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Fabrication-Aware Design for 3DCP Shells Using Genetic Optimization

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Abstract
The architectural industry is in the midst of a paradigm shift where practices transition from unconnected data to context-rich, connected data. New concepts such as smart fabrication, automation and vertical integration create the need for fabrication-aware architectural representation models that allow designers to better engage with new, data-rich manufacturing technologies. 3D Concrete Printing (3DCP) offers many benefits compared to conventional concrete casting, foremost the ability to fabricate complex geometry. There is currently a lack of computational modelling techniques that bridge design and manufacture for 3DCP, making it difficult to predict the printability of designs. This paper demonstrates a unified design-to-fabrication workflow through a Machine Learning approach. 3DCP is used to produce sacrificial formwork for freeform reinforced concrete shell structures. Specifically, genetic optimization is employed in the form-finding and segmentation process to consolidate a series of parameters and establish feedback loops for a fabrication-aware design model.

Keywords: Additive Manufacturing, 3D Concrete Printing, architectural design, integrated workflow, fabrication-aware design, conceptual design, concrete shells.

1. Introduction

1.1. Background and state of the art

With the rise of Industry 4.0 originating in the manufacturing industry, the Architecture, Engineering and Construction (AEC) industry has been experiencing a radical paradigm shift transitioning from unconnected data to information-rich, interlinked data [1]. Resulting concepts, such as the Digital Chain [2] and related robotic fabrication technologies, have emerged that require new design methodologies to take full advantage of them [3]. With the proliferation of parametric design, Building Information Modelling (BIM), sensor-rich environments and learning-based responsive systems among other innovations, design models generate a vast quantity of data for any given project, creating the need to synthesise different data models in order to consider multiple analytical and design perspectives which inevitably results in significantly increased levels of complexity [4]. Manual iteration becomes time and labour-intensive and, at a certain point, impossible. This creates the need to arrive at “better solutions algorithmically, or recursively, rather than intuitively” [5].

Additive Manufacturing (AM), one of the main emerging technologies, offers many benefits compared to conventional manufacturing methods, foremost the ability to create “freeform architecture” [6]. Compared to traditional concrete construction, advantages include reduced material consumption, the possibility of construction without the need for conventional formwork [7] and labour cost reduction

[8]. 3DCP is a particularly suitable technology for parametrically designed geometries [9] coupled with evolutionary and topological optimization [10]. Commercial adoption has been slow due to its complex manufacturing setup and a lack of computational modelling techniques, making it a prototypical candidate for examining the problem of high-dimensional, complex data models in design.

Artificial Intelligence (AI), more specifically Machine Learning (ML), is rapidly becoming an area of intense study in the AEC industry as shown by the bibliometric analysis conducted by Ozerol et al. [11] and Darko et al. [12]. As shown by Campo and Leach [13]. , it is also becoming of interest in the design domain. AI has the potential to improve productivity significantly by processing vast quantities of data efficiently, tackling complex problems and learning in a predictive, nonlinear manner [12]. Because of these benefits, AI is an obvious solution to the problem at hand.

In Additive Manufacturing (AM), the lack of design-oriented AI research is evident, as currently existing research "is mainly focused on the issues of material design and design optimization of the 3DP mixes" [14]. Robotic systems, including robotics for AM, in AEC activities have seen limited research attention [12]. The majority of ML research focuses on image-, text-, voice-based [15] and other numerical applications situated more in the engineering, production automation and optimization realm. Looking at the broader architectural perspective, optimization and creative exploration, often in conjunction with generative design, is the traditional and most represented avenue where ML applications find their use [12], [16], [17], [18]. More recently, precedents can be found in the analysis and prediction of building performance, BIM-related automation, 2D design sketching tools such as Image AI-based visualisation and floor plan generation [19]. However, there is a lack of relevant literature regarding the application of ML in manipulating design geometry and three-dimensional data. The most relevant precedents are found in point cloud-based methods [15], methods using computer vision for adapting in real-time to unknown geometries [20], and methods using ML to implement lightweight prediction models for short-cutting computation-intensive simulations for improving the iterative design process [21], [22].

1.2. Problem Statement

As outlined above, the adoption of 3DCP in commercial settings has been slow due to several critical obstacles. First, the process of 3DCPembodies a large range of parameters that need to be optimised. Environmental and operational parameters of the machinery, material properties, geometric peculiarities and lack of computational modelling techniques all hinder the success of 3DCP. Second, the current established workflow operates on dead design geometry which is separately processed for fabrication, leading to a dichotomy between the design and manufacturing stages. These factors result in a laborious setup for each individual project as well as a stretched-out design-fabrication cycle reliant on trial and error, thus making it difficult to adopt the technology for production environments. From a design perspective, there is an urgent need for data models that can architecturally represent the interlinked design-to-fabrication processes for designers to be able to meaningfully interface with complex digital chains and make informed decisions.

1.3. Objectives

In a larger context, the research into fabrication-aware models is still at an early stage and literature is sparse [24], [25], [26], [27]. This paper contributes to the discourse by demonstrating a fabrication-aware model for the design of steel-reinforced, cast-in-place concrete shells where 3DCP is used to produce sacrificial formwork. Moreover, a ML approach is taken to "synthesise meaningful information for design" [1] and allow for less rigid, flexible forms of representing fabrication data.

A framework for developing integrated, fabrication-aware design models implemented in Rhino3D/Grasshopper is demonstrated. A Machine Learning approach is used to consolidate a series of parameters that would result in exponential complexity in a conventional parametric model. Printing parameters, such as material rheology, inclination angles, buckling under self-weight, printing speed, and design optimization strategies, such as segmentation, reinforcement, modular assembly and topology optimization [28] are considered in the workflow and modularized into feedback loops where possible.

2. Methods

2.1. In situ vs. Off-site prefabrication

For this framework, an off-site prefabrication system was chosen. In comparison to in-situ methods, off-site 3D printing of concrete offers advantages such as improved quality control, reduced labour on-site, and the ability to create complex geometries without temporary supports [29], additionally it offers easier logistics due to the smaller individual pieces. As shown by Lin et. al. [30], prefab systems typically allow for greater degrees of freedom, as the extrusion mechanism can be mounted on robotic arms as opposed to large gantry-type CNC machines that only allow planar printing.

2.2. Reinforcement Strategy

A major obstacle to the commercialization of 3DCP structures is the lack of tested and approved pathways in terms of steel reinforcement [31]. However, 3DCP can be employed to produce formwork which is suitable for casting of commercially approved concrete mixtures in combination with traditional reinforcement strategies. The proposed framework goes a step further and introduces a methodology for producing incrementally casted, reinforced concrete shells. Structures are assembled sequentially and cast segment by segment, thus greatly simplifying the construction process. By adding steel reinforcement, the design is no longer constrained to compression-only geometry.

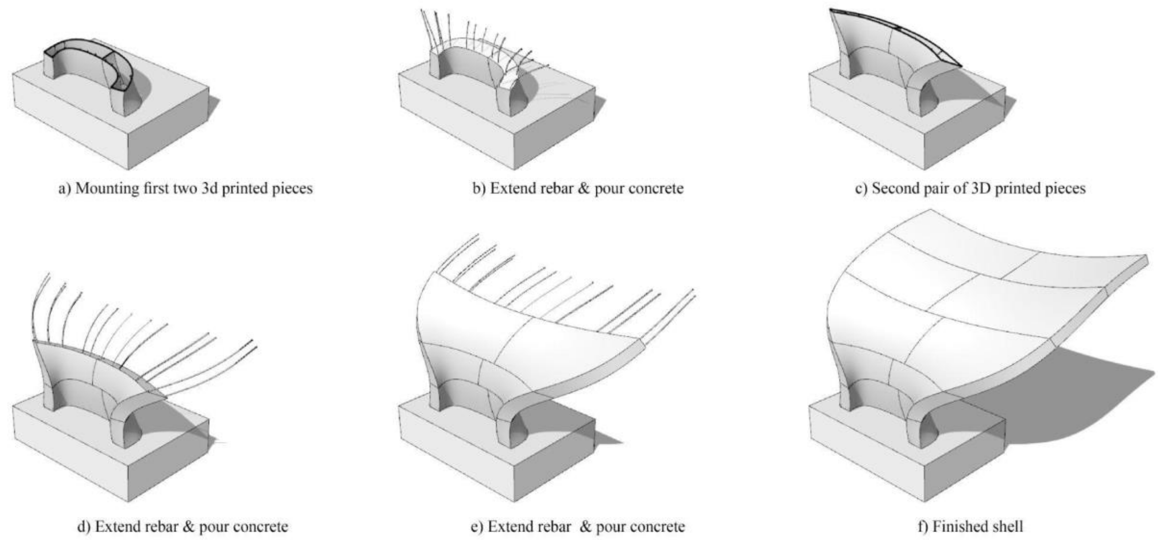

Figure 1: Process of assembly for a shell using 3DCP sacrificial formwork. a) to f) showing steps of incremental assembly of the 3DCP segments, inserting/extending reinforcement and casting with concrete.

2.3. Shell Morphology

The umbrella term of "freeform shells" describes a large variety of morphologies. For the given constraints, not all shell designs are viable. In particular, viable designs must be castable, meaning the form must allow for the possibility to contain liquid concrete while it cures. Additionally, due to the constraints of the current system, segments must have at least one planar end face as they need to be freestanding on a flat print bed. This constraint can be potentially removed by implementing printing on non-conformal surfaces.

2.4. Workflow

The general workflow can be broken down into three stages - Design, Fabrication, Construction. The requirements of each stage should inform the design model in the ideal case. Conventionally, these stages occur separately from each other and the information flow is unidirectional. For example, classical considerations such as concept, aesthetic and site context are addressed in the design stage, then handed over to the fabrication stage where the data is processed independently. Material behaviour, machine constraints among other requirements are considered here. Lastly, in the construction stage, assembly and casting are handled.

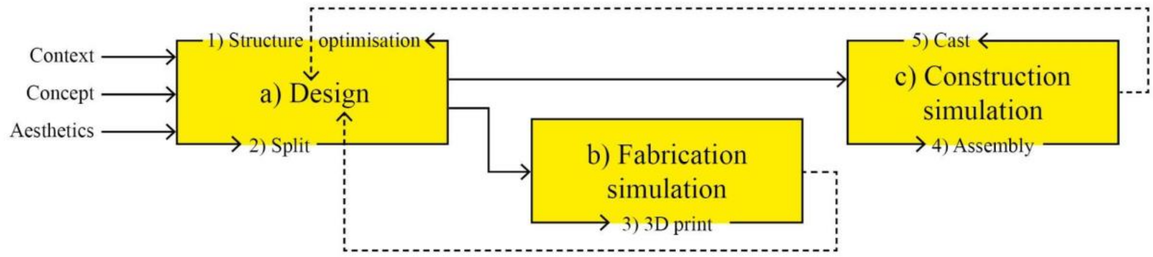

Figure 2: Diagram of the proposed workflow which follows 3 main loops: a) Design, b) Fabrication simulation and c) Construction simulation. There are feedback loops going back to the design phase from b) and c).

The sequential processing of multiple modelling and analytic perspectives results in "complex and brittle multi-scalar design and simulation models" [4]. By adding ML feedback loops that cut across these stages, the framework aims to reduce complexity, brittleness and provide a more resilient design model. This is shown in Figure 2, where feedback loops are introduced to loop back from fabrication and construction to design.

2.5. Machine Learning Components

In the current model, two opportunities in the workflow were implemented where ML could establish feedback loops. In GA Stage 1 (see Figure 3), an automated FEA solution in Karamba3D is used to automate the search and optimization process of the overall shell design. Using a generative, evolutionary loop provides feedback on the overall structural performance of the design. At the moment, only the deflection value of the FEA is added to the fitness score. In subsequent versions, a more comprehensive structural evaluation is envisioned to increase the precision of the fitness score.

In GA Stage 2, the design shape is broken down into 3DCP-ready segments. The segmentation of arbitrary shell structures is not conducive to finding optimal solutions in the traditional intuitive way, as there is a vast quantity of possible combinations, making it not just tedious, but impractical to test manually. Optimal splits are defined by their suitability for the printing process, which is largely dependent on understanding and predicting their rheology during the printing process to prevent collapse.

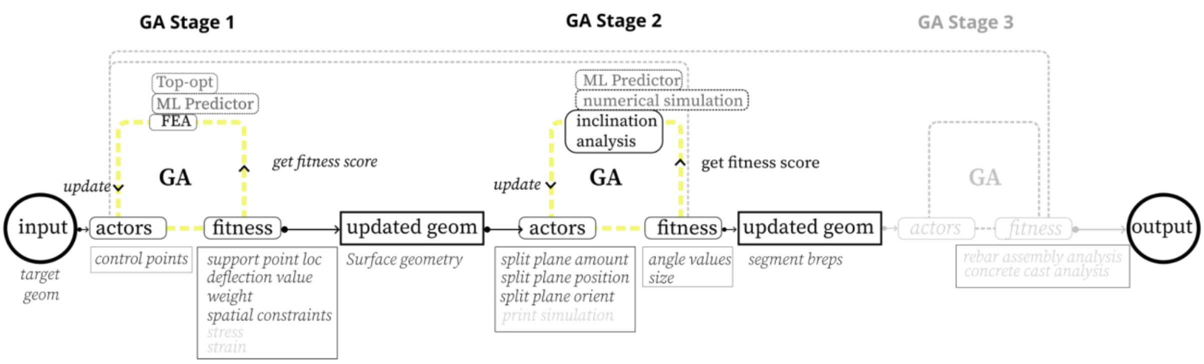

Figure 3: A diagram illustrating the basic setup for GA optimization. Greyed out modules are not yet implemented.

In a conventional model, this information is not represented and must be validated through trial and error. However, by integrating an optimization algorithm in the data model, it is possible to anticipate the fabrication data and include it in the design search space. This allows for faster response times during iterative design exploration, enabling informed design decisions early on (see Figure 3 GA Stage 2). In the current implementation, an heuristic print angle parameter of 40 degrees is used to predict the material behaviour during extrusion and curing. This number has been derived from expert input as well as experimental validation by printing a series of test objects which is shown in the results section. The tasks of structural optimization of the global shell shape and the segmentation for incremental casting are integrated into the design model via two feedback loops using Grasshopper's Galapagos genetic algorithm. Genetic algorithms (GA) are an adaptive heuristic search algorithm able to solve optimization problems in machine learning and fall under the reinforcement learning category. The decision to use evolutionary optimization is based on several factors. First, the task at hand is one of search and optimization. Therefore, some ML algorithms can be naturally ruled out, e.g. neural networks which are typically used for prediction and classification. Second, genetic algorithms are what is known as "lazy learners". They neither require nor usually use any sort of historical or training data but operate directly on the live data. While this leads to increased computation time for each run, it has several advantages for our application. Given the scale and physical fabrication complexity of 3DCP, creating a large enough training data set would require considerable effort and is therefore undesirable. True real-time speed is not a critical concern in this application, so the trade-off is sensible. Third, the solution space is non-differentiable. Given the arbitrary nature of the shell geometries and discrete solution space, a loss function with which to traverse the fitness landscape mathematically is not easily found. Thus, genetic algorithms are better suited for the task, as they operate well under black-box conditions. Convergence to a global maximum is not guaranteed, and the algorithm is adept at finding heuristic optima. This makes genetic algorithms a very versatile and generic tool to naively approach any problem without the need to generate training data or achieve comprehensive parameterization, and one of the very few tools to deal with either non-differentiable functions, discrete functions, or with high dimensional datasets.

2.6. Evaluation Criteria

The generated solution space is evaluated based on a two-stage, combined fitness score. In the first stage, the shell is analysed for structural performance as shown in Figure 4. The deflection value of the representation mesh is calculated for each vertex. The GA adapts the position of predefined control points of the shell with which it modifies the geometry to minimise deflection values and reduce weight.

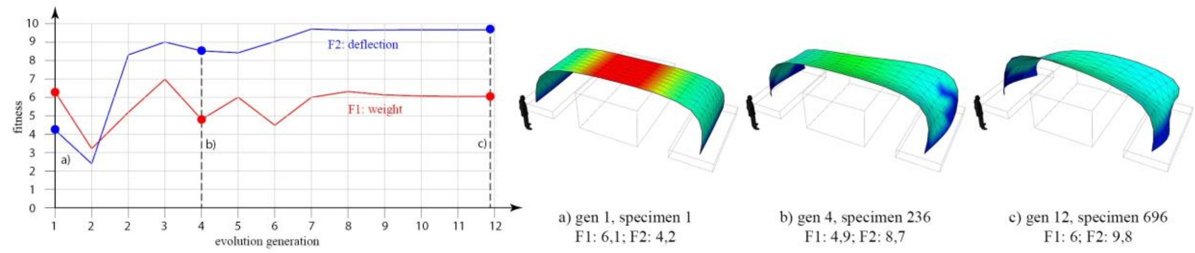

Figure 4: A graph showing the first stage GA for structural optimization of a bridge shell. The algorithm attempts to adapt the initial geometry - shown in a), to minimise deflections and weight of the structure b) and c). The white boxes represent different constraints for the GA, the left and right are supports, the center box represents a clearance volume.

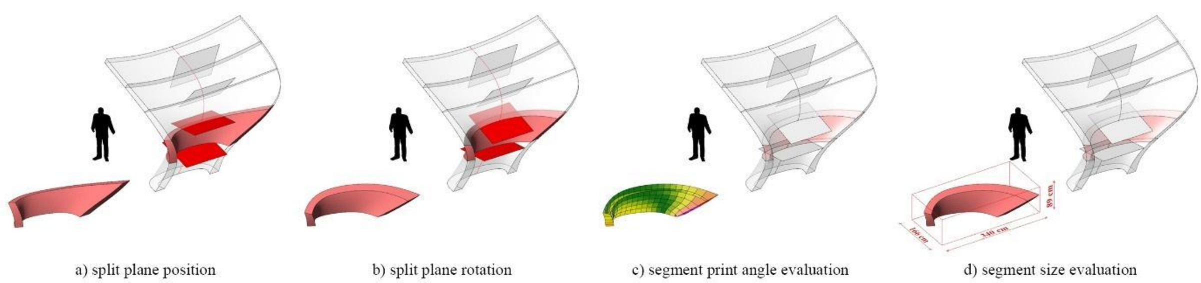

Figure 5: Diagrams showing parameters that influence the splitting of a shell and evaluation criteria for the split segments.

The shell geometry is further analysed in the second stage where it is segmented parametrically along predefined guide curves, which can either be set manually or follow the surface iso curves. The resulting split planes are further modulated in their position and rotation to expand the search space. The generated solutions are evaluated based on an inclination analysis and their size. Inclination is used as an heuristic indicator of printability, wherein geometries exhibiting an inclination of more than the set angle will be deemed unprintable and receive a low fitness score. The size influences the fitness score, as oversized segments do not fit in the print bed bounding box and are, therefore, not printable.

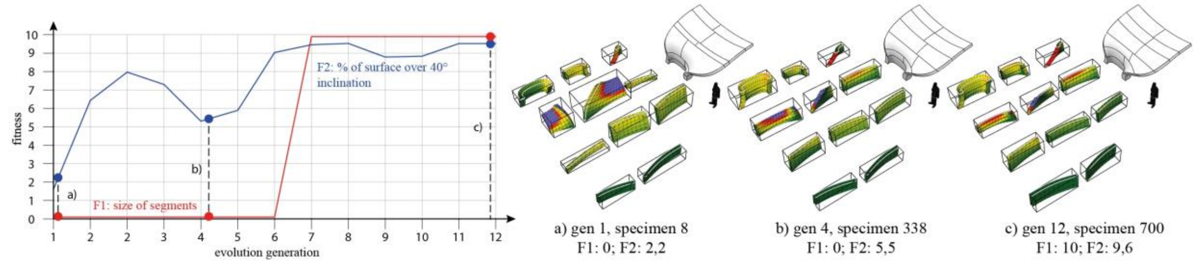

Figure 6: A graph showing the second stage GA optimizing the split segments of a shell according to printability criteria. a), b) and c) show different specimens along the evolutionary axis which demonstrate increasing fitness for F1 (size) and F2 (inclination angle) over time.

3. Results

A series of full-scale 3D printed tests were conducted to validate the maximum inclination angle for 3D printing using a robotic arm mounted extruder. The robot used in the test is a Fanuc M-710iC/50 R-30iB with a custom-built extruder from ZevnikLab that supports 2 component printing of concrete. To ascertain the capabilities of the material to print at an angle three prototypes were tested: 30°, 40° and 50° inclinations from the vertical axis. It was discovered that 30° and 40° inclinations were able to print without any issues, while the 50° inclination collapsed due to buckling on the back side of the shell as shown on Figure 7c). This information was then carried into the GA which assumes a 40° inclination as viable for printing.

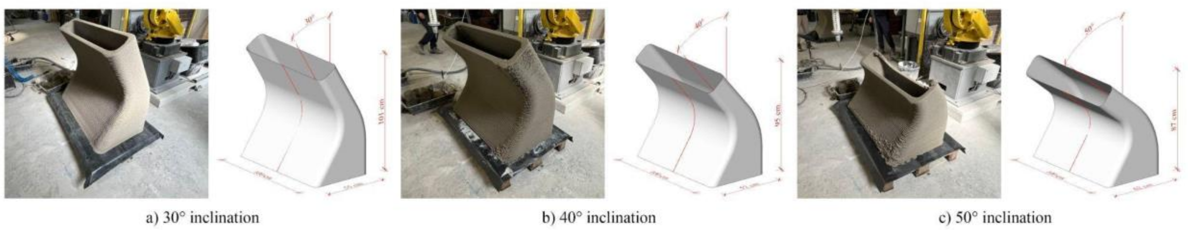

Figure 7: Images showing the 3D printed tests of different inclination angles. The angles of a) 30°and b) 40° were able to successfully print, while the c) 50°inclination collapsed due to buckling.

Three different shell types were designed and evaluated using an optimization algorithm: 1) a bridge spanning 7m, 2) a freeform wall 2,3m high and 3) a cantilever shell that spans 2m. Each shell underwent a two-stage GA optimization. In the first stage a target geometry, which roughly describes the design intent, is used as input (see Figure 8a). The target geometry is evaluated based on structural performance and then modified with a GA to minimise deflection and weight values (see Figure 8b). Since the algorithm does not consider any other fitness criteria related to overall design such as symmetry, which a designer does intuitively, the shells are not completely optimal. This would have to be implemented in the future.

3.1. Shell type 1 – Bridge

The segmentation optimization process shows that 4 out of 18 pieces of the bridge shell have inclinations that are not suitable for printing. The pieces are marked out in red on Figure 8c and 8d. This means that the design would have to be adapted in order to ensure fabrication viability. At this point, a designer must go back to stage 1 optimisation and select a different structurally viable shell. In the future however, the Stage 2 GA segmentation process is envisioned to be fed back into the structural optimisation in Stage 1 to automate the generation of shell geometry that is not only structurally stable but also printable.

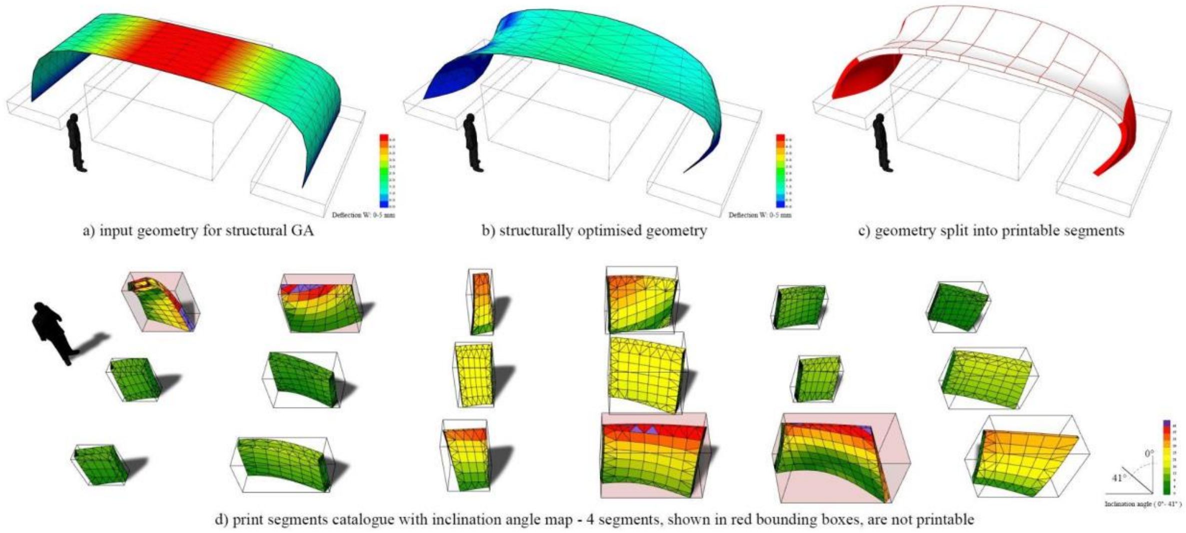

Figure 8: Structure and split optimization of a bridge shell topology; a) shows the input target geometry that is not structurally viable, b) GA applied to structurally optimise the shell topology, c) split pattern using the second stage GA and d) split pieces of the shell with printability evaluation.

3.2. Shell type 2 – Wall

The wall was generated with an additional constraint in stage 1. A horizontal load was added to its top edge that pushes the geometry to deform so that it becomes laterally stable (see Figure 9a and 9b). Compared to the bridge shown above, the wall has no problematic pieces which means the design is printable.

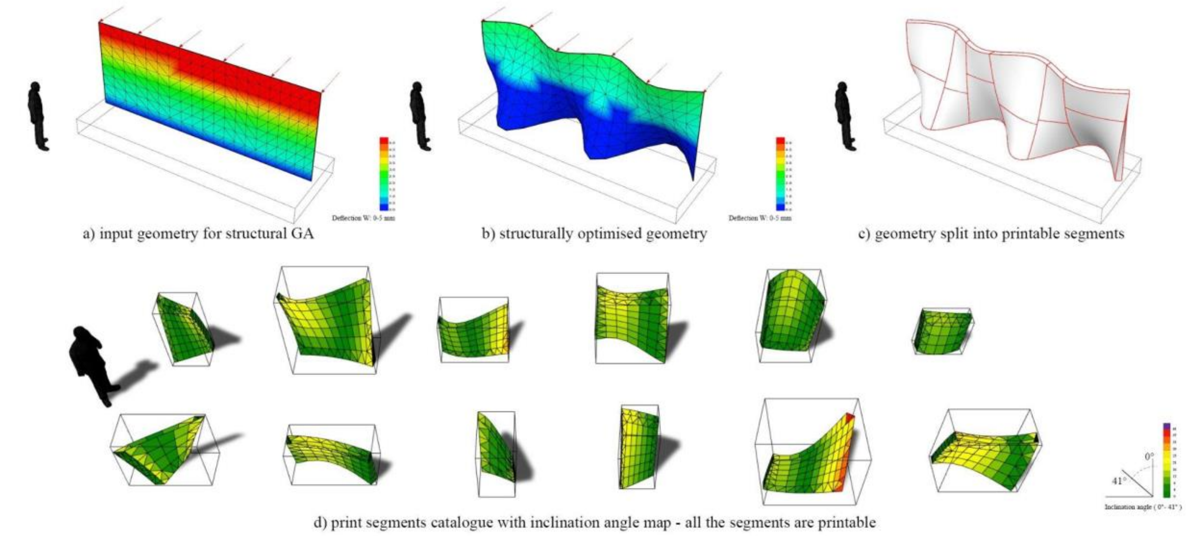

Figure 9: Structure and split optimization of a freeform wall topology; a) shows the input target geometry that is not structurally viable, b) GA applied to structurally optimise the shell topology, c) split pattern using the second stage GA and d) split pieces of the shell with printability evaluation.

3.3. Shell Type 3 – Cantilever

Similar to the bridge shell, the cantilever also shows one problematic piece that demonstrates non-printable geometry as shown in Figure 10c and 10d.

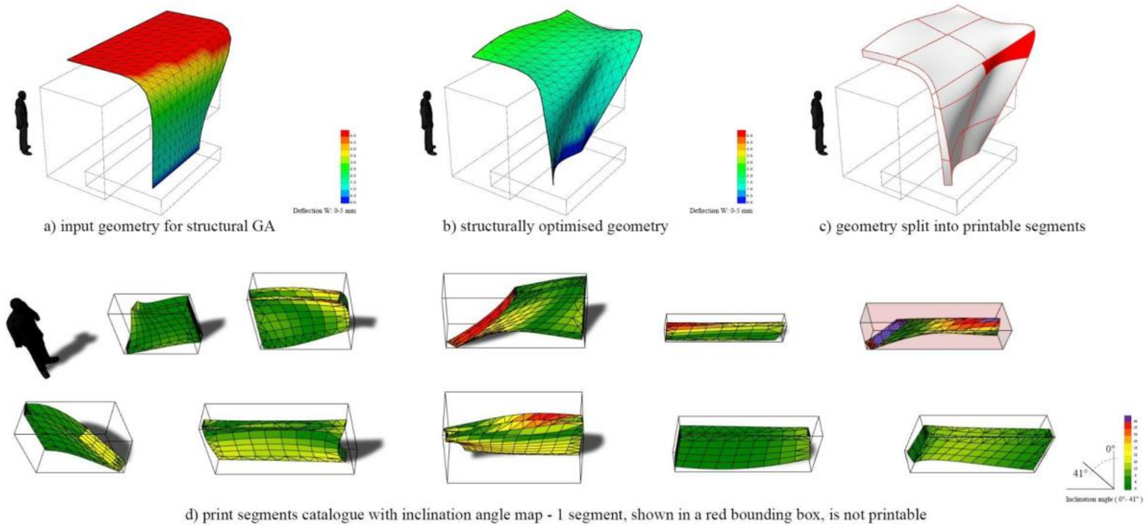

Figure 10: Structure and split optimization of a cantilever shell topology; a) shows the input geometry that is not structurally viable, b) GA applied to structurally optimise the shell topology, c) split pattern using the second stage GA and d) split pieces of the shell with printability evaluation.

3.4. Physical Validation

As a validation of the workflow, one of the pieces from the Shell type 3 was printed in 1:1 scale. The segment required the use of non-planar printing, which means layers are not oriented along the world Z-axis, rather they change in orientation following the local curvature of the segment. This is demonstrated with tests shown in Figure 6. The segment validates the use of GA for structural and split optimization of concrete printed shells. The algorithm was able to produce segments that were printable and behaved according to predictions.

Figure 11: 3D print shell piece. A 3D concrete print of one of the pieces from the Shell type 3 – Cantilever, shown in Figure 9, demonstrating the ability of the GA to correctly split a shell into printable segments.

4. Discussion

The workflow is designed in a way where modules can be upgraded with more precise and optimised components. The herein presented version can be seen as a minimum viable product and serves to validate a section of the full toolchain. For example, the current inclination analysis can be replaced with numerical simulation as outlined by Bhooshan [24]. In turn, the simulation can be replaced with a Machine Learning predictor trained with the simulation data as seen in the KnitCone Project [4], thereby achieving higher accuracy while maintaining near real-time computation speed. Similarly, the structural analysis can be swapped out with a lightweight prediction model. A closed loop feeding printability analysis results into the global shape formation as part of the design process is to be developed.

Future work will look into implementing more of the digital chain for reinforced 3DCP shells. It will look into empirical testing of the produced segments as well as the assembly of full-scale prototypes to validate findings. The aim is to develop a robust design framework for production environments.

In a broader perspective, this paper contributes to the discourse surrounding Industry 4.0 practices in an architectural context. It provides a real-world case study on how to synthesize existing, but disparate, research literature into integrated, fabrication-aware toolchains for the production of complex, robotically fabricated structures. Particularly the use of ML approaches for design applications, while often touted to be an essential component for building smart, integrated workflows, is still in the early stages and lacks real world case studies. Coupling predictive and generative elements in a feedback loop demonstrates that design models can move beyond pre-defined data and respond to performance considerations.

5. Conclusion

In this paper we have demonstrated a novel method for developing a fabrication-aware model for reinforced 3DCP shell structures. This is achieved by combining processes occurring in the various stages of the digital chain into one integrated workflow applying feedback loops using optimization algorithms. We show the possibility of enriching design models with external processes without breaking the data flow.

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