TÉCNICO LISBOA

Optimization in Architecture

Catarina Garcia Belém

Thesis to obtain the Master of Science Degree in

Information Systems and Computer Engineering

Supervisor: Prof. António Menezes Leitão

May 2019

Acknowledgments

I would like to express my respect and gratitude to my supervisor and friend Dr. António Menezes Leitão. He proposed an interesting theme, which proved to be intriguing and challenging. His efforts to arrange research grants and to supply better computational resources were inspiring and encouraged me to fight the difficulties found along the way. His constant support, preoccupation and first-class guidance were invaluable through this thesis. Thanks for everything, especially for encouraging me to pursuit my dreams and for providing me with the flexibility and free-will to tackle this theme as something that I would be proud of.

I would like to thank the members of the research group oriented by my supervisor, the Grupo de Arquitetura e Computação (GAC), for their support and valuable ideas and discussions which undoubtedly improved the practicality of this work - especially, Inês Caetano, Inês Pereira, Renata Castelo Branco, Guilherme Ilunga, and Luís Silveira Santos.

I would also like to thank the Department of Computer Science and Engineering at Instituto Superior Técnico, Universidade de Lisboa for providing me with the foundations for completing this work, as well as for the opportunities to lecture as a teaching assistant during my MSc Thesis. I would also like to thank the Instituto de Engenharia de Sistemas e Computadores - Investigação e Desenvolvimento (INESC-ID) for the financial support provided to me in the form of Bachelor's Research Grants.

Moreover, I am also grateful to the staff and teachers of the Computer Engineering and Information Systems course for their friendship, their availability to discuss different subjects, and for providing an interesting working environment.

To all my friends whose support was invaluable during this period and which encouraged me to constantly push my limits when the task felt too large, I thank you deeply from my heart - especially, Carolina Pereira, Cristiana Tiago, Diogo Magalhães, Filipe Magalhães, Gonçalo Rodrigues, Guilherme Ilunga, Nuno Afonso, Pedro Simão, Rita Amaro, and Telma Correia.

Last but not least, I would like to thank my parents for their friendship, encouragement and caring over all these years, for always being there for me through thick and thin and without whom this project would not be possible. I would also like to thank my sister, brother, and sister-in-law, for their understanding, support and preoccupation throughout this year.

To each and every one of you – Thank you.

Publications

The development of this thesis resulted in several scientific contributions exploring different perspectives of optimization problems:

1. Caetano, I., Ilunga, G., **Belém, C.**, Aguiar, R., Feist, S., Bastos, F., and Leitão, A. (2018). Case Studies on the Integration of Algorithmic Design Processes in Traditional Design Workflows. Proceedings of the 23rd International Conference of the Association for CAADRIA, 1(Giedion 1941), 111–120.

2. **Belém, C.**, and Leitão, A. (2018). From Design to Optimized Design An algorithmic-based approach. Proceedings of the 36th eCAADe Conference - Volume 2, Lodz University of Technology, Poland, 549-558

Abstract

Keywords

Algorithmic Design; Black-Box Optimization; Machine Learning; Surrogate-based Modelling.

Resumo

Palavras Chave

Design Algorítmico; Otimização de caixa-preta; Modelos baseados em aproximações; Aprendizagem Máquina.

Contents

1 Introduction **1**

1.1 From design to Optimized design 4

1.1.1 Building Performance Optimization 5

1.1.2 Algorithmic Design 6

1.1.3 Algorithmic Analysis 6

1.1.4 Architectural Optimization Workflow 6

1.2 Goals 6

1.3 Organization of the Document 6

2 Background **7**

2.1 Single-Objective Optimization 9

2.1.1 Derivative-Free Optimization 9

2.1.2 Optimization Tools in Architecture 9

2.1.2.A Galapagos 9

2.1.2.B Goat 9

2.2 Multi-Objective Optimization 9

2.2.1 Experimental Approach 10

2.2.2 Priori Articulation Approach 10

2.2.3 Pareto-Based Approach 10

2.2.4 Metrics for Multi-Objective Optimization 10

2.2.5 Optimization Tools in Architecture 10

2.2.5.A Octopus 10

2.2.5.B Opossum 10

2.2.5.C Optimo 10

3 Solution **11**

3.1 Architecture Overview 13

3.2 Architecture Design Requirements 13

3.2.1 Problem Modelling 13

3.2.2 Simple Solver 13
3.2.3 Meta Solver 13
3.3 Architecture Design Implementation 13
3.3.1 Problem Modelling 13
3.3.2 Simple Solver 13
3.3.3 Meta Solver 13

4 Evaluation **15**
4.1 Qualitative Evaluation 17
4.2 Quantitative of Applications 17
4.2.1 Ericeira House: Solarium 17
4.2.2 Black Pavilion: Arts Exhibit 17
4.2.2.A Skylights Optimization 17
4.2.2.B Arc-shaped Space Frame Optimization 17

5 Conclusion **19**
5.1 Conclusions 21
5.2 System Limitations and Future Work 21
5.2.1 Optimization Algorithms 21
5.2.2 ML models 21
5.2.3 Constrained Optimization 21

List of Figures

List of Tables

List of Algorithms

Listings

Acronyms

BIM Building Information Modelling

BPO Building Performance Optimization

BPS Building Performance Simulation

CAD Computer-Aided Design

MOO Multi-Objective Optimization

1

Introduction

Contents

1.1 From design to Optimized design 4
1.2 Goals 6
1.3 Organization of the Document 6

The act of making something as fully perfect, functional or effective as possible is a behavior that is constantly sought by us, Humans, in a process known as optimization [1]. Intuitively, through optimization one aims to improve a system in terms of different quantitative measurable aspects. Although usually striving to fully optimize these systems, i.e., to obtain *perfect* systems, it is often the case, that finding a better one or a near-optimal system suffices.

Generally, optimization processes are composed of two main parts: (1) the model of the system to be optimized and (2) the algorithm responsible for finding the optima. Conceptually, the model is a description of the system that is defined in terms of: a set of the system's characteristics, known as variables or unknowns, a set of quantitative measures of the system's performance, referred to as objectives or criteria, and, optionally, by a set of conditions that have to be satisfied to guarantee the system's feasibility, i.e., the system's constraints [2]. The objectives are usually functions of the variables being defined. Subsequent to the model definition, the obtained description can be interpreted as an optimization problem for which the optimal solutions are to be found, thus entering in the second part of an optimization process. In the second part, one executes an optimization algorithm, which encloses a description of the steps necessary to attain optimal solutions, which according to the user's intentions can be the maximization or minimization of the model's objectives.

Depending on the model representation, one is able to classify optimization problems differently with respect, for example, to its objective functions, variables, and determinacy. Due to their relevance in the developed work, in the next two paragraphs, we describe four different optimization classifications. However, we refer the interested reader to [2] for a more detailed and complete description of the different classifications.

One important classification is regarding the cardinality of the solutions sought by optimization processes, thus yielding the continuous and discrete optimization categories. In the former, optimal solutions lie in a potentially infinite set of candidate solutions, whereas in the latter, optimal solutions lie in a finite set. Optimization problems can also be classified as constrained or unconstrained, depending on whether the models explicitly define constraints or not. Moreover, optimization can also be distinguished in terms of the aim of the search that is performed, particularly, whether it is global or local. In local optimization, the search process strives to find a solution that is locally optimal, i.e., for which its value is better than all other points in its vicinity. The points that satisfy the previous property are known as local optima. On the other hand, there are optimization processes that strive to find the globally optimal solutions, i.e., the best of all the local optima.

Optimization is frequently used to address problems involving more than one objective. It is often the case that people face daily decisions involving two or more conflicting objectives, either to effectively manage resources, or just to ponder several factors associated with certain decisions. As an example, consider the decision of how to commute to work: either by car, or by bus. Indeed, in this case, the optimal solution is to take the transport that minimizes the cost and the time spent in the commutation. When considering the two transports, one must consider the time-cost trade-off corresponding to the two different transports: (a) taking the car will incur in more costs but in less time spent in the trip, whereas (b) taking the bus incur in fewer costs but more time spent. This example belongs to the subset of Multi-Objective Optimization (MOO) problems which consider the optimization of more than one objective function.

In addition to day-to-day life decisions, optimization can also be used with different decision and analysis purposes. As a result, several areas, including economy, science, engineering, among others apply optimization as auxiliary tool to maximize the efficiency of the decisions involved. Particularly, architecture is one of the areas where the potential of optimization becomes more visible. The architectural practice can benefit from optimization to reduce the building sector's economic and ecological footprint through the finding of more efficient buildings variants before their construction. Given its importance to the world's sustainability and economy, this thesis focus on the application of optimization processes to enhance the architectural practice, providing, in the following sections, an overview of the involvement and the evolution of such processes in architecture. We end this chapter by highlighting our research goals and by outlining the upcoming document's structure.

1.1 From design to Optimized design

CITE

In the architectural practice, optimization has been gaining relevance for the past few years, especially due to the impact of building construction and building maintenance in the economy and environment. For this reason, designers are shifting from a pure aesthetically-based to performance-based design, where buildings are being optimized to achieve the best possible values regarding different aspects of their design, such as thermal comfort, energy consumption, lighting comfort, structural behavior, cost, among others.

This has only been possible due to the technological improvements in the architectural practice over the last few decades. The adoption of computer science techniques was responsible for the dissemination of digital modelling tools, which allowed the more accurate and efficient design of highly complex buildings. These tools enabled a shift from traditional paper-based approaches to more computerized ones, such as Computer-Aided Design (CAD) and Building Information Modelling (BIM) applications, where changes to designs are trivial and do not require manually erasing and redrawing parts of the original design [3].

Shortly after, the development of computer-based simulation tools allowed designers to simulate their building's behavior regarding specific criteria, and, thus get a measurement of its performance [4]. Through this process, called Building Performance Simulation (BPS), designers could easily validate whether their building's performance satisfied the efficiency requirements and, ultimately, optimize their design by iteratively generating multiple variations of the same design, assessing their performance, and selecting the better ones. Albeit being very primitive, architects now had the elementary mechanisms required for optimizing their building's designs.

1.1.1 Building Performance Optimization

Building Performance Optimization (BPO), a simulation-based optimization approach, treats the results produced by the simulation tool as the functions to optimize. Although invariably suffering from some degree of imprecision and inaccuracy, using these simulations it becomes possible to estimate the performance of complex designs. Particularly, these estimates are beneficial in designs for which analytical solutions are often very difficult or even impossible to derive [5]. In these cases, the objective function, i.e., the function to optimize, is derived from the simulations' results. These objective functions have a domain which corresponds to the range of acceptable designs as specified by the architect.

A known drawback of simulation-based approaches is the time required to achieve reasonable results for complex systems [6] which is associated with different aspects of the problem, namely (1) its **domain** which, depending on the nature of the problem, might use different methodologies to produce the corresponding estimates (e.g., thermal *versus* structural); (2) its **intrinsic structure** which, depending on the attributes and relations of the system, might lead either to simpler or to more complicated computations (e.g., skyscraper *versus* a small house); and (3) its **analytical model**, which has the essential properties of the system we are trying to simulate and that will be used as input to the simulation tool. Generally, the domain and structure do not change for the same problem, albeit there are numerous ways to produce multiple analytical models. Depending on the level of detail of the analytical model, both the computational time and the result of the simulation might change.

Dar exemplo??

In architecture, the generation of each analytical model is a time-consuming and complicated task. On the one hand, it is often necessary to generate multiple models of the same design because of the simulation tools' specificity, i.e., in order to evaluate a design, each simulation tool requires a specialized model of the same design. On the other hand, simulation tools often yield time-consuming processes, where a single simulation can take up to seconds, minutes, hours, days, or even weeks to complete.

In addition to the simulations' specificity and complexity, architectural designs are inherently complex, thus leading to less predictable objective functions, for which mathematical forms are difficult to formulate [7]. For this reason, information about the derivatives of such functions cannot be extracted and methods depending on function derivatives cannot be used to address architectural optimization problems. As a result, classical gradient-based optimization methods can not be used. Instead, other methods that do not rely on the existence of an explicit mathematical form should be used, i.e., methods that treat the optimization functions as black-boxes, relying uniquely on the outputs of numerical simulations.

1.1.2 Algorithmic Design

1.1.3 Algorithmic Analysis

1.1.4 Architectural Optimization Workflow

1.2 Goals

1.3 Organization of the Document

RC references to doc sections/chapters are automatic

This thesis is is organized as follows: Chapter 1 interdum vel, tristique ac, condimentum non, tellus. In chapter 2 curabitur nulla purus, feugiat id, elementum in, lobortis quis, pede. In chapter 3 consequat ligula nec tortor. Integer eget sem. Ut vitae enim eu est vehicula gravida. Chapter 4 morbi egestas, urna non consequat tempus, nunc arcu mollis enim, eu aliquam erat nulla non nibh in **??**. Chapter 5 suspendisse dolor nisl, ultrices at, eleifend vel, consequat at, dolor.

2

Background

Contents

2.1 Single-Objective Optimization 9
2.2 Multi-Objective Optimization 9

One important classification is regarding the cardinality of the solutions sought by optimization processes, thus yielding the continuous and discrete optimization categories. In the former, the optimal solutions lie in a potentially infinite set of candidate solutions, whereas in the latter, the optimal solutions lie in a finite set. Optimization problems can also be classified as constrained or unconstrained, depending on whether the models explicitly define constraints or not.

Optimization can also be distinguished in terms of the aim of the search that is performed, particularly, whether it is global or local. In local optimization the search process strives to find a solution that is locally optimal, i.e., for which its value is better than all other points in its vicinity. The points that satisfy the previous property are known as local optima. On the other hand, there are optimization processes that strive to find the globally optimal solutions, i.e., the best of all the local optima.

2.1 Single-Objective Optimization

Cras dictum. Maecenas ut turpis. In vitae erat ac orci dignissim eleifend. Nunc quis justo. Sed vel ipsum in purus tincidunt pharetra [**?**]. Sed pulvinar, felis id consectetuer malesuada, enim nisl mattis elit, a facilisis tortor nibh quis leo. Sed augue lacus, pretium vitae, molestie eget, rhoncus quis, elit [**?**]. Donec in augue. Fusce orci wisi, ornare id, mollis vel, lacinia vel, massa. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas..

2.1.1 Derivative-Free Optimization

2.1.2 Optimization Tools in Architecture

2.1.2.A Galapagos

2.1.2.B Goat

2.2 Multi-Objective Optimization

Nunc tincidunt convallis tortor. Duis eros mi, dictum vel, fringilla sit amet, fermentum id, sem. Phasellus nunc enim, faucibus ut, laoreet in, consequat id, metus. Vivamus dignissim [**?**]. **??** is automatically compressed to fit text width. You can use `https://www.tablesgenerator.com` to produce these tables, and then copy the LaTeX code generated to paste in the document.

2.2.1 Experimental Approach

2.2.2 Priori Articulation Approach

2.2.3 Pareto-Based Approach

2.2.4 Metrics for Multi-Objective Optimization

2.2.5 Optimization Tools in Architecture

2.2.5.A Octopus

2.2.5.B Opossum

2.2.5.C Optimo

Cras lobortis tempor velit. Phasellus nec diam ac nisl lacinia tristique. Nullam nec metus id mi dictum dignissim. Nullam quis wisi non sem lobortis condimentum. Phasellus pulvinar, nulla non aliquam eleifend, tortor wisi scelerisque felis, in sollicitudin arcu ante lacinia leo.

3

Solution

Contents

3.1 Architecture Overview 13

3.2 Architecture Design Requirements 13

3.3 Architecture Design Implementation 13

Donec gravida posuere arcu. Nulla facilisi. Phasellus imperdiet. Vestibulum at metus. Integer euismod. Nullam placerat rhoncus sapien. Ut euismod. Praesent libero. Morbi pellentesque libero sit amet ante. Maecenas tellus. Maecenas erat. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas.

3.1 Architecture Overview

3.2 Architecture Design Requirements

3.2.1 Problem Modelling

3.2.2 Simple Solver

3.2.3 Meta Solver

3.3 Architecture Design Implementation

3.3.1 Problem Modelling

3.3.2 Simple Solver

3.3.3 Meta Solver

4

Evaluation

Contents

4.1 Qualitative Evaluation 17
4.2 Quantitative of Applications 17

- Relembrar o objectivo do trabalho e dizer como o vamos avaliar de um modo geral introduzindo os proximos subcapitulos.

4.1 Qualitative Evaluation

- Number and Heterogeneity of Available algorithms - Differences / Benefits / Disadvantages when compared to Grasshopper's frameworks

4.2 Quantitative of Applications

- Dizer que de um modo geral começámos de forma incremental por considerar problemas single-objective, nomeadamente a casa da ericeira, que remonta a primeira publicação. Depois evoluimos para a avaliação bi-objetivo de dois casos de estudo reais - Pavilhão Preto para exposições e de uma arc-shaped space frame.

- Comentar a facilidade c/ que alguém que já tem um programa AD consegue acopolar optimização a AD.

4.2.1 Ericeira House: Solarium

4.2.2 Black Pavilion: Arts Exhibit

4.2.2.A Skylights Optimization

4.2.2.B Arc-shaped Space Frame Optimization

5

Conclusion

Contents

5.1 Conclusions 21
5.2 System Limitations and Future Work 21

Pellentesque vel dui sed orci faucibus iaculis. Suspendisse dictum magna id purus tincidunt rutrum. Nulla congue. Vivamus sit amet lorem posuere dui vulputate ornare. Phasellus mattis sollicitudin ligula. Duis dignissim felis et urna. Integer adipiscing congue metus.

Rui Cruz
You should always start a Chapter with an introductory text

5.1 Conclusions

5.2 System Limitations and Future Work

5.2.1 Optimization Algorithms

5.2.2 ML models

5.2.3 Constrained Optimization

Aliquam aliquet, est a ullamcorper condimentum, tellus nulla fringilla elit, a iaculis nulla turpis sed wisi. Fusce volutpat. Etiam sodales ante id nunc. Proin ornare dignissim lacus. Nunc porttitor nunc a sem. Sed sollicitudin velit eu magna. Aliquam erat volutpat. Vivamus ornare est non wisi. Proin vel quam. Vivamus egestas. Nunc tempor diam vehicula mauris. Nullam sapien eros, facilisis vel, eleifend non, auctor dapibus, pede.

Bibliography

[1] M. W. Online, "Merriam Webster Online - Optimization Definition," 2018. [Online]. Available: https://www.merriam-webster.com/dictionary/optimization

[2] J. Nocedal and S. J. Wright, *Numerical optimization*, 2011, no. 2.

[3] B. Ferreira and L. António, "Generative Design for Building Information Modeling," *Proceedings of the 33rd Education and research in Computer Aided Architectural Design in Europe Conference*, vol. 1, pp. 635–644, 2015.

[4] A. Malkawi and B. Kolarevic, *Performative Architecture: Beyond Instrumentality*, 2005, vol. 60, no. 1.

[5] T. G. Kolda, R. M. Lewis, and V. Torczon, "Optimization by Direct Search - New Perspectives on Some Classical and Modern Methods," *Society for Industrial and Applied Mathematics*, vol. 45, no. 3, pp. 385–482, 2003.

[6] A. M. Law and W. D. Kelton, *Simulation modeling and analysis*, 1991, vol. 2.

[7] V. Machairas, A. Tsangrassoulis, and K. Axarli, "Algorithms for optimization of building design: A review," *Renewable and Sustainable Energy Reviews*, vol. 31, no. 1364, pp. 101–112, 2014.