Balancing Design Intent and Performance: An Algorithmic Design Approach

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Coordinating aesthetics and performance is a critical aspect of building design, but it requires information that is rarely available in early design stages. This scenario is further aggravated in design optimization, where the performance analysis of several design variations is needed. It is not surprising, then, to see performance analysis being postponed to later design stages, where changes are expensive and time-consuming. This paper addresses this problem through Algorithmic Design (AD), a design approach based on algorithms that facilitates the integration of performance criteria from early design stages and its combination with creative intents. It proposes an AD-based methodology encompassing the iterative generation and evaluation of facade design solutions that enhances design exploration processes responding to aesthetic, performance, and economic requirements. The proposal is evaluated in the development and structural analysis of a facade, demonstrating its ability to (1) continuously provide relevant insights on the design's structural performance and aesthetic expression and (2) guide the decision-making process towards design solutions successfully balancing creative intents with structural and cost requirements.

Keywords: algorithmic design; algorithmic analysis; creative process; design decision; design exploration process

1. Introduction

Building facade design is context-specific and requires the coordination of multiple criteria (Boswell 2013), such as aesthetic, functional, structural, lighting, thermal, acoustic, and energetic. Unfortunately, balancing the different criteria is often difficult in early design stages due to the inflexibility of most design tools and the complexity of performance evaluation. As a result, only functional and aesthetic requirements are often considered at initial stages, the others being postponed to later stages when the design idea is already well-established (Ciardiello et al. 2020; Turrin, Von Buelow, and Stouffs 2011). However, implementing design changes at these stages (Shi 2010) tends to be a hardworking process based on iterative manual remodelling tasks (Anton and Tănase 2016), making it difficult to balance different design requirements (Xie and Gou 2017).

Some of these limitations can be alleviated with Algorithmic Design (AD), a design approach based on algorithms that (1) facilitates design changes, (2) automates labour-intensive and error-prone tasks, (3) supports higher levels of design complexity, (4) promotes early-stage design analysis and, (5) facilitates the search for the best-performing solutions (Mueller 2014).

In this paper, we address the complexity of building facades by presenting a mathematics-based methodology to support the algorithmic development of facade design solutions that respond to both creative and performance criteria. To narrow the scope of this research, we focus on the coordination of aesthetic and structural performance from early design stages, evaluating the proposal in the development of a facade. After critically reflecting on the results, we discuss the proposal's ability to support performance-aware creative processes, namely, the ability to evaluate several solutions quickly and effortlessly regarding different criteria, facilitating the search for the best ones.

2. Background

2.1. Performance Matters

Currently, a wide range of legislation targeting the building sector requires the performance evaluation of building designs to ensure safety and comfort (Touloupaki and Theodosiou 2017; Machairas, Tsangrassoulis, and Axarli 2014). To that end, several analysis tools were developed (Huang and Niu 2015) to automate the evaluation of different performance criteria, making it easier to understand the effect of design changes (Huang and Niu 2015). Regarding structural analysis tools, relevant examples include

Autodesk's Robot, Frame3DD, Tekla Structures, SAP2000, and SAFE.

Unfortunately, these tools require specialized knowledge and have narrow domain of application, long computation times, limited modelling capability, and the designers fear that they restrict creative processes (Machairas, Tsangrassoulis, and Axarli 2014; Touloupaki and Theodosiou 2017; Huang and Niu 2015). These limitations are further amplified by the need to produce different analytical models containing only the information needed for each analysis tool (Aguiar, Cardoso, and Leitão 2017) and by the poor interoperability between analysis tools and the design tools architects typically use. This causes the analysis tools to be mostly used at late design states to validate the solutions' performance, or not used at all (Touloupaki and Theodosiou 2017; Belém 2019; Ciardiello et al. 2020).

Given the need to iteratively redesign and reanalyse until a good performance is achieved, multiple analytical models must be produced, and several performance evaluations must be done. This results in a repeated remodelling process (Kolarevic 2003) that is often impracticable in terms of time and effort (Machairas, Tsangrassoulis, and Axarli 2014) and that tends to lose information and accumulate errors (Touloupaki and Theodosiou 2017).

Part of these limitations can be overcome through AD (Terzidis 2006), particularly, the generation of analytical models (Aguiar, Cardoso, and Leitão 2017) and the setup of analyses whenever the design changes. Additionally, AD enables the iterative analysis of a wide range of solutions through optimization processes (Mueller 2014), facilitating the search for the best ones in terms of performance and aesthetics.

2.2. Algorithmic-based Evaluation and Optimization Tools

Some AD tools directly interact with analysis tools to evaluate, for instance, structural performance. Grasshopper's plug-ins Karamba3D, KarambaIDEA, GH2Robot, and

Geometry Gym; and Dynamo's Structural Analysis package are relevant examples of structural analysis engines while Grasshopper's plug-ins Kangaroo, K2Engineering, Peregrine, Millipede, and tOpos (Bialkowski 2017; 2016) are relevant examples of structural optimization tools. Nevertheless, these plug-ins depend on visual programming, which, as reported by the design teams of the Morpheus Hotel (Wortmann and Tunçer 2017) and the SoFi Stadium (Warton, May, and Kovacevic 2017), does not scale well with the complexity of design problems (Janssen 2014; Harding and Shepherd 2017), hindering the development and analysis of complex designs (Leitão et al. 2012).

In the context of building performance, the term optimization means the process of making a building as functional or as effective as possible (Nguyen et al. 2014). Architectural problems are usually concerned with multiple performance objectives that need to be contemplated simultaneously. Additionally, often, these objectives conflict with each other, meaning the best solution regarding one of them is generally not the best solution for the others (Khazaii 2016).

Concerning optimization engines for AD tools, popular examples include Grasshopper's plug-ins Galapagos, Wallacei, Opossum, Octopus, Goat, and Sylvereye; and Dynamo's plug-in Optimo. Galapagos, Goat, and Silvereye only address single-objective optimization problems, making it difficult to address the multiple requirements of architectural design problems. Moreover, different design optimization problems require different optimization algorithms (Pereira and Leitão 2020a; Wortmann 2019) but most of these tools provide only a few of them, reducing the chances of finding one that suits the problem at hand.

2.3. Improving Building Facades

Due to their impact in the buildings' visual expression and performance, building facades are one of the most optimized elements in architecture (Evins 2013; Huang and Niu 2015;

Machairas et al. 2014; Stevanović 2013; Touloupaki and Theodosiou 2017). Therefore, several facade design optimization methods have been proposed, including Bouchlaghem's (2000) method based on thermal performance; Wang et al. (2005) multi-objective optimization approach; Ochoa and Capeluto's (2009) NewFacades model based on thermal and visual comfort; Gagne and Andersen's (2012; 2010) tool based on both illuminance and glare levels; Kasinalis et al. (2014) method for quantifying the impact of seasonal facade adaptation; Jin and Overend's (2014) multi-objective optimization tool considering functional, financial, and environmental requirements; Elghandour et al. (2016) performance-oriented approach to improve daylight performance; Pantazis and Gerber's (2018) agent-based framework; and Hofmeyer et al. (2021) simulation toolbox.

These proposals, however, (1) are context-specific (Gagne and Andersen 2010; Ochoa and Capeluto 2009; Wang et al. 2005), (2) have limited modelling flexibility (Bouchlaghem 2000; Gagne and Andersen 2010; Hofmeyer et al. 2021; Jin and Overend 2014; Wang et al. 2005), (3) address a single requirement (Bouchlaghem 2000; Gagne and Andersen 2010), and (4) require knowing in advance which optimization technique best suits the given problem (Jin and Overend 2014; Kasinalis et al. 2014; Wang et al. 2005). Moreover, some do not provide a graphical user interface (Bouchlaghem 2000; Jin and Overend 2014; Kasinalis et al. 2014; Wang et al. 2005), and few directly communicate with the design tools architects use (Bouchlaghem 2000; Jin and Overend 2014; Kasinalis et al. 2014; Ochoa and Capeluto 2009; Wang et al. 2005), causing interoperability issues and hampering the transitions between tools. The few exceptions (Elghandour et al. 2016; Gagne and Andersen 2012; Pantazis and Gerber 2018) are based on visual programming and, thus, suffer from its limitations (Leitão et al. 2012), particularly, scalability (Janssen 2014; Harding and Shepherd 2017).

Regarding design workflows combining AD and structural optimization, Baker et al. (2009) illustrates how structural engineers at Skidmore, Owings & Merrill, LLP (SOM) used AD to search for structurally efficient and aesthetically pleasant solutions. Similarly, Schultz and Katz (2018) used Grasshopper and ANSYS to structurally analyse and optimize the origami facade of the Beijing Greenland Center, reducing material quantity by 10%. Lastly, Herr et al. (2018) combines Grasshopper and Oasys GSA Suite to parametrically explore self-supporting sculptural facade elements based on their structural performance. Nevertheless, none of the presented workflows fully automate design and analysis processes, the first case (Baker et al. 2009) resorting to import and export operations between tools that are prone to errors and loss of information; the second (Schultz and Katz 2018) using different AD tools independently; and the third case (Herr et al. 2018) not using the analysis results to directly affect the solutions.

Concerning structural AD-based methodologies, examples include Fagerström et al. (2014), automating the creation of facade panels and structural members of non-standard design solutions; Lee et al. (2015), integrating design exploration and structural analysis to improve the coordination between architects and engineers and increase the variety of solutions explored; Johan et al. (2019), driving early-stage generative explorations based on material-based constraints, combining C# programs for geometric exploration, Karamba3D for structural analysis, and Galapagos for design optimization; Muehlbauer (2018; 2020), reducing optimization post-processing time and supporting aesthetic-related decisions based on intelligent control systems and user-interaction features; Bertagna et al. (2021), facilitating the generation and both structural and solar radiation evaluation of facade designs at early design stages, using filtering and clustering strategies to improve the organization and presentation of the optimization results; Bao et al. (2021), using multi-agent generative and evolutionary structural topology optimization algorithms; and, lastly, Mueller (2014), providing structural design guidance at early design stages.

Most proposals, however, rely on visual programming environments (Bertagna et al. 2021; Johan et al. 2019; Lee et al. 2015; Muehlbauer 2018; Muehlbauer et al. 2020) that, despite being more user-friendly, often lack the scalability needed to solve complex problems (Leitão et al. 2012, Janssen 2014; Harding and Shepherd 2017). Moreover, they either: (1) do not specifically address facade design problems (Lee et al. 2015; Muehlbauer 2018; Muehlbauer et al. 2020; Mueller 2014); (2) have poor interoperability (Bao et al. 2021); (3) have limited modelling flexibility (Fagerstrom et al. 2014; Lee et al. 2015); or (4) do not use the analysis results to guide the design process (Fagerstrom et al. 2014).

Lastly, within architectural praxis, various building facade designs benefited from structural analysis and optimization strategies. These include the diagrid system of Hearst Tower, by Foster+Partners; the freeform facade structure of Morpheus Hotel, by Zaha Hadid Architects (Piermarini et al. 2018); the curvilinear envelope of Museo Soumaya, by FR-EE (Romero and Ramos 2013); the customized mega frame structure of Leadenhall Building, by Rogers Stirk Harbour + Partners (Krolikowski and Eley 2014); and the bubble-like structure of Water Cube, by PTW Architects (Senses 2007). In most cases, however, such strategies were used only to assess and improve the solutions' feasibility and not to guide the design process.

Considering current literature, there is a lack of methodologies systematizing and structuring the algorithmic generation of building facades that considers the variability of creative processes and the different performance requirements. We address this challenge by adopting an AD strategy that not only encompasses different performance criteria, but also adapts to the context-specificity of architectural practice.

3. Methodology

This investigation focuses on the development of facade design solutions meeting both creative and performance criteria. It proposes a methodology based on the mathematical principles proposed by Caetano and Leitão (2021) and the algorithmic framework for facade design proposed by Caetano et al. (2020) providing several ready-to-use strategies that can be easily combined in the development of novel solutions. The aim is to resolve most of the limitations found in facade design processes, especially when solving larger-scale design problems.

The choice for AD is justified by its mathematical and parametric nature, which provides the flexibility, efficiency, and level of control (Burry 2003; Davis et al. 2011; Janssen 2005) needed to drive design processes guided by multiple criteria and enhance both creative and critical thinking processes (Burry 2003; Terzidis 2006).

The proposed methodology starts with the architect matching the design intent with the framework's algorithmic strategies, identifying the most appropriate ones for generating, evaluating, and manufacturing the idealized solution. The prevailing role of the architects' creativity and design intentions at this stage makes the design problem highly subjective and variable (Fernando et al. 2010), potentially leading to an infinite variety of design scenarios. Therefore, it is not reasonable to expect that this matching process yields a complete algorithmic solution and, thus, the methodology assumes that the architect (1) establishes the designs' parametric dependencies, (2) combines and extends the selected strategies according to the design brief, and (3) evaluates the results regarding subjective criteria, such as aesthetic preferences.

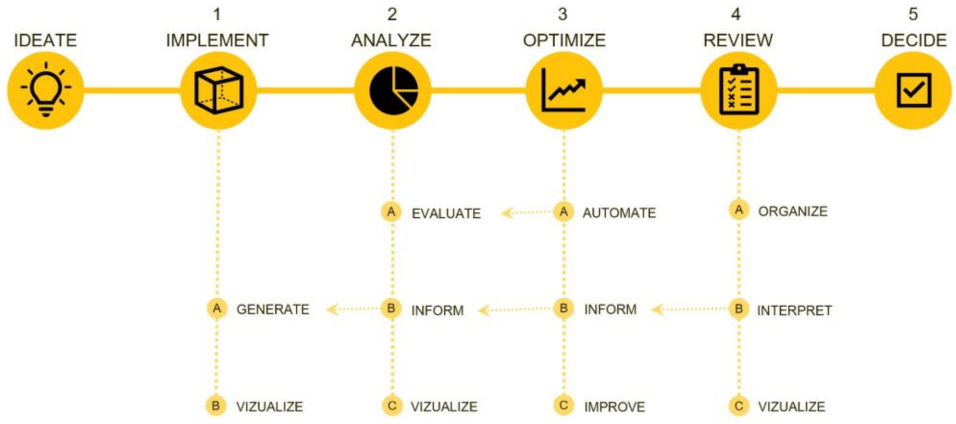

Figure 1. AD methodology: algorithmic implementation (1), exploration (1A), and visualization (1B) of a design idea; design evaluation (2) in a structural analysis tool (2A) with the results driving future design changes (2B) and being graphically displayed in a modelling tool (2C); design optimization (3) based on iterative structural analyses (3A) searching for the best solutions (3B–C); review (A) and organization (4A) of the optimization results and their subsequent interpretation (4B) and visualization (4C) in a modelling/visualization tool; and final decision (5).

To narrow the scope of this research, the paper focuses on early-stage facade design processes balancing aesthetics and structural evaluations, resulting in the five-steps methodology of Figure 1:

(1) Algorithmic implementation and exploration of the design intent.

(2) Structural performance evaluation and visualization.

(3) Optimization of structural performance and cost.

(4) Numerical and graphical analysis of the optimization results.

(5) Selection of the final solution.

To assess the methodology's support for decision-making processes guided by aesthetic and structural criteria, the paper applies the proposal in the development of a facade structure, reflecting on the results in terms of (1) design workflow flexibility, (2) diversity of design scenarios considered, (3) ability to balance measurable and non-measurable criteria, such as design concept and aesthetics, and (4) quality of the final solutions in terms of creative intent and assessed performance.

4. Evaluation

This stage involves the application of the methodology in the design and structural optimization of a facade structure inspired by the Blue Crystal building in Anand, India, designed by KPA Deesign Studio and constructed in 2019: a glazed truss-like facade structure resembling a crystal.

Although this example presents a moderate design complexity that could be addressed with visual programming, we will approach it using textual AD to demonstrate how the proposed methodology supports design processes guided by both creative intents and performance criteria. We use the framework's predefined algorithms (Caetano et al. 2020; Caetano and Leitão 2021) to implement the facade structure, combining them in the Khepri AD tool (Sammer et al. 2019), which interoperates with different design tools (including modelling, analysis, rendering, and visualization ones) and optimization packages (Belém 2019; Pereira and Leitão 2020b).

To achieve this interoperability, each of Khepri's supported tools is abstracted so that a single algorithmic description can generate equivalent models in each of them. This allows us to easily alternate between tools according to each performed task.

4.1. Algorithmic Implementation

The first stage entails the implementation of the design intent in a parametric algorithm describing both the design's guiding principles and degrees of freedom and considering the following design variables: the irregularity of the truss configuration, the amplitude of its three-dimensional effect, the number of triangular panels, and the panels' geometric tiling (Figure 2).

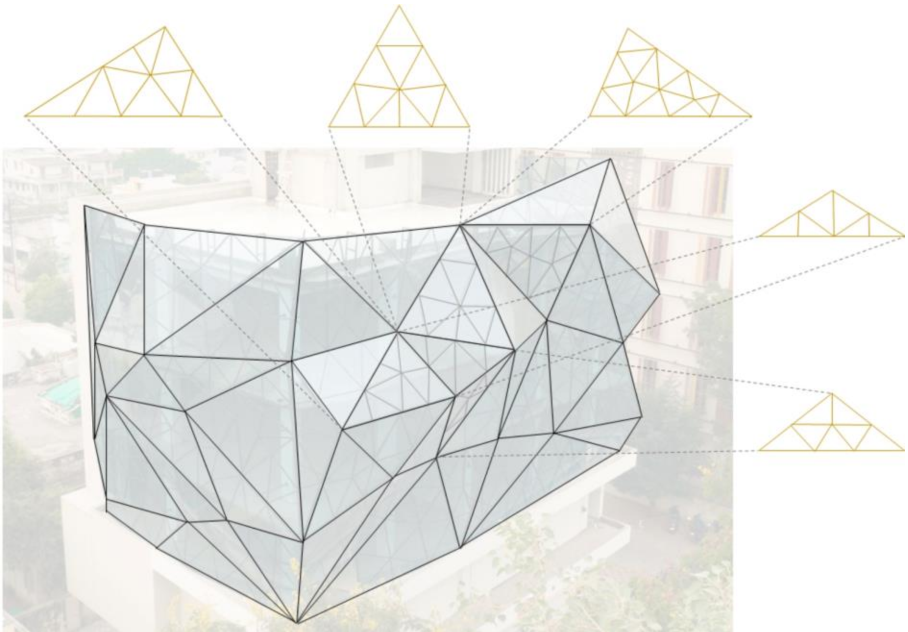

Figure 2. Conceptual representation of some design variables: the irregular truss configuration (black grid); the randomly sized triangular panels (light blue); and their different types of tiling (yellow grid patterns).

The second stage encompasses the computation of the truss-like structure's spatial configuration and the creation of both its metal profiles and glass panels (Figure 3A) based on a set of geometric subdivision rules (Figure 3B). Then, the facade supporting system is implemented, which requires creating horizontal supports connecting the inner slabs to the outer structure while adjusting both their position- and size-related parameters accordingly (Figure 3C). Finally, the previous algorithms are combined into a larger algorithm that generates the entire solution (Figure 3D) and whose parametricity allows the generation and testing of variations.

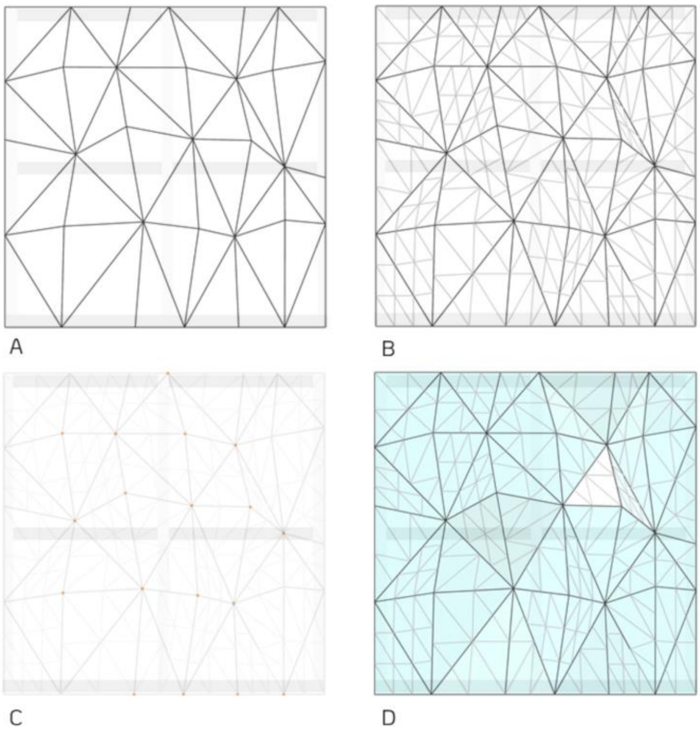

Figure 3. The step-by-step implementation process: creating the truss grid (A), geometric tiling (B), supporting system (C), and glass panels (D).

4.2. Performance-based Design Exploration

The next step encompasses the improvement of the truss design regarding its structural behaviour, which requires specifying its material properties and expected loads. In a first stage, we select Khepri's default steel and glass materials and bar cross-sections, and gravitational loads automatically calculated from the truss self-weight, exploring the design space by iteratively changing the design's parameters and performing structural analyses to assess its structural integrity. During this process, we visualize both the solutions' 3D models and analysis results in the same tool (namely, Rhinoceros 3D), allowing us to, early on, identify potential structural inconsistencies and to understand the impact of design parameters on the solution's structural integrity and visual expression.

Figure 4 illustrates this process with an initial version of the crystal-like structure whose structural analysis in Robot reveals, first, errors in the developed design, such as the existence of overlapping truss bars and the lack of physical connections in some corner nodes (Figure 4A); then, after fixing the errors, the occurrence of structural instabilities deriving from sets of coplanar nodes (Figure 4B); and, lastly, the structure's tendency to deform asymmetrically because of the differently sized supporting bars (Figure 4C). In each iteration, the algorithm is changed according to the analysis results and revaluated to check if all the problems were solved.

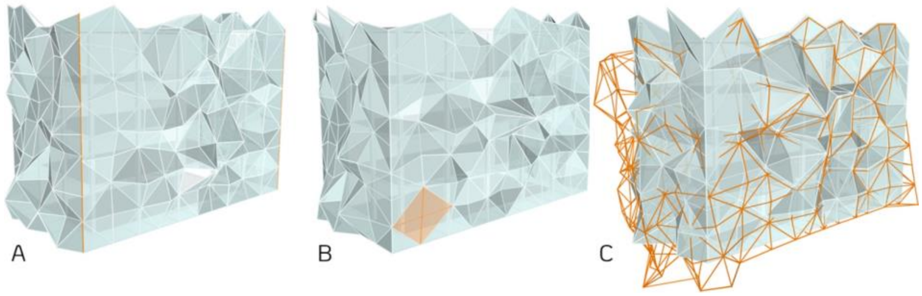

Figure 4. Structural inconsistencies: A. overlapping truss bars; B. coplanar truss nodes; C. asymmetrical truss deformation.

It is important to note that the goal of this stage is not to obtain accurate performance results but rather provide a general idea of how the design behaves to guide future design changes. In this case, it facilitates the identification of the design paths that best coordinate the design intent with the structural requirements. In the next stage, when we aim at increasing the solution's level of detail, we extend the algorithm with additional geometric constraints, such as restricting the irregularity and amplitude of the crystal-like effect, and additional design information, such as physical properties, namely the type of supporting systems, materials and sections, and environmental variables, namely wind loads. We then iteratively repeat the previous generation-analysis-regeneration cycle with different combinations of values, applying optimizers to automate the search for the best solution and make this process viable in terms of time and labour.

4.3. Structural Optimization

This stage entails the search for solutions that best balance the design intent with the need to minimize both the structure's displacement and cost, which is a typical case of conflicting goals (Evins et al. 2012): the stronger the structure is, the more material it tends to require and, thus, the more expensive it becomes. However, structural design does not need to maximize the structure's strength but simply comply with safety standards at the lowest possible cost (Wortmann and Fischer 2020).

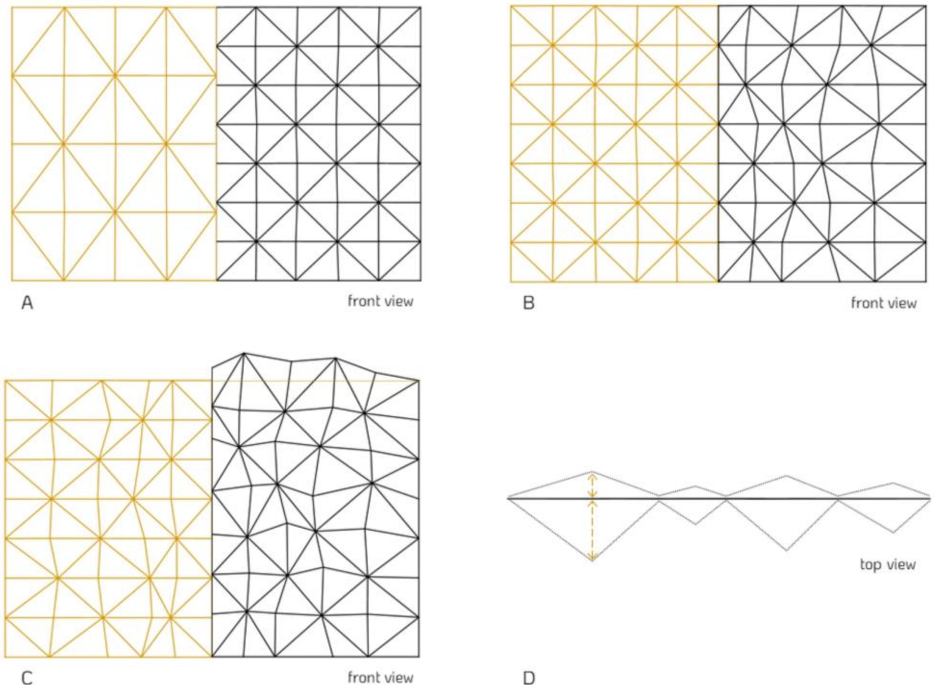

Figure 5. Decision variables: A. number of triangular panels; B. truss irregularity; C. top amplitude; D. inner and outer amplitudes.

To perform the optimization, we combine our algorithmic design with an optimizer, setting, as (1) decision variables, the number of panels (Figure 5A); the truss grid irregularity (Figure 5B); the inner, outer, and top amplitudes (Figure 5C-D) of its three-dimensional movement; and the truss bars' material and section size; and, as (2) optimization goals, the truss maximum displacement and cost (roughly computed from its weight). Moreover, we also set the range of acceptable values for the latter two requirements to ensure that both the safety standards and budget are met. This allows us to (1) avoid solutions above those limits (Figure 6A, green area), including Pareto-optimal ones, and (2) consider as acceptable those solutions that, despite not belonging to the

Pareto front and, thus, not being optimal in terms of cost and strength, may be preferable in terms of design intent.

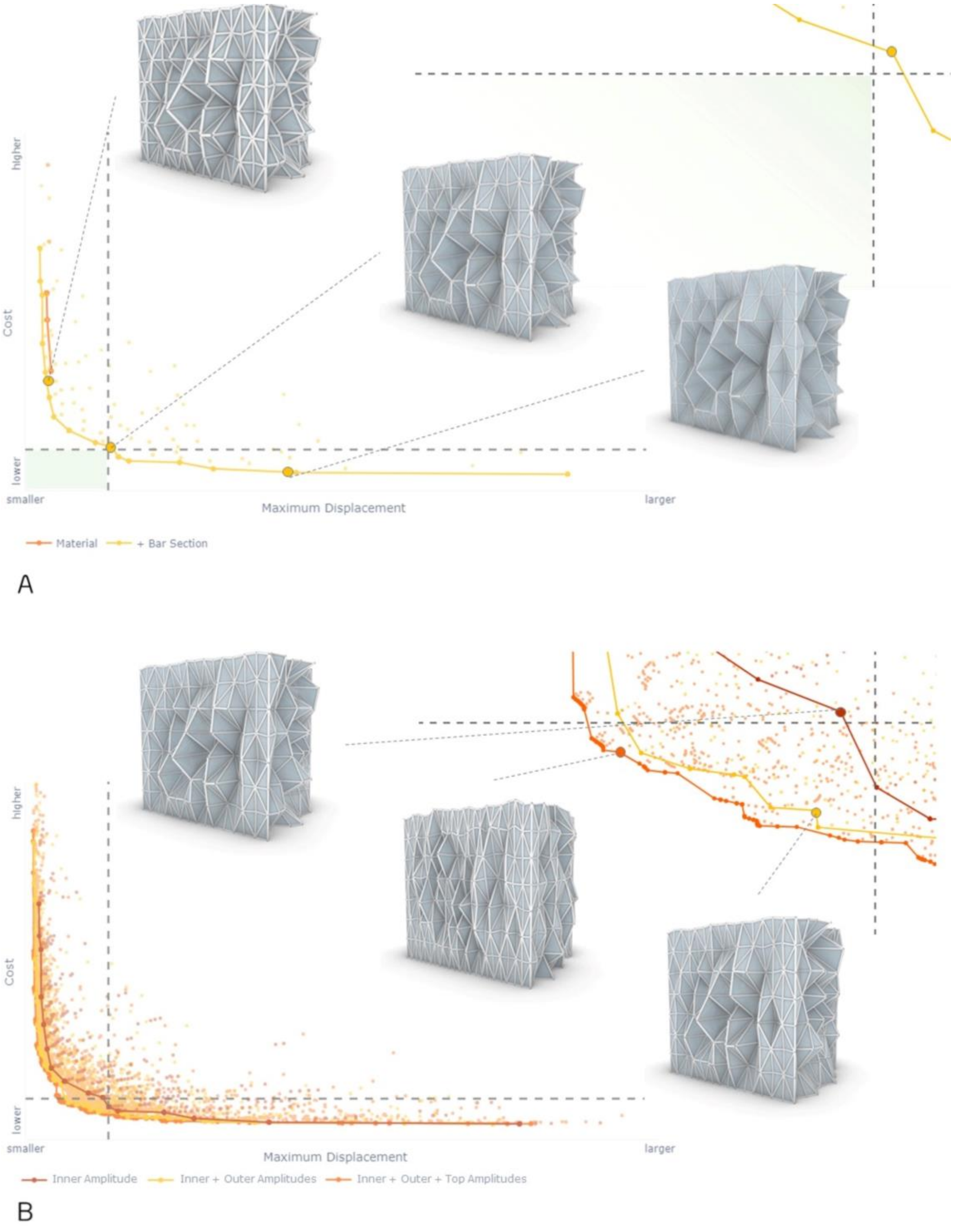

Figure 6. (A) Truss optimization with fixed horizontal supports and different truss bar materials and section sizes: bottom left, the area of acceptable solutions identified in green, being the horizontal and vertical dashed lines the maximum acceptable cost and displacement, respectively; top right, a close-up view of the acceptable area. (B) Truss optimization with the previous variables plus additional variables for different inner, outer, and top amplitudes of the crystal-like effect.

Regarding the optimizer, it is known that different optimization problems are better served by different algorithms (Belém and Leitão 2018; Wortmann 2019; Wortmann et al. 2017). In this case, we use NSGA-II (Deb et al. 2002) because of its good results in architectural optimization problems (Carlucci et al. 2015; Nguyen et al. 2014), particularly those addressing structural analysis (Barraza et al. 2017). Regarding the analysis tool, this time, we use Frame3DD, a non-interactive but faster analysis engine than Robot, due to the need to perform many structural evaluations.

By performing iterative analyses cycles considering the previous results and the impact of each design variable on the solution's aesthetic and performance quality, we increase the likelihood of finding better performing solutions that successfully meet the design intent. Figure 6A illustrates this process, first, only using different materials, each corresponding to an orange dot in the graph, and then, using different materials and section sizes, each combination (material and section) corresponding to the yellow dots. In both cases, the remaining variables are fixed at the values found in the previous stage. The results, however, demonstrate that changing only these two variables is not enough to meet the established goals, since none of the obtained solutions match the acceptable area (Figure 6A green area).

We repeat the optimization, this time allowing other parameters to vary, namely, the inner amplitude, obtaining the results illustrated by the red curve in Figure 6B. As they only result in slight improvements, we also let the outer amplitude vary in the next optimization cycle (Figure 6B, yellow curve), and then the top amplitude (orange curve).

Despite already finding solutions within the acceptable values, we improve them even further in terms of cost and strength by repeating the optimization process, this time by varying, first, the number of panels (Figure 7, orange curve) and then, the truss grid irregularity (Figure 7, yellow curve). However, the design intent is neglected, resulting in solutions with markedly vertical panels that clearly deviate from the desired crystal-like effect (Figure 7).

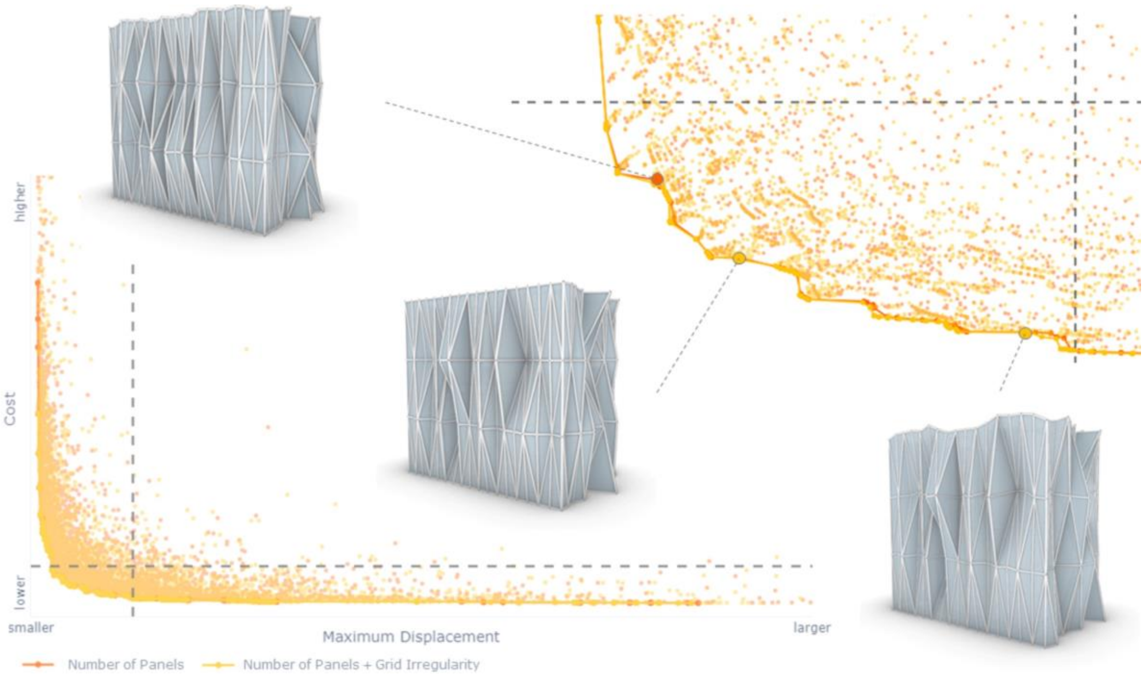

Figure 7. Truss optimization with the previous variables plus a different number of panels (orange) and grid irregularities (yellow).

Given the almost overlapping Pareto fronts of Figure 7, we repeat the previous optimization with a fixed number of panels to see how it impacts the results. Figure 8A shows that the obtained solutions (red curve) are not as good as the previous ones (orange and yellow curves) in terms of cost and strength but are better in terms of design intent (Figure 8A bottom-right image). Considering the ease with which we can test different combinations of values, we can continue refining the coordination between creative and analysis processes by repeating the optimization, for instance, with a smaller number of panels or even additional pinned supports at the truss' bottom nodes (Figure 8B).

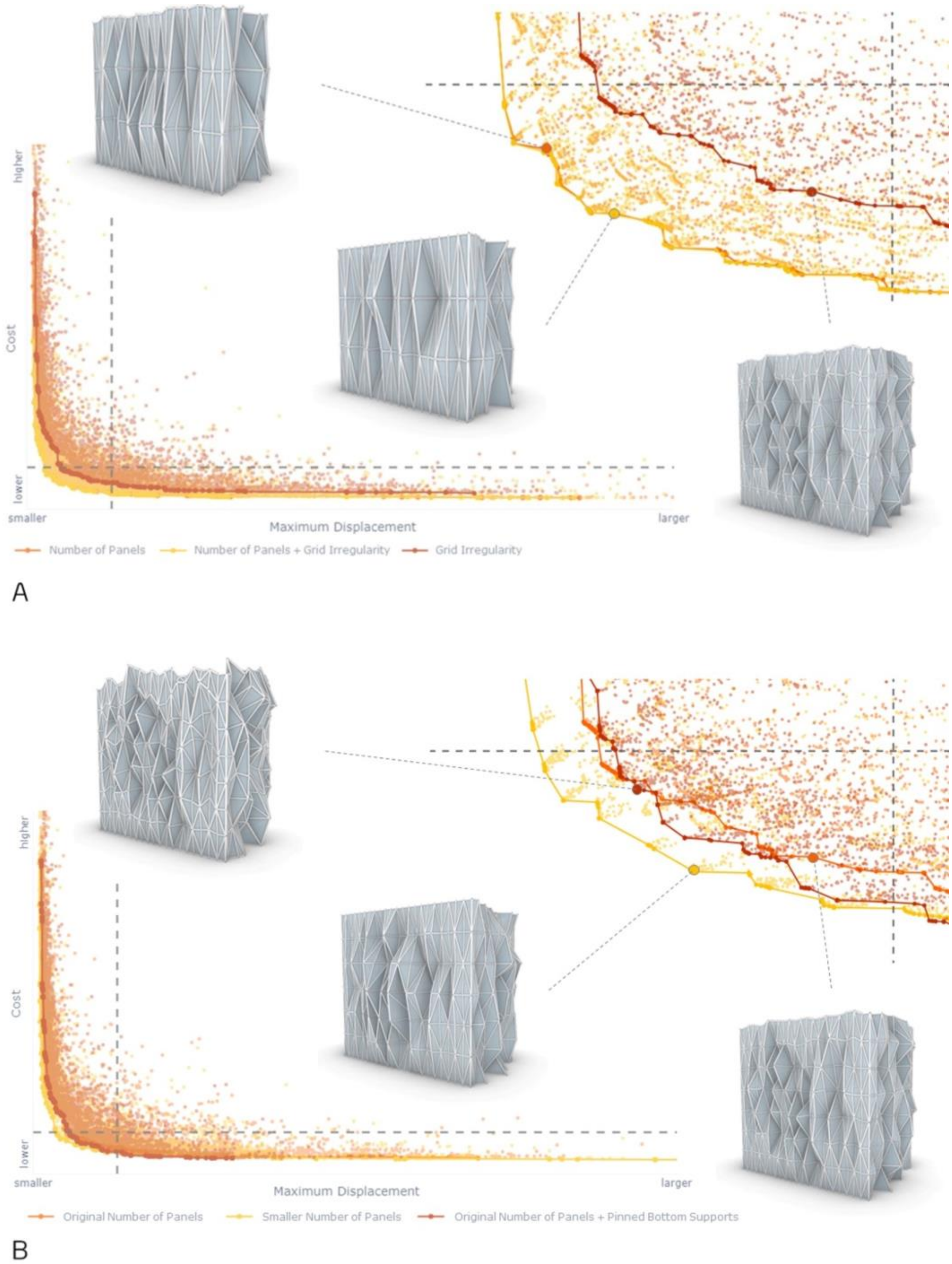

Figure 8. (A) Comparison of the previous truss optimizations (orange and yellow) with the number of panels fixed at its original value (red). (B) Truss optimizations with the number of panels fixed at its original value (orange), at a slightly smaller value (yellow), and at its original value plus the bottom supports pinned (red).

4.4. Revision and Decision

The last step entails the analysis of previous results and the selection of the final solution. It should be noted that the final sample of solutions is the result of all design decisions made throughout the process in terms of the trade-off between design aesthetics and performance. This means that although creative intentions were not quantitatively evaluated during the optimizations, i.e., they were not measured through fitness functions, they influenced the evolution of the project by guiding the adjustments made to the decision variables (e.g., number of panels, truss irregularity, etc.) after each optimization cycle.

To restrict the sample of solutions, we focus on those with the best trade-offs, i.e., Pareto-optimal ones. As none performs better than the others in all criteria, the decision will depend on what we regard as the best balance between design intent, aesthetics, strength, and cost. The interactivity of the graphs in Figures 6-8 facilitates this selection, allowing us to quickly visualize and assess the solutions' geometric configuration just by clicking on the corresponding dot in the graph (Figure 9) and thus, more easily navigate the design space of optimal solutions and find one that successfully balances all requirements. Moreover, the proposed methodology also facilitates the transition to other design stages, directly generating the solutions in the most appropriate tools.

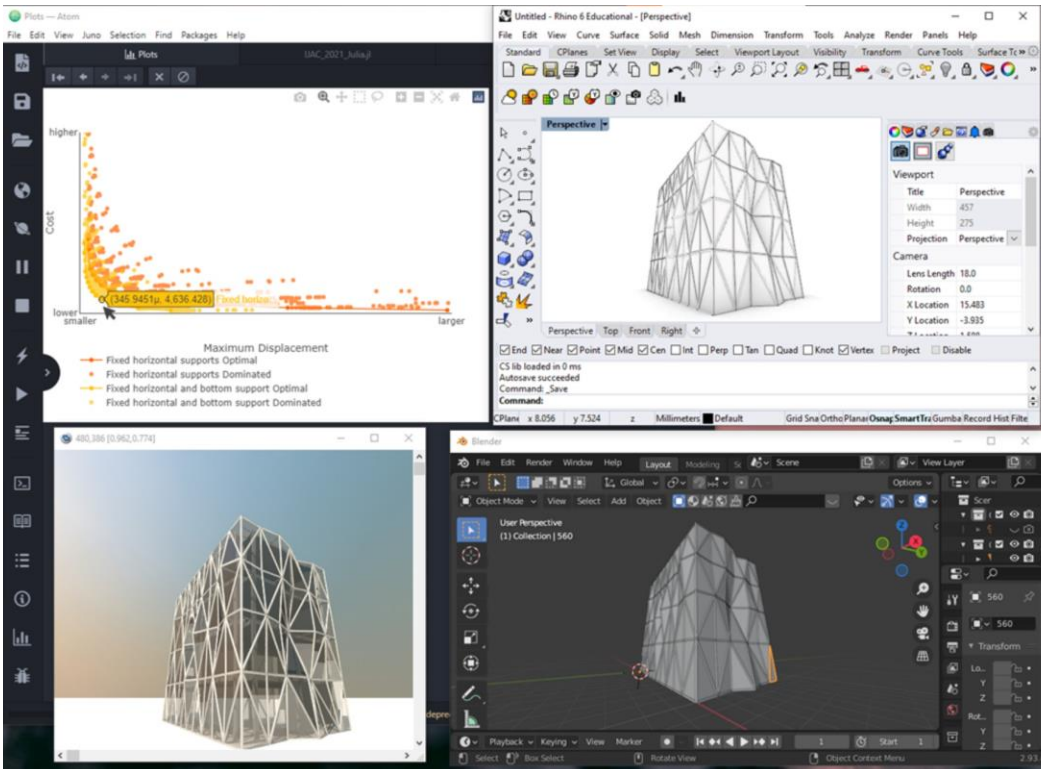

Figure 9. Immediate visualization of a selected solution in multiple tools: a point-and-click in one of its dots triggers the generation of the corresponding 3D model in, for instance, Rhinoceros 3D (top-right), POVRay (bottom-left), or Blender (bottom-right).

After choosing the preferred truss configuration, we can continue detailing the resulting facade design and apply, for instance, different tiling rules to its panels or simply select different glass finishes producing different reflection effects.

5. Results and Discussion

This section discusses the results and makes considerations on the ability of the proposal to support creative processes responding to aesthetic preferences and performance requirements.

Regarding the first stage, the methodology proved to facilitate the algorithmic implementation of the crystal-like structure since it benefits from ready-to-use algorithms that can be easily combined. It also showed to support the iterative development of an algorithm representing both creative intents and aesthetic preferences, facilitating design changes and immediately displaying the results of each change in the selected modelling tool.

In a second stage, the methodology promoted the execution of iterative structural analyses by facilitating the production of multiple truss configurations and their corresponding analytical models containing only the information needed for the analysis. This allowed us to effortlessly assess the solutions' structural integrity and aesthetics after each design change, which was critical to understand the factors influencing both criteria, and the design changes contributing to improve the solutions. Figure 4 illustrates this process: at each iteration, we changed the algorithm according to the structural inconsistencies found, conscientiously guiding the design process towards a structurally realistic solution that simultaneously met our creative intent.

In the optimization stage, the methodology allowed us to effortlessly execute numerous structural and cost analyses and incrementally improve the solutions. Despite the conflicting nature of the selected criteria, the aim was to find a set of economically viable solutions that complied with both the design intent and safety standards rather than yielding the smallest maximum displacement. At this point, the use of the methodology spared us from several tiresome and time-consuming tasks, such as setting up each analysis cycle, producing the corresponding analytical models, and storing the results of each evaluation. This was critical to accelerate the optimization cycles and increase the number of solutions analysed and the accuracy of the results.

The time saved in optimization-related tasks allowed us to focus on creative tasks and adjust the existing aesthetic-related optimization variables, such as the truss irregularity and number of panels. By iteratively changing the values of the decision variables, we could guide the design towards the design intent of creating a crystal-like facade structure, while evaluating its cost and strength. During this process, we visualized the 3D models of the best solutions (i.e., in the Pareto-front) to assess their aesthetic quality, balancing creative intents with the need for a stable and economic structure. Figures 6-8 illustrate the incremental exploration of the trade-offs between subjective and non-measurable criteria, such as design intent and aesthetics, and quantitative criteria, such as structural strength and cost. The ability to quickly alternate between the interactive graphs containing the analyses results and the solutions' 3D model played a critical role at this stage, facilitating the interpretation of the optimization results and their coordination with creative intents in the search for solutions successfully balancing all criteria. Figure 9 illustrates this ability by presenting one of the Pareto front solutions in three different visualization tools.

Finally, the proposal also facilitated alternating between tools according to each performed task, allowing us to use (1) Rhinoceros 3D to visualize the solutions' 3D model and analysis results, (2) Robot and Frame3DD to perform the structural analyses, (3) POVRay to quickly display rendered images of acceptable quality, and (4) Blender to produce higher quality rendered scenes. This interoperability was critical to transition between design stages.

The analysis of the results demonstrates the potential of the proposed methodology to support and enhance creative processes responding to aesthetic intentions and real-world constraints from initial design stages. By allowing different design requirements and stages to mutually influence each other, the methodology extends the range of potential solutions beyond those initially considered. The use of a single algorithmic description containing all design information proved to support a performance-aware creative exploration, allowing (1) coordinating aesthetic intentions and design constraints from early stages, (2) making both informed design decisions and changes, and (3) navigating the design space towards structurally viable, economic solutions simultaneously matching the design intent of creating a crystal-like facade.

The option for a text-based AD approach makes the proposed methodology capable of addressing more complex design problems. However, it also makes its use more difficult, requiring more sophisticated programming skills, which still takes time and effort to learn. In the end, there is a trade-off between the complexity of the design problems that one might address, and the technicality of the tools needed to handle them.

6. Conclusions

This paper proposed an Algorithmic Design (AD) methodology to support creative design processes considering different facade design requirements, placing particular emphasis on aesthetic and performance-related ones. The aim is to provide architects with better insights into their solutions' performance at early design stages and thus promote more informed decision-making processes. By anticipating performance integration to early design stages, where design changes are easier, faster, and cheaper, the proposed methodology also fosters the consideration of well-performing solutions beyond those initially conceived. Moreover, since aesthetics is difficult to quantify and depends upon the qualitative appreciation of the designer, the proposed methodology encourages designers to adapt the optimization incrementally to ensure it fits their preferences instead of trying to define a set of rules to measure aesthetics.

For evaluation purposes, we applied the methodology in the design of a crystal-like facade structure, demonstrating its potential for facilitating the incremental development of the solution, while considering different aesthetic, structural, and economic criteria. As, during this process, the methodology allowed us to iteratively assess the solutions' cost, structural behaviour, and visual expression, and apply design changes accordingly, we could guide the design process in a more conscientious and efficient way. Additionally, by displaying the results of iterative structural and cost analyses graphically, the methodology facilitated the understanding of the impact of design changes in both the solutions' performance and visual expression. The result was a more informed creative process that increased the likelihood of successfully achieving a solution meeting all existing requirements.

For future work, we plan to research strategies to improve design exploration processes, such as (1) reducing the size of the design space considered, by excluding solutions that are visually too similar or allowing the use of conceptual sketches of the design intent to suggest designs aligning with the architect's preferences, (2) improving the way results are presented to the architect, e.g., using colour scales to illustrate the analysis results, and (3) providing a recommender system to guide the designer in improving the solutions performance.

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Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

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