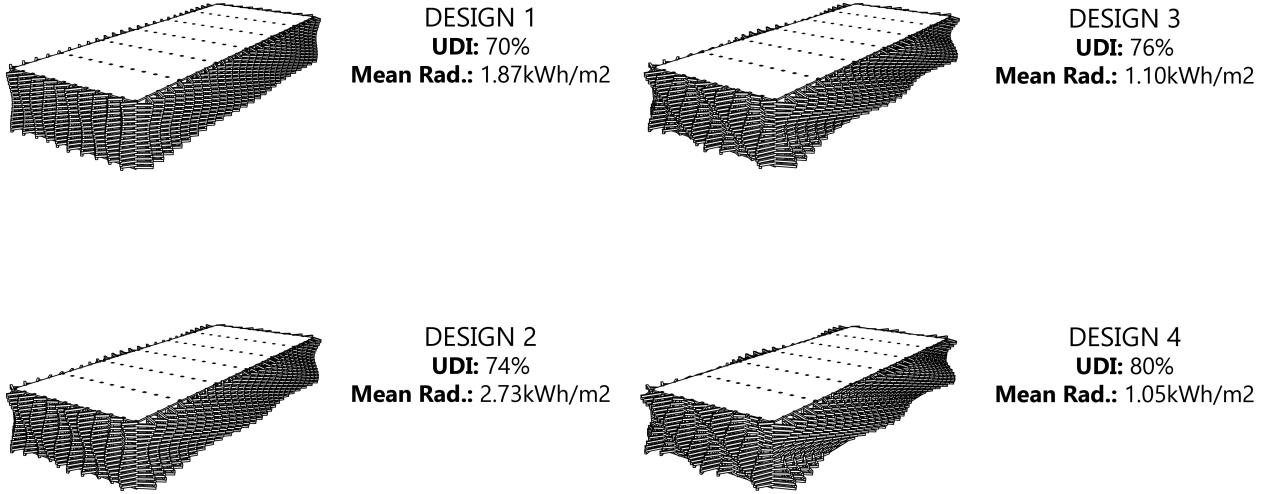


Figure 3.24: Four building versions and respective UDI's and radiation values.

yields the lowest radiation (1.05 Kwh/m²) in the 4 design option.

Chapter 4

Discussion

4.1 Evaluation

In order to develop our conclusions we compared the two optimization methods: parametric, and automated. The parametric method refers to the creation of a parametric model which is then changed parametrically. The automated process refers to a range of values that are set to change the model automatically. Once initiated, this automated process will continue testing different values without further involvement from the designer. As for building the 3D model manually, we considered it to be an impossible task, so we did not test this method.

When comparing these two optimization processes, it is important to distinguish the time that the software requires when generating the model, as well as the time that the designer must spend interacting with the model/software. This distinction is important because if the designers are merely waiting for the program to finish an analysis, then they are free to perform other tasks. In table 4.1, we compare the number of iterations performed for the design, the total time it takes to produce a single iteration (both effective and non-effective work), and the effective work time.

If we consider effective work as a measure of effort, it is verifiable that less effort is required when using the automated method. This method produces a more significant amount of iterations, in less time, and with less effort.

In table 4.1, we can compare the two methods described on the previous sections. For the parametric method, it is easy to produce an iteration of the model. However, the architect has to set up the simulation every time a new model is produced and needs to periodically verify if the simulation has ended before setting up a new simulation. The effective work time also considers the construction of the parametric model. Using an optimization process means that the process of producing new versions of the building and analysing them does not need the architect's

Table 4.1: Comparison between the two methods (changing the wave amplitude).

	Parametric	Automated
Number of Iterations	4	49
Total Time per Iteration	2,5 hours	0,175 hours
Effective Work Time	4,5 hours	2 hours

intervention. In addition using an Algorithmic-Analysis tool has also proven itself advantageous, as explained in previous sections.

4.2 Final Considerations

When compared to manual tools, parametric tools make the exploration of design alternatives fast and effortless. By combining parametric tools with analysis tools, the large variety of design solutions that can be generated and visualized can also be analysed and compared in terms of their performance. This process culminates with the use of optimization algorithms, in which an algorithm drives the design process in search of the shape with the best possible performance.

This method of design driven by performance, i.e. *Performance-Based Design*, has a theoretical impact on architecture: it is as if the discipline is achieving a state where it behaves like a living being that is subjected to evolutionary rules, where only the buildings with the best performances survive while other perish [36]. This approach makes the difference between *form making* and *form finding*: it is Performance-Based Architecture. Furthermore, it proves that this approach can help the designer adapt and find form. The emergence of these methods will certainly have an impact on how architects think their designs, but they are also a reflection of the whole society's evolution, in the way that there is an increasing search for methods that will make our buildings more sustainable.

This thesis shows that optimization processes can help achieve designs with better performances while reducing the time needed to achieve them. The relevance of this research is not only connected with the advantages these processes bring from a practical point of view, but also to the contemporary panorama of thinking and creating architecture.

One of the contributions of this thesis is a new approach for the analysis and optimization of algorithmically generated buildings. We call this approach Algorithmic-Based Analysis. Since the model and the analysis are generated in the same tool, there is no information loss when building the analysis model. The model can be exported to an analysis tool seamlessly and without needing any further manual alterations from the user. This makes the results more accurate and reliable and encourages architects to test a lot more variations of the intended design, allowing the building to be optimized according to its performance. As demonstrated in this thesis, using

this approach has advantages from the very early stages of designing: it is less time-consuming when it comes to finding better design solutions, better performances can be achieved, and making iterations becomes an effortless process.

In a more architecture-related context, the biggest concern when implementing this methodology is that, if used without care, it has the potential to turn architecture into senseless nouvelle shapes, forgetting that it should consider context and cultural background, and have some statement or concept. Architecture is also about preserving a certain urban or historical context, otherwise, we risk cities being transformed into a set of complex shapes without any relationship with each other or with the cultural context in which they are placed. In addition, architecture throughout history has a social and political statement role, and should be connected to a temporal context. To preserve the design intent, it is imperative that the conceptual phase is clear in the designer's mind.

As was presented in section 3.4, the design solution which provides the best possible daylighting performance, measured in terms of UDI, for the considered case study is the one with an amplitude value of 1776 and uses metal sheets for the façade elements. Whether designers wish to keep these characteristics is up to them, as they have the final say in what they want their design to be. After debating these results among themselves, they might decide to keep the optimal amplitude value found, being that this value is as good as any inside the interval of values that they consider acceptable and does not interfere with their design intent. On the other hand, they might also later discover that using metal sheets to cover the façade elements can cause glare produced by the reflection of the daylight on the surface of metal elements and disrupt the working conditions inside the building. Likewise, they might vote against using white paint as the material with the second best UDI value on the argument that paint tends to deteriorate easily, which would significantly increase maintenance costs. They might eventually decide on using Transparent Plastic as an interesting and unique choice for the material of the façade elements which would also provide the best lighting conditions inside the building, after the first two options have been discarded. The result of these design choices can be see in figure 4.1 and figure 4.2.

As for limitations of this research, one of the most significant problems found in optimization processes, which we also encountered in this research, is the difficulty in validating the results. As it is well-known, analysis software, mainly the ones connected with thermal and lighting efficiencies, are not necessarily accurate [18]. Another issue found was the extreme difficulty of exporting the data generated by these software into useful information that the optimization algorithm could use. Computational power was also one of the biggest difficulties found during the optimization process: each analysis takes some time and, therefore, the optimization process takes a long time. These concerns may be tackled in the future.

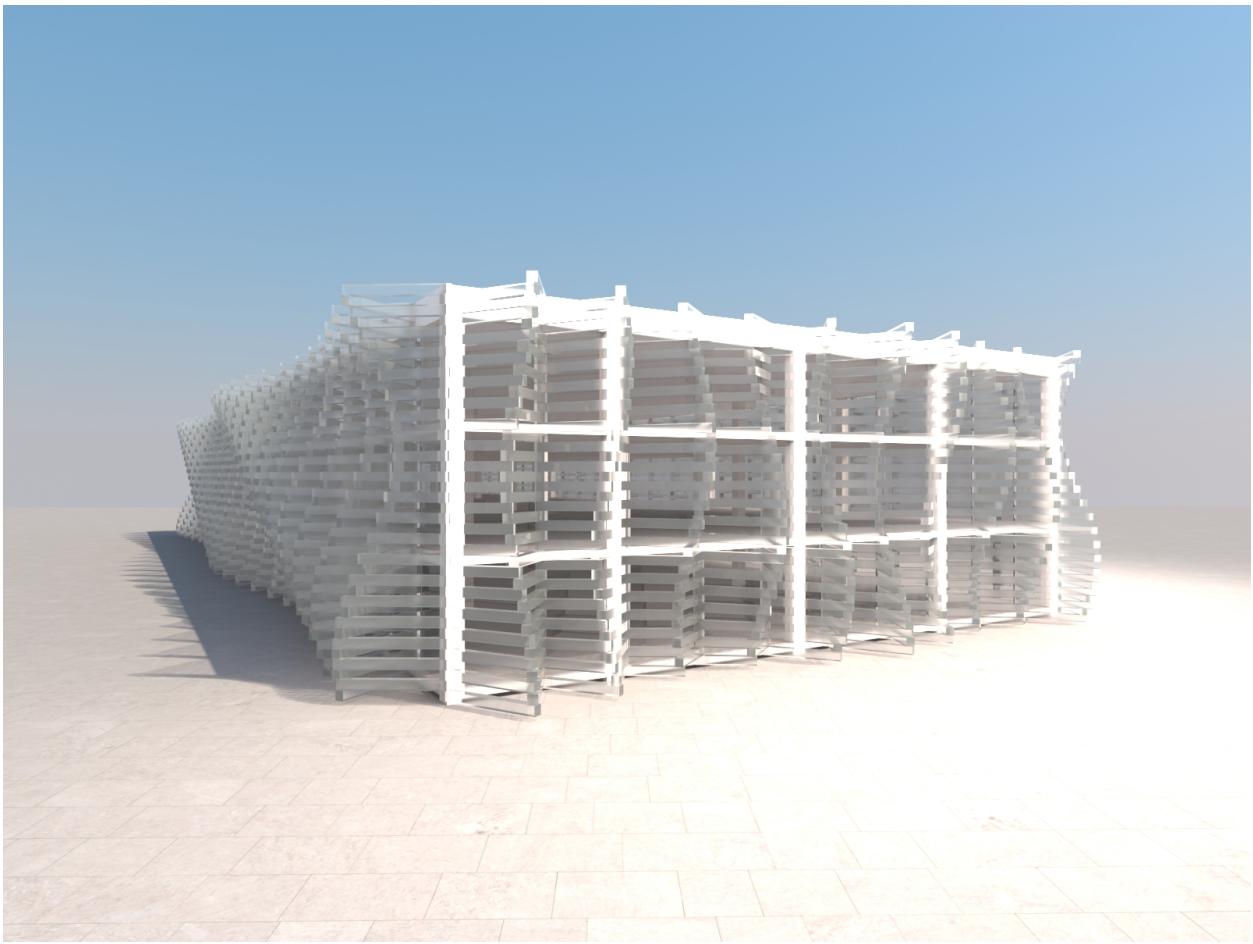


Figure 4.1: Exterior Render



Figure 4.2: Interior Render

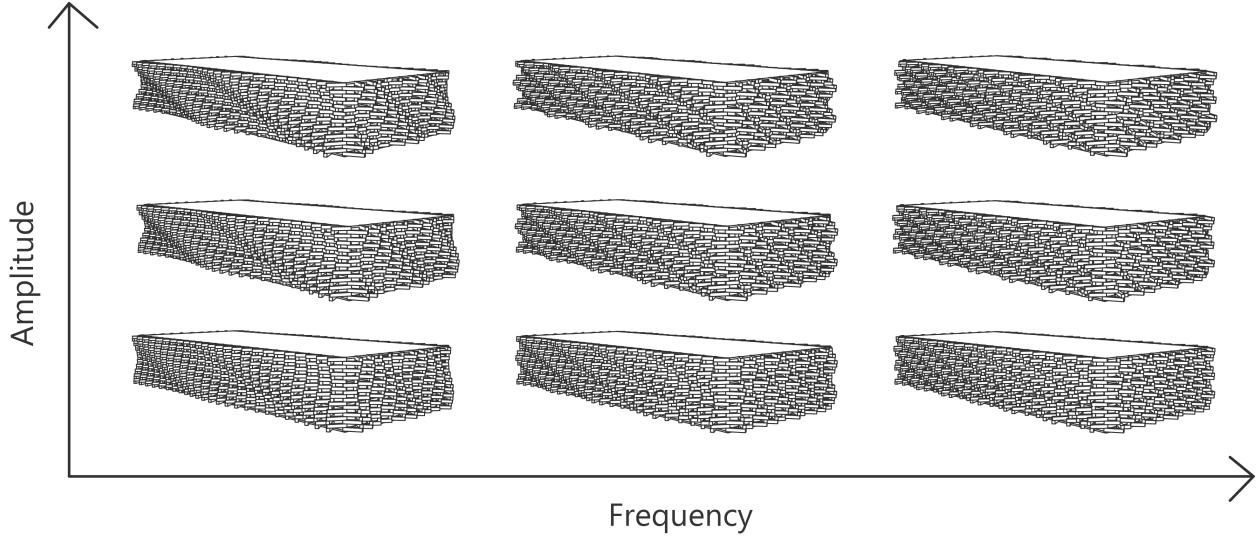


Figure 4.3: Gradation amplitude and frequency.

4.3 Future Work

In the future, we intend to expand our research beyond single criteria optimization and increase the geometric complexity of the projects:

1. Deeper exploration of form-finding. One aspect to be further explored is how the flexibility of the parametric model allows us to find new forms of the design. By introducing new variables to the design, more variations can be explored and the combination of these variables can lead to unexpected outcomes. This process requires looking back at the design concept and adding parameters to the meta-model that allow for additional changes. For the case study presented in this thesis, it could be interesting to change the wave frequency which would expand the design space considerably (figure 4.3).

2. Apply a Multi-Criteria Optimization process. This thesis only completes two single criteria optimizations, and manually compares the trade-offs between four designs generated parametrically. The next step in this research would be to algorithmically connect all the relevant analyses and perform a multi-criteria optimization of the building.

The main issue with multi-objective optimization is the range of different tools that are used, with incompatible formats. By having a single tool that generates the model according to the type of use, the results of different performances are more reliable and truthful to the model. This new process leaves a pathway open for multi-objective optimization.

As mentioned previously, when optimizing more than one objective, there is usually not one single best solution. Instead there is a set of optimal solutions in the Pareto Front. The solutions are not only ranked by how well they

perform according to each criterion. The weight or importance that the designer assigns to each criterion plays a role as well. The complexity of this kind of optimization creates a need for algorithms that can better attain the desired optimal solutions, and run through the design space faster. Thus, in the future, we would like to use genetic algorithms to perform a multi-criteria optimization in order to select the optimal design.

3. Kinetic-Architecture and data. Another topic which requires further exploration is how these processes can inform the façade in the 4th dimension (where the elements of the building move according to the movement of the sun throughout the day), and which is the optimal version of the building for each time of the day and of the year. Once this step is taken, the building should be intelligent enough to gather data for its own use, and adapt its shape accordingly.

4. Explore Optimization on an Urban Scale. The research done in this thesis explores optimization on a building scale. In the future, it would be interesting to tackle the topic of optimization on an urban scale.

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