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ARTICLE

Design of a Computational Model for 3D Concrete Printed Geometry Using Machine Learning and Genetic Optimization

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ABSTRACT

3D Concrete Printing (3DCP) is an emerging technology with well-established benefits and the potential to dramatically change the construction industry. While research in material and process optimization is gaining traction, the architectural application of 3DCP remains relatively underdeveloped. Among many challenges, a lack of suitable computational modelling techniques is often identified as a major obstacle, resulting in simplistic design solutions that do not take full advantage of 3DCP technology. This study proposes a fabrication-aware design model using machine learning (ML), specifically genetic optimization, to address the research gap. 3DCP is used to produce sacrificial formwork for freeform reinforced concrete shell structures. The model conceptualizes a module-based approach to establish interlinked feedback loops across the various stages of a project, enabling fabrication and assembly considerations in the early design phase. Structural behaviour, printability, and segmentation constraints are translated into evaluative criteria within a unified computational workflow implemented in Rhino/Grasshopper, using the Galapagos genetic optimization solver. The framework enables iterative exploration of design options while accounting for both geometric and fabrication-related constraints. Three shell typologies are used to demonstrate the method, including a cantilever, a bridge, and a wall element, supported by a full-scale 3D printed segment for initial validation. This approach enables designers to develop geometries that are specifically tailored to the constraints and opportunities

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of 3DCP, opening new possibilities for meaningful interaction with the design-to-fabrication pipeline of complex 3DCP geometries.

Keywords: 3D Concrete Printing; Computational Design; Evolutionary Optimization; Fabrication Constraints; Reinforced Concrete Shells; Digital Fabrication; Early-Stage Design

1. Introduction

The Architecture, Engineering, and Construction (AEC) industry is undergoing a transformation driven by developments associated with Industry 4.0, characterized by a shift from fragmented data environments toward integrated, information-rich systems [1].

Contemporary design processes rely heavily on parametric modelling, Building Information Modelling (BIM), sensor-based data acquisition, and adaptive computational systems, all of which contribute to the generation of large and complex datasets. As a result, design workflows increasingly require the integration of multiple analytical and design layers within unified data frameworks, leading to significantly higher levels of complexity [2]. Emerging concepts such as the Digital Chain [3] and advancements in robotic fabrication demand new design approaches that can effectively integrate these new technologies [4]. Traditional modes of manual iteration become progressively inefficient, as exploring large design spaces through intuition alone is both time-consuming and difficult to scale. This has led to a growing emphasis on computational strategies capable of generating and evaluating design alternatives in a systematic manner, allowing designers to arrive at improved solutions through algorithmic processes rather than purely intuitive decision-making [5]. Additive Manufacturing (AM), and in particular 3D concrete printing (3DCP), is one of the key technologies in Industry 4.0. Compared to conventional concrete construction, 3DCP has attracted significant interest due to its high potential in sustainability, as it has low waste generation, improved logistics, eliminates the need for formwork, decreases labour requirements and increases worker safety [6].

One of the key architectural advantages of 3DCP is its capacity to manufacture complex "freeform architecture" [7]. This capability positions 3DCP as a particularly compatible technology for parametrically defined designs [8], while also offering potential synergies with other advanced methodologies, such as evolutionary strategies and topology optimization [9].

1.1. State of the Art

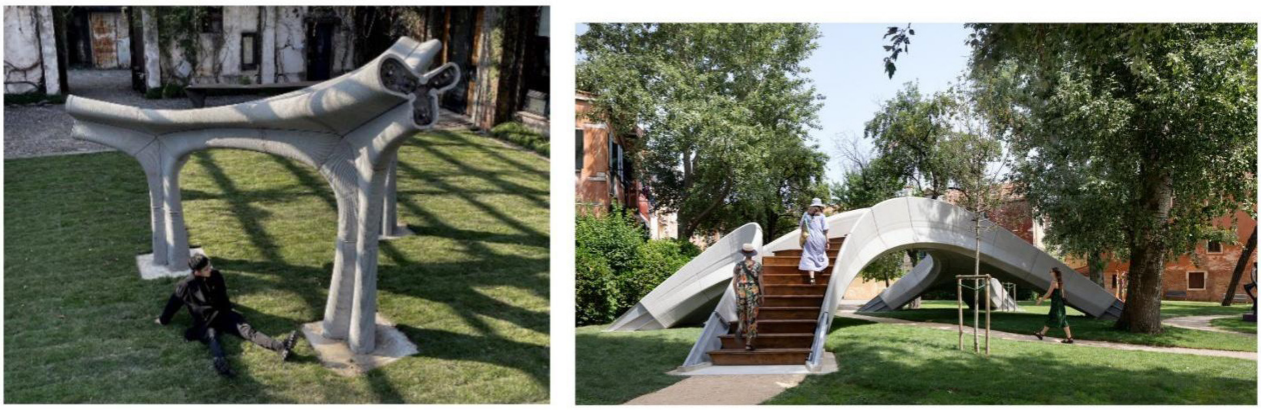
Despite its potential and continued interest from within the AEC community, industry adoption has been difficult because of the challenges of large-scale Additive Manufacturing (AM) [8]. Research emphasis has been on "materials performance, effective construction, improved machine friendliness to users, and implementation in a legitimate approach" [10]. Therefore, design for AM has been largely overlooked. While several exploratory studies have addressed this aspect, for example, in applying topology optimization or bio-inspired design and numerical simulation for design-fabrication feedback loops [7], the current state of the art still does not go beyond "robotic fabrication of primitive huts," as Lynn puts it [11].

AM, including 3DCP, remains in the realm of experimental research. Looking at architectural case studies, the number of commercial buildings constructed with 3DCP technology is increasing; however, there are not many projects that exploit the full potential of 3DCP technology [12]. As shown in **Figure 1**, most of the current projects are single-story houses featuring a rudimentary structural system consisting of load-bearing vertical walls and a standard, commercially available roof. Rounded corners are usually the only significant difference. As is shown by Bhooshan et al. [13] on the example of a 3D printed bridge, and Wu et al. [14] on the example of a 3D printed pavilion (see **Figure 2**), prefab 3DCP allows the construction of more intricate designs that begin to show some of the potentials of 3DCP. However, the complex geometries produced by Wu and Bhooshan require a deep understanding of the design-to-fabrication tool chain, material behaviour, knowledge of handling complex geometry models and creating custom data models, as well as extensive trial &

error testing. Most designers do not have this skill set and resources. As a result, 3DCP projects in practice typically feature primitive geometries that imitate conventional construction and fail to fully utilise the technology. Based on the discussed examples, there is a need for computational models that efficiently represent fabrication and design constraints, which would enable designers to make quick and informed decisions.

(**a**) (**b**) (**c**) (**d**)

Figure 1. Examples of 3D printed houses. (**a**, **b**) The first 3D printed concrete house in Germany [15]; (**c**) 3D-printing of affordable concrete houses in Mexico [16]; (**d**) 3D printed concrete house in Texas [17]. All houses are characterised by the production of vertical walls using 3D-printing; slabs and roof are made with conventional formwork or other materials.



(**a**) (**b**)

Figure 2. (**a**) An example of a 3D printed pavilion, showing the use of 3D printed concrete to produce a complex structural geometry [14]; (**b**) 3D printed concrete bridge, where the geometry is adapted in such a way that the bridge is entirely in compression [13].

Machine learning (ML) provides a potential pathway for addressing these challenges by enabling efficient data processing and the analysis of complex, nonlinear systems through predictive methods [18]. It has gained significant momentum within AEC research [18,19] and is increasingly attracting attention within architectural design discourse [20]. Recent studies have demonstrated the potential of hybrid ML models and computer vision (CV) techniques to revolutionize the assessment and optimization of sustainable concrete. For instance, Peng et al. [21] and Miao et al. [22–24] employed Sparrow Search Algorithm-optimized Extreme Gradient Boosting (SSA-XGB) and African Vulture Optimization Algorithm-optimized XGB (AVOA-XGB) to predict the performance of recycled aggregate concrete (RAC) and glass powder concrete (GPC). Additionally, Luo et al. [25] and Kabir et al. [26] developed computer vision-based systems using DeepLabv3+ and Feature Pyramid Networks (FPN) to automate durability assessments, such as freeze-thaw damage and sorptivity measurements. Miao et al. [23] further employed Generative Adversarial Networks (GANs) to augment datasets, while SHAP analysis revealed dominant features like fly ash dosage and effective water-binder ratio as key contributors to concrete performance. These advancements highlight the shift toward data-driven and automated concrete mix optimisation, integrating performance prediction, multi-criteria optimization and real-time assessment to meet both engineering and environmental goals. While ML is slowly becoming a point of interest in the design domain, a literature review reveals that a substantial majority of current ML research in the AEC industry is concentrated on “issues of material design and design optimization of the 3DCP mixes” [27].

In a broader ML for robotics context, point cloud-based approaches [28], computer vision-based approaches for real-time adaptation to unknown geometries [29], and lightweight prediction models to bypass heavy simulations and enhance the iterative design process [29,30] are the most pertinent precedents.

The most conventional and well-represented way that ML applications are used in architecture is through optimization and early design exploration, frequently in combination with generative design [18,31–33]. The assessment and prediction of building performance, automation pertaining to BIM, 2D design sketching tools, AI-based image visualisation, and the creation of floor plans are examples of more recent precedents [34]. Research on the use of ML with 3DCP robotics in AEC applications is limited [18]. In summary, there's a significant research gap in applying ML to 3DCP from a design perspective. Addressing this gap is key to enabling architects to better engage with Industry 4.0 technologies like 3DCP.

1.2. Problem Statement

Several significant barriers have prevented 3DCP from being widely used in commercial contexts. First, the large number of parameters in the 3DCP process must be optimised, including material characteristics, geometric idiosyncrasies, and operational and environmental parameters of the machinery, which is what the vast majority of research effort is currently focused on. Second, there is a lack of computational modelling approaches that are able to adequately capture all these parameters in one data model. Most pertinently, existing workflows, which operate only on dead geometry, create a dichotomy between the design and manufacturing phases further hindering the more widespread adoption of 3DCP. They draw out the design-to-fabrication cycle which must rely on the individual expertise of practitioners and trial & error validation for every individual project. As a result, most realized 3DCP projects only exhibit primitive, but proven, structures as stakeholders are unable to take on the increased risk of novel geometries. Data models that can structurally depict the interconnected design-to-fabrication processes are strongly needed from a design standpoint for designers to effectively interact with intricate digital chains and arrive at well-informed decisions and improved design solutions.

1.3. Objectives

This study builds upon earlier work by the authors, in which a preliminary framework for fabrication-aware design of 3DCP shell structures was introduced. In that initial study, structural evaluation and fabrication-related considerations, such as segmentation and printability, were explored as largely independent processes [35]. The present research extends this approach by integrating these criteria into a unified genetic optimization workflow. This shift from a sequential to a coupled feedback system enables the simultaneous evaluation of structural behaviour and printability constraints during the design process.

Building on this integration, this paper proposes a methodology for engaging with complex design-to-fabrication toolchains required by 3DCP. It proposes a model for design of reinforced concrete shells that are produced by 3D printing sacrificial formwork segments that are assembled and cast on site. The model adopts a ML approach based on genetic optimization to establish a unified data framework for integrating fabrication data into the design process. Parameters that can cause an exponential increase in data complexity such as design optimization qualifiers like segmentation, reinforcement, modular assembly, and topology optimization [36] as well as printing parameters like material rheology, inclination angles, buckling under self-weight, and printing speed, are processed and synthesized into a series of fitness scores. The focus of this study is on geometric and fabrication-aware design integration rather than detailed material or process modelling. The workflow is implemented in Rhino3D/Grasshopper to demonstrate the methodology using industry-standard tools.

2. Materials and Methods

2.1. Fabrication Strategy

An off-site prefabrication approach was adopted. Compared to in-situ construction techniques, off-site 3DCP offers improved quality control, reduced on-site labour demands, and greater potential for producing geometrically complex components without the need for temporary support structures [37]. The smaller scale of individual elements also simplifies transportation and handling. In contrast to large gantry-based CNC systems, which are typically limited to planar fabrication, prefabrication setups can achieve increased geometric flexibility, particularly when the extrusion system is mounted on a robotic arm, as demonstrated by Lin et al. [38].

2.2. Reinforcement Strategy

A key limitation in the wider adoption of 3DCP structures is the lack of established approaches for integrating steel reinforcement [34]. One way to address this issue is to use 3DCP to fabricate sacrificial formwork and use conventional reinforcement strategies. In this context, the proposed framework uses a process of sequentially assembling and casting concrete shells. This is shown in **Figure 3**. Furthermore, by adding steel reinforcement, the designs are not restricted to compression-only geometry. This is shown by Anton et al. who devised a strategy for inserting straight rebar into 3D printed wall segments [39].

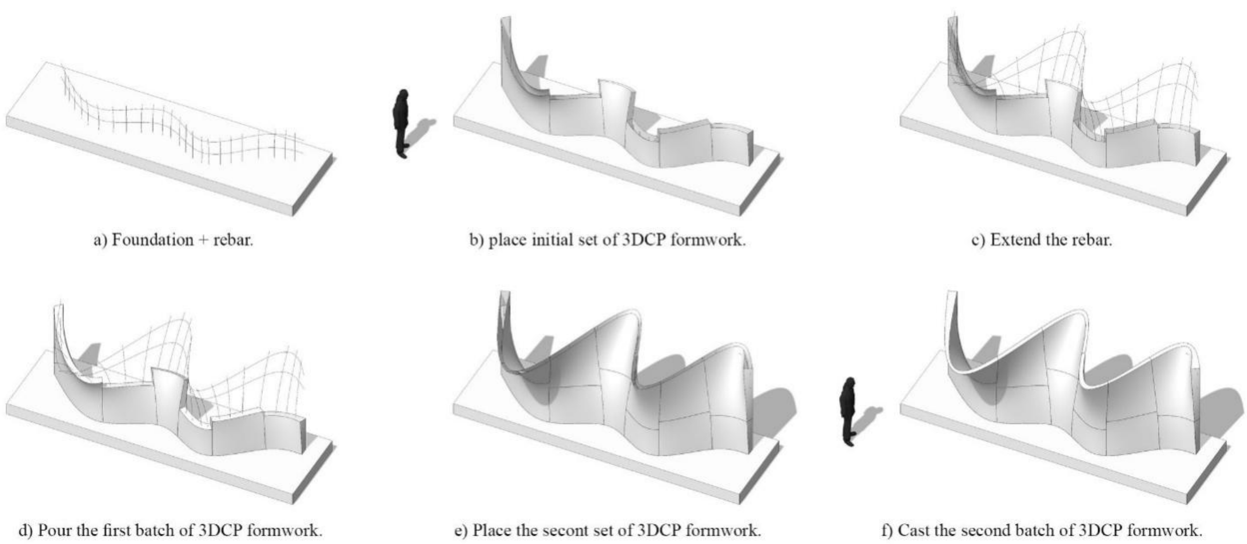


Figure 3. Incremental casting and construction using 3DCP elements as stay-in-place formwork. Images (**a**)–(**f**) show the sequential placement of printed segments, integration of reinforcement, and staged concrete casting.

2.3. Shell Morphology

The broad category of "freeform shells" encompasses a wide range of morphologies. Not all shell designs are feasible given the constraints involved. Specifically, workable designs need to be castable, which means the form needs to have the capacity to hold liquid concrete while it cures. Additionally, because segments must be freestanding on a flat print bed, they must have at least one planar end face. Printing on non-conformal surfaces may be able to overcome this restriction in the future. Within the current implementation, the slicing and fabrication logic is limited to geometries that can be described as "loftable" or generated through section-based sweeps along a guiding curve. This constraint informs both the admissible design space and the selection of examples presented in this study.

2.4. Workflow

The three phases of the general workflow are design, fabrication, and construction. Ideally, the design model should be informed by the requirements of each phase. Conventionally, the information flow is unidirectional only and these phases happen independently of one another. For instance, conventional aspects like concept, aesthetics, and site context are considered during the design phase before being transferred to the fabrication phase, when the data is handled separately. Among other needs, material behaviour and machine limits are considered here. Finally, casting and assembly occur during the building phase. In a conventional workflow, mistakes that occur in the later phases must be manually carried back to the design phase to be amended (usually between different stakeholders) and this can become costly. Our method proposes to link these phases in the computational model through feedback loops so designers can anticipate and design for mistakes from the start. The proposed framework is illustrated in **Figure 4**.

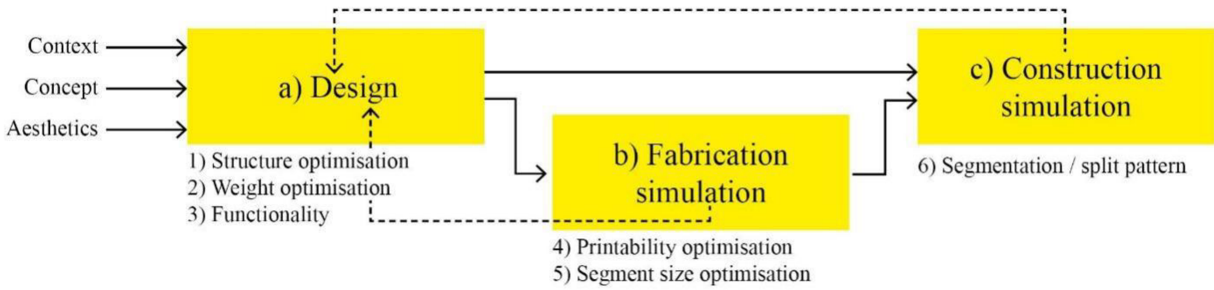


Figure 4. Diagram of the proposed workflow composed of three primary stages: (**a**) design, (**b**) fabrication simulation, and (**c**) construction simulation. Feedback from stages (**b**) and (**c**) is used to iteratively inform and refine the design stage.

2.5. Machine Learning Components

Mirroring the workflow outlined in Section 2.4, several possibilities where ML could create feedback loops were implemented in the current model to test the hypothesis. Grasshopper's Galapagos plugin was used for multi-criteria optimization, functioning as a general-purpose evolutionary solver. Evolutionary optimization was chosen based on a number of considerations.

The primary objectives in this context are search and optimization. Consequently, certain ML algorithms, such as neural networks, which are primarily used for classification and prediction, can be ruled out. Second, genetic algorithms are used in this work because they operate directly on designed solutions and do not depend on pre-existing training data. This has several benefits for our application, even though it increases the computation time for each run. It eliminates the need for training data, which is highly beneficial given the fabrication difficulty of 3DCP. Since immediate feedback is not necessary at the beginning of the design process, slower runtimes are considered an acceptable limitation.

A further challenge relates to the structure of the solution space. The shell geometries explored here do not lend themselves to continuous parameterization, which makes it difficult to define a loss function for guiding the search. In this context, genetic algorithms offer a practical alternative, as they do not rely on explicit gradients or predefined relationships between variables. This makes them suitable for problems involving discrete, idiosyncratic solutions, non-differentiable functions, and high-dimensional parameter sets. Such characteristics are common in design workflows, where not all variables are clearly defined from the outset.

To begin with, the optimization of the overall shell design is automated in GA Stage 1 (see **Figure 5**) using finite element analysis (FEA) in Karamba3D. Design considerations such as deflection values, material usage, user needs, and boundary requirements are analysed here and synthesized into fitness scores. In future iterations, a more rigorous structural analysis could be implemented to improve the accuracy of the fitness score by also accounting for stress and strain. Second, the design shape is divided into segments that are feasible for 3DCP. The segments are evaluated with regard to the printing and assembly process, which largely depends on anticipating material behaviour during deposition to prevent collapse during printing.

Additionally, the bounding box dimensions are checked to make sure that segments fit into the build volume of the printer and satisfy logistical constraints during assembly and construction.

These parameters generate a large number of possible permutations, which are difficult to evaluate with a conventional manual design approach.

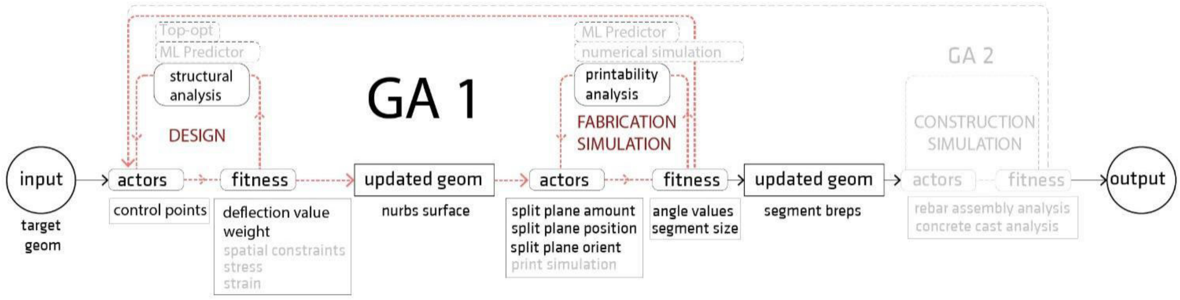


Figure 5. An image showing the optimisation setup for the first cycle. Greyed-out modules are not yet implemented.

However, using ML, the generation and evaluation of permutations can be automated and distilled into numerical values within the data model, thereby incorporating fabrication data into the design process. As a result, iterative design exploration extends into later stages, enabling more informed decisions early in the process (see **Figure 5**). GA Stage 1 represents the first optimization cycle, combining structural evaluation and printability analysis within a single workflow, and constitutes the primary advancement over the authors' previous research.

Experimental Setup and Parameters

To evaluate the effectiveness of the genetic algorithm (GA) components, the following experimental setup and parameters were used in the optimization process.

(1) Genetic Algorithm (GA) Parameters

The optimization was performed using the Galapagos evolutionary solver with the following parameters:

- Population: 20 individuals per generation;
- Initial Boost: Factor of 2, doubling the population size in the first generation to promote broader exploration of the solution space;
- Max. Stagnant: 50 generations, after which the solver terminates if no improvement in fitness is observed;
- Maintain: 5%, preserving a small proportion of the best-performing individuals between generations;
- Inbreeding: 75%, controlling the degree of similarity between selected parent solutions and influencing selection pressure.

Fitness functions:

- Minimize deflection;
- Ensure printability (e.g., avoid collapse during printing and consider maximum segment size).

Constraints:

- Maximum deflection: ≤ L/300 (where L is the span length). For a 2 m cantilever, this was 6 mm;
- Maximum printable inclination: 40° (based on experimental validation);
- Build volume: Segments must fit within the printer's build volume.

(2) Structural Analysis Parameters

- FEA Software: Karamba3D was used for structural analysis;
- Analysis Type: Linear static analysis was performed to evaluate deflection;
- Material Properties: A C25/30 concrete was used;
- Boundary Conditions: Fixed supports for T (translation) x, y, z as well as for R (rotation) x, y, z at the base of the shell structure.

(3) Fabrication and Printability Parameters

- Heuristic Print Angle: A heuristic print angle of 40° was used as the initial threshold for printability, based on expert input and experimental validation;
- Experimental Validation: Several test objects were printed to validate the printability threshold and refine the model's predictions (see the Results section).

(4) Computational Efficiency

- Computation Time: 10–20 min per run;
- Hardware: Standard desktop computer with an Intel i7 processor and 32 GB RAM.

2.6. Evaluation Criteria

2.6.1. Weighted Composite Fitness Function

The current implementation evaluates three primary criteria: (1) **structural performance**, expressed through deflection minimisation; and (2) **printability**, assessed through segment inclination (maximum allowable angle of 40°) and segment size relative to the robot's build volume. Given the limitations of Grasshopper's Galapagos, the two fitness scores ($F_{structural}$ and $F_{printability}$) were combined using a weighted composite fitness function. For example:

$$F_{overall} = \omega_{structural} \cdot F_{structural} + \omega_{printability} \cdot F_{printability}$$

This approach ensures that the optimization balances structural integrity and fabrication, allowing the designer to fine-tune the output for specific project conditions, aligning with the requirements of 3DCP applications. A composite fitness score is used to evaluate the resulting solution space, providing feedback on the performance of the input parameters. This approach can be generalized to:

$$F_{overall} = \omega_{structural} \cdot F_{structural} + \omega_{printability} \cdot F_{printability} + \Sigma(\omega_i \cdot F_i)$$

Where:

- $\omega_{structural}$ and $\omega_{printability}$ are the weights for the structural and printability modules, respectively;
- $F_{structural}$ and $F_{printability}$ are the fitness scores for the structural and printability modules;
- ω_i is the weight assigned to the i-th extra module;
- F_i is the fitness score of the i-th extra module.

2.6.2. Implementation

In the present implementation, Galapagos is used as a single-objective evolutionary solver, with multiple criteria combined into a weighted composite fitness function. In the first stage, as seen in **Figure 5**, the shell's structural and design performance is examined. For every vertex, the representation mesh's deflection value is computed. To minimize deflection values, the GA adjusts the location of the shell's control points set by the designer, resulting in a modified shape. The structural evaluation is performed in Karamba3D using a simplified model intended for iterative optimization. Deflection is assessed against a conservative threshold of 6 mm, with values above this limit considered unacceptable and highlighted in the visual output; for reference, Eurocode suggests a serviceability limit of approximately L/250, corresponding to ~8 mm for a 2 m cantilever. We used a more conservative L/300 threshold. The base of the shell is constrained within a 3 × 3 m foundation footprint with fixed supports, while the cantilever span is controlled by constraining the top nodes in the x-direction to ensure a 2 m projection. The analysis considers self-weight only, as additional load cases (e.g., wind, snow, reinforcement-informed behaviour) were excluded at this stage to maintain computational efficiency within the generative model. The geometry, initially defined as a subdivision surface in Rhinoceros 3D, is discretised into a triangular mesh with an approximate resolution of 0.4 m. Material properties correspond to a 200 mm thick shell of C25/30 concrete, reflecting the final cast structure, while the 3D printed component is treated as sacrificial formwork.

In the second stage, the shell shape is further examined using a custom Grasshopper definition that splits it into parts using curves that are preset or defined by the user (see **Figure 6c**). The search space is expanded by further modulating the position and rotation of the resultant split planes. An inclination analysis and the generated solutions' bounding box size are used to evaluate them. Segments that show inclination angles that would cause collapse during printing get lower fitness values (see **Figure 6d**). Inclination is employed as a heuristic predictor of printability. Similarly, segments that are larger than the printable size also get a lower fitness score. The graphs in **Figure 7** show the optimization process for a shell that starts with a relatively low weight and printability fitness score but a high deflection and segment size fitness values (see **Figure 7a**). The graph in **Figure 7b** displays the average of all the fitness parameters and how they converge to a lower score over roughly 20 generations of evolutionary optimization.

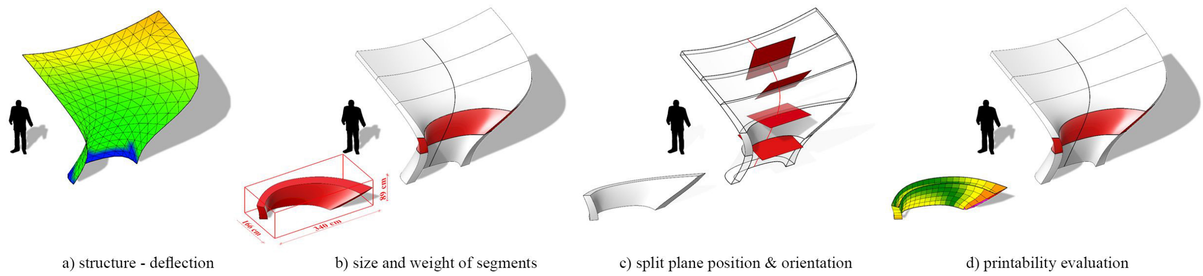


Figure 6. Diagrams illustrating parameters influencing shell segmentation and the criteria used to evaluate individual segments.

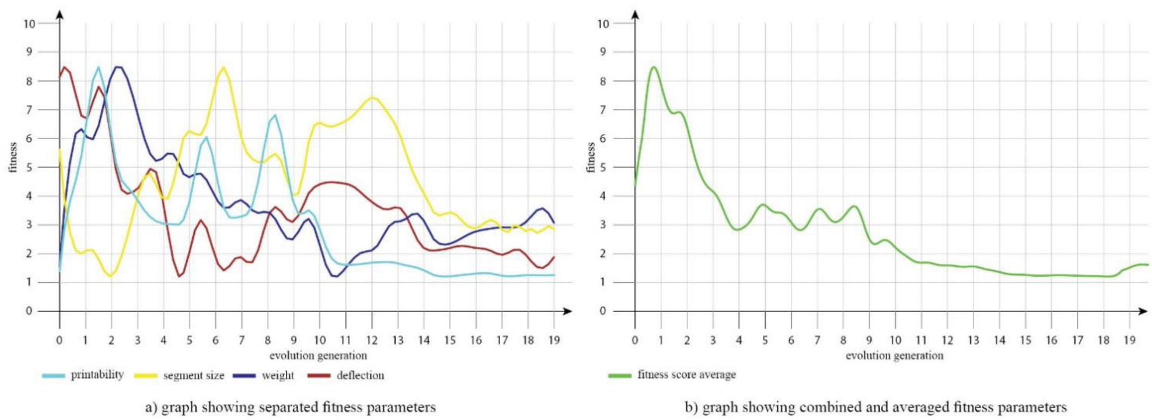


Figure 7. Graphs showing the evolutionary optimization process for a 3DCP shell. The fitness parameters include printability, segment size, weight and structural evaluation (mainly deflection).

Note: Lower values represent better fitness.

3. Results

The design process begins with the input of a rough geometric model, which is evaluated using the framework to generate a fabrication-aware data set (see **Figure 8**). Based on this dataset, the geometry is iteratively adjusted and re-evaluated through repeated optimization runs in conjunction with designer input. Initial tests were carried out on a cantilever shell typology, where optimization could be directed toward different objectives depending on the design intent, including fidelity to the original form, structural performance (see **Figure 9**), or printability (see **Figure 10**).

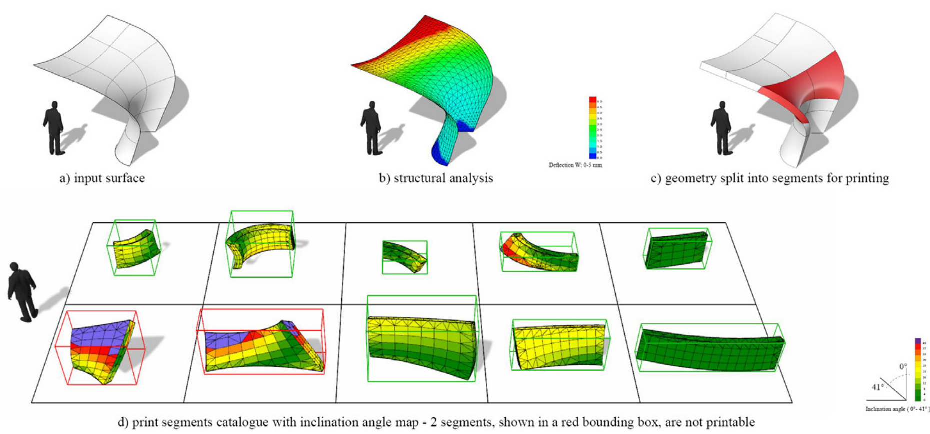


Figure 8. Cantilever shell input geometry for optimization algorithm: (**a**) The input surface; (**b**) Structural analysis that shows excessive deflection values; (**c**) Split pattern using a manual approach; (**d**) Matrix of segments with evaluation of printability, the two pieces coloured red are deemed not printable due to excessive overhangs.

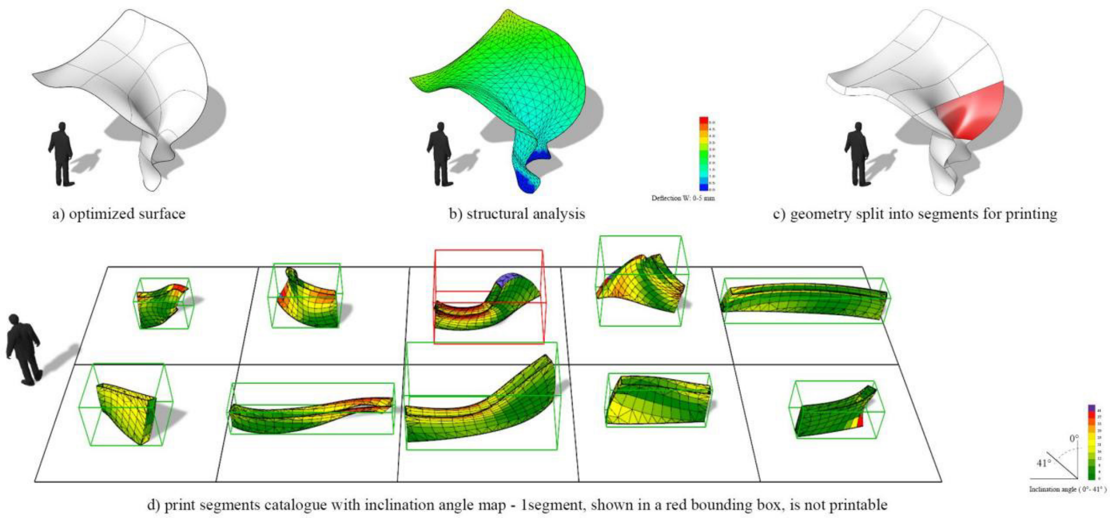


Figure 9. Results of structure and segmentation optimization of a cantilever shell where structural stability (minimal deflection under self-load) is prioritized. (**a**) The optimized surface; (**b**) Structural analysis that shows acceptable deflection values; (**c**) Split pattern using a GA approach; (**d**) Matrix of segments with evaluation of printability.

Note: The segment highlighted in red is deemed not printable, which means the designer can choose to try fixing that individual piece or adjust the optimization process to favour printability instead of structural performance.

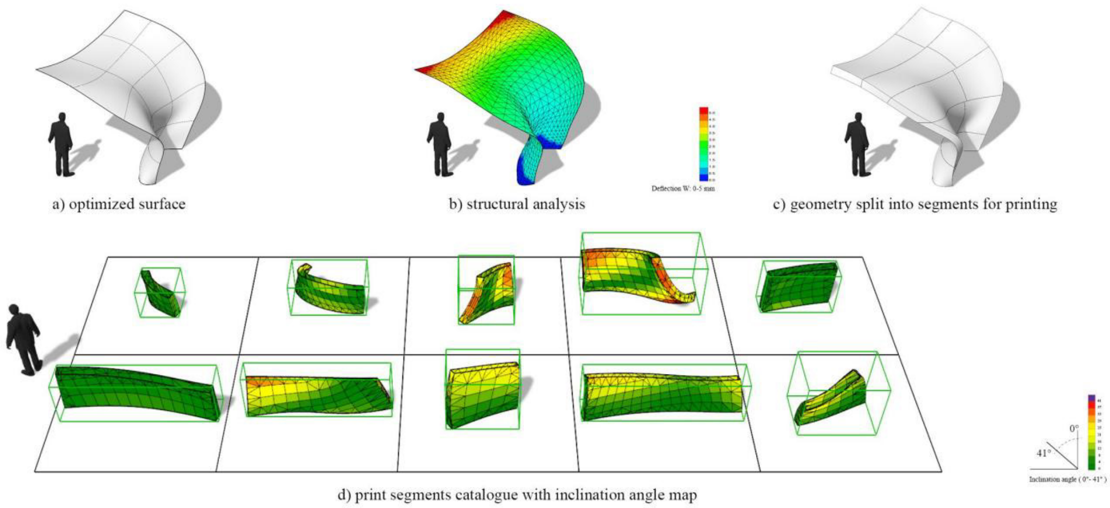


Figure 10. Results of structure and segmentation optimization of a cantilever shell where printability of the split segments is prioritized. (**a**) The optimized surface; (**b**) Structural analysis, which shows improved values compared to **Figure 8;** (**c**) Split pattern using a GA approach; (**d**) Matrix of segments with evaluation of printability, where all segments are deemed printable.

The selection between these outcomes is governed by a weighted multi-criteria evaluation within the optimization framework, where printability and structural performance (e.g., deflection) are assigned adjustable weights. By tuning these weights, the system can prioritise either fully printable solutions or configurations with improved structural behaviour but reduced printability. In the current implementation, printability is incorporated as a penalty term in the fitness function, with non-printable regions contributing negatively to the overall score. As a result, solutions containing such regions are disfavoured during optimization but not strictly excluded, allowing the exploration of trade-offs between competing criteria. For real fabrication scenarios, the framework can be extended by introducing a hard constraint (i.e., zero tolerance for non-printable segments), ensuring that only fully compliant solutions are accepted.

In our tests, each optimization cycle required approximately 10–20 min for the optimization over 20 generations (see **Figure 11**), offering a realistic view of how a designer might engage with the system during early-stage exploration. While this runtime is acceptable for initial prototyping, future implementations could benefit from improved computational efficiency to enhance usability in more time-sensitive design workflows. The framework was first tested on a cantilever shell morphology with a 2 m span.

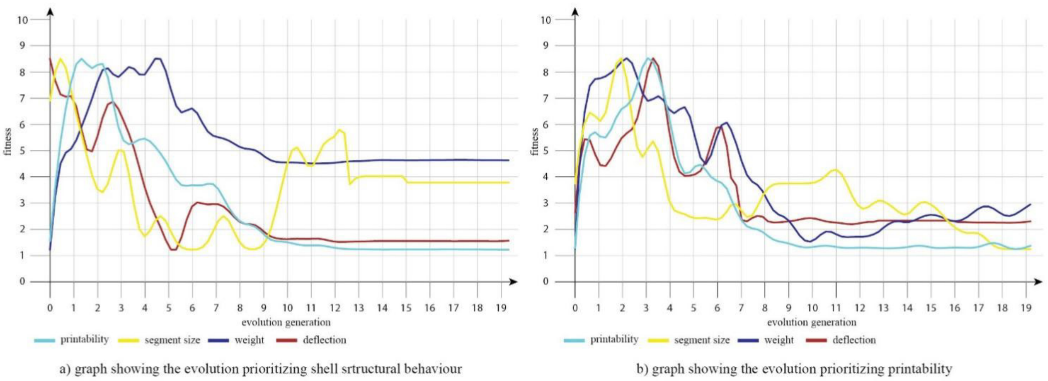


Figure 11. Graphs showing the evolutionary process for the two shells shown in Figures 9 and 10. (**a**) The process that prioritizes structural behaviour corresponding to **Figure 9,** resulting in a larger overall weight of the shell. (**b**) The process that prioritizes printability and segment size, resulting in slightly worse structural performance, corresponding to **Figure 10**.

3.1. Optimization of a Bridge and Wall Shell

Two additional morphologies were tested as proof-of-concept cases representing distinct architectural typologies: a bridge spanning 7 m, and a free-form wall element approximately 2.3 m high (see **Figure 12**). This enabled us to capture a range of structural behaviours and geometric conditions relevant to the proposed framework. Rather than exhaustively sampling the full design space, these cases demonstrate the applicability of the method across differing span conditions, load transfer mechanisms, and orientations. In the current implementation, the slicing and fabrication logic is limited to geometries that can be described as "loftable" or generated through section-based sweeps along a guiding curve, which informed the selection of examples. The proposed methodology is not inherently limited to the tested spans; however, increasing span lengths or introducing higher curvature gradients would likely require refined structural modelling, denser discretisation, and more advanced reinforcement strategies to maintain performance. These aspects were intentionally simplified in the current study and are identified as directions for future work, where the framework could be extended and validated for more demanding structural and geometric conditions.

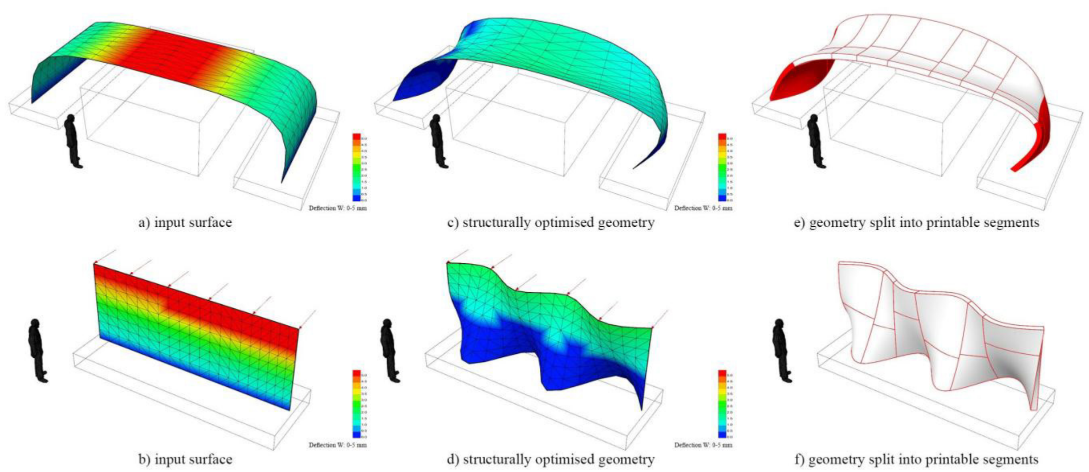


Figure 12. Optimization of a bridge and wall shell typology. (**a**, **b**) The input geometry; (**c**, **d**) Structural optimization which shows acceptable deflection values; (**e**, **f**) Split patterns using a GA approach. In the case of the bridge, 3 pieces were outlined as not printable and are shown in red.

3.2. Physical Validation

The process was validated by printing one of the Cantilever Shell components at a 1:1 scale. The segment necessitated the use of non-planar printing, in which the orientation of the layers changes in accordance with the segment's local curvature rather than along the world Z-axis. The tests displayed in **Figure 13** illustrate this. The framework using GA optimization was successful in generating printed parts that exhibited predictable behaviour.

A set of full-scale 3D printing experiments was carried out to evaluate the maximum feasible inclination angle for robotic extrusion. The tests were performed using a Fanuc M-710iC/50 R-30iB robot equipped with a custom two-component concrete extruder. To assess printability, three prototype geometries were fabricated at inclinations of 30°, 40°, and 50° relative to the vertical axis. The results showed that the 30° and 40° configurations were successfully printed, whereas the 50° case failed due to material sagging, with collapse occurring on the rear side of the shell (see **Figure 14c**). Based on these observations, a 40° inclination was adopted as the operational threshold within the genetic algorithm.

Figure 13. A 3D concrete printed segment from the Cantilever shell, shown in **Figure 10**, which validates the capacity of the optimization algorithm to segment a shell into printable pieces.

Figure 14. Images of 3D printed tests at different inclination angles. Prototypes at (**a**) 30° and (**b**) 40° were printed successfully, while (**c**) the 50° prototype failed due to material sagging at the rear.

The parameters required to rigorously validate the proposed printability threshold, such as replication count, material variability, environmental conditions, and measurement protocols, were not systematically explored within the scope of this study and would require further testing. The 40° value was therefore adopted as a practical working assumption, informed by prior printing experience and corroborated through discussions with industry practitioners such as Zevnik Lab and Incremental 3D, both of whom report similar inclination limits under comparable conditions. The presented angle tests (30°, 40°, 50°) were intended as preliminary calibration rather than statistical validation, with the observed failure at 50° indicating an approximate upper bound for the current setup.

4. Discussion

This study introduces a modular, fabrication-aware design workflow for 3DCP, focused on free-form reinforced concrete shell structures. The following discussion reflects on the current system's limitations and potential for refinement, particularly through the integration of simulation, ML, and optimization techniques. It also considers the broader significance of this approach within the context of digitally integrated, performance-driven design in architecture.

The current version, which validates a portion of the entire toolchain, might be viewed as a minimal viable product. The framework is designed in a way so that the various simulation and optimization data can be modularized and upgraded over time. For instance, as described by Bhooshan [40], numerical simulation can be used in place of the existing inclination analysis. As demonstrated in the KnitCone Project [41], the simulation can then be swapped out for a ML predictor that has been trained using the simulation data, increasing accuracy while preserving computation speed that is near real-time. Likewise, a lightweight prediction model might be used in place of the structural analysis. Further implementation of the digital chain for reinforced 3DCP shells will be investigated in the future. The manufactured segments will be empirically tested, and full-scale prototypes will be assembled to verify the results. A robust architectural framework for production environments is the goal.

Genetic optimization serves as an effective black-box strategy for navigating complex design spaces where analytical gradients are unavailable or difficult to compute. However, its inherent reliance on stochastic processes can introduce excessive randomness in the outcomes, making it challenging to consistently control or predict specific design results. In future work, it may be advantageous to explore more deterministic or hybrid optimization algorithms that offer greater precision and stability, particularly when tighter control over design outputs is required.

A further direction is the development of real-time feedback systems leveraging vision-based methods, allowing the design model to adapt to unpredictable on-site conditions.

From a broader perspective, this study contributes to ongoing discussions surrounding Industry 4.0 approaches in architecture. It demonstrates how existing but fragmented research can be brought together into a fabrication-aware workflow for the design and robotic fabrication of complex structures. In particular, the application of ML techniques to design applications is still in its infancy and lacks real-world case studies, while being hailed as a crucial element in creating intelligent, integrated processes. Design models can respond to performance considerations and go beyond pre-defined data when predictive and generative aspects are combined in a feedback loop.

5. Conclusions

This paper presented a fabrication-aware design framework for reinforced 3D concrete printed shell structures, integrating design, fabrication, and construction considerations within a unified computational workflow. The primary contribution lies in coupling structural evaluation and printability constraints, specifically deflection, segment inclination, and build volume, into a single genetic optimization process, enabling simultaneous assessment of performance and fabrication during early-stage design.

The results demonstrate that such integration allows designers to explore fabrication-informed geometries while navigating trade-offs between structural efficiency and printability. By embedding these constraints directly into the design model, the approach extends the scope of computational design toward a more comprehensive engagement with the digital chain. While the current implementation operates under simplified assumptions, including heuristic printability thresholds and reduced structural modelling, the framework is conceived as modular and extensible. Future work will focus on incorporating more detailed material behaviour, reinforcement strategies, and real-time feedback systems, with the aim of advancing toward fully integrated, production-ready workflows for 3DCP.

Author Contributions

J.L. and T.C. share first authorship. Conceptualization: J.L. and T.C.; Methodology: J.L. and T.C.; Software development and computational implementation (Grasshopper framework and genetic algorithm setup): T.C.; Structural analysis and evaluation: J.L.; Physical prototyping and 3D printing validation: J.L.; Formal analysis: J.L. and T.C.; Investigation: J.L. and T.C.; Visualization: J.L. and T.C.; Writing—original draft preparation: J.L. and T.C.; Writing—review and editing: J.L. and T.C. Both authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data supporting the findings of this study, including the computational design model, Grasshopper scripts, genetic algorithm setup, and structural analysis datasets, are available from the corresponding author upon reasonable request. Due to the experimental and developmental nature of the workflow, certain components of the framework may require specific software environments (Rhino3D/Grasshopper, Karamba3D) for full reproducibility.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the authors used AI-based tools solely for language refinement. No AI tools were used for data analysis, interpretation, or generation of scientific content. All outputs were critically reviewed and edited by the authors. The authors take full responsibility for the integrity and accuracy of the work.

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