Single-instance, multi-target learning of 3D architectural gridshells for material reuse and circular economy

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Abstract
We propose a learning-based method for the assisted design of 3D architectural free-form gridshells which reuse elements from dismantled, old buildings. Given a gridshell design as input, the output is a learned gridshell whose shape has been modified to reuse as many stock elements as possible, while preserving the design intent and optimizing for statics performance. The main idea is to perform multi-target shape optimization as a single-instance machine learning task, featuring differentiable losses that account for both structural and stock constraints. Since our approach enables the reuse of existing elements for new designs, it reduces the need for sourcing new materials and for disposing waste. Therefore, it contributes to switch to a circular economy and alleviate the environmental impact of the construction sector.

Keywords
3D Learning, Multi-agent Learning, Architectural Geometry, Assisted 3D Design, Sustainable Buildings, Environmental Impact, Circular Economy

1. Introduction

The construction sector is responsible for over 35% of the total waste generation in Europe, and for a large fraction of the overall energy consumption and greenhouse gas emissions [1]. Indeed, new constructions require large volumes of material, and demolitions produce large amounts of waste. These figures are expected to rise in the next decades, due to the growing of the population and its demands.

A possible solution to reduce the environmental and societal impact of the construction industry is to recycle or reuse construction materials. Recycling means reprocessing waste to generate new products, while *reusing* means recirculating existing elements and using them for new constructions. In particular, increasing reuse in the construction sector has the potential to save material and energy, as it avoids sourcing new materials, and to reduce waste at the same time.

One of the main barriers that hinder reuse in construction is that the design of structures from stocks of reclaimed elements is totally different from traditional design. Since the designed structure has to conform to the available elements and their characteristics (e.g., length), one has to rethink the whole design process.

In this paper, we propose a method for the assisted design of 3D architectural free-form gridshells from fully-disassembled structures, where the stock of available material includes individual structural elements (beams) of specified length and cross section. 3D gridshell structures are discrete networks of straight bars (the beams) connected by joints at the nodes [2]. Gridshells are ganing momentum in free-form surface design, as they can cover large spaces while keeping the amount of material relatively small. Figure 1 shows three examples of gridshells located in London, Warsaw and Singapore.

Starting from a initial design, we propose a multi-target, learning-based method that aligns the gridshell beams to the stock of available beams, while at the same time improving the statics performance of the whole structure. Differently from existing techniques, which are either based on heuristics for solving assignment problems or on mixed integer optimization, we leverage on recent advances in 3D deep learning for architectural geometry [3], and cast the problem as a single-instance learning task. The input is the original design of a gridshell, and the output is a gridshell whose elements' shape has been modified to reuse as many stock elements as possible, while preserving the design intent and optimizing for statics performance.

The pipeline works in two steps (Figure 2). The first step improves the structural compliance of the gridshell, by means of a neural network featuring a loss that takes stress into account; the second step assigns stock beams to gridshell beams, with the assignment problem modeled using soft constraints included in a differentiable loss.

For the first time, we extend stock-constrained structural optimization to 3D gridshells, which are more complex structures than those addressed by the state of the art, mostly 2D structures made of trusses. Also, for the first time we propose a learning strategy to combine

Ital-IA 2024: 4th National Conference on Artificial Intelligence, organized by CINI, May 29-30, 2024, Naples, Italy
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Figure 1: Examples 3D gridshells: from left to right, the Queen Elizabeth II Great Court at the Britsh Museum in London, Złote Tarasy in Warsaw, Changi Airport Jewel in Singapore.

material reuse and environmental impact minimization with the optimization of structural performance, mandatory to ensure stiffness, equilibrium, and durability of 3D architectural structures.

We describe a real-world case study, in which the size and capacity of the beam stock are defined from an existing building to dismantle in Tuscany, Italy. We demonstrate how our single-instance learning method enables the reuse of a large fraction of the available material for the design of statics-aware 3D freeform gridshells. Our approach can contribute to switch to a circular economy, and to alleviate the environmental impact of architectural buildings.

2. Related work

In response to the pressing environmental and economic demands, reuse strategies are being prioritized in architecture and in the construction industry. The initiatives encompass a variety of structures and constitutive elements (e.g., trusses, beams, and panels), and employ different optimization paradigms to minimize for example material cost and carbon emissions.

In particular, there has been considerable attention to the design of new structures starting from stocks of elements from old structures. Brütting et al. [4] perform layout optimization of bidimensional structures starting from recycled stocks of trusses. The layout optimization starts from a template structure and selects truss elements to determine the final topology. Elements from the batch are matched to their position in the assembled structure through mixed-integer optimization. Similarly, Van Marcke et al. [5] explore truss reuse by organizing recycled trusses to form planar frameworks, rather than undertaking layout optimization. Expanding beyond the flat scenario, Brütting et al. [6] provide an algorithmic solution to build 3D frames made of hexahedral cells of recycled trusses.

Unlike the aforementioned studies, which optimize truss structures, our work targets gridshells consisting of triangular beam nets approximating freeform surfaces. While beams experience axial forces and moments, transverse shear and bending, trusses are only subject to axial forces. Moreover, most existing layout optimization methods seek an optimal shape configuration for the recycled stock from scratch. Instead, we improve an existing design shape provided as input.

Finally, while the works mentioned above assign the available elements through constrained optimization, we define soft constraints to frame the reuse problem into a single-instance machine learning task. We leverage on [3], in which a geometric deep learning model performs statics-driven optimization while preserving the original shape design of the input grid shell. In the present paper, we incorporate a vertex correction optimizer to ensure compatibility of elements with the available stock, and blend the learning model and the optimizer in a multi-target architecture. In this way, we simultaneously achieve two objectives: minimizing static compliance by reducing the strain energy, and enabling the reuse of elements through a soft-constrained beam matching procedure. In contrast, in existing works the only target is the reuse of elements, while the static performance is considered only to guarantee the structure feasibility by including hard constraints [4].

3. Methods and results

Our aim is to reuse building elements from old structures to build new 3D grdshells, which conform to a given design and are also optimal in terms of statics performance. Given a 3D gridshell as input with the sought shape, we learn a new, improved gridshell, in which the shape of the single elements is optimized to conform to the stock of available ones, while the overall shape is optimized to improve statics performance.

The idea is to perform multi-target shape optimization on gridshells as a single-instance machine learning task. Classical multi-target methods usually incorporate all optimization targets into a single loss function, expressed

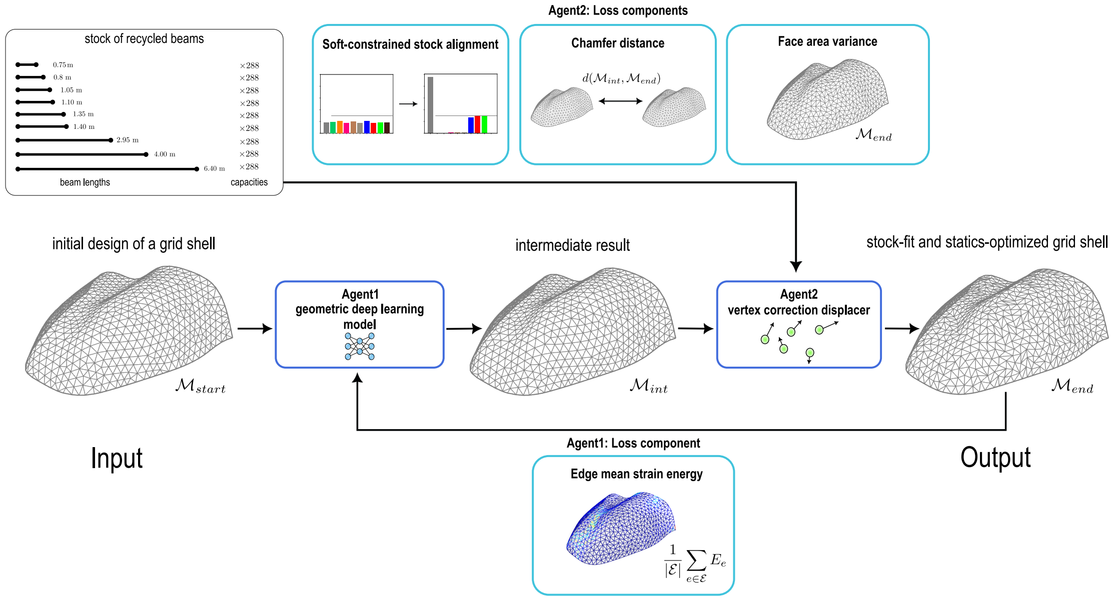


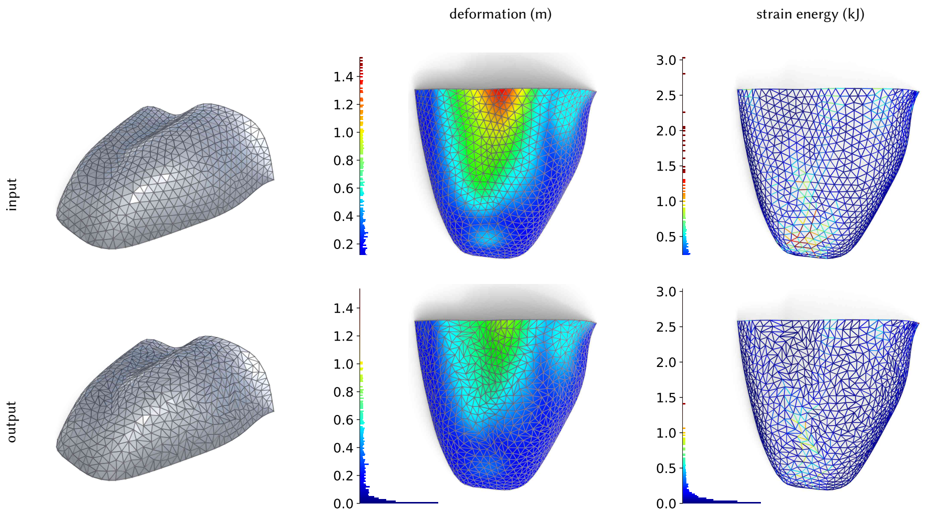
Figure 2: The pipeline of our method. Our single-instance, multi-target learning model involves two agents (blue boxes): a geometric deep learning model (Agent1) and a vertex correction displacer (Agent2). The learning model consumes an input mesh and produces an intermediate shape to be fed to the vertex displacer and to minimize mean strain energy. The displacer optimizes for the assignment of stock beams to gridshell elements, and preserves fairness with respect to the intermediate result (through area variance and Chamfer distance). The agents are driven by different losses (light blue boxes) and collaborate to achieve both material reuse and good statics performance.

as a weighted sum of components. However, assigning weights to components can be tricky, especially if different scales are involved, and if the targets are conflicting. Therefore, instead of using a heterogeneous loss, we involve the interaction of two agents: a geometric deep learning model (Agent1 in Figure 2) and a vertex displacer (Agent2 in Figure 2). Each agent is driven by distinct optimization targets (statics for Agent1, reuse of elements for Agent2) and corresponding loss functions.

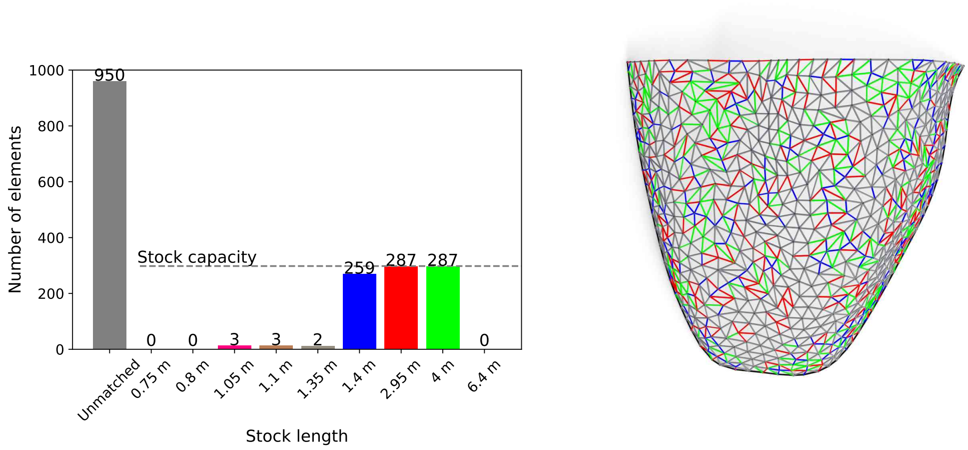
Given a triangle mesh representing the initial grid shell structure, the learning model (Agent1) operates on the mesh geometry to optimize the mean strain energy of the structure. then, the optimizer (Agent2) corrects the new, learned vertex positions to align the beam lengths with the ones available in the stock. We take into account both beam lengths and stock capacity. Indeed, the corrections ensure that the number of beams matched to a particular length does not exceed their capacity in the stock.

Our process is framed as a single-instance learning task, where both agents iteratively learn from the input gridshell structure. Iterations consist of interleaved steps of the two agents. Each agent has its own loss (light blue boxes in Figure 2), and collaboration between the agents is achieved through mutual agreement: the learning model (Agent1) adjusts its weights to enhance the strain energy of the shape corrected by Agent2; in turn, Agent2 displaces vertices to ensure the alignment with the recycled stock, taking care not to increase the Chamfer distance from the shape produced by Agent1. This ensures smooth convergence and, as a byproduct, the final, optimized design is also consistent with the input shape in terms of geometric features.

To test our technique, we identified a disposing industrial building located in Pisa, Tuscany, whose roof bays are made of truss-like structural units adequate to be reused as beams for a new gridshell. We examined the original project of the donor building and extracted a heterogeneous stock of units whose lengths span from 0.75 to over 6 meters, with 288 elements available for each of the 9 available lengths. Figure 3 shows an example 3D gridshell that could be constructed using the stock of elements from the disposed building. Figure 3(a, left) shows the input design and the optimized output; (a, middle) the color-coded expected structure deformation in meters; and (a, right) the edge strain energy of the structure under service load; red (resp. blue) means higher (resp. lower) values. It can be seen that the expected deformation of the optimized structure is significantly lower, implying better statics performance for the building; analogously, the strain energy on edges is significantly reduced.



(a) structural target



(b) reuse target

Figure 3: Results of our method on a sample freeform shape. (a) Left: the shape provided as input and the multi-target optimized output. Middle: the deformation of the structural nodes under the action of Service Load. Right: the strain energy for each beam. (b) Left: a bar diagram showing the assignment of beams to the input stock. Right: the beam assignment shown through colored edges on the output shape.

Figure 3(b, left) reports a bar chart with the assignment of stock elements, and (b, right) the output gridshell with the location of reused elements (color-coded according to their lengths). A large fraction of stock elements has been reused, apart from the shortest and longest ones (note that longer elements can be cut and then reused, yet cutting comes with a cost). Also, the shape and style features of the original design have been fully preserved.

It is important to underline that our method enables the reuse of stock of elements for *any* input gridshell design: Figure 3 only shows an example, whereas many other designs could have been produced. This is different from what is enabled by existing techniques, which only look for compatible designs, given the available stock. Therefore, our technique leaves to the architect complete design freedom, while taking care of structural performance and environmental impact.

4. Conclusions

The reuse of structural elements for the design and fabrication of new architectural structures has the potential to greatly reduce the environmental impact of the construction industry. Increasing reuse comes with the challenge of formulating new design paradigms, which take into account the characteristics of the available material without affecting design freedom. At the same time, such design paradigms should take into account statics performance. In this paper, we define a learning-based technique that addresses all three points above for the design of 3D gridshells, as demonstrated by a real-world case study on the reuse of elements from an existing building.

Acknowledgments

This work was supported by the NextGenerationEU programme under the funding schemes PNRR-PE-AI scheme (M4C2, investment 1.3, line on AI) FAIR "Future Artificial Intelligence Research", grant id PE00000013.

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