



VISUAL ANALYTICS FOR GENERATIVE DESIGN EXPLORATION

An interactive 3D data environment for a computational design system facilitating
the performance-driven design process of a nearly Zero-Energy sports hall

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VISUAL ANALYTICS FOR GENERATIVE DESIGN EXPLORATION

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PREFACE

This graduation research is the final part of my Master curriculum of Building Technology at Delft University of Technology. During the past 5.5 years I have experienced that the architectural design process is rarely based on quantified performances. Instead, decision-making relies on the architects' experience and intuition. I am of the opinion that integration of design computation and computational design in the architectural design process has great potential to improve both quantified and non-quantifiable building performances.

However, there is a clear contrast between computational design methodologies and architectural design processes. Generally speaking, computational design methodologies are goal-oriented, being able to rapidly optimize one or a few quantified objectives. The architectural design process, on the other hand, is explorative in nature; architects excel at making trade-offs between many non-quantified design aspects. Integration of these two distinctive methodologies is therefore a very intriguing topic to me and I am very glad that I had the chance to explore this potential in my final graduation project.

I would like to thank Michela Turrin and Regina Bokel for their informative tutoring sessions and for their enthusiasm throughout the graduation process. I would also like to thank Lucas Pol for his help throughout the graduation process and to the participants of the questionnaire. Finally, but most importantly, many thanks to my parents.

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Delft, Februari 2018

ABSTRACT

Improvement of design performances requires exploration of a larger amount of analyzed design solutions in the early design phase. Computational design systems use parametric modeling, building performance simulations and genetic algorithms to iterate through a large amount of design alternatives, converging towards optimal design solutions. Computational design systems proposed by most existing researches do not enable interconnected analysis of quantitative and qualitative design performances, however, and consequently are rarely used in the field of architecture.

This thesis proposes a visual analytics system that visualizes design geometries and performances of a large data set of design alternatives in a highly interactive data environment. The visual analytics system is developed conjointly to the concept design of a nearly Zero-Energy sports hall. The sports hall is designed using a computational design system that generates a large set of design alternatives and analyzes energy performances, visual comfort performances and thermal comfort performances of each alternative. This thesis develops a prototype of the visual analytics tool to visualize a data set of sports hall design alternatives. Peer review and user experience determine whether the tool as a whole and whether its data analytics methods suit the design-making process of practitioners in the field of architecture. The functionality of the computational design system is assessed by its suitability to facilitate a performance-driven design process.

The computational design system proposed in this thesis uses multiple parametric models to create a varied set of design alternatives. The proposed visual analytics system is a game-like 3D environment. This environment integrates and displays a Self-Organizing map with other data analytics methods and all designs' geometries in a single viewport. Multiple means of interaction facilitate deduction of qualitative and quantitative performances.

The visual analytics system is intuitive in use because of the use of metaphorical visualizations of data analytics methods. Peer review and testing of the visual analytics system indicate that the computational design system proposed in this thesis is generally able to improve design performances. The computational design system is effective in facilitating comparison of design alternatives and in use as a frame of reference throughout the design processes. Furthermore, the visual analytics system has potential in use for educative and documentation purposes.

KEYWORDS

Computational Design, Multi-Objective Optimization, Visual Analytics, Parametric design, Design Exploration, Performance-driven design, Building performance simulations, Sports Hall, Zero Energy, Self-Organizing Maps.

TABLE OF CONTENTS

| | |
|---|-----------|
| ACRONYMS | 13 |
| CHAPTER 1: INTRODUCTION | 17 |
| 1.1 Introduction | 17 |
| 1.2 Definition of Zero-Energy Building | 17 |
| 1.3 Traditional design process vs integrated design process | 17 |
| 1.4 State of the Art | 19 |
| 1.5 Research question | 23 |
| CHAPTER 2: METHODOLOGY | 27 |
| 2.1 Research methodology | 27 |
| 2.2 Assessment | 27 |
| 2.3 Overview of Computational Design System | 27 |
| 2.3.1 Definitions | 27 |
| 2.3.2 Workflow Computational Design System | 28 |
| 2.4 Thesis structure | 29 |
| CHAPTER 3: GENERATIVE DESIGN SYSTEM | 33 |
| 3.1 Introduction | 33 |
| 3.1.1 Design brief | 33 |
| 3.1.2 Workflow GDS | 35 |
| 3.2 Non-destructive evolutionary algorithm | 36 |
| 3.2.1 Optimization process | 36 |
| 3.2.2 Data export | 36 |
| 3.3 Building definition | 37 |
| 3.3.1 Free-form geometries using Delaunay and Voronoi | 37 |
| 3.3.2 Rationalized geometry using repetitive elements | 38 |
| 3.3.3 Geometries following architectural concepts | 38 |
| 3.4 Discussion | 39 |
| CHAPTER 4: PERFORMANCE ANALYSIS SYSTEM | 45 |
| 4.1 Introduction | 45 |
| 4.1.1 Performance objectives | 45 |
| 4.1.2 Workflow PAS | 46 |
| 4.2 Energy performances | 46 |
| 4.2.1 Introduction | 46 |

| | | |
|---------|--|----|
| 4.2.2 | Nearly Zero-Energy criteria | 47 |
| 4.2.3 | PV panel energy potential | 47 |
| 4.2.4 | PV panel energy payback time | 47 |
| 4.3 | Thermal performances | 48 |
| 4.3.1 | Introduction | 48 |
| 4.3.2 | Simulation settings | 48 |
| 4.3.2.1 | Construction | 48 |
| 4.3.2.2 | Activity | 49 |
| 4.3.2.3 | HVAC system | 49 |
| 4.3.2.4 | Urban context | 49 |
| 4.3.3 | Thermal comfort | 50 |
| 4.3.4 | Temperature criteria | 52 |
| 4.3.5 | Validation of simulation results | 53 |
| 4.4 | Lighting performances | 56 |
| 4.4.1 | Introduction | 56 |
| 4.4.2 | Lighting criteria | 56 |
| 4.4.3 | Visual comfort | 58 |
| 4.5 | Validation of preliminary design decisions | 58 |
| 4.5.1 | Introduction | 58 |
| 4.5.2 | Deviation from choice of wall insulation | 60 |
| 4.5.3 | Deviation from choice of window type | 60 |
| 4.5.4 | Deviation from choice of setpoint temperatures | 62 |
| 4.5.5 | Deviation from choice of setback temperatures | 62 |
| 4.5.6 | Deviation from choice of activity schedule | 62 |
| 4.5.7 | Conclusions | 65 |
| 4.6 | Discussion | 66 |

CHAPTER 5: DATA PROCESSING SYSTEM 73

| | | |
|---------|-------------------------------------|----|
| 5.1 | Introduction | 73 |
| 5.1.1 | Purposes | 73 |
| 5.1.2 | Workflow DPS | 73 |
| 5.2 | Dimensionality reduction - SOM | 74 |
| 5.2.1 | Introduction | 74 |
| 5.2.2 | Theory | 74 |
| 5.2.3 | Application | 75 |
| 5.3 | Annual performance data - SBG & AHP | 82 |
| 5.3.1 | Introduction | 82 |
| 5.3.2 | Theory | 82 |
| 5.3.2.1 | Quantified performances | 82 |
| 5.3.2.2 | Non-quantified performances | 82 |
| 5.3.3 | Application | 83 |
| 5.4 | Data classification - Decision tree | 86 |
| 5.4.1 | Introduction | 86 |
| 5.4.2 | Theory | 86 |
| 5.4.3 | Application | 86 |

| | | |
|-------|--|----|
| 5.5 | Data clustering - AHC | 88 |
| 5.5.1 | Introduction | 88 |
| 5.5.2 | Theory | 88 |
| 5.5.3 | Application | 88 |
| 5.6 | Design labels - Pictogram chart | 90 |
| 5.6.1 | Introduction | 90 |
| 5.6.2 | Theory | 90 |
| 5.6.3 | Application | 90 |
| 5.7 | Interrelationships between design aspects - Correlation matrix | 92 |
| 5.7.1 | Introduction | 92 |
| 5.7.2 | Theory | 92 |
| 5.7.3 | Application | 92 |
| 5.8 | Discussion | 93 |

CHAPTER 6: VISUAL ANALYTICS SYSTEM 94

| | | |
|-------|---|-----|
| 6.1 | Introduction | 94 |
| 6.1.1 | Concept | 94 |
| 6.1.2 | Workflow VAS | 94 |
| 6.2 | Visualization and interaction | 97 |
| 6.2.1 | Dimensionality reduction | 97 |
| 6.2.2 | Annual performance data | 98 |
| 6.2.3 | Data classification | 99 |
| 6.2.4 | Data clustering | 99 |
| 6.2.5 | Design labels | 100 |
| 6.2.6 | Interrelationships between building aspects | 100 |
| 6.2.7 | Additional gameplay features | 101 |
| 6.3 | Discussion | 102 |

CHAPTER 7: VALIDATION 105

| | | |
|---------|---|-----|
| 7.1 | Use of the cds to substantiate the design process | 105 |
| 7.1.1 | Data workflow | 105 |
| 7.1.1.1 | Iterative Design System | 105 |
| 7.1.1.2 | Data Analytics System | 106 |
| 7.1.2 | Design exploration in the visual analytics tool | 107 |
| 7.1.3 | Discussion | 110 |
| 7.2 | Peer review of Visual Analytics System | 111 |
| 7.2.1 | Introduction | 111 |
| 7.2.2 | Methodology | 111 |
| 7.2.3 | Results | 112 |
| 7.2.4 | Discussion | 113 |
| 7.2.4.1 | Suitability of the IDS to facilitate the design process | 113 |
| 7.2.4.2 | Suitability of the DAS to facilitate performance-driven decision-making | 114 |
| 7.2.4.3 | Suggestions for future improvements | 114 |
| 7.3 | Questionnaire | 114 |

| | | |
|---|--|------------|
| 7.3.1 | Introduction | 114 |
| 7.3.2 | Methodology | 114 |
| 7.3.3 | Results | 115 |
| 7.3.4 | Conclusions | 117 |
| 7.4 | Discussion | 121 |
| CHAPTER 8: CONCLUSIONS | | 122 |
| CHAPTER 9: RECOMMENDATIONS | | 125 |
| CHAPTER 10: REFLECTION | | 127 |
| 10.1 | Iterative Design System | 127 |
| 10.2 | Data Processing System & Visual Analytics System | 127 |
| 10.3 | Graduation process | 128 |
| 10.3.1 | Graduation topic | 128 |
| 10.3.2 | Relevancy of graduation results | 128 |
| APPENDIX | | 139 |
| Appendix A: Elaboration on building information export | | 139 |
| Appendix B: Elaboration on grasshopper definitions | | 140 |
| B.1 | Delaunay geometry definition | 140 |
| B.2 | Voronoi geometry definition | 140 |
| B.3 | Cubistic geometry definition | 143 |
| B.4 | Polygonal geometry definition | 144 |
| B.5 | Annual solar obstruction definition | 144 |
| B.6 | Data export | 145 |
| Appendix C: Performance values of alternative simulations | | 147 |
| Appendix D: Analysis of loss of topology using adapted SOM algorithm for varying grid sizes | | 150 |
| Appendix E: Correlation matrices of data sets with varying occupancy schedules | | 153 |
| Appendix F: High resolution images of the visual analytics tool | | 154 |
| Appendix G: Design decisions of preliminary sketch design used in peer review | | 165 |
| Appendix H: Correlation matrices of data per parametric model | | 166 |
| Appendix I: Questionnaire | | 167 |
| Appendix J: Questionnaire results | | 180 |

ACRONYMS

| | |
|-----|-----------------------------|
| CDS | Computational Design System |
| IDS | Iterative Design System |
| DAS | Data Analytics System |
| GDS | Generative Design System |
| PAS | Performance Analysis System |
| DPS | Data Processing System |
| VAS | Visual Analytics System |

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

The building sector has significant effects on the natural environment. The building sector accounts for 40% of total energy consumption in the European Union (Directive 2010/31/EU, 2010, p.13) and for 20.1% of the total delivered energy worldwide (EIA, 2016). Furthermore, the energy consumption in the building sector is increasing. From 1990 to 2010, electricity consumption of buildings in Europe has increased by around 1%/year, mainly due to an increase of energy consumption in non-residential buildings (1.5%/year) (Enerdata, 2012). The U.S. Energy Information Administration (EIA, 2016) predicts that the energy

consumption will keep increasing. Their projections predict an annual increase of 1.5% the total energy consumption in the global building sector from 2012 to 2040, which would result in a total energy increase of 51.7% in these 28 years.

In order to decrease global warming and to prevent a critical global temperature rise of 2°C, as well as to achieve a 30% reduction of greenhouse gas emissions by 2020 compared to 1990 levels, the European Union has determined that in 2020 all new buildings should be nearly Zero-Energy Buildings (Directive 2010/31/EU, 2010, p.21).

1.2 DEFINITION OF ZERO-ENERGY BUILDING

A 'Zero-Energy Building' (ZEB) is a building which energy requirements are met by non-polluting, renewable energy sources. ZEBs use methods of energy efficiency to reduce the energy demand and compensate for the remaining needs by means of renewable energy generation. Most ZEBs are connected to the grid. This allows for excess on-site generation to be sent to the grid (usually in summer) and enables energy consumption that exceeds generation (usually in winter). The building's energy balance is therefore usually determined on an annual basis, resulting in a 'Net Zero-Energy Building'. This

method is applied because of current limitations of storage technologies (Torcellini, Pless, Deru & Crawley, 2006).

ZEB calculations account for energy used for heating, cooling, ventilation, domestic hot water, indoor and outdoor lighting, plug loads, process energy and transportation within the building (U.S. Department of Energy, 2015). It is evident that the design of ZEB's requires a large emphasis on quantifiable performance criteria and therefore requires a new method of design. The following subchapter substantiates this assertion.

1.3 TRADITIONAL DESIGN PROCESS VS INTEGRATED DESIGN PROCESS

Traditional architectural design processes usually have the architect develop a conceptual design based on the client's criteria. After a conceptual design has been made, other disciplines are introduced to the design process to implement their systems to the design. Shi & Yang (2013) discern two types of 'green' architects.

The first kind of architect develops a conceptual design through conventional design methodologies and ask other design disciplines to add on sustainable

interventions. As a result, the architectural design may suffer from requirements regarding technological interventions unforeseen by the architect, e.g. the necessity of running a ventilation shaft through a room. Sustainability of the building is sub-optimal if additional measures are required to 'solve' climate-related 'problems' originating from the architectural design, e.g. heat gain of a large, south-facing façade window.

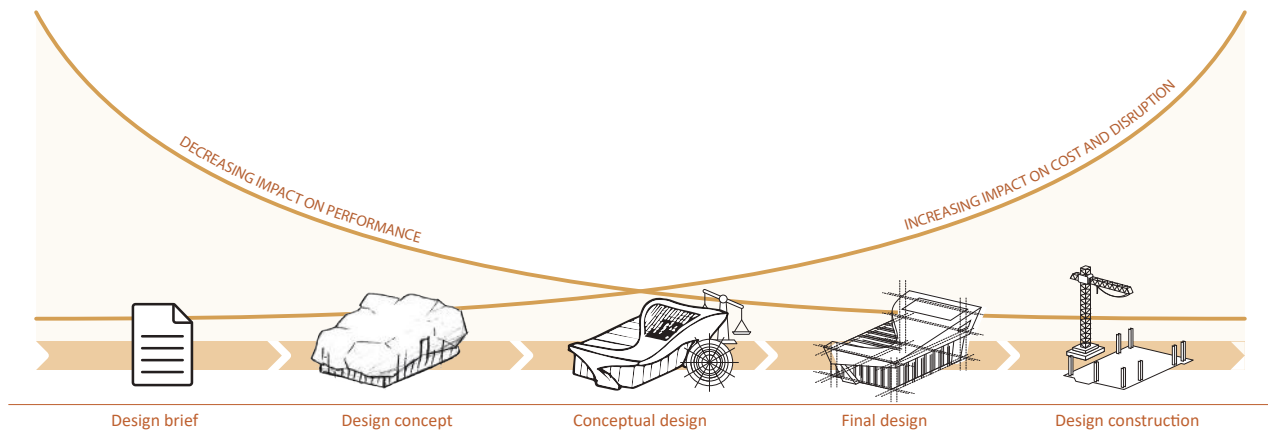


Fig. 1.1: Influence on performance and cost impact during design progress (based on Löhnert, Dalkowski, & Sutter, 2003, p.6).

The second kind of 'green' architect aims for the creation of a sustainable building in the conceptual phase by using non-quantified and conceptual design methods. The performance of the final design depends on intuitive decision-making of conceptual ideas in the early design phase. Incorrect assumptions will result in a sub-optimal conceptual design and may result in problems during later phases of the design process. The great versatility of aspects influencing comfort performances regarding the various aspects of climate design complicates the making of well-informed trade-offs.

Both design strategies rely on non-quantitative decision criteria for decision-making in the early design phase. And although design decisions made in the early design phase have the most influence on the design performance (Shi & Yang, 2013) (Fig. 1.1), they are rarely reviewed due to the amount of time and related costs required to generate and evaluate design options. A survey conveyed by Flager & Haymaker (2007) indicates that the generation and evaluation of one design option takes over a month, of which the majority of the time of the conceptual design process is spent on representing, documenting and coordinating information. Because of the limited time frame in the architectural design process, few design iterations can be considered during the design process. Consequently, sub-optimal design decisions made during the early design phase will most certainly form the base of the detailed design process, resulting in a sub-optimal final design. Optimal conceptual designs regarding both sustainability and architecture are therefore rarely achieved using such design approaches (Brunsgaard, 2009; Hopfe, Struck, & Hensen, 2006; Larsson, 2009; Löhnert, Dalkowski, & Sutter, 2003).

It is evident that Zero Energy Building requires a holistic view on the design process, in which energy- and comfort-related objectives are quantified and integrated from the early conceptual design and the decision-making process is driven by both quantitative and qualitative performance. Many researches have affirmed the capability of multi-disciplinary, multi-objective design processes (also known as integrated design processes) to improve building performance (Brunsgaard, 2009; Larsson, 2009; Löhnert, Dalkowski, & Sutter, 2003; Shi & Yang, 2013; Yang, Sun, Turrin, von Buelow, & Paul, 2015). The concept of multi-disciplinary design processes is based on the observation that changes in a design process are easier to make at the beginning of the design process (Larsson, 2009). Multi-disciplinary design processes therefore aim to facilitate knowledge-driven design choices in the early design process.

The integrated design process is commonly supplemented by computational design methodologies that integrate geometric modelling and building performance simulations tools. These methodologies have proven to be essential tools in the integrated design process to improve design performance for a various amount of reasons. Firstly, the use of computational design for analysis and optimization processes decrease the amount of time required for the development of one design iteration, thus enabling the exploration of a larger portion of the design space (Flager & Haymaker, 2007). Secondly, information of multidisciplinary performance criteria derived from building performance simulations tools results in quantitatively substantiated decision-making. Thirdly, computational design enables a holistic view towards sustainable design that is also aesthetical and functional (Negendahl, 2015).

1.4 STATE OF THE ART

Despite the great added value of computational design methodologies to improve design performance, computational design is rarely used in the early design process (Yang, Sun, di Stefano & Turrin, 2017). The main reason for this is that methodologies do not support rapid generation and analysis of design variations (Flager, Welle, Bansal, Soremekun, & Haymaker, 2009). In most conventional design tools the performance of only one design variation is simulated and analysed. Alternatively, one can generate 'optimal' design solutions by iterating through design solutions using an evolutionary algorithm. Comparison of design variations is time-intensive with these methodologies. Simulation tools are therefore often only used for the verification of a conceptual design, rather than exploration of the design space (Shi, 2010).

Current developments involve non-destructive optimization processes. Non-destructive optimization processes run and store simulations guided by genetic algorithms in order to reach optimal solutions. Designers can analyse the results in the database by means of visual analytics; 'analytical reasoning facilitated by visual interactive interfaces' (Thomas & Cook, 2005). The applicability of visual analytics methodologies is widely researched in various engineering disciplines, such as aerospace and industrial design. These disciplines commonly make use of histograms, scatterplots and parallel coordinates charts for data visualization. Visual analytics tools allow users to analyse multi-variate data through interconnected data representations. One such tool is EDEN, developed by Steed et al. (2013), which aims to enable climate scientists to view high-dimensional data (Fig. 1.2). Another tool is LIVE (Fig. 1.3), for engineering design (Yan et al., 2011). Both tools integrate filtering methods via threshold sliders. LIVE enables hierarchical clustering for further design exploration.

Various researches have transposed these techniques to the field of architecture. Jansen, Rolvink, Coenders & Schevenels (2014) used parallel coordinates charts in combination with a scatterplot as the visualization method for a multidisciplinary optimization system (Fig. 1.4). This visualization method allows for the exploration of relationships between (quantified) input parameters and performance objectives. The research suggests the implementation of an image renderer to allow for non-quantitative design criteria to be considered during the design process. Chen, Janssen & Schlueter (2015) visualized representative design variations of clusters alongside parallel coordinate charts (Fig. 1.5). This method visually summarizes 5000 design variations, and thus facilitates the analysis of large amount of design

variations. Lamping (2016) introduced an interactive post-processing tool comprised of two scatterplots, a parallel coordinates chart and a visual representation of one design alternative (Fig. 1.6). Optimal design variations are highlighted. Chaszar, von Buelow and Turrin (2016) have researched the potential of interactive scatterplots and parallel coordinates charts for multi-variate, multi-objective data visualization (Fig. 1.7). The graphing methods were implemented in ParaGen, a software framework that is used to combine qualitative performance aspects (by means of visual images and data depictions) and quantitative performance aspects (by means of performance data). The design tool depicts a number of design solutions and plots a parallel coordinates chart of these solutions.

The aforementioned researches introduce tools or methodologies to generate and visualize multi-variate, multi-objective data of large quantities of design iterations. These data analytics methodologies largely correspond to methodologies used in other engineering disciplines. However, although these methods may be suitable for engineering disciplines, they are not optimally suitable for architectural design. This is best explained by examining the differences between the design processes of aerospace and architecture industries, because although the design process of both industries consists of comparable design phases (as described by Flager & Haymaker, 2007) and both industries deal with multidisciplinary, multivariate design challenges, there are important differences between the decision-making processes. Whereas engineering industries deal with a number of (mostly) quantifiable performance objectives, architectural decision-making requires trade-offs between both quantifiable and non-quantifiable design aspects, such as aesthetic, financial, ecological, social, cultural, atmospheric, legal and practical criteria. This characteristic of architectural design necessitates an interconnectedness of quantitative and qualitative design performance in data visualization.

Various researches suggest the same. A survey performed by Attia, Beltrán, De Herde & Hensen (2009) shows that 22.9% of architects consider graphical representations alongside building performance simulations the most important aspect of usability and information management (amongst six criteria). Flager et al. (2009) advise a tool that is able to simultaneously explore performance and geometries. This thesis aims to facilitate this, in order to enable architects to make performance-driven design decisions for Zero-Energy Buildings. The topic of this thesis is: 'Visual Analytics for Generative Design Exploration'.

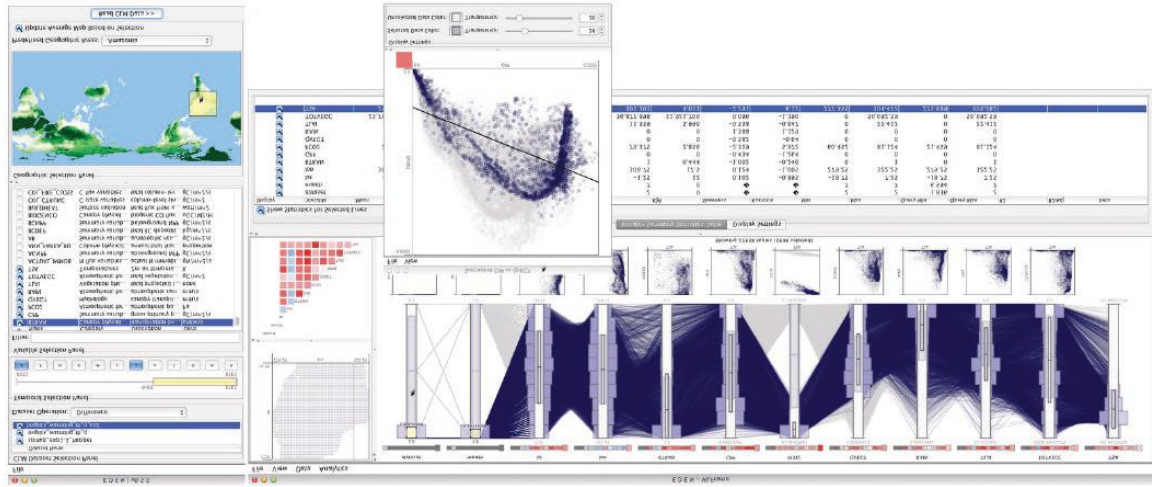


Fig. 1.2: The interface of EDEN (Steed et al., 2013, p.4).



Fig. 1.3: The interface of LIVE. (a) scatter plot of output performance variables; (b) scatter plot of input design variables (displaying clustering results on top of data); (c) text description of decision rules; (d) TreeMap visualization of decision tree; (e) adjustable sliders of ranges of input and output variables (Yan et al., 2011).

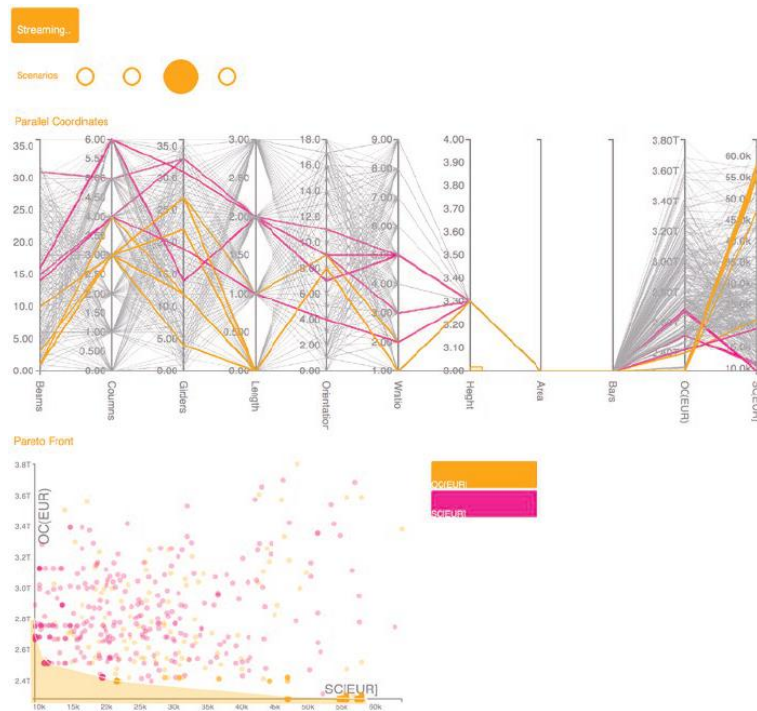


Fig. 1.4: Interactive optimization interface, developed by Jansen et. al (2014, p.6).

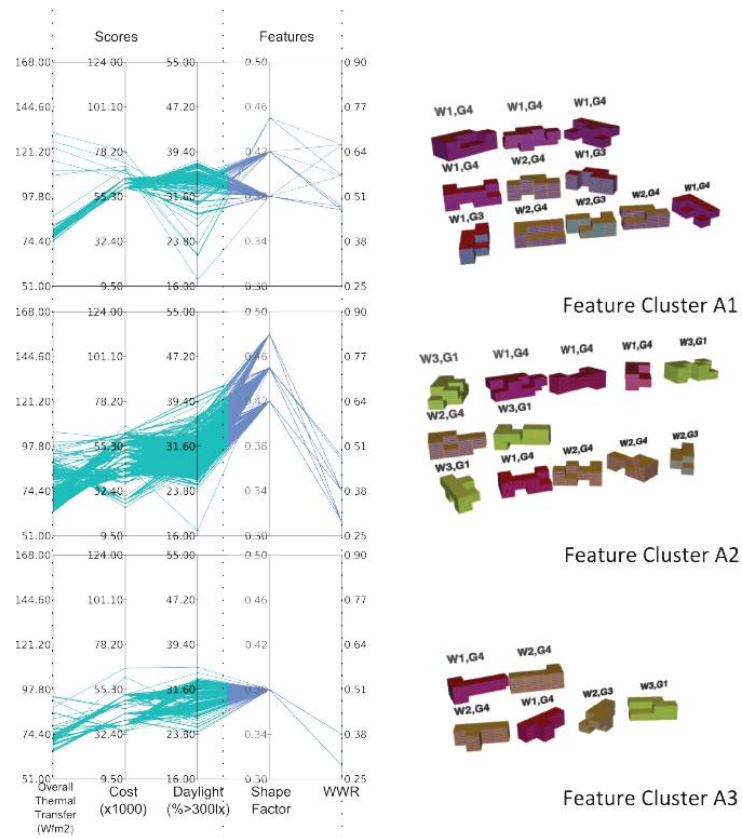


Fig. 1.5: Design performance interface, developed by Chen, Janssen & Schlueter (2015, p.257).

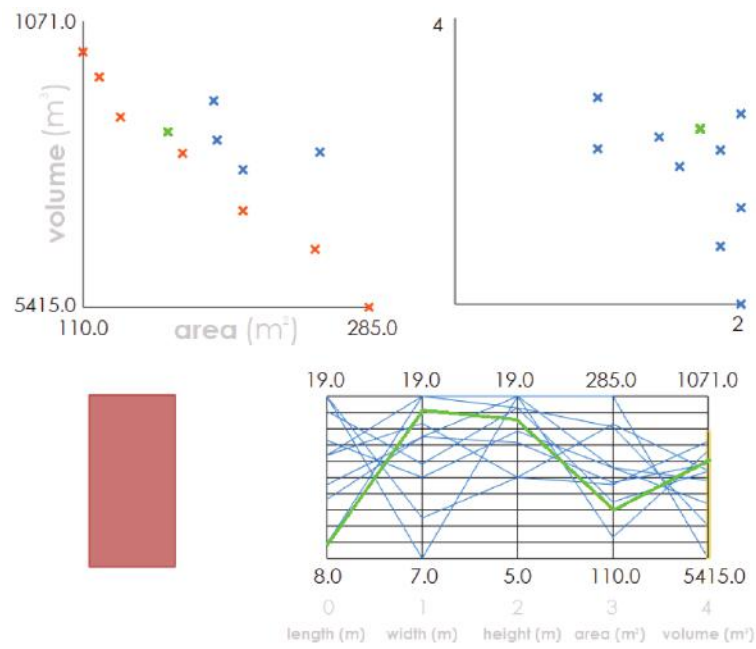


Fig. 1.6: Post-Processing Optimization Tool, developed by Lamping (2016, p.59).

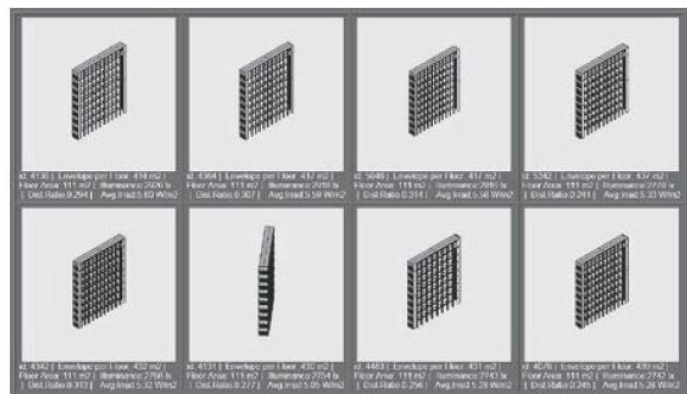


Fig. 1.7: Design solution images and parallel coordinates chart, developed by Chaszar, von Buelow & Turrin (2016).

1.5 RESEARCH QUESTION

Current computational design systems do not facilitate interconnected quantitative and qualitative design performance trade-offs. As a result, they are not accessible to architects and climate designers for decision-making in the early design phase. The objective and final product of this graduation project is a prototype of a visual analytics tool that makes multi-variate, multi-objective decision-making of building performance simulations in the early design phase accessible to architects and climate designers, by allowing for the simultaneous exploration of both quantitative and qualitative performances. Correspondingly, the research question of this thesis is:

How can visual analytics be integrated in a computational design system to make multi-variate, multi-objective decision-making in the early design phase accessible to architects and climate designers?

The visual analytics tool is part of a computational design system that involves generating a data set of a large number of design alternatives and making their design performance data insightful by means of integrating multiple data visualization and interaction methods. Answering the main research question requires an answer to the following sub-questions:

- How can generation of large quantities of design alternatives contribute to extraction of building information for performance-driven design process by architects and climate designers?
- How do quantified and non-quantified design performances influence multi-objective decision-making of architects and climate designers?
- What data analytics methods are suitable for interpretation of high-dimensional building performance simulation data sets by architects and climate designers?
- How can data analytics methods be integrated and visualized in a manner that enables intuitive, goal-oriented exploration of building performance data for architects and climate designers in order to facilitate performance-driven design processes?

‘Intuitive’ in this context is defined as being able to understand how data analytics methods should be used for design exploration, without the need of a profound understanding of the underlying mathematical organization system.

The research methodology of this thesis distinguishes various subsystems of the computational design system. The structure of this thesis is organized according to this classification. Therefore, the structure of this thesis is presented after elaboration on the research methodology, in chapter 2.4.



METHODOLOGY



CHAPTER 2: METHODOLOGY

2.1 RESEARCH METHODOLOGY

The visual analytics tool developed in this thesis is part of a computational design workflow. This workflow involves creating and visualizing a data set of a large number of design alternatives. It consists of various components, each with a distinctive function. Since the functioning of these components depend on the functioning of the system as a whole, both the visual analytics tool and the computational design workflow are characterized by a high interconnectedness of its components. Therefore, the workflow is developed in an iterative process that uses both a research by design and a design by research approach.

Part of the research in this thesis involves finding a computational design workflow that facilitates a performance-driven design approach. This thesis uses a theoretical design assignment as a case study to gain experience in the use of computational design in the

design process. The assignment concerns the design of a nearly Zero-Energy sports hall in Overhoeks, Amsterdam. This thesis explores various methods of accommodating the design process with computational design to gain insight in suitable design processes that facilitate performance-driven design.

The other part of this research concerns the development of the visual analytics tool. Literature research gives the scope of existing data visualization methods that may suit the tool. Both existing visual analytics systems and commonly used data visualization methods are reviewed. Suitable methods of data visualization are determined based on their ability to aid users in finding optimal design solutions. Amongst other criteria, the visualization methods should be suitable for their intended function, should be easy to understand and should complement the tool's other visual analytics methods.

2.2 ASSESSMENT

The performance of the visual analytics tool and the Computational Design System are assessed based on their ability to facilitate a performance-driven design process.

The performances are assessed by (1) the author, who extensively uses and tests the tool to develop the design, (2) Lucas Pol, an MSc Architecture student at

TU Delft, who tests the prototype based on its suitability to improve the performance of his sketch design, and (3) a questionnaire held among MSc Architecture and MSc Building Technology students, as well as a few participants that do not have any experience in the field of architectural, climate and computational design, nor in the field of data analytics.

2.3 OVERVIEW OF COMPUTATIONAL DESIGN SYSTEM

2.3.1 Definitions

The main research question of this thesis concerns the implementation of visual analytics in a computational design system. 'Computational Design System' in this thesis is defined as a computational design approach that involves (1) generating a data set of a large number of design alternatives, (2) determining their performances and (3) making this data insightful by means of integrating multiple data visualization and interaction methods.

The Computational Design System (CDS) consists of various components that have their own distinctive function in the workflow. In this thesis, the components are distinguished as hierarchically classified 'Systems' (Fig. 2.1). The CDS consists of an Iterative Design System, which generates a data set of design alternatives, and a Data Analytics system, that processes and visualizes this data set.

The Iterative Design System, in turn, consists of a Generative Design System and a Performance Analysis System. The Generative Design System generates design alternatives. The Generative Design System may integrate parametric modelling and evolutionary algorithms for automated generation of design alternatives, but may also involve manual design iteration processes. The Performance Analysis System simulates and/or calculates performances of the design alternatives.

The Data Analytics System consists of a Data Processing System and a Visual Analytics System. The Data Processing System uses various (a.o. data mining) algorithms to organize the ‘raw data’ generated by the Iterative Design System for use in the Visual Analytics System. The Visual Analytics System provides an interactive environment that visualizes this data for multi-variate, multi-objective decision-making.

2.3.2 Workflow Computational Design System

Various researches have introduced workflows to generate and analyze building information of design alternatives through direct integration of Grasshopper and modeFRONTIER (e.g. Yang, Sun, Di Stefano & Turrin, 2017). As described in chapter 1.4, data visualization of these researches is not suitable for application in the field of architecture. The main contribution of this thesis is a visual analytics tool that enables visualization of data and design geometries in a highly interactive, game-like 3D data environment, to enable exploration of both quantified and non-quantified performances of a set of design alternatives. In order to do achieve this, the Computational Design System developed in this thesis uses various computer programs for the generation, simulation, processing and visualization of design iterations (Fig. 2.2). Design alternatives are generated using parametric models developed in Grasshopper (version 0.9.0076; Robert McNeel & Associates, 2017b) plug-in for Rhinoceros (version 5.14.522.8390; Robert McNeel & Associates 2017a). Various Grasshopper plug-ins integrate simulation tools in the Grasshopper environment. Building information is processed using modeFRONTIER (version 5.3.0; ESTECO SpA, 2017), Microsoft Excel and the Unreal Engine (version 4.17.1; Epic Games Inc., 2017a). The Unreal Engine is also used to provide a highly interactive environment for visual analytics.

This thesis uses a custom approach to exchange data between software. This approach uses comma-separated (CSV) files as an intermediary between programs. CSV files use a text-based method to store tabular data. Each line in the file contains the information of one data items. Delimiters (e.g. commas) separate the items’ data attributes. This thesis uses an intermediary to enhance robustness, flexibility and versatility. CSV files find widespread use and can be imported by many computer programs. The data generated by the Iterative Design Process can therefore be analyzed by various tools. This is useful during the development of the Computational Design System, since the data can be reviewed using other tools. It also enhances the versatility of the computational design methodology that is the Computational Design System, enabling setup of the methodology using various alternatives to the computer programs used in this thesis. Since CSV files connect each subsystem of the CDS, subsystems can be easily exchanged. The CDS can therefore be used to facilitate an array of design assignments. Fig. 2.3 summarizes the workflow of the Computational Design System.

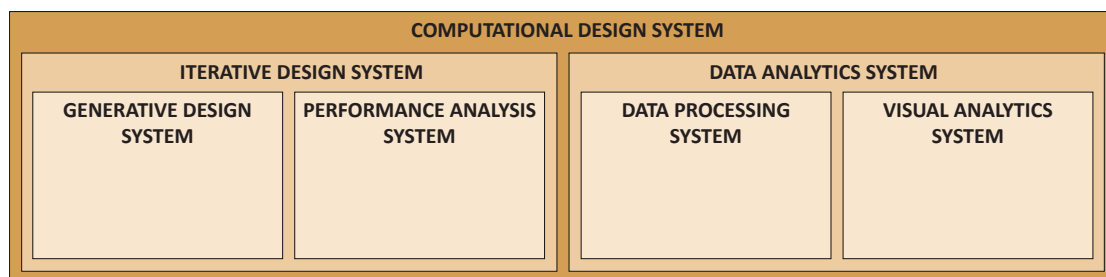


Fig. 2.1: Classification of subsystems in the Computational Design System.

2.4 THESIS STRUCTURE

The main body of this thesis is structured according to the classification of subsystems introduced in chapter 2.3 and visualized in Fig. 2.1.

The thesis first describes the Iterative Design System in Chapter 3 and Chapter 4, which concern the Generative Design System and the Performance Analysis System, respectively. The Data Analytics System is described in Chapter 5 and Chapter 6, which concern the Data Processing System and the Visual Analytics System, respectively.

Each of these chapters are identical in structure. First, the system is introduced. The introduction gives an overview of the system's function in the computational design system, the workflow within the system and the implementation of the system in this thesis's case study. Then, the various components that comprise the subsystem are described in designated subchapters. Each chapter ends with discussion on its respective system.

Chapter 7 presents the results of the Computational Design System and presents validations of its performance.

Chapter 8 presents the conclusions of the Computational Design System and of this research as a whole.

Chapter 10 presents the author's reflection on this research

Chapter 10 gives suggestions on further research in the field of the use of computational design systems in performance-driven design processes.

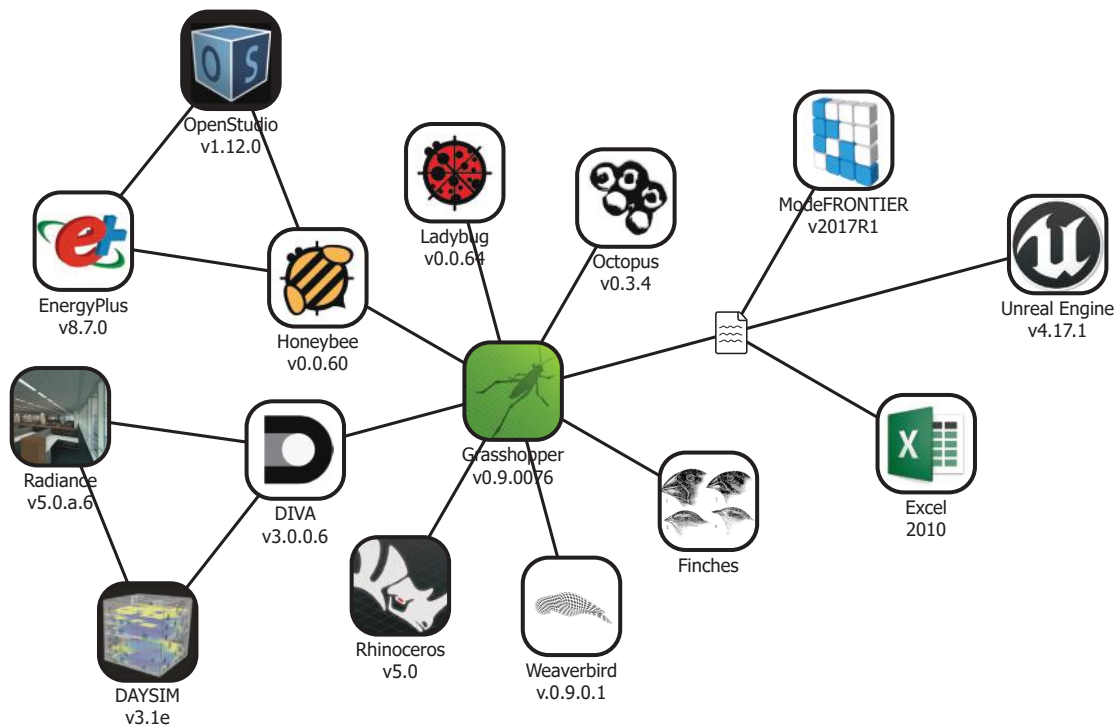


Fig. 2.2: Scheme depicting the interconnectedness of software used in this thesis.

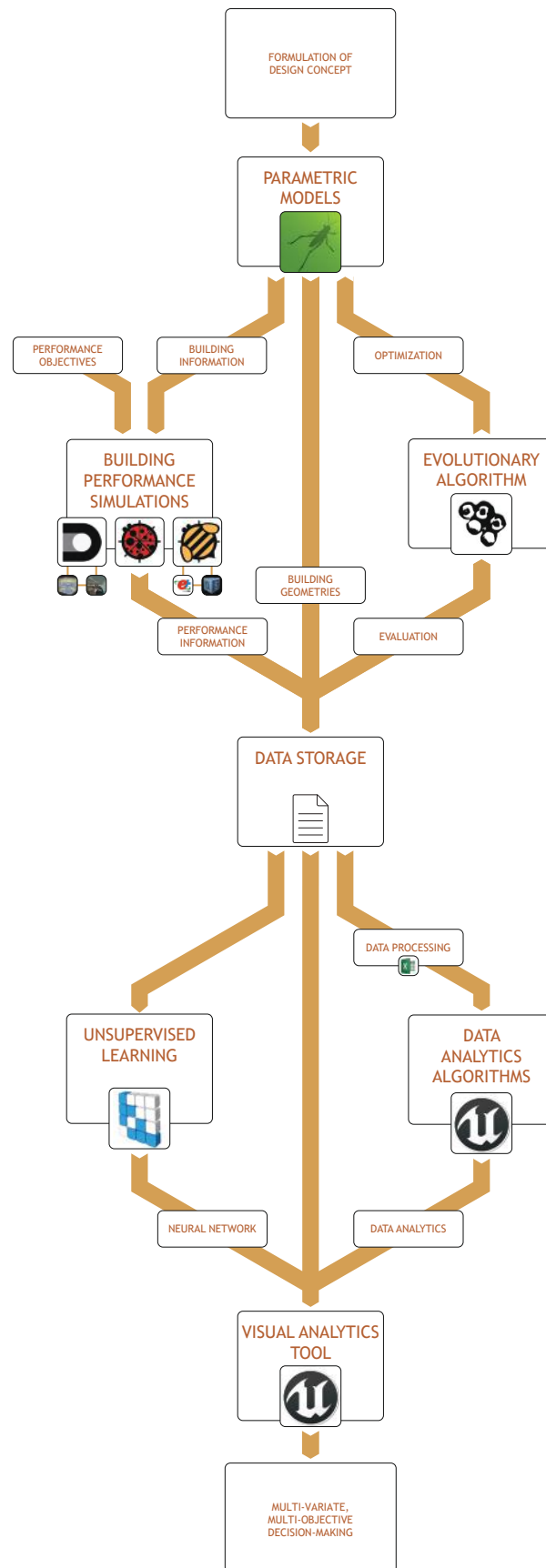


Fig. 2.3: Workflow of the Computational Design System. Feedback loops related to the user (e.g. changes in the design concept because of findings in the visual analytics tool) are not shown in this workflow.



ITERATIVE DESIGN SYSTEM

The Iterative Design System (IDS) generates and simulates design alternatives and exports their building information to data and geometry files. The IDS consists of a Generative Design System (GDS) and a Performance Analysis System (PAS). The GDS concerns the process of generating design alternatives. This thesis uses multiple variations of GDS's that make use of either manual or automated processes to generate designs. The PAS runs building performance simulations of the design alternatives. Various performance objectives are derived from these simulations. Building information of both the GDS and the PAS is saved for use in the DAS.

The IDS set up in this thesis is used to facilitate the design process of a nearly Zero-Energy sports hall for a sports venue in Overhoeks, Amsterdam. The design process takes architectural qualities, energy demands and climate comfort levels into account and therefore uses multi-objective optimization processes.

The IDS is described in the next two chapters. Chapter 3 introduces the sport hall's design brief and describes the GDS. Chapter 4 introduces the quantified performance objectives of the sports hall and describes the PAS.

CHAPTER 3: GENERATIVE DESIGN SYSTEM

This chapter describes the Generative Design System (GDS). The GDS concerns the process of generating design alternatives, which will be analyzed with the Performance Analysis System (PAS) and presented with the Data Analytics System (DAS).

Chapter 3.1 introduces the design brief of this thesis's Iterative Design System (IDS) and describes the corresponding workflow of the Generative Design System. The Computational Design System (CDS) used in this thesis makes use of multiple architectural design variations and thus uses multiple parametric models.

A non-destructive evolutionary algorithm is used to iterate through and to optimize the parametric model. Consequently, the functionality of the evolutionary algorithm influences the development of the parametric models. The non-destructive evolutionary algorithm is described in chapter 3.2.

Chapter 3.3 describes the parametric models, focusing on how the Computational Design System may best facilitate the architectural design process.

Chapter 3.4 summarizes the findings of chapter 3.3 and presents the author's conclusions on how the Generative Design System may best facilitate the architectural design process.

3.1 INTRODUCTION

3.1.1 *Design brief*

The Computational Design System of this thesis facilitates the design process of a nearly Zero-Energy sports hall of a sports venue in Overhoeks, Amsterdam. Overhoeks is a neighborhood in Amsterdam-North, by the river the IJ, right across the river from Amsterdam Central Station. The EYE film museum and the A'DAM tower (also known as the Shell tower) are well-known buildings in this neighborhood.

The destination plan of Overhoeks prescribes a multifunctional program with, amongst others, 2200 dwellings for 4000 citizens (Bestemmingsplan Overhoeks, 2016). Currently, no sports venue is in the vicinity of the neighborhood. Although the urban plan does not explicitly propose sports facilities to accommodate the citizens of Overhoeks, space is reserved for recreational facilities in the neighborhood (Gemeente Amsterdam, n.d.). The sports venue designed in this thesis will be embedded in the neighborhood and will be adjacent to a park (Fig. 3.1). Across the park multiple high-rise buildings are planned, and diagonally is the EYE film museum. The sports hall will be primarily used for training and for regional competitions. However, because of its prime location near the Amsterdam city centre the sports hall should be able to host national and international championships as well.

The sports hall will be a six-court hall, which is appropriate for both purposes. Six-court halls can host clublevel competition games of all sports and high-level competition games of basketball, badminton and volleyball (Sport England, 2000). The hall can be subdivided to host multiple games simultaneously. A six-court hall has minimum dimensions of 34x27x7.6m³, but county and national level badminton games require a height of 9.1m (Sport England, 2000). To fit within the scale of the urban context, it is decided that the court hall will be situated on the first floor, with the lobby and utility functions on the ground floor. The position of the sports hall with regards to the urban context is depicted in Fig. 3.2. Its orientation and shape are defined in the design process.

Since the sports hall hosts games of various levels, the hall has a variable occupancy. Different occupancies have different characteristics, requirements and optima with regards to performance criteria. The Iterative Design System takes variable occupancy into account by means of an annual occupancy schedule predicted by the author. Fig. 3.3 shows the annual predicted occupation of the Overhoeks sports venue. The schedule is presented in Fig. 4.2 and elaborated on in chapter 4.1.



Fig. 3.1: Urban plan Overhoeks, with the sports hall site marked in red (SITE ud, n.d.).

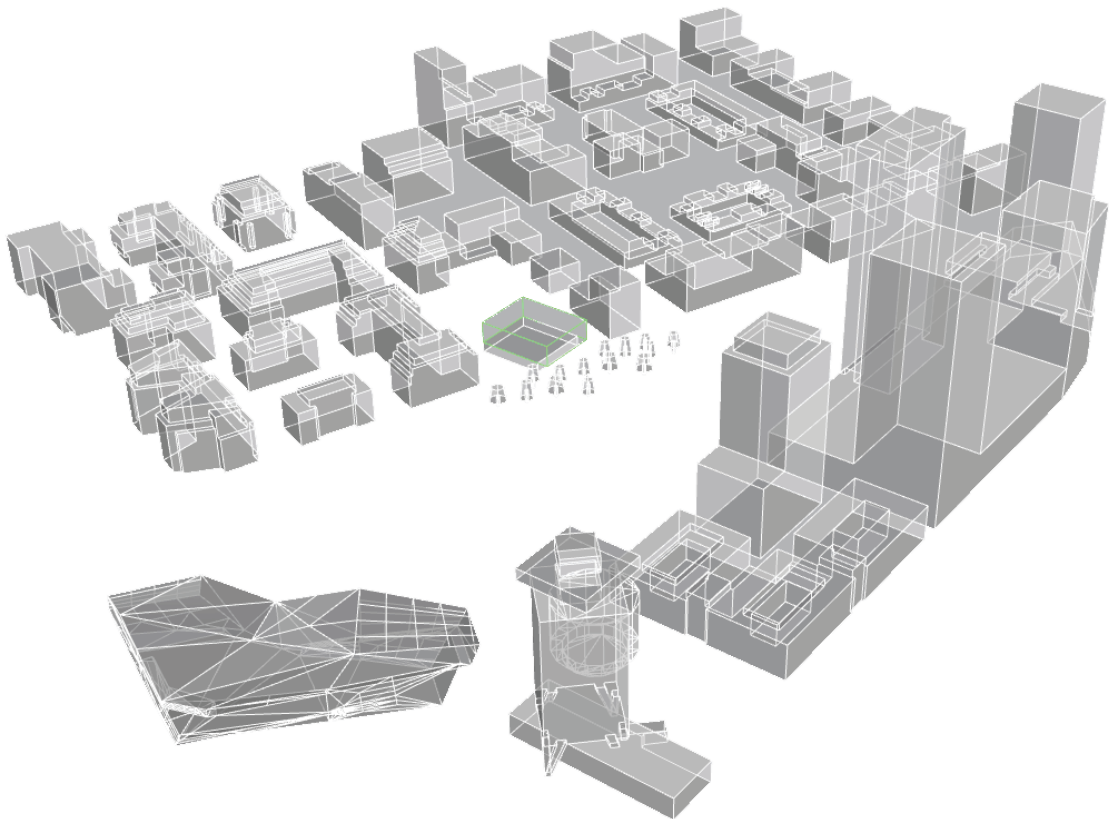


Fig. 3.2: 3D model of the building context. The sports hall is depicted in green.

3.1.2 Workflow GDS

The Generative Design System is set up in Rhinoceros (version 5.14.522.8390; Robert McNeel & Associates 2017a) and makes use of Rhinoceros plug-in Grasshopper (version 0.9.0076; Robert McNeel & Associates, 2017b). The Generative Design System generates building models, which are used by the Performance Analytics System. The Iterative Design System is controlled by a non-destructive algorithm. The algorithm iterates through design alternatives and uses multi-objective optimization to converge to optimal design solutions. Each iteration's building information is exported for use in the Data Processing System and the Visual Analytics System. The Grasshopper definition is available upon request from the author or either mentor.

Since the Performance Analysis System is also set up in Grasshopper, the Generative Design System is connected to the Performance Analysis System within the Grasshopper environment. Throughout the design

process various methods of parametrically defining the building geometry are used. Each method can be connected to the Performance Analytics System. This is facilitated by a custom Grasshopper node (cluster) that collects all required information of a Generative Design System and distributes it to the various components of the Performance Analytics System (Fig. 3.4). This node enables the user to efficiently and swiftly exchange a Generative Design System for another one.

The Data Processing System requires CSV files containing numerical building information, such as building volume, orientation and window areas.

The Visual Analytics System requires building models of each design alternative. The building models are exported as meshes in FBX file format. The wall geometry, window geometry and PV panel geometry are exported as separate files, so that materials can be separately applied in the Visual Analytics System.

| | Amount of simultaneous games | Amount of spectators | Annual occupancy |
|----------------------------------|------------------------------------|-------------------------|---------------------|
| High-level competition games | 1 | 500 | 10% |
| Club level competition games | 4 | 100 | 40% |
| Recreational games and trainings | 6 | 10 | 50% |

Fig. 3.3: Annual occupancy distribution of Overhoeks' sports venue.

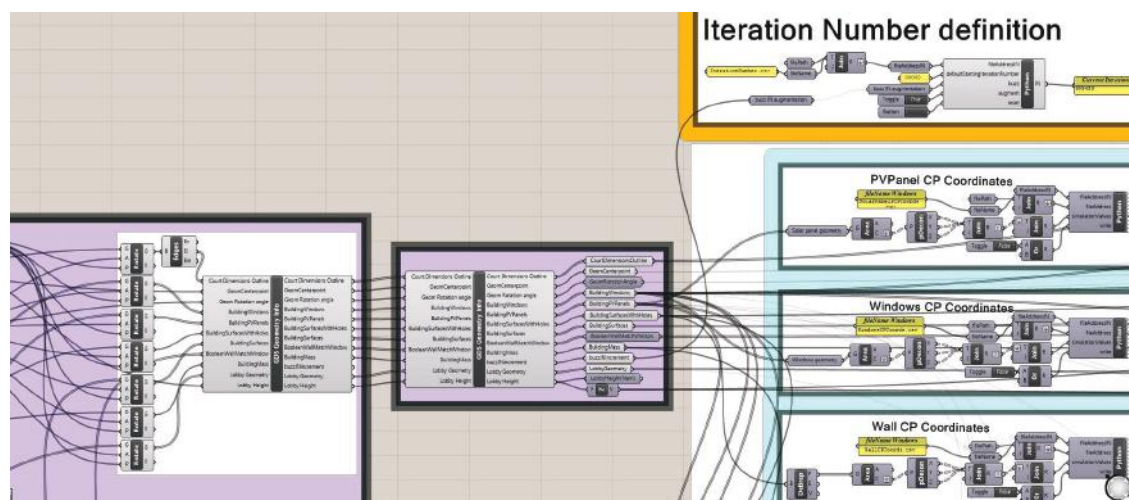


Fig. 3.4: Custom node (m.) connecting the Generative Design System (l.) to the Performance Analysis System (r.).

3.2 NON-DESTRUCTIVE EVOLUTIONARY ALGORITHM

The optimization process of the GDS is based on non-destructive evolutionary algorithms. The GDS uses Grasshopper plug-in Octopus to perform multi-variate, multi-objective optimization. Custom components write and export each building's

information and the plug-in LocalCode exports each building's geometries. The optimization and data writing components together form a non-destructive evolutionary algorithm.

3.2.1 Optimization process

The GDS uses Grasshopper plug-in Octopus (v0.3.4) to perform multi-variate, multi-objective optimization. Octopus uses a genetic algorithm and aims to minimize each performance objective (Vierlinger, 2017). A genetic algorithm creates an initial 'population'; an array of design alternatives ('individuals'). Then, in a looping process, the genetic algorithm (1) determines the fitness of each individual in the population, (2)

culls the fittest individuals (individuals closest to the Pareto front) and (3) creates a new population consisting of the fittest individuals and an amount of new individuals based on these fittest individuals, by means of cross-over ('sexual' reproduction) and mutation. With each generation the genetic algorithm 'converges' to the most optimal design solutions.

3.2.2 Data export

The GDS exports the building geometry and the simulation values of each design alternative.

The GDS writes information to various CSV files, each having their own purpose in the CDS. One CSV file contains the annual performance data of each design alternative. These values are the performance objectives of the evolutionary algorithm and are used to visualize overall performance in the VAS. Another CSV file contains geometry information of each design alternative, which is used to perform clustering. Geometry information used in this thesis concern the following building aspects, calculated by the GDS: floor area, building volume, building orientation, PV panel area, total window area of each façade and annual hours of insolation of each façade's windows. Use of these building aspects (as opposed to slider values, for example) enables use of multiple parametric models and enables users to add 'manually designed' geometries to the data set. Furthermore, this information leads to more in-depth knowledge on interrelationships between design characteristics and building performances. Appendix A describes how the GDS calculates or determines geometry

information. A third CSV file contains both geometry and annual performance information, used by data analytics methods in the Data Processing System to define similarity between designs. For each simulation objective, the GDS writes hourly values of each design alternative to their corresponding CSV files. This information leads to more in-depth knowledge on a design alternative's performance.

The GDS writes a 'log' for each design alternative. This log contains all relevant information of the design alternative. Amongst others, all slider values are written to the log so that the design alternative can be reinstated in the GDS. The various types of CSV files are illustrated in Fig. 3.5.

The building geometries are exported as FBX files using the LocalCodeExport component provided by Grasshopper plug-in Finches (Monchaux, 2017). The geometry is converted to a mesh, which is given a thickness using Weaverbird's Mesh Thicken component (version 0.9.0.1., Piacentino, 2017). Wall, window and solar panel geometries are exported separately so that materials can be easily applied in the VAS.

| Geometric aspects | | Performance aspects | | | |
|-------------------|------|---------------------|----------|-----------|-------|
| | Area | Volume | Awindows | Apvpanels | Glare |
| 1 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 2 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 3 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 4 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 5 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 6 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 7 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 8 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |

| Geometric aspects | | Performance aspects | | | |
|-------------------|------|---------------------|----------|-----------|-------|
| | Area | Volume | Awindows | Apvpanels | Glare |
| 1 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 2 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 3 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 4 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 5 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 6 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 7 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |
| 8 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | ~~~~ |

| Performance aspects | | Hourly sim. values | | | |
|---------------------|-------|--------------------|-----------|------|------|
| | Glare | Awindows | Apvpanels | EPBT | |
| 1 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | 0:00 |
| 2 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | 1:00 |
| 3 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | 2:00 |
| 4 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | 3:00 |
| 5 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | |
| 6 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | |
| 7 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | |
| 8 | ~~~~ | ~~~~ | ~~~~ | ~~~~ | |

| Design values | |
|---------------|------|
| Design No.034 | ~~~~ |
| Slider 1 | ~~~~ |
| Slider 2 | ~~~~ |
| Slider 3 | ~~~~ |
| Area | ~~~~ |
| Volume | ~~~~ |
| Glare | ~~~~ |

Fig. 3.5: Types of CSV files used in the CDS.

3.3 BUILDING DEFINITION

The Computational Design System developed in this thesis uses multiple parametric models to generate design alternatives. The models explore various means of facilitating the architectural design process with the Computational Design System.

Chapters 3.3.1 to 3.3.3 describe the various types of geometries used in the research process. The subchapters mainly discuss the reasoning behind and functionality of each parametric model. Appendix B provides an elaborate explanation of the Grasshopper definitions of the model.

3.3.1 *Free-form geometries using Delaunay and Voronoi*

The initial aim of the GDS was to precede the conceptual design phase by creating a very abstracted, 'amorphous' geometry. Optimized design alternatives of such models were envisioned to fully represent the most optimal building form. The architect would then transform this abstract geometry into an architectural design. This design approach requires a free-form building mass with individually assigned windows and PV panels.

Two parametric models creating abstract, free-form geometries are explored in this thesis. One model makes use of Delaunay triangulation of a three-dimensional point array (Fig. 3.7). The other uses Voronoi partitioning to define each wall (Fig. 3.8). Both methodologies ensure planar, convex surfaces, which is a requirement of the simulation components of the Performance Analysis System.

Delaunay triangulation is defined as following: for a triangulation of three points in a set of points, the triangulation is a Delaunay triangle if no point is within the circumscribed circle of the three points.

The Delaunay definition uses a three-dimensional grid of control points. The points are parametrically defined and are controllable by the evolutionary algorithm. Windows and PV panels are defined per surface segment. The windows are scaled down copies of their respective surface segments and are scaled based on a parametrically defined list of scale factors. Positioning of the PV panels is based on a list of Boolean values.

Voronoi partitioning makes use of a set of points and Voronoi regions corresponding to each point. Each Voronoi region is closer to its corresponding point than to any other point. The region boundary of two neighboring points can be defined as a plane with an origin on the centroid of the two points and with a normal vector parallel to a vector through the two points.

The GDS defines Voronoi partitioning for each wall and for the roof separately and then uses intersection commands to trim the edges. Each wall uses 14 points that can be moved with two vector inputs. The positions of the windows and pv panels are defined using an array of vectors that intersect the building shell. Windows and pv panels are placed on the wall segments that are intersected. Their sizes are parametrically defined.

Since each control point, each window and each PV panel is defined individually, both definitions use a large amount of design parameters (approximately 300 and 200, respectively). Although these methodologies ensure great variation in design alternatives, it impedes the functioning of the evolutionary algorithm since interrelationships between input variables and performance values are difficult to discern. As a result, convergence towards optimal design solutions is hardly achieved and the definitions therefore generate a large amount of undesirable design solutions.

Another disadvantage of both methodologies is that the design results are very expressive. Based on the author's experience, this limits the architectural freedom of the designer, since it is difficult to interpret the building geometry and to create design variations based on these geometries.

3.3.2 Rationalized geometry using repetitive elements

A third parametric model aims to facilitate convergence towards optimal design solutions and to encourage exploration of architectural design alternatives (Fig. 3.9). The definition is set up in a way that drastically reduces the amount of variables. In order to do so, some design decisions are pre-emptively made regarding the effect of design aspects on performances. For instance, south-facing windows are not included in the geometry definition, since initial simulations have indicated that these correlate with the occurrence of glare. Windows are evenly distributed over the façade to improve solar uniformity and are equal in size, shape and orientation to reduce the amount of variables used to define the window geometries. An unfortunate side-effect of this approach is that the influence of context geometry on optimization of parts of the façade is not as evident; the characteristics of a façade window that is shaded by a nearby building cannot differ from the other windows in that façade that are not shaded.

The parametric model uses 40 design variables to create design alternatives. Twelve moveable cornerpoints determine the inclinations of eight wall segments, two per façade. The East and West wall, as well as the roof, are segmented following a zigzag pattern. Sliders control the position of the zigzag's outer corner points and thus influence the facing

direction of the windows and solar panels.

Windows and PV panels are placed on opposing sides of the zigzag elements. The width and the height of the windows are variables and PV panels on the walls are controlled by booleans (on/off).

The parametric model generates generally well-performing design alternatives. A large amount of design alternatives are zero-energy buildings and have adequate performance regarding temperature-related performance objectives. Furthermore, the author does experience a greater sense of architectural freedom with these design alternatives compared to the ones described in the previous subchapter.

Relative differences between the design alternatives are small, however. Likewise, the relative increase of performance is low. Partially because of this, the interrelationships between geometry-related aspects and performances are not influential in the decision-making process. Consequently, the differences between the design alternatives are not as interesting for the user of the Computational Design System.

The following parametric models aim to achieve more variation in geometries. Furthermore, these geometries better approximate the architectural concept envisioned by the author.

3.3.3 Geometries following architectural concepts

The author envisions the sports hall as a robust, rock-like building that serves as a 'counterweight' to the Eye film museum. Two parametric models are set up to approximate this design vision. The architectural concept of both geometries is that of a solid mass that is carved to reveal an inner, more transparent box. The concept leads to similar results as the designs in a sketch of the landscape made during the early stages of the research (Fig. 3.6).

The first model defines the geometry as an orthogonal mass (Fig. 3.10). The mass is split up into large segments and various segments are deleted to create indents. The indents are mostly transparent, with large, vertical windows. The outer mass is mostly opaque, with a few small horizontal windows allow for more equal light distribution. Although the mass is orthogonal, the user of the CDS can reinterpret the designs to create non-orthogonal design alternatives. Simulations of these alternatives verify whether their performance is similar to their orthogonal counterparts.

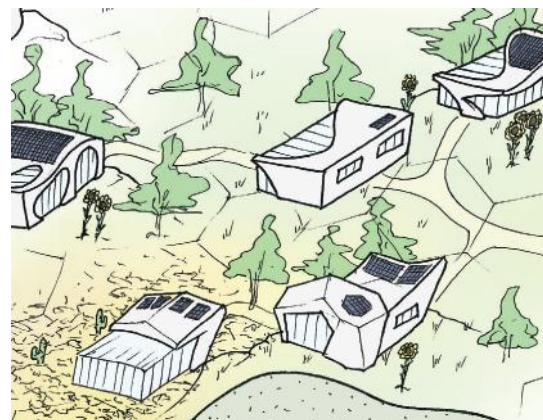


Fig. 3.6: Early stage sketch of the Visual Analytics System, with cubist-inspired designs.

The second model uses a non-orthogonal mass (Fig. 3.11). Each wall is polygonal and can be tilted to either side. The roof is triangulated. The mass is sliced over the West-East axis. Segments of each slice are removed to create indents similar to the definition above.

Both parametric models generate design alternatives that have desirable architectural qualities. The designs of the former definition match the robust architecture of the neighboring apartment blocks. The designs of the latter definition match the sculptural, polygonal architecture of the Eye museum.

3.4 DISCUSSION

The Generative Design System generates a set of design alternatives using parametric models and non-destructive evolutionary algorithms. Exploration of various methods of defining parametric models gives insight in how the Computational Design System best contributes to the architectural design process.

Parametric models using Voronoi and Delaunay tessellation precede the conceptual design phase. These models aim to drive the development of the design concept by giving the designer an initial indication of design aspects that achieve certain performance objectives. Due to the large amount of design flexibility, the parametric models have a large amount of design variables. As a result, convergence of the evolutionary algorithm towards optimal design results is hardly achieved, resulting in a large amount of infeasible design solutions. Furthermore, because of their expressive geometries, interpretation of performance-influencing design aspects is difficult. Consequently, these geometries do not enable the user to create architectural designs based on their building information.

A model that aims to minimize the amount of design variables by implementing preliminary design decisions does not have either of these issues. The 'zigzag' model explored in this thesis generates generally well-performing design alternatives and enables designers to create architectural designs inspired by its abstracted geometries. However, because differences between the design alternatives of the 'zigzag' model explored in this thesis are small, differences between design alternatives are not very interesting to the designer. Use of models with small design flexibility better suits optimization processes in later design stages.

Based on the author's experience, basing parametric models on early architectural design concepts contribute the most to the design process. This methodology ensures that architectural performances are already achieved. Interpretation of design results is easier, since differences between design alternatives are larger. However, optimal design solutions are likely not reached since these models use a sizable amount of design variables.

Exploration of different types of parametric models in the CDS shows advantages and disadvantages for each type. The 'zigzag' model enables optimization towards optimal design solution, whereas the other models allow for exploration of a design concept. Therefore, this thesis recommends to use multiple parametric models to generate a data set of design options. This enables exploration and comparison of multiple architectural concepts. Use of various parametric methods is facilitated by the data workflow of the Computational Design System. The Generative Design System can be exchanged, allowing for analysis of various parametric models as well as non-parametric designs. Furthermore, as described in Chapter 5 & Chapter 6, the Data Analytics System enables simultaneous data processing and visualization of building information of multiple parametric models.

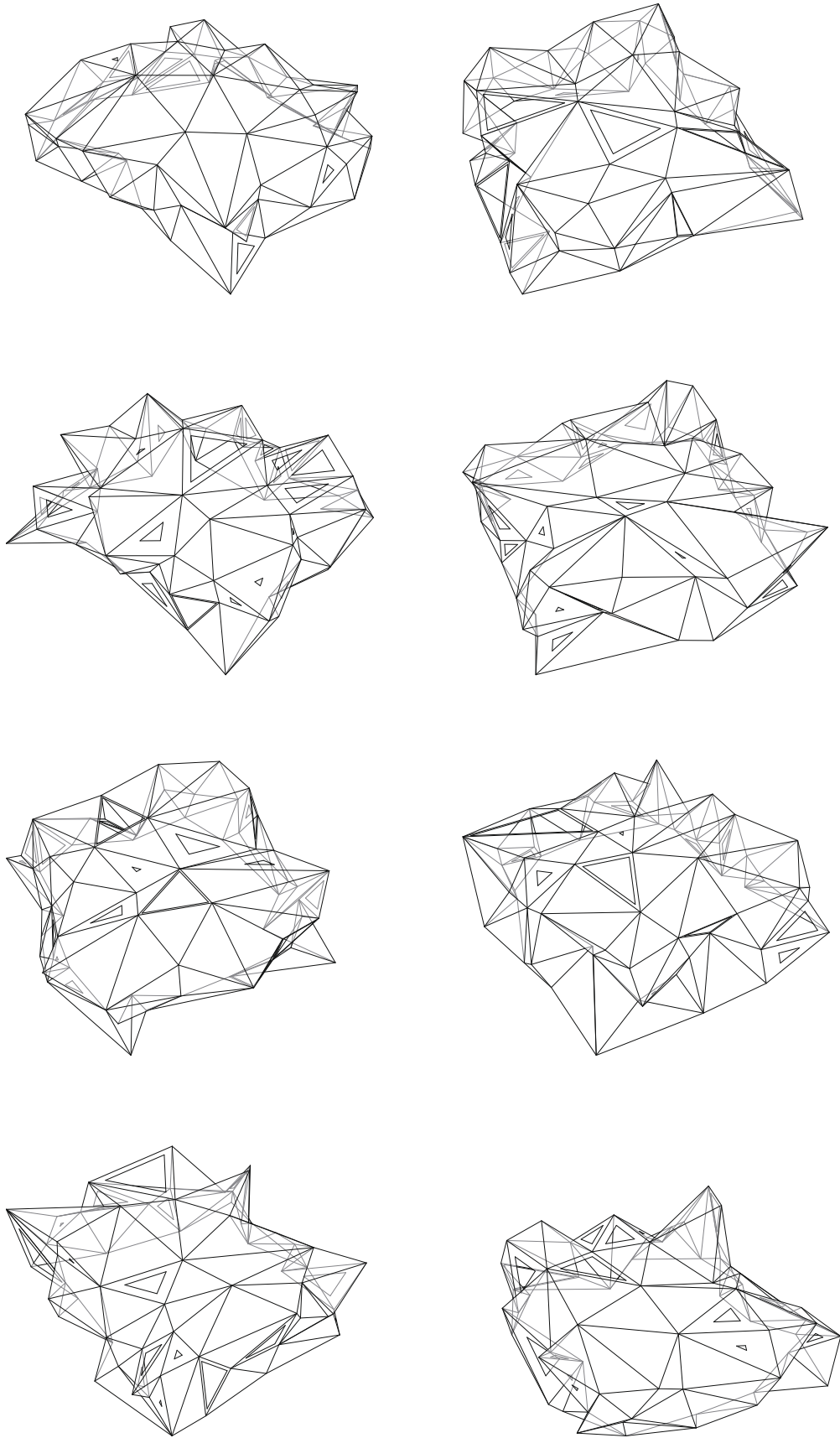


Fig. 3.7: Selection of design alternatives generated using the Delaunay-based parametric model.

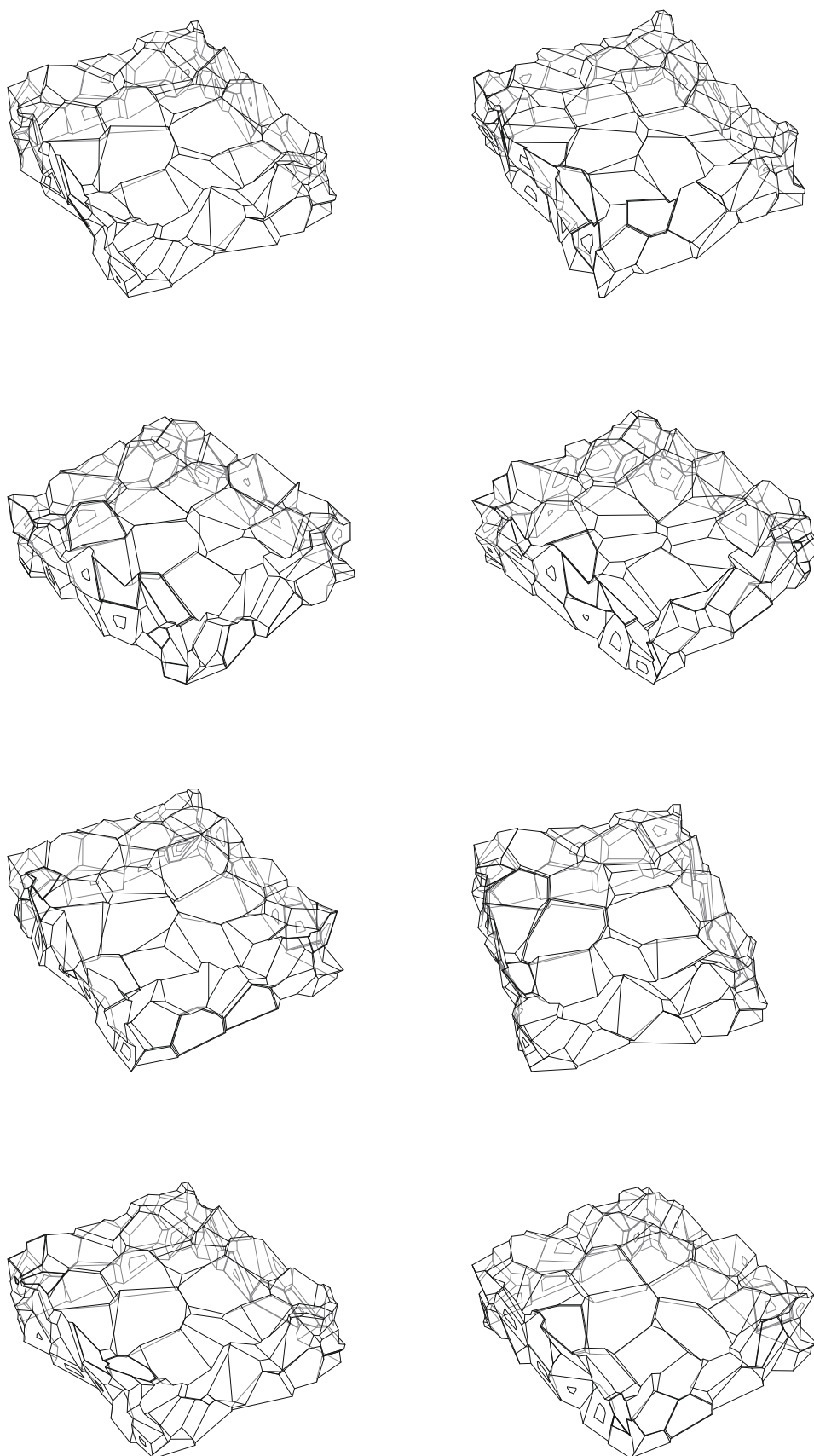


Fig. 3.8: Selection of design alternatives generated using the Voronoi-based parametric model.

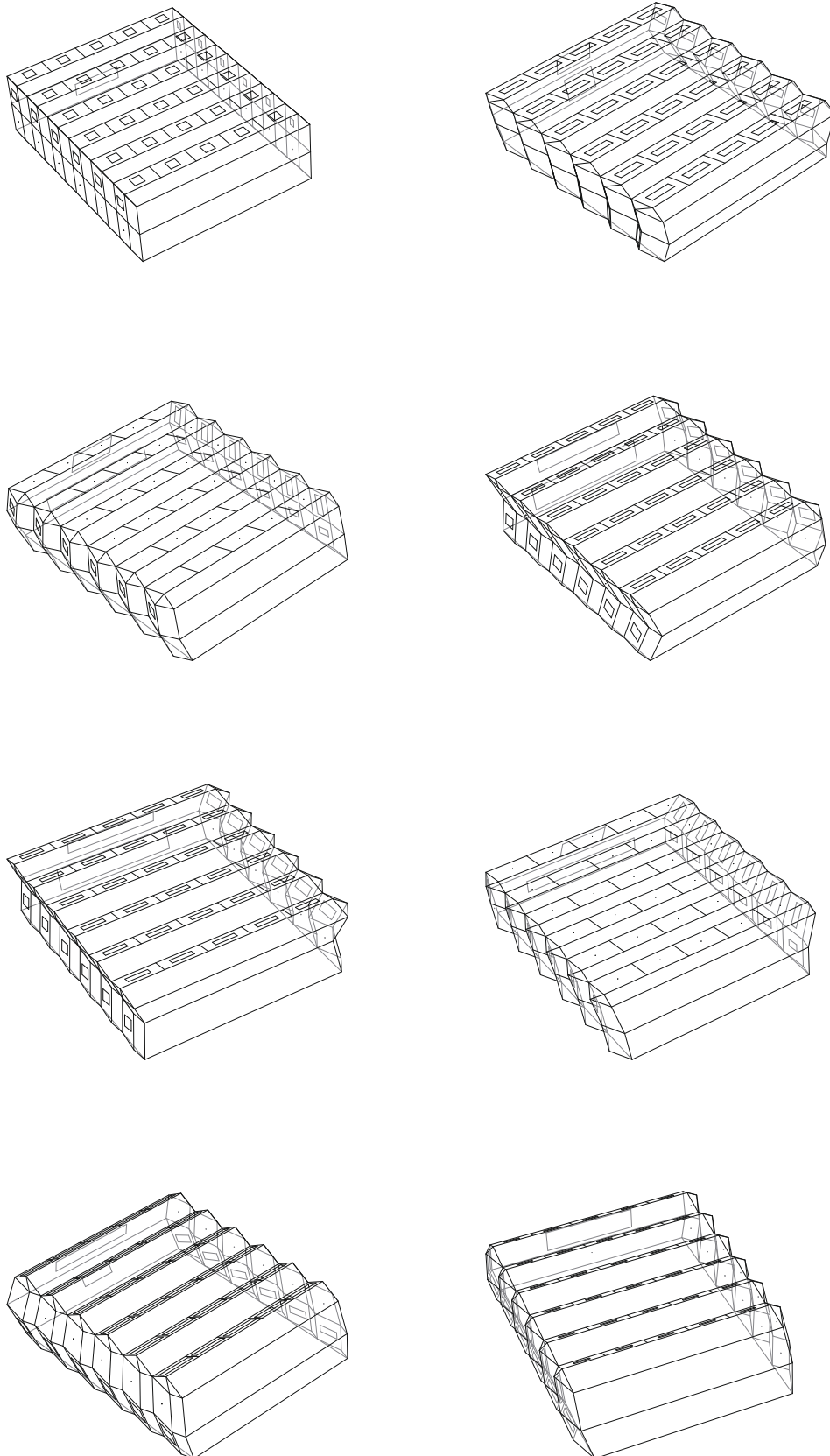


Fig. 3.9: Selection of design alternatives generated using the 'zigzag' parametric model.

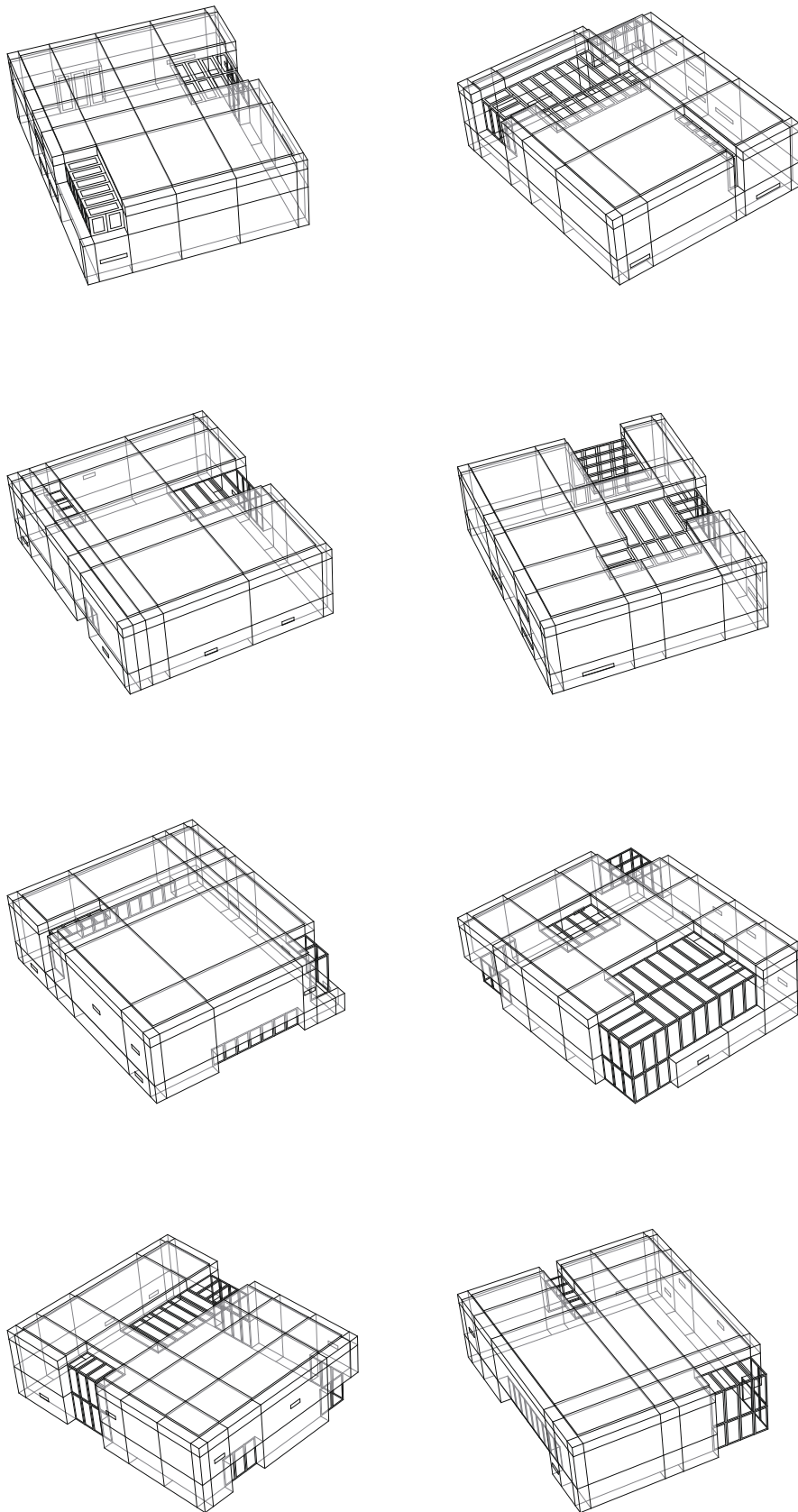


Fig. 3.10: Selection of design alternatives generated using the 'orthogonal mass' parametric model.

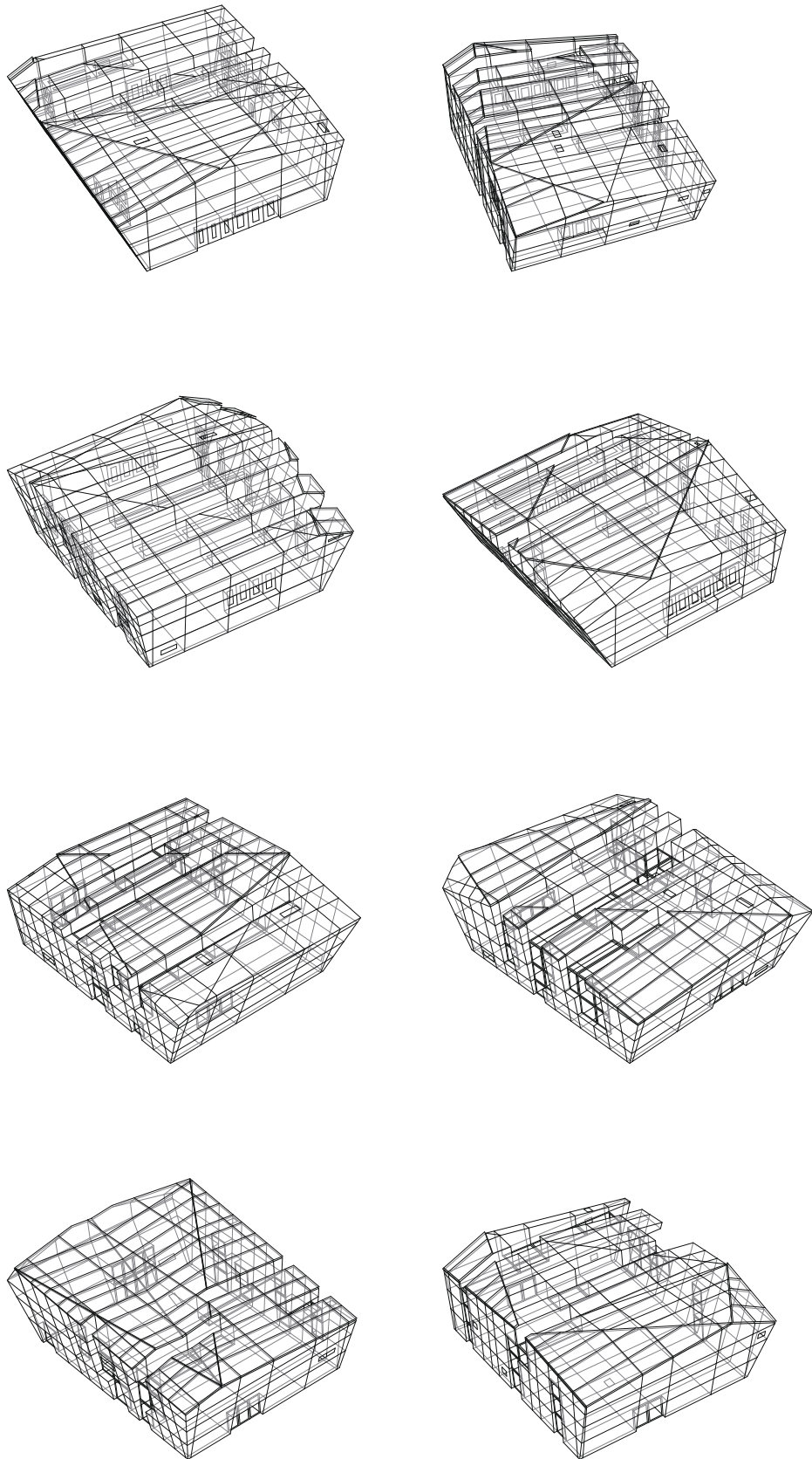


Fig. 3.11: Selection of design alternatives generated using the 'non-orthogonal mass' parametric model.

CHAPTER 4: PERFORMANCE ANALYSIS SYSTEM

This chapter describes the Performance Analysis System (PAS). The PAS determines various performances of the design alternatives generated with the Generative Design System (GDS). The performances are presented with the Data Analytics System (DAS).

Chapter 4.1 Introduces the performance objectives of the sports hall and describes the workflow of the PAS. The PAS runs multiple simulations to analyze building performances. Chapters 4.2 to 4.4 elaborate on the performance objectives of the sports hall and describes the setup of the various analysis componets that comprise the PAS.

4.1 INTRODUCTION

4.1.1 Performance objectives

Sports venues have a significant energy consumption. There are 1.5 million sports and recreational buildings in Europe that together comprise 8% percent of the total building stock. They can account for up to 10% of the total energy consumption of the building sector (LEITAT, 2015). Research by Dutch energy research center ECN (Sipma & Rietkerk, 2016) has concluded that indoor sports accomodations without a swimming pool have an average annual energy consumption of 179 kWh/m² or 216 kWh/m² (representing the building typology's average energy demand and benchmark energy demand, respectively). These values are comparable to the average energy consumption of most other non-residential building types such as offices, museums and hospitals, as measured by the ECN (Sipma & Rietkerk, 2016).

Besides considerable energy demands, sports halls have unique requirements regarding lighting and indoor temperatures because of their significant impact on sports players' performance. Tests performed by Galloway & Maughan (1997) and No & Kwak (2016) show that time of exhaustion is significantly shorter when environmental temperatures are uncomfortable. The Computational Design System developed in this thesis aims to optimize the sports hall design on energy-related performance criteria, thermal and lighting performance criteria, besides architectural qualities. The quantified performance objectives are listed in Fig. 4.1. Rather than solely considering the building's total energy demand, performances of the various energy demands are considered as separate performance objectives, since each are influenced by different building aspects and each may favor different design solutions.

The sports hall designed in this thesis hosts multiple types of sports at multiple competition levels, as well as trainings. Furthermore, the sports hall is open even when no games are played, for administrative purposes (maintanance, cleaning, etcetera). These various activities have different temperature and lighting requirements and different levels of occupation. Therefore, the analyses make use of an annual schedule defined by the author (Fig. 4.2). The occupancy levels are arbitrarily chosen by the author. The metabolism values are derived from the ASHRAE standard on thermal environmental conditions for human occupancy (ASHRAE, 2010). The standard lists the metabolism rates of various tasks, among which tennis (3.6-4.0) and basketball (5.0-7.6) are listed. The schedule consists of a weekday and a weekend schedule that approximate the activity schedule of common neighborhood sports halls. Additionally, it is assumed that the sports hall hosts regional, national, or international championships four times a year, once every season. The championships are assumed to take place on the following dates:

Mar. 3 - Mar. 5
Jul. 7 - Jul. 13
Oct. 26 - Oct. 27
Dec. 19 - Dec. 23

| | |
|-----------|---|
| Energy: | Cooling energy demand (kWh) |
| | Heating energy demand (kWh) |
| | Artificial lighting energy demand (kWh) |
| | PV panel energy gain (kWh) |
| | PV panel energy payback time (y) |
| Lighting: | Glare occurance (hrs/y) |
| | Lighting uniformity (hrs/y) |
| Thermal: | Thermal comfort spectators (hrs/y) |
| | Thermal comfort sports players (hrs/y) |
| | Temperature criteria (hrs/y) |

Fig. 4.1: Quantified performance objectives.

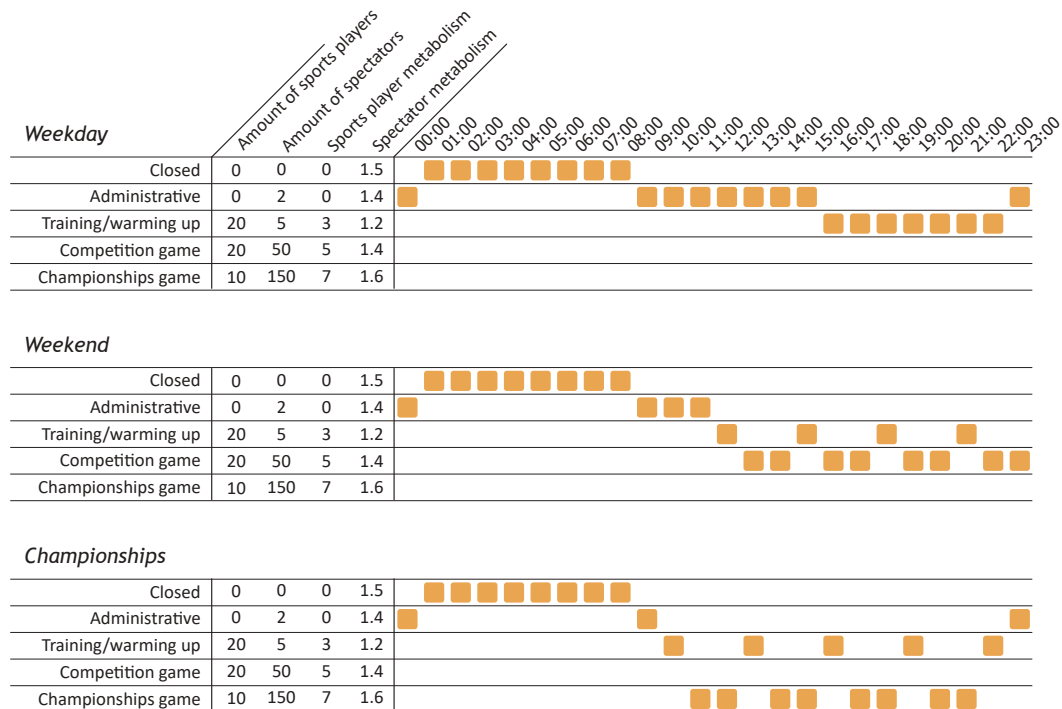


Fig. 4.2: Sports hall weekday, weekend and championship schedules.

4.1.2 Workflow PAS

The Performance Analysis System (PAS) runs multiple simulations on a geometric model of the Generative Design System. The Performance Analysis System is set up in Grasshopper (version 0.9.0076, Robert McNeel & Associates, 2017) and uses various plug-ins to facilitate performance analyses. Performance information is exported for use in the Data Processing System. The Grasshopper definition is available upon request from the author or either mentor.

A custom Grasshopper node (cluster) contains all information of the building model defined in the Generative Design System (Fig. 3.4). The outputs of this node are distributed to the various simulation components of the PAS.

The Data Processing System requires CSV files that contain annual performance information of each design alternative. The Data Processing System also uses hourly performance information to calculate seasonal performances. Both annual and hourly performance are exported.

4.2 ENERGY PERFORMANCES

4.2.1 Introduction

This thesis develops a visual analytics tool for analysis of climate-related design performances. The goal of the tool is to optimize the building's geometric design in its conceptual stage in order to reduce its energy demand as much as possible.

Being a middleware tool for architects and climate designers, this thesis limits itself to the operating energy of a building. More exactly, the PAS calculates

heating and cooling demands, electric lighting consumption and solar energy generation as the main energy-related design objectives, as these are the most influential design-driving energy-related factors for the design of sports halls; together, space heating and electric lighting comprise 68% of a sports hall's energy consumption (Trianti-Stourna et al., 1998).

Energy criteria are presented in chapter 4.2.2. Simulations of the heating, cooling and energy demands are derived from the thermal and visual performance analyses and are therefore described

in chapters 4.3 and 4.4. Simulation of the energy potential of the PV panels is described in the following subchapter, chapter 4.2.3. Calculation of the energy payback time is described in chapter 4.2.4.

4.2.2 *Nearly Zero-Energy criteria*

The sports hall designed in this thesis is aimed to be a (nearly) Zero-Energy Building. Because of discrepancies in e.g. climate, building types and levels of ambition EU countries are allowed to define nearly Zero-Energy Building requirements themselves (LEITAT, 2015). The nearly Zero-Energy Building (nZEB) requirements of EU countries vary between 25 and 175 kWh/m² for new buildings, with an average of 106 kWh/m² (LEITAT, 2015). Most countries do not discern sports buildings as a separate building type; Bulgaria and Slovakia are the only countries to do so. Other countries group sports buildings with other non-residential buildings. The Netherlands do not have a definitive definition for nZEB, but in 2015 the Dutch Government made a proposal. This proposal prescribes a maximum energy demand of 50 kWh/m² for utility buildings. Fossil energy use may be no more than 25 kWh/m², and the share of renewable energies should exceed 50% (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties, 2015). The design brief of the sports hall designed in this thesis assumes these

values to assess whether the designs classify as nZEBs.

The nZEB methodology used in this thesis only takes into account the energy factors that have most influence on the building geometry. Consequently, the methodology only considers the energy potential of PV panels and does not quantify the energy potential of wind turbines, aquifers, implementation of heat recovery in the HVAC system, or other energy-generating or -saving options. Furthermore, the methodology uses primary (on-site) energy as its metric of balance. It is evident that the Computational Design System does not dictate whether a design meets the energy criteria of a (nearly) Zero-Energy building based solely on the quantified energy performances, since many more factors should be taken into account. It should be emphasized that, instead, the Computational Design System is developed to facilitate a design process that minimizes energy demands and maximizes energy potential by means of decision-making based on comparative analysis.

4.2.3 *PV panel energy potential*

The energy generated by PV panels is simulated using a Ladybug's Photovoltaics component. The component takes the EnergyPlus weather file and the solar panel geometries as an input, as well as a number of solar panel properties, which are mentioned below. It simulates hourly energy gain values for each of these surfaces. Because of the computational expensiveness of this large amount of data (which in some cases

exceeds a million values), the GDS sums these values together before writing them to the CSV files.

The solar panels are assumed to have an efficiency of 16% and an effective area of 90%. The average annual solar irradiance in Amsterdam is 1070 kWh/m² (KNMI, n.d., p.54). Assuming optimal orientation, the solar panels have the potential to generate 154 kWh/m² annually.

4.2.4 *PV panel energy payback time*

The performance of a PV panel depends on its orientation; a North-facing panel generates far less energy than a solar panel facing upwards. In extreme cases, a solar panel that is placed in an inefficient location may never generate the amount of energy that was required to produce the panel.

To prevent the GDS from placing solar panels in

inefficient locations the energy payback time (EPBT) of the solar panel array is included as an optimization objective. Fthenakis (2012, p9440) defines EPBT as "the period required for a renewable energy system to generate the same amount of energy as that used by the system from cradle to grave". A lower EPBT therefore directly correlates to an increase of annual

energy gain and, hence, an increase of performance of the solar panel. Based on data from the Ecolnvent (v2.0) database, the cumulative energy demand approximates 4250 MJ-eq/m² for multi c-Si and Ribbon Si PV panels (Laleman, Albrecht & DeWulf,

2011). The cumulative energy demand is the primary energy required for the cradle to grave lifecycle of the system. The evolutionary algorithm aims to maximize the solar panels' energy gain whilst minimizing their average EPBT.

4.3 THERMAL PERFORMANCES

4.3.1 Introduction

Most sports practiced in sports halls require high levels of activity. Conversely, spectators generally have low amounts of activity. Sports halls therefore have conflicting demands on indoor temperature; whereas sports players desire low temperatures to counteract their metabolism's heat generation, spectators require higher temperatures to feel comfortable. Sports federations' regulations on indoor temperatures vary, further complicating the problem. Furthermore, maintaining an optimal indoor temperature is energy intensive: typical sport facilities use 38% of energy for space heating (Trianti-Stourna et al., 1998). The heating and cooling design of a sports hall is intricate, requiring a well-considered

balance between spectator comfort, sports player comfort and energy consumption. Therefore, the PAS includes a thermal analysis, which is performed by OpenStudio via a component provided by Honeybee. The component calculates hourly heating and cooling energy demands and hourly operative temperatures. Custom Grasshopper components use the operative temperatures to determine whether temperature criteria are met and to calculate thermal comfort levels of both sports players and spectators. The Iterative Design System aims to minimize heating and cooling energy demands whilst meeting these performance objectives.

4.3.2 Simulation settings

The OpenStudio simulation component is based on an 'HBZone' and its context geometry. Information on the weather in Amsterdam is derived from an EnergyPlus weather file. The EnergyPlus weather file for Amsterdam is retrieved from the website of EnergyPlus (EnergyPlus, n.d.) and is developed by ASHRAE (2001).

An HBZone contains all information about a building zone relevant to the analysis. Besides the building geometry, the HBZone requires wall and window constructions, ventilation demands, occupancy and activity schedules and heating and cooling temperature setpoints and setbacks. The following subchapters describe these settings.

4.3.2.1 Construction

The PAS uses the wall and glazing constructions listed in Fig. 4.3. The wall construction is a slight simplification of reality, where, amongst others, an air cavity to prevent condensation might be desirable. Since the thermal analysis only requires the thermal resistance of the wall construction and since the thermal resistance predominantly results from the thermal resistance of the insulation material, this abstraction gives sufficiently accurate analysis results. The glazing values correspond to HR++ glazing (VABI, 2017; GLASSOLUTIONS Nederland, 2017).

Wall:
80 mm concrete, λ -value = 1.0W/m*K
140 mm Rockwool, λ -value = 0.035W/m*K (Rockwool B.V., 2017)
140 mm concrete, λ -value = 1.0W/m*K

Glazing :
U-value = 1.1 W/m*K
Solar Heat Gain Coefficient = 0.58
Visible Transmittance = 0.80

Fig. 4.3: Wall and glazing construction properties.

Infiltration through the building envelope is calculated following the calculation method prescribed in NEN8088:2012 (2012). Infiltration is calculated using the following formula:

$$Q_{ve;inf} = f_{wind} * f_{type2} * f_{inf} * (0.13 * q_{v10,spec}) * A_q$$

Where:

$Q_{ve;inf}$ = infiltration air flow in dm³/s

f_{wind} = building volume-related correction factor of infiltration induced by wind pressure.

f_{type2} = building type-related correction factor of adjustment of induced infiltration

f_{inf} = correction factor of the influence of ventilation on induced infiltration

$q_{v10,spec}$ = specific air permeability in dm³/s, calculated with a uniform pressure difference of 10 Pa.

A_q = floor area in m²

The wind-related correction factor f_{wind} is calculated using the following formula:

$$f_{wind} = \max[1; (0.01 * (24 + 0.555 * \sqrt{L^2 + B^2}) + 4.5 * H)^{0.65}]$$

Where L, B and H are the length, width and height of the building, respectively.

For a sports venue with dimensions of 34x27x14.1m³, $f_{wind} = 1.07$.

Correction factor f_{type2} depends on the building typology and is derived from a table presented in NEN8088:2012 (2012, p.40). The table prescribes a correction factor of 1 for buildings with a slanted roof and a correction factor of 0.77 for buildings with a flat roof. Because the roof typology of the buildings generated by the Generative Design System varies, this thesis assumes a correction factor of 1, which has a greater contribution to the infiltration rate.

Correction factor f_{inf} depends on the ventilation type of the building. For buildings with mechanical ventilation $f_{inf} = 1.15$ (NEN8088:2012, 2012, p.41).

The air permeability $q_{v10,spec}$ is the product of three parameters; f_{type} , f_{year} and $q_{v10,spec;calc.}$. Factors f_{type} and f_{year} are correction factors for the building type and the year in which the building is built, respectively. The third parameter $q_{v10,spec;calc.}$ is the calculation value for the specific air permeability, calculated with a uniform pressure difference of 10 Pa. The value of these parameters are deduced from NEN8088:2012 (2012, p.42-43). For the sports hall designed in this thesis, $f_{type} = 1.4$, $f_{year} = 0.7$ and $q_{v10,spec;calc.} = 0.7$.

The floor area of the sports hall is 918m².

Consequently, the infiltration air flow $Q_{ve;inf} = 101.0773$ dm³/s. This corresponds to an infiltration rate of 0.041 ACH, assuming the sports hall's minimum dimensions. The Performance Analysis System uses a slightly higher infiltration rate of 0.05 ACH, to account for possible errors made during building construction.

4.3.2.2 Activity

Two major influences on indoor temperatures are ventilation and heat gain of lighting and equipment. The PAS uses the minimum amount of fresh air per person to define ventilation demands. Sport England (2012, p.32) recommends 8-12 l/s of fresh air per person. The lighting energy demand is set according to the average lighting energy demand for 500 lux. The equipment energy demand is set to 1 W/m², which accounts for the (possible) presence of scoreboards, tv-screens and/or a laptop.

Another influence on the thermal energy demand is the heat gain of the building's occupants. The thermal simulation component requires the metabolic rate to be defined in W/m² floor area. The metabolic rate is converted from Met and can be approximated by 1 Met = 58 W (TheEngineeringToolbox, n.d.). Fig. 4.2 presents the metabolic rates assumed for each activity in the sports hall.

4.3.2.3 HVAC system

The Performance Analysis System uses a VAV (Variable Air Volume) HVAC system. VAV systems enable a constant indoor air temperature, based on setpoint temperatures. VAV systems allow for demand-controlled ventilation, which is especially useful for buildings with varying activities.

Heat recovery is not included in the Performance Analysis System; it is deemed more useful for the user of the Computational Design System to be aware of energy demands that do not include heat recovery, as it is only one of the solutions to reduce the energy demand of the sports hall.

4.3.2.4 Urban context

Shading by surrounding buildings and other objects influences the solar heat gain and, consequently, influences the heating and cooling demand of a building. The context model depicted in Fig. 3.2 contains the context geometry for the simulation. The trees' canopies are abstracted to polygonal threedimensional meshes. The trees' fluctuating shading effects caused by leaf fall and growth is approximated by varying the transparency of the mesh by means of a schedule of monthly transparency values. The transparency values range from 0.2 in summer to 0.8 in winter.

4.3.3 Thermal comfort

A commonly used definition of thermal comfort is proposed by ASHRAE (2010, p.4): “Thermal comfort is that condition of mind that expresses satisfaction with the thermal environment”. Multiple models have been developed to compute thermal comfort. Among the most well-known models is the Predictive Mean Vote (PMV) model, developed by Fanger in 1970. The PMV is an index that predicts the mean value of thermal comfort of a group on a 7-point sensation scale. The PMV is determined based on metabolic rate, clothing insulation, air temperature, mean radiant temperature, air velocity and air humidity (ISO, 2005). Based on the knowledge that non-comfortable people are able to respond to the indoor climate (e.g. by changing their clothing), it is established that a fluctuation of the PMV is perfectly permissible, albeit within limits. These limits are determined by the PPD (Predicted Percentage of Dissatisfied). The PPD is an index developed by Fanger that the percentage of non-comfortable people. The PMV/PPD-model that is derived from the two indices can be usefully translated to a desired indoor temperature. According to van den Linden et al. (2011), this model is preferred over other models in practice for its relative simplicity of use and its compatibility with the use of computing devices.

The PMV model, however, is a static model, which only assumes that thermo-physical aspects are of influence on thermal comfort. Adaptability and psychological aspects influence comfort as well, in particular the influence a person can exert on his surroundings and expectations on climate conditions (van den Linden et al., 2011). As a result, comfort levels fluctuate more with the outdoor temperature than the PMV-model indicates.

ISSO 74 (Boerstra, Hoof & van Weele, 2014) is a Dutch adaptive thermal comfort guideline that takes these fluctuations into account. The guideline combines elements of adaptive and non-adaptive standards. The guideline distinguishes between spaces that have either possibilities of adaptability (e.g. operable windows) or are centrally controlled, because of their aforementioned impact on the occupants’ comfort. A distinction is also made regarding the allowed PPD. For example, buildings with diseased persons fall under Class A. Class A buildings have a high level of expectation on thermal

comfort and therefore should comply with a maximum PPD of 5%. Class D comprises buildings with a low level of expectation (e.g. temporary buildings) and can therefore suffice with a maximum PPD of 25%. New buildings fall under Class B and should comply with a maximum PPD of 10%.

The graph in Fig. 4.4 plots the allowable indoor operative temperatures against the running mean outdoor temperature for Class B-C. The running mean outdoor temperature is a mathematical contraction of the outdoor air temperature and the radiation temperature. The running mean outdoor temperature can be calculated using the following formula (CEN, 2006, p.9):

$$\Theta_{rm} = (1 - \alpha)\Theta_{ed-1} + \alpha * \Theta_{rm-1}$$

Where

Θ_{rm} = Running mean temperature for today

Θ_{rm-1} = Running mean temperature for the previous day

Θ_{ed-1} = Daily mean external temperature for the previous day

α = a constant between 0 and 1. A value of 0.8 is recommended.

ISSO 74 and other thermal comfort guidelines are developed according to available thermal comfort data which are primarily focused on office buildings, or buildings with similar occupant metabolisms and clothing. Boerstra, Hoof & van Weele (2014) prescribe a correction of the temperature limit for ISSO 74 when dealing with ‘unusual’ metabolism or clothing values. This referred method is used for metabolism levels below 2.0. Metabolism of sports players is significantly higher, however. In order to be able to determine thermal comfort of sports players for the design objective in this thesis the comfort limits throughout the year are slightly adjusted to fit their metabolism and clothing characteristics, based on the temperature criteria and recommendations set out in chapter 4.3.4. The minimum and maximum comfort temperatures are set to 18°C and 25°C, respectively. The thermal comfort of spectators is determined following the ISSO guidelines and range from 20°C to 26°C. The paS calculates and optimizes the annual amount of hours that thermal comfort levels are not met. Fig. 4.5 shows how temperature limit levels of spectators and sports players relate to the running mean outdoor temperature.

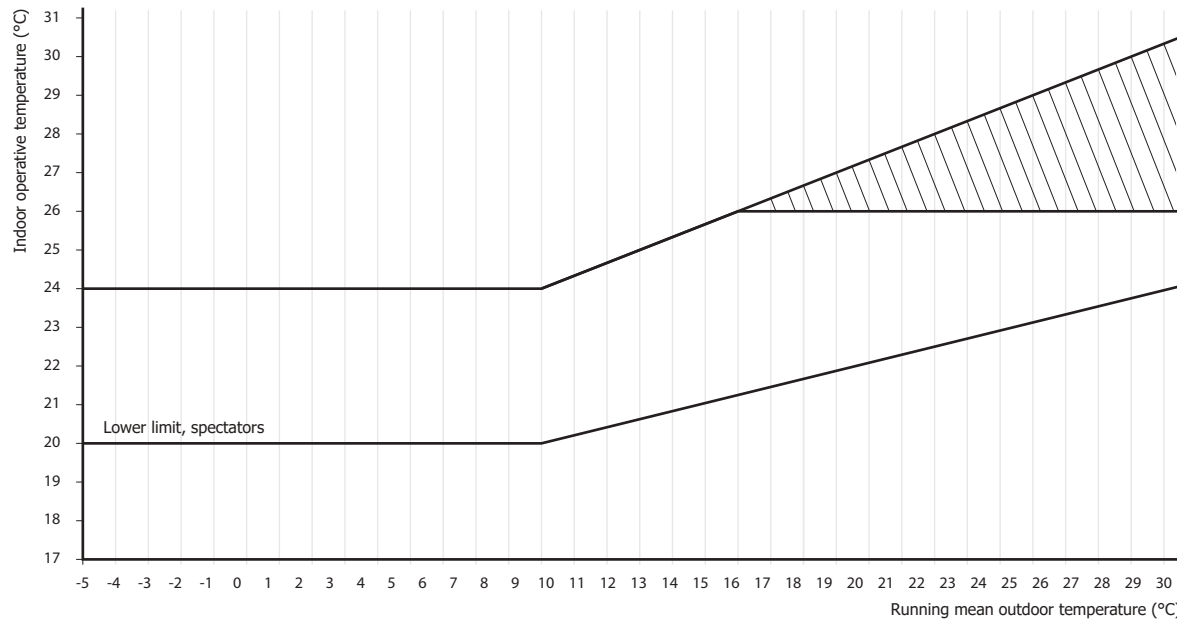


Fig. 4.4: Thermal comfort limit levels of Class B buildings prescribed by ISO 74 (based on Boerstra, Hoof & van Weele, 2014, p.28). In centrally conditioned areas the horizontal upper limits should be used under summer conditions. In areas with possibilities of adaptability, one is allowed to use a higher value as indicated by the shaded triangles.

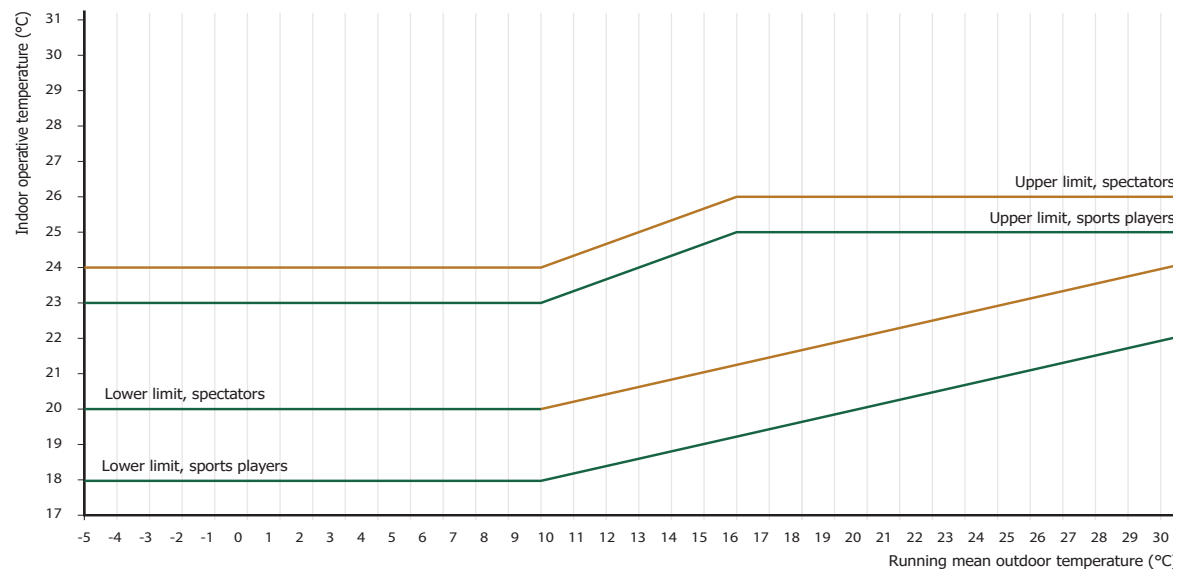


Fig. 4.5: Thermal comfort limit levels of spectators (orange) and sports players (green).

4.3.4 Temperature criteria

Besides thermal comfort levels of sports players and spectators, this thesis considers temperature criteria prescribed by sports and building regulations. Because of the differences in level of activity indoor temperature criteria vary by sport and in some cases by competition level. A distinction can be made between competition games and trainings as well. Generally, the former allows for minimum temperatures of 12°C to 16°C, but trainings may require temperatures of up to 20°C (Sport England, 2012).

Various sports regulations prescribe minimum, aimed for and/or maximum temperatures. The indoor temperature of volleyball games should exceed 10°C (FIVB, 2014). For high-level competitions, values between 16°C and 25°C are prescribed. The temperature during high-level badminton games should be between 18°C and 30°C (BWF, 2017). The temperature during basketball games should be below 28°C and should aim for 18°C (FIBA, 2009). Furthermore, the Basketball ACT (2014) has introduced a heat policy. When indoor temperatures exceed 35°C, game-influencing measures are taken. No other criteria are mentioned by these and other regulations reviewed for this thesis.

To simplify the calculation model, this thesis does not distinguish temperature criteria performances for each sport. Instead, the PAS uses benchmark temperature thresholds based on 'weighed average values' of the aforementioned prescribed criteria. This thesis assumes minimum and maximum indoor operative temperatures of 19°C and 27°C, respectively. These values are chosen based on the notion that the energy consumption for heating and cooling is proportional to the indoor/outdoor temperature difference. The extra energy demand of sports that have stricter temperature criteria are balanced by energy savings during trainings or sports with less strict criteria. Hence, the simulated indoor operative temperatures may exceed not always fulfil the requirements of all sports. Although system sizing of the HVAC system is beyond the scope of this thesis's design assignment, it should be noted that the simulations that use the benchmark minimum and maximum indoor operative temperatures do not facilitate the system sizing of the HVAC system; the HVAC system should be sized according to the maximum ventilation demands based on the temperature criteria set out by the sports regulations.

Thermal performances largely depend on heating and cooling setpoints. Initially, setpoints were parameters that could be controlled by the Iterative Design Process. However, early testing of the Iterative Design System indicated that convergence towards optimal setpoint temperatures proved inefficient,

due to the large amount of design variables of the parametric models of the Generative Design Systems. Therefore the temperature setpoints are fixed, arbitrarily chosen to meet thermal performances most of the time. Of course, the interrelationship between energy demand and thermal comfort performances can be adjusted to either reduce the energy demand or increase thermal comfort. This internal trade-off is not quantified in the Computational Design System, although this may be investigated by use of another CDS that makes trade-offs between energy demands and thermal comfort performances by changing setpoint and setback temperatures as temperatures.

Simulations run with the OpenStudio simulation component in Grasshopper induce different operative temperatures than indicated with the setpoints; with a heating setpoint of 19°C, operative temperatures commonly are 17°C. A possible explanation is that the OpenStudio simulation components regard the air or radiant temperatures of a zone, instead of operative temperatures. Test simulations have indicated that the operative temperatures most commonly meet the temperature criteria if the setpoint values are as follows:

| | |
|-------------------|------|
| Heating setpoint: | 21°C |
| Heating setback: | 13°C |
| Cooling setpoint: | 27°C |
| Cooling setback: | 35°C |

The sports hall designed in this thesis is directly adjacent to the lobby and other accommodations (changing rooms, canteen, warm-up halls, etc.). The indoor temperature of these accommodations are therefore of influence on the energy demand of the sports hall. The temperature thresholds of the accommodations are derived from the indoor operative requirements determined in ISSO 74 (see chapter 4.3.3). Assuming a percentage people dissatisfied (PPD) of 10%, the threshold is 20-27°C. This is in line with recommendations of KNKV and FIBA. KNKV (2017) prescribes a minimum indoor temperature of 18°C and recommends temperatures of 20-22°C. FIBA (2009) recommends indoor temperatures of 20-22°C in winter and a maximum indoor temperature of 27°C in summer.

Normally, Honeybee's thermal simulation component would require the lobby to be defined as a separate 'HBZone' in order to simulate this heat transfer. This is undesirable, since Honeybee does not allow for individual zones to be simulated with the influences of adjacent zones taken into account. If the influence of the lobby were to be taken into account, the thermal simulation component would have to simulate both zones, which would double its simulation time. Instead, the PAS makes use of the

fact that the simulation component facilitates the input of a list of monthly ground temperatures. Since the sports hall is situated on top of the lobby, entering the lobby's temperature values in this node suffices to

define the heat transmission through the sports hall floor. The temperature values of the lobby range from 20°C in winter to 27°C in summer, corresponding to the aforementioned temperature criteria.

4.3.5 Validation of simulation results

Honeybee is under continuous development and new versions are released every few months (McNeel Europe, 2017). Consequently, the version of Honeybee used in this thesis is not yet peer-reviewed. The validity of the Honeybee's thermal analysis components is therefore assessed with a comparison of its simulation results to simulations run with DesignBuilder. DesignBuilder (v5) is a building energy simulation program based on EnergyPlus (DesignBuilder Software Ltd, 2017). Similar to Honeybee, DesignBuilder uses user-defined zones, building constructions and schedules and provides a calculates a range of performance data, such as heating, cooling, lighting and equipment energy demands and solar and occupancy heat gains.

As mentioned in chapter 4.3.2, the PAS does not simulate the lobby zone to determine the influence of heat transfer between the lobby zone and the sports hall on the performance of the sports hall. Instead, the PAS uses a list of monthly ground temperatures that represent the indoor temperatures. The validation method presented in this chapter also determines whether this modification provides sufficiently accurate results.

The validation method draws comparisons between three simulations. The first simulation is run in DesignBuilder and includes a second zone below the sports hall that represents the lobby. The second simulation is run in DesignBuilder and uses monthly ground temperatures to represent the lobby. The third simulation is run in Honeybee, which also uses the monthly ground temperatures. A comparison between the second and third simulation verifies whether Honeybee's thermal simulation component provides sufficiently accurate results. Comparisons of the first simulation to the second and third simulation verify whether the abstraction of the lobby is sufficiently accurate.

The three simulations use identical weather files, building constructions and activity schedules. The two programs do not provide identical HVAC systems, so the two most similar systems are chosen instead. The building geometries are identical and are constructed as an orthogonal box with windows on the West-, East- and North façade. To reduce the chance of causality, the three simulations are also run for a different building, that has larger windows on the East and West façades and a narrow, window on the North façade. An overview of the settings of each simulation is presented in Fig. 4.6. Simulation results are presented in Fig. 4.7. Simulation files are available on request from the author or either mentor.

The first and second simulations provide very similar results. It can therefore be safely concluded that simplification of the lobby geometry to a list of ground temperatures still provides accurate simulation results.

The dissimilarity between the Honeybee simulations and the DesignBuilder simulations is slightly larger. These differences might be caused by possible differences in the HVAC system or might have been the result of slight discrepancies between settings that are not accessible through Honeybee's components. The Honeybee simulations are deemed sufficiently accurate compared to the DesignBuilder simulations, especially when taking into account the fact that the Computational Design System developed in this thesis aims to facilitate the early design phase, where the level of detail of the designs is limited and decision-making is largely based on comparative assessment.

| | DesignBuilder with lobby zone | DesignBuilder without lobby zone | Honeybee |
|-----------------------------------|--|--|--|
| Construction | | | |
| Location (.epw file) | Amsterdam | Amsterdam | Amsterdam |
| Context geometry | Not included | Not included | Not included |
| Lobby definition | Abstracted to a list of ground temperatures | Abstracted to a list of ground temperatures | Abstracted to a list of ground temperatures |
| Wall, roof and floor construction | 0.08 m 'Cast Concrete' 0.14 m 'Glass fibre/wool' (0.035 W/m-k) 0.10 m 'Cast Concrete' | 0.08 m 'Cast Concrete' 0.14 m 'Glass fibre/wool' (0.035 W/m-k) 0.10 m 'Cast Concrete' | 0.08 m 'Cast Concrete' 0.14 m 'Glass fibre/wool' (0.035 W/m-k) 0.10 m 'Cast Concrete' |
| Window construction | 'Dbl Elec Abs Bleached 6mm/13mm Arg' SHGC = 0.743 Visual transmission = 0.752 U-Value = 1.499 W/m2-K | 'Dbl Elec Abs Bleached 6mm/13mm Arg' SHGC = 0.743 Visual transmission = 0.752 U-Value = 1.499 W/m2-K | 'Dbl Elec Abs Bleached 6mm/13mm Arg' SHGC = 0.743 Visual transmission = 0.752 U-Value = 1.499 W/m2-K |
| Activity | | | |
| Occupancy schedule | Mon-Fri: 9.00-17.00 Weekends: 7.00-22.00 | Mon-Fri: 9.00-17.00 Weekends: 7.00-22.00 | Mon-Fri: 9.00-17.00 Weekends: 7.00-22.00 |
| Heating setpoint | 23 °C | 23 °C | 23 °C |
| Heating setback | 13 °C | 13 °C | 13 °C |
| Cooling setpoint | 26 °C | 26 °C | 26 °C |
| Cooling setback | 35 °C | 35 °C | 35 °C |
| Occupancy density | 0.059 p/m ² (52 p) | 0.059 p/m ² (52 p) | 0.059 p/m ² (52 p) |
| Metabolic rate | 'Basketball 2' (657 W/p) | 'Basketball 2' (657 W/p) | 'Basketball 2' (657 W/p) |
| Equipment energy demand | 1 W/m ² | 1 W/m ² | 1 W/m ² |
| Lighting energy demand | 7.2 W/m ² | 7.2 W/m ² | 7.2 W/m ² |
| HVAC | | | |
| Fresh air | 8 l/s-person | 8 l/s-person | 8 l/s-person |
| Infiltration rate | 0.05 ac/h | 0.05 ac/h | 0.05 ac/h |
| Mech. vent per area | 0 l/s-m ² | 0 l/s-m ² | 0 l/s-m ² |
| Definition | Max (per person or per area) | Max (per person or per area) | Max (per person or per area) |
| HVAC system | 'VAV, Air-cooled Chiller, Reheat' | 'VAV, Air-cooled Chiller, Reheat' | 'VAV, Air-cooled Chiller, Reheat' |
| Heating supply temp. | 35 °C | 35 °C | 35 °C |
| Cooling supply temp. | 13 °C | 13 °C | 13 °C |
| Heating COP | 0.85 | 0.85 | 0.85 |
| Cooling COP | 1.8 | 1.8 | 1.8 |
| Heat recovery | 0 | 0 | 0 |
| Coefficient of Performance | 1.8 | 1.8 | 1.8 |

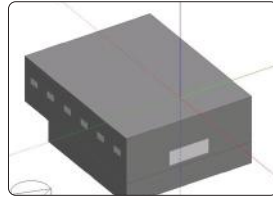
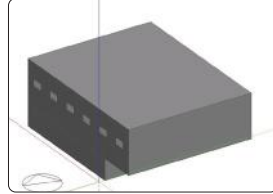
Fig. 4.6: Simulation settings for comparative analyses in DesignBuilder and Grasshopper.

Design 1

Floor Area
Volume
Wall area
Window area

Annual heating e. demand
Annual cooling e. demand
Annual lighting e. demand
Annual equipment e. demand
Total annual energy demand

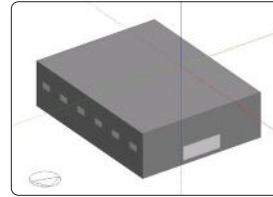
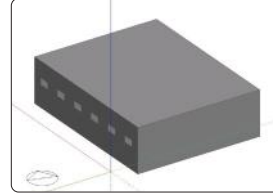
DesignBuilder with lobby zone



879 m²
 8442 m³
 1171 m²
 57.3 m²

19512 kWh
 4004 kWh
 25408 kWh
 3528 kWh
 59.7 kWh/m²

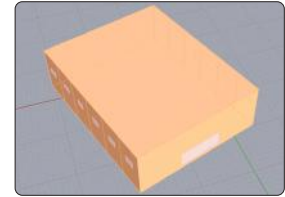
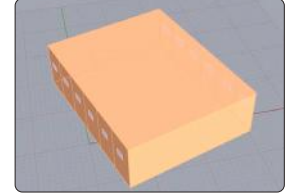
DesignBuilder without lobby zone



879 m²
 8442 m³
 1171 m²
 57.3 m²

20176 kWh
 3927 kWh
 25408 kWh
 3528 kWh
 60.3 kWh/m²

Honeybee



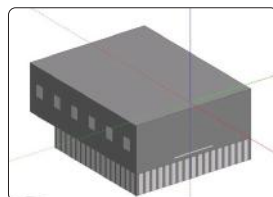
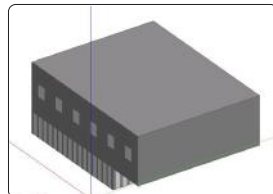
879 m²
 8442 m³
 1171 m²
 57.3 m²

22170 kWh
 4301 kWh
 25408 kWh
 3528 kWh
 63.0 kWh/m²

Design 2

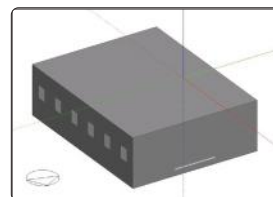
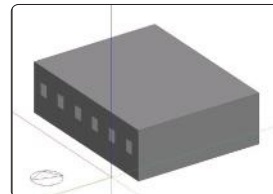
Floor Area
Volume
Wall area
Window area

Annual heating e. demand
Annual cooling e. demand
Annual lighting e. demand
Annual equipment e. demand
Total annual energy demand



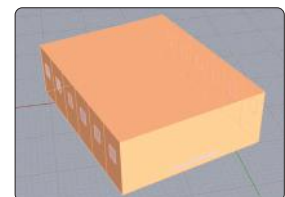
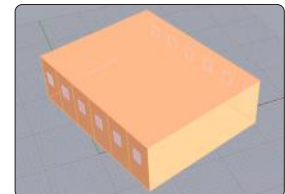
879 m²
 8442 m³
 1269 m²
 172.2 m²

21915 kWh
 4134 kWh
 25408 kWh
 3528 kWh
 62.5 kWh/m²



879 m²
 8442 m³
 1269 m²
 172.2 m²

21047 kWh
 4106 kWh
 25408 kWh
 3528 kWh
 61.5 kWh/m²



879 m²
 8442 m³
 1269 m²
 172.2 m²

22145 kWh
 4668 kWh
 25408 kWh
 3528 kWh
 63.5 kWh/m²

Fig. 4.7: Simulation results of comparative analyses run in DesignBuilder and Honeybee.

4.4 LIGHTING PERFORMANCES

4.4.1 Introduction

Lighting of sports halls has large effects on the performance of the players. Because of the speed of many sports, players need to quickly perform visual tasks. Inadequate lighting design may cause shadows or glare, as a result of which the sports players may be unable to keep track of rapid movements. Sports halls must therefore comply with strict regulations regarding lighting. Since different sports use different objects and have different common fields of view, their regulations vary.

Most sports buildings therefore rely on artificial lighting in order to create a controllable, glare free environment. Daylight entering the court is not allowed for competition level sports games of badminton (BWF, 2017) and strictly advised against for table tennis (sportscotland, 2012). Although other sport regulations do not explicitly mention daylight, it is generally not recommended for high-level sports games. Electric energy consumption of artificial lighting can be considerable, however: 30% of the average sports facility's energy consumption is used by lighting (Trianta-Stourna et al., 1998). Proper integration of daylight in the design of a sports hall can considerably reduce energy consumption. Daylight is also a significant factor of the aesthetical

and atmospheric quality of a building and is widely recognised to contribute to the psychological well-being of a building's occupants. Commonly, sports halls host recreational and club level games most of the times, for which natural daylight is generally welcome (sportscotland, 2012). A proper integration of daylight in the design of a sports hall can therefore definitely improve both its architectural and its environmental performance.

The daylight analysis is run using Daysim (Reinhart, 2017). Daysim is a Radiance-based daylighting analysis software. The Daysim simulation casts rays that bounce on the geometries and calculates the lighting intensity on a series of sensor points. Honeybee provides a daylighting simulation component that integrates Daysim in the Grasshopper environment. However, the version of Honeybee used in this thesis did not facilitate more than one ambient bounce. As a result, simulations run with the component gave inaccurate results, since lighting diffusion was incorrectly simulated. Instead, Grasshopper plug-in DIVA (version 4.0.2.24, Solemma LLC, 2017) is used to perform Daysim lighting simulations.

4.4.2 Lighting criteria

Sports regulations define lighting performance criteria in mean horizontal illumination levels. These criteria prescribe the minimum illuminance of the playing field, measured 1m above the playing field. Minimum illumination criteria depend on the sport and on the level of competition. The mean horizontal nominal illumination of, for example, a basketball training is 200 lux, whereas the mean horizontal nominal illumination of a national game is 750 lux.

The UK implementation of EN 12193:2007 (BSi, 2007) prescribes normative illumination levels for a number of sports played in various indoor sports venues. In this standard sports are categorized by illumination criteria. The criteria used by this thesis are visualized in figh. These are the strictest lighting criteria set by the standard and thus meets the criteria of all sports that will be practised in the sports hall designed in this thesis.

| I Top level competition | II Mid-level competition | III Low level competition |
|-------------------------------|--------------------------------|---------------------------------|
| 750 lux 0.7 | 500 lux 0.7 | 300 lux 0.5 |

Fig. 4.8: Mean horizontal nominal illumination level requirements for various sports at various competition levels (measured 1 m above playing field). Values derived from the UK implementation of EN 12193:2007 (BSi, 2007) and affirmed by FIBA (2009) and KNKV (2016).

For television coverage of sports games, horizontal light levels should exceed 1000 lux (Trianti-Stourna et al., 1998). Fig. 4.8 defines minimum criteria for non-broadcasted games, which should be met at all circumstances. However, various sports regulations recommend higher illuminance values. FIVB (2014) prescribes light levels of 1500 lux for competitive volleyball games. ITTF (2017) prescribes light levels of 1000 lux on the playing surface for World, Olympic and Paralympic title competitions and 600 lux for other games. BWF (2017) recommends a lighting level of 1000 lux for non-broadcasted high-level badminton games and 1800-2000 lux for broadcasted games. FIBA (2014) prescribes minimum light levels of 2000, 1400 and 1000 lux for broadcasted level 1,2 and 3 games, respectively. The performance objectives of the CDS are based on non-broadcasted games, but additional lighting can be installed to achieve higher light levels.

Besides minimum lighting levels, illuminance uniformity should also be aimed for. Uniformity is calculated using the following formula:

$$U = E_{h,min} / E_{h,mean}$$

Where $E_{h,min}$ and $E_{h,mean}$ represent the minimum and mean illumination levels of the measured plane, respectively.

For low level 'large object' games uniformity should exceed 0.5. For any other game, uniformity should exceed 0.7 (Fig. 4.8).

When regarding non-broadcasted games, vertical illuminance levels are sufficient when horizontal illuminance criteria sufficiently are met (FIBA, 2009).

The lighting performance of a building is assessed by grid-based lighting calculations. The size of the grid depends on the sports hall's size. EN 12193:2007 (BSi, 2007) states that the maximum grid size can be estimated using the following formula:

$$p = 0,2 * 5 \log d$$

Where:
 p = grid size
 d = longer dimension of the reference area

This formula results in a grid size of 2.35m for a six-court sports hall ($l = 34m$). The PAS uses a larger grid size of 5m, however. Increasing the grid size drastically reduces the simulation time, and the reduced accuracy is still sufficient for this stage of the design process.

As previously stated, the illuminance level requirements in Fig. 4.8 should be met under all circumstances. Aging of lighting equipment will inevitably result in a loss of light intensity. The design of lighting equipment should account for this effect. As a rule of thumb, lighting equipment calculations of the design should therefore use a maintenance factor of 0.8 (KNKV, 2016; FIBA, 2014). Thus, if regulations prescribe that the minimum illumination should be 500 lux, the lighting design is calculated with minimum values of 625 lux. Alternatively, the reduction factor can be integrated in the lighting emissions of the simulated luminaires. For LED lighting, a factor of 0.9 may be used.

The PAS simulates lighting levels caused by daylight using Grasshopper plug-in DIVA. Contrary to the lighting analysis component provided by Honeybee, DIVA merely simulates daylight levels and does not facilitate artificial lighting in the simulation. Artificial lighting is therefore implemented in the PAS using custom calculations, using the following method.

Firstly, a daylight simulation is run. Based on these values, the necessity of artificial lighting is determined; if daylighting does not meet the minimum lighting criteria, artificial lighting is required.

Since various activities require various lighting intensities, the luminaires are subdivided in three groups for energy reduction purposes. For activities with low lighting requirements (200 lux), only one group with 24 luminaires is turned on. A second group is turned on in addition to the first one for activities with lighting requirements of 500 lux, totaling 48 luminaires. Switching on the third group of luminaires meets lighting requirements of 750 lux, with 64 luminaires in total. The luminaire used in the PAS are common in sports halls and are derived from TRILUX GmbH & Co. KG (2017). The luminaire has an energy consumption of 105W. The PAS calculates the annual energy demand of the luminaire array and attempts to minimize it by increasing insolation.

For each sensor point, the illuminance resulting from daylight and the illuminance resulting from the luminaires are summed. Lighting uniformity is calculated based on these values. Since the amount of ambient lighting bounces is limited to 4 (in order to reduce calculation times), the PAS uses a uniformity factor of 0.7 as acceptable lighting uniformity. Lighting uniformity is calculated and optimized based on the annual amount of hours uniformity is not met.

4.4.3 Visual comfort

Visual comfort depends on differences in brightness. Too large differences cause glare, which may affect the sports players' performance and should thus be prevented. Glare in sports halls must be evaluated using the Unified Glare Rating (UGR) method (BSi, 2007). Glare is calculated using the following formula (CIE, 2007, p.7):

$$UGR = 8 \log \left[\frac{0,25}{L_b} \sum \frac{L^2 \omega}{p^2} \right]$$

Where:

L_b is the background luminance (cd/m^2);

L is the luminance of the luminous parts of each luminaire in the direction of the observer's eye (cd/m^2);

ω is the solid angle of the luminous parts of each luminaire at the observer's eye (steradian).

p is the Guth position index for each individual luminaire which relates to its displacement from the line of sight.

The steradian in this formula is calculated by dividing the area of the spherical area of each window by the squared distance between the spherical triangle and the spectator. The PAS achieves this by projecting the windows onto a sphere with the spectator's position as its centerpoint, calculating the area of each projected window and dividing it by the squared radius of the sphere.

The Guth position index is derived from the chart found in Fig. 4.9 and is based on three factors. 'V' is the vertical distance (Z) between the eye and the source. 'L' is the horizontal lateral distance (XY) between the eye and the source. 'R' is the distance from the

spectator's eye to the vertical plane normal to the line of vision in which the source is located. See Fig. 4.10.

For sports halls, glare levels should meet $UGR \leq 22$ (CEN, 2002). For reference, this limit is identical to the glare limit of a reception desk (ETAP NV, n.d.). For the determination of the UGR limit value the observer's position is specified at the location where the spacing to height ratio is 1:1. LED armatures commonly used in sport facilities often have integrated shielding to meet the UGR requirement for sports halls (Fagerhult BV, 2016; ETAP Export Department, n.d.; EVA Optic B.V., 2017). Glare in this thesis therefore only concerns glare caused by daylight.

The PAS calculates the UGR for two opposite sides in the sports hall based on ceiling and window illuminance levels in the spectators' fields of view. The Iterative Design System optimizes the annual amount of hours the UGR of 22 is not met for either of the two spectators.

Most sports regulations, do not quantify (additional) limitations regarding glare, but state the importance of the visual comfort on the quality of sports and suggest an even distribution of light sources. Additionally, ITTF (2017) suggest the placement of lights outside of the playing field and, along with the Badminton World Federation (BWF, 2017), prescribe walls of a darker color than the playing field, in order to maintain a clear visibility of the ball or shuttle. These aspects are not implemented in the PAS but are taken into account in the design process of the sports hall.

4.5 VALIDATION OF PRELIMINARY DESIGN DECISIONS

4.5.1 Introduction

The performance analyses run in the PAS depend on several preliminary design decisions, such as the wall insulation, window type, setpoint temperatures, setback temperatures and the occupancy activity schedule. These design decisions are based on assumptions made by the author. The designer may, however, decide to change either of these design decisions during the design process, which influence the performances of each design alternative. Consequently, it is possible that the a data set generated by the Iterative Design System becomes unusable when design decisions deviate from preliminary assumptions.

It is likely that the simulation results are different when either of the design decisions are changed. Nevertheless, the data set is still useful if it allows the user of the Data Analytics System to deduce relative design performances between design alternatives or to deduce interrelationships between building aspects. Both of these conditions enable the user to make informed design decisions without having to rerun the complete Iterative Design System, since in either case the user would be able to extrapolate approximate performances based on a reduced number of simulations with the new design decisions.

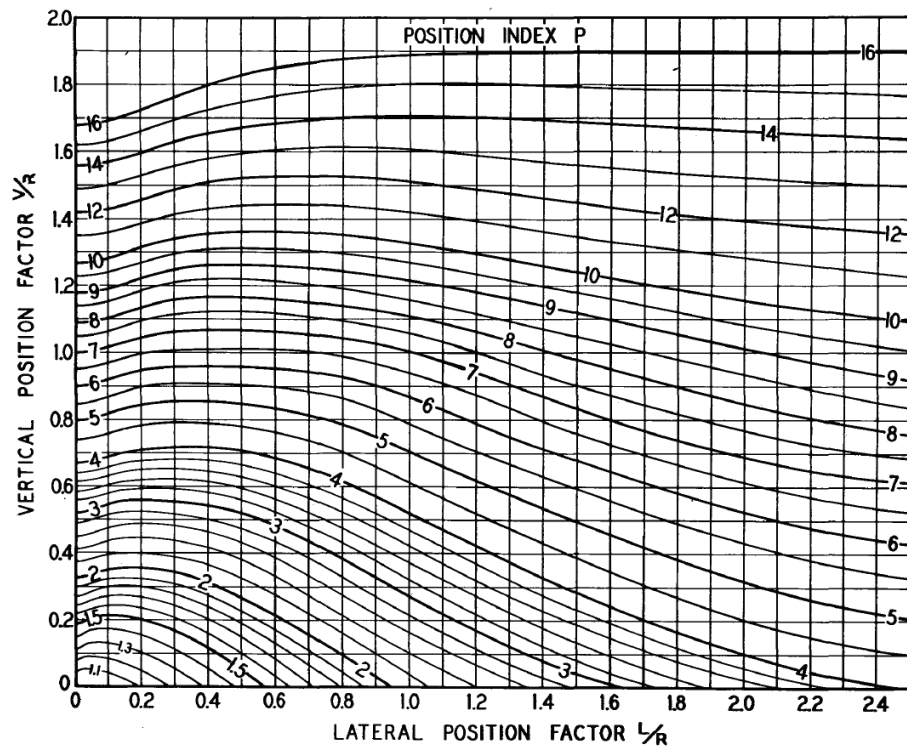


Fig. 4.9: Guth position index chart. The chart is used to determine the position index of sources located at various positions in the visual field (Luckiesh & Guth, 1949, p.660).

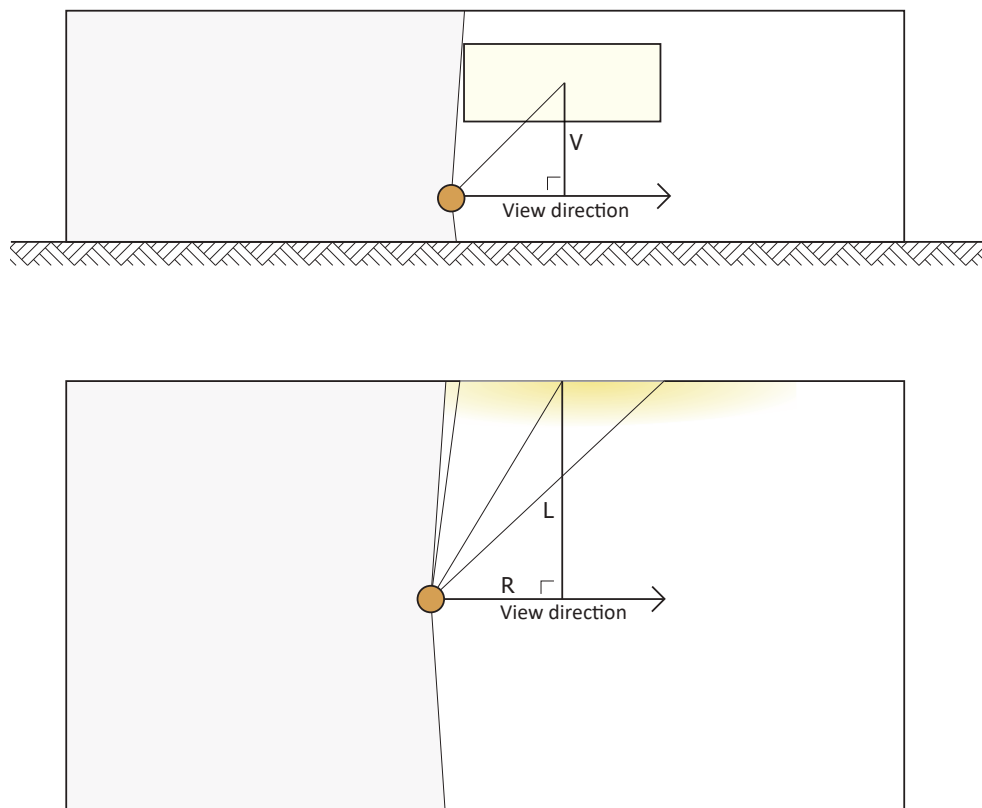


Fig. 4.10: Calculation methodologies of the 'V'-, 'R'-' and 'L'-'factors as calculated in the PAS.

This chapter verifies whether the usability of the Computational Design System is affected when design decisions made during the design process deviate from either of the five aforementioned preliminary design assumptions.

The influence of changing the wall insulation, window type, setpoint temperatures or setback temperatures is tested by running additional simulations of five design alternatives that will be compared to simulations with the 'default' settings.

Since these four design aspects are common aspects of the architectural design aspects, one may

consider that these four design decisions are largely based on the designer's expertise. The actual activity and occupancy of the sports hall, on the other hand, is more difficult to predict and is most likely to differ from the preliminary assumptions. Furthermore, the activity schedule has considerable influence on 8 of the 10 performance objectives considered in this thesis and has perhaps the largest impact on the total energy demand. The influence of the activity schedule on the building performances is therefore analyzed more elaborately.

4.5.2 Deviation from choice of wall insulation

The Performance Analysis System developed in this thesis assumes an insulation layer of 140mm, which it is deemed suitable for low-energy designs. However, during the design process the designer may decide to deviate from this insulation thickness for various reasons. Therefore, simulations using an insulation layer of 140 mm are compared to simulations using an insulation layer of 100 mm.

A comparison between the simulation results are presented in Fig. 4.11. Changing the insulation value of the wall to 100 mm reduces the cooling energy demands of the sports halls and increases their heating energy demands. It also influences the thermal performances.

The relative differences between the two analyses indicate slight correlation between the insulation value and the heating and cooling energy demands, the thermal comfort of spectators and the temperature criteria. The deviations between design alternatives is large, however. Furthermore, the influence of the insulation value on thermal comfort levels of sports players is unpredictable. In conclusion, when the design process deviates from the preliminarily assumed insulation thickness of 140mm, the Computational Design System does not effectively facilitate making of well-informed design decisions. Instead, new performance simulations would have to be run.

4.5.3 Deviation from choice of window type

The choice of window influences solar transmission, heat gain and building insulation. Correspondingly, the choice of window influences energy, lighting and thermal performances. The Performance Analysis System developed in this thesis makes use of double glazing with slightly reduced solar transmission. During the design process, the author gained interest in the potential of translucent glazing for both architectural and climate-related design qualities. Correspondingly, this subchapter compares the use of double glazing to the use of translucent glazing. The translucent glazing has a U-value of 1.25 W/m²K, SHGC of 0.3 and visible transmittance of 0.51. These values are derived from CPI Daylighting (2014)

Simulation results are presented in Fig. 4.12. The results show a decrease of the cooling energy demand and an increase of heating and lighting energy demands when using translucent glazing as opposed to double glazing. Glare is considerably improved, whilst lighting uniformity remains unaffected. The glazing type also

influences indoor operative temperatures, which in turn influences thermal performances.

There is a similarity between the relative differences of the glare performances of each design alternative, as well as thermal comfort performances. The other performances show a slight similarity in the relative differences between the performances of each design alternative. Consequently, the data set generated with the Iterative Design System does not facilitate making informed design decisions when the designer decides to use translucent glazing instead of transparent glazing.

When only considering the performances of the three designs that are based on the 'non-orthogonal mass definition', similarity between relative differences is increased, however. When the user of the Computational Design System only considers designs based on the 'non-orthogonal mass definition', they are able to estimate cooling, heating, glare, lighting uniformity and thermal comfort performances with

Absolute differences

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 937 | -21589 | 0 | 0 | 0 | 0 | 0 | -6.3 | -1.6 | 3.1 |
| Alt #002 | 1009 | -15854 | 0 | 0 | 0 | 0 | 0 | -6.7 | -1.8 | 4.3 |
| Alt #003 | 883 | -20432 | 0 | 0 | 0 | 0 | 0 | -5.7 | 0.1 | 3.9 |
| Alt #004 | 388 | -19049 | 0 | 0 | 0 | 0 | 0 | -11.5 | 1.7 | 0.2 |
| Alt #005 | 1698 | -25032 | 0 | 0 | 0 | 0 | 0 | -6.7 | 0.7 | 4.9 |

Relative differences

| | Co. Energy % | He. Energy % | Li. Energy % | PV Energy % | PV EPBT % | Glare % | Li. Unif. % | ThCmf. Spec % | ThCmf. Sprt % | Temp. Crit. % |
|----------|--------------------|--------------------|--------------------|-------------------|-----------------|------------|-------------------|---------------------|---------------------|---------------------|
| Alt #001 | 133 | 78 | 100 | 100 | 100 | 100 | 100 | 89 | 91 | 177 |
| Alt #002 | 114 | 81 | 100 | 100 | 100 | 100 | 100 | 89 | 93 | 123 |
| Alt #003 | 128 | 77 | 100 | 100 | 100 | 100 | 100 | 90 | 101 | 178 |
| Alt #004 | 126 | 69 | 100 | 100 | 100 | 100 | 100 | 78 | 113 | 213 |
| Alt #005 | 131 | 64 | 100 | 100 | 100 | 100 | 100 | 87 | 104 | 206 |

Fig. 4.11: Comparison of simulation performances of simulations run with different wall insulation thicknesses for a selection of five design alternatives.

Absolute differences

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 2060 | -9264 | -2540 | 0 | 0 | 39.6 | 2060 | -9.8 | -1.3 | 6.5 |
| Alt #002 | 4328 | -14246 | -9470 | 0 | 0 | 40.2 | 4328 | 0.1 | -4.1 | 14.7 |
| Alt #003 | 2053 | -8280 | -534 | 0 | 0 | 41.7 | 2053 | -3.4 | -1.1 | 7.9 |
| Alt #004 | 327 | -2485 | 0 | 0 | 0 | 37.2 | 327 | 0.0 | -1.2 | 0.3 |
| Alt #005 | 3017 | -8207 | -3156 | 0 | 0 | 38.0 | 3017 | -9.2 | -1.0 | 8.6 |

Relative differences

| | Co. Energy % | He. Energy % | Li. Energy % | PV Energy % | PV EPBT % | Glare % | Li. Unif. % | ThCmf. Spec % | ThCmf. Sprt % | Temp. Crit. % |
|----------|--------------------|--------------------|--------------------|-------------------|-----------------|------------|-------------------|---------------------|---------------------|---------------------|
| Alt #001 | 221 | 89 | 91 | 100 | 100 | 287 | 90 | 98 | 124 | 1122 |
| Alt #002 | 204 | 83 | 60 | 100 | 100 | 280 | 100 | 93 | 127 | 278 |
| Alt #003 | 204 | 89 | 98 | 100 | 100 | 294 | 97 | 98 | 120 | 932 |
| Alt #004 | 121 | 94 | 100 | 100 | 100 | 243 | 100 | 97 | 106 | - |
| Alt #005 | 174 | 84 | 89 | 100 | 100 | 250 | 91 | 98 | 117 | 994 |

Fig. 4.12: Comparison of simulation performances of simulations run with different glazing types for a selection of five design alternatives.

relative certainty. Therefore, the user may be able to make substantiated design decisions when only considering these performance objectives and design alternatives. It should be noted that the sample size of the design alternatives based on 'non-orthogonal mass

definition' is insufficient to properly substantiate this conclusion. Analyses of additional design alternatives would be required to verify whether the data of design alternatives made with the 'non-orthogonal mass' can be used to make informed design decisions.

4.5.4 Deviation from choice of setpoint temperatures

The heating and cooling setpoint temperatures of the default simulations are 21°C and 27°C, respectively. Preliminary simulations have shown that with these values thermal performance criteria are met most of the year. Choosing different setpoint temperatures influence the thermal performances and the heating and cooling demands. Therefore, the aforementioned temperatures are compared to heating and cooling setpoint temperatures of 19°C and 25°C, respectively.

The simulations with default setpoint temperatures and adjusted setpoint temperatures are presented in Fig. 4.13. As expected, the temperature setpoints have great influence on heating and cooling energy demands. Changing the setpoint temperatures also affects thermal comfort performances, since indoor temperatures do not meet thermal comfort standards. The amount of hours temperature criteria are met is increased, likely because maximum indoor temperatures are lower.

There is no clear similarity in the relative differences between the performances of each design alternative. The relative differences of fourth design alternative in particular vary greatly from the relative differences of the other designs. Consequently, when the design process deviates from the previously assumed setpoint temperatures, the data set generated with the Iterative Design System does not accurately represent relative performances between design alternatives and thus cannot be used to make design decisions.

When only considering the three designs that are based on the 'non-orthogonal mass definition' the influence of the setpoint temperature on cooling energy, heating energy, thermal comfort of spectators is fairly predictable, however. This suggests that the user may still be able to make informed design decisions when considering only designs made using the 'non-orthogonal mass definition'. As explained in chapter 4.5.3, this sample size is insufficient to draw conclusions and additional analyses are required to verify this assertion.

4.5.5 Deviation from choice of setback temperatures

Setback temperatures control indoor temperatures during unoccupied hours. Using setback temperatures has the potential to reduce the energy demand. The heating and cooling temperature setbacks used in the Performance Analysis System are 13°C and 35°C, respectively. This subchapter analyses whether changing these setback temperatures to 17°C and 32°C effects the performances.

Fig. 4.14 shows that changing the setback has a small effect on the total energy demand, temperature criteria and thermal comfort of spectators. It does

positively effect the thermal comfort of the sports players, however. A possible explanation is that early morning heating of the building reaches desirable indoor temperatures more quickly.

Because the relative differences between performance values of the default simulations and the simulations with adjusted setback temperatures are small, it is concluded that the default data set can be safely used to make substantiated design decisions when deviating from preliminarily assumed setback temperatures.

4.5.6 Deviation from choice of activity schedule

The activity schedule used in this thesis (Fig. 4.2) is largely based on assumptions made by the author. This subchapter analyzes what the consequences in

potential deviations from these assumptions are with regards to the usability of the Data Analytics System for substantiated decision-making. In order to do so,

Absolute differences

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | -2267 | 27122 | 0 | 0 | 0 | 0 | 0 | -1.6 | -18.3 | 6.8 |
| Alt #002 | -2456 | 25177 | 0 | 0 | 0 | 0 | 0 | -5.7 | -23.7 | 11.8 |
| Alt #003 | -2225 | 25169 | 0 | 0 | 0 | 0 | 0 | -0.7 | -17.3 | 8.4 |
| Alt #004 | -1513 | 19752 | 0 | 0 | 0 | 0 | 0 | -9.3 | -2.4 | 0.2 |
| Alt #005 | -3561 | 21767 | 0 | 0 | 0 | 0 | 0 | -2.1 | -10.1 | 8.9 |

Relative differences

| | Co. Energy % | He. Energy % | Li. Energy % | PV Energy % | PV EPBT % | Glare % | Li. Unif. % | ThCmf. Spec % | ThCmf. Sprt % | Temp. Crit. % |
|----------|--------------------|--------------------|--------------------|-------------------|-----------------|------------|-------------------|---------------------|---------------------|---------------------|
| Alt #001 | 62 | 156 | 100 | 100 | 100 | 100 | 100 | 97 | 48 | 2306 |
| Alt #002 | 78 | 157 | 100 | 100 | 100 | 100 | 100 | 91 | 49 | 206 |
| Alt #003 | 64 | 160 | 100 | 100 | 100 | 100 | 100 | 99 | 51 | 2138 |
| Alt #004 | 55 | 187 | 100 | 100 | 100 | 100 | 100 | 81 | 86 | 243 |
| Alt #005 | 67 | 196 | 100 | 100 | 100 | 100 | 100 | 96 | 66 | 1465 |

Fig. 4.13: Comparison of simulation performances of simulations run with different setpoint temperatures for a selection of five design alternatives.

Absolute differences

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 43 | -1144 | 0 | 0 | 0 | 0 | 0 | -0.3 | -1.3 | -0.1 |
| Alt #002 | -28 | -1468 | 0 | 0 | 0 | 0 | 0 | -0.6 | -1.1 | -0.1 |
| Alt #003 | -5 | -316 | 0 | 0 | 0 | 0 | 0 | -0.0 | -0.4 | -0.0 |
| Alt #004 | 3 | 1214 | 0 | 0 | 0 | 0 | 0 | 0.2 | 0.3 | 0.0 |
| Alt #005 | 89 | -2098 | 0 | 0 | 0 | 0 | 0 | -0.2 | -0.2 | 0.0 |

Relative differences

| | Co. Energy % | He. Energy % | Li. Energy % | PV Energy % | PV EPBT % | Glare % | Li. Unif. % | ThCmf. Spec % | ThCmf. Sprt % | Temp. Crit. % |
|----------|--------------------|--------------------|--------------------|-------------------|-----------------|------------|-------------------|---------------------|---------------------|---------------------|
| Alt #001 | 101 | 99 | 100 | 100 | 100 | 100 | 100 | 100 | 93 | 99 |
| Alt #002 | 100 | 98 | 100 | 100 | 100 | 100 | 100 | 99 | 95 | 100 |
| Alt #003 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 98 | 100 |
| Alt #004 | 100 | 103 | 100 | 100 | 100 | 100 | 100 | 101 | 102 | 100 |
| Alt #005 | 101 | 95 | 100 | 100 | 100 | 100 | 100 | 100 | 99 | 100 |

Fig. 4.14: Comparison of simulation performances of simulations run with different setback temperatures for a selection of five design alternatives.

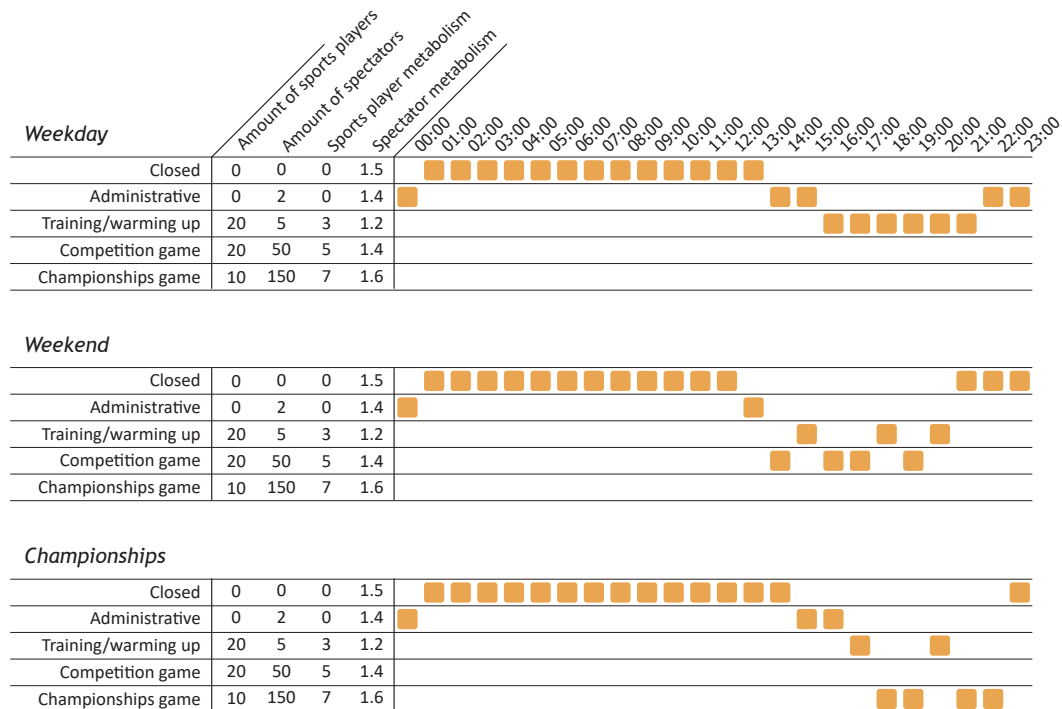


Fig. 4.15: Alternative occupancy schedule that uses the sports hall for nine hours a day.

the entire data set containing all design alternatives generated by the Generative Design System are simulated and compared for two different activity schedules. With the 'default' schedule (which is used in the Data Analytics System described in Chapter 5 and Chapter 6) the sports hall is in use for 17 hrs/day and with the other activity schedule the sports hall is in use for 9 hrs/day. The alternative schedule is shown in Fig. 4.15. The activity schedule influences the various energy demands of the building, as well as the lighting and thermal comfort criteria.

Fig. 4.16 presents the differences between performance values of twenty randomly selected design alternatives corresponding to analyses run with either activity schedule. Unsurprisingly, energy demands are lower when the amount of operative hours is lower. The percentage of time glare is occurring during operative hours is also lower with the nondefault activity schedule, most likely because the building is not used during the morning and thus has relatively more hours without daylighting. Performances of the temperature-related objectives are also generally improved. Lighting uniformity shows no to little improvement with the new activity schedule.

The relative differences of glare and lighting energy are similar between design alternatives. The relative performances of the design alternatives are therefore largely similar. Cooling energy, lighting uniformity and

thermal comfort performances show similarity to a lesser extent. Relative differences between heating energy demands and temperature criteria vary most between design alternatives. Here, there is a clear discrepancy between buildings generated using different parametric models. When comparing design alternatives that use the same parametric model, the relative differences of glare, thermal comfort performances and cooling, heating and lighting energy demands large correspond between design alternatives. Consequently, the overall performances of the designs relative to other design alternatives generated with the same parametric model are largely unchanged.

To determine whether a changes in the occupancy schedule affects the interrelationship between building aspects correlation matrices of the two data sets are compared. Correlation matrices show correlation coefficients between variables. The correlation coefficients range from -1 to 1, where 1 indicates strong positive correlation, -1 indicates strong negative correlation and 0 indicates no correlation. Chapter 5.7 provides a detailed explanation of correlation matrices.

The correlation matrices are generated in ModeFrontier (version 5.3.0; ESTECO SpA, 2017) and show correlation between both geometry and performance aspects. A comparison between the correlation matrices is drawn by calculating the

difference between the values of the correlation matrices. This gives an indication of relative changes of the correlation between building aspects between the two data sets. The correlation matrices are presented in Appendix E.

Fig. 4.17 shows the relative differences of each cell of the two correlation matrices. Naturally, correlation between building aspects and PV-related performance aspects is identical, since these values are not influenced by building activity. Differences in correlation between building aspects and energy and lighting performances are also largely neglectable. The differences of cooling energy, lighting energy, glare and lighting uniformity are mostly smaller than 5%. Differences of correlations with heating energy are mostly smaller than 10%.

The correlation matrices indicate that the relative differences between design alternatives are small when considering energy and lighting performances. Consequently, running a few simulations with an alternative activity schedule would enable the user of the Computational Design System to extrapolate corresponding performance values of each design alternative with relative certainty. Therefore, for these performance objectives, the user of the Computational Design System can predict the relative performances between design alternatives for changes in the activity schedule on these performance objectives with relative safety. Furthermore, the average difference between the correlations of the correlation matrices are small; 3.1%. This suggests that, in general, the relative difference between design alternatives is small.

To further analyze this assertion, Self-Organizing Maps of both data sets are compared. Self-Organizing Maps project high-dimensional data on a two-dimensional field. Self-Organizing Maps are topology preserving, meaning that closely related design alternatives are plotted closely together. Chapter 5.2 provides a detailed explanation on Self-Organizing Maps. The two Self-Organizing Maps are generated using both building information and performance

values. Consequently, relative differences between performance values would entail differences between the Self-Organizing Maps.

The Self-Organizing Maps of the two data sets are presented in Fig. 4.18. Bearing in mind that the second Self-Organizing Map is rotated approximately 45° compared to the first Self-Organizing Map, the Self-Organizing Maps of the two data sets are largely similar. Interrelationship between design alternatives is generally maintained; closely related design alternatives are plotted in similarly close vicinity and the two Self-Organizing Maps present near-identical clusters. This indicates that changes of the occupancy schedule do not have a great effect on relative differences between design alternatives.

The data sets are also compared using the visual analytics tool developed in this thesis. The visual analytics tool integrates various data analytics methods in a game-like environment, which uses the metaphor of a rural landscape to visualize data in an intuitive manner. Two landscapes are generated with either data set. The landscapes are visualized in Fig. 4.19. Similar to the aforementioned Self-Organizing Map, the landscapes are rotated relative to each other. Nevertheless, the landscapes are largely similar. Hills and valleys, visualizing designs with relatively better and worse overall performances, are largely the same. The ground type is also largely similar. Furthermore, as shown in Fig. 4.20, the data typology is largely the same, with design alternatives distributed in similar groupings.

In conclusion, changes of building activity do not have a tremendous effect on the decision-making process of the designer. The influences on the performances of design alternatives are generally predictable, and so is the influence of the activity schedule on the correlation matrices of building aspects. Therefore, the data set generated and visualized with the Computational Design System can still be used to make substantiated design decisions when the activity schedule of the sports hall is different from the preliminary assumed schedule.

4.5.7 Conclusions

The Performance Analysis System developed in this thesis uses several preliminary design decisions that influence the simulation performances. When the design process deviates from any of these design decisions, design decisions based on an 'outdated' data set may cause incorrect trade-offs that affect performance of the sports hall. This subchapter presents an analysis that indicates whether deviating

from preliminary decisions on wall insulation, window type, setpoint temperatures, setback temperatures or building activity would render the data set unusable to make informed design decisions.

The influences of changing the wall insulation on building performances are unpredictable. Therefore, when deciding to change wall insulation, a new data

set should be generated. Changes of the window construction and of the setpoint temperatures also influence building performances. Their influences on building performances are more predictable, however, and based on comparisons between three design alternative it appears that the data set may still be of use if the buildings are derived from the same parametric model. This assertion needs to be verified with additional analyses. Changing the setback temperatures has little effect on building performances. Therefore, the Computational Design System can be used for comparative decision-making when deviating from the preliminarily assumed setback temperatures. The activity schedule of the sports hall influences eight out of ten performance objectives. However, relative influence of a change in activity on the performances are similar for each design alternative if they are generated using the same parametric model. Therefore, designers can extrapolate design performances with relative certainty.

In four out of these five cases, (parts of) the Computational Design System can still be used to make substantiated design decisions, based on comparative assessment of design results or based on interrelationships between building aspects. Nevertheless, the user of the Computational Design System should be aware of the fact that design performances may change when a design decision made during the architectural design process deviates from a preliminary design assumption. Rerunning a few simulations with the new design decision to determine its influence on relative building performances, similar to the method of this chapter, informs the user whether (part of) the current data set can be used to make substantiated trade-offs or whether a new data set should be generated.

4.6 DISCUSSION

The Performance Analysis System determines various performances of the design alternatives generated with the Generative Design System. The performance objectives of the sports hall designed in this thesis are energy, visual comfort and thermal comfort performances. Building prescriptions and sports regulations give insight in performance criteria regarded by the PAS. The PAS runs building simulations using Grasshopper plug-ins DIVA, Ladybug and Honeybee to determine performances of the sports hall designs.

The design variables considered in the Iterative Design Systems are all related to building geometry. Consequently, the PAS uses preliminary design decisions to determine climate-related building aspects. Comparison of performance simulations that use different wall insulation values, glazing types, setback temperatures or occupancy schedules suggest that in most cases, the data set of the CDS can still be used for comparative assessment of design alternatives when the architect reconsiders one of these preliminary design choices. Rerunning a few simulations provides the architect with sufficient knowledge to make appropriate design decisions using an 'outdated' data set of simulated design alternatives.

Absolute differences

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 1475 | 16131 | 8461 | 0 | 0 | 17.3 | -3.7 | -12.3 | -29.3 | -5.2 |
| Alt #002 | 927 | 7320 | 11498 | 0 | 0 | 18.3 | 0.1 | -16.4 | -23.9 | -3.5 |
| Alt #003 | 1886 | 7883 | 3741 | 0 | 0 | 17.3 | -11.4 | -9.3 | -25.3 | -1.2 |
| Alt #004 | 1571 | 13738 | 7290 | 0 | 0 | 19.3 | -5.7 | -10.3 | -26.2 | -2.8 |
| Alt #005 | 1727 | 9478 | 7230 | 0 | 0 | 18.3 | -7.7 | -10.3 | -23.3 | -1.4 |
| Alt #006 | 2688 | 15753 | 1867 | 0 | 0 | 18.3 | -14.1 | -10.7 | -27.8 | -5.0 |
| Alt #007 | 1653 | 5918 | 11532 | 0 | 0 | 17.3 | 0.4 | -12.1 | -21.7 | 0.1 |
| Alt #008 | 2718 | 11337 | 1751 | 0 | 0 | 17.6 | -14.6 | -12.3 | -26.8 | -3.2 |
| Alt #009 | 1591 | 11411 | 10625 | 0 | 0 | 18.3 | 0.7 | -12.4 | -26.3 | -3.1 |
| Alt #010 | 1588 | 6404 | 8448 | 0 | 0 | 18.8 | -4.1 | -12.1 | -24.1 | -1.9 |
| Alt #011 | 2005 | -8504 | 11665 | 0 | 0 | 17.3 | 0.0 | -16.1 | -13.3 | 2.6 |
| Alt #012 | 1850 | -7421 | 11655 | 0 | 0 | 17.3 | 1.2 | -15.9 | -12.4 | 3.9 |
| Alt #013 | 1869 | -7720 | 11650 | 0 | 0 | 17.3 | 0.7 | -15.8 | -13.3 | 2.8 |
| Alt #014 | 1816 | -9220 | 11665 | 0 | 0 | 17.3 | 0.0 | -16.7 | -11.3 | 0.3 |
| Alt #015 | 2806 | -6573 | 7614 | 0 | 0 | 17.3 | -3.2 | -13.9 | -12.3 | 1.9 |
| Alt #016 | 1397 | -6703 | 11671 | 0 | 0 | 17.3 | 0.0 | -15.9 | -14.6 | -0.2 |
| Alt #017 | 935 | -7494 | 11676 | 0 | 0 | 17.3 | 0.0 | -20.1 | -11.8 | -0.2 |
| Alt #018 | 2153 | -306 | 6667 | 0 | 0 | 17.3 | -7.7 | -12.7 | -18.9 | -0.3 |
| Alt #019 | 1385 | -6439 | 11676 | 0 | 0 | 17.3 | 0.0 | -16.1 | -14.3 | 0.1 |
| Alt #020 | 805 | -9758 | 11676 | 0 | 0 | 17.3 | 0.0 | -22.9 | -9.6 | -0.4 |

Relative differences

| | Co. Energy % | He. Energy % | Li. Energy % | PV Energy % | PV EPBT % | Glare % | Li. Unif. % | ThCmf. Spec % | ThCmf. Sprt % | Temp. Crit. % |
|----------|--------------------|--------------------|--------------------|-------------------|-----------------|------------|-------------------|---------------------|---------------------|---------------------|
| Alt #001 | 171 | 124 | 154 | 100 | 100 | 139 | 96 | 82 | 36 | 59 |
| Alt #002 | 184 | 111 | 164 | 100 | 100 | 144 | 100 | 76 | 38 | 24 |
| Alt #003 | 161 | 113 | 128 | 100 | 100 | 139 | 85 | 86 | 41 | 92 |
| Alt #004 | 164 | 121 | 148 | 100 | 100 | 152 | 93 | 84 | 40 | 78 |
| Alt #005 | 160 | 115 | 144 | 100 | 100 | 144 | 91 | 84 | 44 | 90 |
| Alt #006 | 148 | 127 | 115 | 100 | 100 | 144 | 80 | 84 | 45 | 82 |
| Alt #007 | 169 | 110 | 165 | 100 | 100 | 139 | 100 | 81 | 45 | 101 |
| Alt #008 | 147 | 119 | 114 | 100 | 100 | 140 | 79 | 82 | 46 | 88 |
| Alt #009 | 173 | 118 | 165 | 100 | 100 | 144 | 101 | 81 | 39 | 73 |
| Alt #010 | 181 | 110 | 153 | 100 | 100 | 147 | 95 | 82 | 40 | 77 |
| Alt #011 | 202 | 71 | 166 | 100 | 100 | 139 | 100 | 73 | 59 | 200 |
| Alt #012 | 191 | 74 | 167 | 100 | 100 | 139 | 101 | 73 | 61 | 183 |
| Alt #013 | 198 | 73 | 166 | 100 | 100 | 139 | 101 | 73 | 59 | 195 |
| Alt #014 | 234 | 69 | 166 | 100 | 100 | 139 | 100 | 71 | 61 | 139 |
| Alt #015 | 165 | 75 | 153 | 100 | 100 | 139 | 96 | 77 | 65 | 110 |
| Alt #016 | 221 | 87 | 164 | 100 | 100 | 139 | 100 | 74 | 53 | 87 |
| Alt #017 | 201 | 85 | 164 | 100 | 100 | 139 | 100 | 67 | 55 | 62 |
| Alt #018 | 159 | 99 | 143 | 100 | 100 | 139 | 91 | 80 | 51 | 98 |
| Alt #019 | 219 | 87 | 164 | 100 | 100 | 139 | 100 | 73 | 53 | 108 |
| Alt #020 | 188 | 80 | 164 | 100 | 100 | 139 | 100 | 62 | 59 | 0 |

Fig. 4.16: Comparison of simulation performances of simulations run with different activity schedules for a random selection of twenty design alternatives.

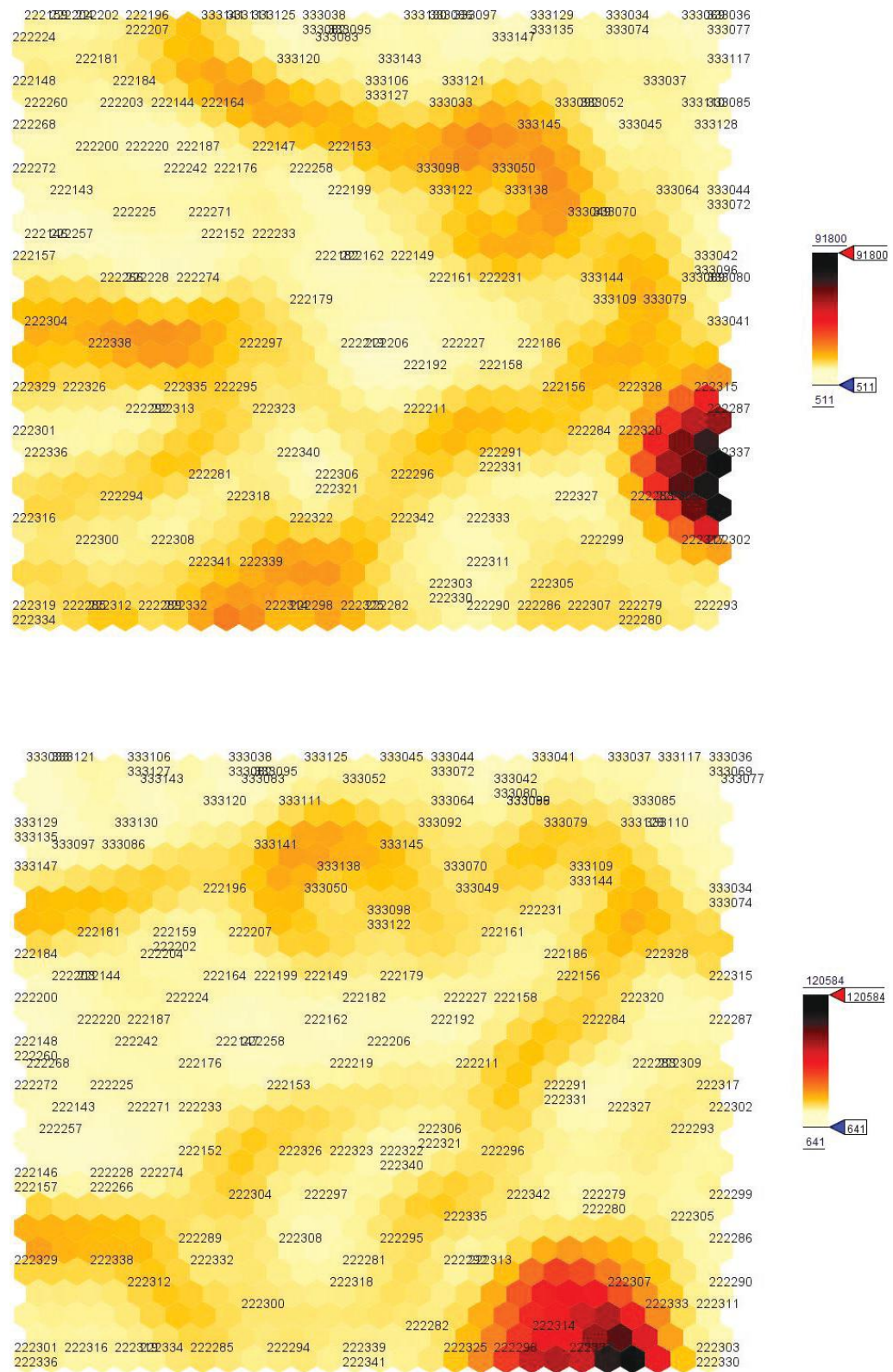


Fig. 4.18: Self-Organizing Maps of data sets of 150 design simulations using a schedule with 17 operative hours a day (t.) and 9 operative hours a day (b.) (version 5.3.0; ESTECO SpA, 2017). Each design alternative is represented by a six digit ID number and each cell of the Self-Organizing Map is represented by a hexagon. The color of the hexagon indicates the average relative distance between that hexagon and its six neighbors. Yellow indicates lowest and red indicates highest relative distances.

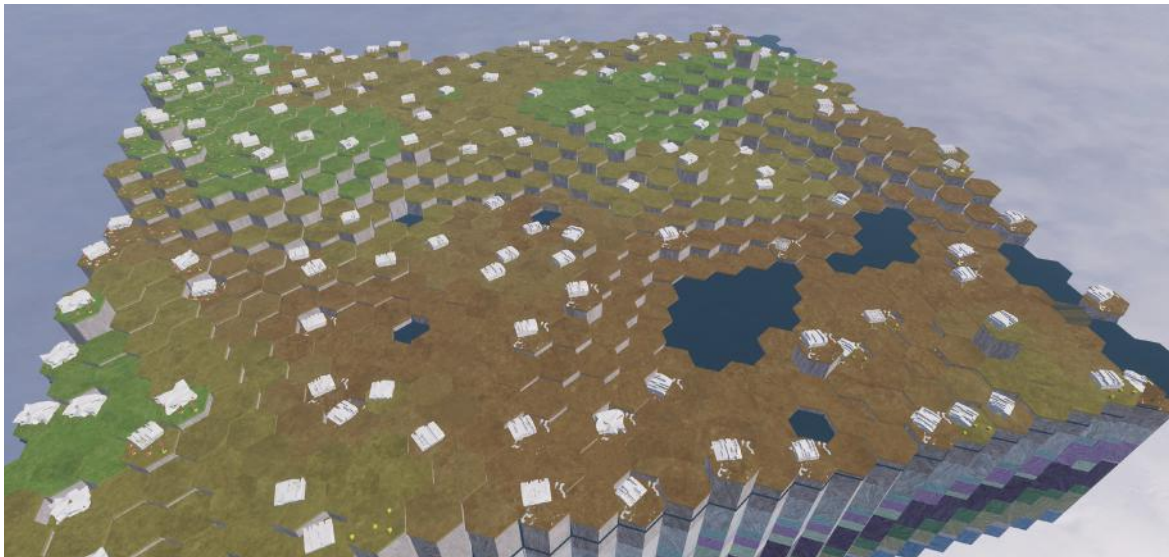
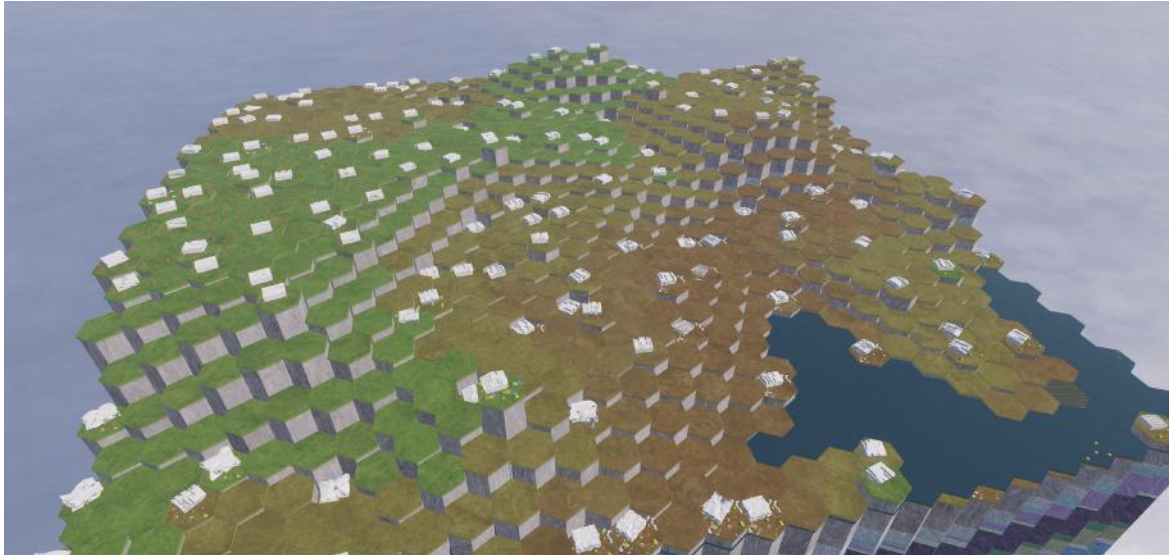


Fig. 4.19: Bird's eye view of the visual analytics tool showing a data sets of 150 design simulations using a schedule with 17 operative hours a day (t.) and 9 operative hours a day (b.). Though the designs are slightly rotated on the landscape, similarity between the two data sets is noticeable.

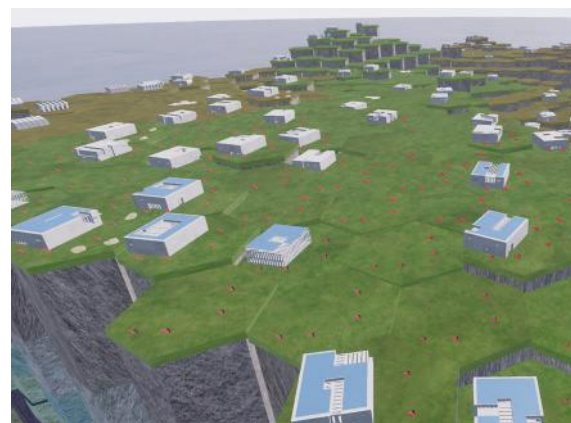
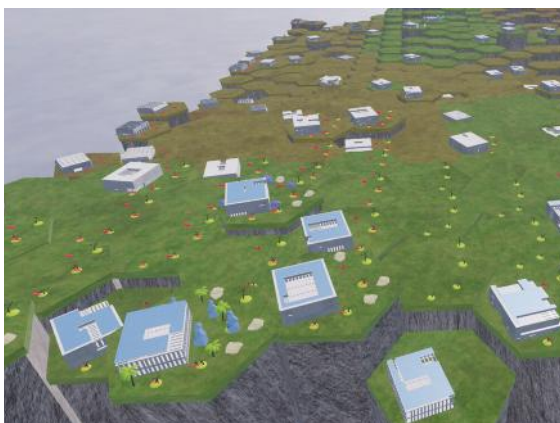


Fig. 4.20: Close up view of the visual analytics tool showing a data sets of 150 design simulations using a schedule with 17 operative hours a day (l.) and 9 operative hours a day (r.). Comparison of the two images show that data topology (i.e. interrelationship between design alternatives) is similar.



The Data Analytics System (DAS) processes and visualizes the building information generated with the Iterative Design System. The goal of the DAS is to present the building information in an intuitive way that facilitates multi-variate, multi-objective design exploration and decision-making of large sets of design alternatives for practitioners in the field of architecture.

The DAS consists of a Data Processing System and a Visual Analytics System. The Data Processing System imports 'raw data' of the Iterative Design System and uses various algorithms to process the data for use in the Visual Analytics System. The Visual Analytics System is a high-interactive data environment that visualizes these algorithms.

The DAS is described in the next two chapters. Chapter 5 describes the various algorithms used to process the design information. Chapter 6 describes the Visual Analytics System and shows visualizations derived from the visual analytics tool developed in this thesis.

CHAPTER 5: DATA PROCESSING SYSTEM

This chapter describes the Data Processing System (DPS). The DPS uses various algorithms to process the data generated with the Iterative Design System (IDS) for visualization in the Visual Analytics System (VAS).

Chapter 5.1 introduces the DPS and describes the workflow of the DPS.

Chapters 5.2 to 5.7 describe the algorithms that comprise the DPS.

Discussion on the DPS is presented in chapter 5.8.

5.1 INTRODUCTION

5.1.1 Purposes

The goal of the Data Analytics System is to substantiate multi-variate, multi-objective decision-making in the early design phase by visualizing performances of a large set of design alternatives and by enabling comparative assessment of designs. In order to do so the DAS fulfills various functions:

- Navigation through large data sets.
- Visualization of interrelationships between data items in high-dimensional data
- Visualization of performances of high-dimensional data
- Determination of interrelationships between design aspects and performances

Various data analytics methods are integrated in the DPS to fulfill distinctive functions. The following subchapters describe the data analytics methods used in this thesis. The subchapters are arranged corresponding to the functions described above.

This chapter repeatedly uses the term ‘normalizing’. Normalizing data concerns extrapolating values from one range to another. In this chapter, all values are normalized to a range of 0-1, according to the formula in Fig. 5.1. To avoid redundancy, each instance of ‘normalizing to a range of 0-1’ is abbreviated to ‘normalizing’ in this chapter, unless stated otherwise.

5.1.2 Workflow DPS

The DPS makes use of the Unreal Engine (version 4.17.1; Epic Games Inc., 2017a) and modeFRONTIER (version 5.3.0; ESTECO SpA, 2017) for its various algorithms. The DPS uses the design information generated by the IDS and processes it for use in the VAS.

The IDS generates multiple CSV files. The CSV files can be directly imported by the algorithms of the DPS.

Although most of the DPS and the VAS make use of

the same software environment (the Unreal Engine) data transfer between the systems mainly uses CSV files. This method has two advantages. Firstly, it allows access to the processed data without need of the VAS, which is especially useful during the development phase of the CDS. Secondly, it improves the run-time performance of the visual analytics tool, especially during boot.

For an item with attribute A in a data set with respective attributes ranging from A_{\min} to A_{\max} :

$$A_{\text{norm}} = (A - A_{\max}) / (A_{\min} - A_{\max})$$

Fig. 5.1: Formula to normalize data. This formula considers A_{\min} as the best-performing attribute. This is in line with the performance objectives of the Performance Analysis System, which are all minimized (to correspond to other performance objectives, PV energy gain is expressed as a negative number).

5.2 DIMENSIONALITY REDUCTION - SOM

5.2.1 Introduction

Interrelationships between data items are difficult to visualize for data sets with more than three dimensions. Dimensionality reduction methods are used to project high-dimensional data on a low-dimensional field in order to facilitate the interpretation of high-dimensional data. Principle component analysis and the Hyperspace Pareto Frontier are examples of algorithms that facilitate dimensionality reduction.

Principle component analysis (PCA) achieves dimensionality reduction by using only the two most linearly uncorrelated data variables. In other words, variables that meet a certain degree of correlation (e.g. total window area and glare occurrence) are 'merged'. Though widely used in many scientific disciplines, PCA is not suitable for the VAS, most importantly because PCA limits the amount of data variables that are used to determine correlations, whereas CDSs used in the field of architecture may analyze many performance objectives that do not necessarily correlate (e.g. when using an IDS that optimizes glare, acoustics, the loadbearing structure and building costs amongst other factors).

The Hyperspace Pareto Frontier is a projection of multivariate data onto a two-dimensional scatter plot. This is achieved by summing multiple

dimensions on a single axis by means of the Hyper-Space Digital Counting method. The Hyper-Space Digital Counting method rests on the idea that points on a (two-dimensional) plane can be projected onto a (one-dimensional) line without losing the topology of the data (Agrawal, Lewis & Bloebaum, 2006). The Hyperspace Pareto Frontier requires the right selection of objective grouping; to achieve an even distribution of design points, the grouped objectives should have a high positive correlation. If the objectives have a negative correlation, the design points are clustered, and if there is no correlation, the design points are scattered. The Hyperspace Pareto Frontier thus requires sufficient correlation between data attributes. Additionally, both PCA and the Hyperspace Pareto Frontier may cause cluttering of data items.

Elastic map methodologies are able to prevent cluttering. Elastic maps use a low-dimensional manifold that approximates the data set. Self-Organizing Maps use a similar methodology to project high-dimensional data onto a two-dimensional field. The VAS uses a Self-Organizing Map with a slightly adapted algorithm that prevents cluttering. An added benefit of the use of a Self-Organizing Map is that it is able to approximate non-simulated areas of the design space, comparable to response surface methodology.

5.2.2 Theory

A Self-Organizing Map (SOM) is an unsupervised neural network used for high dimensional data organization and visualization invented by Tuevo Kohonen. SOMs are inspired by the occurrence of topology-preserving characteristics of the brain (Kohonen, 1995) and to explain the functioning of SOMs, it is beneficial to explain these characteristics.

In many areas in the brain, neurons are arranged in the same order as their respective sensory organs. An example is the somatotopic map (Fig. 5.2), which comprise the organization of the motor area of the brain. In the arrangement of neurons the physical arrangement of the members of the body can be distinguished. However, instead of a three-dimensional typology, neurons are arranged in a linear array. Similar phenomena occur in the retinotopic and tonotopic areas of the brain (the organization of the visual and tonal system, respectively). Kohonen (1995) believes that the brain is able to form reduced representations of the most relevant facts without loss of knowledge about their interrelationships by

using the same principle, which has been the main inspiration for the invention of SOMs. Similar to how the arrangement of neurons is a one-dimensional projection of three-dimensional information, SOMs are a low-dimensional topology preserving representation of high-dimensional data (Kohonen, 1995). In other words, SOMs are commonly a 2-dimensional array on which high-dimensional data items are mapped, projecting similar data items to nearby locations (Fig. 5.3).

In order to do so, a SOM uses a sheet-like nodal network, in which each node corresponds to a coordinate on the 2-dimensional map. Each node is associated with a weight vector. The items of the data set are considered as an n-dimensional vector of weights (Pediroda & Poloni, 2008). Using a looping process, the nodal network is adjusted corresponding to a random data item. This is done in two stages; a competitive stage and a cooperative stage. In the competitive stage, a Voronoi tessellation is created of

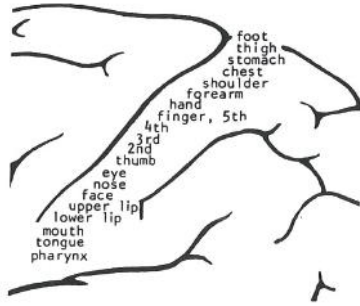


Fig. 5.2: The somatotopic map (Kohonen, 1995, p.72).

the nodal network. The randomly selected data item lies within the Voronoi region of one nodal point. This nodal point's position is adjusted according to the data item's weights vector, to meet its weight even closer. To preserve the topology of the data the neighboring nodal points are also adjusted during the cooperative stage. Their adjustment factor depends on the distance from the center nodal point and on the learning rate. The learning rate determines the level of convergence of the process. Low convergence requires long computation time. High convergence decreases computation time, but may result in errors. In functionality, the nodal network can be compared to a fish net that is cast to catch a school of fish. The

fish net wraps around the school and each fish is caught in one of the net's holes. Naturally, fish that swam closely together when they were caught will be close together in the fishnet.

With the net wrapped around the data set, one can imagine that the centerpoint of each cell in the nodal network has their own values (i.e. coordinates) in the data cloud (Fig. 5.4). These values are assigned to their corresponding cells. When the looping process of the nodal network is completed and the 'net' is optimally wrapped around the data set, the net is unfolded to a two-dimensional map. As a final step, each data item is then assigned to the cell that it's most similar to.

SOMs are commonly visualized as an orthogonal or a hexagonal lattice grid. The nodal network's size and the amount of data determine whether multiple data items do or do not contain multiple data items. Nodes may not be assigned any data items if their vector weight is not similar enough to the vector weights of the data sets. The SOM is often visualized in a U-matrix, where the cells are shaded to show their distances to neighboring cells. Bright areas correspond to closely related vectors and dark areas correspond to jumps in the data set vectors (Kohonen, 1995). Alternatively, the cells can be shaded or colored to show the value of an input parameter (Fig. 5.5).

5.2.3 Application

The Self-Organizing Map in the DAS has two main purposes: multi-dimensional scaling with topology preservation and the approximation of non-simulated areas of the design space (similar to response surface methodology). Its clustering ability is purposely avoided: since the aim of the VAS is to be able to show all simulated designs, the (non-interactive) clustering of designs is not beneficial.

To avoid clustering, the amount of grid cells should therefore be equal to or bigger than the amount of data items. The extent to which the amount of grid cells exceeds the amount of data items may be decided by the user, as it depends on the intended use of the CDS. Increasing the ratio between the amount grid cells and data items improves topology preservation between designs. Furthermore, since the aspect values are calculated for the empty cells, they can be used to extrapolate areas of the design space that are not covered by the simulations. This may be desirable if the design space is broad and the user expects that areas of the design space are not covered by the simulations. If the simulated designs do cover

the desired design space and the SOM is not needed to interpolate values in between design alternatives, the ratio can be decreased. This consequently decreases the size of the landscape in the visual analytics system. In this thesis, a ratio of approximately 5:1 is used.

The Self-Organizing Map is generated in modeFRONTIER, an 'integration platform for multi-objective and multi-disciplinary optimization' (Primavera, 2014). Both geometric and performance aspects are used to determine similarity between items. ModeFRONTIER generates a table with each cell's aspect values, which is exported as a CSV file for use in the VAS.

ModeFRONTIER does not facilitate the export of a table with each cell's corresponding design alternative. This is therefore reinstated in the Unreal Engine. The calculation methodology used to assign the design alternatives to their cells is different from the methodology used in modeFRONTIER to assure that no clusters are formed.

The calculation methodology relies on the fact that each design alternative is assigned to the cell that it is

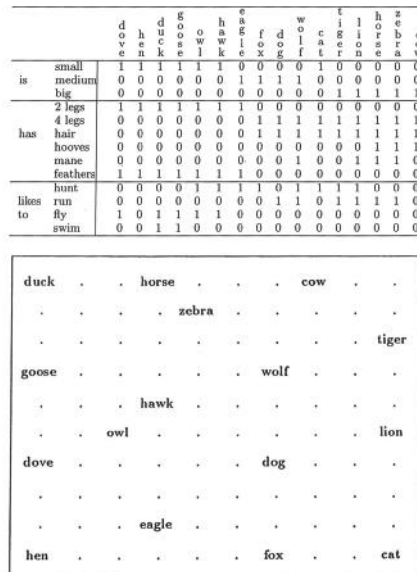


Fig. 5.3: Self Organizing Map (Kohonen, 1995, p.116).

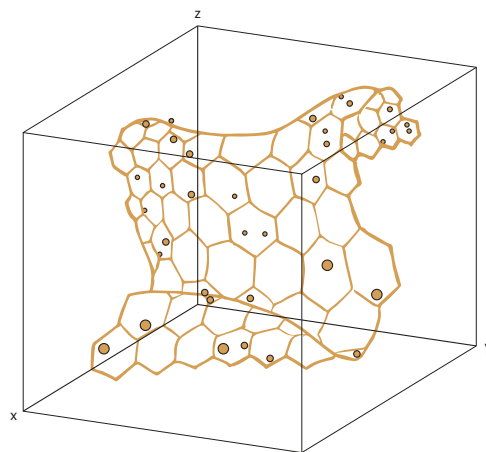


Fig. 5.4: Nodal network wrapped around a set of bivariate data items.

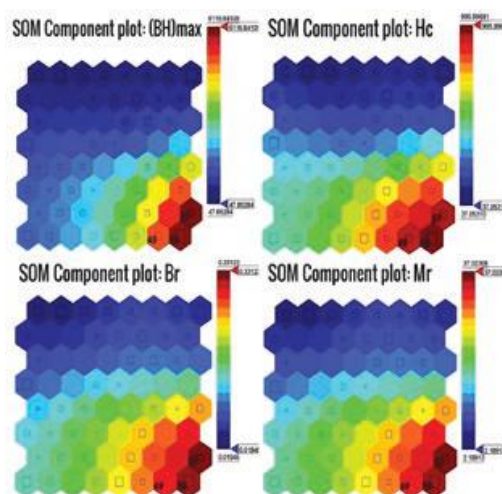
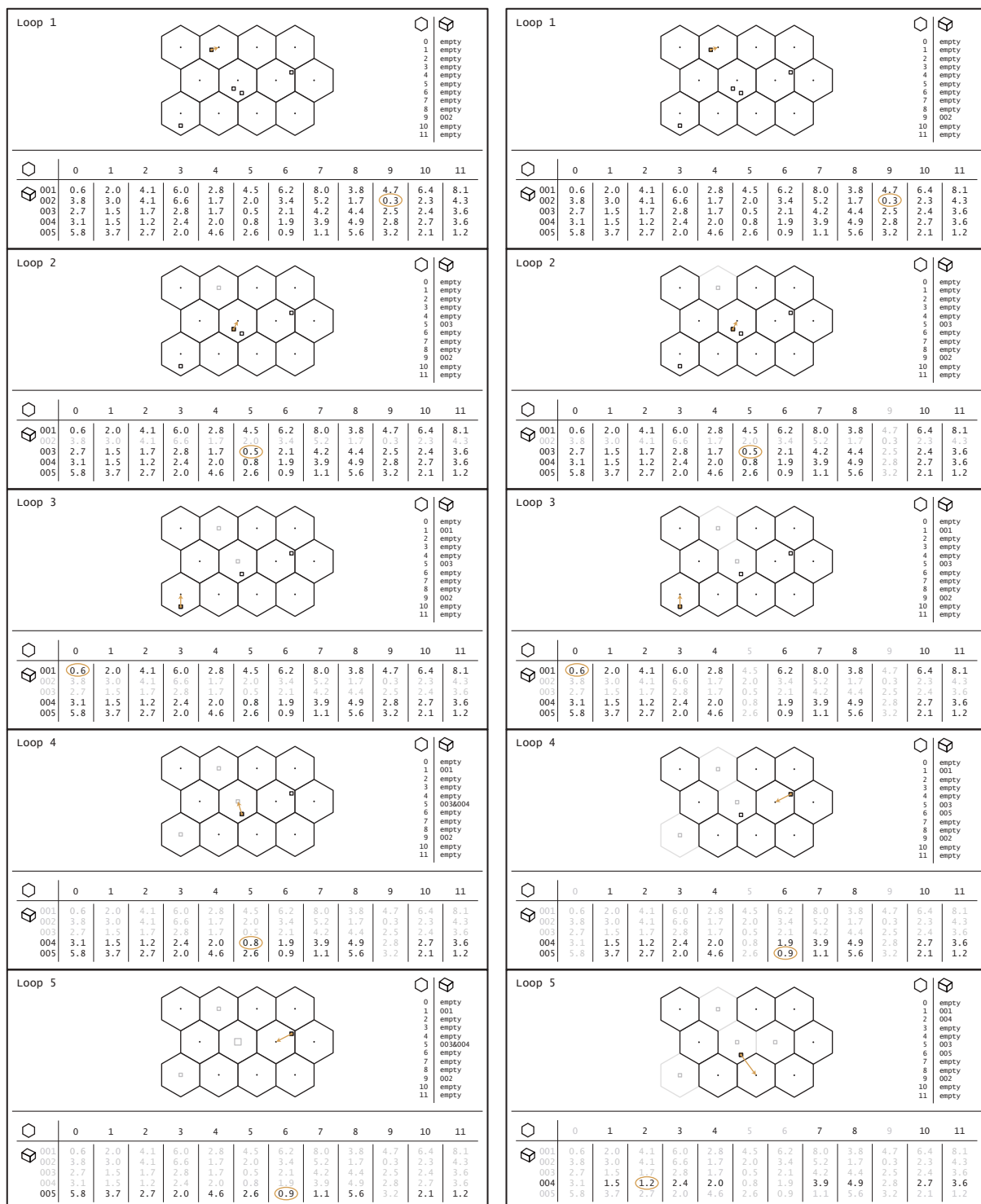


Fig. 5.5: SOM component plots. The colors correspond to values for various parameters (Jha et al. 2017, p.5).



closest to. In other words, for each design alternative its corresponding grid cell is the one with the lowest Euclidean distance to the design alternative. Consider a table in which the Euclidean distance between each design alternative and each cell is calculated. To exactly recreate the Self-Organizing Map that is generated in modeFRONTIER (i.e. with cluttering), the following steps need to be repeated until all design alternatives are assigned to their corresponding cells (Fig. 5.6,l.): (1) find the match with the lowest Euclidean distance, (2) assign the design alternative to the cell, (3) remove design alternative from table. The DPS of this thesis, performed in the Unreal Engine, adds an additional step that prevents cluttering (Fig. 5.6,r.): (1) find the match with the lowest Euclidean distance, (2) assign the design alternative to the cell, (3) remove design alternative from table, (4) remove cell from table. This way, when a cell already is assigned a design, it cannot be assigned an additional design. Furthermore, this method assures that for a cell that would ordinarily contain multiple design alternatives, the design alternative that is most similar is assigned to it. The difference between the two methods is shown in Fig. 5.7. Scenario analysis, presented in Appendix D, shows that the loss of topology and the chance of loss of topology is minimal when ratios between SOM's grid cells and data items exceed 3:1.

The algorithm that generates the SOM in this thesis requires two data sets: one with the geometric and performance values of the design alternatives and one with the geometric and performance values of the SOM cells. The first is exported from the IDS in Grasshopper and the latter is exported from modeFRONTIER. After loading the data sets in the Unreal Engine, the Engine firstly normalizes the values. Then, the design alternatives are assigned to their corresponding cells following the pseudocode depicted in Fig. 5.8. A dictionary of the cells' corresponding design variations is exported as a CSV file. Thus, the matching process, which is fairly computationally expensive, only needs to be run at first boot. After that, the visual analytics system can retrieve the information directly from the CSV file.

Another alteration the DPS makes to the 'traditional' Self-Organizing Map is that the values of the design alternatives 'override' the values of their corresponding cells (Fig. 5.9). The reason for this is that the user of the visual analytics system generally is more interested in the (simulated) performance of the design alternative itself, rather than the (extrapolated) performance of the area of the design space that the cell covers. Since the performance values of the cells

are overridden, their area of the design space is not accessible anymore. They are, however, approximated by the performance values of the design alternatives. The difference between the 'new' and 'original' values depends on the ratio of empty cells to cells with a matching design alternatives and can therefore be influenced by the user, who determines this ratio. Selecting a very high ratio, e.g. a ratio of 20 cells for each design alternative means that the differences between the cells are smaller and, consequently, the differences between the design alternatives and their corresponding cells are small. If the user selects a very low ratio, the designs have fewer cells to match to and are therefore more likely to have greater differences between their corresponding cells. The user might prefer the former ratio if he is interested in the design alternatives in the non-simulated design space and the latter if he is only interested in the design alternatives that are simulated.

The DAS also incorporates a U-matrix. The U-matrix is a visualization of each cell's average distance to its neighboring cells. It is therefore a useful tool in identifying data clusters, whose distinctiveness may have gotten lost in the dimensional scaling. ModeFRONTIER does not have a function to export information of the U-matrix. Instead, this is reinstated in the Unreal Engine.

In order to do so, a cube coordinate system is first defined. A cube coordinate system uses three axes. For hexagonal grids, each of these axes are offset by 120° and are the normal vectors of the sides of the hexagon. A cube coordinate system is useful in identifying neighboring cells, since the neighbors' values for one of the three axes is identical and the other axes increment and decrement by 1. See also Fig. 5.10. Another characteristic of the cube coordinate system is that the sum of the coordinates always equals zero. Therefore, a coordinate can be derived from the other two coordinates. The cube coordinate system can be calculated from the array indices and grid size, according to the formulas presented in Fig. 5.11. In order to calculate the U-matrix values, the Unreal Engine finds the neighboring cells of each cell based on the cube coordinate system, calculates their normalized distance to the cell and then averages it. See Fig. 5.12.

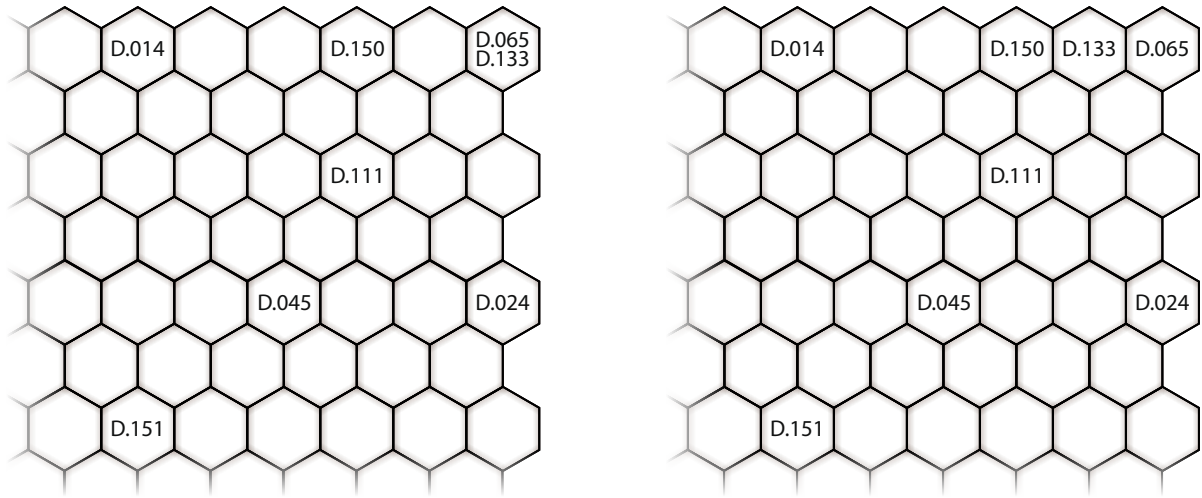


Fig. 5.7: Part of the S.O.M. with corresponding designs, retrieved from ModeFrontier (l.) and from the Visual Analytics System (r.).

With data set of design alternatives D with attributes A and data set with SOM grid cells C with attributes A :

```

make empty map (dictionary) of eucl.distances  $M_E$ 
make empty map (dictionary) of designs assigned to cells  $M_C$ 
length  $L$  = amount of rows in  $D$ 
while  $M_C.length < L$ :
    For each design alternative  $I_D$  in  $D$ :
        For each cell  $I_C$  in  $C$ :
            Eucl.distance  $E = \sqrt{(A_{1,R} - A_{1,R0})^2 + (A_{2,R} - A_{2,R0})^2 + \dots + (A_{n,R} - A_{n,R0})^2}$ 
             $M_E.append I_D | I_C : E$ 
        for  $I_D$  and  $I_C$  with  $E_{min}$  in  $M_E$ :
             $M_C.append I_C : I_D$ 
             $D.remove I_D$ 
             $C.remove I_C$ 
    for each  $I_C$  in  $C$ :
        find  $I_C$  in  $M_C$ 
        if null:
             $M_C.append I_C : "empty"$ 

```

Fig. 5.8: Pseudocode SOM.

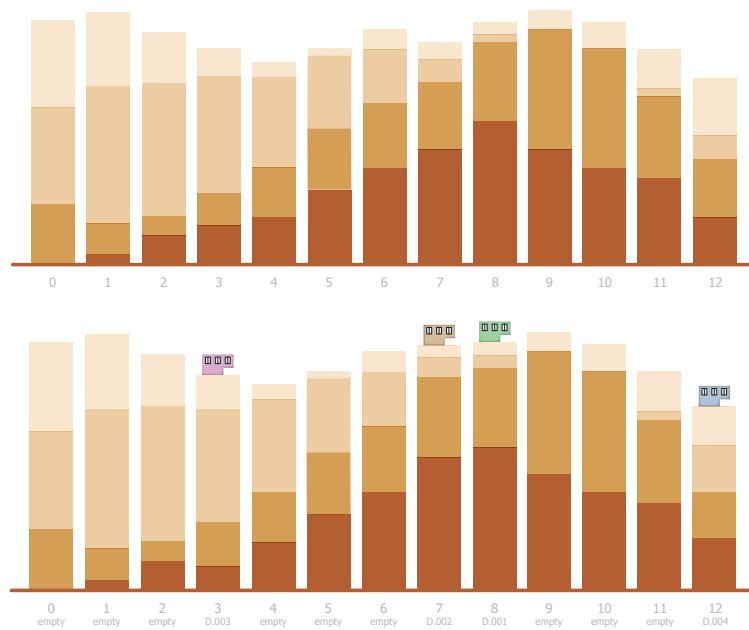


Fig. 5.9: The (simulated) performance values of the design alternatives (top left) override the (extrapolated) performance values of the cells of the Self-Organizing Map (top right). This example also shows how the prevention of clustering influences the visualization of the design space. Ordinarily, both the orange and green design alternative would be assigned to cell 8. Since the visual analytics system prevents this, the (less similar) orange design alternative is instead assigned to cell 7.

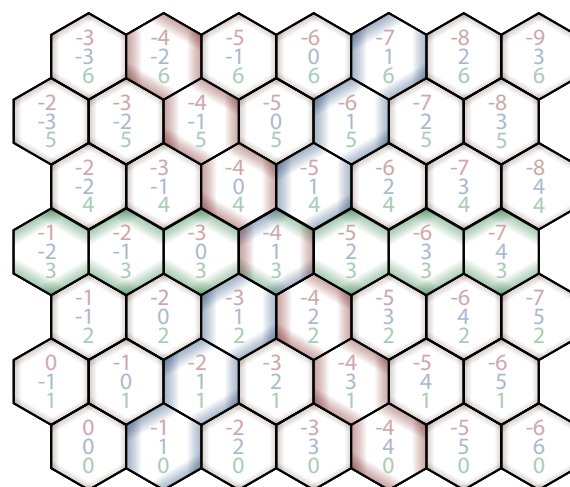


Fig. 5.10: Example of a cube coordinate system in a hexagonal grid.


```

make empty dictionary of hexagonal coordinates  $M_c$ 
for each grid cell  $I_c$  in  $C$ :
     $I_x = \text{rounddown}(I_c.\text{index} / S)$ 
     $I_y = I_c.\text{index} \% S - \text{rounddown}(0.5 * I_c.\text{index}/S)$ 
     $I_z = 0 - (I_y + I_x)$ 
     $M_c.\text{append } I_c:(I_x, I_y, I_z)$ 

```

Fig. 5.11: Pseudocode cube coordinate system.

```

With normalized data set of design variables and performance values:
With cube coordinate system  $M_c$ :
make empty dictionary of U-matrix distances  $M_u$ 
for each grid cell  $I_c$  in  $M_c$ :
    Amount of neighbors  $N = 0$ 
    find key  $C_o$  of  $(I_x+1, I_y, I_z-1)$ :
        for  $C_o$  in  $C$ :
            Eucl.dist.  $E = \sqrt{(I_{c,1} - I_{c,o,1})^2 + (I_{c,2} - I_{c,o,2})^2 + \dots + (I_{c,n} - I_{c,o,n})^2}$ 
             $I_c.\text{value in } M_u += E$ 
             $N += 1$ 
    find key  $C_o$  of  $(I_x+1, I_y, I_z+1)$ :
        for  $C_o$  in  $C$ :
            Eucl.dist.  $E = \sqrt{(I_{c,1} - I_{c,o,1})^2 + (I_{c,2} - I_{c,o,2})^2 + \dots + (I_{c,n} - I_{c,o,n})^2}$ 
             $I_c.\text{value in } M_u += E$ 
             $N += 1$ 
    find key  $C_o$  of  $(I_x-1, I_y+1, I_z)$ :
        for  $C_o$  in  $C$ :
            Eucl.dist.  $E = \sqrt{(I_{c,1} - I_{c,o,1})^2 + (I_{c,2} - I_{c,o,2})^2 + \dots + (I_{c,n} - I_{c,o,n})^2}$ 
             $I_c.\text{value in } M_u += E$ 
             $N += 1$ 
    find key  $C_o$  of  $(I_x, I_y+1, I_z-1)$ :
        for  $C_o$  in  $C$ :
            Eucl.dist.  $E = \sqrt{(I_{c,1} - I_{c,o,1})^2 + (I_{c,2} - I_{c,o,2})^2 + \dots + (I_{c,n} - I_{c,o,n})^2}$ 
             $I_c.\text{value in } M_u += E$ 
             $N += 1$ 
    find key  $C_o$  of  $(I_x-1, I_y, I_z+1)$ :
        for  $C_o$  in  $C$ :
            Eucl.dist.  $E = \sqrt{(I_{c,1} - I_{c,o,1})^2 + (I_{c,2} - I_{c,o,2})^2 + \dots + (I_{c,n} - I_{c,o,n})^2}$ 
             $I_c.\text{value in } M_u += E$ 
             $N += 1$ 
    find key  $C_o$  of  $(I_x, I_y-1, I_z+1)$ :
        for  $C_o$  in  $C$ :
            Eucl.dist.  $E = \sqrt{(I_{c,1} - I_{c,o,1})^2 + (I_{c,2} - I_{c,o,2})^2 + \dots + (I_{c,n} - I_{c,o,n})^2}$ 
             $I_c.\text{value in } M_u += E$ 
             $N += 1$ 
     $I_c \text{ in } M_u /= N$ 

```

Fig. 5.12: Pseudocode SOM U-Matrix.

5.3 ANNUAL PERFORMANCE DATA - SBG & AHP

5.3.1 Introduction

The Self-Organizing Map is an effective method of organizing high-dimensional data on a two-dimensional field and thus effectively makes high-dimensional data insightful. It does not, however, provide an easy-to-read overview of the cells' performances.

5.3.2 Theory

The Computational Design System takes both quantified and non-quantified performances into account. Consequently, since the overall performance of design alternatives depends on both types of performances, the DAS is able to visualize the overall performance of both quantified and non-quantified performances.

5.3.2.1 Quantified performances

For multi-objective optimization of data sets, multiple optimal design solutions can be defined. Multi-objective optimization finds the best possible tradeoffs between objectives by determining Pareto efficiency. Pareto efficiency is the state in which it is not possible to improve one objective without worsening another objective. The set of solutions that are Pareto optimal comprise the Pareto front.

Various data visualization methods facilitate the deduction of the Pareto front. Scatterplots are an effective method to deduce Pareto front of bi- or tri-variate data, but fail to show Pareto fronts of high-dimensional data sets.

The Hyperspace Pareto Frontier aims to visualize the Pareto Front of high-dimensional data by projecting multivariate data onto a two-dimensional scatterplot. This is achieved by summing multiple dimensions on a single axis by means of the Hyper-Space Digital Counting method. The Hyper-Space Digital Counting method rests on the idea that points on a (two-dimensional) plane can be projected onto a (one-dimensional) line without losing the topology of the data (Agrawal, Lewis & Bloebaum, 2006). This is achieved by creating a path through the data points on the plane, which is subsequently projected on the line. The Hyperspace Pareto Frontier depends on a correct selection of objective grouping: to achieve an even distribution of design points, the grouped objectives should have a high positive correlation. If the objectives have a negative correlation, the design

When considering a large data set of design alternatives an overview of the overall performances of the designs is desired, in order to quickly find the design alternatives of interest.

points are clustered, and if there is no correlation, the design points are scattered.

This thesis uses a stacked bar graph to visualize overall performance. Like histograms, stacked bar graphs consist of columns to visualize data values. The height of the column corresponds to the data value. Stacked bar graphs stack multiple values of each data item. Contrary to common use, the DPS normalizes the performance data to facilitate the stacking of various types of performance aspects. The total height of the stacked columns of a design alternative corresponds to the design's overall performance.

5.3.2.2 Non-quantified performances

Non-quantified performances of design alternatives can be quantified using a methodology comparable to the analytic hierarchical process. The analytic hierarchical process (AHP) is a multi-criteria decision-making method, with particular use in group decision making in the fields of business and politics. The AHP uses ratio scales derived from paired comparisons to determine the best-fitting alternative to achieve a goal. The comparisons can be taken from measurements or can be based on relative preferences or feelings (Saaty, 1987).

The following four steps give a simplified explanation of the AHP.

(1) Firstly, a goal is discerned. That goal is decomposed into criteria and alternatives (possible solutions) are determined.

(2) Then, for each criteria, alternatives are compared in pairs. The user of the AHP determines the level of preference of one alternative over the other for that criteria, using a range from 'equal importance' to 'extreme importance'. After preference levels are set for all pairs for each criteria, the total preference level of each alternative is calculated by summing their importance levels and normalizing the values by

dividing it by the sum of all importance levels.

(3) Then, the preference levels of the criteria for the goal are set. For each pair of criteria, the user determines the relative importance of one criterion over the other to reach the goal. Similar to step 2, total performance values are calculated and normalized.

(4) Finally, based on the aforementioned values assigned to the criteria and to the alternatives, the overall performance of each alternative is calculated, using the following formula:

$$P = \sum (F_c * P_c)$$

Where:

P = Overall performance

F_c = Weight factor of the criterion

P_c = Alternative's normalized performance of a criterion

5.3.3 Application

The designs' overall performance is visualized using a method best described as a combination of a stacked bar graph and an analytic hierarchical process.

Each design's overall performance is determined by summing the relative performance of each performance objective. The relative performance is determined by normalizing the data. Each performance aspect is normalized to a range of 0-1, in which performances of 0 and 1 correspond to that aspect's worst and best performance in the data set, respectively.

Comparable to setting criteria priorities in the analytic hierarchy process, the user can alter the range of each performance aspect in the VAS in order to match the influence of each performance aspect to their criteria priorities. If the user considers adequate thermal comfort levels of sports players to be twice as important as the thermal comfort levels of spectators, for example, the user can multiply the former by a factor of two.

Performance values are normalized based on their corresponding performance aspect only. In other words, cooling energy values are only normalized based on other cooling energy values and heating energy values are only normalized based on other heating energy values. This has multiple reasons. Firstly, it allows the user of the VAS to quickly retrieve the worst and best design for a specific performance criteria. Secondly, it allows the user to set priorities based on each aspect individually. Hence, the total performances in the annual performance visualization are not based on the numerical values of each performance aspect, but are based on relative performances and priorities set by the user. Users can set threshold values between which performances are normalized (Fig. 5.13).

The alternative with the highest value for P is the most suitable solution to reach the goal.

Although the AHP is an effective decision-making process and tool for structured discussion for small data sets, the process is inefficient for large data sets; a data set of 200 alternatives requires 19,900 pairwise comparisons for each criterion. Instead, the VAS has a simplified method of determining preferences between criteria and between alternatives.

A consequence of the aforementioned method of normalizing values is that the stacked bar graph does not sum performances with identical performances. For example, if the annual cooling demands of a set of design alternatives range from 0 to 12,000 kWh and annual heating demands range from 0 to 36,000 kWh, the stacked bar of a design with a cooling and heating energy demand of 8,000 kWh and 12,000 kWh respectively is equally big to a design with respective demands of 4,000 and 24,000 kWh (Fig. 5.14). Although the former design requires 8,000 kWh/y less energy than the latter, the stacked bar graph shows equal total performance. This is a deliberate feature of the VAS, since it encourages the user to reflect on the relevancy of each performance objective. The DAS contains a decision tree to indicate total energy demand (chapter 5.4). If the user would nevertheless rather express total energy performance in the stacked bar graph, the energy performances could be summed and represented as a single bar in the stacked bar graph. The user could switch between both visualizations using a simple toggle provided by the Visual Analytics System.

Additional performance objectives can be manually appended to the stacked bar graph within the VAS. For any non-quantified performance objective, users of the VAS can rate design alternatives with a score between 0 and 1 (worst and best performance of the design alternatives in the data set, respectively), as shown in Fig. 5.15. An advantage of this method is that it can be used as a structured and rational technique to determine trade-offs between design alternatives based on both quantified and non-quantified performance objectives. This enhances the use of the CDS as a discussion tool in the decision-making process.

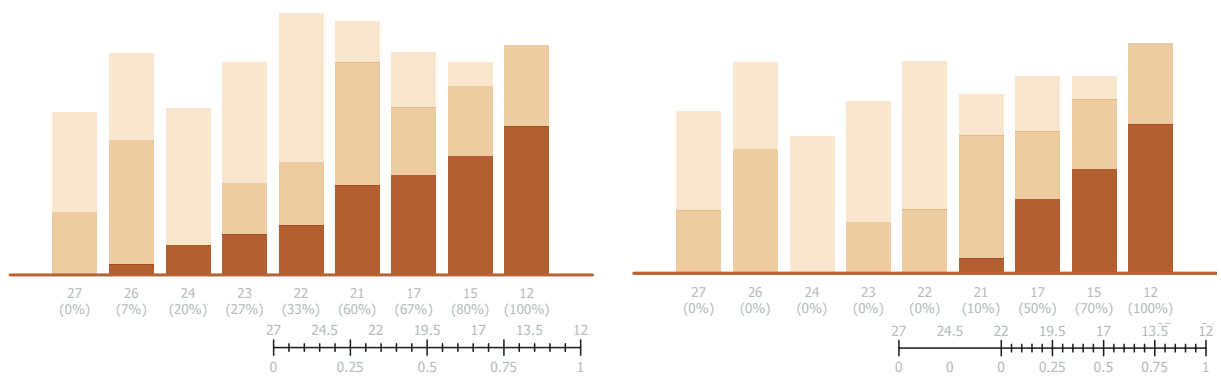


Fig. 5.13: The UGR in a sports hall may not exceed 22. However, because of the normalizing, by default the stacked bar graph (l.) does assign a performance value bigger than zero to the values with a UGR>22. By setting the threshold for glare to 22 (r.), all values bigger than 22 are assigned a performance of 0%, and are thus considered equally bad.

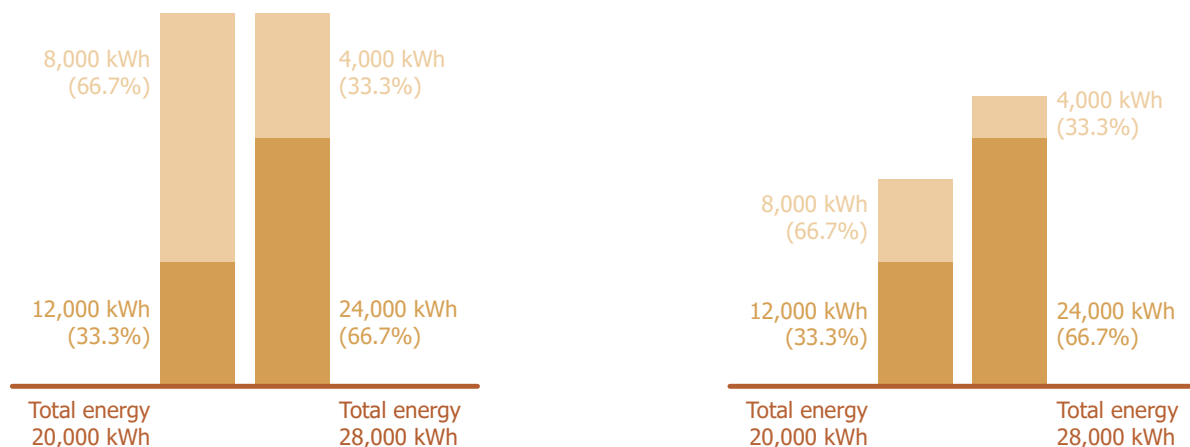


Fig. 5.14: Normalizing of the values in a stacked bar graph may result in unequal equilibrium between performance aspects (l.). To overcome this, the performance aspects can be scaled to accurately represent the equilibrium between aspects (r.).

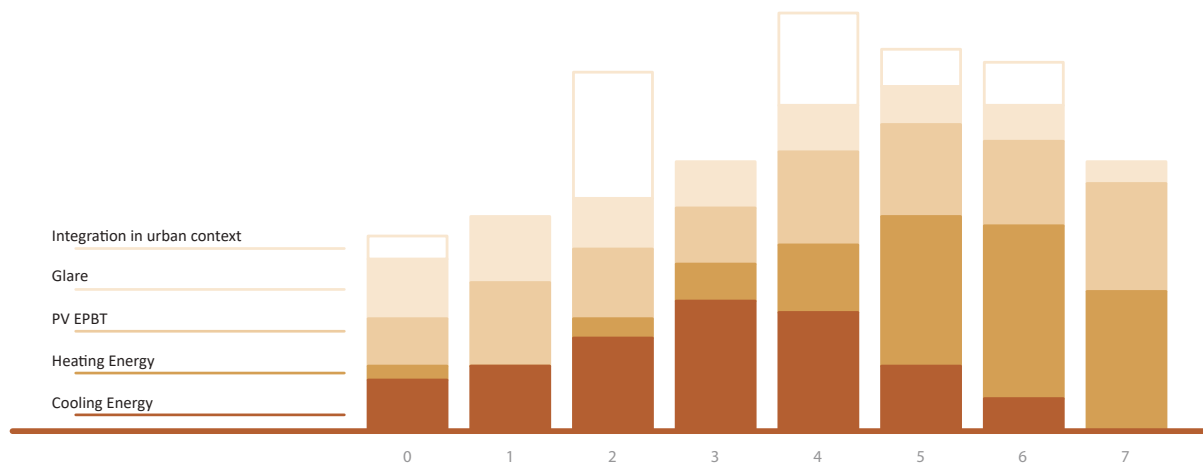


Fig. 5.15: Use of the analytic hierarchal process to add non-quantified performances to the stacked bar graph. In the graph above, users defined relative quality of design alternatives' integration in the urban context for cells 0, 2, 4, 5 and 6.

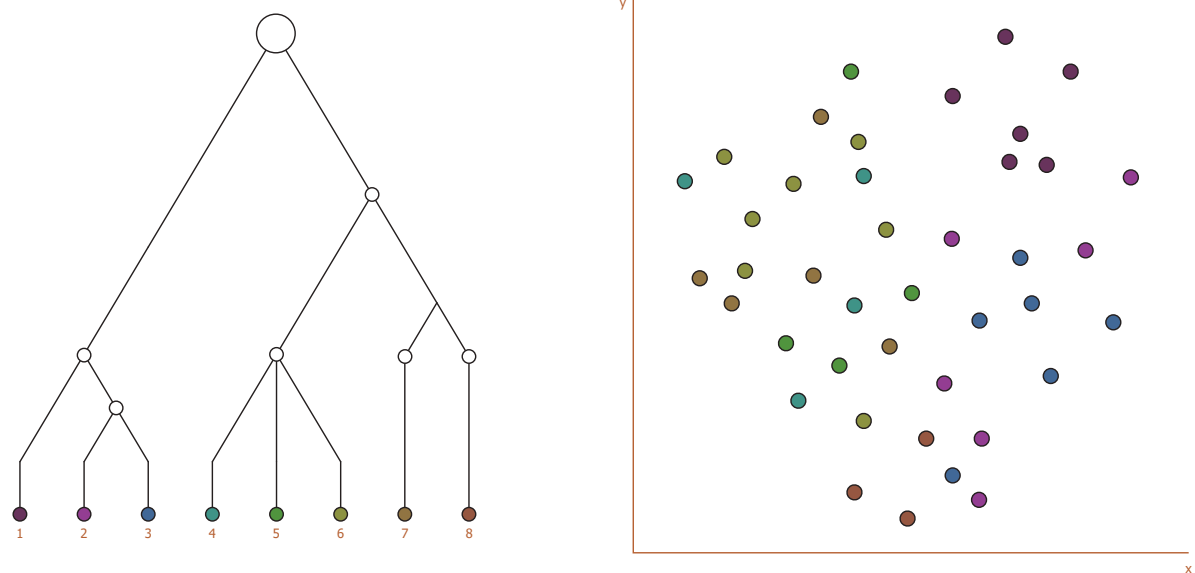


Fig. 5.16: Decision tree for data classification (l.). Data items presented in the scatterplot (r.) are colored correspondingly.

5.4 DATA CLASSIFICATION - DECISION TREE

5.4.1 Introduction

The Computational Design System makes use of large data sets that may contain hundreds of design alternatives. Since thoroughly reviewing each of these design alternatives is time-consuming, the VAS provides tools that aid the user in finding design spaces of interest.

One such tool implemented in the VAS is a classification method that classifies design alternatives based on user-defined criteria. The VAS uses a decision tree to create subsets of a data set.

5.4.2 Theory

A decision tree uses a tree structure of conditional statements to subdivide a data set into classes (Fig. 5.16). A decision tree consists of nodes that analyze attributes of data items and correspondingly assign data items to subsets. The nodes are hierarchically structured. The root node creates two or more subsets of the entire data set and should therefore have the most important conditional statement. Branch nodes further subdivide the subsets. Leaf nodes correspond to each final subset's class labels.

Various algorithms, such as the ID3 algorithm (Quinlan, 1986), are able to build decision trees based on machine learning, but because of their ease of use and ease of understanding decision trees are also commonly built manually. This thesis also uses a manual approach of defining a decision tree, to encourage consideration of design variables and to enhance user flexibility.

5.4.3 Application

Classification of design alternatives in the Data Analytics System is best described as a process of giving each design alternative a 'label' that represents the corresponding subset. This label is visualized in the Visual Analytics System as a landscape feature (see chapter 6.2.3).

Classification of design alternatives is performed in the Unreal Engine. The Data Analytics System uses a binary decision tree based on a series of 'Branch' flow control gates provided by the Unreal Engine. The 'Branch' gate reads a Boolean value and outputs an execution flow corresponding to that value (i.e. if Condition = true, Execute A, if Condition = false, Execute B) (Epic Games Inc., 2017b). The final execution flow determines which 'label' is assigned to each design alternative.

It should be noted that the use of a binary decision tree instead of a non-binary decision tree does not impose limitations on the classification process; as depicted in Fig. 5.17, identical subsets can be defined through slightly different processes. The choice to use a binary decision tree is based on the use of a 'Branch' gate.

Although there are algorithms that provide methods of machine learning to determine relevant subsets, the Data Analytics System developed in this thesis uses user-defined classification criteria. This gives the user the opportunity to classify design alternatives based on their preferences. This thesis classifies design alternatives based on total annual energy consumption, expressed in kWh/m². The total energy consumption is defined the sum of the annual performance objectives considered in this thesis; heating, cooling, lighting energy demands and PV panel energy gain. This supplements the algorithm of the stacked bar graph (chapter 5.3), which deliberately does not sum energy demands and energy gain.

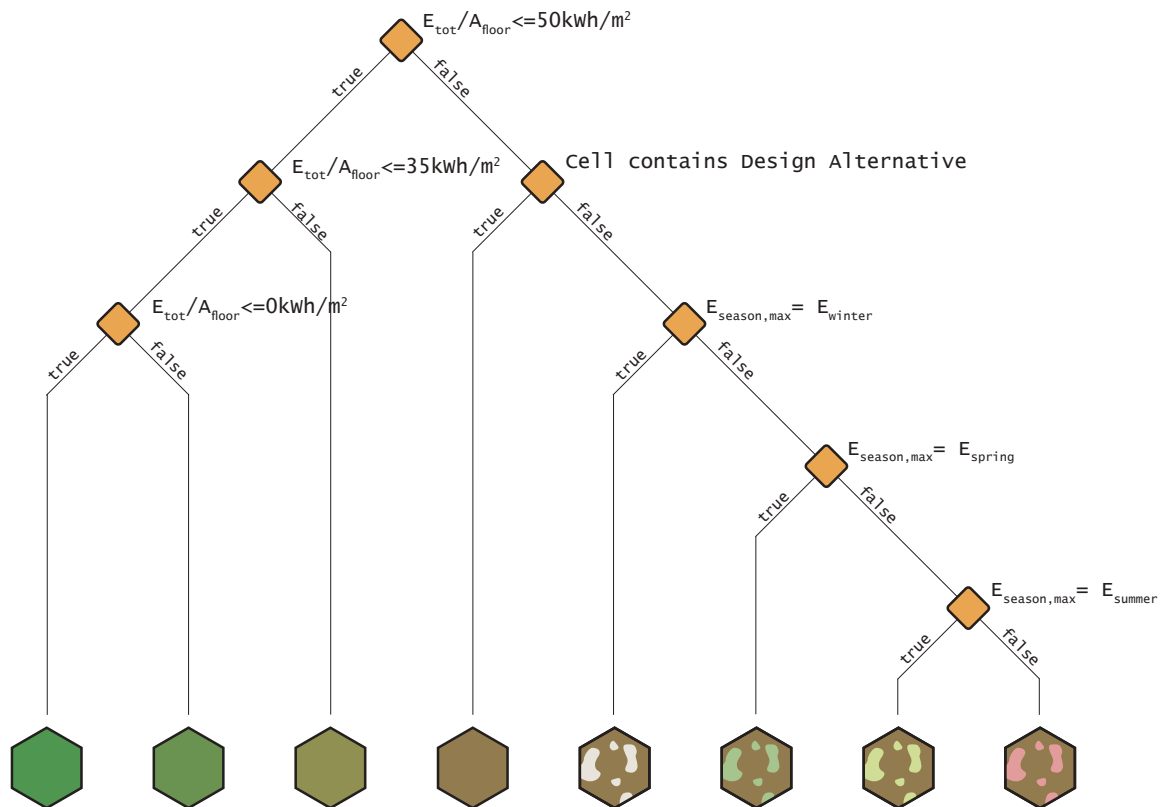
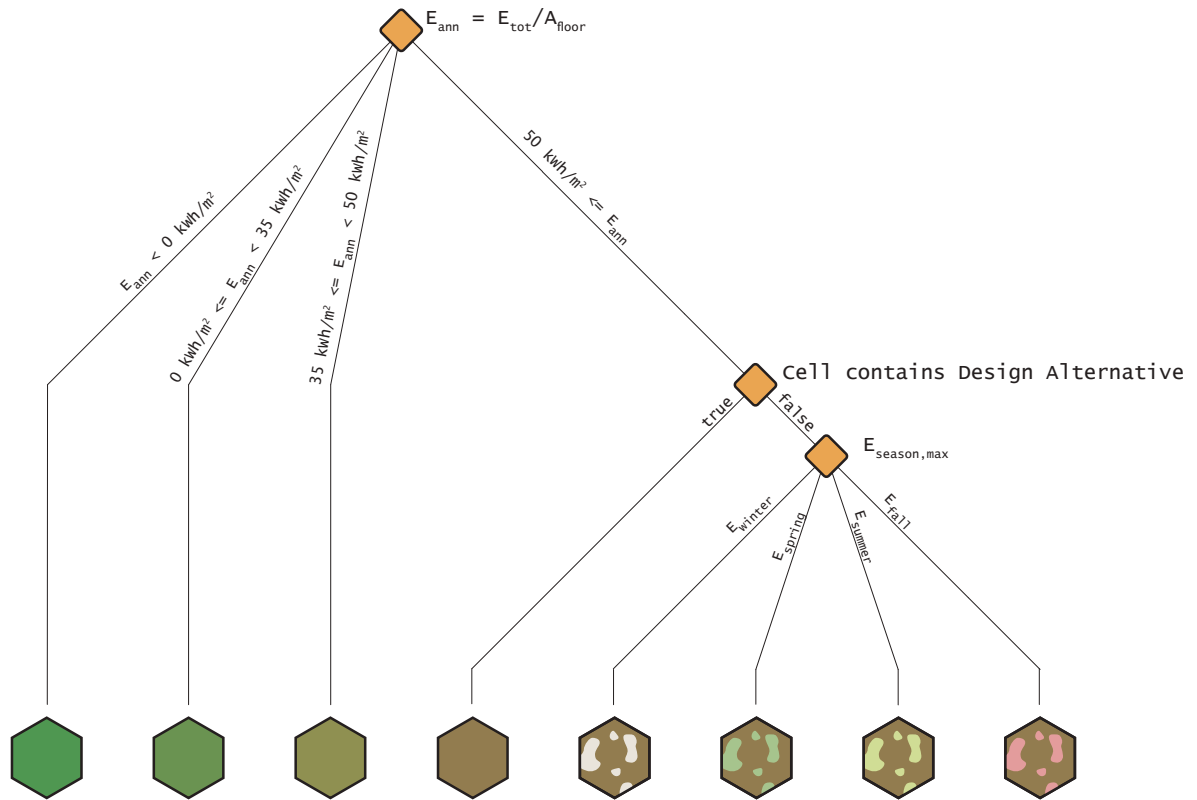


Fig. 5.17: Non-binary tree (top) and binary decision tree (bottom) used to classify the cells of the SOM based on energy performance. Both decision trees determine which cells of the Self-Organizing map are Zero-Energy ($\leq 0 \text{ kWh/m}^2$), nearly Zero-Energy ($\leq 35 \text{ kWh/m}^2$), have low energy performance ($\leq 50 \text{ kWh/m}^2$) or have very low energy performance ($> 50 \text{ kWh/m}^2$). The decision tree creates subsets of the cells with very low energy performance based on in which season the energy demand is highest. This is based on hourly performance data and therefore is not possible for cells that do contain a design alternative.

5.5 DATA CLUSTERING - AHC

5.5.1 Introduction

The purpose of clustering in the Visual Analytics System is to rapidly find design spaces of interest by reviewing a reduced amount of design alternatives.

The VAS uses hierarchal clustering to reduce the amount of design alternatives that are visualized. Hierarchal clustering, in contrast to other clustering techniques, such as K-means clustering (Fig. 5.18), does not require an initialization step to determine the amount of clusters. Instead, it uses an iterating process in which the amount of clusters is determined

by the amount of iterations. Hierarchal clustering provides the possibility to vary the amount of clusters. Furthermore, hierarchal clustering are widely used (Tan, 2006). Grasshopper's method of data processing makes use of 'data trees', which closely resemble visualization techniques for hierarchal clustering. This is a relevant consideration factor for the choice of clustering methods for the Visual Analytics System, since users are already familiar with the clustering technique.

5.5.2 Theory

Methods for hierarchical clustering are either agglomerative or divisive. Agglomerative techniques consider data items as single-item clusters. Then, successively, the two closest clusters are merged until an all-encompassing cluster is defined. Divisive techniques inverse this process, splitting an all-encompassing cluster until single-item clusters are reached. The distance between clusters can be defined using various methods (Fig. 5.19). The choice of linkage method depends on various criteria, a.o. data structure (Ferreira & Hitchcock, 2009; Almeida, Barbosa, Pais & Formosinho, 2007). Correspondingly, no method is uniformly the best.

Hierarchical clusters can be visualized as a dendrogram or as a nested cluster diagram (Fig. 5.20).

The application of hierarchical clustering has been researched as a way to explore architectural design alternatives (Sileryte, D'Aquilio, Di Stefano, Yang & Turrin, 2016). The research applied two clustering types: one based on performance values and one based on design parameters. In the research's case study, both types were suitable to determine relationships between design parameters and performance objectives.

5.5.3 Application

Clustering is done based on the design variables of the IDS, thus clustering design alternatives with similar geometries. To account for the versatility of the range of aspects' values, the data set is normalized in Excel.

The algorithm used in this thesis is agglomerative centroid clustering. With centroid clustering, clustering is performed based on the cluster averages. This linkage method is chosen because it most closely resembles the visualization of a dendrogram and the visualization of the agglomerative clustering in the VAS. Hence, it is the most 'intuitive' linkage method for the users of the VAS.

Clustering is performed in the Unreal Engine. With each design alternative assigned to a unique cluster, the Engine calculates the Euclidean distance between

each two clusters. The cluster combination with the lowest Euclidean distance are set as a new cluster, for which its centroid between the two children's aspects are set as the new aspects. The children clusters are removed from the list and the algorithm recalculates the Euclidean distances until one, all-encompassing cluster remains. See also Fig. 5.21. The information on clustering required by the DAS is exported to CSV files so that it can be retrieved after the first boot.

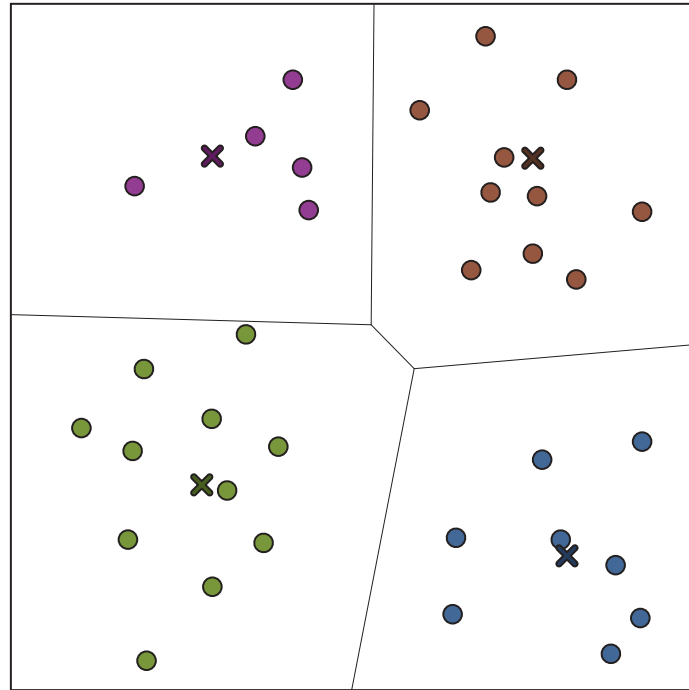


Fig. 5.18: Example of K-means clustering.

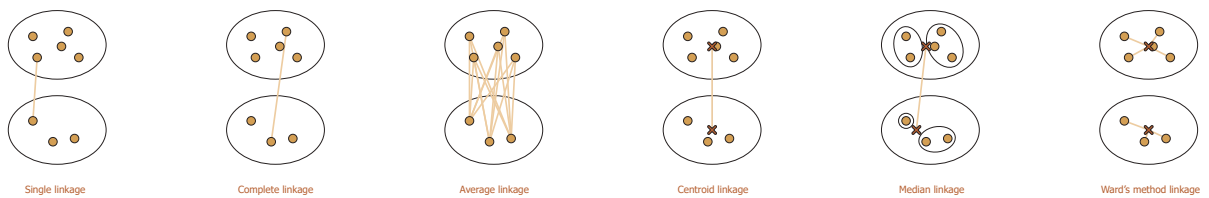


Fig. 5.19: Hierarchical clustering linkage methods.

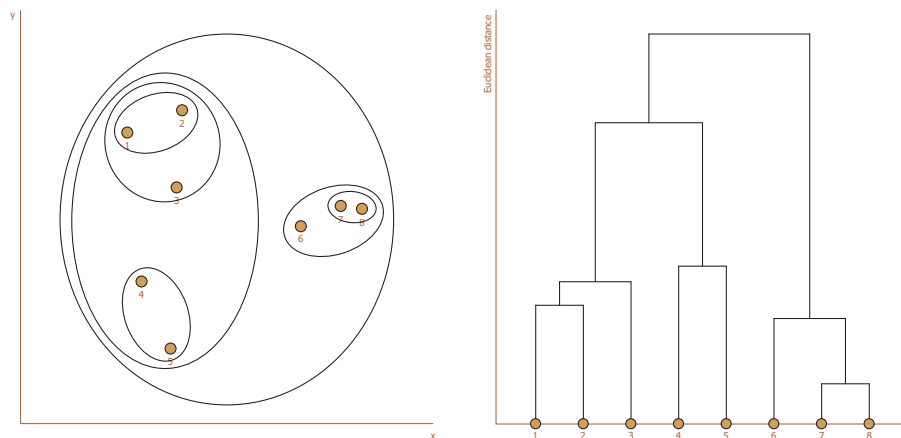


Fig. 5.20: Hierarchical clustering visualized as a nested cluster diagram (l.) and a dendrogram (r.).

with normalized data set D with aspects A :

```

length  $L$  = amount of rows in  $D$ 
clusters  $C$  = data set  $D$ 
while amount of new clusters  $n_{c,n} < L-1$ :
    make empty array  $A_e$ 
    for each design alternative  $I$  in  $C$ :
        for each other design alternative  $I_o$  in  $C$ :
            if  $\text{index}.I < \text{index}.I_o$ :
                Eucl.dist.  $E = \sqrt{((A_{1,I} - A_{1,I_o})^2 + \dots + ((A_{n,I} - A_{n,I_o})^2)$ 
                Append  $E$  to  $A_e$ 
    for  $I$  and  $I_o$  with  $E_{\min}$  in  $A_e$ :
        Set new cluster  $C_n$  to  $I_{\min} - I_{o,\min}$ 
        for each  $A$  in  $C_n$ :
             $A = (A_I + A_{I_o})/2$ 
         $C.\text{remove } I$ 
         $C.\text{remove } I_o$ 
     $C.\text{append } C_n$ 

```

Fig. 5.21: Pseudocode agglomerative hierarchal clustering.

5.6 DESIGN LABELS - PICTOGRAM CHART

5.6.1 Introduction

Although the stacked bar graph implemented in the Data Analytics System (chapter 5.3) is an effective tool to find relative performances between design alternatives, tests with an early version of the Visual Analytics System (see also chapter 7.2) indicated that

finding the designs with best- and worst-performing performance objectives could be further facilitated. The Visual Analytics System therefore makes use of pictograms to indicate the designs with best or worst performances.

5.6.2 Theory

Pictograms are images that represent a data value. The image commonly corresponds to the data attribute (e.g. an icon of a person to represent population).

Pictogram charts contain a collection of icons and visualize data similar to a bar graph. Pictogram charts can be used to visualize both numerical and categorical

data. A threat of the use of pictogram charts is that they lose effectiveness when visualizing large amounts of data, since large amounts of pictograms are hard to interpret. The DAS developed in this thesis therefore uses means of interaction to provide a highly adjustable pictogram chart.

5.6.3 Application

The Data Analytics System uses a binary alternative of the pictogram chart, in which pictograms represent Boolean values that correspond to best and worst performances. Each performance objective is represented by two icons, one representing the worst performance and one representing the best performance.

For each cell of the Self-Organizing Map, the performance values are compared to their respective threshold values. If the cell's performance exceeds either value, a corresponding pictogram is spawned on the tile. By default, the threshold values are the

minimum and maximum value of the performance objective, but this is adjustable by the user (see also chapter 5.3.3).

The latter feature offers the possibility of using the pictogram chart in its traditional sense; the amount of icons may indicate to what extent a threshold value is exceeded. See also Fig. 5.22. This, however, is not implemented in the visual analytics tool developed in this thesis. Because of the author's limited experience with the Unreal Engine, this feature would be computationally expensive.

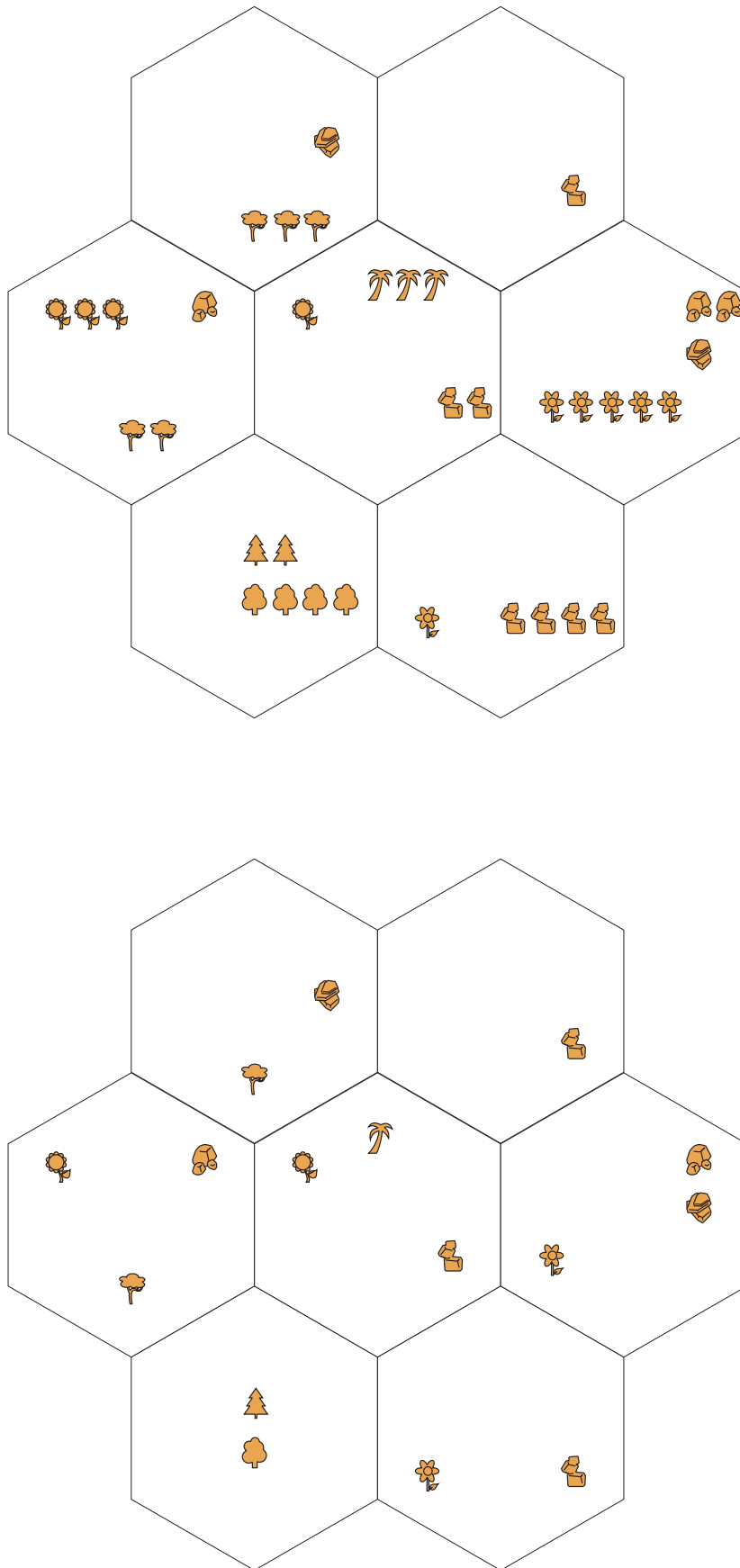


Fig. 5.22: Traditional pictogram chart (top) and binary pictogram chart (bottom) in the Data Analytics System.

5.7 INTERRELATIONSHIPS BETWEEN DESIGN ASPECTS - CORRELATION MATRIX

5.7.1 Introduction

Using the aforementioned data analytics methodologies the user is able to make trade-offs between design alternatives by means of comparative assessment. These methodologies also enable the user to predict influences of design variables by comparing design alternatives. However, some influences of design variables on performances may be ambiguous, especially when the building aspects are numerous,

or when a design variable is not visual in the design geometry (e.g. setpoint temperatures).

The Data Analytics System therefore makes use of a correlation matrix, which determines interrelationships between building aspects. Analysis of the interrelationships between design aspects further informs the designer on the effects of design decisions.

5.7.2 Theory

A correlation matrix is a matrix of Pearson's correlation coefficients. Correlation is a calculation methodology of the interrelationship between two continuous variables. Pearson's correlation coefficient is a measure of the strength of a linear association between two variables. Pearson's correlation coefficients are calculated using the following formula:

$$r_{x,y} = (n(\Sigma xy) - (\Sigma x)(\Sigma y)) / \sqrt{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma y^2 - (\Sigma y)^2]}$$

Where:

$r_{x,y}$ = Pearson's correlation coefficient

x = variables x

y = variables y

The Pearson's correlation coefficient ranges from -1 to +1, where $r = -1$ indicates strong negative correlation, $r = +1$ indicates strong positive correlation and $r = 0$ indicates no correlation (Fig. 5.23).

The correlation matrix is commonly visualized with the use of colors that correspond to Pearson's correlation coefficients, so that highly correlated and uncorrelated variables can be retrieved quickly and intuitively.

5.7.3 Application

The correlation matrix used in the Data Analytics System is a square matrix that contains correlation coefficients of both design variables and annual performances. Design variables are the building's orientation, floor area, volume, PV panel area, window areas of four façades and the roof and the annual hours of direct daylighting through the windows of each façade.

Various researches have introduced guidelines that qualify correlation based on Pearson's correlation coefficients. However, as Cohen (1988) points out, for various reasons correlation coefficients may be fallible. Consequently, guidelines may be considered somewhat arbitrary, as correlation depends on context. Hence, the Data Analytics System does not use such guidelines. Instead, the Data Analytics System calls for the designer's expertise to interpret correlation between design variables.

The correlation matrix is generated in mode-FRONTIER (version 5.3.0; ESTECO SpA, 2017) and exported to an Excel (.XLS) file. This file may then be exported as a CSV file for implementation in the Visual Analytics System.

5.8 DISCUSSION

The Data Processing System uses various algorithms to process building information generated with the Iterative Design System. In the introduction of this chapter the following functions of the Data Analytics System are set out:

- Visualization of interrelationships between data items in high-dimensional data
- Visualization of data attributes
- Navigation in large data sets.
- Determination of interrelationships between design aspects and performances

A Self-Organizing Map is used to project high-dimensional data on a two-dimensional plane. The algorithm of the Self-Organizing Map is adjusted so that only one design alternative generated by the Iterative Design System is assigned to a cell; other design alternatives are assigned to neighboring cells and override their data. The algorithm presented in this thesis functions well when the amount of SOM cells exceeds the amount of design alternatives by a ratio of 3:1. A minimum ratio of 5:1 is recommended in order to improve visualization of interrelationships between design alternatives.

Normalizing data makes it possible to stack and visualize all quantified performances using a stacked bar graph. This is an easily interpreted visualization of design alternatives' overall performances. Integration of the analytic hierarchal process in the stacked bar graph enables quantification of qualitative and non-quantified performances. In conjunction with a decision tree and pictogram charts the stacked bar graph facilitates quick derivation of the areas of the design space that are of interest to the user of the Computational Design System.

Agglomerative hierarchal clustering, data classification and the SOM's U-matrix facilitate navigation of large data sets, based on varying design aspects. Agglomerative hierarchal clustering is based on design geometry. Use of agglomerative hierarchal clustering enables users to find areas of the design space that correspond to specific geometries. Data classification labels SOM cells using a user-defined decision tree. SOM's U-matrix shows distances between cells of the SOM, thus showing data structures in high-dimensional data.

A correlation matrix is used to determine interrelationships between design aspects. This can be used to extract information with regards to design improvements.

Together, the data analytics methods presented in this chapter fulfil each function of the Data Analytics System. Correspondingly, integration of these data analytics methods substantiates multi-variate, multi-objective decision-making of large sets of design alternatives.

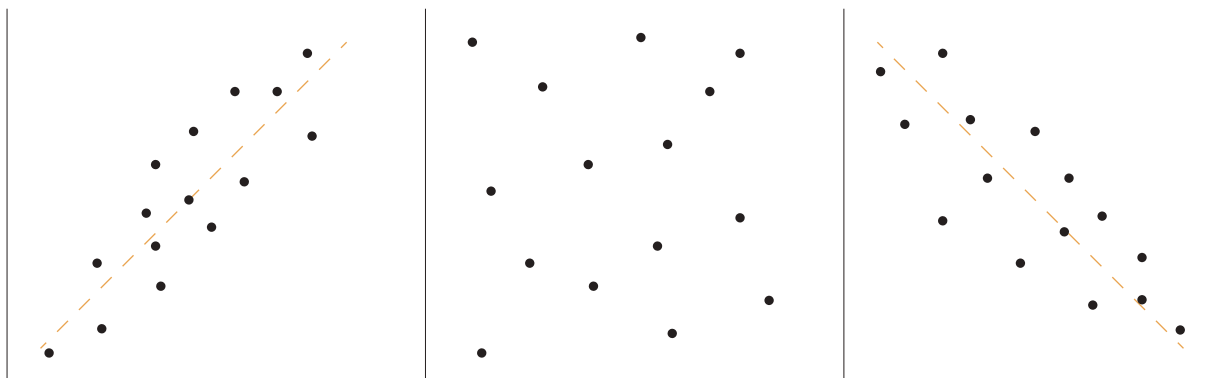


Fig. 5.23: Graphs showing positive correlation (l.), no correlation (m.) and negative correlation (r.).

CHAPTER 6: VISUAL ANALYTICS SYSTEM

This chapter describes the Visual Analytics System (VAS). The VAS provides multi-variate, multi-objective design exploration and decision-making of a large set of design alternatives for practitioners in the field of architecture. The VAS integrates and visualizes the algorithms of the Data Processing System (DPS).

Chapter 6.1 introduces the VAS and describes the workflow of the VAS.

Chapter 6.2 explains how the various algorithms are implemented and explain how the user can interact with the VAS.

Chapter 6.3 presents the discussion on the VAS.

6.1 INTRODUCTION

6.1.1 Concept

Difficulties of visualizing large multi-variate and multi-dimensional data sets were already mentioned in Chapter 1. Most importantly, current visualization techniques fail to show relationships between data items in high-dimensional data sets and cluttering of data items in large data sets is an issue with most visualization technologies.

This thesis introduces a Visual Analytics System (VAS); a high-interactive data environment with the goal of making multi-variate, multi-objective design exploration and decision-making of generative design systems accessible to architects and climate designers. Since an important characteristic of the architectural design process is design by comparative decision-making the Visual Analytics System visualizes all design alternatives simultaneously and facilitates exploration of the design space by various methods of data visualization. Issues of cluttering are prevented by high levels of interactivity and by the use of an overarching theme to integrate the various visualization methods.

Issues of cluttering are prevented by high levels of interactivity. Furthermore, the VAS uses visual metaphors to present data analytics methods, which are integrated using an overarching theme.

The use of an overarching theme is inspired by Chernoff's faces (Fig. 6.1). Chernoff's faces generate a face for each data item. Data values of each item are assigned to facial features that can vary in shape, size and location. The faces are mapped on a sheet, enabling comparison between data items. This visualization method allows readers to intuitively deduce similarities and difference of high-dimensional data items.

Similar to how Chernoff's faces uses facial features to visualize data properties, the VAS uses a rural landscape, in which characteristics of the landscape are used as metaphorical representations of data visualization methods (Fig. 6.2). Each design geometry is positioned in the landscape. Interpreting the landscape's features around a design alternative will lead to the understanding of performances of and interrelationships between design variations. The user controls a flying camera with which he can fly through the landscape, using the WASD-buttons and the mouse. The user is thus encouraged to 'zoom in and out' on areas of the design space; analyzing individual buildings or analyzing the design space as a whole, respectively.

6.1.2 Workflow VAS

A prototype of the VAS is scripted using the Unreal Engine, a game engine developed by Epic Games Inc. (version 4.17.1, 2017a). Game engines are integrated development environments that provides reusable software components that together define user actions,

visualizations, animations, sounds, physics, and more. Game engines are optimized for computer games and are thus effective tools to develop an environment for user interaction and object visualization.

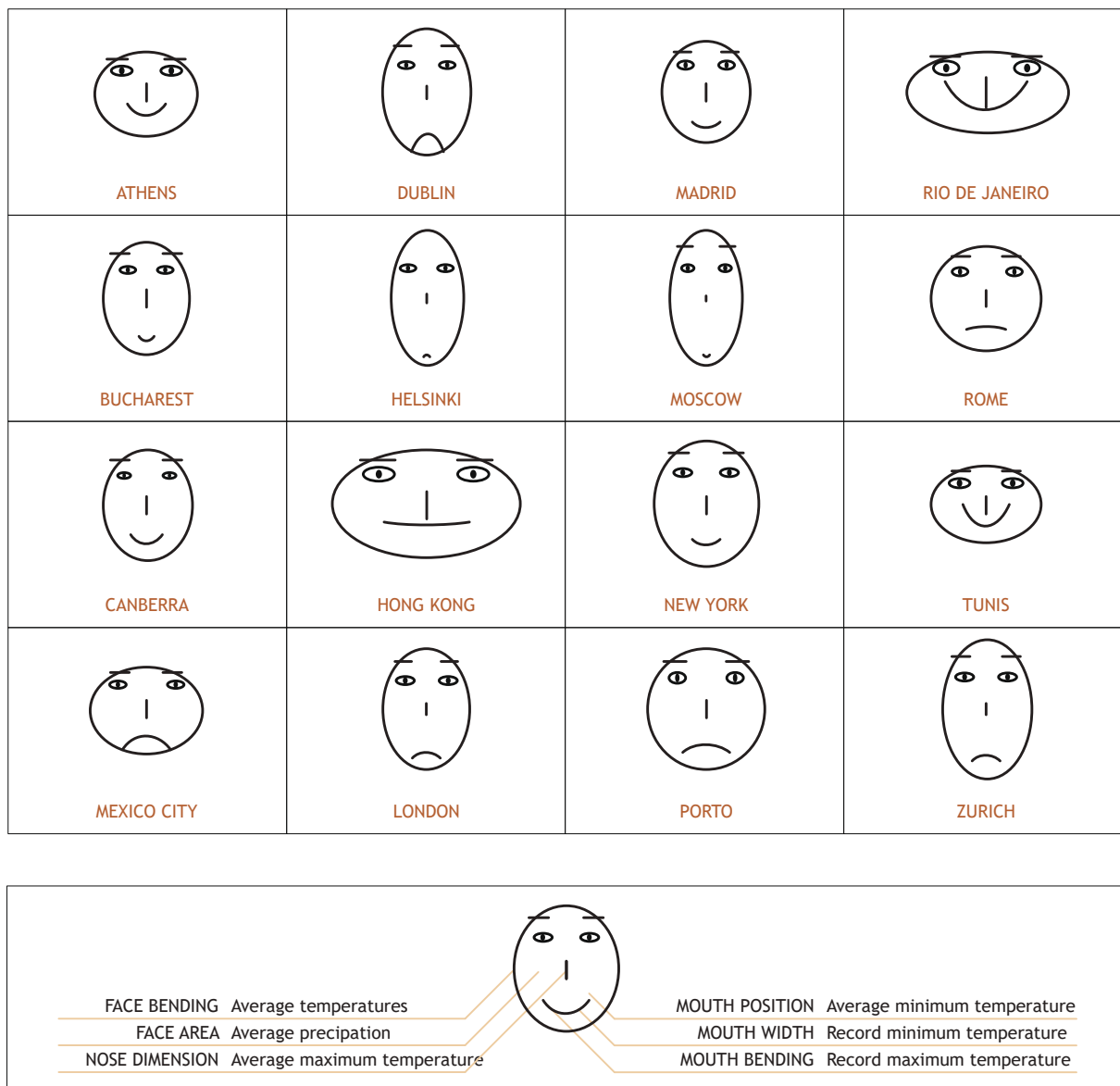


Fig. 6.1: Climate data of some cities presented using Chernoff's faces (derived from Mazza, 2009, p.58).

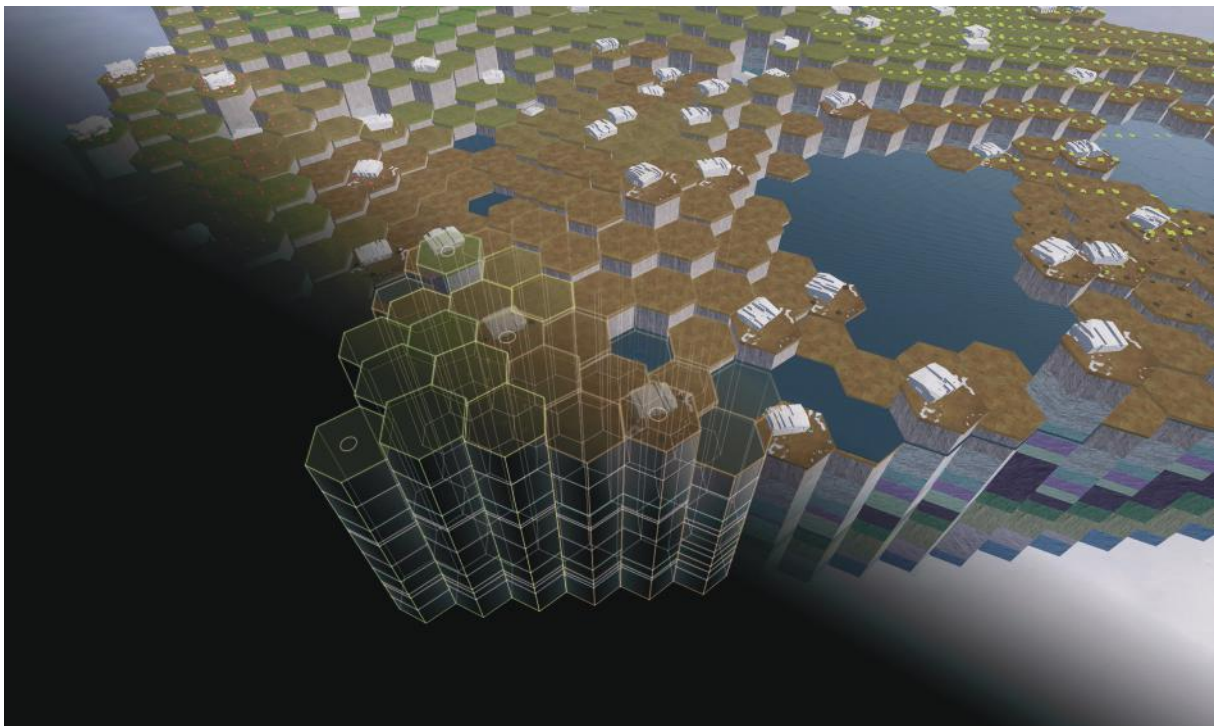
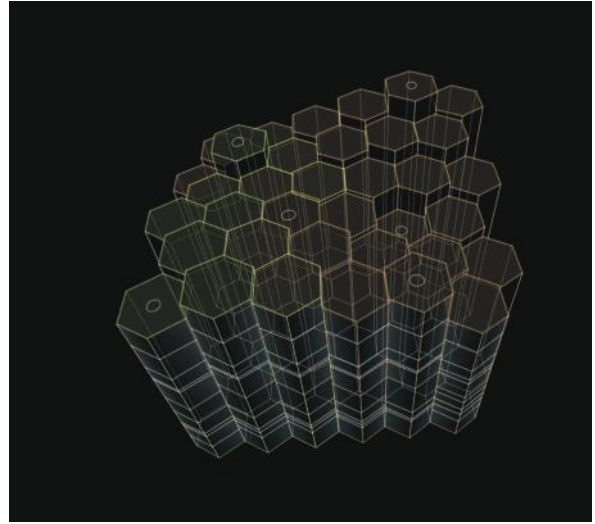
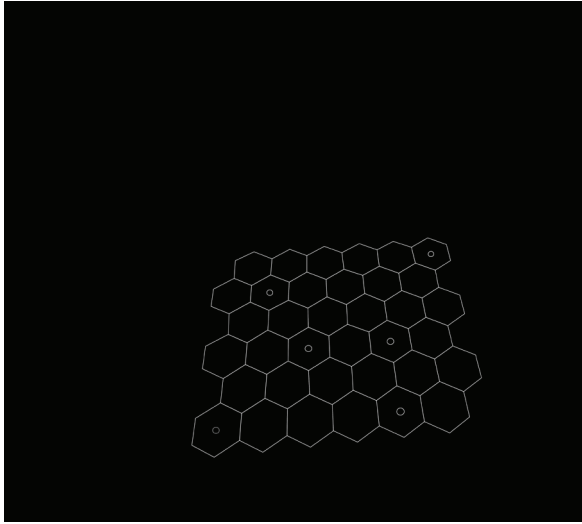


Fig. 6.2: Data analytics methods visualized using the metaphor of a landscape.

The Unreal Engine uses a node-based visual scripting editor similar to Grasshopper (Fig. 6.3). Objects in the world each have their own script attached to it, which handles that object's data processing and gameplay logic. The script executes changes based on events, which can be time-related or can be based on user interactivity. Alternatively, events can be instantiated by other objects. Various nodes facilitate data transfer between objects.

By default, the Unreal Engine is not optimized for spreadsheet-based data workflows such as the

workflow developed in this thesis. The VAS therefore uses Rama's Victory plug-in (2014) to facilitate the import of CSV files. This plug-in provides an additional set of components to the component library of the Unreal Engine. One such component enables the import of rows of text as an array of strings.

The next chapter presents the features of the Visual Analytics System. High resolution images of the figures used in this chapter can be found in Appendix F.

6.2 VISUALIZATION AND INTERACTION

6.2.1 Dimensionality reduction

The Self-Organizing Map forms the grid of the landscape (Fig. 6.4). The meshes of the designs are placed on the landscape according to their corresponding cells (Fig. 6.5). Because of the functionality of the Self-Organizing Map similar designs are plotted in close vicinity of each other.

The VAS implements a U-matrix filter similar to the filter provided in ModeFrontier, which filters out empty cells based on their average distance to neighboring cells. Increasing the filter's slider value removes cells with a large average distance. The filter can therefore be used to identify data clusters and their remoteness from other data items. The filter deletes cells that exceed the filter's distance. Visually, this creates a series of canyons (Fig. 6.6).

Since the distance between cells is inversely proportional to the density of data items, the filter has a secondary benefit. The generative design process makes use of an evolutionary algorithm, which converges to the optimal areas of the design spaces and therefore generates a larger amount of similar designs that are in the optimal areas of the design space. The filter can therefore be used to inspect elitism of the IDS. Additionally, the filter may be used to identify mutations. Mutations are often outliers in the data set and, as a result, are likely to have the greatest distance to other design alternatives. In conclusion, the U-matrix filter therefore implicitly facilitates the determination of the optimal design space and provides a method to find unexplored (non-simulated) areas of the design space.

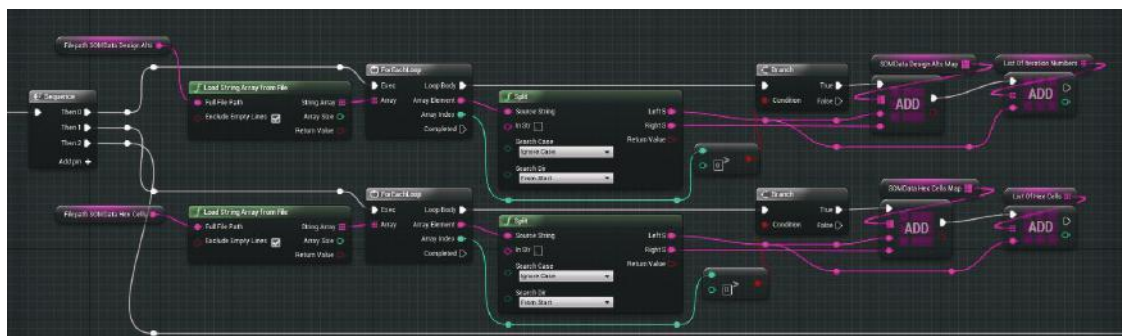


Fig. 6.3: Excerpt of the Unreal Engine script of the VAS. This segment loads two CSV files that contain the design alternatives' data and the SOM's cells' data, writes the data to their respective dictionary ('map') and creates a list of design alternatives and of SOM cells.

6.2.2 Annual performance data

Each performance aspect that is part of the stacked bar graph is visualized as a soil layer of the landscape (Fig. 6.7). Since the thicknesses of the soil layers depend on the corresponding cell's performances, the landscape's heights give an indication of each cell's overall importance. Hills indicate better performing areas of the design space, whereas valleys indicate a lower performance.

Hovering over the tiles in the landscape shows their performances (Fig. 6.8). Selecting a cell shows the other cells' relative performances to that cell, expressed in percentages. Design alternatives can thus be compared.

On boot, each aspect of the stacked bar graph in the VAS is normalized to a range of 0-1. Because performance values are normalized based on their relative performance, each aspect is considered equally important and for each aspect there is a design with zero performance and one with maximum performance. The VAS introduces two methods of interaction to influence normalization of performance aspects (Fig. 6.9).

The first method allows a user to scale the range of an aspect in order to increase the thickness of its soil layer. Users can thus specify which performance aspects are considered to be more important. If, for example, a user considers glare to be twice as important as all other aspects, the glare can be scaled by a factor two. If a user considers the energy payback time of a PV panel not important at all, he can scale its soil layer to 0, effectively removing the aspect's influence on the determination of the designs' overall performance. The landscape is instantly regenerated and may form new hills and valleys. See also Fig. 5.14.

The second method allows users to set the domain for which the values are normalized. Users can set thresholds with this method. The aspects of the design alternatives that fall outside the domain are either set to 0 (when their performance is equally undesirable to the minimum threshold value) or to 1 (when their performance is equally desirable to the maximum threshold value). See also Fig. 5.13. The landscape is adjusted accordingly. An additional advantage of this feature is that it successfully removes the effects of outliers in the data set.

A filter facilitates quick filtering of lesser-performing results. The filter ranges from 0% (no filtering) to 100% (all but one designs are filtered out) and is visualized as a water level that can be raised up until all but one hexagons are submerged (Fig. 6.10).



Fig. 6.4: Visual Analytics System visualizing a set of 150 design alternatives.



Fig. 6.5: Building meshes are spawned on the tiles of the Self-Organizing Map.

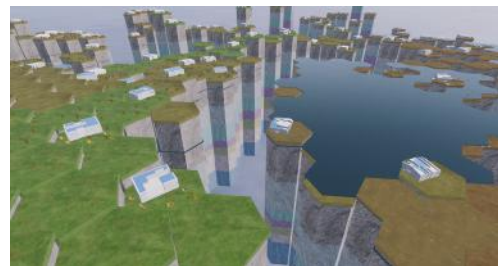


Fig. 6.6: Canyons are used as a visual metaphor to visualize the SOM U-matrix.

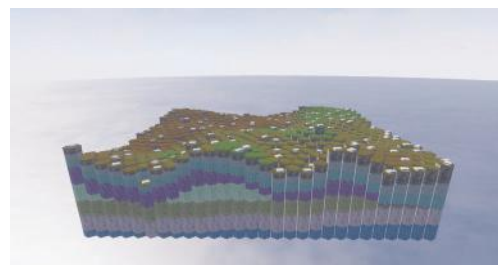


Fig. 6.7: Annual performance data is visualized by soil layers. The total thickness of the soil (and thus the height of the landscape) corresponds to overall performance.

6.2.5 Design labels

The pictogram chart is visualized by means of 'icons' that populate the landscape in the form of trees, rocks and flowers. Icons are placed when a tile exceeds a minimum or maximum performance value, determined by threshold values. Drawing loose metaphorical references, maximum performances of energy-related performance objectives are visualized as trees, lighting-related performance objectives are visualized as flowers and temperature-related performance objectives are visualized as rocks. Minimum performances are visualized as dead trees and flowers and as shattered rocks (Fig. 6.13). These icons are chosen as a loose reference to their performance objectives to promote intuitive interpretation of data. Naturally, when using the Computational Design System in another design assignment, e.g. for structural optimization of a high-rise building, icons can be changed to suit its performance objectives.

By default, the threshold values are the minimum and maximum values of each performance objective of the data set. A menu allows the user to manually input these threshold values. As mentioned in chapter 6.2.2, this provides the user with a method to manually define threshold values that correspond to the user's criteria and is a way to remove the influence of outliers of the data set on the configuration of the landscape. A third advantage is that it can be used to quickly find all design alternatives that exceed a certain performance value. If the user sets a threshold value so that 15% of the tiles exceed its value, for example, the Visual Analytics System spawns icons on all of these tiles. Using this method, the user can efficiently and intuitively determine clusters based on performance values.

Icons may be hard to find if they are placed in valleys in the landscape or if the landscape consists of a large amount of tiles. Therefore, pressing a button spawns colored beacons matching each icon (Fig. 6.14). The user may use this feature to quickly find design alternatives with best or worst performances.

6.2.6 Interrelationships between building aspects

Whereas the data analytics methodologies described in the previous chapters compare design alternatives, the correlation matrix compares building aspects. The correlation matrix is therefore not implemented in the landscape that is described

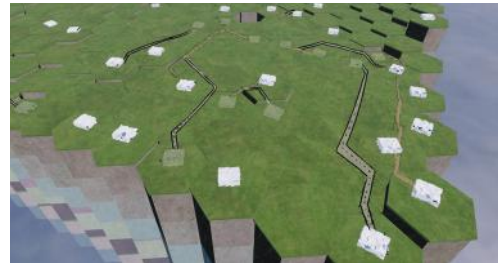


Fig. 6.12: Visualization of agglomerative hierarchical clustering as a road network.



Fig. 6.13: The pictogram chart is implemented in the Visual Analytics System by placing corresponding objects on the tiles.



Fig. 6.14: Beacons visualize design alternatives with best or worst performances.

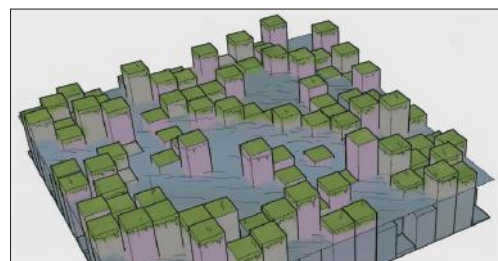


Fig. 6.15: Sketch showing how the correlation matrix may be the basis of a second landscape that is used to determine interrelationships between building aspects.

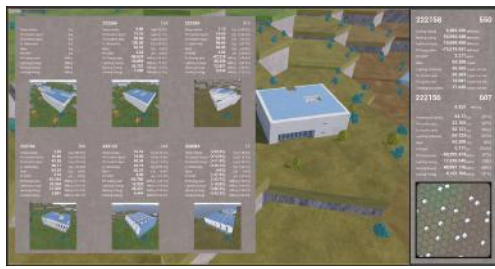


Fig. 6.16: Menu showing 6 design alternatives bookmarked by the user. Relative performances compared to the tile the user hovers over (currently tile #607) are automatically calculated.



Fig. 6.17: Users may control a character to walk through the landscape.

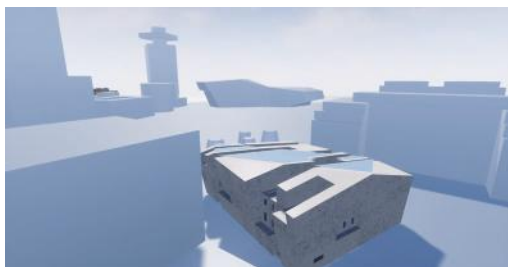


Fig. 6.18: Pressing a button spawns context geometry around a design alternative. Please note that the author envisions that the context geometry would have textures in a more developed version of the visual analytics tool.

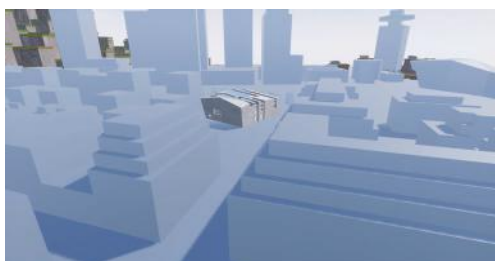


Fig. 6.19: Pressing a button spawns context geometry around a design alternative. Please note that the author envisions that the context geometry would have textures in a more developed version of the visual analytics tool.

thusfar. Instead, it is envisioned to be the starting point of a new landscape that is focused on comparing design aspects instead of design alternatives (Fig. 6.15). The two landscapes complement each other and are to be used side by side.

The correlation matrix forms the grid of a rectangular landscape. Each tile of the landscape corresponds to one cell of the matrix. The height of the landscape is based on the correlation coefficients, where the minimum height corresponds to the lowest correlation coefficient and the maximum height corresponds to the highest (positive or negative) correlation coefficient. Thus, hills of the landscape indicate strong correlation between building aspects and valleys indicate little to no correlation. A filter similar to the one described in chapter 6.2.2 facilitates quick determination of the most influential design aspects.

This landscape allows for implementation of additional data visualization methodologies that further facilitate analysis of design aspects. This, however, falls outside the scope of this research. Future research may investigate data analytics methodologies that further facilitate analysis of interrelationships between design aspects.

6.2.7 Additional gameplay features

Conjointly to data analytics methods various gameplay features are implemented to further accommodate substantiated decision-making. These features concern both quantified and non-quantified (architectural) performances.

A feature that further facilitates comparison between design alternatives is a bookmarks menu (Fig. 6.16). The user can add a number of design alternatives to the bookmarks. Relative performances between bookmarks and the tiles the user hovers over while flying around are automatically calculated. Bookmarks allow the user to document relevant design information extracted from the Visual Analytics System. Bookmarks in the Visual Analytics System are added with a single click of a button, encouraging a highly-interactive method of using bookmarks.

The main menu shows a mini-map of the landscape. Depending on user preferences this mini-map may be a photorealistic top-down view of the landscape or may visualize various data-related aspects in a stylized manner. An additional menu presents a larger version

of the mini-map. On each side of the mini-map a section of the landscape is presented. These sections show the soil layers of the landscape and thus give further indication of the relative performances of the landscape.

Various gameplay features accommodate analysis of architectural qualities. One such feature is the ability to walk around designs (Fig. 6.17). By default, the user of the Visual Analytics System flies around the landscape. Pressing a button changes the user's character from a flying camera to a human character, with which the user can walk through the landscape.

Another feature facilitates analysis of the designs' performance with regards to urban context (Fig. 6.18 & Fig. 6.19). Pressing a button spawns context geometry around the tile the user hovers over. Combined with the ability to walk around the designs as a human character, this gives greater sense of the scale of designs and of lines of sight and consequently provides a means to substantiate decision-making based on urban context.

6.3 DISCUSSION

The Visual Analytics System visualizes large data sets of multi-dimensional building information for design exploration and substantiation of the design process.

The Visual Analytics System is a highly interactive, game-like data environment. The Visual Analytics System uses the overarching concept of a 'rural landscape' to make use of data analytics technologies accessible to architects. Characteristics of the landscape correspond to various data analytics methods. Visualizations of the data analytic methods correspond to their functionality and loosely refer to performance objectives of the design assignment of this thesis. By 'terraforming' the landscape, users can influence visualization of data analytics method and can use this to reveal building information of interest. Additional gameplay features further accommodate data mining. Gameplay features include a bookmarks folder for comparison of selected design alternatives, the possibility to spawn context geometry for analysis of urban context and the possibility to walk through design alternatives in first person view.

Not implemented in the visual analytics tool is visualization of design aspects of each design alternative; current menus only show design performances. Visualization of design aspects in these menus - accompanying the VAS's visualizations of design geometries - may facilitate manual comparison between design alternatives to deduce interrelationships between design variables.

In summary, the VAS realizes simultaneous visualization of all data analytics methodologies of the Data Processing System. Together, these visualization techniques enable deduction of both quantified and non-quantified performances in a single environment. Exploration of the design space is encouraged because of high levels of interactivity. Easily understood metaphors for high-dimensional data enable intuitive analysis of building information.

CHAPTER 7: VALIDATION

This chapter validates whether the Computational Design System effectively facilitates performance-driven decision-making in the architectural design phase. The Computational Design System (CDS) is tested by various people to gain insight in the functionality of the various aspects of the CDS. It should be noted that, because of the author's limited coding experience, the agglomerative hierarchical clustering and analytic hierarchical process are not integrated in the visual analytics tool developed in this thesis. The visual analytics tool integrates all other data analytics methods as described in Chapter 6.

Chapter 7.1 elaborates on the author's use of the Computational Design System. This chapter sets out the full workflow of the CDS used to design a nearly

Zero-Energy sports Hall, describes how the author uses the Visual Analytics System to explore design alternatives and presents the author's notes based on his experience with the Visual Analytics System.

Chapter 7.2 presents a peer review performed by an MSc Architecture student. This peer review verifies the performance of the Visual Analytics System and the Computational Design System as a whole.

Chapter 7.3 describes the results of a questionnaire held among students in the field of architecture, climate design and computational design. This questionnaire gives insight in the functionality of the data analytics methods of the Visual Analytics System and quantifies whether the Computational Design System contributes to improvements in design performances.

7.1 USE OF THE CDS TO SUBSTANTIATE THE DESIGN PROCESS

The CDS is developed through several iterations. This chapter describes the final iteration of the CDS and describes the author's use of the CDS to facilitate his design process of the sports hall.

Chapter 7.1.1 elaborates on the data workflow of the CDS.

Chapter 7.1.2 describes the author's use of the Visual Analytics System. This chapter illustrates how

the author envisions the use of the various data analytics methods implemented in the Visual Analytics System. Hence, this chapter, conjointly to the peer review and questionnaire (presented in chapter 7.2 and 7.3 respectively), verifies whether the intended means of interaction with and interpretation of the data analytics methods are suitable.

Chapter 7.1.3 presents the author's notes based on his experience with the Computational Design System.

7.1.1 Data workflow

7.1.1.1 Iterative Design System

Traditional architectural design processes often explore multiple design concepts. Similarly, the data set of the CDS consists of design alternatives generated with all five parametric models described in chapter 3.3.

The Iterative Design System (IDS) is used to generate >100 design alternatives of the 'orthogonal mass' parametric model, >100 design alternatives of the 'zigzag' geometry and 60 design alternatives of the 'non-orthogonal mass' geometry. Since the author has limited coding experience and is inexperienced with performance optimization in the Unreal Engine,

performance of the visual analytics tool developed in this thesis decreases when the size of the data set exceeds 200 design alternatives. Therefore, only 50 design alternatives of the 'orthogonal mass' geometry and of the 'zigzag' geometry are presented in the Visual Analytics System. Using Excel, the best 50 design alternatives of both typologies are found (based on the sum of normalized performances).

Of the 'non-orthogonal mass' geometry 60 design alternatives are generated and presented in the Visual Analytics System.

Since the Voronoi and Delaunay geometries had substantial influence on the design process, they

are represented in the landscape by a selection of 5 design alternatives of both models that are included in the data set.

Finally, three ‘manually constructed’ designs are included (courtesy of L. Pol) (Fig. 7.1). These designs are made in Rhino. Geometries are loaded in Grasshopper and simulations are run as usual using the Performance Analysis System. In summary, the data set consists of the following design alternatives:

- 60 ‘Non-orthogonal mass’ geometry
- 50 ‘Orthogonal mass’ geometry
- 50 ‘Zigzag’ geometry
- 5 Voronoi geometry
- 5 Delaunay geometry
- 3 Manually constructed designs

For the IDSs of the first three building definitions, the non-destructive evolutionary algorithm uses a population size of 15. With a total amount of 100> design alternatives, Octopus generated at least 7 generations for each parametric model, which is estimated to be sufficient to be able to slightly converge towards optimal design solutions. A population size of 15 is fairly modest and chances are that areas of the design space are not covered by the initial population. The IDS therefore uses a high mutation rate of 0.8, so that mutated design variations are considerably different from their predecessors and therefore are able to cover the previously missed areas of the design space. The settings used in Octopus are summarized below:

Elitism: 0.500
Mutation probability: 0.750
Mutation rate: 0.800
Crossover rate: 0.800
Population size: 15-20

The ten performance objectives described in Chapter 4 and listed in Fig. 7.2 are used by the Octopus to determine fitness of each design alternative. Building information and design geometries are exported to CSV and FBX files using the methods described in chapter 3.2.2.

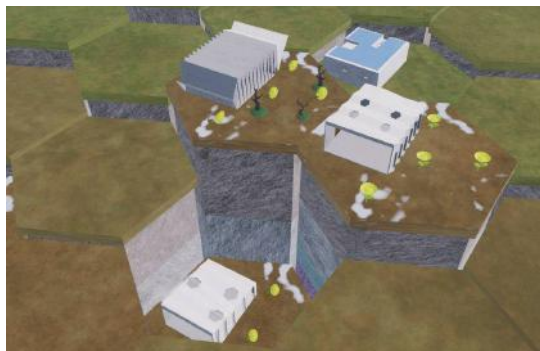


Fig. 7.1: Three manually constructed designs (courtesy of Pol, L.) and one ‘orthogonal mass’ geometry in the VAS.

7.1.1.2 Data Analytics System

The data set generated with the IDS is used to generate the Self-Organizing Map. The Self-Organizing Map (SOM) is generated in ModeFrontier and exported as a CSV file. The SOM used in this thesis makes use of a hexagonal grid of 28*28 cells for a total amount of 784 cells. This corresponds to a ratio of 4.6 cells to each design alternative. Both geometric and performance aspects are used to determine topology preservation between design variables. The aspects used by the SOM are listed in Fig. 7.2.

ModeFrontier is also used to generate correlation matrices. One correlation matrix uses the data set consisting of the design alternatives generated using the ‘non-orthogonal mass geometry’, ‘orthogonal mass geometry’ and ‘zigzag geometry’ parametric models. Three other correlation matrices use the building data of only one of each of these types. The correlation matrices are presented in Appendix H.

Using Excel, seasonal performances of the design alternatives are calculated from hourly performance values. This is used to classify tiles that contain design alternatives with the decision tree.

CSV files of the design variables and performance values of the design alternatives and of the cells of the SOM are copied to a designated folder that is read by the Unreal Engine. At first boot the Unreal Engine imports these CSV files and uses them to assign each design alternative to the cells of the SOM. This information is also exported to a CSV file for later use.

Floor area (m²)
Volume (m³)
Total façade area (m²)
Orientation (°)
PV Panel area (m²)
Total north-oriented window area (m²)
Total east-oriented window area (m²)
Total south-oriented window area (m²)
Total west-oriented window area (m²)
Total sky-oriented window area (m²)
Insolation north-oriented windows (hrs/yr)
Insolation east-oriented windows (hrs/yr)
Insolation south-oriented windows (hrs/yr)
Insolation west-oriented windows (hrs/yr)
Insolation sky-oriented windows (hrs/yr)
Cooling energy demand (kWh/yr)
Heating energy demand (kWh/yr)
Lighting energy demand (kWh/yr)
PV energy gain (kWh/yr)
PV EPBT (yrs)
Glare (%/year not met)
Lighting uniformity (%/year not met)
Thermal comfort spectators (%/year not met)
Thermal comfort sports players (%/year not met)
Temperature criteria (%/year not met)

Fig. 7.2: Building aspects used to generate the Self-Organizing Map.

7.1.2 Design exploration in the visual analytics tool

This chapter describes the author's use of the Visual Analytics System to draw design conclusions. This chapter follows the author's process of using the visual analytics tool.

Starting the visual analytics tool generates the landscape and positions the player character above the landscape, providing a bird's eye view of the entire design space. The author firstly flies around the landscape to inspect the data set. A few erroneous design alternatives are immediately noticeable; incorrect building geometries and jumps in the landscape's heights suggest defects in the generation or simulation of these design alternatives (this is known by the author; because of the complexity and computational expensiveness of the Grasshopper definition, lag spikes caused a few design alternatives to fail. Most are manually removed through data mining in Excel). Aside from these erroneous design alternatives, the large majority of the design space shows predictable and accurate results. Naturally, erroneous design alternatives are ignored in the design exploration process.

Groupings of design alternatives with similar performances are firstly derived, using various methods. Data classification, visualized by the grass type in the landscape, gives an immediate overview of the total energy demands within the design space. The tool shows that a large amount of design alternatives are Zero-Energy or nearly Zero-Energy buildings. Use of the stacked bar graph in conjunction with the water filter quickly reveals areas of the design space with best and worst performances. Setting the scale factor of all but one performance objective to zero reveals areas of the design space with best and worst performances for that performance objective. The U-matrix shows clusters of similar design alternatives. The three main parametric models quite clearly form three distinctive clusters. Varying threshold values and the icons that are spawned correspondingly further visualizes groupings of design alternatives with similar performances.

The U-matrix shows that the parametric models quite clearly form distinctive clusters (Fig. 7.3). The stacked bar graph and the U-matrix show that designs generated with the 'orthogonal mass' model are generally similar, whereas differences between designs generated with the 'non-orthogonal mass' model are largest. The aforementioned methods of exploration show that design alternatives generated with the 'zigzag' parametric model have best overall performance. These design alternatives generally have high energy and lighting uniformity performances. Most of the designs generated with

the 'zigzag' parametric model are Zero-Energy buildings. Nearly half of the designs generated using the 'orthogonal mass' form a clearly distinguishable cluster of similar design alternatives (Fig. 7.4). These designs all have worst lighting uniformity and lighting energy performances of the data set. On the other hand, designs generated with the 'orthogonal mass' model have generally high PV energy gain and EPBT performances. Design alternatives generated with the 'non-orthogonal mass' model show greatest variation in performances.

Quick analysis of clusters provides a general idea of the range of performances of the design space. Performances of areas of the design space are now analyzed more in-depth, by using the stacked bar graph and pictogram charts to visualize design's performances and by using the correlation matrix to find interrelationships between design variables and performances. Because the three main parametric models form distinctive clusters, these groups are analyzed independently.

The design alternatives that are generated from the 'zigzag' parametric model are generally well-performing in terms of glare, lighting uniformity and energy demands (Fig. 7.5). A likely cause of the relatively low energy demands of these design alternatives is that the parametric model generally generates designs with low volume and low wall area; the correlation matrix indicates that there is a strong interrelationship between the heating energy and building volume (+0.83) and total façade area (+0.88). Remarkably, the correlation matrix also shows strong correlation between the heating energy and floor area (-0.92). It should be noted that these factors may be influenced by causation. Correlation between heating energy and floor area, for example, may be caused by the fact that the 'non-orthogonal mass' design alternatives have consistently low floor areas and high building volumes. It is expected that the designer's expertise is used to validate these correlations.

The 'orthogonal mass' design alternatives are the designs with best thermal performances. The correlation matrix shows that thermal performances have high correlation with cooling energy. The area of sky-oriented windows also has large influence on the thermal performances; increasing the window area decreases thermal performances. Both interrelationships suggest overheating in summer. Inspection of hourly simulation values show that this is indeed the case.

The 'non-orthogonal mass' designs generally have the lowest cooling energy demands and have above-average thermal comfort performances and lighting uniformity. Furthermore, they have the highest

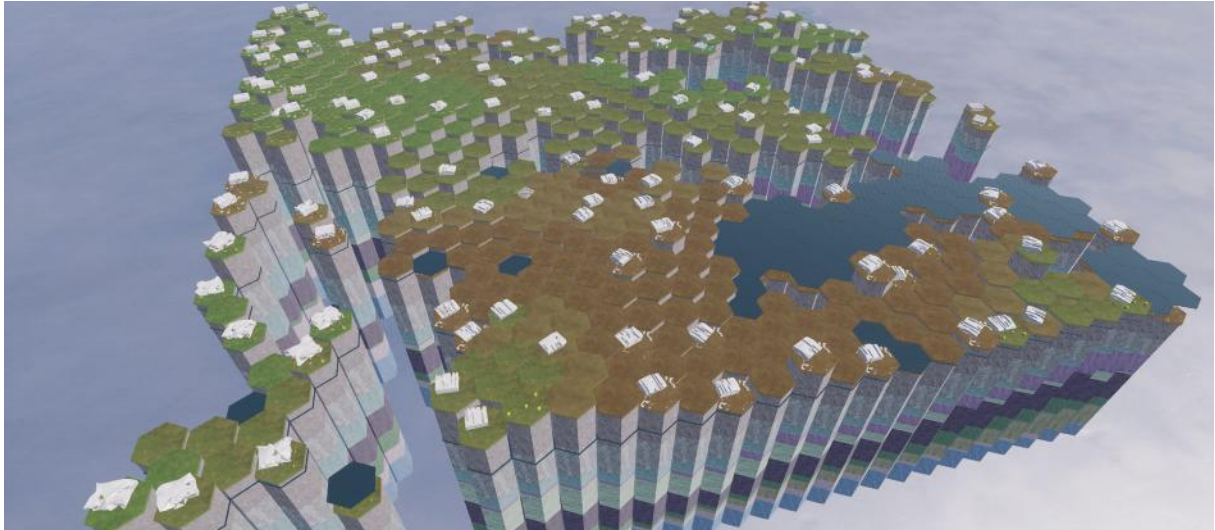


Fig. 7.3: The U-matrix, decision tree, stacked bar graph and water filters show clearly distinguishable clusters corresponding to the parametric model used in the Iterative Design System.

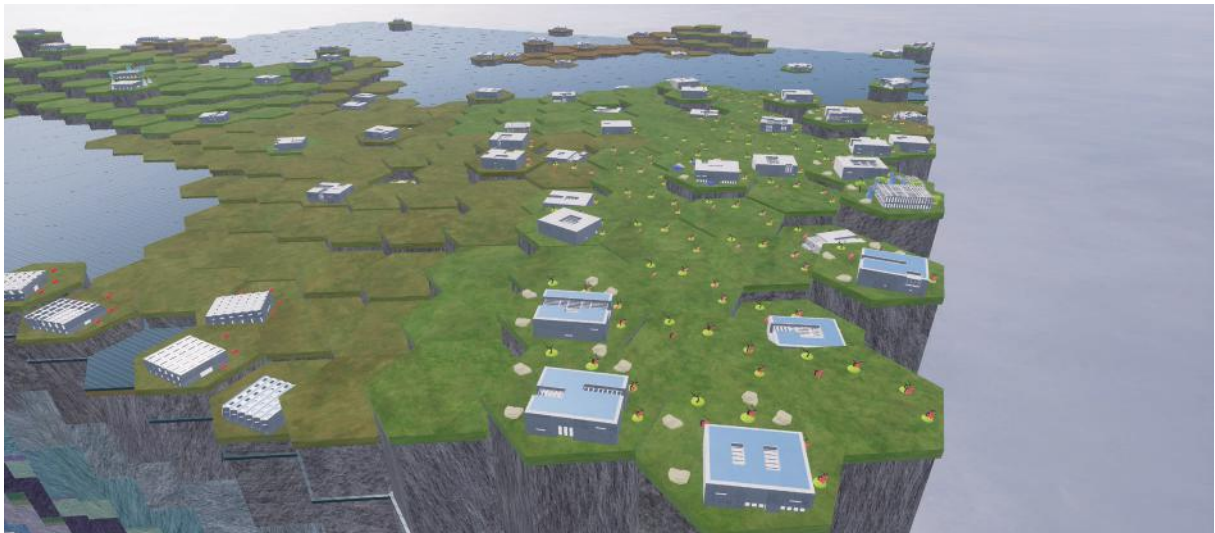


Fig. 7.4: Cluster of similar design alternatives made with the 'orthogonal mass' parametric model.

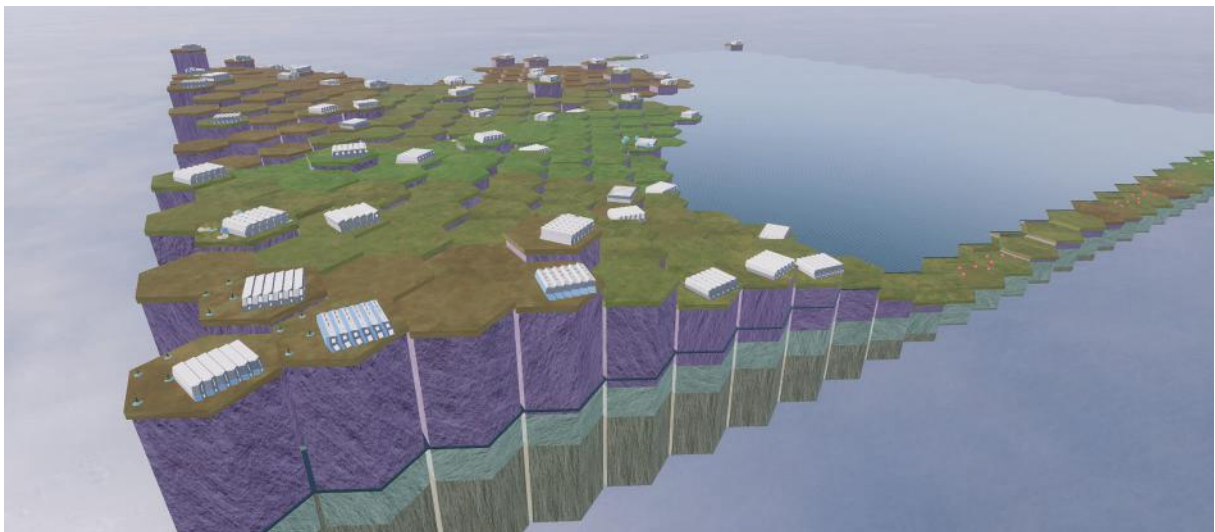


Fig. 7.5: The stacked bar graph shows that designs made with the 'zigzag' parametric model have best lighting performances.

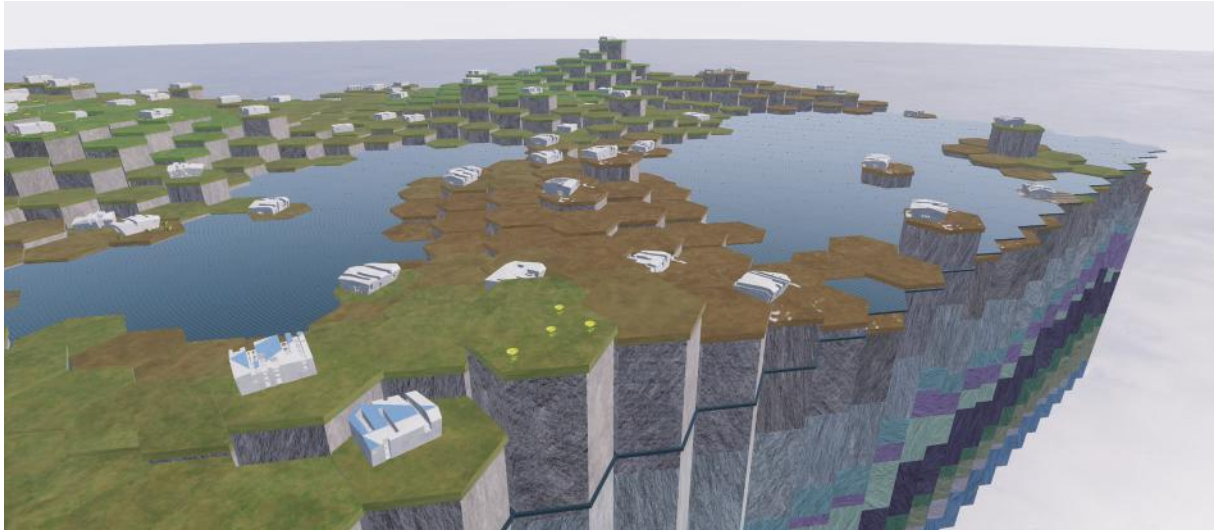
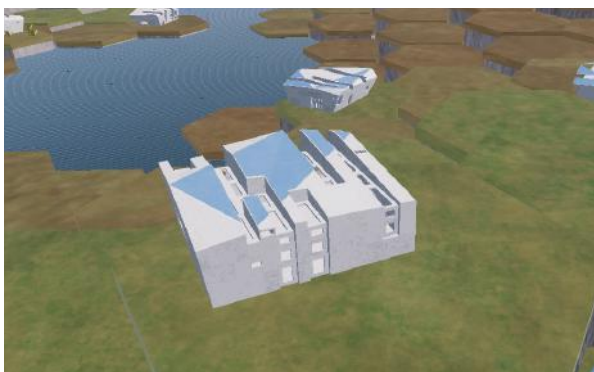
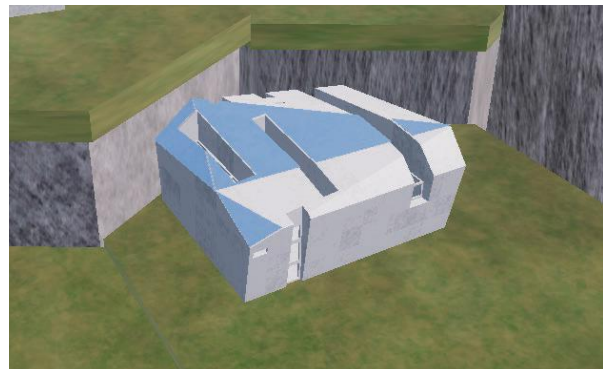
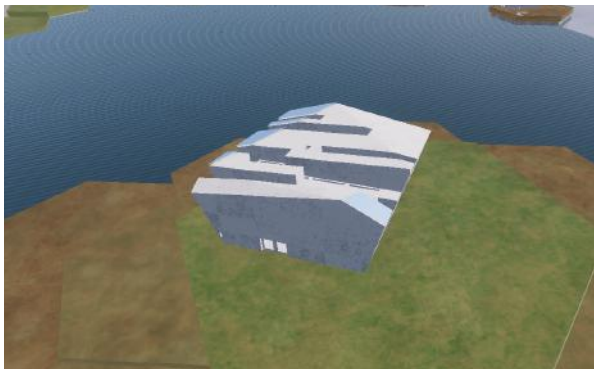
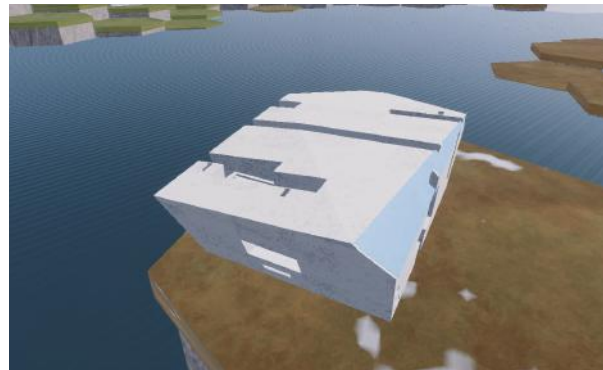
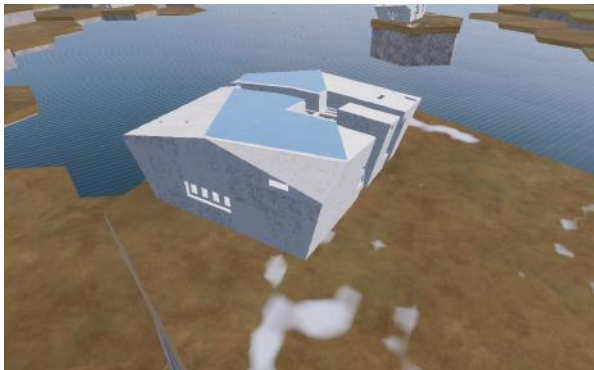


Fig. 7.6: The stacked bar graph and water filter shows peaks of well-performing design alternatives made with the 'non-orthogonal mass' parametric model.



| | | | | | | |
|-------------|-------|-------|-------|-------|-------|--------|
| Co. Energy | 3520 | 2579 | 3766 | 3299 | 2032 | kwh/yr |
| He. Energy | 77897 | 80118 | 82030 | 71339 | 74436 | kwh/yr |
| Li. Energy | 22561 | 22357 | 19249 | 28530 | 29330 | kwh/yr |
| PV Energy | 42753 | 32847 | 80945 | 73392 | 87216 | kwh/yr |
| PV EPBT | 4.8 | 4.4 | 3.2 | 4.5 | 4.1 | yr |
| Glare | 60.2 | 61.8 | 61.8 | 58.8 | 59.7 | %/yr |
| Li. Unif. | 77.7 | 76.9 | 68.5 | 93.7 | 96.6 | %/yr |
| ThCmf.Spec. | 53.7 | 55.1 | 56.2 | 52.6 | 51.0 | %/yr |
| ThCmf.Spnt. | 16.4 | 15.3 | 16.9 | 16.0 | 14.5 | %/yr |
| Temp.Crit. | 6.5 | 3.7 | 8.0 | 5.7 | 1.1 | %/yr |

Fig. 7.7: A few selected design alternatives using the 'non-orthogonal mass' model with above-average performances. Performances of the four presented designs are shown in the table below, in order of appearance

architectural qualities, according to the author. Conversely, these designs have generally high heating energy demands, likely due to high building volumes and exterior wall areas, and have below-average glare and lighting performances. A correlation matrix of the design data of the 'non-orthogonal mass' (Appendix H) suggests that glare and lighting performances can be improved by increasing the area of the sky-oriented windows. Heating energy demand can be reduced by reducing the building volume. As described above, variance between 'non-orthogonal mass' designs is relatively high. Correspondingly, difference in design performances is high. A few designs generated using the 'non-orthogonal mass' model have generally high performances, though their overall performances are slightly lower than some other designs in the simulated design space (Fig. 7.6 & Fig. 7.7).

Quantified performances are of varying influence on the exploration process. Heating, cooling and lighting energy demands as well as glare and lighting uniformity are very relevant and influential factors of performance-driven decision-making. These performance objectives largely depend on the building geometry and can therefore be optimized in conjunction with architectural design. The energy gain and energy payback time of the PV panels has less influence on the decision-making process. These performances have relatively low influence on building geometry and that in most design alternatives the energy potential of the PV panels satisfies the requirements and EPBT is acceptable (<4 years). Furthermore, their behaviour is very predictable. In the very early design phase, a general idea of the required area of the PV panels is therefore sufficient to

inform the decision-making process. Thermal comfort performances provide the least information for the decision-making process. The decision-making process is least influenced by thermal comfort performances. Due to lack of causation between building geometry and thermal comfort performances, thermal comfort performances provide little relevant information of trade-offs in building geometry.

The CDS is not used to select a single best design. Instead, the author uses the CDS to discover building information that can be used to inform the architectural design process. The following steps in the design process describe how the CDS informs the decision-making process and how it would be a continuously integrated aspect of the design process:

Despite the fact that they generally have less overall performance, the 'non-orthogonal mass' designs are chosen as the starting point of the new design alternatives for its architectural qualities. However, the building volume is significantly reduced to reduce energy demands and sky-oriented windows are introduced for more equal light distribution. Based on the generally high lighting performances of the 'zigzag' model, windows are distributed more evenly. The parametric model can be changed accordingly. Rerunning the Iterative Design System provides a new set of design alternatives that are more similar and have generally higher performances. Alternatively, design alternatives can be manually constructed in Rhino, simulated with the Performance Analysis System and appended to the Visual Analytics System. These new designs can be assigned to (empty) tiles that do not present relevant information.

7.1.3 Discussion

This chapter summarizes the author's experience with the Computational Design System to facilitate the design process of a sports hall. The author's experience with the visual analytics tool shows that the data analytics methods that comprise the landscape function well and facilitate quick extraction of design results. The Visual Analytics System is useful in showing areas of the design space with similar performances. Therefore, the Visual Analytics System can be used effectively to compare design concepts. Furthermore, the Visual Analytics System can be used to quickly retrieve design alternatives with optimal performances, thus facilitating selection of the 'best' design alternative.

Discerning interrelationships between design aspects and building performances is difficult, both when manually comparing design alternatives and

using the correlation matrices. Difficulties of manually comparing design alternatives stem from the large amount of design variables. This makes it difficult to attribute influences on building performances to design aspects. The primary difficulty in use of the correlation coefficient matrices is that correlation matrices do not show clear and predictable correlations between design aspects. Most correlation coefficients in the correlation matrices are smaller than 0.5 (and bigger than -0.5). In other words, aside from a few exceptions, correlation between building aspects is small. Therefore, it is hard to determine design improvements. Improving the selection of building aspects used in the correlation matrix might increase its functioning and suitability to facilitate the design process. Decreasing the amount of design variables or increasing the amount of simulations run for each

parametric model will lead to a greater similarity between design alternatives and may therefore improve deduction of performance-influencing design aspects.

This chapter gives a preview of the potential of use of the Computational Design System integral to the design process in a back-and-forth process of design and reflection. The data workflow described in chapter 7.1.2 illustrates that the data flow between subsystems

is simple and flexible. Use of CSV files makes appending design alternatives to the data sets used by the Visual Analytics System easy. An added benefit of using the Computational Design System integral to the design process is that the Visual Analytics System grows into a documentation of the design process. This enables users to keep track of design improvements and to use their data set of design alternatives as a frame of reference for their most recent design.

7.2 PEER REVIEW OF VISUAL ANALYTICS SYSTEM

7.2.1 Introduction

User experience is an important criterion in the functionality of the Visual Analytics System; the Visual Analytics System should be an efficient and effective tool for goal-oriented design exploration and designers should feel encouraged to use it during their design process. Therefore, an early version of the visual analytics tool is reviewed by Lucas Pol, an MsC Architecture student at TU Delft. Use of the visual analytics tool by Pol verifies whether the Computational Design System suits the early architectural design process and whether the visual analytics tool and its data analytics methodologies effectively facilitate substantiating design decisions. Furthermore, this peer review tests whether the means of deriving performance information are effective and intuitive.

7.2.2 Methodology

Prior to testing the visual analytics tool, Pol made a sketch design of the sports hall, largely based on urban context- and architecture-related performance criteria. The main argumentation and design decisions of the sketch design are presented in Appendix G. Pol aims to use the visual analytics tool as a means to guide his design process to improve design performances.

Simulated building performances of the sketch design are presented in Fig. 7.8. A comparison between performance analyses of the sketch design and of a design made after the use of the visual analytics tool indicates whether the design's performances are improved. The design alternatives generated by the Iterative Design System thus are used as a means to derive performance-influencing building aspects in order to improve the initial sketch design. A short explanation of the principles, application, visualization

| | <i>Sketch design</i> | |
|--------------|----------------------|--------------|
| Co. Energy | 8049 kwh/year | 9126 kwh/yr |
| He. Energy | 48947 kwh/year | 49576 kwh/yr |
| Li. Energy | 30311 kwh/year | 29154 kwh/yr |
| PV Energy | 20989 kwh/year | 20958 kwh/yr |
| PV EPBT | 2.92 years | 2.92 yrs |
| Glare | 61.3 %/year not met | 63.3 %/yr |
| Li. Unif. | 42.4 %/year not met | 42.8 %/yr |
| ThCmf.Spec. | 9.9 %/year not met | 52.6 %/yr |
| ThCmf.Sprrt. | 15.4 %/year not met | 24.7 %/yr |
| Temp.Crit. | 0.77 %/year not met | 30.6 %/yr |

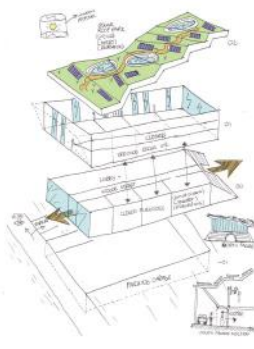


Fig. 7.8: Simulated performances of Lucas's sketch design developed before use of the visual analytics tool. Performance values are derived with an early version of the PAS and may therefore show inaccurate results. The performance values shown on the right are simulated with the final version of the PAS.

and means of interaction of the data analytics methodologies used in the visual analytics tool is presented to Pol before testing. This information is meant to have a similar level of detail to user manuals of commercial computer programs.

This peer review is performed with an early version of the visual analytics tool. The tool visualizes a data set that consists of 125 design alternatives generated using the parametric model described in chapter 3.3.2 and 25 designs generated using Voronoi tessellation (chapter 3.3.1). The data set is generated using an

early version of the Performance Analysis System. Because of errors in the thermal analysis component of this version of the Performance Analysis System, heating and cooling energy performances and thermal performances differ slightly from actual values. This was not known at the time of testing.

Data analytics methods implemented in the version of the visual analytics tool used in this peer review are the Self-Organizing Map and the Stacked Bar Graph. The visual analytics tool did not facilitate setting thresholds of performance aspects. The Self-Organizing Map consists of $(28 \times 28 =) 728$ cells.

7.2.3 Results

This subchapter firstly describes Pol's use of the visual analytics tool. Then, the design decisions made following the use of the tool are listed. Finally, simulations of the two designs are compared.

Pol firstly flew around the landscape to get a feel of the means of interaction with the visual analytics tool, comparing performances between design alternatives. Observation of buildings on hills and in valleys of the landscape gave a preliminary indication of performance-influencing design variables. The 'water' filter facilitates quick determination of best- and worst-performing designs.

Pol used a manual approach to investigate interrelationships between design variables and performance aspects using the following method. First, he scaled every performance of the stacked bar graph to zero, resulting in a completely flat landscape. Then, one by one, the scale factor of each performance objective is set to one while the scale factors of other performance objectives remain zero. As a result, the height of the landscape shows the relative performances between design alternatives of that performance objectives. Performance-

influencing design variables were derived by analyzing the (~20-30) buildings on the hills and in the valleys of the landscape. This educated Pol about building performances and corresponding design variables. Pol documented his conclusions on the design variables that has most influence on each performance objective. Notes on changes of the sketch design are listed in Fig. 7.9.

These conclusions are considered in the subsequent design process and are used to improve the sketch design. The subsequent design process resulted in two slightly different design alternatives; one without windows on the east façade and one with small windows on the east façade. Building performances of these designs are presented in Fig. 7.10. The simulations show considerable improvements of thermal performances. Cooling energy demand is also improved, which is in line with Pol's goal of reducing overheating. On the other hand, the design changes increase heating energy demand. Furthermore, despite the fact that Pol's design decisions were aimed to improve glare and solar uniformity, lighting performances are largely unaffected.

- *"The design is changed based on design variables that influence each or most of the performance objectives.*
- *Fins are introduced on the west façade. The east façade has an opaque character because spectator stands are on this side of the sports hall.*
- *The previously ascending roof geometry is changed to create 'hills', so that parts of the roof are oriented towards the north. The roof height is lowest on the south-west corner and highest on the north-east corner.*
- *The geometry of the south side is designed to cover the windows of the south façade to prevent glare and overheating.*
- *Since they amount little to daylight, the sizes of the windows in the east, south and west façades are decreased to account for issues like glare and overheating."*

Fig. 7.9: Notes on changes of the sketch design after use of the visual analytics tool (L. Pol, personal communication, October 21, 2017)

| | Improved design #1 | | | | |
|-------------|--------------------|--------|---------|-------|--------|
| Co. Energy | 6364 | kwh/yr | (-21%) | 6437 | kwh/yr |
| He. Energy | 49156 | kwh/yr | (+0.4%) | 54061 | kwh/yr |
| Li. Energy | 30311 | kwh/yr | (0%) | 28925 | kwh/yr |
| PV Energy | 52147 | kwh/yr | (+148%) | 52147 | kwh/yr |
| PV EPBT | 3.22 | yr | (+10%) | 3.22 | yr |
| Glare | 63.3 | %/yr | (+3%) | 0.0 | %/yr |
| Li. Unif. | 42.3 | %/yr | (-0.3%) | 42.5 | %/yr |
| ThCmf.Spec. | 7.9 | %/yr | (-21%) | 54.2 | %/yr |
| ThCmf.Spnt. | 13.7 | %/yr | (-11%) | 20.4 | %/yr |
| Temp.Crit. | 0.37 | %/yr | (-52%) | 20.0 | %/yr |
| | Improved design #2 | | | | |
| Co. Energy | 4773 | kwh/yr | (-41%) | 6299 | kwh/yr |
| He. Energy | 55449 | kwh/yr | (+13%) | 58035 | kwh/yr |
| Li. Energy | 30540 | kwh/yr | (0%) | 28925 | kwh/yr |
| PV Energy | 52147 | kwh/yr | (+148%) | 52147 | kwh/yr |
| PV EPBT | 3.22 | yr | (+10%) | 3.22 | yr |
| Glare | 61.4 | %/yr | (+0.1%) | 0.0 | %/yr |
| Li. Unif. | 42.5 | %/yr | (-0.2%) | 42.6 | %/yr |
| ThCmf.Spec. | 5.3 | %/yr | (-47%) | 54.5 | %/yr |
| ThCmf.Spnt. | 7.7 | %/yr | (-50%) | 20.5 | %/yr |
| Temp.Crit. | 0.06 | %/yr | (-679%) | 19.6 | %/yr |

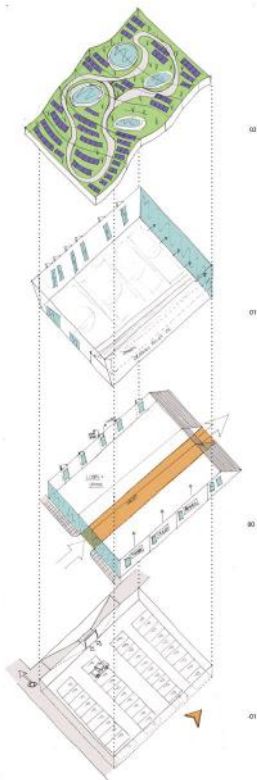


Fig. 7.10: Simulated performances of Lucas's improved design developed after use of the visual analytics tool. Performance values are derived with an early version of the PAS and may therefore show inaccurate results. The performance values shown on the right are simulated with the final version of the PAS.

7.2.4 Discussion

This chapter presents Pol's conclusions on his experience with the visual analytics tool. Firstly, his conclusions related to the Iterative Design System are presented in chapter 7.2.4.1. These substantiate whether the Iterative Design System suits the design process followed by Pol. Conclusions with regards to the Data Analytics System are presented in chapter 7.2.4.2. The final subchapter presents Pol's suggestions to improve the visual analytics tool.

7.2.4.1 Suitability of the Iterative Design System to facilitate the design process

"I have not discovered any notable discrepancies between design assumptions made for the sketch design and the buildings generated by the Computational Design System. An explanation might be that I already took certain designs aspects into account, like building orientation, sloping of the roof towards the south and the placing of windows in a specific place or not.

Going through all the different aspects and noting the most influential design variables, in terms of both the visual impact and the performance values, seemed to steer the design in the right direction, climate wise.

During use of the visual analytics tool it became apparent that the differences between design alternatives are small. Though some performances differed a lot, design alternatives did not show interesting and useful results with regards to architectural qualities.

Since there was not a lot of contrast between different design alternatives, they don't have a lot of impact on the design in this stage of the design process. Greater differences between design alternatives would increase the contrast between the designs' performances. This would improve the ability to find interrelationships between design variables and performances. In the early conceptual design stage this could help define the main building shape in combination with considerations regarding architectural design-related performances, such as urban context. In later design stages the variation between designs could be smaller to analyze whether certain small differences influence building performances." (L. Pol, personal communication, October 21, 2017).

7.2.4.2 Suitability of the Data Analytics System to facilitate performance-driven decision-making

“The visual analytics tool generally worked quite well. The hill landscape makes it easy to read the data set as a whole and facilitates finding clusters of design alternatives that have similar performances. Related to this, the soil layers make it easy to find the most influential design variables for each performance objective. Flooding of the island by using the water filter helped me to focus on best and worst designs.

Features that could improve the tool in terms of operability, according to my findings, are the following. Firstly, the use of bookmarks could help compare different results. This option would show more than two results. Secondly, the colors of the visual analytics tool appeared a bit dim. Increasing the lightness or contrast could improve reading it a lot. Lastly, the visual analytics tool would benefit from the possibility to set maximum and a minimum values as a filter. This way, relative performances will be shown more clearly according to the user’s desired performance criteria and design considerations.” (L. Pol, personal communication, October 21, 2017).

7.2.4.3 Suggestions for future improvements

“The following features could be implemented to improve operability of the software, though they may not necessarily fall within the scope of this graduation research.

Highlighting selected buildings could further benefit visualization of design alternatives. The user would click on a tile of the visual analytics tool and the tile would be extruded from the ground, similar to the visualization of agglomerative hierarchical clustering in the Visual Analytics System. Performance values can be projected on their respective soil layers, so that they are visualized in the display port. Computer games have similar features. An example is Rome II: Total War, where selected units are highlighted (Fig. 7.11). The use of highlights could also be used to export data visualizations for presentations or discussions with clients.

Another feature could be to visualize the size of, for example, the HVAC system in or besides a building, in order to accurately define the space required within the design.” (L. Pol, personal communication, October 21, 2017).



Fig. 7.11: Units highlighted in Rome II: Total War (Valve Corporation, n.d.).

7.3 QUESTIONNAIRE

7.3.1 Introduction

The Visual Analytics largely depends on intuition to facilitate extraction of building information. However, people have different means of interpreting information, so ‘intuition’ is subjective. The questionnaire presented in this chapter provides further validation of the functioning of the Computational Design System and the Visual Analytics System. The questionnaire substantiates (1) whether a design process supported by a Computational Design

System leads to better-performing designs than designs made using traditional design processes and (2) whether the Visual Analytics System as a whole and whether its individual features support the design process of architects.

7.3.2 Methodology

The questionnaire consists of two main parts. In the first part the participant is asked to optimize a sports hall design using a parametric model of the sports hall design. By changing the design’s orientation, volume, window sizes and other factors the participant attempts to optimize the design based

on their expertise in the field of performance-driven architectural design. This method aims to approximate traditional design processes, where optimization in the early design stages depends on non-quantified trade-offs. In the second part the participant is asked to use the visual analytics tool to find an ‘optimal’

design solution in a data set of design alternatives. Both parts of the questionnaire use the 'zigzag' parametric model, since it uses the least amount of design variables and is therefore easiest to control in the manual optimization process. Quantified performances of the first design are not known to the participant during either part of the questionnaire.

Building performance simulations of both designs are compared to indicate whether the visual analytics tool effectively leads to better-performing design alternatives. Questions about the decision-making process during both optimization processes

indicate whether the participants are more confident in their decision-making processes when using the visual analytics tool. The questionnaire also includes questions about the data analytics methods implemented in the Visual Analytics System. These questions give an indication whether the data analytics methods contribute to performance-driven decision-making with the Visual Analytics System. Finally, questions are asked about whether the participant thinks that the visual analytics tool is an effective tool to facilitate performance-driven decision-making. The questionnaire is presented in Appendix I.

7.3.3 Results

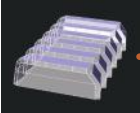

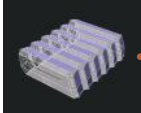

The questionnaire is held among 5 MSc Architecture and MSc Building Technology students and 3 participants with no experience in the fields of architectural design and data analytics. The latter group gives further insight in whether the features of the Data Analytics System facilitate intuitive decision-making. Participants' individual ratings and written responses are presented in Appendix J.

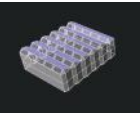

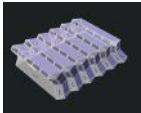

Fig. 7.12 shows simulation results of the participants' designs selected in either part of the questionnaire. Comparison of performance values of the two designs shows that overall design performance of the design selected in the visual analytics tool is generally slightly higher than the one manually optimized. Each participant was able to improve at least half of the quantified performance objectives. The figure suggests that participants are generally able to select designs of which performances that they consider most important are improved.

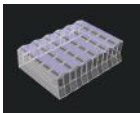

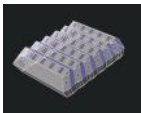
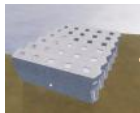
An interesting observation is that participants made use of the visual analytics tool in different ways. Some participants focused highly on climate-related performances, whereas others focused on comparison of architectural designs. Participants used different features of the visual analytics tool to assist their decision-making process. One Architecture student argued that the architectural concept (design vision) developed during the manual optimization process would be lost when selecting any other design of the visual analytics tool. Instead, this participant used the visual analytics tool to verify the design made during the first part of the questionnaire. For this participant the visual analytics tool functioned as a frame of reference in the design process.

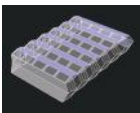
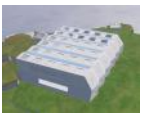
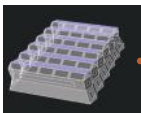

Fig. 7.13 shows the average level of confidence of aspects of the design processes rated by participants with experience in the field of architecture. Qualitative answers are quantified, where a rating of 1 corresponds to 'Strongly disagree' and a rating of 5 corresponds to 'Strongly agree'. The figure shows that participants with experience in the field of architecture are slightly more confident about their design process when using the CDS, compared to traditional design processes. Confidence in determining priorities among performance objectives is higher when using the CDS, compared to traditional design processes. They are also more confident that the optimal design solution is found with the use of the CDS than in traditional design process. Conversely, substantiation of design decisions is deemed better when using traditional design processes. Participants with experience in the field of architecture are most confident that they found the optimal design solution when they are using the manual optimization process. A possible explanation is that participants have full control over design geometry using this method.

Fig. 7.14 shows confidence ratings of all participants. Ratings are largely similar to ratings presented in Fig. 7.13, with two exceptions. Fig. 7.14 shows that participants are more confident that use of the CDS involves well-determined priorities among performance objectives compared to traditional design processes. Furthermore, participants are more confident that use of the CDS leads to optimal design solutions. Evidently, participants with no experience in the field of architecture are significantly more confident in their decision-making when using the CDS.

| Student Architecture | | | | | | Student Architecture | | | | | |
|-----------------------|---|---|---|--|--|---|---|---|--|--|--|
| |  |  | | | |  |  | | | | |
| Co. energy (kwh/yr) | 7138 | 4003 • | - | | | 8164 | 6217 | - | | | |
| He. energy (kwh/yr) | 32696 | 20471 | - | | | 34769 • | 18997 | - | | | |
| Li. energy (kwh/yr) | 19384 • | 29340 | + | | | 15402 | 25470 | + | | | |
| PV energy (kwh/yr) | 177659 • | 15028 | - | | | 137221 | 135886 | - | | | |
| PV EPBT (yrs) | 3.9 | 5.3 • | + | | | 3.1 | 3.8 | + | | | |
| Glare (%/yr) | 63.3 | 61.8 | - | | | 63.3 | 61.8 | - | | | |
| Li. Uniformity (%/yr) | 68.6 | 99.2 | + | | | 57.9 • | 85.0 | + | | | |
| Th.cmf. spec. (%/yr) | 50.5 | 42.7 | - | | | 51.3 | 44.1 | - | | | |
| Th.cmf. sprt. (%/yr) | 21.6 | 19.0 | - | | | 22.3 | 22.1 • | - | | | |
| Temp. Criteria (%/yr) | 20.3 | 5.2 | - | | | 25.2 | 16.9 • | - | | | |

| Student Building Technology | | | | | | Student Building Technology | | | | | |
|-----------------------------|---|---|---|--|--|---|---|---|--|--|--|
| |  |  | | | |  |  | | | | |
| Co. energy (kwh/yr) | 6597 • | 7814 • | + | | | 7673 • | 5444 • | - | | | |
| He. energy (kwh/yr) | 28957 • | 22534 • | - | | | 25205 • | 26220 • | + | | | |
| Li. energy (kwh/yr) | 16080 | 20562 | + | | | 16307 | 19935 • | + | | | |
| PV energy (kwh/yr) | 109396 • | 147704 • | + | | | 140571 • | 85785 | - | | | |
| PV EPBT (yrs) | 3.3 | 3.5 | + | | | 3.3 | 4.1 | + | | | |
| Glare (%/yr) | 62.6 | 61.8 | - | | | 62.5 | 61.8 | - | | | |
| Li. Uniformity (%/yr) | 59.6 | 72.4 | + | | | 59.9 | 44.8 | - | | | |
| Th.cmf. spec. (%/yr) | 48.4 | 48.2 | - | | | 49.8 | 45.9 | - | | | |
| Th.cmf. sprt. (%/yr) | 21.3 | 22.9 | + | | | 22.8 | 19.6 | - | | | |
| Temp. Criteria (%/yr) | 25.3 | 23.9 | - | | | 22.0 | 16.1 | - | | | |

| Student Building Technology | | | | | | Participant with no experience in the field of architecture | | | | | |
|-----------------------------|---|---|---|--|--|---|---|---|--|--|--|
| |  |  | | | |  |  | | | | |
| Co. energy (kwh/yr) | 10922 • | 7814 • | - | | | 9035 | 8455 | - | | | |
| He. energy (kwh/yr) | 24034 | 22534 • | - | | | 28960 • | 27429 | - | | | |
| Li. energy (kwh/yr) | 13772 | 20562 | + | | | 15027 • | 14044 | - | | | |
| PV energy (kwh/yr) | 74378 | 147704 • | + | | | 68738 • | 8529* • | + | | | |
| PV EPBT (yrs) | 3.1 | 3.5 | + | | | 3.1 | 3.9* • | + | | | |
| Glare (%/yr) | 62.5 • | 61.8 | - | | | 63.3 | 61.8 | - | | | |
| Li. Uniformity (%/yr) | 43.2 | 72.4 | + | | | 56.4 | 42.2 | - | | | |
| Th.cmf. spec. (%/yr) | 51.4 | 48.2 | - | | | 51.5 | 51.1 | - | | | |
| Th.cmf. sprt. (%/yr) | 28.9 | 22.9 | - | | | 24.4 | 23.4 | - | | | |
| Temp. Criteria (%/yr) | 37.4 • | 23.9 | - | | | 30.5 | 27.7 | - | | | |

| Participant with no experience in the field of architecture | | | | | | Participant with no experience in the field of architecture | | | | | |
|---|---|---|---|--|--|---|---|---|--|--|--|
| |  |  | | | |  |  | | | | |
| Co. energy (kwh/yr) | 13495 | 5444 • | - | | | 12217 | 6217 | - | | | |
| He. energy (kwh/yr) | 25924 | 26220 | + | | | 24963 | 18997 | - | | | |
| Li. energy (kwh/yr) | 11861 | 19935 | + | | | 12207 | 25470 | + | | | |
| PV energy (kwh/yr) | 104726 • | 85785 • | - | | | 93491 • | 135886 | + | | | |
| PV EPBT (yrs) | 3.1 • | 4.1 • | + | | | 3.1 • | 3.8 | + | | | |
| Glare (%/yr) | 63.3 | 61.8 | - | | | 63.3 | 61.8 | - | | | |
| Li. Uniformity (%/yr) | 42.7 | 44.8 | + | | | 41.9 | 85.0 | + | | | |
| Th.cmf. spec. (%/yr) | 59.8 | 45.9 | - | | | 57.1 | 44.1 | - | | | |
| Th.cmf. sprt. (%/yr) | 36.6 | 19.6 | - | | | 33.7 | 22.1 • | - | | | |
| Temp. Criteria (%/yr) | 44.8 • | 16.1 | - | | | 40.9 | 16.9 • | - | | | |

* The participant chose this design alternative with the intention to add additional PV panels. The selected design was the most optimal for all other performances, according to the participant.

Fig. 7.12: Performances of designs selected by 8 questionnaire participants using a manual optimization approach (l.) and using the visual analytics tool (r.). Orange dots indicate the three performance objectives that are ranked most important in the decision-making process.

Fig. 7.15 shows how participants rated individual features of the visual analytics tool. Features are generally rated high, indicating that all data analytics methods implemented in the visual analytics tool are suitable for the purposes of the CDS. Implementation of the stacked bar graph is especially rated well; all participants strongly agree that visualizing individual performance objectives contributes to the decision-making process of the participants and that visualization of and interaction with the stacked bar graph achieves this purpose. Fig. 7.16 displays normalized ratings for each question to show relative performances. Both figures show that the SOM's D-matrix and the decision tree contributed least to their decision-making process. Multiple participants stated that the main cause is that the time set out for the use of the visual analytics tool was too short to explore the level of detail of these data analytics techniques.

Fig. 7.17 shows average ratings of general questions of the VAS and the CDS. Participants are generally very positive about the visual analytics tool. All participants agree that the visual analytics tool is

effective in visualizing performances of a data set of design alternatives and that the tool has the potential to facilitate design exploration and to improve substantiation of decision-making in the design process. A point of attention is that not all participants agree whether use of the VAS encourages the user to create more sustainable or better-performing design alternatives. A possible explanation mentioned by one participant is that some performance objectives are 'irrelevant', alluding to thermal comfort performances. Noteworthy is that final comments of two participants made explicit that the visual analytics tool is 'fun' to use.

Most participants, both with and without experience in the field of architecture, communicated that use of the CDS gives them great insight in design performances and makes them more aware of performance-related criteria. The majority would consider using the CDS and the VAS in a design project. Some participants communicated that they are more likely to use the CDS for design optimization in later design stages.

7.3.4 Conclusions

This questionnaire is set up to answer two questions:

(1) Does a design process supported by a Computational Design System lead to better-performing designs than designs made using traditional design processes?

(2) Does the Visual Analytics System as a whole and do its individual features support the design process of architects?

Comparison of designs selected by either a manual optimization process or the Visual Analytics System shows that quantified performances are generally slightly improved. Furthermore, participants, especially participants with no experience in the field of architecture, feel more confident about their design process when using the CDS. However, multiple participants state that some performance objectives are not relevant for the decision-making process. Furthermore, some participant mentioned that they are more inclined to use an Iterative Design System for design optimization, as opposed to exploration. In conclusion, integration of the Computational Design System in the design process leads to better-performing designs, though use of the Iterative Design

System can be optimized to suit either comparative assessment of design concepts or optimization of a specific design.

Participants are generally very positive about the Visual Analytics System. The Visual Analytics System and its features are generally perceived intuitive and participants are positive that the VAS has the potential to contribute to the design process of architects. Use of the SOM for multi-dimensional scaling and integration of the stacked bar graph for visualization of design performances are the most successful features of the visual analytics tool. The decision tree and D-matrix have found less use, though this can be contributed to the limited amount of time set out for the use of the visual analytics tool. Participants mentioned that the visual analytics tool is 'fun' to use, which further indicates that the VAS is intuitive in use and that it encourages performance-driven design. In short, the Visual Analytics System and its features are intuitive in use and participants are confident that it leads to better-performing architecture. Therefore, the Visual Analytics System and its features succeed in supporting the design process of practitioners in the field of architecture.

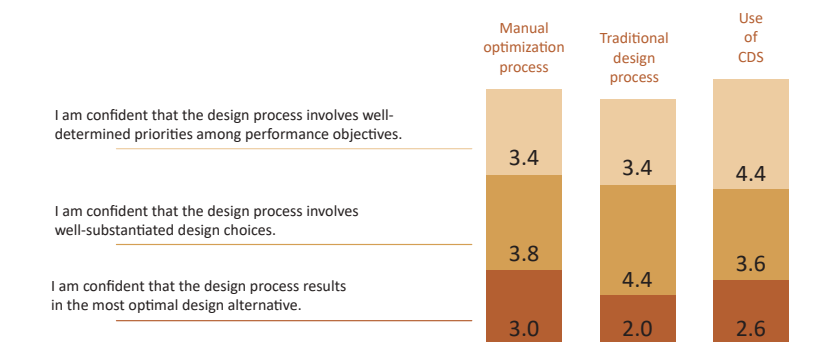


Fig. 7.13: Stacked bar graph showing confidence in design processes of Architecture and Building Technology students. Ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree). Individual ratings are presented in Appendix J, Fig. A.15.

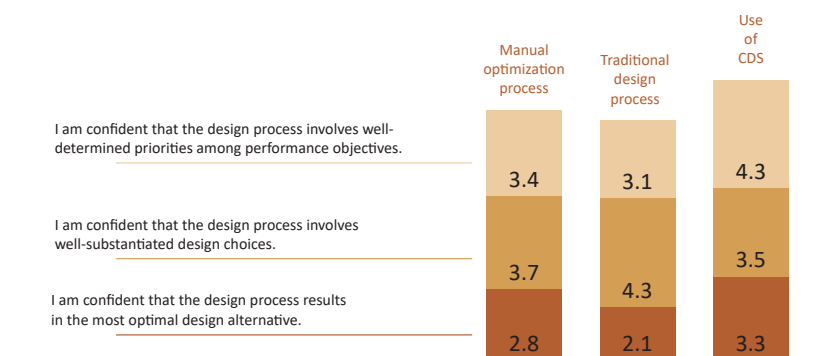


Fig. 7.14: Stacked bar graph showing confidence in design processes of all participants. Ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree). Individual ratings are presented in Appendix J, Fig. A.15.

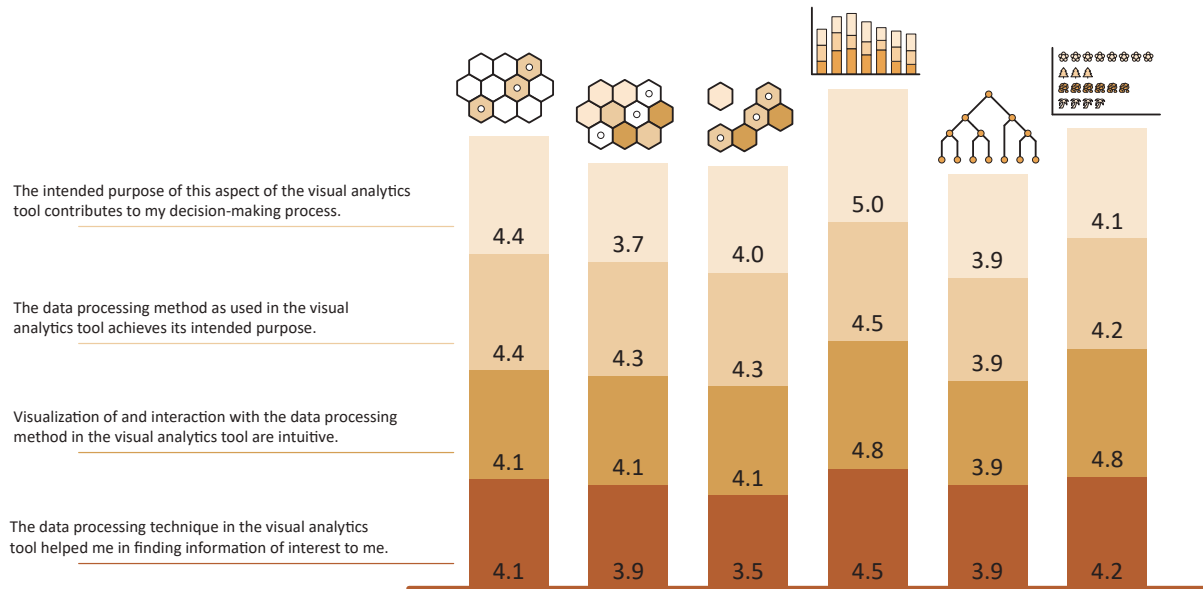


Fig. 7.15: Stacked bar graph showing performance of data analytics methods in the visual analytics tools. Presented ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree). Individual ratings are presented in Appendix J, Fig. A.16.

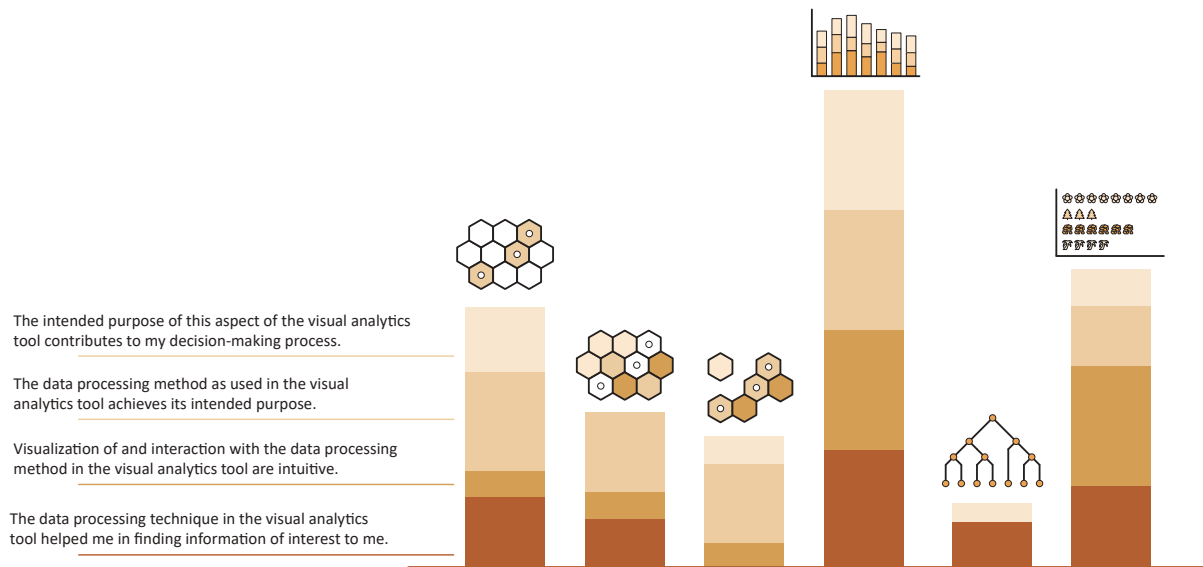


Fig. 7.16: Normalized stacked bar graph showing performance of data analytics methods in the visual analytics tools.

| | |
|--|-----|
| The visual analytics tool has the potential to improve visualization of the performances of design alternatives, compared to traditional design processes. | 4.9 |
| The visual analytics tool has the potential to improve substantiation of decision-making in the design process, compared to traditional design processes. | 4.4 |
| The visual analytics tool has the potential to facilitate exploration of a larger amount of design alternatives, compared to traditional design processes. | 4.8 |
| The visual analytics tool has the potential to lead to a better understanding of building performances, compared to traditional design processes. | 4.5 |
| Use of the visual analytics tool encourages me to create more sustainable and/or better-performing designs, compared to traditional design processes. | 3.6 |
| Use of the visual analytics tool has the potential to result in better-performing architecture, compared to traditional design processes. | 4.4 |
| I would consider using an Iterative Design System to generate a data set of design alternatives in a design project. | 4.3 |
| I would consider using the visual analytics tool in a design project to visualize a data set of design alternatives. | 4.4 |

Fig. 7.17: Average ratings of questionnaire responses. These questions concern a 'commercial' version of the visual analytics tool. Presented ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree). Individual ratings are presented in Appendix J, Fig. A.17.

7.4 DISCUSSION

Functioning of the Computational Design System and the Visual Analytics System is assessed based on their ability to facilitate a performance-driven design process. The CDS and the VAS are tested by the author, an MSc student and participants of a questionnaire. The author's experience of development and use of the CDS, peer review of an MSc architecture student and a questionnaire held among participants with and without experience in the field of architecture reveal the following strengths and weaknesses of the CDS and the VAS:

EXPLORATION

The CDS enables exploration of large, high-dimensional data sets, facilitating comparative assessment of design concepts and of design alternatives. The data analytics methods implemented in the VAS are suitable for design exploration and optimization and visualization and interaction are perceived intuitive. Organization of design alternatives using Self-Organizing Maps and visualization of performances using the stacked bar graph are the most effective features of the Visual Analytics System to derive building information in a limited time frame. Other features can be used in conjunction to these methods to get more in-depth knowledge of data structure, design performances and interrelationships between design variables.

Use of the VAS by the author shows the benefits of integrating data analytics methods in a single viewport. Using multiple data analytics methods in conjunction enables deduction of groupings of similar design alternatives in the design space. The VAS shows overall performances of these groupings in an intuitive manner. Because the VAS is highly interactive, information can be quickly retrieved. Another noteworthy benefit of high interactivity is that the tool is very forgiving. Changes in the landscape provide instantaneous visual feedback of multiple data analytics methods and, as a result, making mistakes in setting filters, thresholds, etc. are immediately noticeable. For similar reasons, errors in the data set (such as a failed performance simulation) are also very noticeable.

OPTIMIZATION

Comparison of design alternatives developed using 'traditional design processes' and using the CDS shows that design performances are generally slightly improved when using the CDS. Participants of the questionnaire and the peer reviewer see potential in use of the Visual Analytics System for design optimization in later design phases.

The current Iterative Design System can be further improved to facilitate design optimization, however. Due to the large amount of design variables of most parametric models convergence towards optimal design solutions is hardly achieved. Another consequence of the large amount of design variables is that similarity between design alternatives is small and correlation between design variables is limited. Hence, discerning interrelationships between design variables and building performances is difficult. Further reducing the amount of design variables may improve optimization of the Iterative Design System.

PV and thermal comfort performances contribute little to the decision-making process, since they have little influence on building geometry. Lighting performances are also of lesser importance compared to energy performances. Reconsidering the implementation of these performance objectives may further improve the suitability of the Iterative Design System to substantiate the architectural design process.

DOCUMENTATION

The Computational Design System enables users to append design alternatives to the data set. This enables use of the Visual Analytics System as a documentation of the design process. Designs made throughout the design process - either designed manually or through parametric models - can be used as a frame of reference for new designs.

VISUALIZATION

The previous paragraphs explain that the VAS is effective in visualizing high-dimensional data of large data sets. Another quality of the VAS is that visual representations of the designs are relatively high quality. The ability to walk through design alternatives and through the urban context facilitates users to get a sense of scale and of architectural qualities. This shows potential in use for interactive design visualization.

COMMUNICATION AND EDUCATION

A noteworthy strength of the CDS is that users are more aware of climate-related performances. Questionnaire participants – both with and without experience in the field of architecture - feel more confident in their decision-making when using the CDS. Furthermore, multiple participants communicated that the questionnaire is 'fun' to use.

The questionnaire indicates potential of the VAS for communication with clients, facilitating easily-understandable comparison between design options. The questionnaire also shows potential of further development of the VAS for educative purposes.

CHAPTER 8: CONCLUSIONS

To meet the European Union's directive to build nearly Zero Energy Buildings in 2020 an emphasis on quantifiable performance objectives in the early design process is required. The application of building performance simulations to support decision-making in the design process supports assessment of building performances, but because these methodologies typically do not capacitate the rapid generation of design alternatives they are rarely used for design exploration in the early design phase. Computational design systems aim to facilitate design exploration by the production of large quantities of data. Current visual analytics techniques, however, do not facilitate simultaneous exploration of quantitative and qualitative design performance of multi-variate, multi-dimensional data sets.

This thesis introduces a visual analytics tool that is able to simultaneously visualize quantified and non-quantified design performances of large data sets of design alternatives. The visual analytics tool is part of a computational design system that involves generating a data set of a large number of design alternatives and making their design performance data insightful by means of integrating multiple data visualization and interaction methods. The tool integrates various data analytics methods, using a landscape as a visual metaphor to visualize features and encourages exploration of the design space by high levels of interaction. The Computational Design System is tested using a case study, which involves the performance-driven design process of a nearly Zero-Energy sports hall in Overhoeks, Amsterdam. Following a research-by-design process methods of facilitating the design process are explored. The author's experience of development and use of the CDS, peer review of an MSc architecture student and a questionnaire held among participants with and without experience in the field of architecture give insight in the suitability of the Computational Design System to facilitate performance-driven decision-making.

This chapter presents the main research conclusions of this thesis. Firstly, each of the four sub-questions introduced in chapter asdf is answered. Then, this chapter provides an answer to the main research question: "How can visual analytics be integrated in a computational design system to make multi-variate, multi-objective decision-making in the early design phase accessible to architects and climate designers?"

HOW CAN GENERATION OF LARGE QUANTITIES OF DESIGN ALTERNATIVES CONTRIBUTE TO EXTRACTION OF BUILDING INFORMATION FOR PERFORMANCE-DRIVEN DESIGN PROCESS BY ARCHITECTS AND CLIMATE DESIGNERS?

This thesis shows that the best way to contribute to the architectural design process through design exploration is by enabling comparison between multiple design concepts. The data workflow set up in this thesis enables generation of a data set that consists of design alternatives generated by multiple parametric models, as well as manually constructed design alternatives. Tests of the use of the Computational Design System indicate that the Computational Design System facilitates comparative assessment of design alternatives. Furthermore, the Computational Design System enables the user to efficiently append design alternatives to the data set, thus supporting the continuous design process. The Computational Design System can therefore be used as a documentation of the design process.

Flaws of the Computational Design System are long simulation times and low convergence towards optimal design results. Both are caused by a high amount of design parameters. Regardless, the Computational Design System gives great insight in the general performance of each design concept. The Computational Design System is therefore suitable for exploration in the very early conceptual design phase. When a more specific design direction is taken in later design stages, parametric models can be set up to focus on design optimization. New design alternatives can either be added to the existing data set or can be visualized in a new data environment.

HOW DO QUANTIFIED AND NON-QUANTIFIED DESIGN PERFORMANCES INFLUENCE MULTI-OBJECTIVE DECISION-MAKING OF ARCHITECTS AND CLIMATE DESIGNERS?

The Computational Design System runs multiple building performance simulations to determine various performance objectives. Quantified performance objectives consist of energy-, lighting- and thermal-related performances. Users are generally able to improve overall performance of their design alternative by using the Computational Design System. Use of the Computational Design System indicates that design aesthetics and energy-related performances are the most influential factors on the

architectural design. Building volume and window size and positioning, in particular, have large effects on these performances. Thermal and lighting-comfort-related performances have less influence on the building's geometry. Thermal comfort performances are largely dependent on heating and cooling setpoint temperatures and can thus be optimized by extra heating and cooling. The influence of PV panel performances on the architectural design process is marginal, since energy demands are commonly met and design alternatives commonly meet (nearly) Zero-Energy design standards.

Trade-offs between performance objectives vary from person to person; some users of the Computational Design System favor comparison of design geometries over performances, whilst others use the Computational Design System to find design alternatives with best climate-related performances. Nevertheless, the Computational Design System encourages users to take both types of performance objectives into consideration. Thus, although the influence of quantified and non-quantified design performances on multi-objective decision-making vary, a trade-off between the two is generally achieved.

WHAT DATAANALYTICS METHODS ARE SUITABLE FOR INTERPRETATION OF HIGH-DIMENSIONAL BUILDING PERFORMANCE SIMULATION DATA SETS BY ARCHITECTS AND CLIMATE DESIGNERS?

Data analytics integrated in the Computational Design System fulfil four purposes:

- Visualization of interrelationships between data items in high-dimensional data
- Visualization of data attributes
- Navigation in large data sets.
- Determination of interrelationships between design aspects and performances

The Computational Design System uses the following data analytics methods to fulfil these purposes:

- Self-Organizing Map
- Stacked bar graph (in conjunction with analytic hierarchal process)
- Decision tree
- Pictogram charts
- Agglomerative hierarchal clustering

Each of these methods is suitable for interpretation of high-dimensional data, according to users of the Computational Design System. An adapted version of the Self-Organizing Map is an effective tool to project design alternatives with high-dimensional performance data onto a two-dimensional plane while avoiding cluttering. A stacked bar graph, a decision tree and pictogram charts process annual performance data for visualization of performances. The Self-Organizing Map, stacked bar graph, decision tree, pictogram charts and hierarchal clustering all enable navigation of the design space through quick derivation of areas of the design space with similar characteristics. Interrelationships between design aspects can be derived from correlation matrices and by manually comparing design geometries.

HOW CAN DATA ANALYTICS METHODS BE INTEGRATED AND VISUALIZED IN A MANNER THAT ENABLES INTUITIVE, GOAL-ORIENTED EXPLORATION OF BUILDING PERFORMANCE DATA FOR ARCHITECTS AND CLIMATE DESIGNERS IN ORDER TO FACILITATE PERFORMANCE-DRIVEN DESIGN PROCESSES?

The aforementioned data analytics methods are integrated in a highly interactive, game-like data environment developed using the Unreal Engine. The environment uses the visual metaphor of a landscape to visualize data analytics methods. Design geometries are spawned on tiles of the landscape and characteristics of the landscape gives insight in the performances of design alternatives and the design space. Users can 'terraform' the landscape to deduct relevant building information. Users can fly around the landscape and walk through design alternatives in first person view. Additional gameplay features further facilitate deduction of building information.

Users perceive the use of the data environment as very intuitive. They are able to use data analytics methods with little explanation of their functionality and are able find design alternatives or design spaces of interest very effectively. This suggests potential of use of the Computational Design System for educative purposes and use for communication between architects and clients.

HOW CAN VISUAL ANALYTICS BE INTEGRATED IN A COMPUTATIONAL DESIGN SYSTEM TO MAKE MULTI-VARIATE, MULTI-OBJECTIVE DECISION-MAKING IN THE EARLY DESIGN PHASE ACCESSIBLE TO ARCHITECTS AND CLIMATE DESIGNERS?

The architectural design process is characterized by trade-offs between both quantified and non-quantified performances. This thesis explores integration of computational design and visual analytics in the design process to substantiate decision-making of architects and climate designers.

The architectural design process often explores multiple design processes throughout the design process. The computational design system developed in this thesis therefore enables the use of multiple parametric and non-parametric models to generate a data set of design alternatives corresponding to multiple design concepts. The use of non-destructive evolutionary algorithms to iterate through design alternatives enables optimization of a design concept.

This thesis visualizes this data using an intuitive, highly interactive and game-like data environment. The environment integrates multiple data analytics methods to visualize building performances. Quantified building performances are visualized conjointly to design geometries, enabling architects to make trade-offs between both quantified and non-quantified performances. Users are quickly able to find relevant building information through means of interaction. This thesis verifies that use of this visual analytics environment improves overall design performance.

The use of CSV files as an intermediary between subsystems of the computational design system enhances flexibility and versatility of the computational design system. The ability to append design alternatives to the data set enables use of the computational design system throughout the design process, providing a means of documenting the design process through the data environment.

Peer review and the author's experience verify that a highly-interactive, game-like environment is a very effective tool to visualize high-dimensional data. Use of easily understood visual metaphors facilitate intuitive use of data analytics methods to analyze building information, enabling users with limited knowledge on these data analytics methods to find optimal design solutions. This shows potential in use of the data environment for communication and discussion purposes, facilitating multi-objective decision-making in multi-disciplinary design processes.

In conclusion, integration of an intuitive, highly interactive, game-like data environment in a computational design system makes multi-variate, multi-objective decision-making in the early design phase accessible to architects and climate designers, by providing means of exploration, optimization, visualization, documentation and communication.

CHAPTER 9: RECOMMENDATIONS

- The data analytics methods in the Visual Analytics System are currently mostly based on annual performance data. Future development of the Visual Analytics System could introduce means to visualize hourly or daily performances to enable the designer to further substantiate their decision-making process. An example is the introduction of a toggle that switches between hourly, daily and annual performances, visualizing the landscape accordingly. Using a slider, the user can iterate through the hours or days of the year, which provides immediate visual feedback of the Visual Analytics System.
- The parametric models that comprise the Generative Design Systems in this thesis use large amounts of design variables in order to create design alternatives with high level of variation. Along with long simulation times of the Performance Analysis System this affects convergence of the evolutionary algorithm towards optimal design solutions. The influence of PV panels on the design process in this thesis already indicated that some design aspects can be individually optimized. Research could be conducted on the potential of decentralized, computationally inexpensive simulation and optimization of distinctive design aspects to increase convergence towards design solutions (Fig. 9.1). Alternatively, research could investigate the use of surrogate modelling techniques may provide a means to approximate optima of the design space.
- Currently, the subsystems of the Computational Design System are linearly arranged, with few ways to feedback data to preceding subsystems. The Computational Design System could integrate machine learning techniques to determine user preference patterns in the Visual Analytics System. This can be fed back to the Generative Design System, influencing the optimization process (Fig. 9.2).
- Continued development of the Visual Analytics System could explore further potential of the VAS in multiple facets of design regarding exploration, optimization, design visualization, education and documentation. Examples include integration of means of machine learning, development of a commercially available toolbox, integration of VR and further implementation of gameplay elements.

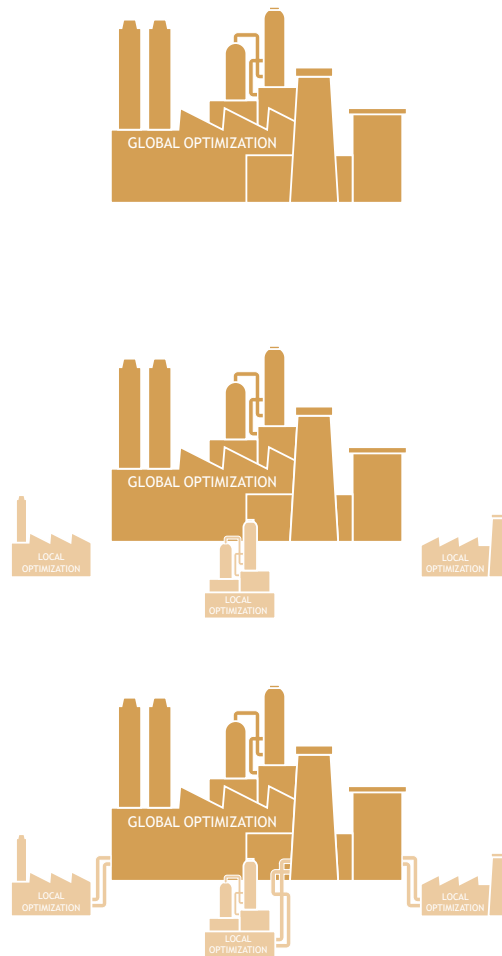


Fig. 9.1: Current CDS is used for global optimization (t.). Future research may consider decentralized optimization process for local optimization of performances (m.). It would be interesting to investigate the potential of using local optimization process to steer global optimization processes towards optimal design solutions (b.)

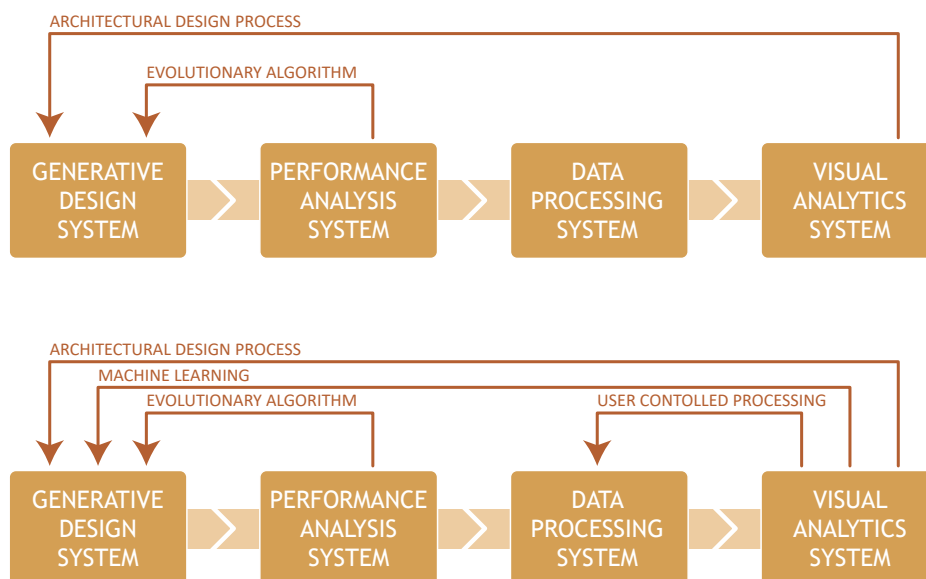


Fig. 9.2: Current feedback loops (t.) and recommendations for additional feedback loops (b.).

CHAPTER 10: REFLECTION

This chapter presents the author's reflection on the graduation process. This chapter first reflects on the Iterative Design System. Then, the Data Analytics System is discussed. Finally, the reflection on the graduation process as a whole is presented.

10.1 ITERATIVE DESIGN SYSTEM

The Iterative Design System (IDS) has been developed mainly using a research by design approach, where various tests throughout the research process give insight in the functioning of the IDS. Exploration of various means of facilitating the design process gives insight in how the Iterative Design System can best facilitate decision-making in performance-driven design processes.

The design brief, describing the design variables and performance objectives, was determined at an early stage of the research process. The design brief was chosen to closely resemble an architectural design process, since the suitability of the Computational Design System to contribute to 'realistic' design processes is an important aspect of its relevancy. At

the time, however, complexity of this large amount of aspects was not recognized. Reducing the amount of design variables and performance objectives may have provided the opportunity to improve processing of analysis results. Focusing on fewer design aspects interrelationships between design aspects and performances may have been clearer, which may have benefitted research conclusions.

Nevertheless, five out of ten objectives have had great influence on the design processes of the author and the peer reviewer. Consequently, the IDS is in line with the main research question of this thesis, which concerns multi-variate, multi-objective decision-making.

10.2 DATA PROCESSING SYSTEM & VISUAL ANALYTICS SYSTEM

Development of the Data Analytics System (DAS) uses both a research by design and a design by research approach. Literature study indicates flaws of current visual analytics tools and provides an understanding of suitable data analytics methods. Development and testing of a prototype of the Visual Analytics System provides an understanding of its functionality.

Designing the DAS alongside continuous testing was an effective way to determine suitable data analytics methods. It also gave insight in the importance

of various aspects that literature research did not provide, such as means of interaction, operability and user experience.

The prototype of the visual analytics tool is elaborate. An advantage is that results of personal testing and peer review have been very insightful to determine the level of intuitivity of the use of the DAS. A drawback is that development of the prototype was time-intensive, which took away from further optimization of the data analytics methods and of the functionality of the IDS.

10.3 GRADUATION PROCESS

10.3.1 Graduation topic

The research question is, in my opinion, a very relevant topic; I see great potential in the use of computational design in the various stages of the architectural design process, but have experienced the difficulties in interpreting information in various simulation tools. Furthermore, various Msc Architecture students have expressed a certain reluctance to use computational design in their design process. Various researchers in the field of design exploration and optimization have indicated the necessity of further research in data visualization in the field of architecture.

A curious phenomenon is that data analytics

methods used in other engineering industries do not meet the demands of practitioners in the field of architecture. Experience in the field of architecture and research throughout this graduation process suggest that there is a large difference in design approaches between these disciplines; most engineering disciplines focus on optimization of one or a few quantifiable performance criteria, whereas the architectural design approach is characterized by exploration and high-dimensional trade-offs. This graduation research acknowledges this difference in design approaches, which may be a relevant contribution to current research.

10.3.2 Relevancy of graduation results

Various MsC Architecture students have observed that the design flexibility is limited by the use of generative design in the architecture process. This indicates that the use of a computational design system may not be applicable in design processes comparable to theirs. This thesis explores various parametric models with the aim to maintain high design flexibility. In the end, the use of multiple parametric models that follow architectural design concepts are seen as a suitable computational design approach for traditional design processes.

Research conclusions indicate that the computational design system does not optimally facilitate performance-driven design processes. Most notably, the system shows flaws in the analysis of interrelationships between design aspects. Hence, this graduation research does not contribute much to the assessment of data analytics methods.

However, development of the computational design system involved a considerable focus on user experience. Peer review and the author's experience indicate that the use of a game-like environment that is highly interactive encourages performance-driven decision-making. High level of interactivity and features inspired by computer games provide novel ways of extracting building information.

A noteworthy observation concerning relevancy is that computational design systems may not be relevant for small design projects, since the absolute improvements in (e.g.) energy-related performances do not weigh against the effort of setting up the computational design systems. Computational design systems are applicable in bigger projects, though, when performances are of greater consequence (whether that is related to sustainable aspects, financial aspects, or to social-cultural impact). The VAS provides ways to visualize and quantify performances that can invoke and substantiate discussion among a multi-disciplinary design team, further contributing to its suitability in large design projects.

I am convinced that the computational design system in this thesis has the potential contribute to sustainable development. The computational design system facilitates a new approach on sustainable design in which both architectural qualities and sustainable performances can be considered in the design process. Use of the system may prevent clashes between the two aspects and thus may benefit both energetic performance and architectural quality.

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APPENDIX A: ELABORATION ON BUILDING INFORMATION EXPORT

The Iterative Design System exports 16 design aspects, listed below:

Floor area (m2)
Volume (m3)
Total façade area (m2)
Orientation (°)
PV Panel area (m2)
Total north-oriented window area (m2)
Total east-oriented window area (m2)
Total south-oriented window area (m2)
Total west-oriented window area (m2)
Total sky-oriented window area (m2)
Insolation north-oriented windows (hrs/yr)
Insolation east-oriented windows (hrs/yr)
Insolation south-oriented windows (hrs/yr)
Insolation west-oriented windows (hrs/yr)
Insolation sky-oriented windows (hrs/yr)

Floor area, volume, total façade area, orientation and PV panel area are logically derived from the parametric model's B-reps.

Windows are grouped based on their orientation, using the method described below. The orientation is determined using the Face Normal component, which returns a vector with a length of 1.

Normal vector V_{norm} is deconstructed in its component parts. Considering Pythagorean theorem and the fact that the vector length of V_{norm} always equals one, the windows are sky-oriented if they meet one of the following criteria:

$$0 < V_{norm,z} < 45$$
$$135 < V_{norm,z} < 180$$

If the window is not sky-oriented, it is grouped under one of the wind directions-oriented classes. In order to do so, the angle between each wind direction and a vector with components $X = V_{norm,x}$, $Y = V_{norm,y}$, and $Z = 0$ is calculated. If the angle is smaller than 45 degrees, the window is oriented towards that orientation.

Insolation is calculated using a list of 8760 vectors that represent hourly solar rays. Intersection commands determine whether vectors intersect with the building or context mesh or whether they intersect with the windows. The total amount of unobstructed solar hours is averaged for each group of windows.

APPENDIX B: ELABORATION ON GRASSHOPPER DEFINITIONS

B.1 DELAUNAY GEOMETRY DEFINITION

The Delaunay geometry is defined using Delaunay triangulation of a three-dimensional array of points. This method is computationally inexpensive and allows for non-orthogonal surfaces and works with planar surfaces, the latter being a requirement imposed by the simulation software. Delaunay Triangulation is defined as following: for a triangulation of three points in a set of points, the triangulation is a Delaunay triangle if no point is within the circumscribed circle of the three points.

The following method is used to define Delaunay geometry (Fig. A.10):

A point cloud is parametrically defined using Gene Pools for the X-, Y-, and Z-values of the point coordinates. Since Delaunay triangulation of a three-dimensional array of points does not guarantee a closed geometry, the point cloud is projected on a spherical plane that uses the building's center as its center point. The sphere points can be used to define Delaunay triangulation. To do so, a Voronoi diagram is generated using the Facet Dome component.

A Voronoi diagram can be derived from the Delaunay triangulation by connecting the center points of the circumscribed circles. Conversely, Delaunay triangulation can be derived from the

Voronoi diagram and its corresponding set of points (P) using the following logic:

For each Voronoi corner point, if there are three points in set P with equal distance from the Voronoi corner point and there is no point in set P with smaller distance from the Voronoi corner point, the triangulation of the three points in set P is a Delaunay triangle.

Using this method the Delaunay triangulation is derived from the spherical Voronoi diagram of the projected set of points. For each Voronoi cornerpoint, its distance to each Delaunay control point (sphere point) is calculated. The lists of distances and their corresponding points are then sorted by size. If the first three list items of the sorted list are equal, the three points are equally far apart and there are no points that are closer to the Voronoi corner point. If this is the case, the triangulation of the three points is a Delaunay triangle. The list of the building's control points and the list of their corresponding sphere points are in the same order. Hence, Delaunay triangulation of the sphere points can be extrapolated back to the original control points using synchronous sorting (Sort List command).

B.2 VORONOI GEOMETRY DEFINITION

The Voronoi-based geometry is defined by creating a Voronoi surfaces for each wall and for the ceiling and by trimming each wall with the other walls. The methodology is largely based on suggestions given by D. Jonkers (personal communication, , 2017).

For each wall, a list of points is distributed on a rectangular surface. The surfaces is offset to either side, and a bounding box is defined between these two surfaces. The points are projected onto both surfaces with parametrically defined vectors. Then, Grasshopper's Voronoi3D-component is used, taking projected points and the bounding box as an input. The component draws closed B-reps based on a three-dimensional Voronoi diagram. Using this method, culling each surface that does not intersect with the offset surfaces returns the Voronoi wall geometry

(Fig. A.2). Duplicate surfaces are removed by testing the similarity of their centerpoints. Finally, the wall surfaces are joined to create one polysurface. Each wall is trimmed by its neighboring walls. The walls are joined and capped to create a floor. The result is a closed B-rep that represents the building mass.

The positions of the windows are determined by projecting points onto the wall and ceiling segments, using parametrically defined vectors. The wall segments are scaled to define the window geometries. The scale factors of each window are individually defined and are parametric. PV panels are defined in a similar manner. Contrary to the windows, the PV panels are not scaled and instead cover the entire wall segment.

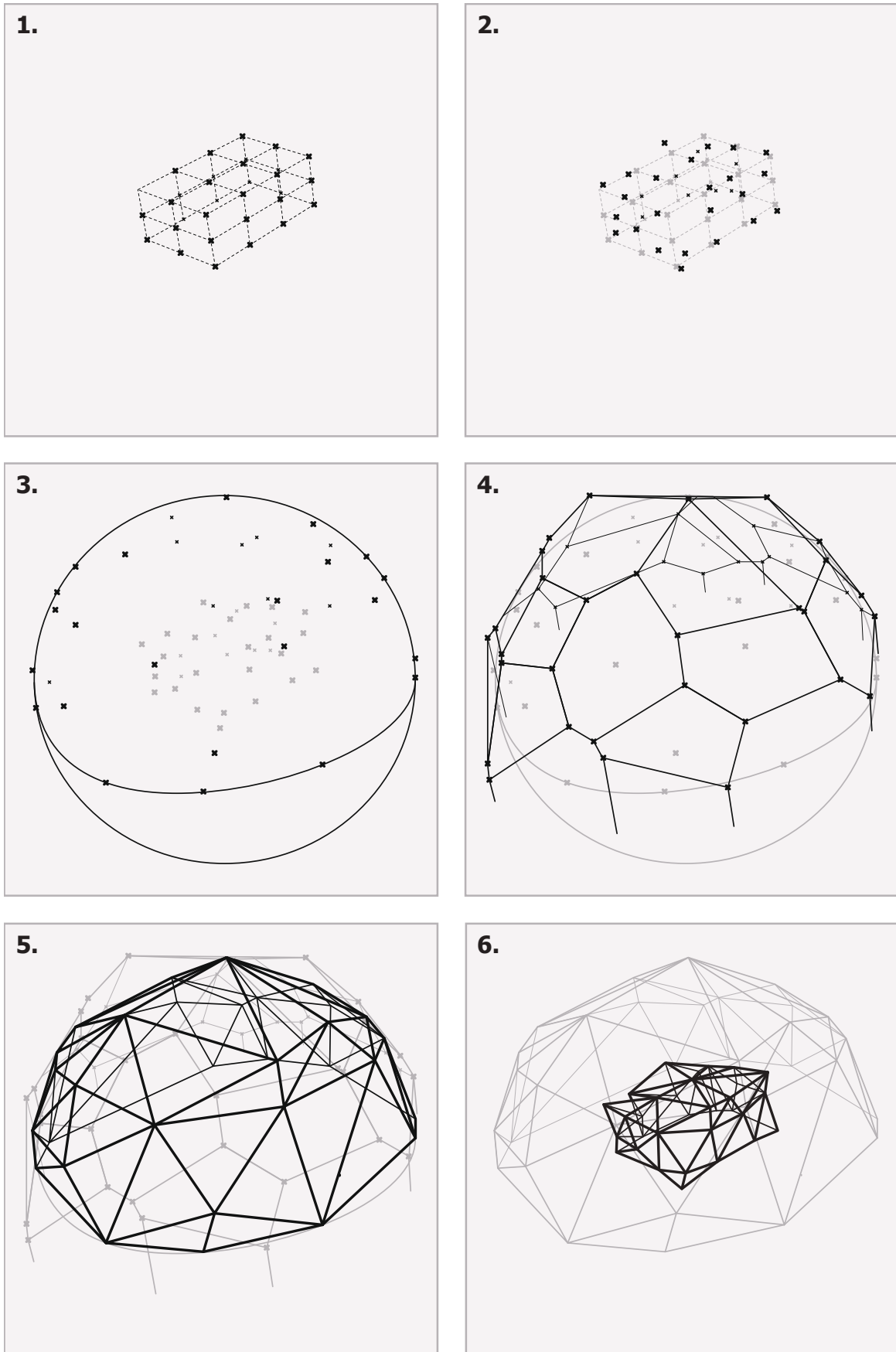
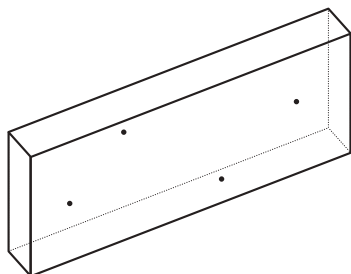
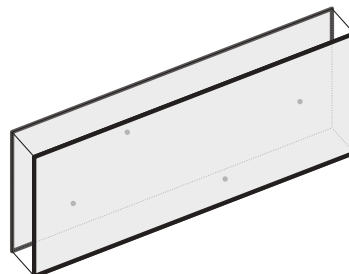


Fig. A.1: Delaunay triangulation derived from a set of control points.

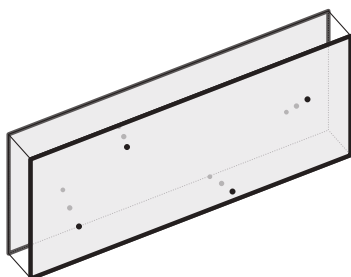
a.



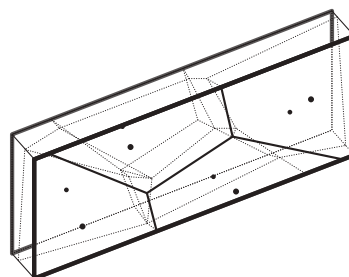
b.



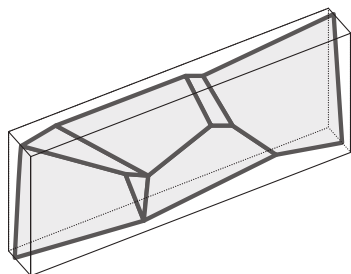
c.



d.



e.



f.

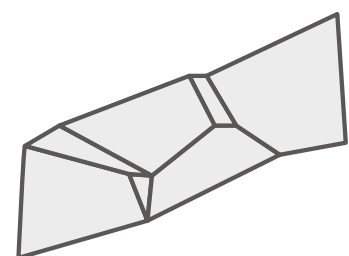


Fig. A.2: Façade geometry derived from 3D Voronoi partitioning

B.3 CUBISTIC GEOMETRY DEFINITION

The geometry definition is based on three B-reps. A bigger and a smaller B-rep represent the outer and inner volume of the geometry. Some sections of the outer volume are carved out to reveal the inner geometry. In order to determine which sections are carved out, the B-reps are split into segments of which some are removed. The geometries are split so that the

Splitting of the B-reps and the carving of the outer geometry are controlled by the third 'reference' B-rep that encompasses the outer and the inner B-rep. The reference B-rep is sliced on the X-, Y- and Z-axes, in parallel. Thus, three lists are created; one containing horizontal slices of the B-rep, one containing vertical slices parallel to the X-axis and one containing vertical slices parallel to the Y-axes (Fig. A.3).

Selecting one slice of each list and performing Solid Intersection operations returns one segment of the B-rep. Using this method, each segment in the array of box segments can be found by intersecting a slice of each list. Fig. A.4 gives an example of how individual segments can be retrieved. This method resembles a three-dimensional coordinate system, in which the coordinate values are the indices of each list of slices.

The coordinates are parametrically defined and are controlled by the evolutionary algorithm. The coordinates retrieve segments that will comprise the exposed areas of the inner cube. Unfortunately, Grasshopper does not allow for diagonally adjacent exposed areas, since this results in non-manifold edges and, hence, does not result in a closed B-rep. This is only the case when the outer mass is diagonally intersecting with itself, so when the two exposed areas do share a neighboring exposed area, the building mass does not have non-manifold edges (Fig. A.5).

Therefore, if two coordinates would result in diagonally adjacent exposed areas, the coordinates are removed. In order to do so, a script is run parallel to the B-rep segmentation. For each combination of two coordinates, the script determines whether they are diagonally adjacent. This is the case when their Euclidean distance = $\sqrt{2}$. If they are, the script determines whether the points share a common neighbor (Euclidean distance = 1). If they do not have a common neighbor, the coordinates would return a geometry that has non-manifold edges. Therefore, they are removed from the list.

The remaining points return the segments of the inner cube that will be exposed. Intersections with the outer geometry determine which of the outer geometry segments should be removed. A Solid Union operation of the outer geometries and inner geometries returns the building mass and automatically removes interior faces. The solid

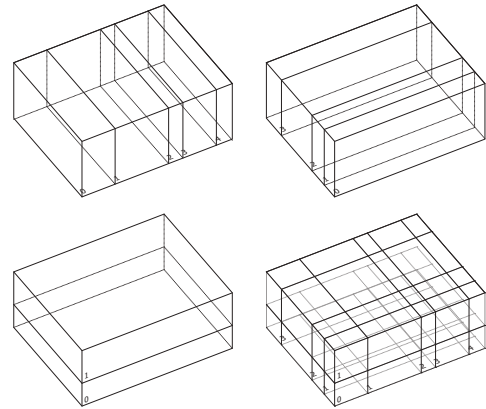


Fig. A.3: Slicing of the B-rep over the X-, Y- and Z- axis and over all axes, respectively.

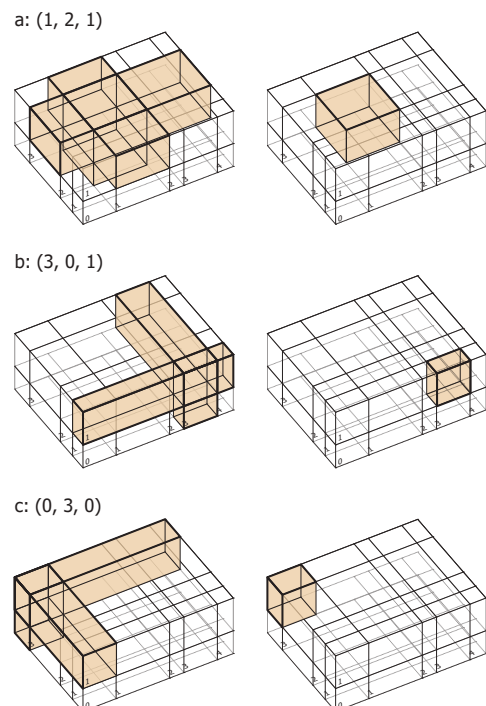


Fig. A.4: Coordinate system to retrieve building segments.

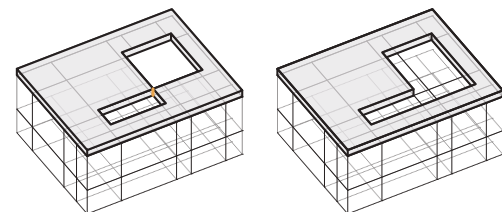


Fig. A.5: Non-manifold edge (l.) is prevented by removing additional building segments (r.).

B-rep is then exploded again, after which the inner faces, outer faces and floor are separated. The inner faces are sliced into equal segments of approximately 2.0 m wide. A window is defined on each of these segments by offsetting the segments' B-rep edges by a parametrically defined distance and using an Edge Surface operation. The locations of the small windows

of the outer geometry are defined by projecting points on the outer geometry using parametrically defined vectors. Using these points, the corresponding outer wall segments are found. The centerpoints of these segments are used as the centerpoints of the windows. The windows have a fixed height and a variable width.

B.4 POLYGONAL GEOMETRY DEFINITION

This definition is comparable to the definition described in chapter B.3, but is adapted in various ways in order to reduce computation time. The definition makes use of an outer and an inner B-rep. The inner B-rep is a box and the outer B-rep is a polygonal mass.

The polygonal mass is defined using a series of points. The four lower corner points are fixed. Moving these points with four parametrically defined movement vectors determines the upper corner points. Planarity of each wall is ensured, since the vectors have identical inclination over the wall's tilting axis. A plane is drawn through the four points and on that plane a fifth point is drawn. A polyline is drawn through the five points and is used to define a Boundary Surface. The upper corner points are triangulated define the roof segments.

The outer B-rep is segmented using a similar approach to the approach described in chapter B.3. However, since this geometry only carves slices over the X-axis, a different approach to remove non-manifold edges is used.

A list of Boolean values controls a Cull Pattern component that determines which segments are removed. The list is hierarchically organized; it uses a

branch for each slice of the geometry and the values in each branch relate to each building segment in the corresponding slice.

Hence, non-manifold edges can be easily found by looking for adjacency and diagonal adjacency of 'false' Booleans. A non-manifold edge occurs when two segments are diagonally adjacent without a common neighboring segment. Conversely, a non-manifold edge occurs when two neighboring segments are removed without removing either or both of their common neighboring segments. The neighboring items of the list of Booleans can be found using Flip Matrix and Shift List components in the following orders:

Neighbor over Y-axis: flip matrix -> shift list -> flip matrix
Neighbor over X-axis, right: shift list
Neighbor over X-axis, left: shift list (neg.)
Diagonal neighbor, right: flip matrix -> shift list -> flip matrix -> shift list
Diagonal neighbor, left: flip matrix -> shift list -> flip matrix -> shift list (neg.)

Then, a series of 'Nor', 'And' and 'Or' gates determine whether non-manifold edges occur. If that is the case, the definition prevents one of the building segments from being removed.

B.5 ANNUAL SOLAR OBSTRUCTION DEFINITION

Firstly, windows are grouped based on their orientation; North, East, South, West, or upwards. Each window's facing direction is found using the Face Normal component. Upwards-facing windows are found by deconstructing the normal vectors and using the height of the vector to calculate the angle between the normal vector and the Z-axis vector. Since the normal vector's length is 1, the angle can be found using the formula below. If $0 < \alpha < 45^\circ$ the window is considered to face upwards.

$$\alpha = \cos^{-1} (V_{l,z} / 1)$$

Where:

$V_{l,z}$ = the length of the window's normal vector's in the Z-direction

α = angle between the window's normal vector and the Z-axis

The remaining windows are subdivided based on the four wind directions. To calculate the angle of the vectors on the XY-plane, the window's normal vectors are deconstructed and reconstructed using only their X- and Y- values. Each wind direction is expressed as a

vector (Y, X, -Y and -X for N.,E.,S. and W., respectively). Then, for each window the angle between its normal vector and each wind direction is calculated. If $0 < \alpha < 90^\circ$ the window is considered to face towards that direction.

After grouping the windows based on their orientation, the cumulative window areas of each orientation are calculated. Then, the average annual hours of direct sunlight is calculated for each window. For each hour of the year a line is drawn through each window's centerpoint following the solar radiation

vector. The context geometry and the building's wall geometry are converted to a mesh. A Mesh|Line Intersection component determine at what hours of the year the mesh obstructs the solar radiation for each window; if there is no intersection between the mesh and a line, the sun is not obstructed for that hour of the year and the window is exposed to direct sunlight. The amount of unobstructed daylight hours are summed for each window. Then, they are averaged for each group of windows.

B.6 DATA EXPORT

The building information is exported using custom Python components. An ID number ('Iteration Number') is assigned to each design iteration and is included with all exported information. When using the non-destructive evolutionary algorithm in the Iterative Design System the Iteration Number increments by one for each design loop. The Iteration Number is defined by a custom Python component.

The iteration number is stored as a single integer in a designated CSV file. A custom Python component reads the iteration number, increments it by one and overwrites the file with the new iteration number each time the component receives an update ('buzz') (Fig. A.6).

Building information is exported using the Python component presented in Fig. A.7. The component reads the designated CSV file and appends the building information as a new line in the CSV file. The building information should be inputted as a single string that includes all values, concatenated with commas. In this thesis, the string is defined in Grasshopper using Text Join and Concatenate components.

fileAddressIN: file address containing the iteration number
 defaultStartingIterationNumber = a number indicating the first number in the series of iteration numbers
 buzz = any kind of input that assures an update when the Python component needs to be run. The Iterative Design System in this thesis uses the building geometry
 increment = Boolean that disables the script if false
 reset = Boolean that resets the iteration number to the defaultStartingIterationNumber if true

```
with open(fileAddressIN, 'r') as f:
    currentIterationNumber = f.read()
if currentIterationNumber == "" or reset == True:
    increment=False
    currentIterationNumber = defaultStartingIterationNumber
    with open(fileAddressIN, 'w') as wr:
        wr.write(str(currentIterationNumber).zfill(5))
if increment==True:
    with open(fileAddressIN, 'w') as wr:
        newIterationNumber = int(currentIterationNumber.strip('')) +1
        wr.write(str(newIterationNumber).zfill(5))
IN = str(int(currentIterationNumber.strip('')) +1).zfill(5)
```

Fig. A.6: Python component script used to define the Iteration Number.

fileAddressIN: a file address that contains a single number that increments each iteration
 fileAddress: file address of the CSV file
 simulationValues: a single string containing the information to be written to the file
 write: Boolean that writes the file if true

```
with open(fileAddressIN, 'r+') as INfile:
    currentIterationNumber = INfile.read()

with open(fileAddress, 'a') as file:
    if write == True:
        IDNumber = str(currentIterationNumber).zfill(5)
        file.write("\n" + str(IDNumber) + ',' + str(simulationValues))
```

Fig. A.7: Python component script used to write building information to a CSV file.

APPENDIX C: PERFORMANCE VALUES OF ALTERNATIVE SIMULATIONS

Default simulations with insulation thickness = 140 mm

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 3769 | 75849 | 27215 | 37460 | 3.29 | 60.8 | 89.5 | 52.5 | 16.7 | 7.3 |
| Alt #002 | 8480 | 69510 | 14168 | 48607 | 3.20 | 62.6 | 54.8 | 55.1 | 22.7 | 23.0 |
| Alt #003 | 4031 | 66965 | 29324 | 96842 | 3.39 | 63.3 | 96.6 | 52.7 | 17.8 | 8.8 |
| Alt #004 | 1859 | 42359 | 29859 | 81625 | 3.22 | 63.3 | 100.0 | 40.9 | 14.2 | 0.3 |
| Alt #005 | 7113 | 44411 | 26621 | 85522 | 4.80 | 63.3 | 88.1 | 46.3 | 19.6 | 9.6 |

Alternative simulations with insulation thickness = 100 mm

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 2833 | 97438 | 27215 | 37460 | 3.29 | 60.9 | 89.5 | 58.8 | 18.3 | 4.0 |
| Alt #002 | 7471 | 85365 | 14168 | 48607 | 3.20 | 62.6 | 54.8 | 61.8 | 24.5 | 18.6 |
| Alt #003 | 3147 | 87397 | 29324 | 96842 | 3.39 | 63.3 | 96.6 | 96.6 | 17.6 | 4.9 |
| Alt #004 | 1471 | 61409 | 29859 | 81625 | 3.22 | 63.3 | 100.0 | 100.0 | 12.6 | 0.1 |
| Alt #005 | 5414 | 69443 | 26622 | 85522 | 4.80 | 63.3 | 88.1 | 88.1 | 19.0 | 4.6 |

Alternative simulations with glazing type = translucent double glazing

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 1709 | 85114 | 29755 | 37460 | 3.29 | 21.2 | 99.3 | 53.8 | 13.5 | 0.6 |
| Alt #002 | 4152 | 83757 | 23638 | 48607 | 3.20 | 22.4 | 54.8 | 59.2 | 17.8 | 8.3 |
| Alt #003 | 1978 | 75245 | 29859 | 96842 | 3.39 | 21.5 | 100.0 | 53.8 | 14.8 | 0.9 |
| Alt #004 | 1532 | 44844 | 29859 | 81625 | 3.22 | 26.0 | 100.0 | 42.1 | 13.5 | 0.0 |
| Alt #005 | 4096 | 52618 | 29778 | 85522 | 4.80 | 25.3 | 97.2 | 47.3 | 16.7 | 1.0 |

Alternative simulations with setpoint temperatures = 19 and 25°C

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 6046 | 48727 | 27215 | 37460 | 3.29 | 60.9 | 89.5 | 54.1 | 35.1 | 0.3 |
| Alt #002 | 10936 | 44333 | 14168 | 48607 | 3.20 | 62.6 | 54.8 | 60.8 | 46.4 | 11.1 |
| Alt #003 | 6255 | 41795 | 29324 | 96842 | 3.39 | 63.3 | 96.6 | 53.4 | 35.1 | 0.4 |
| Alt #004 | 3372 | 22607 | 29859 | 81625 | 3.22 | 63.3 | 100.0 | 50.2 | 16.6 | 0.1 |
| Alt #005 | 10674 | 22644 | 26622 | 85522 | 4.80 | 63.3 | 88.1 | 48.3 | 29.8 | 0.7 |

Alternative simulations with setback temperatures = 17 and 32°C

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 3726 | 76993 | 27215 | 37460 | 3.29 | 60.9 | 89.5 | 52.8 | 18.1 | 7.2 |
| Alt #002 | 8509 | 70978 | 14168 | 48607 | 3.20 | 62.6 | 54.8 | 55.7 | 23.8 | 23.0 |
| Alt #003 | 4036 | 67281 | 29324 | 96842 | 3.39 | 63.3 | 96.6 | 52.8 | 18.2 | 8.8 |
| Alt #004 | 1856 | 41146 | 29859 | 81625 | 3.22 | 63.3 | 100.0 | 40.7 | 14.0 | 0.3 |
| Alt #005 | 7024 | 46510 | 26622 | 85522 | 4.80 | 63.3 | 88.1 | 46.5 | 19.9 | 9.6 |

Default simulations with activity schedule of 17 hrs/day

| | Co. Energy kwh/yr | He. Energy kwh/yr | Li. Energy kwh/yr | PV Energy kwh/yr | PV EPBT yrs | Glare %/yr | Li. Unif. %/yr | ThCmf. Spec %/yr | ThCmf. Sprt %/yr | Temp. Crit. %/yr |
|----------|-------------------------|-------------------------|-------------------------|------------------------|-------------------|---------------|----------------------|------------------------|------------------------|------------------------|
| Alt #001 | 3562 | 83074 | 24189 | 61299 | 3.4 | 61.8 | 82.1 | 54.9 | 16.4 | 7.5 |
| Alt #002 | 2032 | 73437 | 29330 | 87218 | 4.1 | 59.7 | 96.6 | 51.0 | 14.5 | 1.1 |
| Alt #003 | 4982 | 70367 | 17187 | 12973 | 7.6 | 61.8 | 63.0 | 56.8 | 17.9 | 13.9 |
| Alt #004 | 4018 | 77638 | 22455 | – | – | 56.3 | 77.4 | 54.0 | 17.5 | 10.0 |
| Alt #005 | 4586 | 70956 | 23523 | 56843 | 3.2 | 59.7 | 80.7 | 54.0 | 18.3 | 12.7 |
| Alt #006 | 8325 | 74708 | 14247 | 28355 | 6.2 | 59.8 | 55.1 | 55.8 | 22.7 | 22.9 |
| Alt #007 | 4031 | 66965 | 29329 | 11239 | 19.8 | 61.8 | 96.6 | 52.7 | 17.8 | 10.1 |
| Alt #008 | 8480 | 69511 | 14300 | 16858 | 10.6 | 61.3 | 55.2 | 55.1 | 22.7 | 24.5 |
| Alt #009 | 3769 | 75849 | 27027 | – | – | 59.7 | 89.0 | 52.5 | 16.7 | 8.3 |
| Alt #010 | 3557 | 69141 | 24535 | 8474 | 14.7 | 58.6 | 82.5 | 53.5 | 16.3 | 6.5 |
| Alt #011 | 3966 | 20886 | 29459 | 14806 | 5.4 | 61.8 | 100.0 | 42.7 | 18.8 | 5.2 |
| Alt #012 | 3875 | 20960 | 29078 | 4281 | 9.8 | 61.8 | 97.6 | 42.7 | 19.1 | 8.5 |
| Alt #013 | 3772 | 21287 | 29212 | 15473 | 5.6 | 61.8 | 98.4 | 43.1 | 18.8 | 5.8 |
| Alt #014 | 3174 | 20804 | 29459 | 19280 | 5.2 | 61.8 | 100.0 | 40.9 | 17.6 | 1.2 |
| Alt #015 | 7119 | 19632 | 21848 | 59517 | 4.6 | 61.8 | 75.3 | 47.0 | 23.1 | 20.0 |
| Alt #016 | 2556 | 44234 | 29853 | 91385 | 3.2 | 61.8 | 100.0 | 44.7 | 16.2 | 1.0 |
| Alt #017 | 1859 | 42359 | 29859 | 81625 | 3.2 | 61.8 | 100.0 | 40.9 | 14.2 | 0.3 |
| Alt #018 | 5822 | 52133 | 22342 | 71291 | 3.2 | 61.8 | 76.6 | 51.9 | 19.7 | 16.7 |
| Alt #019 | 2546 | 44088 | 29859 | 86460 | 3.2 | 61.8 | 100.0 | 44.1 | 16.1 | 1.2 |
| Alt #020 | 1723 | 39143 | 29859 | 86514 | 3.2 | 61.8 | 100.0 | 38.0 | 13.9 | 0.0 |

Alternative simulations with activity schedule of 9 hrs/day

| | Co. Energy % | He. Energy % | Li. Energy % | PV Energy % | PV EPBT % | Glare % | Li. Unif. % | ThCmf. Spec % | ThCmf. Sprt % | Temp. Crit. % |
|----------|--------------------|--------------------|--------------------|-------------------|-----------------|------------|-------------------|---------------------|---------------------|---------------------|
| Alt #001 | 2087 | 66942 | 15728 | 61299 | 3.4 | 44.5 | 85.8 | 67.2 | 45.7 | 12.7 |
| Alt #002 | 1105 | 66116 | 17832 | 87218 | 4.1 | 41.3 | 96.5 | 67.4 | 38.5 | 4.7 |
| Alt #003 | 3095 | 62484 | 13446 | 12973 | 7.6 | 44.5 | 74.4 | 66.2 | 43.2 | 15.1 |
| Alt #004 | 2447 | 63900 | 15165 | – | – | 37.0 | 83.0 | 64.3 | 43.6 | 12.8 |
| Alt #005 | 2859 | 61478 | 16293 | 56843 | 3.2 | 41.4 | 88.4 | 64.3 | 41.6 | 14.1 |
| Alt #006 | 5637 | 58954 | 12380 | 28355 | 6.2 | 41.6 | 69.2 | 66.5 | 50.6 | 27.9 |
| Alt #007 | 2378 | 61047 | 17797 | 11239 | 19.8 | 44.5 | 96.2 | 64.8 | 39.5 | 10.0 |
| Alt #008 | 5762 | 58174 | 12550 | 16858 | 10.6 | 43.7 | 69.8 | 67.4 | 49.5 | 27.7 |
| Alt #009 | 2177 | 64439 | 16402 | – | – | 41.3 | 88.3 | 64.9 | 43.0 | 11.4 |
| Alt #010 | 1968 | 62737 | 16087 | 8474 | 14.7 | 39.8 | 86.6 | 65.6 | 40.4 | 8.3 |
| Alt #011 | 1962 | 29390 | 17794 | 14806 | 5.4 | 44.5 | 100.0 | 58.8 | 32.1 | 2.6 |
| Alt #012 | 2025 | 28382 | 17424 | 4281 | 9.8 | 44.5 | 96.3 | 58.6 | 31.5 | 4.7 |
| Alt #013 | 1903 | 29007 | 17562 | 15473 | 5.6 | 44.5 | 97.7 | 58.9 | 32.2 | 3.0 |
| Alt #014 | 1358 | 30025 | 17794 | 19280 | 5.2 | 44.5 | 100.0 | 57.6 | 28.9 | 0.9 |
| Alt #015 | 4312 | 26205 | 14234 | 59517 | 4.6 | 44.5 | 78.5 | 60.8 | 35.4 | 18.1 |
| Alt #016 | 1159 | 50937 | 18182 | 91385 | 3.2 | 44.5 | 100.0 | 60.6 | 30.8 | 1.2 |
| Alt #017 | 924 | 49853 | 18182 | 81625 | 3.2 | 44.5 | 100.0 | 61.1 | 26.1 | 0.5 |
| Alt #018 | 3669 | 52439 | 15675 | 71291 | 3.2 | 44.5 | 84.3 | 64.6 | 38.6 | 17.0 |
| Alt #019 | 1162 | 50527 | 18182 | 86460 | 3.2 | 44.5 | 100.0 | 60.2 | 30.4 | 1.2 |
| Alt #020 | 918 | 48901 | 18182 | 86514 | 3.2 | 44.5 | 100.0 | 60.9 | 23.5 | 0.4 |

APPENDIX D: ANALYSIS OF LOSS OF TOPOLOGY USING ADAPTED SOM ALGORITHM FOR VARYING GRID SIZES

This thesis uses a custom algorithm to attribute data items to SOM cells. Because of the author's limited experience in programming, the algorithm implemented in the visual analytics tool is slow; it requires approximately two hours to match 150 design alternatives to 984 grid cells. Functionality of the algorithm is therefore tested using a scenario analysis, presented in this appendix.

A data set of 156 items is used to generate SOMs of various sizes in modeFRONTIER. Each size equals or approximates a specific ratio. Visualizations of the SOMs, derived from ModeFRONTIER, are shown in Fig. A.8. ModeFRONTIER shows the amount of design alternatives attributed to a cell by drawing squares in the cells. The size of a square relates to the amount of data items of the corresponding cell.

These visualizations are used to analyze potential areas where loss of topology may occur. The methodology used approximates a 'what-if' analysis; In a repeating process, the author picks a cell where data items exceed one data item and redistributes its items to neighbouring cells. This effectively mimics the behaviour of the algorithm proposed in this thesis. The author uses a 'worst case scenario' approach to redistribute data items. Loss of topology occurs when data items cannot be redistributed to neighboring cells, but instead are forced to cells that are further away from the original cell.

The scenario analysis indicates that loss of topology occurs when ratios between grid cells and data items are 1:1 or 2:1. Therefore, the algorithm proposed in this thesis is not suitable when the amount of grid cells of the SOM is similar to the amount of data items. Loss of topology is small when the ratio is 3:1. For larger ratios no loss of topology occurs. Hence, the algorithm functions suitably well when the ratio exceeds 3:1. Regardless, it should be noted that use of the Visual Analytics System without topology preservation is not likely to have great effect on the decision-making process of the user.

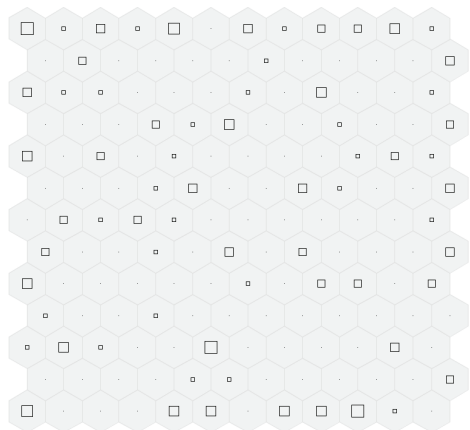
The dataset consists of 156 design alternatives (in all cases)

156 cells (1:1 ratio)

max. amount of design alternatives in cell: 6

Estimated chance of loss of topology preservation: VERY HIGH
Estimated extent of loss of topology preservation: EXTENSIVE
Estimated amount of loss of topology preservation: VERY HIGH

Areas of conflict:

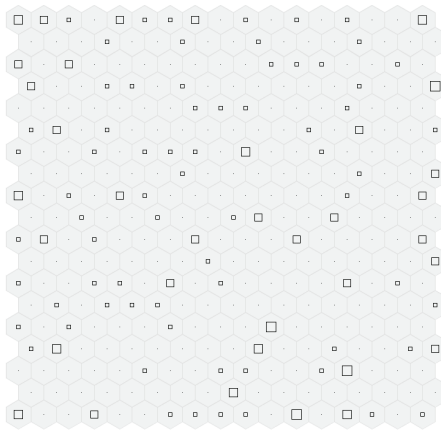


322 cells (2:1 ratio)

max. amount of design alternatives in cell: 4

Estimated chance of loss of topology preservation: VERY HIGH
Estimated extent of loss of topology preservation: AREA AROUND A COUPLE OF CELLS
Estimated amount of loss of topology preservation: HIGH

Areas of conflict:

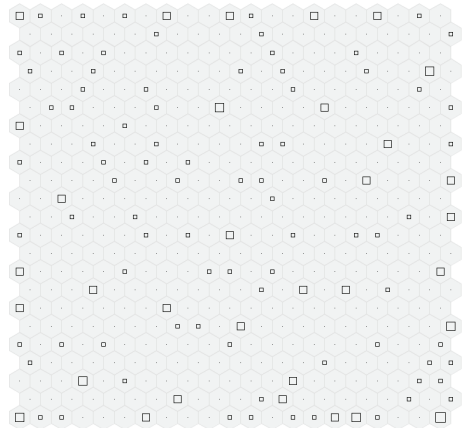


482 cells (3:1 ratio)

max. amount of design alternatives in cell: 4

Estimated chance of loss of topology preservation: MODERATE
Estimated extent of loss of topology preservation: AREA AROUND A COUPLE OF CELLS
Estimated amount of loss of topology preservation: MODERATE

Areas of conflict:

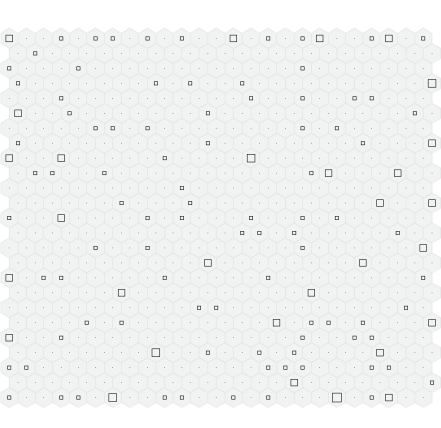


156 cells (4:1 ratio)

max. amount of design alternatives in cell: 4

Estimated chance of loss of topology preservation: MODERATE/LOW
Estimated extent of loss of topology preservation: AREA AROUND VERY FEW CELLS
Estimated amount of loss of topology preservation: LOW

Areas of conflict:

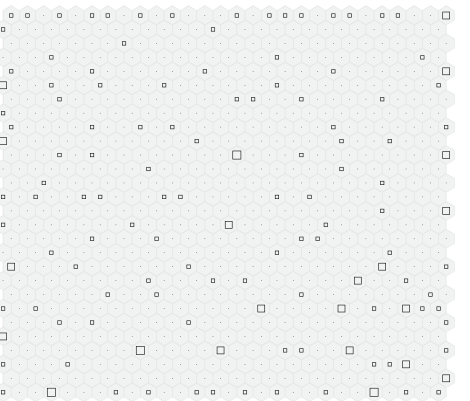


984 cells (5:1 ratio) - Current landscape

max. amount of design alternatives in cell: 3

Estimated chance of loss of topology preservation: VERY LOW
Estimated extent of loss of topology preservation: AREA AROUND ONE OR TWO CELLS
Estimated amount of loss of topology preservation: LOW

Areas of conflict:



1225 cells (8:1 ratio)

max. amount of design alternatives in cell: 2

Estimated chance of loss of topology preservation: EXTREMELY LOW
Estimated extent of loss of topology preservation: AREA AROUND ONE OR TWO CELLS
Estimated amount of loss of topology preservation: VERY LOW

Areas of conflict:

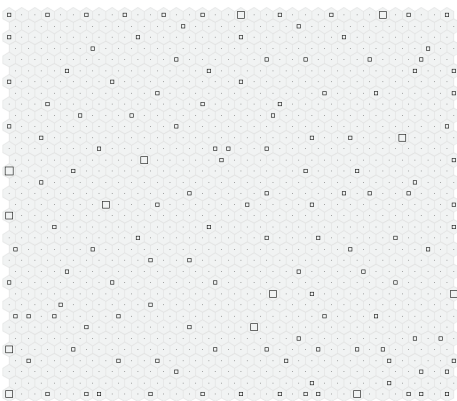


Fig. A.8: SOMs generated in modeFRONTIER (v.5.3.0; ESTECO SpA, 2017).

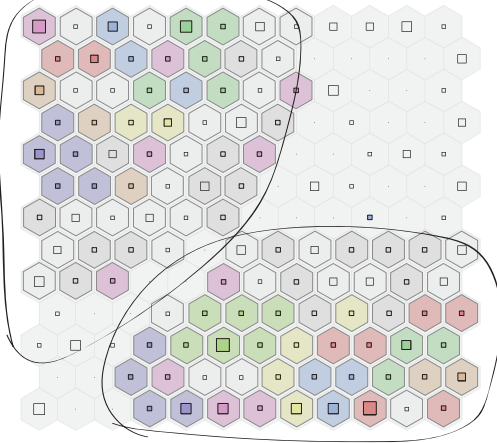
The dataset consists of 156 design alternatives (in all cases)

156 cells (1:1 ratio)

max. amount of design alternatives in cell: 6

Estimated chance of loss of topology preservation: VERY HIGH
Estimated extent of loss of topology preservation: EXTENSIVE
Estimated amount of loss of topology preservation: VERY HIGH

Areas of conflict:

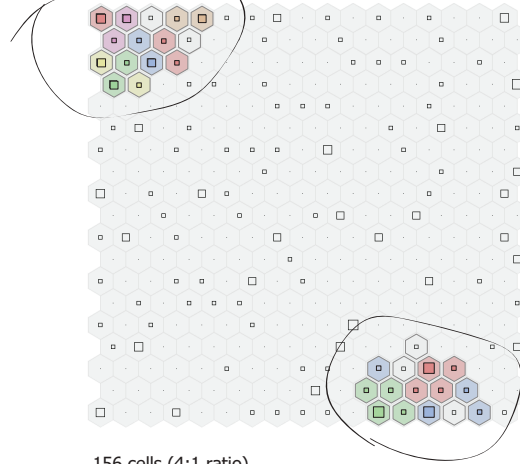


322 cells (2:1 ratio)

max. amount of design alternatives in cell: 4

Estimated chance of loss of topology preservation: VERY HIGH
Estimated extent of loss of topology preservation: AREA AROUND A COUPLE OF CELLS
Estimated amount of loss of topology preservation: HIGH

Areas of conflict:

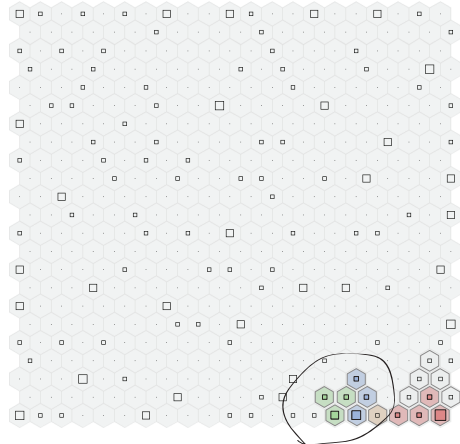


482 cells (3:1 ratio)

max. amount of design alternatives in cell: 4

Estimated chance of loss of topology preservation: MODERATE
Estimated extent of loss of topology preservation: AREA AROUND A COUPLE OF CELLS
Estimated amount of loss of topology preservation: MODERATE

Areas of conflict:

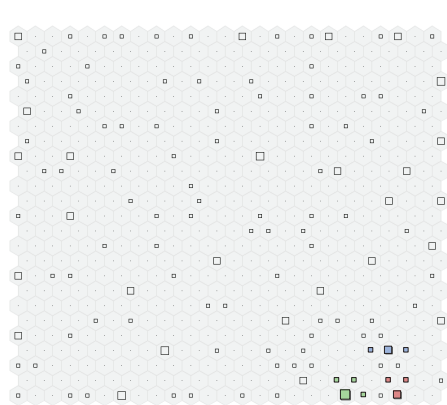


156 cells (4:1 ratio)

max. amount of design alternatives in cell: 4

Estimated chance of loss of topology preservation: MODERATE/LOW
Estimated extent of loss of topology preservation: AREA AROUND VERY FEW CELLS
Estimated amount of loss of topology preservation: LOW

Areas of conflict:

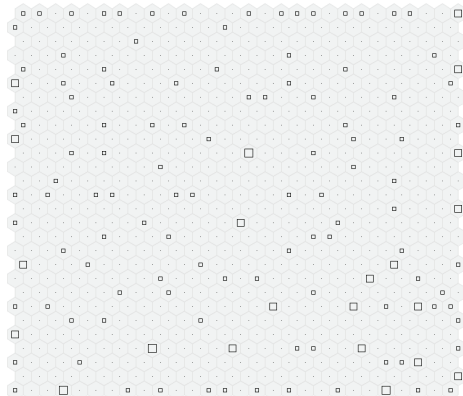


984 cells (5:1 ratio) - Current landscape

max. amount of design alternatives in cell: 3

Estimated chance of loss of topology preservation: VERY LOW
Estimated extent of loss of topology preservation: AREA AROUND ONE OR TWO CELLS
Estimated amount of loss of topology preservation: LOW

Areas of conflict:



1225 cells (8:1 ratio)

max. amount of design alternatives in cell: 2

Estimated chance of loss of topology preservation: EXTREMELY LOW
Estimated extent of loss of topology preservation: AREA AROUND ONE OR TWO CELLS
Estimated amount of loss of topology preservation: VERY LOW

Areas of conflict:

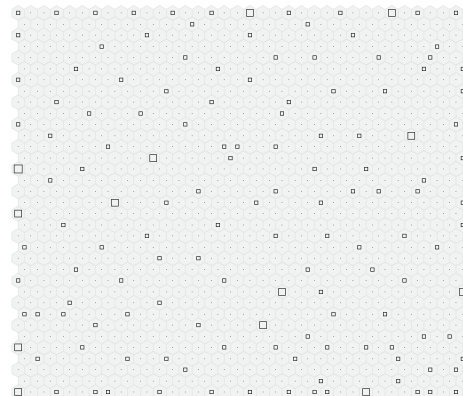


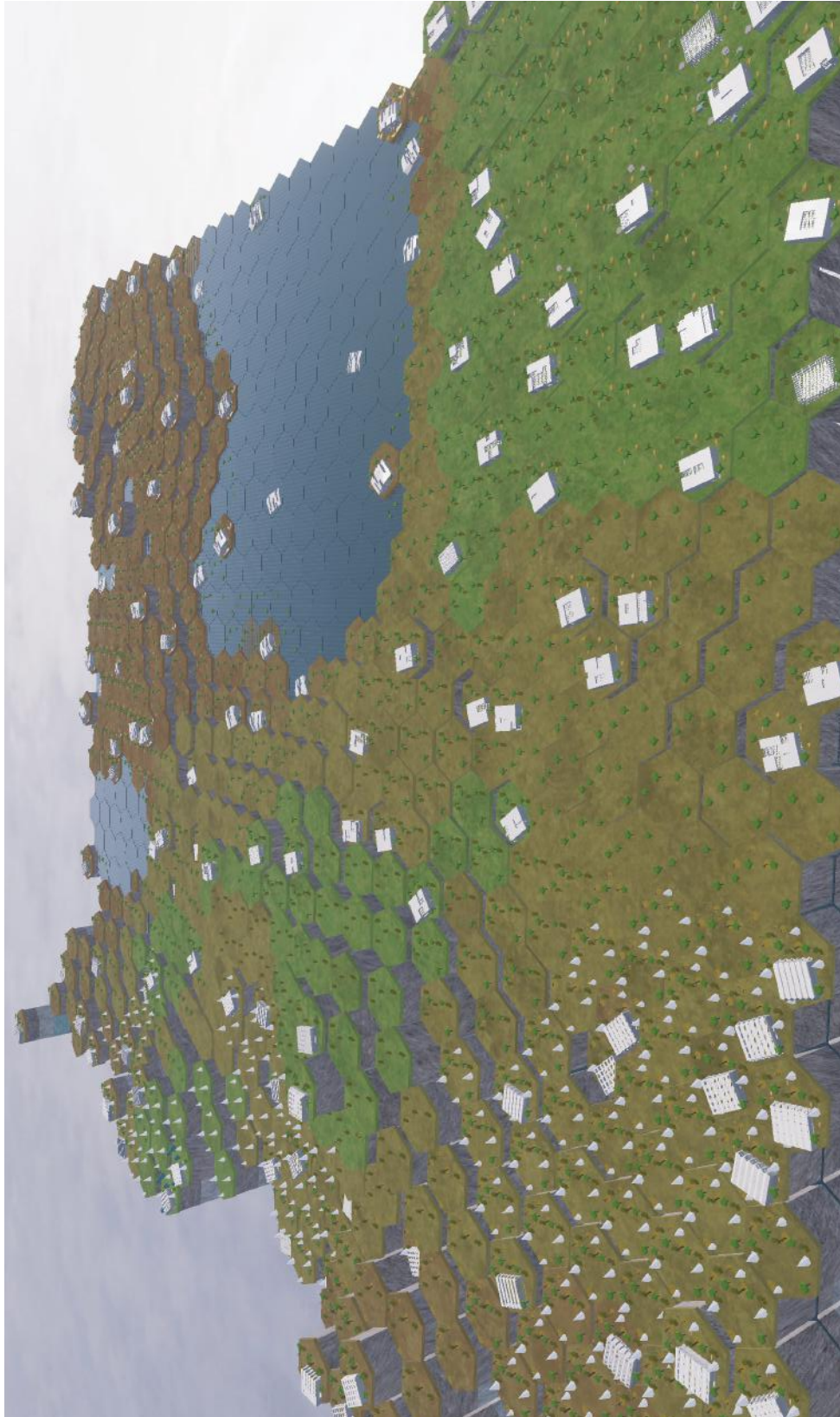
Fig. A.9: Scenario analysis. Clusters of potential conflict are identified and circled. Design alternatives in cells that contain more than one data item are manually redistributed to identify potential loss of topology.

APPENDIX E: CORRELATION MATRICES OF DATA SETS WITH VARYING OCCUPANCY SCHEDULES

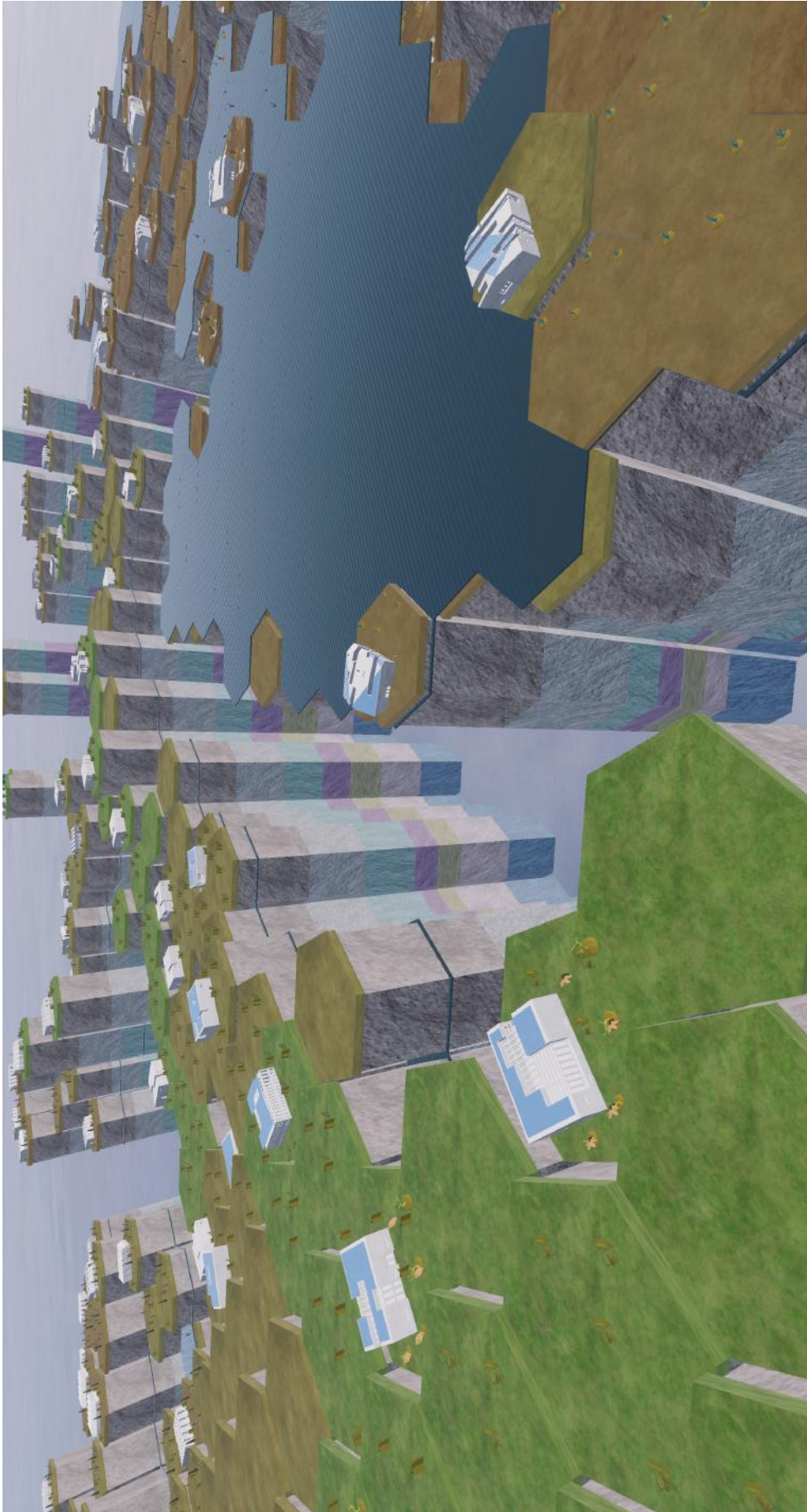
| | B01_FloorArea | B02_Volume | B03_ExposedWallArea | B04_Orientation | B05_PVPanelArea | B06_WallAreaNorth | B07_WallAreaEast | B08_WallAreaSouth | B09_WallAreaWest | B10_WallAreaSky | B11_WallAreaNorth | B12_WallAreaEast | B13_WallAreaSouth | B14_WallAreaWest | B15_WallAreaSky | E1_CoEnergy | E2_HotEnergy | E3_Latency | E4_PVEnergyGain | E5_PVEBT | L1_Glare | L2_Uniformity | T1_ThCnSpec | T2_ThCnSpec | T3_TempCriteria |
|---------------------|---------------|------------|---------------------|-----------------|-----------------|-------------------|------------------|-------------------|------------------|-----------------|-------------------|------------------|-------------------|------------------|-----------------|-------------|--------------|------------|-----------------|----------|----------|---------------|-------------|-------------|-----------------|
| B01_FloorArea | 1 | | | | | | | | | | | | | | | | | | | | | | | | |
| B02_Volume | -0.688 | 1 | | | | | | | | | | | | | | | | | | | | | | | |
| B03_ExposedWallArea | -0.726 | 0.923 | 1 | | | | | | | | | | | | | | | | | | | | | | |
| B04_Orientation | -0.105 | 0.141 | 0.067 | 1 | | | | | | | | | | | | | | | | | | | | | |
| B05_PVPanelArea | -0.130 | 0.067 | 0.068 | 0.146 | 1 | | | | | | | | | | | | | | | | | | | | |
| B06_WallAreaNorth | 0.204 | -0.090 | -0.186 | -0.027 | -0.045 | 0.092 | 1 | | | | | | | | | | | | | | | | | | |
| B07_WallAreaEast | -0.652 | 0.393 | 0.381 | -0.103 | -0.103 | -0.368 | 0.497 | 1 | | | | | | | | | | | | | | | | | |
| B08_WallAreaSouth | 0.407 | -0.232 | -0.283 | -0.103 | -0.368 | 0.497 | -0.110 | -0.157 | 1 | | | | | | | | | | | | | | | | |
| B09_WallAreaWest | 0.292 | -0.067 | -0.169 | -0.169 | -0.169 | -0.169 | -0.169 | -0.169 | -0.169 | 1 | | | | | | | | | | | | | | | |
| B10_WallAreaSky | -0.904 | 0.371 | 0.409 | 0.141 | -0.114 | -0.114 | -0.114 | -0.114 | -0.114 | -0.114 | 1 | | | | | | | | | | | | | | |
| B11_WallAreaNorth | -0.435 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | 1 | | | | | | | | | | | | | |
| B12_WallAreaEast | -0.462 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | 1 | | | | | | | | | | | | |
| B13_WallAreaSouth | -0.462 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | 1 | | | | | | | | | | | |
| B14_WallAreaWest | -0.462 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | 1 | | | | | | | | | | |
| B15_WallAreaSky | -0.462 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | -0.246 | 1 | | | | | | | | | |
| E1_CoEnergy | 0.474 | 0.318 | -0.926 | -0.008 | -0.141 | -0.122 | 0.119 | -0.055 | 0.122 | 0.588 | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | |
| E2_HotEnergy | -0.264 | -0.301 | 0.830 | 0.093 | 0.072 | 0.119 | -0.055 | 0.122 | 0.588 | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | |
| E3_Latency | -0.264 | -0.301 | 0.830 | 0.093 | 0.072 | 0.119 | -0.055 | 0.122 | 0.588 | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | |
| E4_PVEnergyGain | -0.141 | -0.122 | 0.119 | -0.055 | 0.122 | 0.588 | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | | | | |
| E5_PVEBT | -0.141 | -0.122 | 0.119 | -0.055 | 0.122 | 0.588 | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | | | | |
| L1_Glare | -0.122 | 0.119 | -0.055 | 0.122 | 0.588 | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | | | | | |
| L2_Uniformity | -0.082 | 0.489 | -0.082 | -0.122 | 0.119 | -0.055 | 0.122 | 0.588 | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | | |
| T1_ThCnSpec | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | | | | | | | | | | |
| T2_ThCnSpec | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | | | | | | | | | | |
| T3_TempCriteria | -0.616 | 0.451 | 0.276 | | | | | | | | | | | | | | | | | | | | | | |

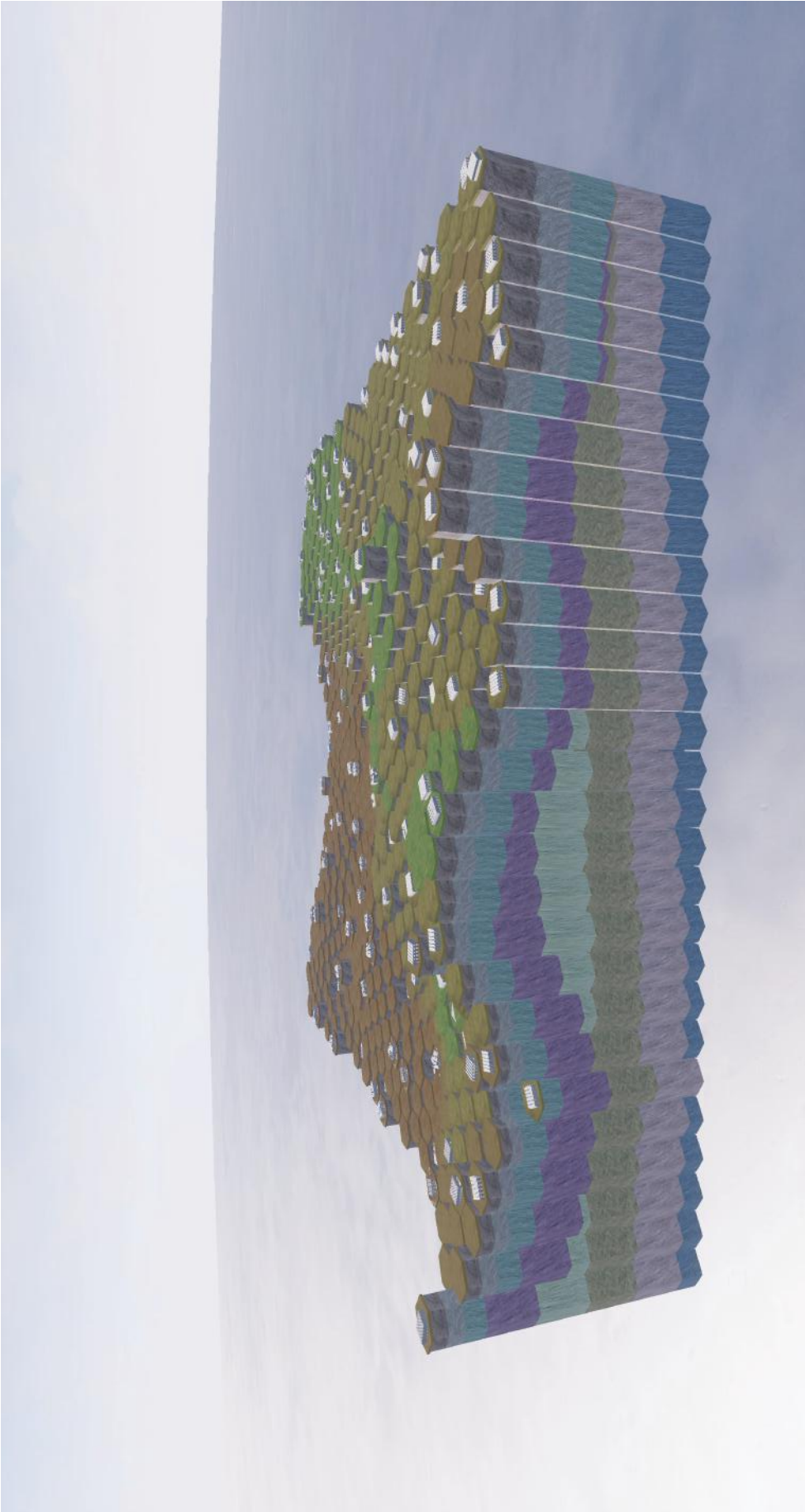
Fig. A.10: Correlation matrices of data sets of 150 design alternatives simulated with occupancy schedules of 17 hrs/day (L.) and 9 hrs/day (r.)

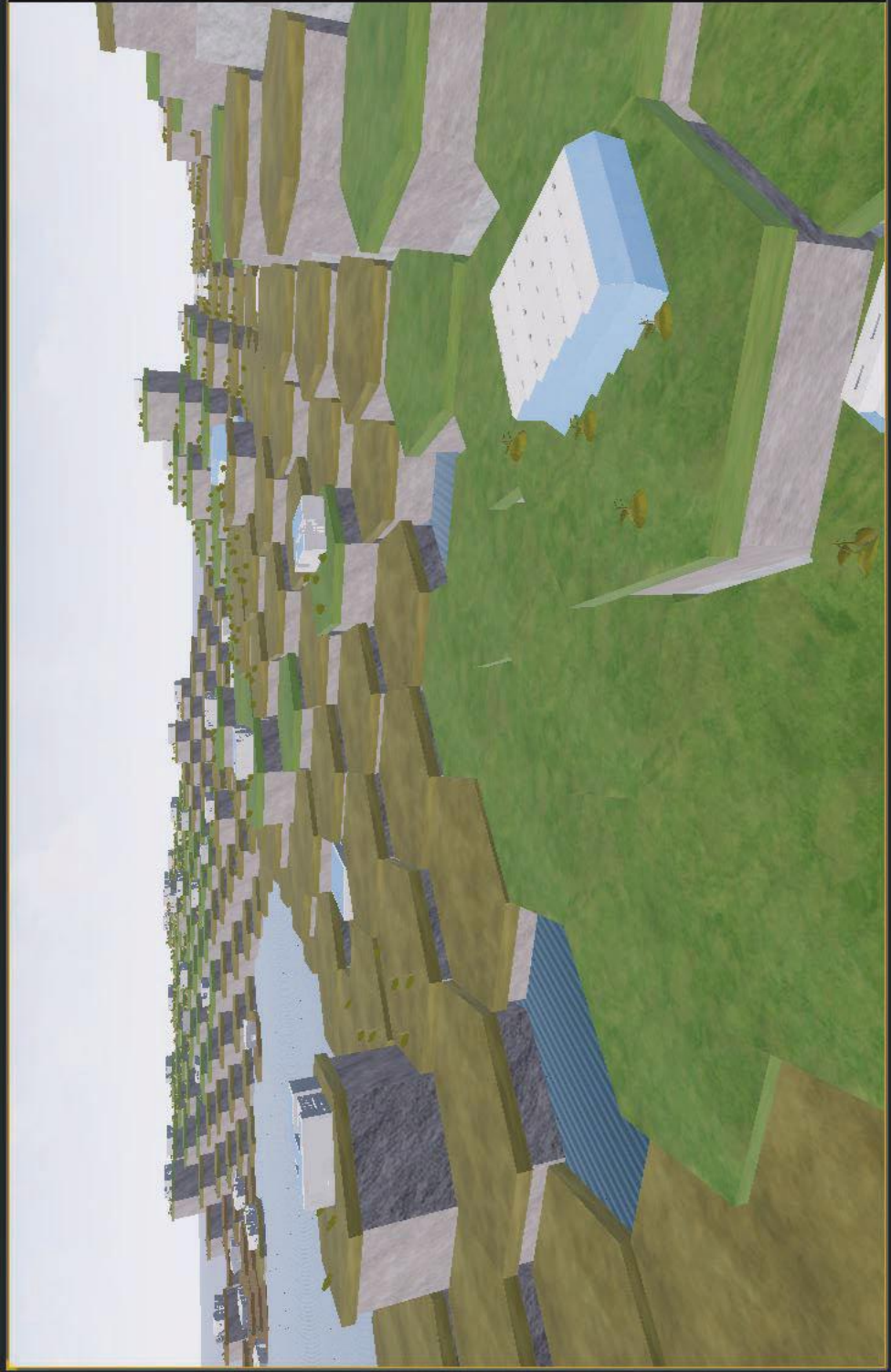
APPENDIX F: HIGH RESOLUTION IMAGES OF THE VISUAL ANALYTICS TOOL











222271

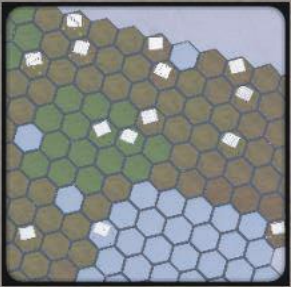
145

| | |
|----------------------|-----------------------|
| Cooling Energy | 1,923.08 kWh/year |
| Heating Energy | 43,357.316 kWh/year |
| Lighting Energy | 29,858.535 kWh/year |
| PV Energy Gain | -92,545.922 kWh/year |
| PV EPBT | 3.217 years |
| Gate | 63.288 kWh/year |
| Lighting Uniformity | 100 %/year not met |
| Th comfort spec | 41.817 %/year not met |
| Th comfort opt | 14.305 %/year not met |
| Temperature Criteria | 0.426 %/year not met |

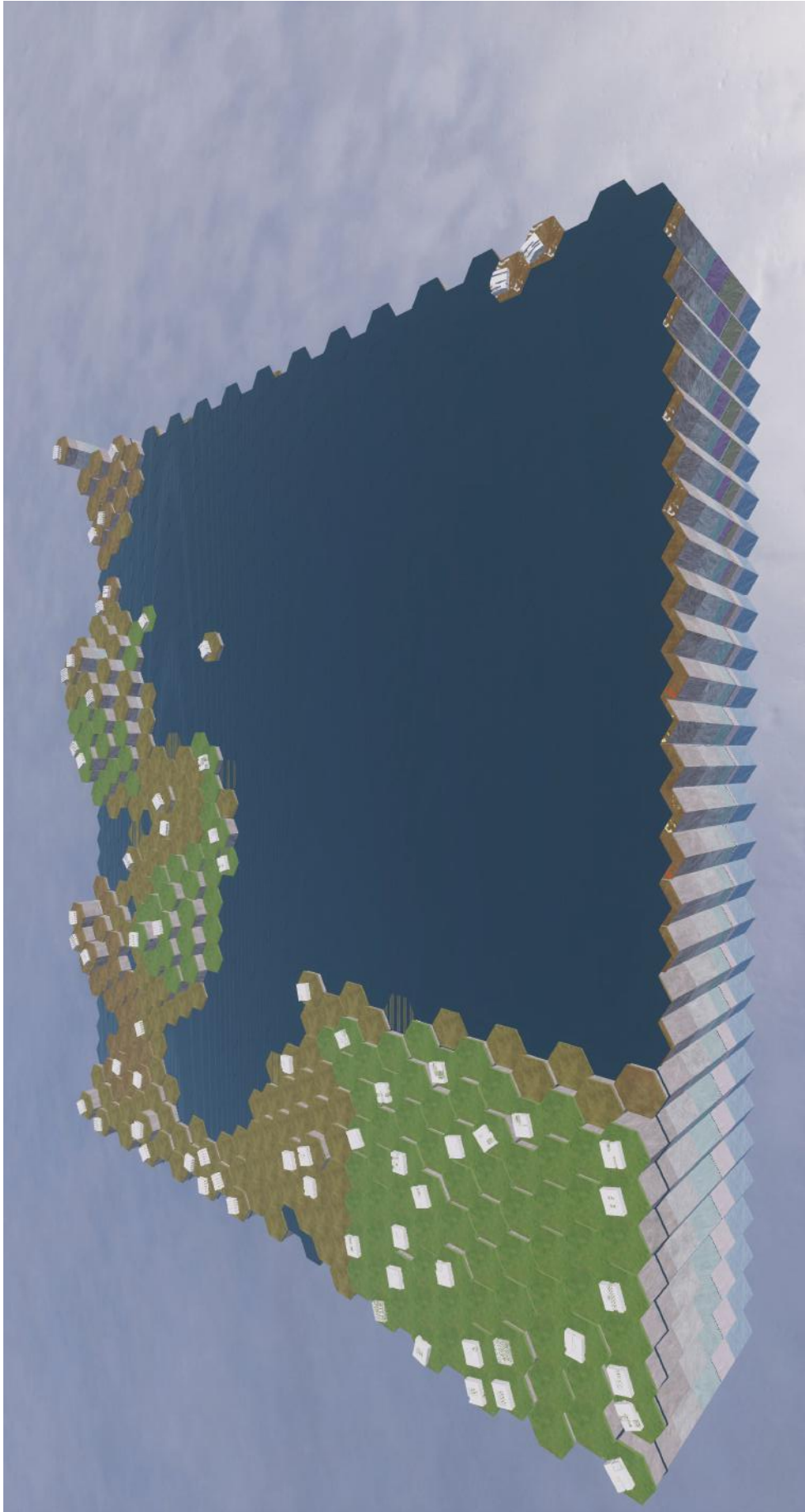
333144

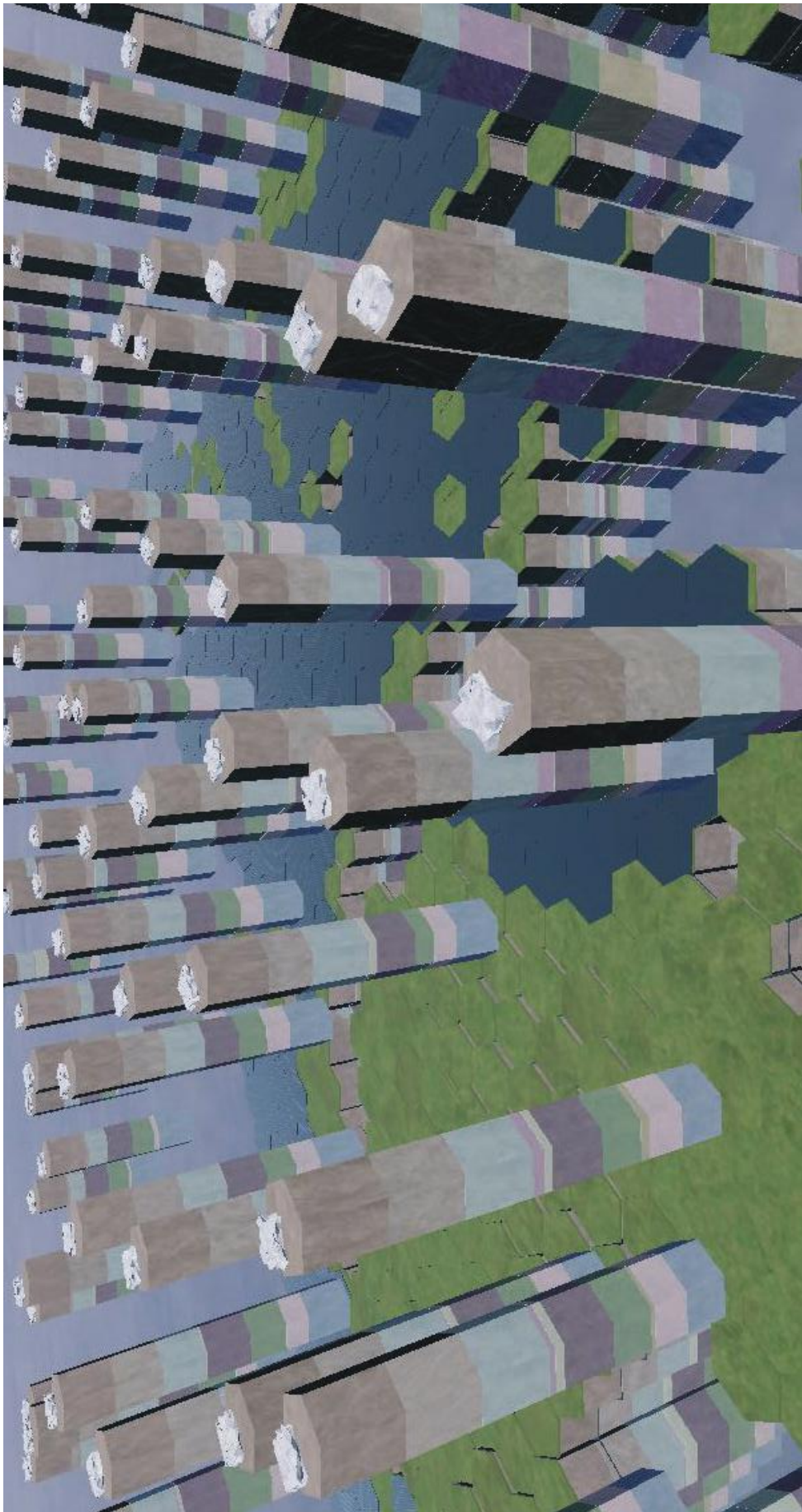
583

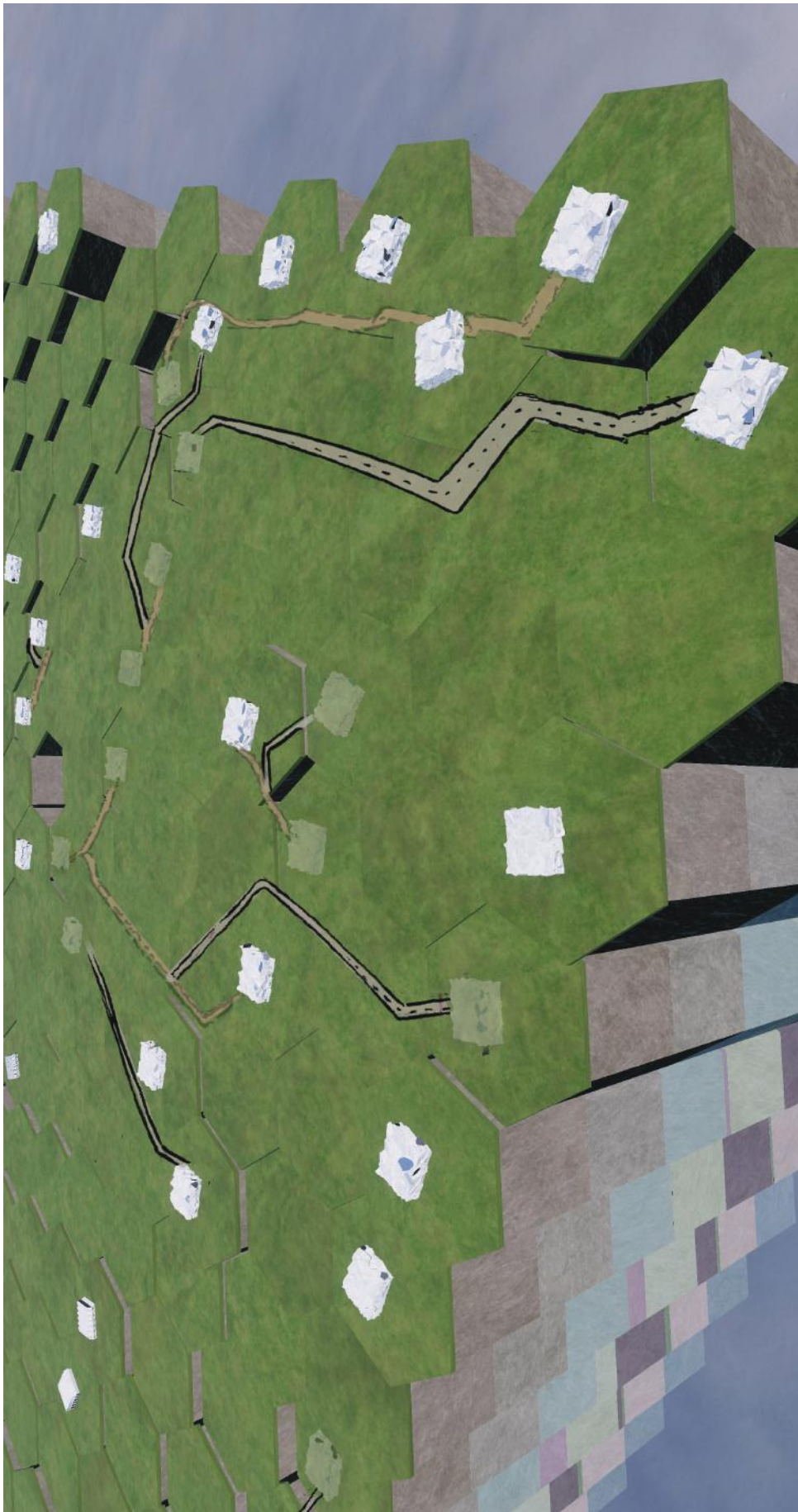
| | |
|----------------------|-------------------------|
| Temperature Criteria | -34.679 kWh/m2 |
| Th comfort opt | 31.72 %/y (18%) |
| Th comfort spec | 24.315 %/y (28%) |
| Lighting Uniformity | 48.75 %/y (51%) |
| Gate | 46.882 %/y (92%) |
| PV EPBT | 63.288 %/y (0%) |
| PV Energy Gain | 3.588 %/y (99%) |
| Lighting Energy | -80,153.469 kWh/y (62%) |
| Heating Energy | 16,009.245 kWh/y (87%) |
| Cooling Energy | 22,768.285 kWh/y (95%) |
| | 9,540.745 kWh/y (17%) |















APPENDIX G: DESIGN DECISIONS OF PRELIMINARY SKETCH DESIGN USED IN PEER REVIEW

Design:

- The building fills a gap in terms of sport functions.
- The roof will be used for sporting, aesthetic and energy purposes. It is a solar park meant for sporting, walking and provides an interesting view for the inhabitants of the surrounding residential structures.
- It contains the possibility for usage of other functions like a small cinema, theatre and lecture spaces.
- The sporting hall itself is connected to the park through a double colonnade and is supposed to draw people through and into the building.
- The sports hall itself has a very open northern façade directed towards the square. It should be able to open up completely so the it can be combined with the square for a market or convention. These are connected through stairs.
- A parking garage in the basement, the ground is already dug away this makes it easier.
- The appearance should approach the something in the direction of the Eye. This to balance the Eye-building.

Basic principles:

- The roof is sloped towards the south to provide covering and the placement of solar panels.
- The roof lights provide, together with the main façade on the north side daylight.
- There are one or two windows aimed towards the west made of translucent glass to provide interesting views for the houses on the other side of the road.
- The east side is mainly closed.
- The south side is provided with a open façade as well to so a passer-by can see inside the building. This is supposed to make the building more inviting for the user.

APPENDIX H: CORRELATION MATRICES OF DATA PER PARAMETRIC MODEL

| | B01_FloorArea | B02_Volume | B03_ExposedWallArea | B04_Orientation | B05_PVPanelArea | B06_WAreaNorth | B07_WAreaEast | B08_WAreaSouth | B09_WAreaWest | B10_WAreaSky | B11_WiShadingNorth | B12_WiShadingEast | B13_WiShadingSouth | B14_WiShadingWest | B15_WiShadingSky | E1_CoEnergy | E2_HeEnergy | E3_LiEnergy | E4_PVEnergyGain | E5_PVEPBT | L1_Glare | L2_LiUniformity | T1_ThCmSpec | T2_ThCmSpt | T3_TempCriteria | |
|---------------------|---------------|------------|---------------------|-----------------|-----------------|----------------|---------------|----------------|---------------|--------------|--------------------|-------------------|--------------------|-------------------|------------------|-------------|-------------|-------------|-----------------|-----------|----------|-----------------|-------------|------------|-----------------|------|
| B01_FloorArea | 1.00 | 0.25 | 0.51 | 0.10 | 0.38 | -0.04 | - | 0.38 | -0.01 | -0.24 | 0.20 | - | 0.12 | 0.03 | 0.02 | -0.11 | -0.58 | 0.27 | -0.40 | -0.26 | - | 0.32 | -0.31 | -0.07 | -0.19 | |
| B02_Volume | 0.25 | 1.00 | 0.70 | -0.14 | 0.02 | 0.22 | - | -0.13 | 0.24 | -0.14 | 0.19 | - | 0.05 | 0.09 | -0.35 | -0.11 | 0.42 | 0.04 | -0.03 | -0.25 | - | -0.05 | -0.04 | -0.17 | -0.09 | |
| B03_ExposedWallArea | 0.51 | 0.70 | 1.00 | -0.31 | 0.15 | -0.09 | - | 0.04 | -0.04 | -0.48 | 0.33 | - | -0.11 | -0.06 | -0.35 | -0.61 | 0.03 | 0.55 | -0.14 | -0.33 | - | -0.46 | -0.55 | -0.65 | -0.61 | |
| B04_Orientation | 0.10 | -0.14 | -0.31 | 1.00 | 0.16 | 0.08 | - | 0.11 | 0.31 | 0.29 | -0.09 | 0.38 | - | 0.27 | 0.38 | 0.07 | 0.52 | -0.08 | -0.40 | -0.12 | 0.19 | - | -0.34 | 0.41 | 0.57 | 0.52 |
| B05_PVPanelArea | 0.38 | 0.02 | 0.15 | 0.16 | 1.00 | -0.10 | - | 0.07 | -0.19 | 0.11 | -0.19 | - | 0.27 | -0.01 | 0.20 | 0.05 | -0.22 | -0.02 | -0.98 | -0.31 | - | -0.02 | -0.05 | 0.07 | 0.05 | |
| B06_WAreaNorth | -0.04 | 0.22 | -0.09 | 0.08 | -0.10 | 1.00 | - | -0.13 | 0.51 | -0.23 | 0.19 | - | -0.10 | 0.08 | -0.44 | 0.19 | 0.44 | -0.32 | 0.04 | -0.19 | - | -0.28 | 0.38 | 0.14 | 0.20 | |
| B07_WAreaEast | - | - | - | - | - | - | 1.00 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | |
| B08_WAreaSouth | 0.38 | -0.13 | 0.04 | 0.11 | 0.07 | -0.13 | - | 1.00 | -0.22 | 0.00 | -0.01 | - | 0.07 | 0.41 | 0.16 | 0.13 | -0.31 | 0.05 | -0.06 | 0.10 | - | 0.15 | 0.03 | 0.17 | 0.06 | |
| B09_WAreaWest | -0.01 | 0.24 | -0.04 | 0.31 | -0.19 | 0.51 | - | -0.22 | 1.00 | -0.42 | 0.10 | - | -0.17 | 0.09 | -0.41 | 0.05 | 0.16 | -0.02 | 0.17 | -0.19 | - | 0.03 | 0.16 | 0.05 | 0.07 | |
| B10_WAreaSky | -0.24 | -0.14 | -0.48 | 0.29 | 0.11 | -0.23 | - | 0.00 | -0.42 | 1.00 | -0.40 | - | 0.42 | 0.15 | 0.57 | 0.81 | 0.25 | -0.80 | -0.13 | 0.34 | - | -0.80 | 0.71 | 0.78 | 0.82 | |
| B11_WiShadingNorth | 0.20 | 0.19 | 0.33 | -0.09 | -0.19 | 0.19 | - | -0.01 | 0.10 | -0.40 | 1.00 | - | 0.01 | -0.22 | -0.63 | -0.36 | -0.03 | 0.34 | 0.16 | -0.06 | - | 0.36 | -0.32 | -0.37 | -0.39 | |
| B12_WiShadingEast | 0.12 | 0.05 | -0.11 | 0.27 | 0.27 | -0.10 | - | 0.07 | -0.17 | 0.42 | 0.01 | - | 1.00 | 0.05 | 0.23 | 0.40 | -0.01 | -0.32 | -0.29 | -0.03 | - | -0.32 | 0.28 | 0.41 | 0.40 | |
| B13_WiShadingSouth | 0.03 | 0.09 | -0.06 | 0.38 | -0.01 | 0.08 | - | 0.41 | 0.09 | 0.15 | -0.22 | - | 0.05 | 1.00 | 0.13 | 0.35 | 0.01 | -0.28 | -0.01 | -0.04 | - | -0.24 | 0.24 | 0.38 | 0.34 | |
| B14_WiShadingWest | 0.02 | -0.35 | -0.35 | 0.07 | 0.20 | -0.44 | - | 0.16 | -0.45 | 0.57 | -0.63 | - | 0.23 | 0.13 | 1.00 | 0.41 | -0.24 | -0.32 | -0.18 | 0.13 | - | -0.29 | 0.25 | 0.44 | 0.39 | |
| B15_WiShadingSky | -0.11 | -0.11 | -0.06 | 0.52 | 0.05 | 0.19 | - | 0.13 | 0.05 | 0.81 | -0.36 | - | 0.40 | 0.35 | 0.41 | 1.00 | 0.23 | -0.93 | -0.10 | 0.21 | - | -0.85 | 0.91 | 0.98 | 0.99 | |
| E1_CoEnergy | -0.58 | 0.42 | 0.03 | -0.08 | -0.22 | 0.44 | - | -0.31 | 0.16 | 0.25 | -0.03 | - | -0.01 | 0.01 | -0.24 | 0.23 | 1.00 | -0.49 | 0.21 | 0.09 | - | -0.57 | 0.55 | 0.11 | 0.32 | |
| E2_HeEnergy | 0.27 | 0.04 | 0.55 | -0.40 | -0.02 | 0.32 | - | 0.05 | -0.02 | -0.80 | 0.34 | - | -0.32 | -0.28 | -0.32 | 0.93 | -0.49 | 1.00 | 0.06 | -0.20 | - | -0.97 | -0.92 | -0.85 | -0.94 | |
| E3_LiEnergy | -0.40 | -0.03 | -0.14 | -0.12 | -0.98 | 0.04 | - | -0.06 | 0.17 | -0.13 | 0.16 | - | -0.29 | -0.01 | -0.18 | -0.10 | 0.21 | 0.06 | 1.00 | 0.37 | - | 0.05 | 0.01 | -0.10 | -0.09 | |
| E4_PVEnergyGain | -0.26 | -0.25 | -0.33 | 0.19 | -0.31 | -0.19 | - | -0.12 | -0.19 | 0.34 | -0.06 | - | -0.03 | -0.04 | 0.13 | 0.21 | 0.09 | -0.20 | 0.37 | 1.00 | - | -0.20 | 0.23 | 0.22 | 0.23 | |
| E5_PVEPBT | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 1.00 | - | - | - | - | |
| L1_Glare | 0.32 | -0.05 | 0.46 | -0.34 | -0.02 | -0.28 | - | 0.15 | 0.03 | -0.80 | 0.36 | - | -0.32 | -0.24 | -0.29 | -0.85 | -0.57 | 0.97 | 0.05 | -0.20 | - | 1.00 | -0.87 | -0.76 | -0.88 | |
| L2_LiUniformity | -0.31 | -0.04 | -0.55 | 0.41 | -0.05 | 0.38 | - | 0.03 | 0.16 | 0.71 | -0.32 | - | 0.28 | 0.24 | 0.25 | 0.91 | 0.55 | -0.92 | 0.01 | 0.23 | - | -0.87 | 1.00 | 0.85 | 0.93 | |
| T1_ThCmSpec | -0.07 | -0.17 | -0.65 | 0.57 | 0.07 | 0.14 | - | 0.17 | 0.05 | 0.78 | -0.37 | - | 0.41 | 0.38 | 0.44 | 0.98 | 0.11 | -0.85 | -0.10 | 0.22 | - | -0.76 | 0.85 | 1.00 | 0.96 | |
| T2_ThCmSpt | -0.19 | -0.09 | -0.61 | 0.52 | 0.05 | 0.20 | - | 0.06 | 0.07 | 0.82 | -0.39 | - | 0.40 | 0.34 | 0.39 | 0.99 | 0.32 | -0.94 | -0.09 | 0.23 | - | -0.88 | 0.93 | 0.96 | 1.00 | |
| T3_TempCriteria | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | |

Fig. A.11: Correlation matrix of design alternatives generated with the 'zigzag' parametric model.

| | B01_FloorArea | B02_Volume | B03_ExposedWallArea | B04_Orientation | B05_PVPanelArea | B06_WAreaNorth | B07_WAreaEast | B08_WAreaSouth | B09_WAreaWest | B10_WAreaSky | B11_WiShadingNorth | B12_WiShadingEast | B13_WiShadingSouth | B14_WiShadingWest | B15_WiShadingSky | E1_CoEnergy | E2_HeEnergy | E3_LiEnergy | E4_PVEnergyGain | E5_PVEPBT | L1_Glare | L2_LiUniformity | T1_ThCmSpec | T2_ThCmSpt | T3_TempCriteria |
|---------------------|---------------|------------|---------------------|-----------------|-----------------|----------------|---------------|----------------|---------------|--------------|--------------------|-------------------|--------------------|-------------------|------------------|-------------|-------------|-------------|-----------------|-----------|----------|-----------------|-------------|------------|-----------------|
| B01_FloorArea | 1.00 | 0.12 | 0.50 | 0.00 | -0.28 | -0.34 | -0.46 | -0.26 | -0.40 | -0.11 | 0.14 | 0.15 | 0.57 | -0.04 | 0.24 | -0.10 | -0.67 | 0.26 | 0.28 | - | -0.28 | 0.26 | -0.35 | -0.04 | -0.14 |
| B02_Volume | 0.12 | 1.00 | 0.39 | 0.12 | 0.86 | -0.08 | -0.30 | -0.19 | -0.31 | -0.38 | -0.42 | -0.06 | 0.05 | -0.29 | -0.61 | -0.39 | -0.18 | 0.34 | -0.86 | - | 0.39 | 0.34 | -0.38 | -0.43 | -0.37 |
| B03_ExposedWallArea | 0.50 | 0.39 | 1.00 | 0.16 | 0.28 | -0.36 | -0.81 | -0.53 | -0.73 | -0.79 | -0.21 | -0.29 | 0.29 | -0.93 | -0.20 | -0.79 | -0.72 | 0.81 | -0.28 | - | -0.13 | 0.81 | -0.38 | -0.75 | -0.79 |
| B04_Orientation | 0.00 | 0.12 | 0.16 | 1.00 | 0.20 | -0.19 | -0.24 | -0.11 | -0.15 | -0.23 | -0.23 | -0.18 | 0.16 | 0.25 | -0.17 | -0.20 | -0.20 | 0.18 | -0.20 | - | -0.02 | 0.18 | -0.27 | -0.25 | -0.17 |
| B05_PVPanelArea | -0.28 | 0.86 | 0.28 | 0.20 | 1.00 | 0.02 | -0.21 | -0.21 | -0.20 | -0.52 | -0.47 | -0.14 | -0.10 | -0.26 | -0.73 | -0.54 | -0.02 | 0.39 | -1.00 | - | 0.42 | 0.39 | -0.40 | -0.58 | -0.50 |
| B06_WAreaNorth | -0.34 | -0.08 | -0.36 | -0.19 | 0.02 | 1.00 | 0.28 | -0.03 | 0.21 | 0.20 | -0.06 | -0.23 | -0.29 | 0.04 | -0.03 | 0.21 | 0.41 | -0.25 | -0.02 | - | -0.04 | -0.28 | 0.38 | 0.25 | 0.25 |
| B07_WAreaEast | -0.46 | -0.30 | -0.81 | -0.24 | -0.21 | 0.28 | 1.00 | 0.43 | 0.70 | 0.72 | 0.24 | 0.31 | -0.34 | -0.11 | 0.18 | 0.66 | 0.86 | -0.77 | 0.21 | - | 0.16 | -0.77 | 0.80 | 0.62 | 0.67 |
| B08_WAreaSouth | -0.26 | -0.19 | -0.53 | -0.11 | -0.21 | -0.03 | 0.43 | 1.00 | 0.28 | 0.60 | 0.17 | 0.04 | -0.32 | 0.33 | 0.18 | 0.64 | 0.41 | -0.69 | 0.21 | - | 0.08 | -0.68 | 0.62 | 0.62 | 0.63 |
| B09_WAreaWest | -0.40 | -0.31 | -0.73 | -0.15 | -0.20 | 0.21 | 0.70 | 0.28 | 1.00 | 0.80 | 0.42 | 0.14 | -0.22 | -0.02 | 0.24 | 0.54 | 0.74 | -0.61 | 0.20 | - | 0.06 | -0.62 | 0.73 | 0.55 | 0.53 |
| B10_WAreaSky | -0.11 | -0.38 | -0.79 | -0.23 | -0.52 | 0.20 | 0.72 | 0.60 | 0.80 | 1.00 | 0.28 | 0.33 | -0.16 | 0.06 | 0.40 | 0.99 | 0.63 | -0.93 | 0.52 | - | 0.04 | -0.94 | 0.92 | 0.96 | 0.98 |
| B11_WiShadingNorth | 0.14 | -0.42 | -0.21 | -0.23 | -0.47 | -0.06 | 0.24 | 0.17 | 0.42 | 0.28 | 1.00 | 0.11 | -0.08 | 0.17 | 0.31 | 0.26 | 0.15 | -0.25 | 0.47 | - | -0.19 | -0.26 | 0.28 | 0.30 | 0.24 |
| B12_WiShadingEast | 0.15 | -0.06 | -0.29 | -0.18 | -0.14 | -0.23 | 0.31 | 0.04 | 0.14 | 0.33 | 0.11 | 1.00 | 0.18 | -0.47 | -0.03 | 0.32 | 0.05 | -0.33 | 0.14 | - | -0.09 | -0.30 | 0.14 | 0.26 | 0.28 |
| B13_WiShadingSouth | 0.57 | 0.05 | 0.29 | 0.16 | -0.10 | -0.29 | -0.34 | -0.32 | -0.22 | -0.16 | -0.08 | 0.18 | 1.00 | -0.12 | 0.14 | -0.15 | -0.49 | 0.22 | 0.10 | - | -0.03 | 0.23 | -0.34 | -0.14 | -0.19 |
| B14_WiShadingWest | -0.04 | -0.29 | -0.03 | 0.25 | -0.26 | 0.04 | -0.11 | 0.33 | -0.02 | 0.06 | 0.17 | -0.47 | -0.12 | 1.00 | 0.33 | 0.09 | -0.02 | -0.03 | 0.26 | - | -0.10 | -0.04 | 0.10 | 0.12 | 0.08 |
| B15_WiShadingSky | 0.24 | -0.61 | -0.20 | -0.17 | -0.73 | -0.03 | 0.18 | 0.18 | 0.24 | 0.40 | 0.31 | -0.03 | 0.14 | 0.33 | 1.00 | 0.40 | 0.06 | -0.29 | 0.73 | - | -0.17 | -0.30 | 0.34 | 0.46 | 0.36 |
| E1_CoEnergy | -0.10 | -0.39 | -0.79 | -0.20 | -0.54 | 0.21 | 0.66 | 0.64 | 0.54 | 0.99 | 0.26 | 0.32 | -0.15 | 0.09 | 0.40 | 1.00 | 0.55 | -0.93 | 0.54 | - | -0.02 | -0.93 | 0.89 | 0.98 | 0.99 |
| E2_HeEnergy | -0.67 | -0.18 | -0.72 | -0.20 | -0.02 | 0.41 | 0.86 | 0.41 | 0.74 | 0.63 | 0.15 | 0.05 | -0.49 | -0.02 | 0.06 | 0.55 | 1.00 | -0.70 | 0.02 | - | 0.28 | -0.71 | 0.81 | 0.51 | 0.58 |
| E3_LiEnergy | -0.26 | 0.34 | 0.81 | 0.16 | 0.39 | -0.25 | -0.09 | -0.25 | -0.33 | 0.22 | -0.03 | -0.29 | -0.45 | -0.36 | 0.77 | 0.01 | 0.05 | 0.09 | -0.33 | - | 1.00 | -0.86 | -0.87 | -0.84 | -0.84 |
| E4_PVEnergyGain | 0.28 | -0.86 | -0.28 | -0.20 | -1.00 | -0.02 | 0.21 | 0.21 | 0.20 | 0.52 | 0.47 | 0.14 | 0.10 | 0.26 | 0.73 | 0.54 | 0.02 | -0.39 | 1.00 | - | -0.42 | -0.39 | 0.40 | 0.58 | 0.50 |
| E5_PVEPBT | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 1.00 | - | - | - | - | - |
| L1_Glare | -0.28 | 0.39 | -0.13 | -0.02 | 0.42 | 0.04 | 0.16 | 0.08 | 0.06 | 0.04 | -0.19 | -0.09 | -0.03 | -0.10 | -0.17 | 0.02 | 0.28 | -0.12 | -0.42 | - | 1.00 | -0.13 | 0.08 | -0.03 | 0.05 |
| L2_LiUniformity | 0.26 | 0.34 | 0.81 | 0.18 | 0.39 | -0.28 | -0.77 | -0.68 | -0.62 | -0.04 | -0.26 | -0.30 | 0.23 | -0.04 | -0.30 | -0.93 | -0.71 | 1.00 | -0.39 | - | -0.19 | -0.89 | -0.88 | -0.95 | -0.95 |
| T1_ThCmSpec | -0.35 | -0.38 | -0.84 | -0.27 | -0.40 | 0.38 | 0.80 | 0.62 | 0.73 | 0.92 | 0.28 | 0.14 | -0.34 | 0.10 | 0.34 | 0.89 | 0.81 | -0.88 | 0.40 | - | 0.08 | -0.89 | 1.00 | 0.90 | 0.89 |
| T2_ThCmSpt | -0.04 | -0.43 | -0.75 | -0.25 | -0.58 | 0.25 | 0.62 | 0.62 | 0.55 | 0.96 | 0.30 | 0.26 | -0.14 | 0.12 | 0.46 | 0.98 | 0.51 | -0.87 | 0.58 | - | -0.03 | -0.88 | 0.90 | 1.00 | 0.96 |
| T3_TempCriteria | -0.14 | -0.37 | -0.79 | -0.17 | -0.50 | 0.25 | 0.67 | 0.63 | 0.53 | 0.98 | 0.24 | 0.28 | -0.19 | 0.08 | 0.36 | 0.98 | 0.58 | -0.94 | 0.50 | - | 0.05 | -0.95 | 0.89 | 0.96 | 1.00 |

Fig. A.12: Correlation matrix of design alternatives generated with the 'orthogonal mass' parametric model.

| | B01_FloorArea | B02_Volume | B03_ExposedWallArea | B04_Orientation | B05_PVPanelArea | B06_WAreaNorth | B07_WAreaEast | B08_WAreaSouth | B09_WAreaWest | B10_WAreaSky | B11_WiShadingNorth | B12_WiShadingEast | B13_WiShadingSouth | B14_WiShadingWest | B15_WiShadingSky | E1_CoEnergy | E2_HeEnergy | E3_LiEnergy | E4_PVEnergyGain | E5_PVEPBT | L1_Glare | L2_LiUniformity | T1_ThCmSpec | T2_ThCmSpt | T3_T |
|--|---------------|------------|---------------------|-----------------|-----------------|----------------|---------------|----------------|---------------|--------------|--------------------|-------------------|--------------------|-------------------|------------------|-------------|-------------|-------------|-----------------|-----------|----------|-----------------|-------------|------------|------|
|--|---------------|------------|---------------------|-----------------|-----------------|----------------|---------------|----------------|---------------|--------------|--------------------|-------------------|--------------------|-------------------|------------------|-------------|-------------|-------------|-----------------|-----------|----------|-----------------|-------------|------------|------|

APPENDIX I: QUESTIONNAIRE

QUESTIONNAIRE

This questionnaire is for the completion of the MSc Building Technology graduation research of Jamal van Kastel. The research question of the graduation research is:
How can visual analytics methods be integrated in a computational design system to make multi-variate, multi-objective, performance-driven decision-making of a large set of design alternatives accessible to architects and climate designers?
During the graduation process a visual analytics tool has been developed. This questionnaire aims to test the functionality of the visual analytics tool.
Information derived from this questionnaire will be used in the graduation research. A summary of all questionnaires will be presented in the thesis.

This questionnaire consists of the following parts:

1. Introduction (10 min.)
2. Manual optimization of a sports hall design (10 min.)
3. Questions about your decision-making process during the manual optimization (5 min.)
4. Explanation of the data processing methods in the visual analytics tool (10 min.)
5. Use of the visual analytics tool to find optimal design alternatives (10 min.)
6. Questions about your experience with the various aspects of the visual analytics tool (15 min.)
7. Questions about your experience with the visual analytics tool as a whole (5 min.)

You will be asked to optimize a sports hall building following “traditional design processes” and following a computer-aided design process, of which the visual analytics tool is part of. Please enter your email address if you want to receive the simulation results of both your designs. Your email address will be kept confidential and will not be shared with any third party. Leave this field blank if you do not wish to receive the simulation results.

Email address: _____

Please enter your (current or previous) occupation:

MsC student - Architecture ☐
MsC student - Building Technology ☐
No occupation related to the field of architecture ☐
Other: _____

Fill out to what extent you agree or disagree with each of the following statements. Please select one answer per row.

| | Untrue | Slightly untrue | Neither true nor false | Slightly true | True | Don't know / No opinion |
|--|-----------------------|-----------------------|------------------------|-----------------------|-----------------------|-------------------------|
| I have experience in the field of architectural design. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I have experience in the field of climate design. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I have experience in the field of Zero-Energy design. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I have experience in the field of computer-aided design. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I have experience in the field of data analytics. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

1.

Firstly, you are given a short introduction on the graduation research. Amongst others, this presentation introduces the purpose statement of the research. The purpose of this research is to develop a visual analytics tool that facilitates design exploration and design optimization for decision-making in the field of architecture and climate design.

The visual analytics tool is a high-interactive data visualization tool that visualizes a large data set of design alternatives and their corresponding performances and allows the user to explore this data environment in order to find or determine the best-performing design alternatives.

The aim of this questionnaire is to test the functionality of the visual analytics tool. Most importantly, this questionnaire tests

- (1) whether a design process supported by the visual analytics tool leads to better-performing designs than designs made using traditional design processes and
- (2) whether the visual analytics tool as a whole and whether its current features support the design process of architects.

The visual analytics tool is tested using a case study, which concerns the design of a nearly-Zero Energy sports hall. Besides energy consumption, the sports hall is optimized for various thermal comfort and visual comfort objectives, listed below:

- Annual cooling energy demand; the annual amount of energy needed to cool the building in order to meet thermal performance objectives. The HVAC system ventilates 8 l/s per person.
- Annual heating energy demand; the annual amount of energy needed to heat the building in order to meet thermal performance objectives. The HVAC system ventilates 8 l/s per person.
- Annual lighting energy demand; the annual amount of energy needed for artificial lighting. Artificial lighting is not used when daylight provides adequate lighting levels. The required light level depends on the occupancy and ranges from 250 lux (for trainings) to 700 lux (for championships)
- PV energy gain; the energy gain from the photovoltaic cells on the building.
- PV EPBT; the energy pay-back time of the PV panels. The energy pay-back time is the time required by the PV panels to deliver the energy needed to construct them. The energy pay-back time thus indicates the effectiveness of the PV panels' orientation.
- Lighting uniformity; the uniformity of the light levels of the playing field. Lighting uniformity is expressed as the annual amount of hours of inadequate uniformity. Lighting uniformity is calculated using a grid of sensor point, in which the similarity of the illuminance of adjacent sensor points should be higher than a factor of 0.7.
- Temperature criteria; minimum and maximum indoor operative temperatures of 19°C and 27°C, respectively. Temperature criteria are expressed as the annual amount of hours comfort levels are not met.
- Thermal comfort of the spectators; measured using an adaptive comfort model (ISSO 74) and expressed as the annual amount of hours comfort levels are not met. Depending on the running mean outdoor temperature, indoor operative temperatures should range from 20°C to 26°C.
- Thermal comfort of the sports players; measured using an adaptive comfort model (ISSO 74) and expressed as the annual amount of hours comfort levels are not met. Depending on the running mean outdoor temperature, indoor operative temperatures should range from 18°C to 25°C.
- Architectural qualities; this performance objectives may include various non-quantified performance objectives, such as aesthetics, integration in the urban context, sociological performances, etcetera.

2.

You are given a parametric model of the sports hall that has the same design constraints as the parametric model used to generate the design alternatives in this questionnaire's visual analytics tool. You are asked to 'manually optimize' the design of the sports hall based on your expertise in the field of architecture, by changing the sliders to change the geometry.

Optimization should be based on the performance objectives listed below. Behind each performance objective the average performance of the simulations in the visual analytics tool are listed. This information substitutes information on sports halls' performance that designers could otherwise derive from literature research. You have 10 minutes to determine the geometry that you think is the most optimal.

- Cooling energy (4,300 kWh / year)
- Heating energy (52,000 kWh / year)
- Lighting energy (23,000 kWh / year)
- PV energy gain (55,000 kWh / year)
- PV energy payback time (5.8 years)
- Lighting Uniformity (66 % / year not met)
- Thermal comfort of spectators (8.9 % / year not met)
- Thermal comfort of sports players (13 % / year not met)
- Temperature criteria (1.6 % / year not met)
- Architectural qualities

Room for comments to the surveyor:

3.

The following questions are about the decision-making process of your manual optimization.

Please rank the following performance objectives from 1 to 11, based on the trade-offs you made choosing the "best" design alternative. Assign 1 to the most important performance objective and 11 to the least important performance objective.

| | |
|-----------------------------------|--------------------------|
| Architectural qualities | <input type="checkbox"/> |
| Cooling energy | <input type="checkbox"/> |
| Heating energy | <input type="checkbox"/> |
| Lighting energy | <input type="checkbox"/> |
| PV energy gain | <input type="checkbox"/> |
| PV energy payback time | <input type="checkbox"/> |
| Lighting Uniformity | <input type="checkbox"/> |
| Glare | <input type="checkbox"/> |
| Temperature criteria | <input type="checkbox"/> |
| Thermal comfort of spectators | <input type="checkbox"/> |
| Thermal comfort of sports players | <input type="checkbox"/> |

Fill out to what extent you agree or disagree with each of the following statements. Please select one answer per row.

| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|--|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| I am confident that I was able to determine my priorities among the various performance objectives | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I am confident that I made well-substantiated design choices in the decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I am confident that I have found the most optimal design alternative. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

The following questions are about traditional design processes in general, i.e. design approaches commonly used in practice. Please answer the questions with regards to the aforementioned performance objectives.

| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|---|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| I am confident that traditional design processes involve well-determined priorities among performance objectives. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I am confident that traditional design processes involve well-substantiated design choices. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I am confident that traditional design processes result in the most optimal design alternative. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Room for comments to the surveyor:

4.

You are now given a presentation on the various components of the visual analytics landscape. The presentation provides a short explanation of each of the components. The information presented in the presentation intends to match the information that in a commercial software tool would be derived from a “quick look in the manual”.

Room for comments to the surveyor:

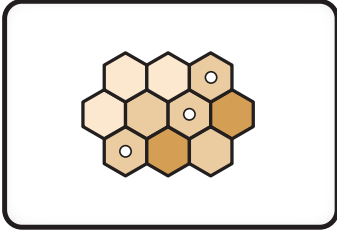
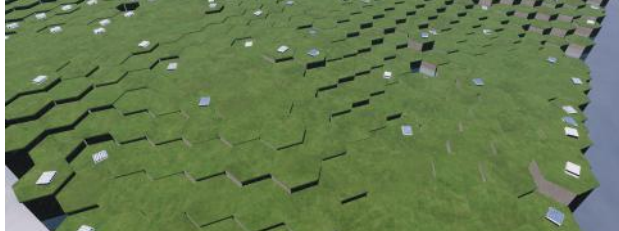
5.

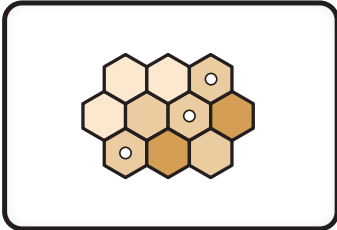

You are invited to use the visual analytics tool in order to find the “best” design alternative, based on your preferences. Similar to the manual optimization process, you have 10 minutes to find your “best” design. After those 10 minutes, you may spend additional time in the visual analytics tool to explore its various aspects.

Room for comments to the surveyor:

6.

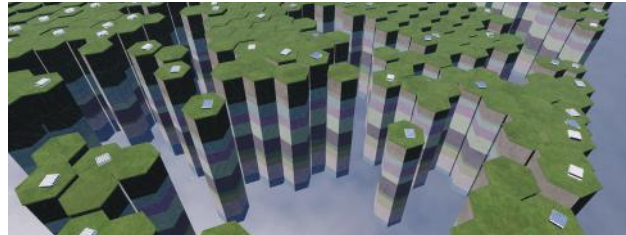
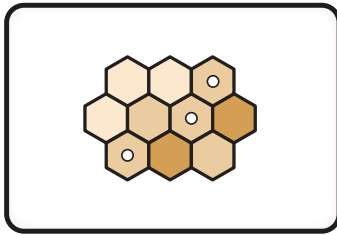
On the following pages you are asked to fill out to what extent you agree or disagree with each of the following statements based on the presentation on the visual analytics tool and on your experience with the visual analytics tool. Please select one answer per row.

| | Intended purpose | Data processing method | Visualisation(s) in landscape | Organize and visualize each design alternative | Self-Organizing Map | Buildings plotted on a hexagonal grid | | | |
|--|-----------------------|------------------------|---|--|-----------------------|---------------------------------------|-----------------------|-----------------------|-----------------------|
| | | |  |  | | | | | |
| | | | | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
| The intended purpose of this aspect of the visual analytics tool contributes to my decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing method as used in the visual analytics tool achieves its intended purpose. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Visualisation of and interaction with the data processing method in the visual analytics tool are intuitive. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing technique in the visual analytics tool helped me in finding information of interest to me. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

| | Intended purpose | Data processing method | Visualisation(s) in landscape | Supplement data set with non-simulated designs | Self-Organizing Map | Empty cells in the hexagonal grid | | | |
|--|-----------------------|------------------------|---|--|-----------------------|-----------------------------------|-----------------------|-----------------------|-----------------------|
| | | |  |  | | | | | |
| | | | | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
| The intended purpose of this aspect of the visual analytics tool contributes to my decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing method as used in the visual analytics tool achieves its intended purpose. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Visualisation of and interaction with the data processing method in the visual analytics tool are intuitive. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing technique in the visual analytics tool helped me in finding information of interest to me. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Intended purpose
Data processing method
Visualisation(s) in landscape

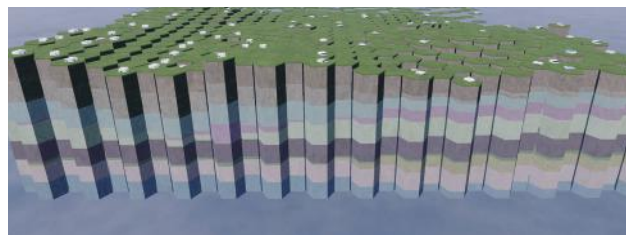
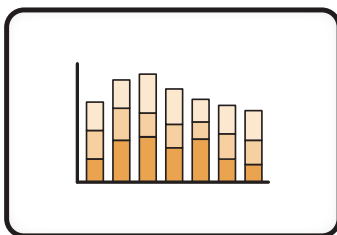
Show interrelationship of design alternatives
Self-Organizing Map - D matrix
Canyons



| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|--|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| The intended purpose of this aspect of the visual analytics tool contributes to my decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing method as used in the visual analytics tool achieves its intended purpose. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Visualisation of and interaction with the data processing method in the visual analytics tool are intuitive. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing technique in the visual analytics tool helped me in finding information of interest to me. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Intended purpose
Data processing method
Visualisation(s) in landscape

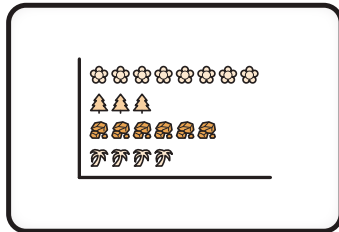
Show total performance of design alternatives
Stacked bar graph + analytic hierarchy process
Soil layers and corresponding landscape heights



| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|--|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| The intended purpose of this aspect of the visual analytics tool contributes to my decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing method as used in the visual analytics tool achieves its intended purpose. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Visualisation of and interaction with the data processing method in the visual analytics tool are intuitive. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing technique in the visual analytics tool helped me in finding information of interest to me. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Intended purpose
Data processing method
Visualisation(s) in landscape

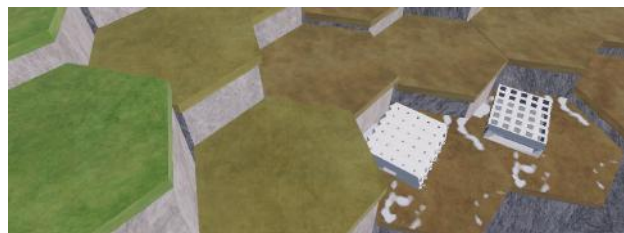
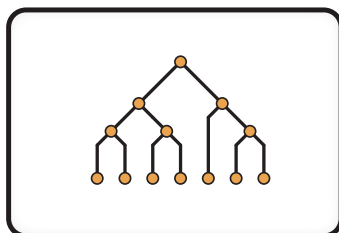
Indicate designs with best and worst performances
Pictogram chart
Various pictograms (trees, flowers and rocks)



| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|--|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| The intended purpose of this aspect of the visual analytics tool contributes to my decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing method as used in the visual analytics tool achieves its intended purpose. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Visualisation of and interaction with the data processing method in the visual analytics tool are intuitive. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing technique in the visual analytics tool helped me in finding information of interest to me. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Intended purpose
Data processing method
Visualisation(s) in landscape

Classify designs based on energy demand
Decision tree
Surface type (grass, dirt, ..)



| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|--|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| The intended purpose of this aspect of the visual analytics tool contributes to my decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing method as used in the visual analytics tool achieves its intended purpose. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Visualisation of and interaction with the data processing method in the visual analytics tool are intuitive. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The data processing technique in the visual analytics tool helped me in finding information of interest to me. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

7.

The following questions are about your general experience with the visual analytics tool.

Please rank the following performance objectives from 1 to 11, based on the trade-offs you made choosing the “best” design alternative. Assign 1 to the most important performance objective and 11 to the least important performance objective.

| | |
|-----------------------------------|--------------------------|
| Architectural qualities | <input type="checkbox"/> |
| Cooling energy | <input type="checkbox"/> |
| Heating energy | <input type="checkbox"/> |
| Lighting energy | <input type="checkbox"/> |
| PV energy gain | <input type="checkbox"/> |
| PV energy payback time | <input type="checkbox"/> |
| Lighting Uniformity | <input type="checkbox"/> |
| Glare | <input type="checkbox"/> |
| Temperature criteria | <input type="checkbox"/> |
| Thermal comfort of spectators | <input type="checkbox"/> |
| Thermal comfort of sports players | <input type="checkbox"/> |

The following questions are about your general experience with the visual analytics tool. Fill out to what extent you agree or disagree with each of the following statements. Please select one answer per row.

| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|--|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| I am confident that I was able to determine my priorities among the various performance objectives | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I am confident that I made well-substantiated design choices in the decision-making process. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I am confident that I have found the most optimal design alternative in the provided design space. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Room for comments to the surveyor:

The following questions are about the potential of the visual analytics tool. For these questions, please consider a '**commercial**' version of the visual analytics tool, i.e. a tool that is more developed with regards to control options, customizability and user friendliness than the visual analytics tool you have used. Fill out to what extent you agree or disagree with each of the following statements. Please select one answer per row.

| | Strongly agree | Agree | Neither agree nor disagree | Disagree | Strongly disagree | No opinion |
|--|-----------------------|-----------------------|----------------------------|-----------------------|-----------------------|-----------------------|
| The visual analytics tool has the potential to improve visualization of the performances of design alternatives, compared to traditional design processes. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The visual analytics tool has the potential to improve substantiation of decision-making in the design process, compared to traditional design processes. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The visual analytics tool has the potential to facilitate exploration of a larger amount of design alternatives, compared to traditional design processes. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| The visual analytics tool has the potential to lead to a better understanding of building performances, compared to traditional design processes. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Use of the visual analytics tool encourages me to create more sustainable and/or better-performing designs, compared to traditional design processes. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Use of the visual analytics tool has the potential to result in better-performing architecture, compared to traditional design processes. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I would consider using an iterative design system to generate a data set of design alternatives in a design project. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I would consider using the visual analytics tool in a design project to visualize a data set of design alternatives. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Room for comments to the surveyor:

The most important qualities of the visual analytics tool are:

The greatest weaknesses and threats of the visual analytics tool are:

179

APPENDIX J: QUESTIONNAIRE RESULTS

| Experience | Student Architecture | | Student Building Technology | | | Participant w/o relevant experience | | | Average |
|-----------------------|-------------------------|---|--------------------------------|---|---|--|---|---|---------|
| Architectural design | 5 | 5 | 5 | 5 | 5 | 1 | 1 | 1 | 3.5 |
| Climate design | 4 | 4 | 5 | 5 | 5 | 1 | 1 | 1 | 3.3 |
| Zero-Energy design | 5 | 3 | 4 | 4 | 5 | 1 | 1 | 1 | 3.0 |
| Computer-aided design | 2 | 2 | 4 | 5 | 4 | 1 | 1 | 1 | 2.5 |
| Data analytics | 1 | - | 2 | 4 | 4 | 1 | 1 | 1 | 2.0 |

Fig. A.14: Questionnaire responses about participant's experience in relevant fields. Ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree).

| Manual design optimization | Student Architecture | | Student Building Technology | | | Participant w/o relevant experience | | | Average |
|---|-------------------------|---|--------------------------------|---|---|--|---|---|---------|
| Able to determine priorities between performances | 3 | 4 | 4 | 2 | 4 | 3 | 4 | 3 | 3.4 |
| Able to make substantiated trade-offs | 5 | 4 | 5 | 2 | 3 | 3 | | 4 | 3.7 |
| Able to find most optimal design | 2 | 5 | 4 | 1 | 3 | 1 | 4 | 2 | 2.8 |
| Traditional design processes | Student Architecture | | Student Building Technology | | | Participant w/o relevant experience | | | Average |
| Able to determine priorities between performances | 4 | 5 | 4 | 2 | 2 | 2 | 4 | 2 | 3.1 |
| Able to make substantiated trade-offs | 5 | 4 | 5 | 4 | 4 | 4 | 4 | 4 | 4.3 |
| Able to find most optimal design | 2 | 3 | 2 | 1 | 2 | 2 | 3 | 2 | 2.1 |
| Use of CDS | Student Architecture | | Student Building Technology | | | Participant w/o relevant experience | | | Average |
| Able to determine priorities between performances | 5 | 4 | 4 | 5 | 4 | 3 | 5 | 4 | 4.3 |
| Able to make substantiated trade-offs | 4 | 3 | 3 | 4 | 4 | 3 | 4 | 3 | 3.5 |
| Able to find most optimal design | 2 | 3 | 2 | 4 | 2 | 5 | 3 | 5 | 3.3 |

Fig. A.15: Responses on participant's confidence in the functioning of various aspects of the design processes considered in the questionnaire. Ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree).

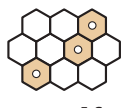


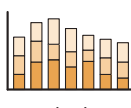
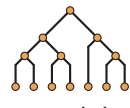

| |  Self-Organizing Map (1) |  Self-Organizing Map (2) |  Self-Organizing Map (3) |  Stacked Bar Graph |  Decision tree |  Pictogram chart |
|-------------------------------|---|---|---|--|---|---|
| Intended purpose | 4.4 | 3.7 | 4.0 | 5.0 | 3.9 | 4.1 |
| Data analytics method | 4.4 | 4.3 | 4.3 | 4.5 | 3.9 | 4.2 |
| Visualization and interaction | 4.1 | 4.1 | 4.1 | 4.8 | 3.9 | 4.8 |
| Data analytics technique | 4.1 | 3.9 | 3.5 | 4.5 | 3.9 | 4.2 |
| Total average | 4.2 | 4.0 | 4.0 | 4.7 | 3.9 | 4.3 |

Fig. A.16: Responses on suitability of individual data analytics methods. Ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree).

| Use of CDS | Student Architecture | | Student Building Technology | | | Participant w/o relevant experience | | | Average |
|--|-------------------------|---|--------------------------------|---|---|--|---|---|---------|
| VAS has potential to improve visualization | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 4.9 |
| VAS has potential to improve substantiation | 4 | 5 | 4 | 4 | 4 | 5 | 4 | 5 | 4.4 |
| VAS has potential to facilitate design exploration | 5 | 4 | 5 | 5 | 4 | 5 | 5 | 5 | 4.8 |
| VAS leads to better understanding of performances | 5 | 5 | 4 | 4 | 4 | 5 | 4 | 5 | 4.5 |
| VAS encouraged to create more sustainable designs | 2 | 4 | 2 | 4 | 4 | 5 | 4 | 4 | 3.6 |
| VAS results in better-performing architecture | 4 | 4 | 4 | 5 | 4 | 5 | 4 | 5 | 4.4 |
| I would consider use of IDS in a design project | 4 | 3 | 5 | 5 | 4 | 5 | 4 | 4 | 4.3 |
| I would consider use of VAS in a design project | 5 | 4 | 5 | 5 | 3 | 5 | 4 | 4 | 4.4 |

Fig. A.17: Questionnaire responses about general questions on the VAS and CDS. Ratings correspond to degree to which participants agree to the statement (1 - Strongly disagree, 5 - Strongly agree).

“Similar designs around my preferred design with better performances, because it makes it easier to improve the building without change the design”

“Gives a good overview of all ‘climate’ design properties in combination with design alternatives. Landscape/ colors/objects are clear. The strong visual presentations help you understand it quicker, this makes it easy to use.”

“[The most important qualities of the visual analytics tool are] generation of lots of designs and grouping of designs; creates overview/insight, [because] this is very quick using the visual analytics tool compared to traditional design.”

“[The most important qualities of the visual analytics tool are] The clear clustering of different design. Landscapes per design, [because] as a designer you get a clear view of how certain designs perform.

“Quick overview of great array of aspects. Although many options are given, the user can quickly move towards a cluster of options to explore more in depth there.”

“It shows the buildings with the best performances in a very understandable way, even when you’re an amateur.”

“The tool gives quick insight in (clarity of) what the advantages are and what the differences are. If something changes in a building, it is clear what effect it has with regards to performances.

“[The most important qualities of the visual analytics tool are] being able to quickly see the results, which saves time, [and] being able to quickly try different aspects within a design, [because] it makes making choices between aspects easier.

Fig. A.18: Questionnaire responses about the most important qualities of the visual analytics tool.

“Too many performance objectives, because some aren’t relevant but still create buildings which are high performance because of irrelevant objectives”

“The objectives are not that clear. Some weren’t completely intuitive in my opinion, because sometimes they mean something positive sometimes not. More time would definitely get me used to the system”

“Threat; losing control because of too many designs. Weakness; many irrelevant designs, suggests that it ‘does not work’”

“[The greatest weaknesses and threats of the visual analytics tool are] the interaction by the end user, [because] one already needs to know how to make a parametric model”

“Too much info, because the user could get lost.”

“The decision tree is very firm. It is directing you towards the green. You might miss a building on a brown soil, that can be better with just a small adjustment.”

“The base design slightly forces you towards the final design.”

Fig. A.19: Questionnaire responses about the greatest weaknesses and threats of the visual analytics tool.

“I’m not sure I could get an overview of all the criteria and design options in the time that I had”

“Maybe try to move around as other architecture programs like Rhino, would facilitate the use for users not used to this system”

“Awesome!”

“The tool needs some practicing, but it is fun. It sure helps you to find the best option in a very pleasant way. You don’t have to be an expert in data, you can see what is best. One can easily change some parameters and see what will come out.”

Fig. A.20: Other questionnaire remarks.





| | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
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| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 | 65 | 66 | 67 | 68 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 | 80 | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 | 97 | 98 | 99 | 100 |
|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|