MSc thesis in Building Technology

Generating building envelopes using multi-objective optimization techniques

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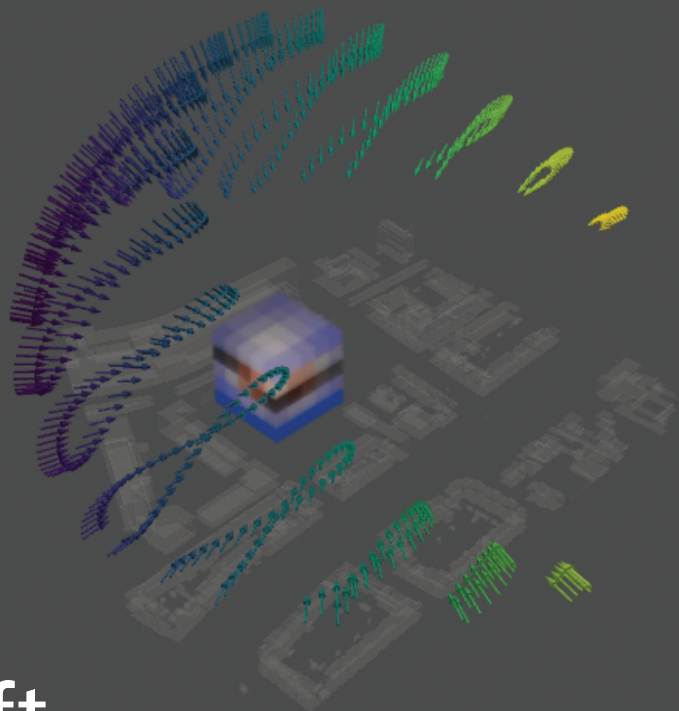

TU Delft

GENERATING BUILDING ENVELOPES USING MULTI-OBJECTIVE OPTIMIZATION TECHNIQUES

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ABSTRACT

This thesis concerns the application of different multi-objective optimization (MOO) methods and strategies for finding the optimal envelope for a given building plot and lighting performance indicators. More specifically, the PV potential and daylighting potential of the building are maximized using different optimization solvers. Auxilliary objectives are introduced to constrain the model to a certain compactness and size. The method utilises an existing data framework called TopoGenesis and solves the problem using the PyGmo library.

A ray tracing is used to find all possible collisions between the objective test points and the building mass and environment. The problem is first presented as a standard integer programming problem, but solving this problem is not feasible if complexity needs to be kept at a reasonable level. An alternative method of continuous optimization is therefore proposed that uses (meta)heuristics to find an optimal solution for maximizing the objective functions. The occupation status of the massing is used as inputs for the decision variables.

After the application of this method on small scale toy problems, a few of the design options are selected and evaluated by their performance indicators, as well as the measure with which the option makes sense from a more traditional design perspective. The comparison of the performance and results of both methods give insight into the recommended workflow, settings, and pitfalls for finding an optimal solution to a multi-criteria design problem with visibility objectives. From the initial results, the Non-Sorted Genetic Algorithm seems to be the best option for solving these types of problems, and the PV potential objective is validated. The Daylighting potential objective performs less satisfactory and suggestions are made on alternative approaches for this metric.

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ACRONYMS

1 INTRODUCTION

Increases in labour, land, and development costs have decreased the attractiveness of affordable housing projects in the Netherlands. In the past, government policies were instituted to create new subsidized housing projects, but these have largely been discontinued, decreased in scope or scale, or privatized. Combined with the current general housing shortage, high quality but affordable housing has started to become a scarcity [Nijskens and Lohuis, 2019; Boelhouwer, 2020].

Due to an increasing need to limit greenhouse gas emissions and the significant share of almost 40% of the building industry in this aspect [IEA, 2016], making the building industry more sustainable is a high priority for governments and corporations alike. Both reducing emissions during construction and finding more sustainable ways of providing energy for the operation of buildings are strategies that can be employed to achieve these goals. One of the avenues for achieving these goals is implementing smarter designs with regards to energy usage, in particular the sun's energy.

1.1 SOLAR RESOURCES

Direct insolation can supply the building with energy from photovoltaics, as well as heat up the building (thereby decreasing heating demand). At the same time, daylight access has been proven to increase productivity in offices [MacNaughton et al., 2021], increase the value of real estate [Turan et al., 2020], increase student performance in schools [Elkington, 1999] and more generally provide an increase in mood and health [Aries et al., 2015]. Regarding daylighting and insolation, the Dutch Building Decree (Bouwbesluit) has determined that living spaces (verblijfsruimten) receive an area of daylighting according to a minimal amount of m2, or a percentage of that living spaces' area. The way this is calculated is through calculating the area of all valid openings in the facade and reducing this area by factors such as projection angle, shadings or obstructions, window frosting etc. The result of this is the equivalent daylight area. The calculation of this equivalent daylight area has certain disadvantages however.

Firstly, aspects that influence this value need to be known beforehand. This means overhangs, shadings, window angles etc. all need to be known when estimating if the minimum demands can be met by the current design. In the earliest design stages however, these factors may still be unknown or up for debate. Secondly and more importantly, these calculations only take factors into account that are inside the building parcel and only estimate the daylighting for the proposed building and not its effects on the surrounding area. This means that any shading by surrounding buildings and the shading by the proposed building on surrounding areas might be neglected in this phase of the design. To remedy this problem, municipalities usually employ their own norms for insolation and daylight access on top of the equivalent daylight area method. Most municipalities use (a modified version of) the TNO norms which state:

- at least 2 possible hours of insolation per day in the period of 19th of february – 21st of October (8 months) in the centre of the windowsill inside the window" (lenient norm)

- at least 3 possible hours of insolation per day in the period of 21st of february – 22nd of November (10 months) in the centre of the windowsill inside the window (strict norm)

The The Hague municipality for example modifies the 'lenient' norm by adding that only solar positions of 10° or more may be taken into account, while the entire facade may be taken into account, regardless of window position. [Zonneveldt; L, 2005]

Both passive heating and active energy generation by the sun are attractive options for designers, but balancing these factors with other design variables is a complex task that has to be considered as early as possible in the design process, since here the largest difference can be made on the eventual performance of the building [Paulson, 1976]. Building envelopes represent the boundaries of the mass that a building can potentially assume. They are tools used in the early design stages to limit the maximum extents of a design and also to ensure certain design objectives can still be achieved. Generally, the objectives that these envelopes are created for pertain to solar access (solar envelopes). The goal of implementing a solar envelope in the design phase of a project is to ensure the building and its surroundings are exposed (or remain exposed) to the sun for a certain period of the year. A building envelope applied in the early design stages plays an important role regarding energy performance [Depecker et al., 2001].

1.2 MAKING DECISIONS

It can be recognized that the variables described in the previous section can be interconnected, conflicting, or reinforcing towards each other. To make decisions on multiple variables and diverging goals, several industries have successfully applied operations research techniques such as Multi-Objective Optimization (MOO) and Multi-Criteria Decision Analysis (MCDA) in the past. There is an increasing trend to also apply these techniques to the built environment [Huang et al., 2011]. This means there exists a gap between what is currently standard practice and what is possible. This thesis is an attempt to research the nature of this gap, find a workable methodology for a specific set of energetic, climatic, and solar design objectives, and explore the merits of the different approaches to such problems as described in this paragraph. In the next section, a brief overview of the proposed problem will be given.

1.3 PROBLEM STATEMENT

In order to introduce the general problem, the following input, output, and objectives of the to be developed method are identified. A solar envelope will be created for to get an idea of the optimal massing of a building to make efficient use of the sun's energy. Two of the objectives relate to the solar performance of the building massing and can be used to get a sense of the suitable solar envelope, while the other objectives have an auxiliary function to better control the final shape of the mass. These objectives as well as their objective functions and the reasoning behind their inclusion are formalized in more detail later in the paper:

Input	Type	Unit	Description
x	$[x_i] b \times 1$ $x_i \in \mathbb{N}$	none	Array of indices for all possible voxels in the configuration
$\mathbf{F}_1$	*function*	kWh/year	Objective function for the PV Performance of the configuration
$\mathbf{F}_2$	*function*	lux/year	Objective function for the Daylighting Performance of the configuration
$\mathbf{F}_3$	*function*	none	Objective function for the Relative Compactness of the configuration
$\mathbf{F}_4$	*function*	none	Objective function for the Urban Density of the configuration
Output	**Type**	**Unit**	**Description**
C	$[C_i] b \times 1$ $[C_i] \in [0,1]$	none	Configuration of the occupation status of the massing, expressed as an array of decision variables

Problem: Given an array **x** of b amount of voxels and the objective functions $\mathbf{F}_1$, $\mathbf{F}_2$, $\mathbf{F}_3$ and $\mathbf{F}_4$, the method must produce a combination of decision variables **C** that is not dominated by other configurations in regards to its performance towards these objectives

Table 1.1: Overview of the multiple-objective problem statement

1.4 THESIS STRUCTURE

The rest of the thesis is organised as follows: Chapter 2 establishes the research framework: Disciplinary approach and scope, current literature and methods, and research questions are given. The objectives and objective functions as introduced in table 1.1 are explored in more detail. Chapter 3 describes the developed method: first by its constituent toy problems and then as a proposed complete method. Finally, an application of the method on the case study is provided. Chapter 4 concerns the evaluation of the developed methods. Conclusions and further research is presented here. Finally, Chapter 5 contains the personal and academic reflection. At the back, Chapter 6, there is an appendix containing the results and flowcharts, pseudocode, and visualisation of the developed algorithms.

2 RESEARCH FRAMEWORK

This chapter presents the research framework within which the thesis takes place. First, the approach and scope are given from a disciplinary perspective. Some relevant literature for the development of the method is then explored. After this, the general objectives, research questions, deliverables, and design objectives are described and the final section of the chapter formalises these objectives into a problem statement that can be used in the following chapter to devise the main method.

2.1 DISCIPLINARY APPROACH AND SCOPE

The context, objective, scope, research questions, and objective functions are identified in the following sections. Along with this, the relevant scientific background is explored through the literature review. This includes topics such as the state of MOO and MCDA (both general and more specifically in relation to the building industry), solar simulations, and generative design in the building industry.

After this, the key design objectives are modified so they can be included in the method. For each objective, a simulation or calculation is done to find the performance of each voxel for the entire year towards this objective. These aggregated scores are then compared using different MOO methods. Scoring is measured per voxel so that the impact of the inclusion of a certain voxel in the mass can be extimated. The resulting values for each variable are then used to generate different massings (configurations) in the form of toy problems, and these massings can then be evaluated on how well they perform per each different MOO method.

From this, the research will conclude with suggestions on what optimization methods perform best for what purpose and in what context. The results are validated by comparing the relative performance of a sample of the optimal solutions to a daylighting simulation using Radiance, a common tool used for lighting analysis. This should give an idea if the results are realistic. From there, a verdict can be reached on whether the method works for only the objectives researched in the paper or whether it is valid for different problems as well. The problem is explored and described in detail from section 2.3 to 2.5 and is interdisciplinary in nature as illustrated by the Euler diagram in figure 2.1.

2.1.1 scope

The research concerns the testing of different optimization strategies with a specific set of criteria. It must describe a methodology for implementing MOO methods to find (near) optimal massings at a building scale. This means that the scales above this (neighbourhood, city, region) as well as below it (room, building detail, component) are not included in the research. The results of the research should however be suitable for use as a baseline to make informed design decisions. The focus and purpose of the research is to aid in the earliest stages of the design process without limiting the freedom of the designer too much. This means that the end result will always concern a configuration of voxels and their performance towards the criteria applied in the method, and will never represent an actual zoning of the rooms or design of the building. The diagram below is used to illustrate the intended posi-

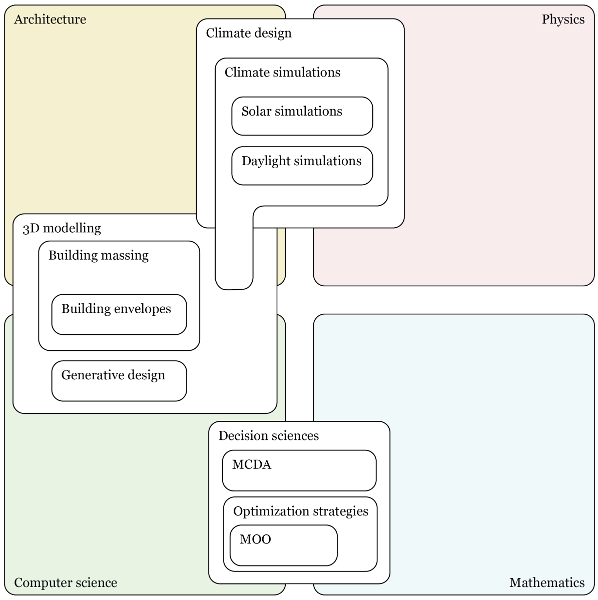


Figure 2.1: Euler diagram of the relevant disciplines and research areas

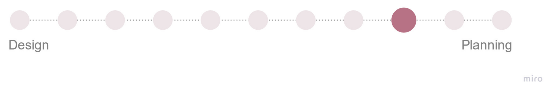


Figure 2.2: Positioning on design-planning axis (own image, emblematic)

tioning on an axis that represents planning or design intent.

For practical reasons, some simplifications and assumptions also have to be made on the goals that are considered when applying the MOO. By limiting the number of criteria we can keep the focus of the research on the performance and ease of use of the MOO methods in the context of generative building design. The result is a voxel cloud representing a mass that corresponds to the solar envelope. Specifically, the considered objectives are as follows:

1. PV potential of the massing
2. Daylighting potential of the massing
3. Heat retention potential of the massing (constraint-like)
4. Floor Space Index of the massing (constraint-like)

In 2.4 and 3, how these criteria are calculated will be explained in further detail. All aspects beyond this that might influence the building performance are not to be taken into account during the research. Examples of this include but are not limited to: Structural design, facade design, (functional) zoning, construction techniques, shading strategies, alternative sustainable energy generation, artificial lighting strategies, (end) users, cost analysis, rent estimation, proximity to amenities etc. Python will be the language used for programming the method in order to ensure reproducibility and more convenient library integration.

Below is an overview of aspects included and excluded within the scope of the research:

Within the scope

- MOO strategy and methods in Python
- Daylight and sunlight simulation methods in Python
- Heat retention strategy through building compactness
- Generative design strategy
- Early design massing (conceptual stage and planning stage)

These matters relate to the subject but fall outside the scope of the research project:

- Structural design
- Facade design
- Zoning and function assignment
- Construction techniques
- Material analysis
- Window shading strategy and glare analysis
- Artificial lighting strategy
- Energy generation strategy
- End user or actor research
- Cost and benefit analysis
- Accessibility analysis
- Anything below the building plot scale (room/detail/component)
- Anything above the building plot scale (neighbourhood/city/regional)
- Late design development (design development stage and construction design stage)
- Occupancy stage building performance
- Post-Occupancy stage building performance evaluation

2.2 EXISTING LITERATURE, METHODS, AND LIBRARIES

In the next section, the most important conclusions of the literature study on daylighting simulations and MOO and MCDA methods have been collected to give an overview of the topics and writers researched and the lessons learned from these texts. Searches were conducted using Google Scholar. At the end of the section, relevant libraries that apply these methods are listed.

2.2.1 daylighting simulations with Radiance

The research into simulation of daylighting is predominantly focused around offices, schools and hospitals etcetera, i.e. non-domestic buildings. This is mainly because the activities pursued in these types of buildings require more and higher quality daylighting [Tavares and da Costa Silva, 2008]. The most commonly used tool for these types of simulation is RADIANCE and trust in these types of tools is on the rise [Reinhart and Walkenhorst, 2001]. However when analysing the accuracy of different daylight simulation methods, Reinhart and Herkel find that the quality of a simulation is highly dependent on whether hourly illuminances are considered in the estimations. This means it is important to simulate these hourly values and include them in the decisionmaking in the design phase of a building project. The Radiance method is put forward as a user-friendly approach to daylight simulation for novice users and is becoming one of the standard methods taught in architecture schools[Ward, 1995]. This is due to the method "being a powerful ray tracing program that enables accurate and physically valid lighting and daylighting simulations" [Compagnon, 1997]. This method works by combining deterministic and stochastic ray-tracing in order to achieve speed as well as accuracy [Ward, 1994].

The influence of daylighting on the thermal performance of a building is another field of interest for researchers in daylighting. A study attempts to reduce energy demands for heating and lighting finds that the correct design parameters can reduce these demands significantly while increasing daylighting performance [Zhang et al., 2017]. Daylighting simulation can accurately predict actual daylighting values according to Reinhart and Walkenhorst and Labayrade et al., but is highly dependent on finding the correct parameters for the simulations. One review of daylighting metrics finds that in residential architecture, matters such as access to direct sunlight over the year are often overlooked and argues for inclusion of direct sunlight into existing daylighting metrics [Dogan and Park, 2019].

Another relevant piece of research in daylight simulations especially its application for generative design and MCDA is that of Anastasia Florou which describes a feed-forward optimization methodology for precomputing the rays that impact daylighting and insolation in order to use these values for a space allocation problem. These rays are coupled with a discretized representation of a building massing to create an 'interdependency graph' to find the relations between all possible rays and voxels in the model. See figure 2.3 for reference towards how this is structured. An array that contains, for each voxel V, towards every other voxel V, whether each ray R is blocked or not by that voxel. This feed-forward approach is suitable for the application of MCDA on space allocation problems. However the objective of this research is to search a larger decision space and also to deal with objectives that have physical properties and deal with units, and are not psychological factors. In the next section, this distinction between MCDA and MOO that needs to be defined for the project is explained in more detail.

2.2.2 multi-criteria decision analysis and multi-objective optimization

In urban planning, decisions are made during several planning phases that have implications on various domains and scales for different actors. For an individual or group of people, it is (practically) impossible to understand all interdependencies within the decision space. Subjective or context-specific decisions cannot definitively be taken beforehand, but these decisions can be analysed beforehand. By anticipating how these decisions affect the performance of the building, they can be altered beforehand to produce better results.

The first approach to such multi-objective problems as described in the introduction is the use of mathematical programming. These methods can be used when the problem can be brought to a closed (mathematical) form and will yield fast results with high accuracy. Mixed-Integer Linear Programming (MILP) is suitable for problems as described in this thesis since it allows to quickly generate a multitude of plans and include both continuous and discrete decision variables. Schüler et al. successfully implement a MILP method on a neighbourhood (and lower) scale. Specifics are provided on what aspects of the model are standard and which ones are novel but no detailed guide on the implementation is provided. This method is a form of Mathematical Programming (MP) and similar or analogous methods to this include Linear Programming (LP), Constraint Programming (CP), Integer Programming (IP), Quadratic Programming (QP), and Binary Integer Programming (BIP). A drawback of using integer solvers as opposed to continuous solvers is that compu-

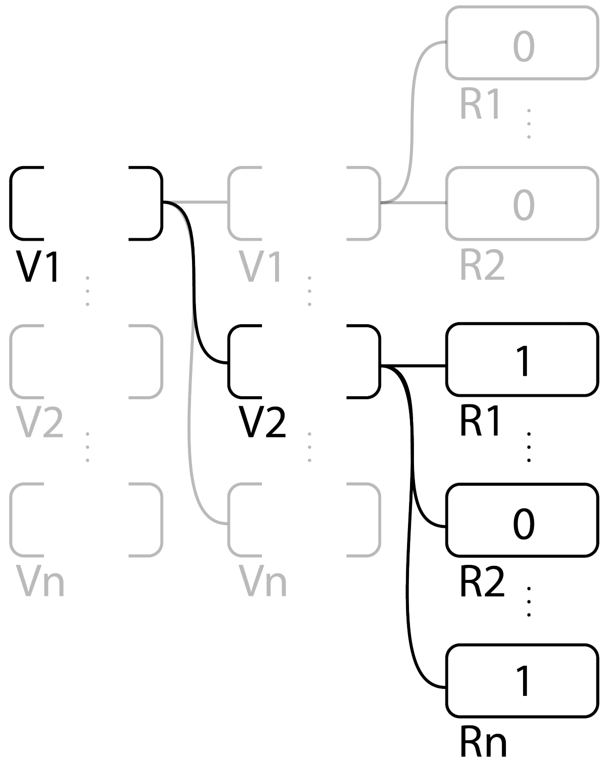


Figure 2.3: The structure of the interdependency graphs used for a MCDA approach to the problem: nested arrays of hits and misses.

tationally, they are much harder to solve. These difficulties originate in the larger dimensions, multiextremeness, and inaccurate values of coefficients of these problems [Sergienko and Shylo, 2006].

Another key piece of literature reviews the use of MCDA in the context of architecture and urban planning with regards to energy efficient construction and concludes that a modified Analytic Hierarchy Process (AHP) (fuzzy) is applied the most in general, followed by Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Complex Proportional Assesment (COPRAS). For the selected methods, the authors examine the capability to decompose the decision problem, improve the transparency of the decision processes, facilitate comparison of various decision alternatives, and identify their strengths and weaknesses. Weaknesses include: For AHP/TOPSIS a lack of consideration of interactions between various design criteria. Simple Additive Weighting (SAW) and ÉLimination et Choix Traduisant la REalité (Elimination and Choice Translating Reality) (ELECTRE) were rated lower in terms of ability in pair comparison or ability to manage low quality input data. A hybrid approach is becoming increasingly popular. To make comprehensive assessments, it is better to use two or three different types of MCDA or a combination of the two [Ogrodnik, 2019].

In another inventory research, Multi-Attribute Utility Theory (MAUT), AHP, Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), ELECTRE and Differential Evolution - Simulated Annealing (DRSA) are described by their performance in respect to ten criteria that sustainability assessment tools should satisfy. The review shows that MAUT and AHP are fairly simple to understand and have good software support. Only MAUT achieves robust results, while ELECTRE, PROMETHEE and DRSA are non-compensatory approaches, accept a variety of thresholds, but suffer from rank reversals. DRSA is less demanding in terms of preference elicitation. DRSA also emerges as the easiest method, followed by AHP, PROMETHEE, and MAUT, while ELECTRE is regarded as fairly difficult to use and understand [Cinelli et al.,

	AHP	MAUT	DRSA	PROMETHEE	ELECTRE
ease of use	-	/	+	/	-
compensation	-	-	+	-	+
support	+	+	/	+	/
thresholds	-	/	+	+	+

Table 2.1: Overview the most popular of the examined MCDA methods. DRSA seems to be the most promising option

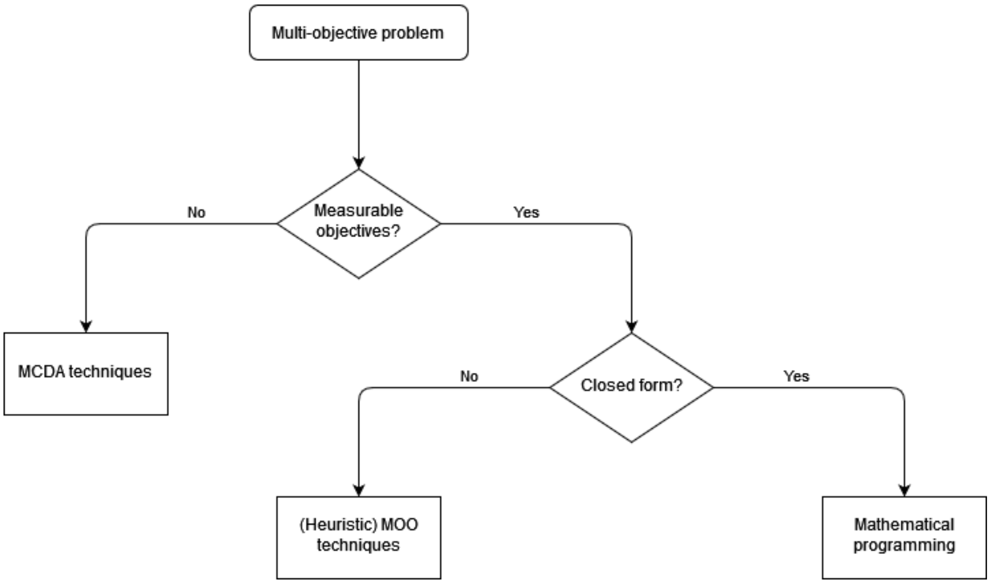


Figure 2.4: The process of selecting a suitable technique for multi-objective problems.

2014]. A general grouping of MCDA approaches is proposed by Slowinski et al. who distinguish the methods by three underlying psychological theories: utility function, outranking relation, and sets of decision rules. This also gives information as to the kind of problems MCDA methods are suitable for: problems that have no exact, measurable objectives but instead objectives that relate more to psychological factors. These objectives generally are immeasurable and relate to a smaller decision space. The table 2.1 gives a comparison of some of the more relevant of the methods researched in regards to criteria that we are interested in such as their ease of use or intuitiveness, their ability to compensate or use trade-offs, the support and documentation available, and the ability to use threshold values which can be used to model conditionals (such as the blockage of a ray of light).

One approach to multi-objective problems is using a heuristic method as opposed to an exact method such as a programming. Caldas applies a genetic algorithm and simulated annealing for finding the best trade-offs between conflicting objectives such as building costs, energy consumption, and embedded greenhouse gasses and successfully generates building geometries. Nagy et al. argue that applying such methods allow designers to explore a wider range of design options than would be possible using traditional methods. They apply the Non-dominated Sorting Genetic Algorithm (2) (NSGA-II) for generative design. This algorithm seems to perform well when compared to other solvers [Deb et al., 2002]. Many other heuristic global optimization methods exist and have successfully been applied for solving multi-objective problems in the built environment such as Modified Ant Colony Optimization (MACO) [Shea et al., 2006], Non-Sorted Particle Swarm Optimization (NSPSO) [Liu, 2008], or DRSA [Buitrago et al., 2016].

It can be concluded that there are a multitude of decision support methods available that can be applied to the problem as described in previous sections. The main takeaway from the studied literature has to be that there is no definite answer to which method is best, although for different problems, different techniques are more suitable. Due to inaccuracies and uncertainties inherent in MCDA and heuristic MOO, employing a hybrid method and testing and comparing multiple types of methods generally seems to be the desirable strategy. An exact method is often desirable but heuristic methods are generally easier to implement and utilise. Finally, a recommendation for selecting a suitable approach to multi-objective problems can now be made in figure 2.4.

2.2.3 python libraries for optimization

Several libraries were examined. Google's OR tools offers extensive documentation and tutorials and enables linear, integer, and constraint optimization. CVXOPT enables quadratic optimization capabilities, while SciKit-Criteria offers many different MCDA methods such as ELECTRE, Weighted Sum Method (WSM), and TOPSIS. Finally, PyGmo offers many evolutionary algorithms for optimization such as NSGA-II and MACO.

2.3 OBJECTIVES

The objective of the research is to devise a general methodology or workflow for generating building massings of high-performing solar and climatic configurations in dense urban contexts by using multi-objective optimization techniques. To achieve this, the problem must first be formulated in such a way that it can be understood on a mathematical level. If possible, these formulas are then used in a mathematical programming of the problem. Else, a heuristic method is applied to the problem.

This method is to be applied in an environment that can represent the context of the Randstad area in the Netherlands; a highly developed, interconnected, dense urban region. To do this, toy problems are used to research and illustrate the mechanisms at play on a small scale, and a test case in Rotterdam is then used to validate the results on the major scale. A conclusion has to be drawn on what method(s) and approaches of MOO are most useful for these specific objectives. Ideally, this conclusion can be extended to a general recommendation on what method is most valid and practical for the more general type of socio-spatial-climatic objectives that are pursued in the early stages of building design and planning projects. A simplified representation of the process can be seen in image 2.5.

2.4 RESEARCH QUESTION

Taking into account the objectives of the research, we can formulate the following main research question to be answered:

> **"How can we utilize Multi-objective optimization techniques to generate massings of high-performing solar-climatic configurations in a dense urban context?"**

Looking at this question and the research objectives in a more detailed manner raises sub-questions and objectives. These pertain to the terms **MCDA**, **high performance**, **massing**, and **solar-climatic configurations**.

1. What exactly are the (solar-climatic) objectives we are pursuing and what are the objective functions of the objectives?

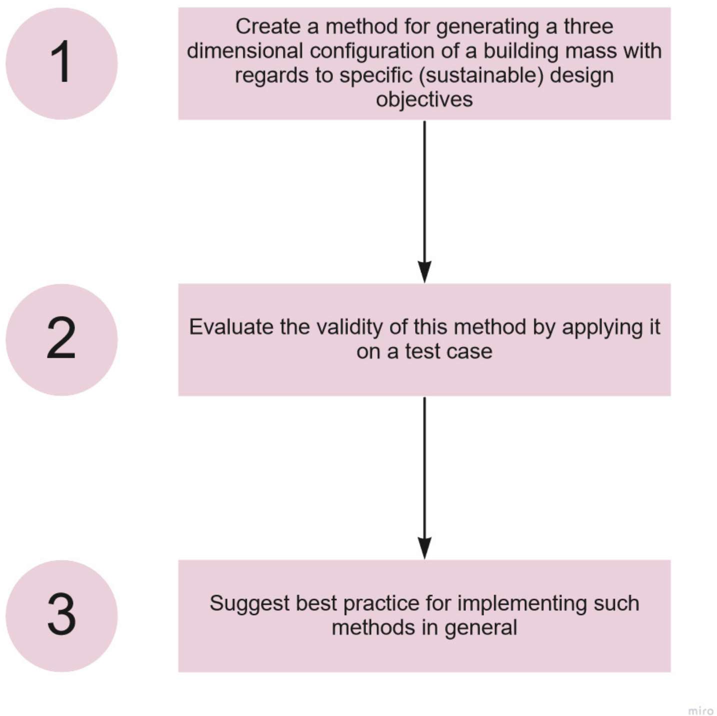


Figure 2.5: The research goals simplified

2. What type of problem are we trying to solve (in a mathematical sense)?
3. Of the examined MOO methods, which ones are most suitable for our type of problem?
4. How can we define the performance of our massing? In other words, how can we validate whether the massing performs better than alternative configurations?
5. Can we generalize the application of these techniques for other configurational problems? In other words, can we apply the developed methodology on problems with different objectives?

2.4.1 deliverables

At the end of the research process, the following products should exist:

1. An inventory of decision support strategies available to us. Of this inventory, the most relevant methods for our problem need to be identified and tested.
2. A mathematical formulation of the design problem to be used as input for the MOO solving methods when possible. Alternatively, if a mathematical formulation of the problem as a whole can not feasibly be used to generate the building massing, a mathematical formulation for finding the objective functions that can be utilized to generate the building envelope should be provided.
3. A methodology for applying MOO on the criteria of solar, daylighting, spatial, and energetic performance. This will be created as a program that can be used independently of any CAD software so as to ensure accessibility and reproducibility. More concretely, this will be in the form of Jupyter notebooks. The

input will consist of a planning area and its attributes represented mathematically as mentioned in the first point, while the output consists of the decision variables and the performance of the configuration that can be generated with these variables.

4. In the thesis' conclusion, a judgment will be made on the examined MOO methods and their usefulness for this particular set of decision criteria. Finally, a general recommendation is made on the application of these techniques on similar design problems.

2.4.2 design objectives

Traditionally, projects referred to a 'bottom line' (or financial feasibility) as the only metric of success of a project. With the increasing concern about environmental and social sustainability, Elkington and others advocate a more holistic perspective on development and have defined a new 'triple bottom line'. This is known as People, Planet, Profit (or more recently, prosperity). These categories provide a framework for sustainable development by creating a bottom line for the social, environmental, and economical effects a project may have [Elkington, 1999]. By taking this approach to the problem, we can define and group our own design objectives within this framework to make an attempt to approach the design problem integrally.

Creating a massing that has a high solar performance clearly relates to the environmental aspect of a project by enabling usage of the sun's energy in the form of passive heating and active (PV) energy generation, thereby saving on energy usage during the building's lifecycle. Researchers have argued that sustainable building corporations are more profitable [Ansari et al., 2015], while other researchers find that the link between the socio-environmental sustainability of the building itself and its value is less pronounced but that there *is* an increase in premium price and rate of absorption [Mangialardo et al., 2018] while others still have even found that there is no evidence supporting any of these claims [Warren-Myers, 2012]. Nevertheless, from Mangialardo et al. it can be inferred that even if the value itself of the building is not increased, the (economic) attractiveness of a project can be positively influenced by a more sustainable design development, both economically and socially.

From all of this, it can be learned that while the direct financial gain from adopting the three bottom lines may be difficult to prove or quantify, it still is in the interest of the developer to invest in these aspects in order to increase the economic feasibility. The characteristics of a building may influence multiple aspects of this triple bottom line theory and the following objectives can be formulated to emulate the approach a developer *may* have to such a project:

People:
Daylighting of the building & daylighting of the surroundings: As previously mentioned, daylight access increases student performance in school and generally increases health and mood [Aries et al., 2015; Elkington, 1999]. It can be concluded that it is important to maximize the daylight access of the buildings' users as well as the residents and pedestrians in the surroundings of the building.

Planet:
PV energy yield of the building: Recent PV developments ensure that net zero energy usage in urban contexts can be achieved under the right conditions [Li et al., 2015]. Starting from the 1st of January 2021 (later delayed to 1st of July 2021), all newly built buildings in the Netherlands must be Bijna Energie Neutraal Gebouw (Near Energy Neutral Building) (BENG) (Near Energy Neutral Buildings in Dutch) [Ollongren, 2019]. These demands mean that (1) the maximum energy demand in

kWh/m2.year of usage space AND the ratio between area of the facade and the heated area of the building, (2) the maximum amount of primary fossil fuel usage in kWh/m2.year of usage space and (3) the share of renewable energy % are all set at fixed values for each type of building. An example: for residential buildings with a facade area/heated area of less than 1.5, the maximum energy demand cannot exceed 55 kWh/m2.year, primary fossil fuel usage must be under 30 kWh/m2.year, and the share of renewable energy must be over 50% [Ollongren, 2019]. Practically, this means for us that we now know that new building projects need to take into account a multitude of demands that get stricter over time. For building planners this means that these demands have to be ensured in the design phase.
Heat retention of the building: As we know from the BENG demands mentioned above, the ratio between the area of the facade and the heated area of the building influences the ability of a (planned) building to pass the minimum requirements to be labeled (near) energy neutral. Another way to view this metric is the building's compactness. Compactness can mean multiple things: Catalina et al. handle it as relative compactness by taking the volume to surface ratio and comparing it to the most compact shape with the same volume, arguing that a more compact building loses less heat through its exposed surfaces. Others have simply analysed the ratio between facade area and volume and found a strong correlation between this value and the building energy consumption (r=0.91) [Depecker et al., 2001]. This value only seems to hold up in harsh climates and the relation is less pronounced in moderate climates such as that of the Netherlands, meaning this metric is less accurate for the test case.

Profit:
Floor Space Index of the building: The floor space index of a building plot is the total floor area of the building over the plot area. It is a direct indicator of the density of the urban fabric. Density of the urban fabric and land/real estate value are directly related according to [Ottensmann, 1977]. This means that we can assume that it is in the interest of the developer to maximize this value in order to maximize profits off the lands usage.

The five objectives outlined above all have an optimal massing that correspond to the best performing building configuration. The exercise of the thesis is to find a method to generate a massing that performs well in all five of these criteria without compromising too much in any of the criteria. In the next section, each criterion as well as the total problem will be presented in formal terms.

2.5 OBJECTIVE FUNCTIONS

Now that the categories of the objectives have been defined, the next step is to formalize the design objectives and afterwards the totality of the problem in mathematical functions. Starting with the two main objectives that relate to the solar performance of the configuration. These objectives are the potential to generate Photovoltaic energy, and the potential for access to daylight.

2.5.1 functions

The **PV potential** (F_1) of a building or massing can be calculated as follows:

$$F_1 = \sum_{i \in [0,n)} \sum_{j \in [0,m)} V_{i,j} W_i A \tag{2.1}$$

Where:

i indicates the index of the test points in the solar positions (hours of the year)
n indicates the total number of test points in the solar positions (hours of the year)
j indicates the index of the test point on the roof of the building
m indicates the total number of test points on the roof area of the building
$V_{i,j}$ indicates the visibility status of the ith solar position from the jth test point
W_i indicates the global horizontal radiation of the ith solar position in Wh/m^2
A indicates the area of a voxel in m^2

The resulting value F_1 is a measure of the PV potential of the configuration. The unit is Wh and gives an indication of the total expected solar radiation on the roof of the configuration for the entire year. This value can be used to estimate the performance of PV panels installed on the roof of the configuration.

The **Daylighting potential** (F_2) of a building or massing can be calculated as follows:

$$F_2 = \sum_{i \in [0,n)} \sum_{k \in [0,p)} V_{i,k} L_i A \tag{2.2}$$

Where:

i indicates the index of the test points in the solar positions (hours of the year)
n indicates the total number of test points in the solar positions (hours of the year)
k indicates the index of the test point on the facade of the building
p indicates the total number of test points on the facade of the building
$V_{i,k}$ indicates the visibility status of the ith solar position from the kth test point
L_i indicates the direct normal illuminance of the ith solar position in hectolux (hectolux since this is the unit used in the Radiance tool)
A indicates the area of a voxel in m^2

The resulting value F_2 is a measure of the Daylighting potential of the configuration. The unit is (hecto)lux and gives an indication of the illuminance; luminous flux received per unit of surface area for the entire year. This metric gives an indication on the amount and intensity of the direct sunlight received by the facade; relevant for window, balcony, and shading in the later design phases. Aggregation of these values normally is not done over the entire year but in order to remain consistent with the other objectives this is the case in this method. Furthermore, in full simulations, the indirect component of the daylight also plays a major role in the total illuminance. This is however discarded in the optimization since this (a) complicates the objective function and (b) the direct component is an often overlooked metric as proposed by Dogan and Park.

For the **Heat retention potential** of the building, the following two approaches can be taken as previously identified: the simple method of floor area over surface area (shape coefficient or building coefficient C_f) which works for harsh climates used by Depecker et al. and the more advanced relative compactness R_c of the building compared to the most compact shape with the same volume used by Catalina et al..

(1) $C_f = S_e / V_b$ [Depecker et al., 2001]
and
(2) $R_c = 6 \times V_b^{\frac{2}{3}} \times S_c^{-1}$ [Catalina et al., 2011]

The similarities between the two methods can be seen clearly. Method 2 (R_c) is used in the remainder of the thesis to guarantee accuracy of results since within the context of a Dutch climate, method 1 (C_f) would not be as valid and also is not a dimensionless measure of performance. The result is objective function F_3:

$$F_3 = 6 \times V_b^{\frac{2}{3}} \times S_c^{-1} \tag{2.3}$$

Where:

S_c corresponds to the surface of the envelope
V_b corresponds to the inner volume of the building

The resulting value F_3 is a measure of the relative compactness of the entire configuration. It is a dimensionless value, where a value of $F_3 = 1$ corresponds to a perfectly cube-shaped configuration. A value lower than 1 approaches a spherical shape and a value higher than 1 means the shape is less compact than a cube of the same volume. The lower the value, the more the configuration will be able to retain it's heat and minimize losses through the exposed facade.

For the **Urban Density** of the configuration, the Floor Space Index is used as a measure of performance. A target value is set beforehand as is usually the case in urban development projects.

$$F_4 = \frac{2w}{w+t} \tag{2.4}$$

Where:

w corresponds to the Floor Space Index of the building
t corresponds to the target Floor Space Index of the building

This value F_3 reaches 1 when the target compactness is reached, and after this yields diminishing returns on extra added floor space. The previous two objective functions are dimensionless and essentially function as (soft) constraints in order to limit the amount of space that gets allocated in the final configuration and ensure some measure of contiguity between the assigned voxels.

2.5.2 standard integer programming formulation

If we now want to optimize any configuration, it is desirable to bring it into a standard form. For the entire configuration, if we want to define the problem as a mathematical programming that we can quickly solve using for example the simplex method, we need to bring it to this form [Murty, 1983]:

Maximize:
$f(x_1, x_2, ..., x_n) = c_1x_1 + c_2x_2 + \ldots + c_nx_n$

subject to:
$a_{11}x_1 + a_{12}x_2 + ...a_{1n}x_n \leq b_1$
$a_{21}x_1 + a_{22}x_2 + ...a_{2n}x_n \leq b_2$
$\vdots$
$a_{m1}x_1 + a_{m2}x_2 + ...a_{mn}x_n \leq b_m$

$x_1, x_2, ..., x_n \geq 0$

Where:
f is the objective function
x is the decision variable
n is the total number decision of variables
c is the cost (or gain) value
a is the constraint value
m is the total number of constraints
b is the constraint boundary

In matrix form this becomes:
$\mathbf{x} = (x_1, x_2, ..., x_n)^T$
$\mathbf{c} = (c_1, c_2, ..., c_n)^T$
$\mathbf{b} = (b_1, b_2, ..., b_m)^T$

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \ddots & & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{pmatrix}$$

This can then be written as:

Maximize: $\mathbf{c}^T\mathbf{x}$
subject to: $\begin{cases} \mathbf{Ax} \leq \mathbf{b} \\ \mathbf{x} \geq \mathbf{0} \end{cases}$

It is important to note that this notation corresponds to the standard notation of a (integer) programming problem and represents the objective score for the entire configuration and not its constituent parts. If the objective functions as described in the previous section are added into this framework, it quickly appears how the problem is not linear nor straightforward to solve.
Assuming that the totality of the potential building volume available is discretzsed into n number of voxels that can represent the presence or absence of building mass and define a variable x for each of these voxels. This gives the following decision variables:

$$0 \leq x_1, x_2, ..., x_n \leq 1$$

and

$$x \in \mathbb{Z}$$

After all, a building either occupies a space or it does not occupy that space. The problem is now a (binary) integer programming problem. If the potential building volume can be discretized into sufficiently small parts, a suitable resolution for the massing can be achieved. When this approach is now applied to the objective functions, a problem arises: In equations 2.1 through 2.4, it is shown what the objective functions should look like. When these are rewritten to include these binary decision variables as in the standard formulation, it is found that that the occupation status of a voxel may influence the cost value of any of the other voxels in regards to $F1$ and $F2$, see image 2.6, and that the performance does not change linearly with the changing of the decision variables:

It is theoretically possible to overcome these problems. The nonlinearity problem can be solved by piecewise linearization. Theoretically, by adding auxilliary constraints on the variables, it should be possible to set the cost values for the daylighting performance and solar performance variables c_n to 0 when one of the variables that influences variable x_n is in an active state (i.e. one of these variables

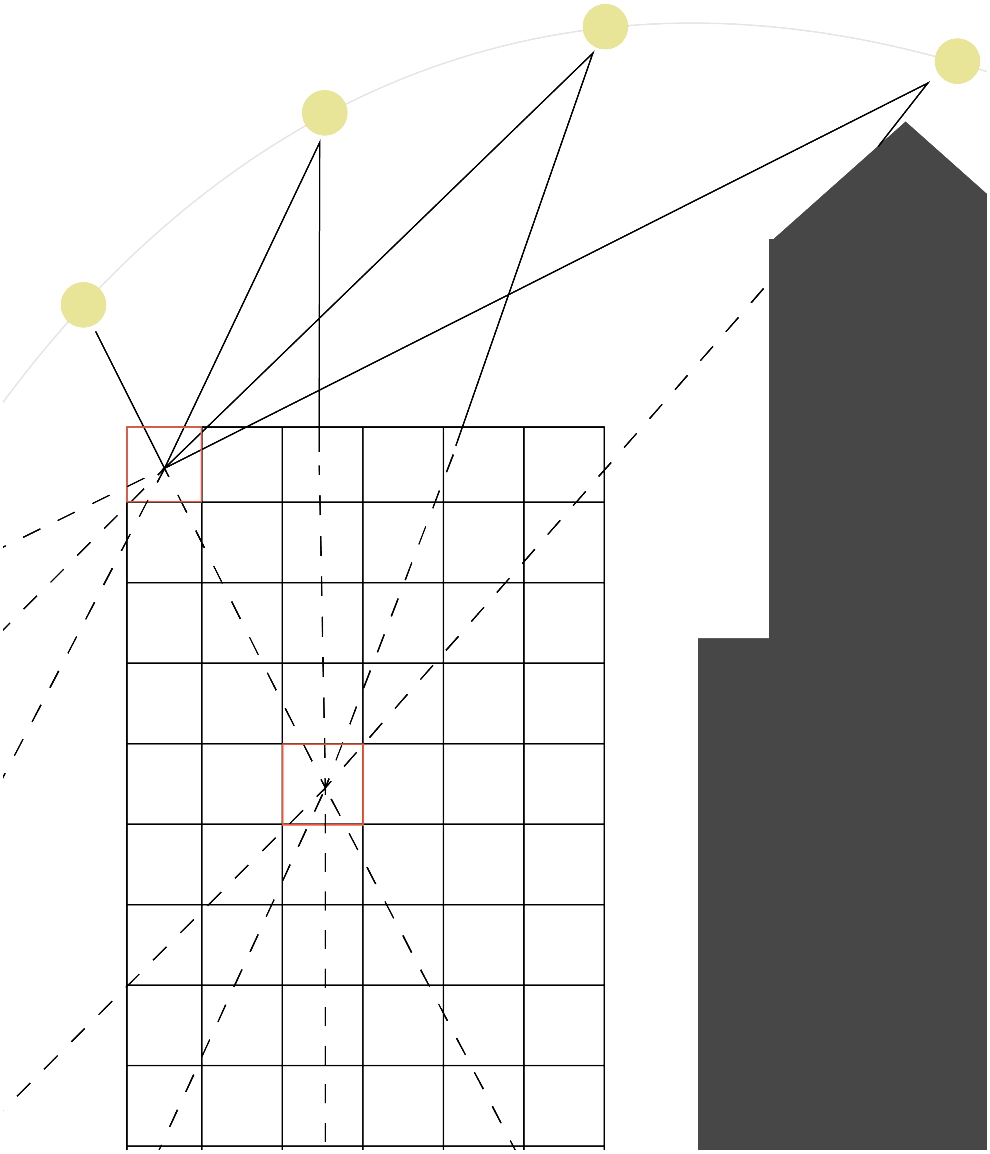


Figure 2.6: The interdependency problem. If we want to determine the value of a voxel (in red) we need to know how much sun it catches, as well as how much it blocks other voxels. However, if a voxel does or does not exist(i.e. it's occupation status is 1 or 0), the voxels that influence it and are influenced by it need to have their score updated as well. This in turn might again influence the value of the original voxel.

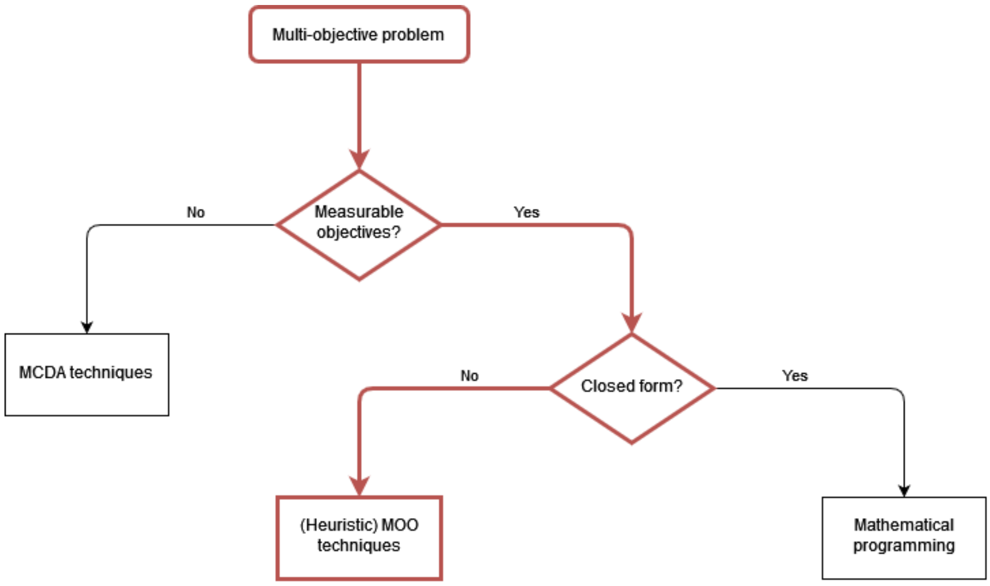


Figure 2.7: The chosen decision-support method: Multi-Objective Optimization. It is desired to compare the performance of many configurations on quantifiable metrics, but the problem is too complex to be reasonably be brought to a closed form

holds value 1) [AIMMS, 2016]. This requires an exponentially increasing number of constraints when the resolution of the model is increased by adding variables (voxels) that could all potentially block rays coming from the sky or sun towards the target voxel. Furthermore, if this method successfully were to be applied, a final problem arises. Lets define the objective function by simply adding the costs together as follows:

$$f(x) = \sum_{i=0}^{n} x_i(c_{1i} + c_{2i} + c_{3i} + c_{4i} + c_{5i})$$

Where:
c_1 is the FSI cost
c_2 is the building daylighting potential cost
c_3 is the surroundings daylighting potential cost
c_4 is the heat retention cost
c_5 is the PV potential cost
n is the number of voxels

This would theoretically give us (when the nonlinearity and interdependency problems are solved) a workable programming. However we are now comparing 'apples to oranges'. For instance, an increase of 10% past the required value in FSI is desirable but if the added square meterage also causes the other four criteria to lose a 2% points, the new solution is formally speaking *more optimal*, but would likely not be considered better in the eyes of an architect, client, or developer. More possibilities for weighting and normalization are required and a closed-form mathematical programming is not an option for the problem.

It can be concluded from the previous section that the problem is not linear in nature and is not straightforward to solve. An alternative method for generating a solution to the problem will need to be found. Furthermore, the target values (goal) and weight for each objective are not included in this formulation. A more nuanced approach to the problem is desired that can find (near) optimal solutions, ensures more control on the scalability and guarantees realistic computation times. Due to the large solution space, implementation and solving difficulty has to be limited by dealing with the interdependency problem without applying a prohibitive amount of constraints and a heuristic is looking to be a more attractive approach to solving the problem. The next chapter (3), describes how the objectives are integrated into the method in more detail.

3 METHOD

Now the implemented method is described that generates near-optimal configurations. In order to explain the method design process best, the subproblems will be solved before proposing the complete solution to the problem. To do this, the chapter is structured as follows: First, toy problems are defined to illustrate how each design objective of the optimization is related to its spatial configuration. This is done through the creation of several toy problems that will be solved on a smaller scale. The final toy problem shows how we the objective functions can be utilized to feed into a solver that outputs a ranking of many configurations. These configurations are then brought simulated in chapter 4 to compare their (relative) performance. In the final section of each toy problem, an overview is given of the computation and simulation speeds along with a visualisation of the result.

3.1 TERMINOLOGY

Before we can move on to the core of the implementation details, it is important to define some terms and make clarifications on what the words that often return in the chapter mean. Certain definitions are vague and can be used interchangeably, while other specialized terms have no clear bounds. The following glossary attempts to elucidate the meaning of all of these concepts to help understand what is meant by them.

3.1.1 generative design

- Lattice: A scalar field within a discrete 2D or 3D space. Represented as an array of values that can represent spatial qualities.
- Voxel: A portmanteau of volume and element, like a pixel in 3D. In this work: a single value within the lattice array.
- Mass: A group (array) of voxels representing the (maximum) volume of the building.
- Configuration: An ordering (in 2D or 3D space) of voxels
- Massing: The process of obtaining the mass from a given design space.
- Envelope: Boundary of the mass
- Stencil: The neighborhood definition in a discrete 2D or 3D space.
- Environment field: Scalar, simulated values on a 2D or 3D grid with the same structure as the voxel lattice.

3.1.2 decisionmaking

- Objective: The goal of the decision-maker. The objective consists of at least two design criteria.
- Decision variable: A quantity that the decision-maker controls.

- Decision space: The range of values these variables can take on.
- Global decision variable: A decision variable that affects the performance of the entire design space.
- Local decision variable: A decision variable that affects the performance of an aspect of the design space.
- Design criteria: Physical attributes of the final design.
- Design variable: A decision variable specifically applied to one of the design criteria.
- Design space: The range of values that these variables can take on.
- Performance indicator: An aggregated value that quantifies the performance towards a design criterion.
- Performance estimator: An estimated value of the performance towards a design criterion.
- Global performance indicator: A performance indicator that informs the state of the configuration as a whole concerning a certain design criterion.
- Local performance indicator: A performance indicator that informs the state of a segment of the configuration concerning a certain design criterion.
- MCDA: The evaluation of multiple conflicting criteria.
- MCDM: The decision-making on multiple conflicting criteria.
- Function: Mathematical function.
- Spatial function: Space usage or occupation type (in an architectural sense).
- Cost function: Mathematical function for calculating scalar values of a voxel towards a design criterion. 'Cost' is used to calculate desirable (for example sunlight received) as well as undesirable (for example sunlight blocked) performance indicator values.
- Objective function: Mathematical function for calculating the performance of a configuration towards the objective. This function combines at least two cost functions.
- Heuristic: A method to find an approximate solution to a problem
- Metaheuristic: A procedure to find or create a heuristic to solve a problem
- Potentials: The ratio between the current performance of a configuration towards a design criterion and the maximum performance towards that design criterion

3.1.3 daylighting and solar

- Radiance: The density of radiant flux per unit of emmitting surface area and unit of solid angle. W/sr/m2
- Irradiance: The density of radiant flux per unit of receiving surface area. W/m2
- Luminance: The luminous intensity per unit of emitting surface area. Candela/m2.
- Illuminance: Total luminous flux per unit of receiving surface area. Lux.

- Visibility: The unobstructed view towards a target direction from a point of interest.
- Closeness: The distance (euclidean) between two points in 2D or 3D space.

3.1.4 clarifications

Now that these definitions have been clarified it is important to note a few things. While heuristics are generally specific to a certain problem, metaheuristics are more general by nature and can be applied to a larger number of problems. Exploring the subtle differences and similarities between the two definitions can be an entirely separate subject of study. Therefore, from now on the term heuristics will be used without diving into the details of correct terminology. When heuristic is used from now on, it refers to a: Non problem-specific strategy that guides the search process by efficiently exploring the decision space to find near-optimal solutions. [Blum and Roli, 2003].

Regarding the definitions of design criteria and decision criteria, design variable and decision variable, design space and decision space, cost function and performance indicator/estimator, mass, envelope and configuration, multi-objective optimization and heuristics/metaheuristics, and design and decision space: These many definitions with only subtle differences tend to be confusing. From the literature studies, it seems the terms are often used interchangeably as well, adding to the muddle of words. It is therefore now important to refer back to the problem statement and generally chapter 2 for clarification. To reiterate and simplify: the goal of the research is to design a methodology for generating building **configurations** that perform well in regards to certain **design criteria**, by employing **multi-objective optimization** techniques. To do this, **objective functions** need to be defined that can be fed into a solver that can use a **heuristic** method to generate outputs which can finally be **validated**. The next section gives an illustration of this methodology design by the usage of toy problems.

3.2 TOY PROBLEMS

All coding of the problems as well as the test case application has been done in Microsoft VSCode using Jupyter notebooks. To ensure open access and reproducibility, the Thesis Repository is hosted on GitHub. This work builds on a structure called TopoGenesis which is *an open-source Python package that provides topological structures and functions for Generative Systems and Sciences for various application areas such as:*

- generative design in architecture and built environment
- generative spatial simulations
- 3D image processing
- topological data analysis
- machine learning

This framework allows for the quick and easy construction of lattices and enables us to use efficient methods and libraries such as NumPy arrays for the preparation and processing of our functions in 3D. [Azadi and Nourian, 2020]

The following flowchart 3.1 gives a simplified overview of the inputs and outputs that will be needed to develop the method. Decision variables are generated by an optimizer. These variables are used to construct a configuration (mesh) from which the configurations' PV potential, Daylighting potential, and Floor space index are calculated. The optimizer will find several best configurations. Of these, a sample will be taken to be examined by their relative performance: If the relative performance is comparable, the approach was successful.

3.2.1 T.P.1 environment and voxelization

The first toy problem concerns the preparation of the environment and voxelization of the maximum building volume. The user input is a mesh that represents the planning area, the dimensions and location of the building's maximum boundaries, and the number of divisions for the voxelization (i.e. the resolution of the method to be applied). In the example below (3.2a), this is set as a cube with dimensions of 75x75x75 m, a division of 5, creating as output 125 voxels of 5x5x5 m as can be seen in figure 3.2a.

3.2.2 T.P.2 solar path

The next output that is needed is an array of vectors for the positions (directions) of the sun throughout the year. The user inputs a .epw file as weather file for the location. In this instance, a .epw file of Amsterdam is used, approximating the local climate. A location longtitude (4.3571 E) and latitude (52.0116 N) is also needed. Then, the Sunpath function from Ladybug, an environmental simulation tool, is called to actually generate the hours of year that are needed. Each day, every hour, for every sun position with a z-coordinate above 0, the current hour of the day, along with the solar direction, Global Horizontal Irradiance (GHI) and Direct Normal Illuminance (DNI) are outputted into arrays. For the settings mentioned above, this yields a total of 4460 test solar positions (hours of the year where the sun is above the horizon), see also figure 3.2b.

3.2.3 T.P.3 PV potential of the lattice

Now the objective functions are ready to be included. For the purpose of demonstrating the objective functions through the next four subsections, a random configuration is created. Starting with the PV potential of the lattice, the PV potential of the configuration is calculated by finding the roof voxels, adding test points on the roof, raytracing with the environment and for all rays that did not hit; summing the intensity values in wH on each voxel (as reference for later) and also summing all the values for the entire configuration. For reference, see also figure 3.3. To achieve this, the equation 2.1: $F_1 = \sum_{i \in [0,n)} \sum_{j \in [0,m)} V_{i,j} W_i A$ can be included for usage within the TopoGenesis framework with voxels. The highest values reached as can be seen in image 3.4b occur at the top of the roof where there are no obstructions. At 110474089 Wh on a yearly basis for each mesh face, or 883.8 kWh/m^2 yearly, these values are in line with expectations for yearly averages in the Netherlands [Dupont et al., 2020].

3.2.4 T.P.4 Daylighting potential of the lattice

Similar to the previous toy problem, by calculating the intersections between test points on the facade faces of the lattice and the context, an estimation can also be made on the yearly daylight potential. To achieve this, the equation 2.2: $F_2 = \sum_{i \in [0,n)} \sum_{k \in [0,p)} V_{i,k} L_i A$ is included. The flowchart 3.5 gives insight to the needed inputs and outputs. The yearly lux values give an indication of the amount of (direct) sunlight the facade may receive in a year. Matters such as glare and heat gain are ignored in this case since they are heavily influenced by design decisions such as materiality and window, shading, and balcony dimensions. Furthermore, a drawback of this approach is that it simply sums the values for each solar hour

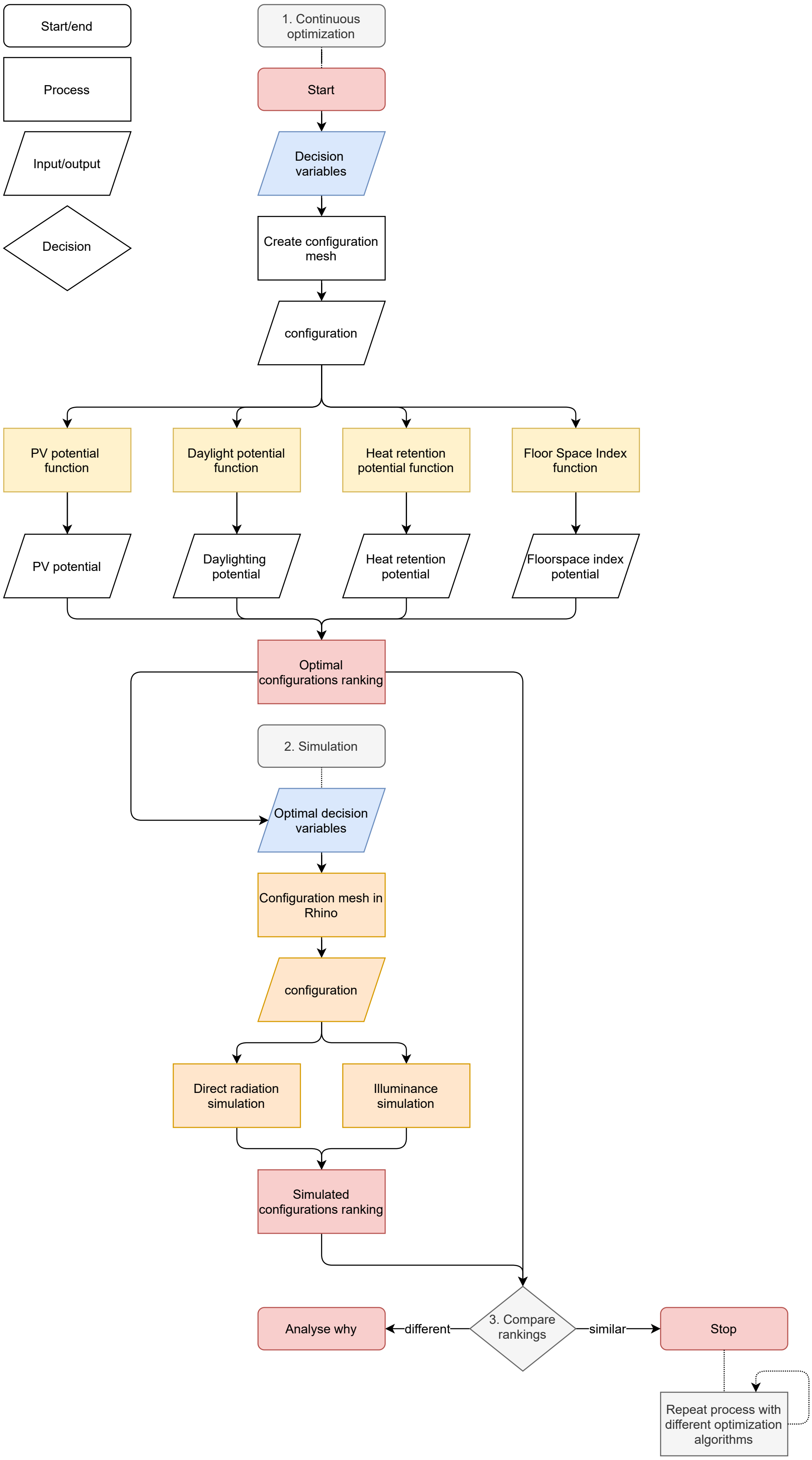


Figure 3.1: The data-flow diagram of the proposed method. A more detailed version image 6.1 can be found in the appendix.

(a) (b)

Figure 3.2: (a) The result of the first toy problem: In red a simple 5x5x5 'rubik's cube' with voxels of size $15m^3$ and in light gray the imported environment. (b) The result of the sun pathing toy problem: the arrows are directed towards the centre of the lattice.

without taking the indirect component into account, so accuracy and validation may be an issue as also explored later in the next chapter. The maximum yearly value received on one of the facade faces is 683 gigalux, amounting to around 6 gigalux/m^2 on a yearly basis at maximum. For the daylighting and PV potential, the Pyembree library is used to greatly reduce computation times.

3.2.5 T.P.5 Heat retention potential of the lattice

The objective implemented is the heat retention potential of the lattice. This objective is included to ensure the resulting configuration remains contiguous and as compact as possible to ensure heat losses are limited by the buildings shape. The formula 2.3 $F_3 = 6 \times V_b^{\frac{2}{3}} \times S_c^{-1}$ is used to minimize the surface area to volume ratio.

As mentioned in chapter 2, there are two methods for calculating the relative compactness of a configuration that are both valid to some extent. For the purpose of demonstrating the difference in results between the two methods, a random configuration is generated and then analysed.

The first method according to Depecker et al.:

$C_f = S_e / V_b$

Where:

S_e corresponds to the surface of the envelope
V_b corresponds to the inner volume of the building

The second method according to Catalina et al.:

$R_c = 6 \times V_b^{\frac{2}{3}} \times S_e^{-1}$

Where:

S_e corresponds to the surface of the envelope
V_b corresponds to the inner volume of the building

When two configurations are generated to compare the results from these calculations, it is found that the output of both methods generally relate to each other in a 1:10 ratio. When the configuration becomes more extreme however, the ratio

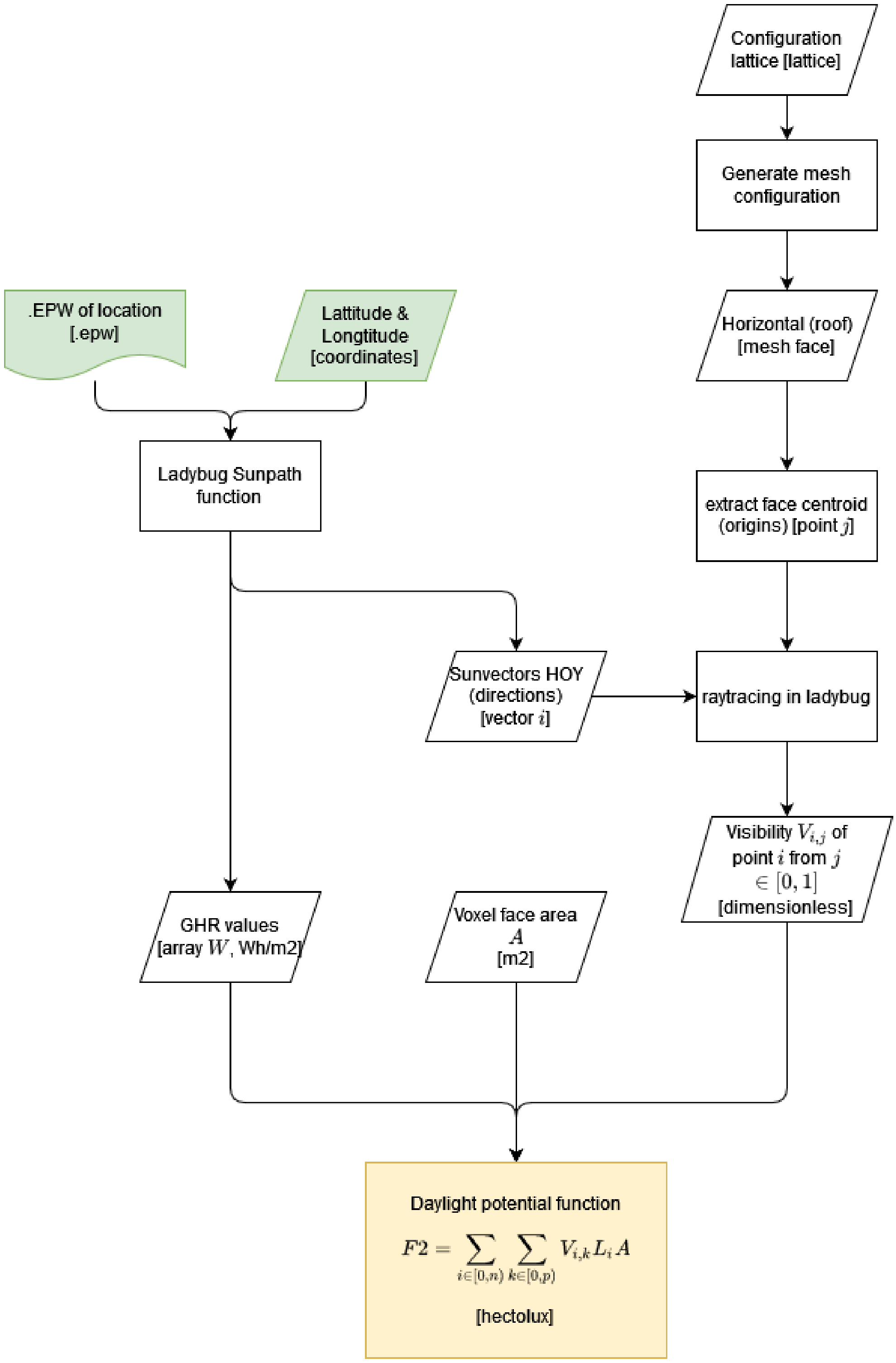
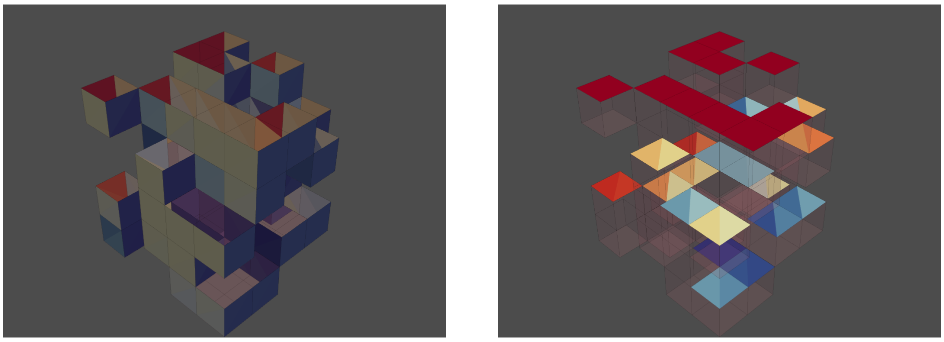


Figure 3.3: The flowchart for the first objective: maximizing yearly solar irradiation on the roof.



(a) (b)

Figure 3.4: (a) The result of the daylight potential toy problem: red values indicate higher yearly illuminance values. (b) The result of the PV potential toy problem: Red values indicate higher solar irradiation values.

between the two methods for computing compactness is no longer 1:10 and the relative compactness is a more reliable method for edge cases such as these.

3.2.6 T.P.6 Urban Density of the lattice

The final objective is in place to ensure there is a limit to the amount of voxels that are selected by the optimization process. This is achieved by using the formula 2.4: $F_4 = \frac{2w}{w+t}$. This constrains the amount of selected voxels by never growing past a value of 2, no matter how many voxels are selected. At the same time, it ensures approximately the correct amount of voxels are selected. The score of the selected random configuration is 0.837, indicating that it is close to the target FSI but has not reached this value yet.

3.2.7 T.P.5 optimization

For optimization, the PyGmo library is used. This library contains many algorithms, but for demonstrative purposes the only algorithms shown in this chapter are the NSGA-II, Improved Harmony Search (IHS), and NSPSO. For the dimension of the decision variables x, n (the total number of voxels) is used. The bounds are set between (0,1) and it is specified that there are 0 integer variables: optimization occurs continuously to avoid the issues with integer optimization mentioned earlier. Later on, the decision variables are rounded to be able to find the configuration. The number of generations g is set at 100, while the starting population size p is set at 64 for one run and 128 for another run, meaning there will be 64 or 128 individuals used for crossover and mutation. Pygmo can accept the cost functions that have been defined earlier and now the next step is to simply run the optimization and extract the results as can be seen in figure 3.10.

Optimization takes around 11 hours for the settings described above. The results are interesting: it can immediately be seen that NSGA-II yields the best results. In the left column of solutions, the initial (seed) population is also highlighted in grey, while in the left column in dark grey, the solutions of the optimization with a smaller population can also be seen. Interestingly, the results do not significantly improve with a larger population size. The five best solutions are highlighted and examined in more detail. These are solutions 0, 1, 3, 4, and 5. The target FSI was set at 3, meaning the goal is to have around 75 voxels in the final configuration. The results have been added in table 3.1. Upon inspection of the generated shapes in figure 3.11, several things can be noted. The most optimal shape has several 'gorges' running along the edges where light can penetrate deep into the building. At the same time, the roof area is maximized. The second-best solution is an almost completely

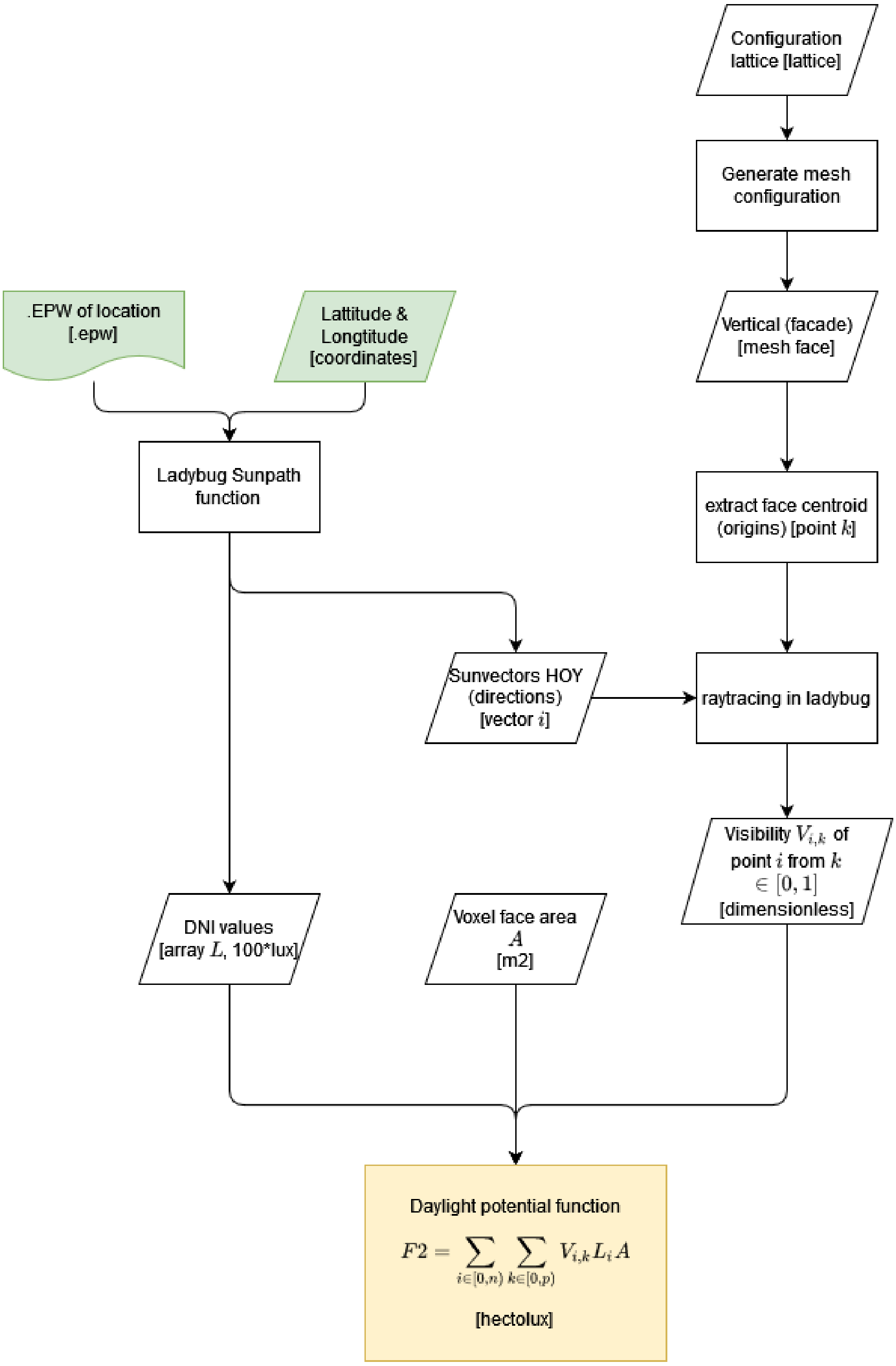


Figure 3.5: The flowchart for the second objective: maximizing yearly illuminance on the facade.

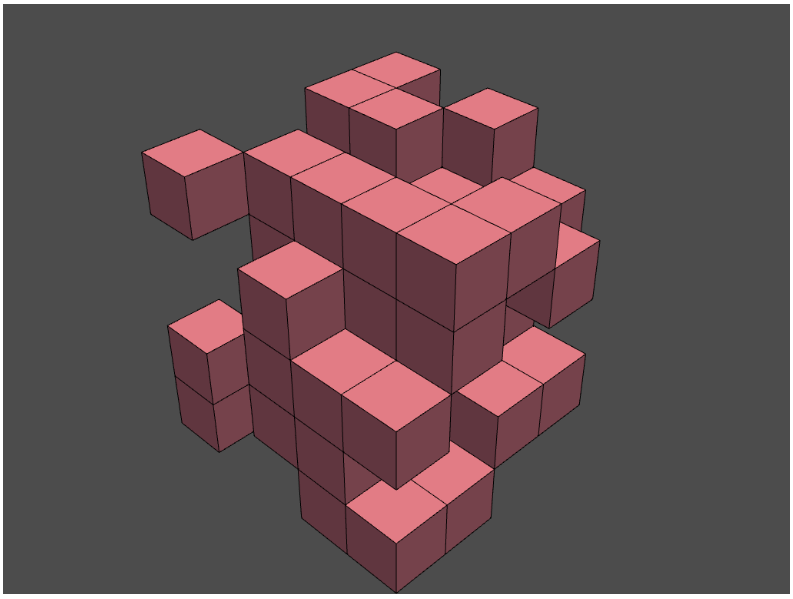


Figure 3.6: The random configuration has a relative compactness of 2.02, indicating it is not a compact configuration.

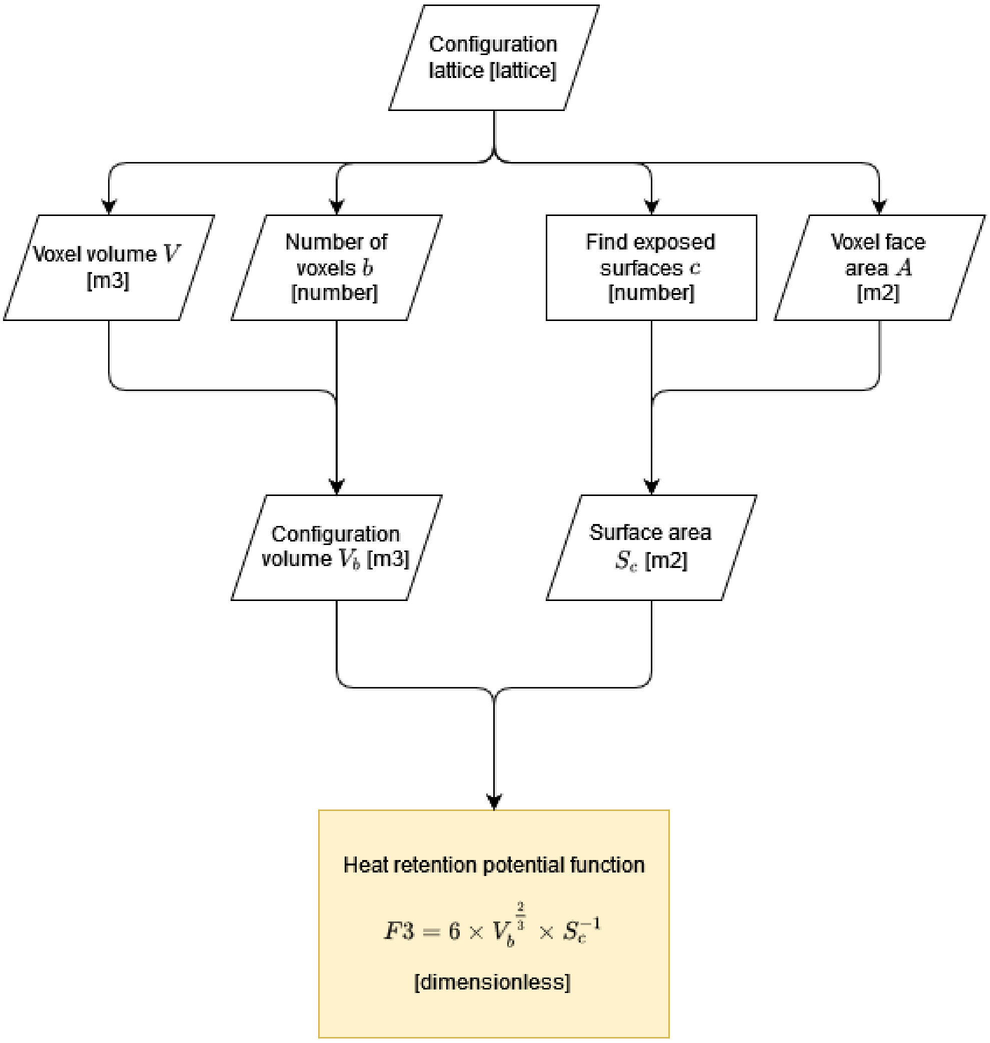


Figure 3.7: The flowchart for the third objective: maximizing the compactness of the configuration.

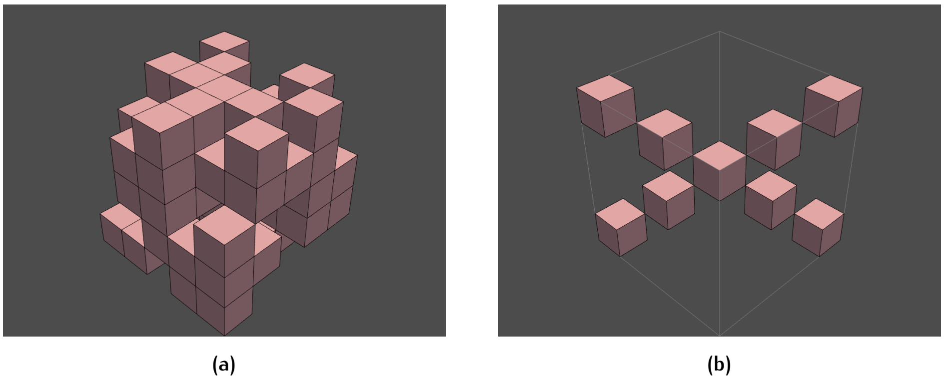


Figure 3.8: (a) This is another randomly generated configuration. The score according to the simple method is: 0.197 while according to the advanced method the score is: 1.956. (b) The score of this edge case configuration according to the simple method would be 0.37, while according to the advanced method, the score is 4.39

	F1 PV	F2 Daylight	F3 Compactness	F4 FSI	Voxels
3.11a	-8.090	-4.616	1.880	-1.038	81
3.11b	-5.696	-6.623	1.293	-1.211	115
3.11c	-3.964	-8.110	1.693	-1.080	88
3.11d	-7.376	-5.246	1.867	-0.951	68
3.11e	-3.905	-8.091	1.667	-1.107	93

Table 3.1: The optimization results: The best five solutions and their objective values for PV potential (**F1**) in gWh/year, daylighting potential in gLux*100/year (**F2**), relative compactness (**F3**), and floor space index (**F4**)

filled configuration with a few voxels cut out of the centre. The third and fifth configurations are very similar in score and appearance, with a hollowed out core. Finally the fourth configuration has a hollow core as well as a large roof area, but does not achieve the target FSI value. Due to the discretisation of the results after the optimization, some detail may be lost in the final results.

From these toy problem optimizations, several things can be concluded. First, the question that is asked of the solver informs the answer: it is important to take a critical look at the cost functions since these determine the outcome of the optimization and they mostly perform well. When picking the algorithm, NSGA-II clearly outperforms the other methods as can be seen by figure 3.10. IHS and NSPSO do not reach the pareto front that NSGA reaches, but do improve on the starting situation. In the next chapter, some improvements to the method in regards to the objective functions will be presented, as well as a validation of the estimated solar performance of the envelope by pairwise comparison. The chapter will conclude with the most important lessons learned and suggestions for further development of the model.

	F1 PV	F2 Daylight	F3 Compactness	F4 FSI	Voxels
3.11a	-7.977	-6.034	1.661	-0.998	319
3.11b	-6.524	-7.343	1.380	-1.082	377
3.11c	-7.974	-6.007	1.604	-1.012	328
3.11d	-7.203	-6.772	1.380	-1.074	371
3.11e	-4.726	-8.847	1.838	-0.966	299

Table 3.2: The optimization results: The best five solutions and their objective values for PV potential (**F1**) in gWh/year, daylighting potential in gLux*100/year (**F2**), relative compactness (**F3**), and floor space index (**F4**)

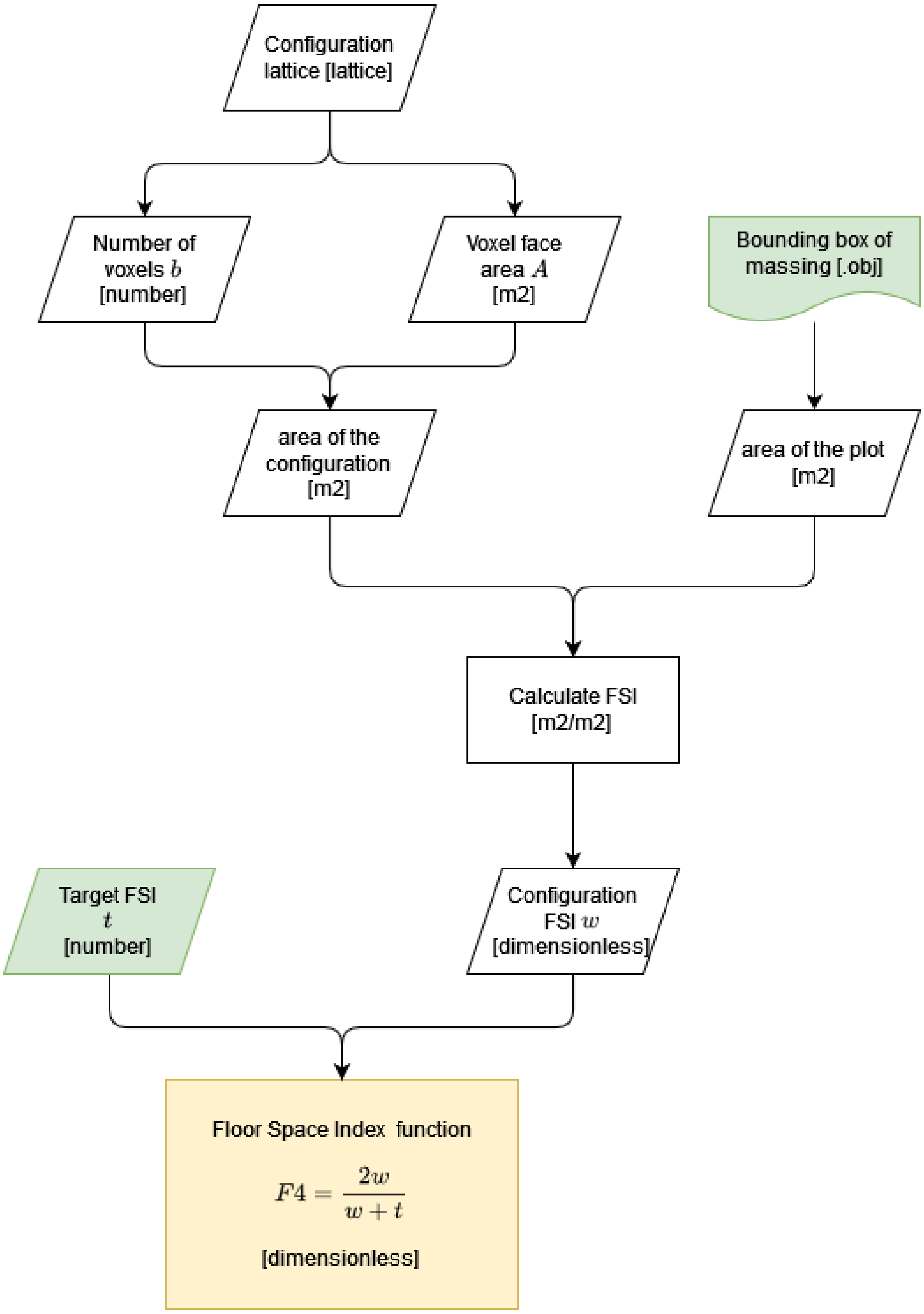


Figure 3.9: The flowchart for the fourth objective: constraining the configuration at approximately the desired size.

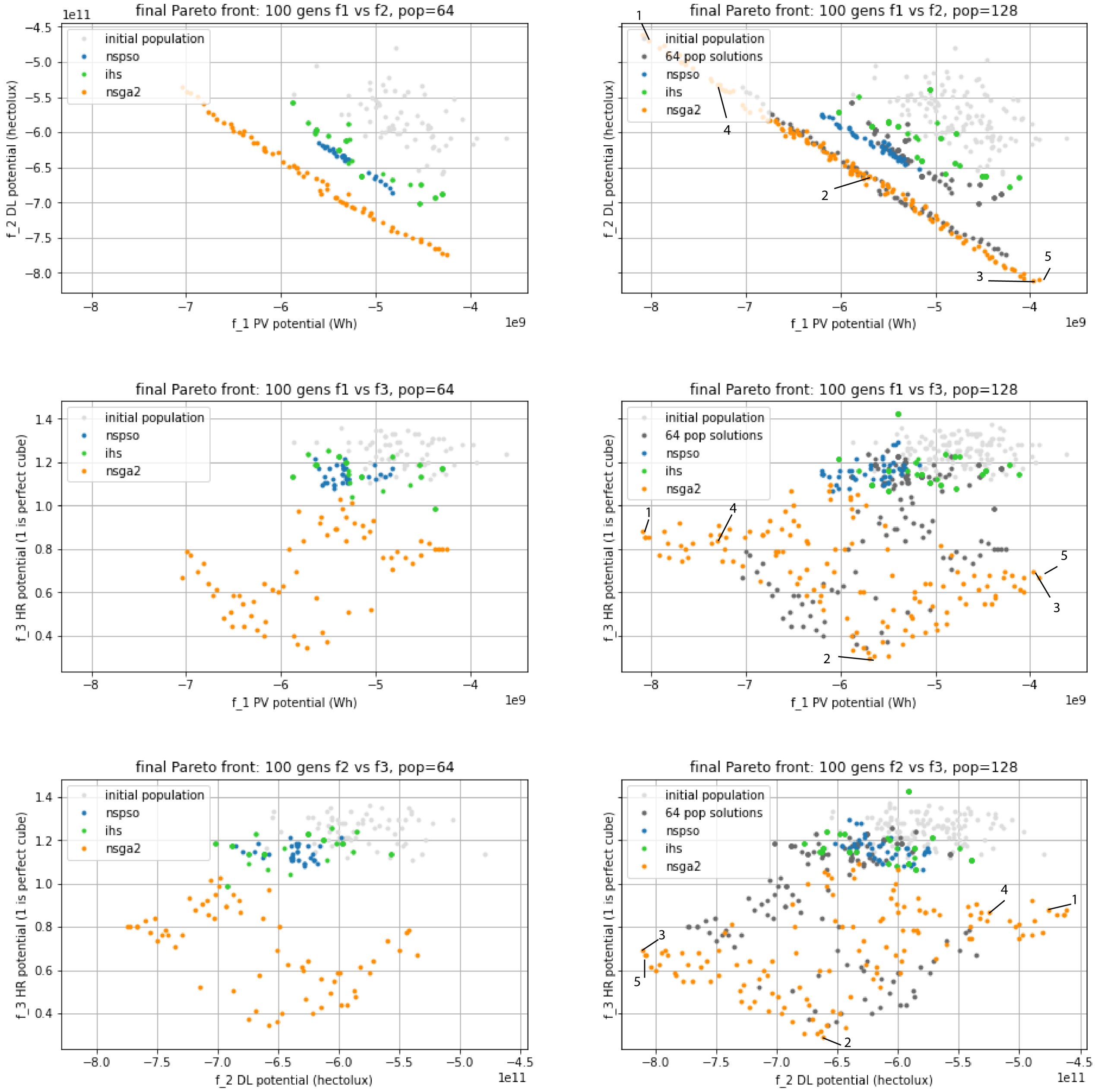
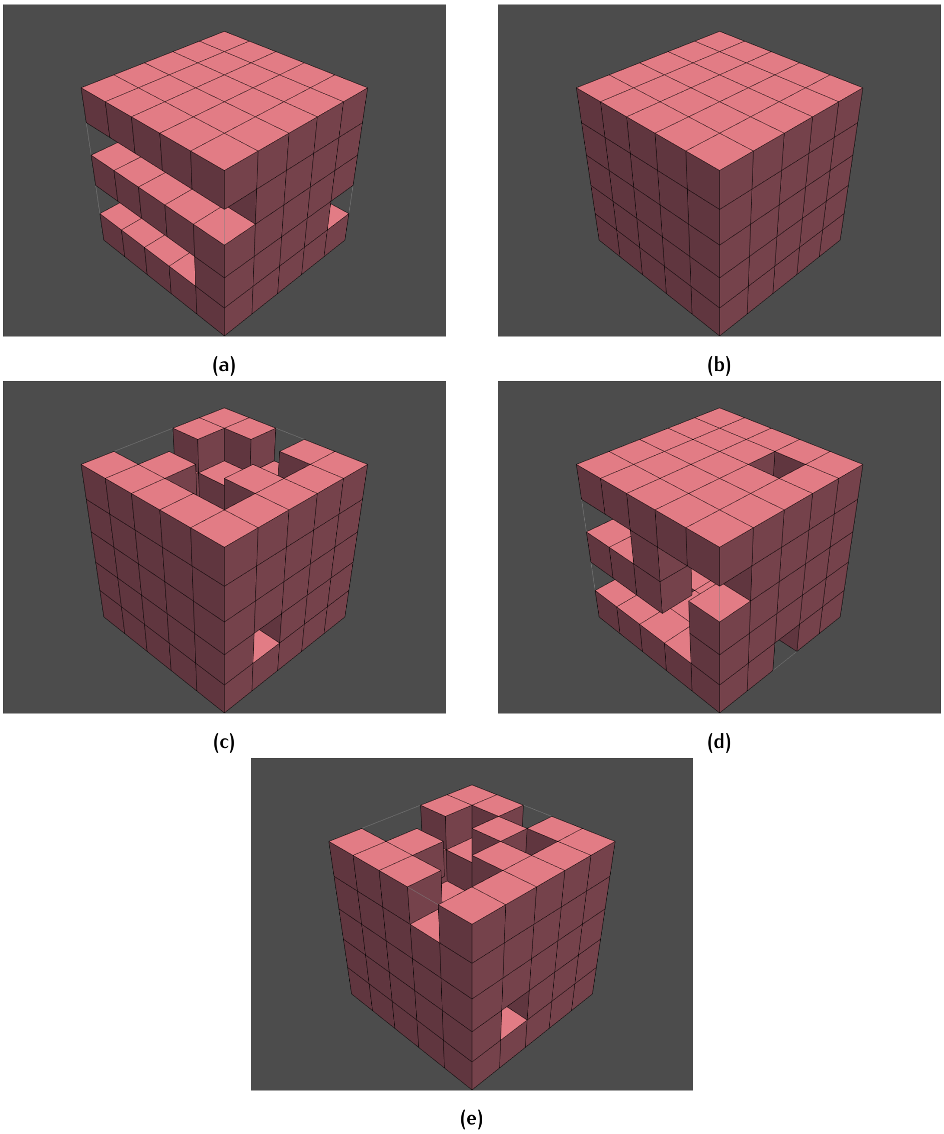


Figure 3.10: Output of the final toy problem: Pareto frontiers of non-dominated solutions with regards to the main objectives F1 (PV potential) and F2 (Daylight potential).



(a) (b) (c) (d) (e)

Figure 3.11: The five best performing configurations after applying the optimization.

4 EVALUATION

In the previous chapter, the method that can be used for calculating optimal massings in regards to certain objectives has been described. The toy problems give an illustration of the techniques used, but the accuracy and validity of the results is difficult to assess at such a low resolution. For this reason, a more detailed simulation of the methods as described in the previous section is presented. The environment remains the same, but the simulation takes place inside Rhino, a 3D modelling software. The simulations are run using Ladybug and Honeybee, two tools that utilize the Radiance method for conducting solar analysis. This chapter describes the implementation of the validation and the lessons learned from said implementation.

4.1 METHOD VALIDATION

The process for validating the performance of the developed method is as follows: First, a sample of 5 configurations is taken from the optimal solutions, the meshes corresponding to these configurations are imported into Rhino and Grasshopper, where they are used for a detailed simulation. The analysis uses Ladybug and Ladybug-Honeybee, two tools developed for radiation analysis and daylight analysis respectively. The resulting yearly values are compared to the estimated values, and to the estimated values of the other configurations, to get a sense of the performance of the developed method. This process can be seen in figure 4.1.
The validation of the yearly irradiation values is done using Ladybug, a plug-in for Grasshopper in Rhino3D. The analysis period is set to the entire year for every hour, creating a cumulative sky matrix. The offset is set at 1cm from the roof test points, and for each mesh face, a test point is generated. The results can be viewed in table 4.1. The ranking in simulated values is consistent with the ranking of the estimated values. The values themselves fall within a small margin of error (<5%) between the simulated and achieved values, indicating that the applied method works as expected for estimating PV potential of the final configuration. In figure 4.2, the values are mapped on the corresponding voxels.

The validation of the yearly illuminance values is done using Honeybee, an extension of the Ladybug tool that offers more extensive daylighting simulation methods using Radiance. Honeybee is used since this can give yearly values for the illuminance of the test mesh. The simulation is set to 'annual daylight simulation'. The offset is set at 1cm from the facade test points, with the 'grid' parameter set at 7.5

Yearly solar irradiation (gWh/year)		
configuration	estimation	simulation
4.2a	8.090	7.755
4.2b	5.696	5.643
4.2c	3.964	3.995
4.2d	7.376	7.116
4.2e	3.905	3.934

Table 4.1: Total global horizontal irradiation estimate in gWh/year (l) and total simulated irradiation in gWh/year (r)

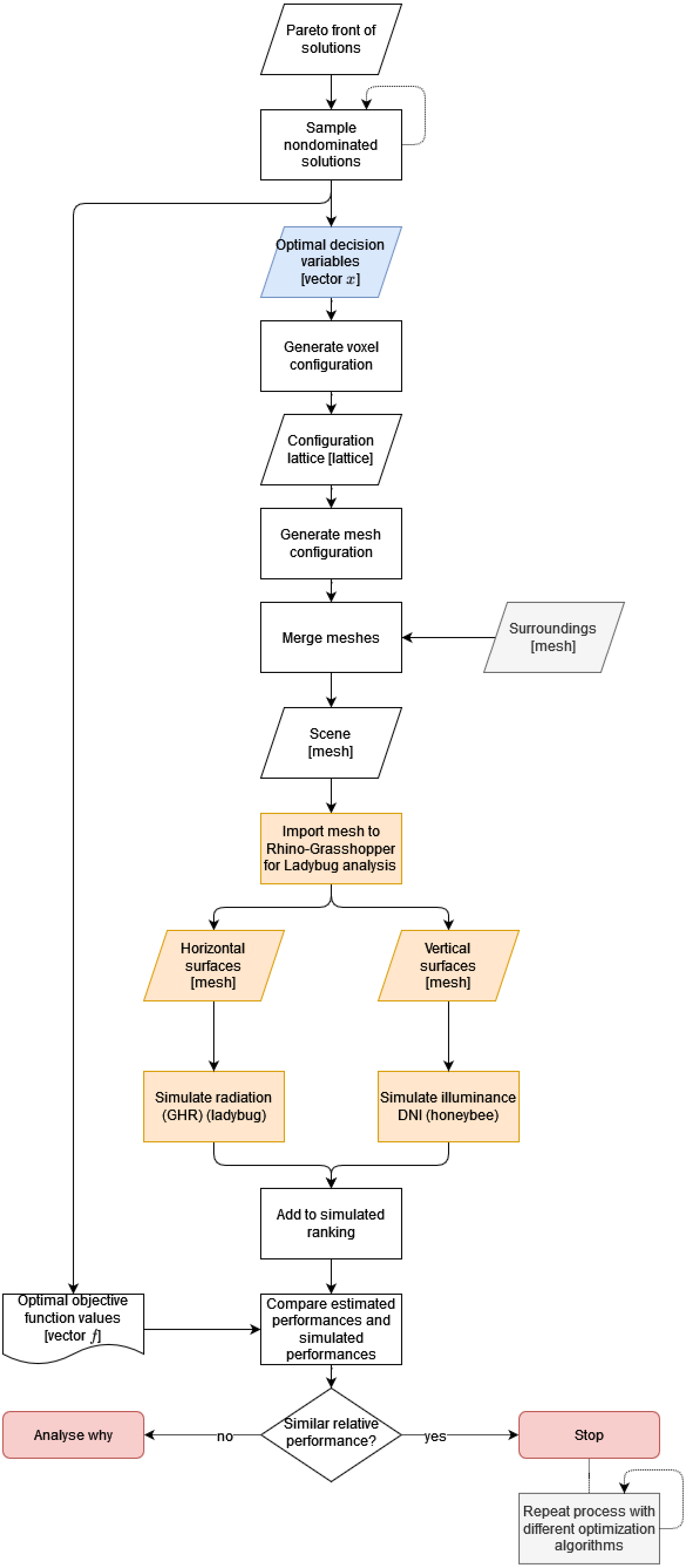


Figure 4.1: The process for validating the estimated solar performance (PV and daylighting)

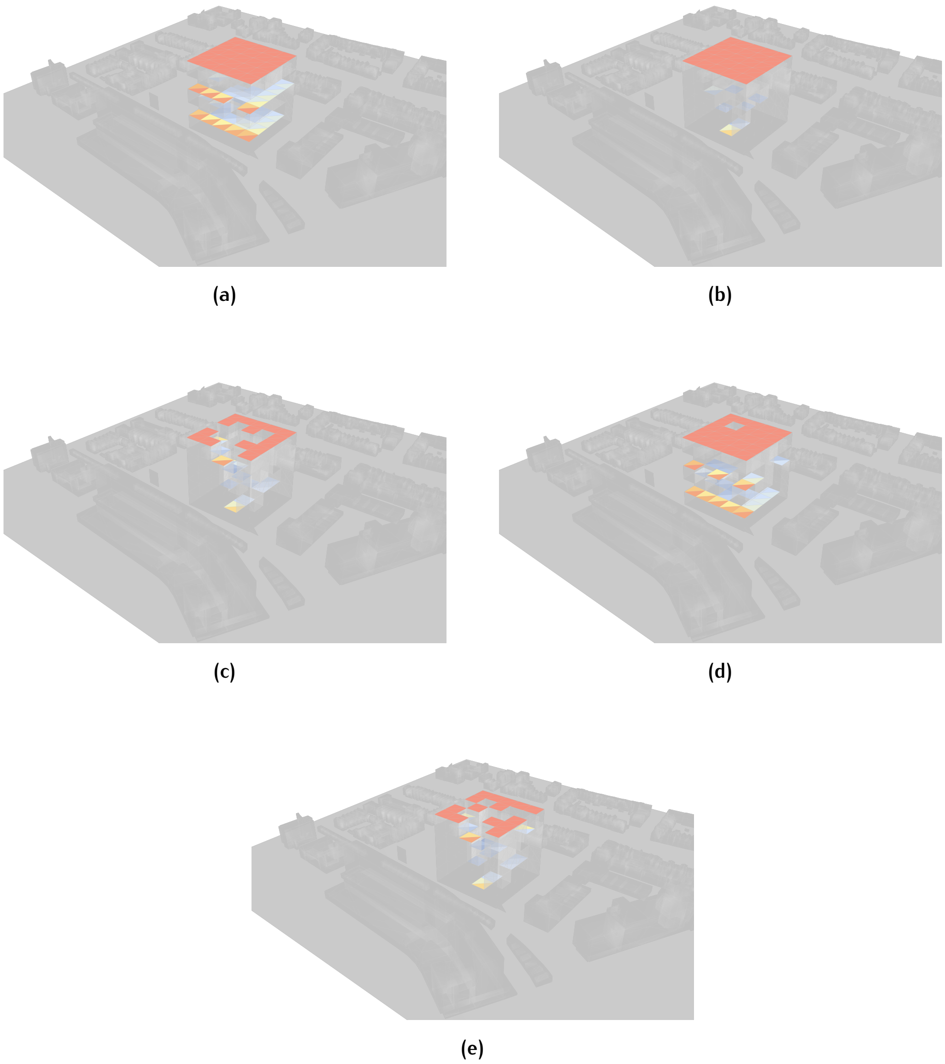


Figure 4.2: The five best performing configurations after simulation using Ladybug. Red indicates higher yearly cumulative irradiation values.

Yearly illuminance (*100 gLux)		
configuration	estimation	simulation
4.3a	4.616	4.995
4.3b	6.623	5.057
4.3c	8.110	5.656
4.3d	5.246	4.649
4.3e	8.091	5.635

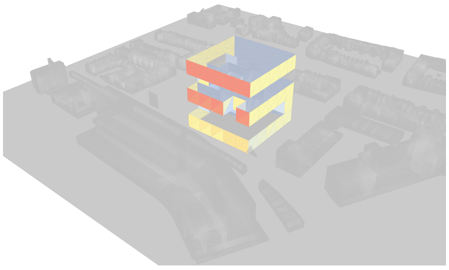
Table 4.2: Total accumulated illuminance estimate in 100*gLux/year (l) and total simulated illuminance in 100*gLux/year (r)

m due to simulation speed concerns, creating 4 test points for each voxel face (or 2 test points per mesh face). The results can be viewed in table 4.2. The ranking in simulated values this time is inconsistent with the ranking of the estimated values, furthermore the values themselves have a much greater margin of error (>20%) between the simulated and achieved values in both directions. The exact reason for this remains unclear, but is likely influenced by several factors. First, the simulation in Honeybee is more accurate because it deals with direct and indirect sunlight. Honeybee uses Radiance for the modeling, while Ladybug uses a cumulative sky and then computes the solar hits only. Furthermore, reflections off the context influence the total illuminance values calculated, while in the estimation, only the direct values for direct normal illuminance are used. At the same time, the grid size is such that the results are less accurate than desired and the angle of incidence is not taken into account like in the simulation. Finally, due to the inputs required by Honeybee, the context is represented as a BRep (boundary representation), a geometry type in Rhino. The input content is a mesh however, and in the conversion between mesh and BRep, some accuracy will be lost as well. The inconsistent ranking indicates that as a measure of the *relative* performance of each alternative configuration, the proposed method is unsuitable. The results are mapped on the meshes in table 4.3.

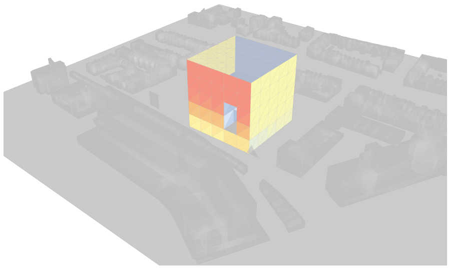
4.2 CONCLUSION

A method for finding optimal configurations in regards to multiple objectives has been described. In the previous section, the results of the optimization were compared with a simulation in order to validate the results and find a generalized workflow for the application of the techniques studied. When comparing the objective scores from the output of the optimization and the simulated values after the fact, the validity of the objective function for estimating the solar irradiation can be confirmed. The values line up and the relative scores of the configurations are identical. The validity of the proposed method for estimating daylighting potential is put in question however because the final scores and estimated scores are dissimilar. Three reasons for this have been proposed: Firstly, the simulation is expected to be more accurate since it takes the reflected (indirect) values of illuminance into account. Secondly, the grid size was set at a low resolution since computation was prohibitively long. Finally due to the surrounding envirenment being changed, some inconsistencies may arise. A different approach to the daylighting objective function is recommended. The FSI and compactness objectives, being strictly speaking 'unitless' ratios perform more consistently than the visibility objectives.

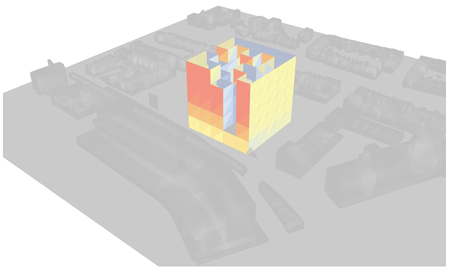
Besides the inconsistencies described above, the output of the model will always be dependent on the exact question asked. Taking a different approach in regards to the solvers, parameters, and objectives will always yield different results. Even if all factors remain consistent, the results might still be different since heuristics are



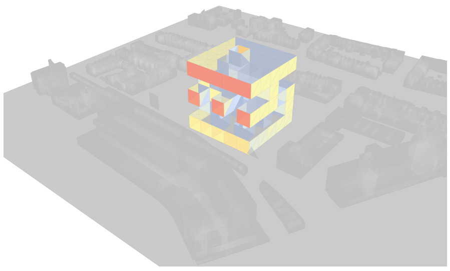
(a)



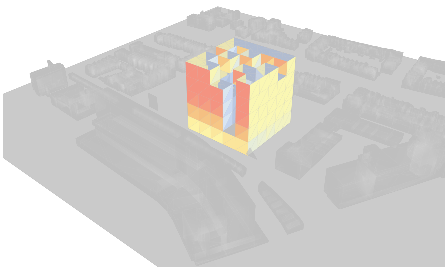
(b)



(c)



(d)



(e)

Figure 4.3: The five best performing configurations after simulation using Radiance in Honeybee. Red indicates higher yearly cumulative illuminance values.

used for solving the problem. The NSGA-II algorithm seems to perform with the best results of all available solvers, although the reasons for this remain unclear.

At the same time, the framework itself is robust and allows quick simulation, computation, and adaptation towards different objectives which enables fast testing and exploration of design alternatives and design goals. Results are outputted at a reasonable time even with 128 population. The strength of the method lies in the fact that the decision variables directly correspond to the configuration mass, allowing a one-on-one translation of the output to the actual objective.

4.3 FURTHER RESEARCH RECOMMENDATIONS

The implementation results raise questions that would be interesting for further research but fall outside of the scope of the thesis. The framework for a successful method is in place and overall it performs well and as expected. When given a more detailed inspection however, there seem to be some inconsistencies in the expected output and the actual results as mentioned in the previous section. Several reasons for this have been mentioned and the following aspects can be identified as potential further research:

- Verify if the daylighting objective function works as intended. To do this, it first needs to be validated if no errors have been made in the implementation of the objective function.
- If the inconsistencies persist: verify if the decision variables output and input indexing is consistent. Implementing a morton-ordering to ensure this consistency has been suggested for this in the past.
- Use another metric of performance for the daylighting aspect. Metrics that are used in practice include estimating the total sunlight hours or calculating the sky view factor, or using the equivalent daylight area. This last metric however falls outside the scope of the research since it pertains to the design of the openings as well.

If this has been achieved and it can be verified that the output matches the expected values, several improvements can still be made to the model as well as some matters can still be explored:

- Finding out why the NSGA-II method performs best of the three methods studied.
- Expanding the number of optimization methods examined by branching out to another suite of solvers such as SKCriteria.
- Increasing the resolution at which the simulations and optimizations can be ran by using better hardware or cloud-based methods.
- Expanding the number of objectives by adding more cost functions.
- Further research into the difference in result and performance of continuous vs. discrete solvers.

Finally, to ensure the reproducibility of the method as well as encourage others attempting to apply MCDA techniques in the field of generative design and space allocation, it is desirable to produce a sort of 'recipe' or infographic. This would describe exactly the steps to be taken and pitfalls to be evaded as explained in the thesis in an intuitive manner that can be used as a sort of cheat-sheet by (other) developers. As has been suggested by Ogrodnik and as mentioned earlier in the research, it is desirable to employ a combination of optimization strategies for achieving multiple objectives in generative and energy optimization. A database of all possible strategies with their respective strengths and weaknesses, as well as a unified library that combines the different options available from which to use these strategies would be a valuable addition to the field.

5 REFLECTION

Due to the increasing pressure on the housing market, finding livable shelter for reasonable prices has started to become a major social, economical, political, and technical issue. As a future member of not only the housing market but also a citizen in the Netherlands and an employee in the field of architecture, this issue is important to me. Additions to the building supply need to be made but the challenge is to do so in a sustainable manner. To solve this, building planners will need to rely more and more on new techniques to build responsibly. The building industry however is notoriously inert when innovation is concerned and it is therefore essential to explore the potential of all aspects that can help with solving the crisis.

Within my studies at the faculty of architecture however, there seems to be a stereotype that you either are an architect, the artist who designs the buildings, or anyone else, who are concerned with the planning, technical details, financing, politics, simulations etc. of buildings and neighbourhoods. This black-white approach is detrimental to the field and to me, the ultimate architect can take the most integral perspective and look at all diverging aspects of a plan in a holistic way. This is where the field of computer science and mathematics can be a great boon, simply as a tool to support one's decision. However, there are not many courses that are offered that teach 'actual' generative design with regard to the many aspects that have to be considered when building, and beyond a few mandatory courses on 3D modelling, might go under the radar of a student. Multi-criteria decision analysis and multi-objective optimization has been widely applied to other industries, but in construction (engineering) less so. The large number of diverging actors and factors in construction design and engineering are fertile ground for research into MCDA methods. With an increasing adoption of digital methods from the industry, this topic within the field of Architecture and specifically Building technology is increasingly relevant with regular new research and development into space allocation, building massings, and energy systems. The benefits of this to the industry are promising but consistency, validation, and reproducibility remain issues. The goal of the research was therefore to develop such a methodology to learn about the benefits and difficulties of implementing such a method into an early design stage.

By education, I am not a mathematician or programmer. This has provided some difficulties while developing the method. Conventions, notations, best practices and even syntax, data structures, and general concepts that might seem trivial to others were unknown at the beginning of the research project. The research I have presented in the previous chapters is therefore first and foremost an exercise and demonstration, and not a proposal for the very best method to solve these kinds of problems. The lessons learned lie mostly in how I would approach a comparable problem if starting over again. I have learned about the general concepts involved in applying these methods as well as most importantly: the question you ask already holds the answer to the problem: the phrasing of the objectives (and therefore also the choosing of the objectives) is a critical aspect of finding a workable method. If the objective and variables relate to each other in a more straightforward way, modeling and therefore solving the problem becomes a much more straightforward matter. Having to do it all over again, I would therefore be much more mindful of what exactly it is I want to achieve by applying these methods. The research method as described was a valid approach to the problem in my opinion. Nevertheless, some issues were encountered and the graduation process was delayed. I did not at all times take full advantage of my mentors and was overly hesitant to ask for help or provide updates. The lighting especially is in my opinion an underdeveloped aspect of the research. The CoVid pandemic certainly did not help in this regard since a lot of the study was done at home, but in the future I should commit myself to more readily ask for help or support when I need it. Also, simply working in proximity to someone else has helped a great amount in regards to motivation. Another issue I ran into was that of having an overly ambitious scope at the beginning of the research process. Limiting the number of aspects to research was a good decision that could have been taken earlier in hindsight.

The results are quite satisfactory but some matters might still warrant further exploration. Mainly finding alternative ways to define the daylighting potential (aside from the yearly illuminance) of the configuration is of interest to me. I am however content with the framework itself and all the new techniques and libraries I have learned to use. Beyond that, I think the research is a valuable addition the the field that can help planners and designers alike to make informed decisions and I am excited to continue working on these kind of problems. When used correctly, and with the increasing performance of computers, new techniques, and new research, these methods can greatly improve the quality of the buildings we live in in the future.

6 APPENDIX

Pseudocode and flowchart of the logic for the cost and objective functions can be found below. Refer to MY THESIS REPOSITORY where I will be uploading all relevant code, images, and the paper.

System specs:
Processor Intel(R) Core(TM) i7-8750H CPU @ 2.20GHz 2.21 GHz
Installed RAM 16,0 GB (15,9 GB usable)
System type 64-bit operating system, x64-based processor
Windows 10 Home Version 20H2

Input: Decision variables x, solar directions v, GHI g, environment e
Output: F_1: the configuration's PV potential

H,V $\leftarrow$ *constructhorizontalmesh*, *constructverticalmesh* : (x)
$M \leftarrow$ *tm.concatenate* : (H, V)

R: *tile:* daylighting ray v for each centroid c in x;
C: *tile:* centroid c for each ray v;
I: *tile:* irradiance m for each centroid c in x;
$i \leftarrow 0$ **to** len(x) $j \leftarrow 0$ **to** len(v) $h \leftarrow$ compute collisions of $R_i j$ to $C_i j$ through M;
if $h = 0$ **then**
    // the ray was unobstructed
    F_1 += $I_i j * (1 - h)$;
end
return F_1

Algorithm 1: F1 (x, v, g, e)

Input: Decision variables x, solar directions v, DNI n, environment e
Output: F_2: the configuration's daylighting potential

H,V $\leftarrow$ *constructhorizontalmesh*, *constructverticalmesh* : (x)
$M \leftarrow$ *tm.concatenate* : (H, V)

R: *tile:* daylighting ray v for each centroid c in x;
C: *tile:* centroid c for each ray v;
I: *tile:* illuminance m for each centroid c in x;
$i \leftarrow 0$ **to** len(x) $j \leftarrow 0$ **to** len(v) $H \leftarrow$ compute collisions of $R_i j$ to $C_i j$;
if $H = 0$ **then**
    // the ray was unobstructed
    F_2 += $I_i j * (1 - h)$;
end
return F_2

Algorithm 2: F2 (x, v, n, e)

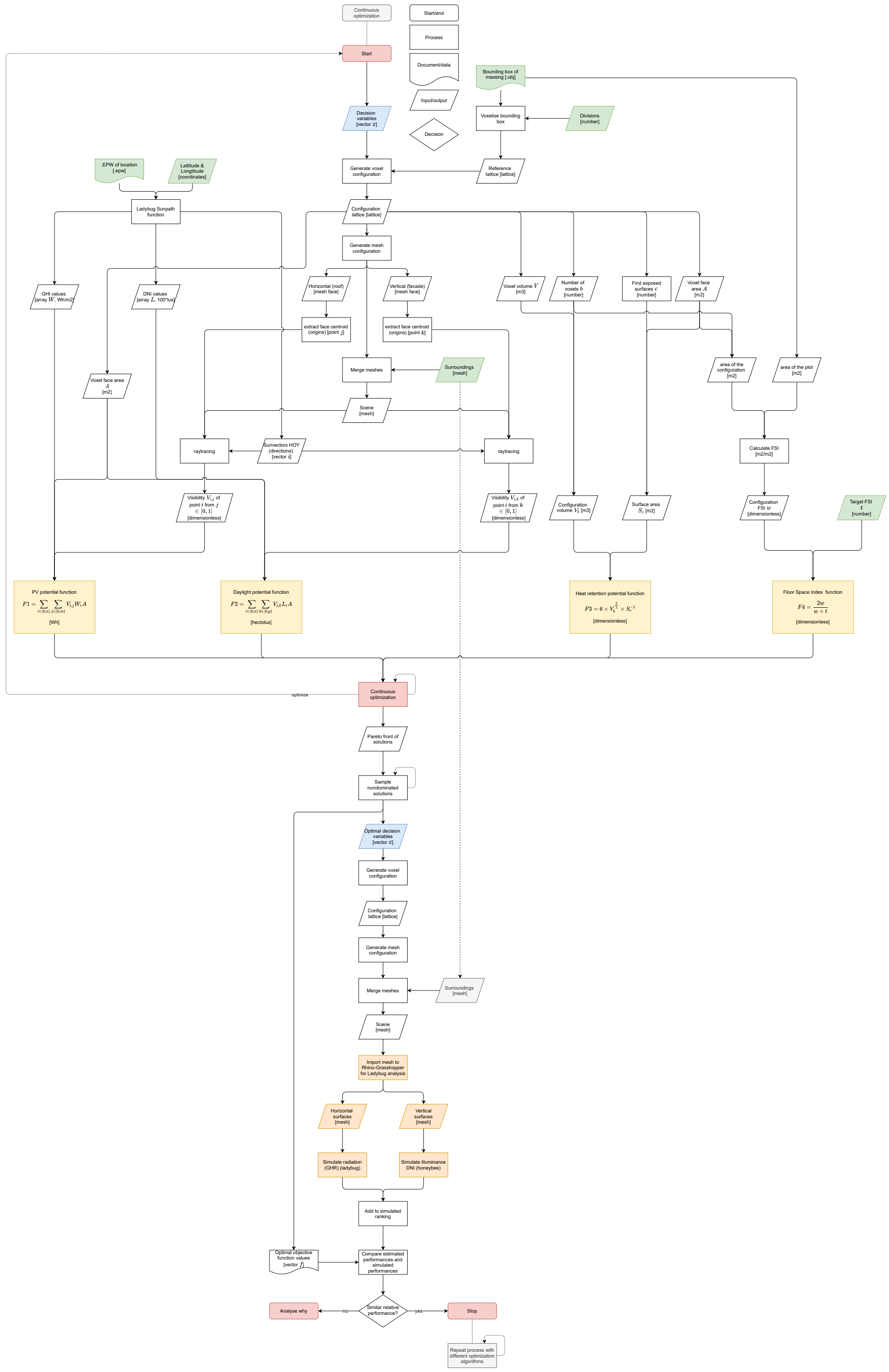


Figure 6.1: Dataflow diagram showing the relation between the inputs, outputs, optimization process and objective functions, and the final validation of the method (zoom in).

Input: Decision variables x, reference lattice l
Output: F_3: the configuration's compactness

L = $l.unit[0]$;
V_b = $L^3 * count.nonzero(x).round$ f $\leftarrow$ get exposed faces of $x * l$;
$A_b = f * L^2$;
F_3 = 6*$V_b^($2/3)/A_b ;
return F_3

Algorithm 3: F3 (x, l)

Input: Decision variables x, target FSI T, reference lattice l
Output: F_4: the configuration's Urban Density potential

A_plot =l.unit[0]$^2 * l.dim[0] * l.dim[1]$;
configA = count.nonzero(x)*$l.unit[0]^2$;
FSI = configA / A_plot F_4 = 2*FSI/(FSI+T) ;
return F_4

Algorithm 4: F4 (x, T, l)

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