Digital Framework for Structural Design Optimization

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Abstract
This paper aims to present a digital framework that employs the Parametric Design methodology to leverage the Structural Design Optimization in the conceptual design phase. A review was conducted to understand the existing techniques, methods, and algorithms used in parametric design to impact structural designs positively. A framework encompassing the following design phases is proposed: parametric geometry definition, automatic association of structural model, structural analysis through finite element method, multi-objective optimization via a genetic algorithm, and design space exploration. The developed framework was applied to a conceptual development of a gridshell dome by exploring several Voronoi tessellation configurations. The developed framework allows the project team to select optimized structural arrangements in the early phases of the design process, which reduces material costs while improving structural safety.

Keywords: Parametric Design, Multi-objective Optimization, Structural Design, Voronoi Gridshell.

1 Introduction

Modeling, analysis, and optimization are central concepts in Structural Design and constitute essential activities to ensure the project's safety and economy (Chi et al. 2015). With the recent advances in technologies applied to structural design, these activities started to receive a certain degree of automation. Two paradigms that allow automation and integration of those activities with the other processes in all the disciplines involved in Architecture, Engineering and Construction (AEC) projects are Building Information Modeling (BIM) and Parametric Design.

The increasing use of computers in the design workflows has stimulated the integration of different computational techniques, such as building simulation, evolutionary optimization algorithms, and new fabrication methods. Nowadays, computers are no longer just electronic drawing platforms but rather devices for new design approaches. Specifically, regarding structural design, the trends for the development of current practice due to integration with BIM technologies are the performance-oriented Parametric Structural Design and the early design-phase Structural Optimization.

This paper aims to propose a workflow for developing structural conceptual designs within the Parametric Design methodology and formulate a multi-objective optimization problem for the Design Space exploration, ensuring a set of optimal solutions for the structure in early design phases.

This paper is organized as follows: Section 2 presents the necessary concepts related to the Parametric Design paradigm and Multi-Objective Optimization; the proposed framework, with the design activities and used software, is described in Section 3; Section 4 develops an application example and the results obtained; Section 5 summarizes the addressed concepts and results, and also discusses the limitation of the proposed framework and propose future works.

2 Background

2.1 Parametric Design

Caetano and Leitão (2020) define Parametric Design as a design process based on algorithm thinking that uses parameters and rules to restrict them. The authors also mention that Parametric Design is related to the BIM paradigm, which uses associative geometry and topological relationships concepts to establish the dependencies between different objects in a model.

Tedeschi (2016) presents the development of algorithm thinking in architectural projects. By employing an algorithm – a process to perform a specific task through a finite list of well-defined instructions – the designer creates a process to generate models instead of only generating a single model. Therefore, it becomes possible to deal with designs of superior complexity.

Shea et al. (2005) took advantage of the form generation potential of Parametric Design to explore optimized structural solutions. The generative project transforms the computer from a modeling assistant to a model generator, allowing the development of methods focused on performance.

The digital tools to implement a parametric design are usually applications and plugins of modeling software that use a Visual Programming Language (VPL) or scripting. A VPL allows users to create algorithms by linking graphical elements instead of writing codes. Some typical commercial VPL applications are Grasshopper3D integrated with the geometric modeling software Rhinoceros, and Dynamo, for the BIM modeling software Revit.

The Parametric Design Paradigm makes possible the exploration of a set of designs generated by the developed algorithms called Design Space. Then, optimization methods can be used for the early selection of the best solutions among a set of possible ones, according to the user-defined criteria.

2.2 Multi-objective Optimization

Multi-objective optimization is the process of systematic and simultaneous optimization of a set of generally conflicting objective functions (Marler & Arora 2004). As opposed to traditional optimization (with a single objective function), a solution (or a set of solutions) to the optimization problem needs the definition of adequate optimality criteria, as, for example, Pareto's criteria.

A solution is considered optimal in the sense of Pareto, also said non-dominated solution, if there is no other solution in the space of viable solutions that is better according to one of the objectives without causing a worsening of at least another one conflicting objective (Zavala et al. 2014). The Pareto's frontier (or optimal frontier) of an optimization problem is the set of all non-dominated solutions.

An extensive literature review regarding heuristic methods applied to structural optimization (Zavala et al. 2014) indicates that these approaches are appropriate to Structural Engineering. The 51 papers reviewed by the authors implement heuristics to structural optimization (of structural sections, form, and topology) that uses strategies based on evolutionary algorithms, particle swarm optimization, and simulated annealing. Another work (Deb et al. 2002) points out the majority utilization of genetic algorithms, especially the NSGA-II (Non-dominated Sorting Genetic Algorithm).

Different tools use the NSGA-II for the Grasshopper3D. For example, the plugin Galapagos applies the NSGA-II and the Simulated Annealing methods to mono-objective functions. On the other hand, the plugins Octopus and Wallacei (Makki et al. 2018) allow the use of NSGA-II to solve multi-objective problems. Therefore, the development of a parametric design by using VPL algorithms and solving a given optimization problem can be carried out in a shared environment.

3 Method

A literature review of related work that implemented parametric structural design methodologies (Mueller & Ochsendorf 2015) (Brown et al. 2020) (Pan et al. 2019) (Gomes et al. 2018) allowed the definition of a framework to perform multi-objective optimization in a parametric structural design. The activities involved in the parametric design process were studied to develop a systematization of tasks and appropriate tools to perform them. The developed framework was then applied to an application example to investigate its benefits and shortcomings.

3.1 Proposed Framework

The necessary steps to perform a structural parametric design using optimization are depicted in Figure 1. The activities and used software are described below:

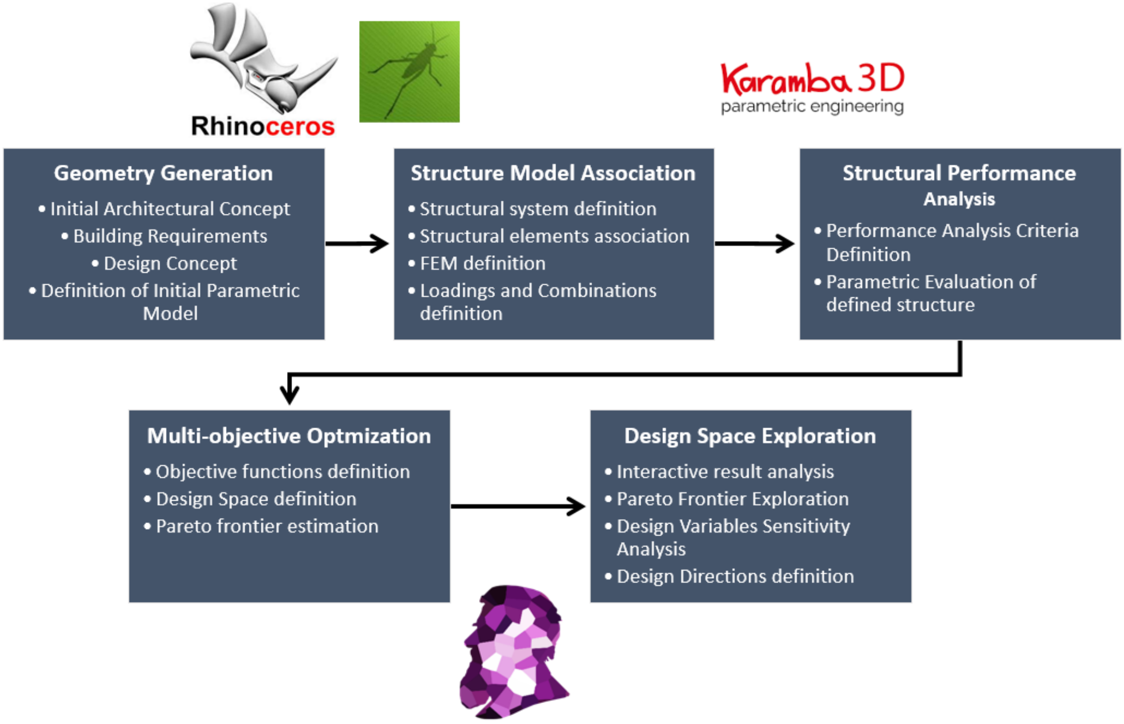

Figure 1. Proposed Framework.

Geometry Generation: consists of generating the form of the construction based on the design assumptions that will guide other structural modeling decisions. In this stage, the VPL algorithm and the design parameters are defined. The latter will ultimately define the geometry. In this paper, the software Rhinoceros and the plugin Grasshopper3D are used for these purposes.

Structure Model Association: uses algorithms for the automatic generation of the structural model associated with the geometry and structural parameters. In this paper, the finite element plugin Karamba3D (Preisinger & Heimrath 2014) is used to associate the finite elements with geometric model components (lines and surfaces).

Structural Performance Analysis: consists of the calculation of loads, boundary reactions, displacements, and other important information concerning the structure behavior that will allow the assessment of its performance indices. In this stage, the Karamba3D plugin is used to solve the finite element model of the structure.

Multi-Objective Optimization: the objective of this step is to determine the multi-objective optimization problem's Pareto frontier, which ensures the selection of reasonable solutions. In this stage, the following are also set up: design variables (parameters defined in previous stages – of form, structural section, and/or topology) and their upper and lower bounds; the objective functions (parameters that will be used to assess performance) and the constraints, if they exist, that restricts the design variables and objective functions. In this paper, the plugin WallaceiX is used to solve the optimization problem.

Design Space Exploration: in this stage, to explore the design space, the designer might utilize Data Science techniques due to the significant amount of information and simulations involved (Brown et al. 2020) (Pan et al. 2019). Therefore, classification, clusterization, and regression algorithms are used to model the design space and help designers to extract the best solutions. In this paper, the plugin WallaceiAnalytics is used for this purpose.

3.2 Framework Application Example

The application of the proposed workflow is illustrated by optimizing the structure of a gridshell dome with a Voronoi tessellation in the conceptual phase, which has been widely used in digital architecture (Lima 2017).

Gridshell is a structural typology that uses a linear elements mesh to discretize a surface. Its structural behavior, like shell structures, is optimized to bear self-load and constant distributed overloads but is very susceptible to buckling (Tonelli et al. 2016) (Lima 2017).

4 Findings

In this section, the results obtained from applying the proposed workflow for solving the structure optimization problem of a gridshell dome with a Voronoi tessellation in the conceptual phase are discussed.

The VPL algorithm developed in Grasshopper to optimize the parametric design of the Voronoi Gridshell is shown in Figure 2. This algorithm encompasses the first four steps of the proposed framework (Figure 1).

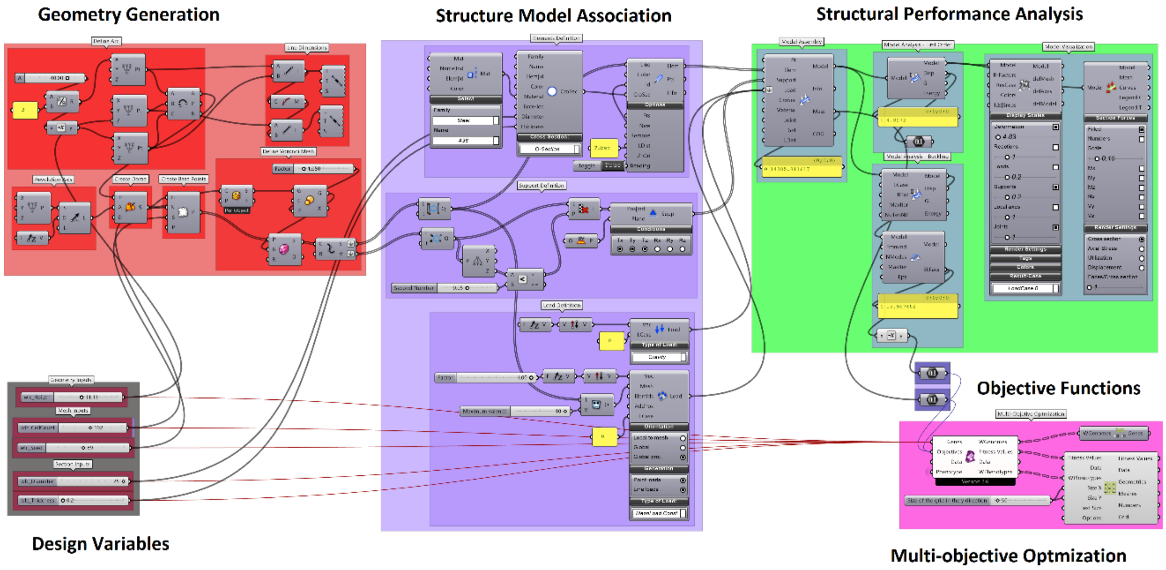

Figure 2. Grasshopper VPL Algorithm to Parametric Structural Design Optimization of Voronoi Gridshell.

4.1 Geometry Generation

The Voronoi Gridshell geometry generation, presented in Figure 3, consists of performing the following steps: (1) the geometry of the dome is defined by a circle-arc, based on two variables, diameter, and height (Figure 4.A); (2) revolution of the arc around its vertical mean line, giving rise to the spherical cap surface that serves as a base to the gridshell (Figure 4.B); (3) generation of aleatory points in the surface, based on two mesh variables: quantity of points and random seed (Figure 4.C); and (4) the Voronoi mesh is defined based on the aleatory points, creating a mesh of plane surfaces, tangent to the spherical cap at the aleatory points, whose intersections generate the edges of the gridshell (Figure 4.D).

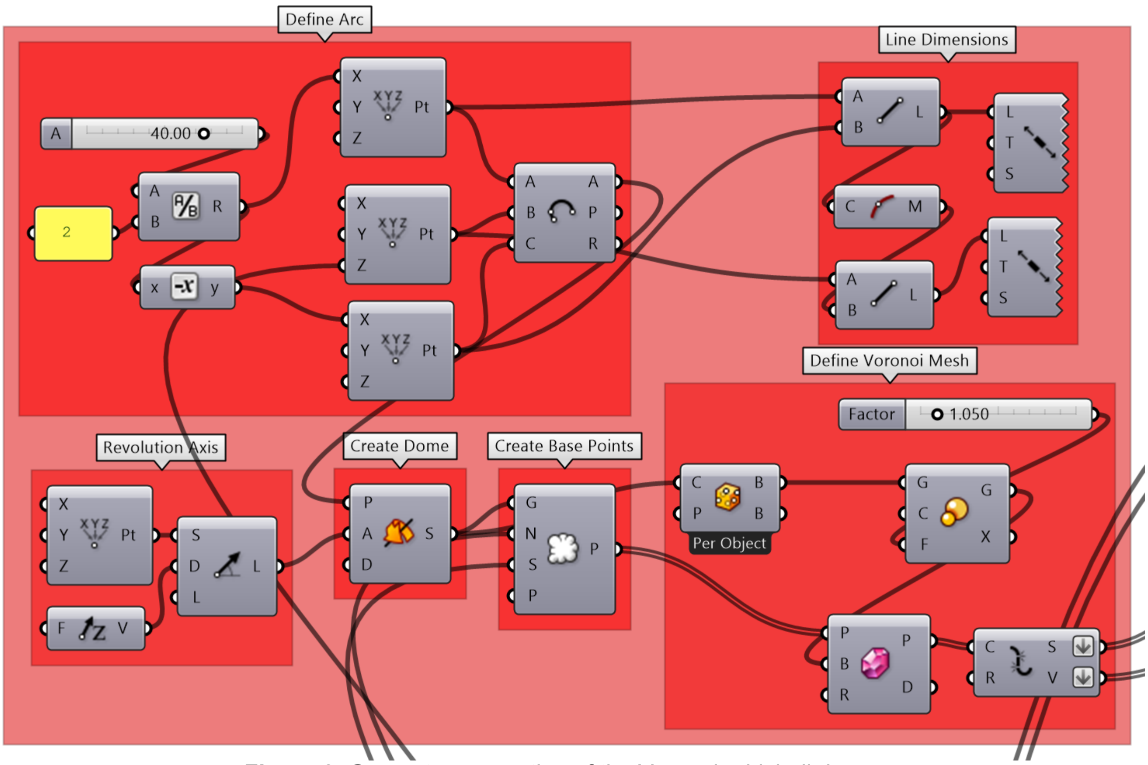

Figure 3. Geometry generation of the Voronoi gridshell dome.

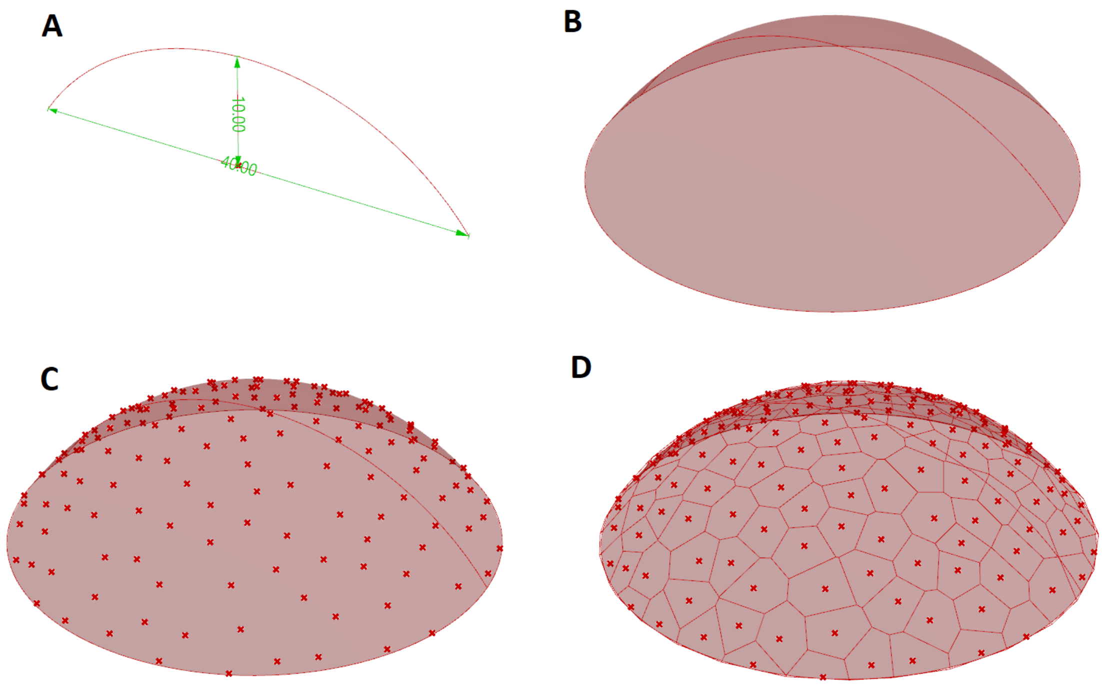

Figure 4. Steps of Geometry generation.

4.2 Structural Model Association and Analysis

A structural model is associated with the generated geometry, based on the generation of tubular steel (A36) beam elements in the Voronoi mesh edges. The steel tubes have as section variables the diameter and thickness, allowing for the structural section optimization. Also, pined supports restricting translation along the cartesian axis are inserted in the endpoints of the inferior edges. The structural loads applied are the self-weight and a distributed overload of 1kN/m^2.

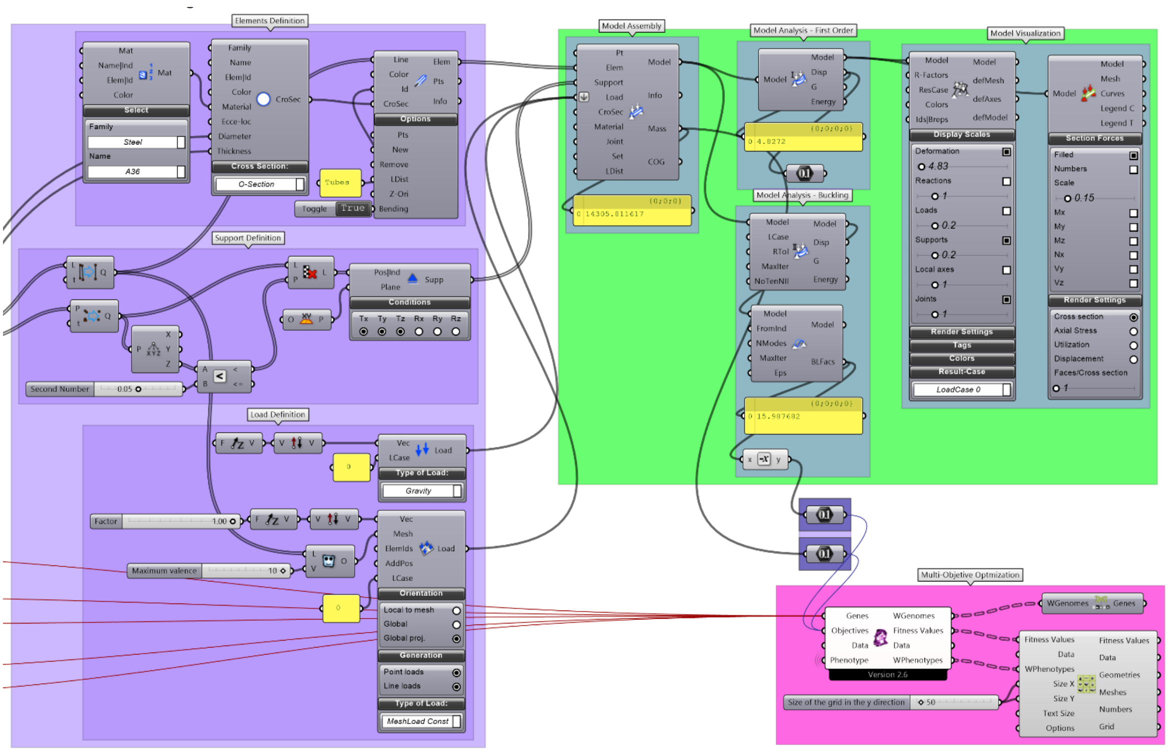

Figure 5. Structural Model Association and Structural Analysis Steps.

The Structural Model is created and analyzed by using the plugin Karamba3D. One of the possible configurations for the Voronoi Gridshell is presented in Figure 6, in which the structural model with the nodal equivalent loads appears on the left, the results of beam utilization in the center (red for compression and blue for tension), and the structural displacement on the right.

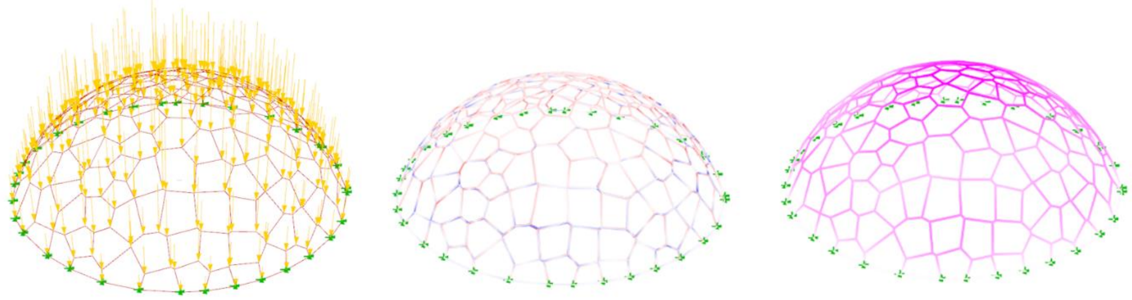

Figure 6. Finite Element Models of the Voronoi Gridshell and possible results given by Karamba3D.

For the calculation and analysis of the model, the first and second-order Karamba3D solvers were employed. The first-order results are used for the structure displacement calculation. The second-order results are used by the buckling modes verification algorithm and to the critical buckling load factor. An example of the global buckling mode of the structure is presented in Figure 7.

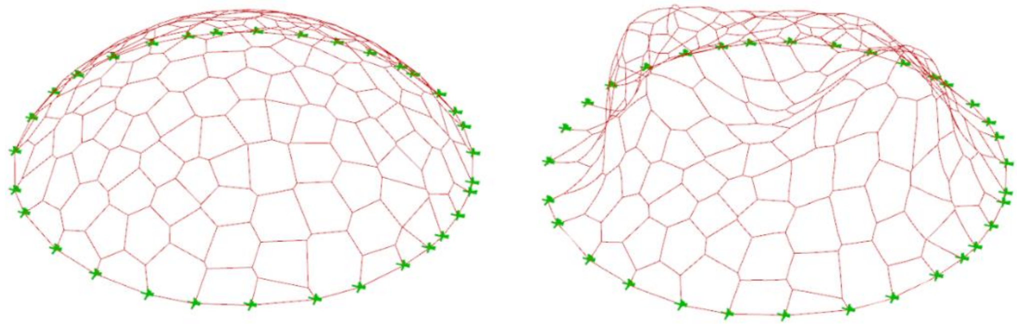

Figure 7. Example of a global Buckling mode.

4.3 Multi-objective Optimization and Design Space Exploration

The formulation of the Voronoi gridshell multi-objective optimization problem is based on the geometry generation, structural model association, and analysis algorithms. In this application example, the design variables are the: (1) dome height, varying continuously between 8 and 16 meters; (2) number of base points, integer varying from 100 to 300; (3) random seed for the generations of points, integer varying from 1 to 200; (4) steel tube diameter, integer varying between 5 and 25 centimeters, and; (5) steel tube thickness, varying continuously between 0.2 and 3.0 centimeters. The dome diameter was kept fix at 40 meters.

The objective functions for the optimization problem are defined as: (1) the critical buckling load factor – a scalar that multiplied by the overload will cause the structure to buckle; and (2) the total steel mass. The former objective relates to the design safety to buckling, a critical design factor concerning rigid gridshells, and should be maximized. The latter objective is related to the material cost of the structure that should be minimized. Since the employed optimization tool solves the minimization problem, the maximization of the critical buckling load factor is solved based on the minimization of its reciprocal.

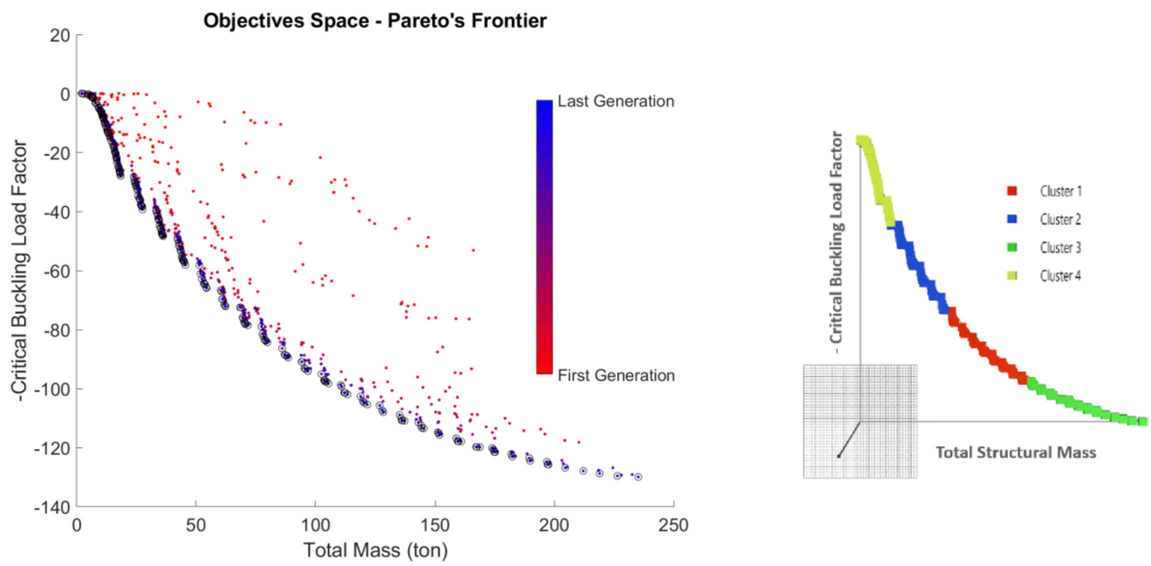

Figure 8. Objective Space and Clusterization of Pareto's frontier.

A genetic algorithm optimization was performed using 100 generations of 50 individuals, totalizing 5.000 computed structures over an (in theory) infinite design space (due to the continuity of some design variables). Figure 8 shows the localization of individuals on the Objective Space (left), which gets closer to the Pareto frontier with the advancement of generations, also, the clusterization of the Pareto frontier (right) in 4 groups of the 391 non-dominated solutions, through the K-means algorithm.

Figures 9 and 10 present the distributions of critical buckling load factors and the total structure mass according to the genetic evolution of the 100 first generations, respectively. The distribution of each objective function according to the genetic simulation is plotted in the left, while the first and last generations have its distributions compared in the right. It's possible to observe, in both cases, the scattering of the distribution in the last generation, representing the exploration of the space of possible configurations in search of non-dominated solutions.

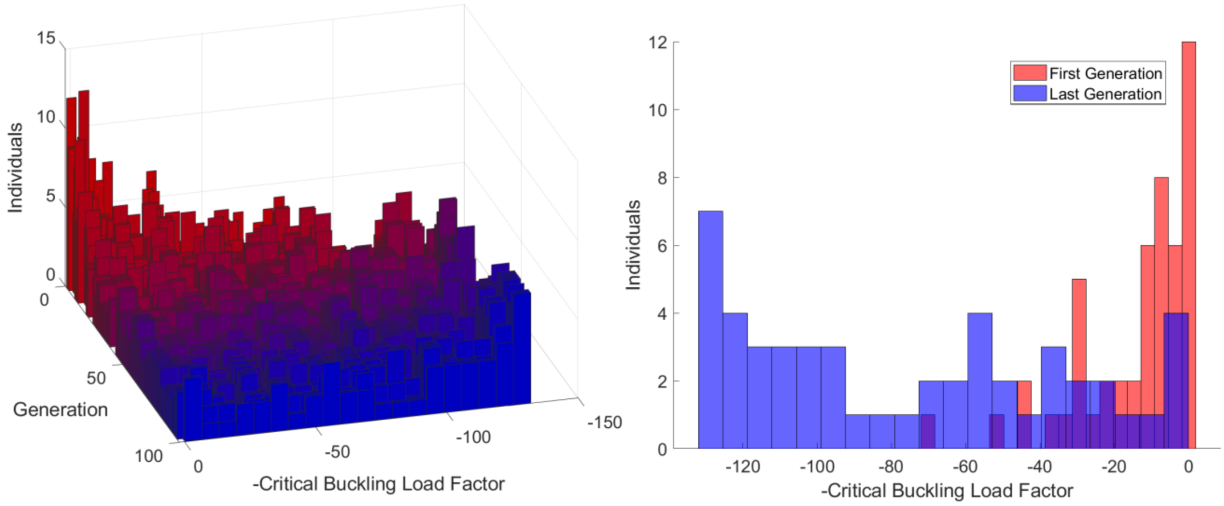

Figure 9. Distribution of Critical Buckling Load Factors according to the genetic evolution of 100 first generations.

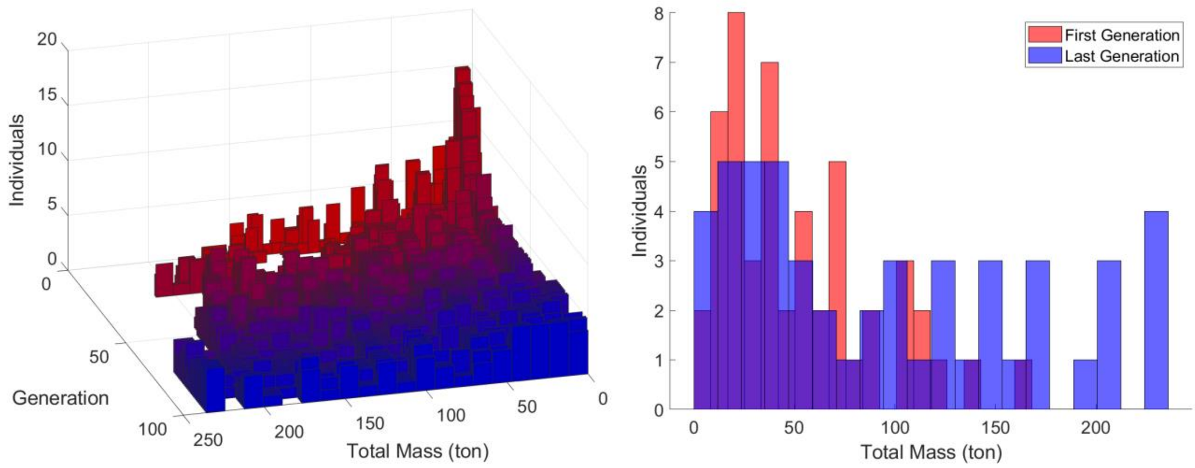

Figure 10. Distribution of the Total Structure according to the genetic evolution of 100 first generations.

After the Pareto frontier clusterization, one way of exploring the design space is to investigate the central individual of each cluster more thoroughly. Figure 11 shows the Voronoi mesh for the central individuals of the clusters presented in Figure 8, as well as their performances. The conflict between the objective functions, i.e., the maximization of buckling safety and the minimization of material cost, can be verified. Thus, determining a reasonable and appropriate balance between these conflicting objectives is crucial to more aware decision-making.

Table 1 presents the numerical values of design variables of the central individuals in each cluster. Based on these values, one can verify the Pareto frontier tendencies. For example, as all dome heights were around 12 meters, all the tube diameters were selected as the maximum allowed (25 centimeters), and the mesh refinement (number of base points) is close to the maximum allowed value (300) in all the cases. Based on the Design Space behavior close to the Pareto frontier, the design team can infer what variables should be more carefully analyzed and what design direction leads to a better solution.

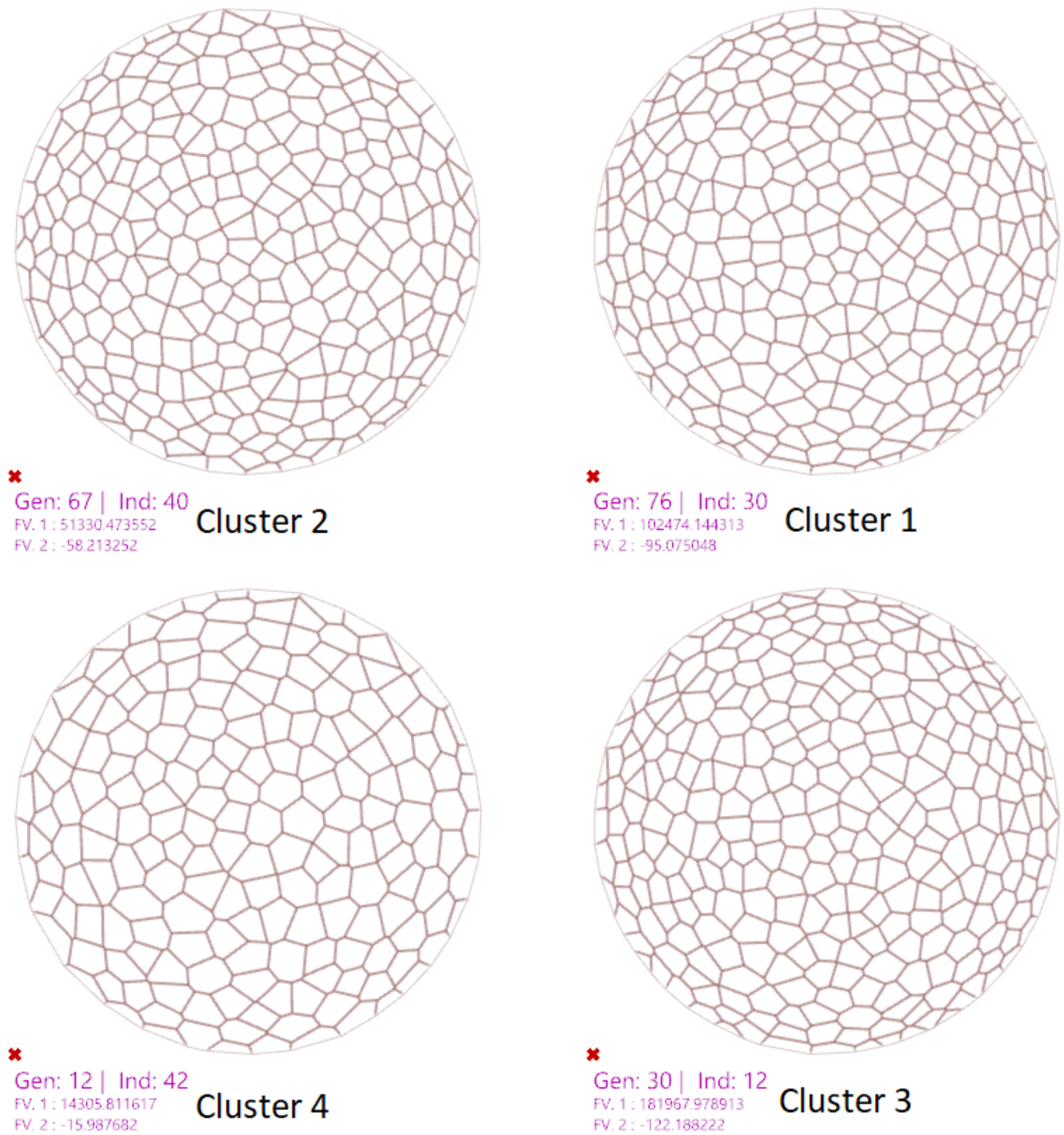

Figure 11. Representative individuals of each cluster and its respective objective factors.

Table 1. Representative Individuals Design Variables.

Design Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Dome Height (m)	12.67	11.94	12.66	11.11
Number of Cells	286	280	293	192
Random Seed	81	129	81	89
Tube diameter (cm)	25	25	25	25
Tube thickness (cm)	1.2	0.6	2.2	0.2

5 Conclusion

This paper proposes a framework for developing parametric structural designs and the formulation of multi-objective optimization problems to explore the design space, ensuring a set of optimized solutions for the structure in the early design stage.

The proposed framework was applied to an example in the structural optimization of a Voronoi gridshell concept. Our objective was not to discuss the details of a Gridshell structural behavior or even the advantages and disadvantages of the Voronoi tessellation. This example was used only to show the benefits of a parametric design process in the conceptual design of structures.

It is clearly shown that the proposed workflow provides solutions closed to the optimal frontier of the design space in the conceptual design stage, allowing to discard the less practical solutions. As the multi-objective optimization problems do not present a single optimal solution, a set of non-dominated solutions are achieved, which should be further analyzed by the designer, considering the reached performances for each objective function, to determine the best result according to the design premises.

Finally, it is worth mentioning that this study is a continuing work. Future steps aim to implement the BIM Integration of the parametric solutions with BIM modeling software through IFC export and direct integration plugins. Another perspective is to map the proposed framework in an workflow for collaborative parametric design, identifying the activities, responsibilities, and information exchange to achieve a practical IDM encompassing all the presented stages.

References

Brown, N. C., Jusiega, V., & Mueller, C. T. (2020). Implementing data-driven parametric building design with a flexible toolbox. Automation in Construction, 118, 103252.

Caetano, I., & Leitão, A. (2020). Architecture meets computation: an overview of the evolution of computational design approaches in architecture. Architectural Science Review, 63(2), 165-174.

Chi, H. L., Wang, X., & Jiao, Y. (2015). BIM-enabled structural design: impacts and future developments in structural modelling, analysis and optimisation processes. Archives of computational methods in engineering, 22(1), 135-151.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE transactions on evolutionary computation, 6(2), 182-197.

Gomes, C., Parente, M., Azenha, M., & Lino, J. C. (2018). An integrated framework for multi-criteria optimization of thin concrete shells at early design stages. Advanced Engineering Informatics, 38, 330-342.

Lima, F. F. (2017). Digital architectures by the Voronoi diagram and Delaunay triangulation. Revista Projetar-Projeto e Percepção do Ambiente, 2(2), 52-60. (In portuguese)

Makki, M., Showkatbakhsh, M., & Song, Y. (2018). Wallacei: An evolutionary and Analytic Engine for Grasshopper 3D.

Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. Structural and multidisciplinary optimization, 26(6), 369-395.

Mueller, C. T., & Ochsendorf, J. A. (2015). Combining structural performance and designer preferences in evolutionary design space exploration. Automation in Construction, 52, 70-82.

Oxman, R. (2017). Thinking difference: Theories and models of parametric design thinking. Design studies, 52, 4-39.

Pan, W., Turrin, M., Louter, C., Sariyildiz, S., & Sun, Y. (2019). Integrating multi-functional space and long-span structure in the early design stage of indoor sports arenas by using parametric modelling and multi-objective optimization. Journal of Building Engineering, 22, 464-485.

Preisinger, C., & Heimrath, M. (2014). Karamba—A toolkit for parametric structural design. Structural Engineering International, 24(2), 217-221.

Shea, K., Aish, R., & Gourtovaia, M. (2005). Towards integrated performance-driven generative design tools. Automation in Construction, 14(2), 253-264.

Tedeschi, A., & Design, A. A. A. (2014). Parametric strategies using Grasshopper. Le Penseur.

Tonelli, D., Pietroni, N., Puppo, E., Froli, M., Cignoni, P., Amendola, G., & Scopigno, R. (2016). Stability of statics aware voronoi grid-shells. Engineering Structures, 116, 70-82.

Zavala, G. R., Nebro, A. J., Luna, F., & Coello, C. A. C. (2014). A survey of multi-objective metaheuristics applied to structural optimization. Structural and Multidisciplinary Optimization, 49(4), 537-558.