Graduation Plan

Master of Science Architecture, Urbanism & Building Sciences

Graduation Plan: All tracks

Submit your Graduation Plan to the Board of Examiners (Examencommissie-BK@tudelft.nl), Mentors and Delegate of the Board of Examiners one week before P2 at the latest.

The graduation plan consists of at least the following data/segments:

Personal information	
Name	Namrata Baruah
Student number	5326664

Studio		
Name / Theme	Building Technology Graduation Studio / Computational Design	
Main mentor	Michela Turin	Design Informatics
Second mentor	Charalampos Andriotis	Structural Design
External Supervisors	Dr. Alberto Pugnale and Gabriele Mirra	University of Melbourne
Argumentation of choice of the studio	-	

Graduation project	
Title of the graduation project	Integrated bio-inspired Design by AI: Using cell structure patterns to train an AI model to explore topology optimization design ideas.
Goal	
Location:	-
The posed problem,	Computational design has shown high potential in numeric performance-driven approaches. However, designers do not exclusively use numeric performance to develop design ideas. The development of a design idea depends also on the designer's knowledge and experience, including reasoning from inspirations. Such an approach tends to limit the search for optimal solutions and converge on a design solution rather quickly. AI can help open up ideas and expand the palette of architecture. There have been successful case studies of training an AI model and generating new data. Precedents have shown how inspirations from nature can suggest valid design directions – beyond the mere formal

	similarity toward functional principles. The thesis investigates this direction. In particular, this thesis explores the ability of AI to extract patterns from different cell structures occurring in nature, which can be explored further for generating innovative design propositions for topology optimization.
research questions and	How can AI **extract** useful information from a dataset of cellular solid structure patterns and **reuse** it to generate new patterns for structural design? Sub question: How can the AI generated patterns be used to explore topology optimization design ideas?
design assignment in which this result.	-

The main design task is constructing a dataset from samples of natural patterns of (organic and inorganic) cell structures and training an AI model. The focus will be on artificially modelling the patterns of the cellular solids with a grasshopper script. All the 3D models will then be converted to a 2D binary image; which represents perforations and connections. This should be done while ensuring that: i). There are several samples similar to each other. ii). Some features are recurring in all samples. Once the dataset is complete, it can be used for the AI model training. The result of the trained AI model will be the generation of new perforation patterns, which can help increase the diversity of design ideas. The generated patterns can be further applied to an arbitrary shell structure and used to subtract the material to explore different solutions to topology optimization problems. The objective is to compare the structural performance (using FEM or if feasible, using multi objective optimization) of the generated patterns and verify that the AI-generated designs spaces result in a greater variety of examples while ensuring a still good structural performance. The comparative aspects are focused more than the 'allowability' of the results.

Process

Method description

The research has 5-stages according to different assessments described below:

Stage 1: Build background knowledge

In the first stage, the emphasis is on learning the concepts of Python, AI, Deep Learning, TensorFlow and Keras, Autoencoders, Variational Auto Encoders, in that order, and other necessary topics. The primary source of learning is online videos and tutorials. This stage is necessary for learning the skills, techniques, and technical know-how for later training an AI model.

Stage 2: Analysis of Precedents and Previous Researches
In the second stage, existing literature on AI in design was studied, focusing on structural optimization. Dr. Alberto and Ph.D. candidate Gabriele Mirra's paper on 'Comparison between human-defined and AI-generated design spaces for the optimization of shell structures' influenced filtering the focus of the literature search. With their help, an approach to build on their existing research was explored. There is literature available on AI learning from human-defined design space, but there is a need of exploring nature-defined design spaces eg. natural patterns, and forms. The properties of cellular solids depend directly on the shape and structure of the cells, exploring the shape and topology of the cell walls might prove to be interesting for application in topological optimization. Thus, for this thesis, natural cell structures were selected as the study for creating the dataset for the AI model to train on.

Stage 3: Creating Dataset and Benchmark Testing
In the third stage, the domain of natural cell structures is explored for use as datasets. The selection of the data and its representation play an important role in the performance of the AI model. The task would be to explore the geometry and patterns and decide on the representation of the data for making the dataset and choosing the design variables to construct the design space. Thus, to have better control over the data, the dataset will be artificially created by modeling the patterns of the cellular solids with a grasshopper script. Testing of the AI model will happen simultaneously. The model will be written in Python, using TensorFlow and Keras library and Convolutional Neural Networks. It will be tested with a benchmark pre-existing dataset to assess its performance. This step is important to ensure that the model works correctly before introducing the new dataset. The desired outcome of this stage will be to have a completed dataset and a working AI model to train.

Stage 4: Training and Comparison
In this stage, the model will be trained with the new dataset created in Stage 3. During training, the VAE (AI model) will extract implicit design variables from the dataset and generate the design space. As the design space is defined by AI-selected variables, it can make the outcome less predictable and more diverse. The AI-generated patterns, after training, will be used as a UV map for an arbitrary shell for topology optimization. The objective is to compare the structural performance of the generated patterns and verify that the AI-generated designs spaces result in a greater variety of examples while ensuring a still good structural performance. The comparative aspects are focused more than the 'allowability' of the results.

Stage 5: Results and Conclusion
The last stage will focus on documenting the results and concluding the findings. The final report with the reflection and conclusion will be completed.

Literature and general practical preference

[The literature (theories or research data) and general practical experience/precedent you intend to consult.]

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- Anders Boesen Lindbo Larsen, Søren Kaae Sønderby, Hugo Larochelle, and Ole Winther. 2016. Autoencoding beyond pixels using a learned similarity metric. In Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48 (ICML'16). JMLR.org, 1558–1566.
- Aristid Lindenmayer, Mathematical models for cellular interactions in development I. Filaments with one-sided inputs, Journal of Theoretical Biology, Volume 18, Issue 3, 1968, Pages 280-299, ISSN 0022-5193, https://doi.org/10.1016/0022-5193(68)90079-9.
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- Inês P. Rosinha, Krist V. Gernaey, John M. Woodley, Ulrich Krühne. Topology optimization for biocatalytic microreactor configurations. Editor(s): Krist V. Gernaey, Jakob K. Huusom, Rafiqul Gani, Computer Aided Chemical Engineering, Elsevier, Volume 37, 2015, Pages 1463-1468, ISSN 1570-7946, ISBN 9780444634290, https://doi.org/10.1016/B978-0-444-63577-8.50089-9.
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- M.P. Bendsøe, O. Sigmund. Topology optimization: theory, methods and applications. (2nd ed.), Springer, New York (2003).
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- Pearce (1980), Structure in Nature is a Strategy for Design, The MIT Press; Reprint edition.
- Renaud Danhaive, Caitlin T. Mueller, Design subspace learning: Structural design space exploration using performance-conditioned generative modeling, Automation in Construction, Volume 127, 2021, 103664, ISSN 0926-5805, https://doi.org/10.1016/j.autcon.2021.103664.
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Reflection

What is the relation between your graduation (project) topic, the studio topic (if applicable), your master track (A,U,BT,LA,MBE), and your master programme (MSc AUBS)?

The Building Technology Track emphasizes research, technological design and innovation, and working with the newest technology. The relevance of this project with my track lies in the use of new techniques and materials. In the field of structural optimization, the solutions depend on the representation of the design space. Expanding the design space can lead to more freedom in the range of possible solutions. There has been extensive research carried out in that aspect, focused mainly on two approaches: ' Super-structure' and 'Super-structure free.' (Boonstra,2018) (Voll et al, 2012). But for both these approaches, the bound of the design space depend on the experience and experience of the designer. The new AI-based approach can help increase the range of solutions from the design space as the VAE extracts implicit design variables from the dataset (Gabriele Mirra. et al, 2021). The VAE-generated design space is defined by AI-selected variables, which can make the solutions less predictable and more diverse. Thus, providing a more qualitative exploration of design ideas.

Nature has evolved complex and apt topologies to solve all sorts of problems. The investigation of such a framework can help provide important physical insight as well as valid design directions. So, there is a clear need to explore such complex structures in nature. The existing topology optimization methods rest on sound mathematical foundations. A computational method, however, can only compute a finite amount of data while satisfying a set of constraints. This leads to a single optimal predictable solution. To improve that, current AI models have the potential to extend the scope of the solutions. This thesis aims to bridge that gap and explore such natural cell structures for their topology through an AI-generated design space and test them for their structural performance.

What is the relevance of your graduation work in the larger social, professional and scientific framework?

There is a need for approaches between full design space enumeration and single solution optimization as existing data-driven approaches are reductive. Until recently, the computational tools have mainly been used for analytical purposes in structural design. Now, their role is becoming more versatile and is being used in the generation of design concepts too. The designers must have the correct tools to aid in their design process. The AI-generated design space can provide a larger variety of solutions which may lead to new possibilities. Hence, a more qualitative exploration of ideas.

During the Conceptual design phase of a project, major decisions regarding geometry, structure, massing are made. These decisions account for 75% of the final product costs (Hsu, 2000). To make efficient, safe, and cost-effective structures, it has become imperative that the structural design be integrated with the conceptual design phase. There is a need for exploration of design solutions in structural design. An AI-generated design space can help to explore more design ideas before converging on a solution. It adds to the designer’s creativity in introducing a larger set of options to pick and choose from. As Designers are generating more data than ever before, AI can offer new ways to amplify human intellect and creativity.

Timeline
The timeline is added as a separate appendix for clearer view

Timeline

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