Learning From the Sea: Scaling the Biomimetic Performance of Seashell Structures for Carbon Reduction in Gridshell Buildings

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Abstract

Our project explores the use of Machine Learning (ML) to generate structural and carbon surrogates from images of seashells, reducing carbon in the construction of gridshell buildings.

Seashells exhibit evolved geometries that are optimised over hundreds of millions of years for load distribution, structural resilience and material efficiency. By leveraging the natural curvature, spiral growth and aperture scaling of seashells, our project extracts quantifiable performance patterns from real shell specimens. Machine Learning (ML) enables us to reverse-engineer those forms from photographs to reconstruct them parametrically in Grasshopper (Rhino3D) software. The resulting digital twin is subjected to structural and carbon evaluation using surrogate models, allowing us to test how morphological changes - such as compression, elongation, or scaling affect the shell's efficiency as a building. This approach transforms natural structures into generative, low-carbon design tools.

Objectives

To create ML-augmented workflow allowing designers to:

1) Extract and classify geometric data from any image of a seashell to create a digital twin in 3D software.

2) Predict structural and carbon performance of altered forms using ML-based surrogate models.

3) Use these models to provide accurate real-time feedback on the structural efficiency and carbon cost of early design stage iterations for form and material optioneering.

Impacts

a) Contributed to the de-carbonisation of the AEC sector by enabling early-stage feedback on form–material–carbon relationships, supporting the UK's net-zero built environment target for 2030.

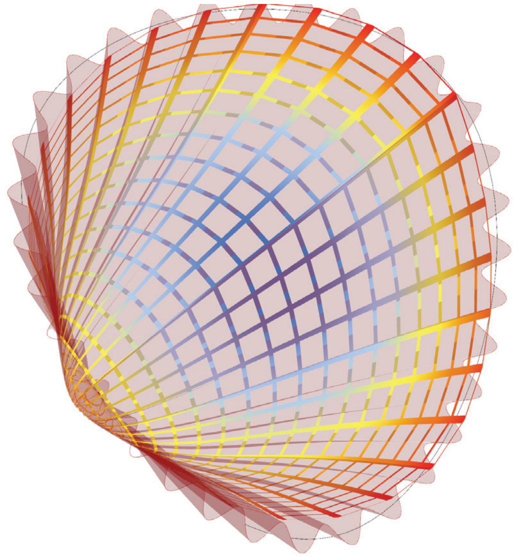
b) Reduced computational cost and time of structural analysis through the use of image-based surrogate models, making performance modelling accessible during early concept design.

c) Supported green skills development in Morecambe through public engagement, school outreach, and AI workshops delivered alongside Grimshaw Architects.

d) Demonstrated a replicable model for bioinspired design workflows using ML, influencing industry partners and public understanding of AI's potential positive role in sustainable architecture.

Learning from the Structural Efficiency of Seashells

Seashell growth follows principles of logarithmic scaling, spiral symmetry, and efficient curvature traits that confer significant strength-to-weight ratios. Natural forms such as conches, bivalves, and gastropods have long inspired architects and engineers exploring biomimetic design including Heinz Isler's shell studies and Frei Otto's form-finding experiments. Our work is inspired by the design and construction of the Eden Morecambe Project, built near to our Lancaster University, itself inspired by the shape of seashells. The building takes the form of multiple mollusc seashell forms that encompass a series of spaces that explore the ecologies and tidal cycles of the Irish Sea.



Eden Project Morecambe

In collaboration with Grimshaw, the architects of Eden Project Morecambe, we embedded AI workflows within real project stages to evaluate how image-derived shell geometries could inform the carbon efficiencies of the seashell inspired gridshell forms of the building.

Fig 1. Eden Morecambe 3D render (Grimshaw Architects)

Results

CARBON & STRUCTURAL EFFICENCIES

Form variants inspired by real shell types achieved up to **38% reductions in embodied carbon** compared with final stage Finite Element Analysis. Team testing enabled real-time carbon optioneering with architects and engineers, with results suggesting that early-stage feedback can materially affect design direction whilst significantly reducing carbon expenditure at early design ideation.

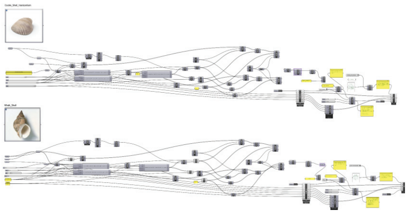


Fig 3. Rhino3D Grasshopper Defintions of Cockle and Whelk Shells

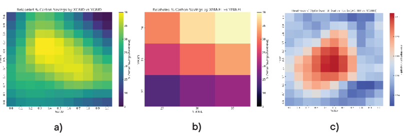


Fig 4. a) % carbon saving in kg CO2 for different forms b) for different structural grids and c) beam utilisation ratios for different forms.

Methods & Techniques

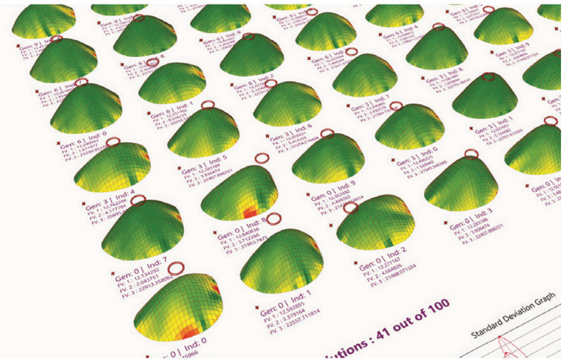


Fig 5. Creating a synthetic dataset of FEA performance data (inc. total mass and utilisation ratios of structure) across a solution space comprising varied form and grid spacing.

A convolutional neural network was trained on 1,090 synthetic shell variants for each shell type using real photographs and parametric data to learn image-to-parameter regression. Shell types were classified and reconstructed in Grasshopper via a live API. A second model predicted scalar performance outputs and RGB image maps for structural stress and thickness. Surrogates were validated against Karamba3D FEA simulations. Materials were varied parametrically (concrete, steel, timber) to measure embodied carbon. Forms were varied over structural grid and UV axes. This reduced simulation time by over 90%, whilst enabling real-time exploration of form and material changes.

Fig 6. Gradio site showing original shell images (left) with matched closest ML-classified and parsed shell geometries (right) in Grasshopper3D