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	Amy Sterrenberg
Student number	4593057

Studio		
Name / Theme	Deep Generative Design: Beyond Human- and Computer-aided Design (BT track; Sustainable Structures Theme)	
Main mentor	Dr. Charalampos Andriotis	Sustainable Structures (SD)
Second mentor	Dr. Michela Turrin	Computational Design (DI)
Argumentation of choice of the studio	Since beginning my studies at TU Delft, one of my main interests has been computational and parametric architectural design and the opportunities that these technologies bring to the field of architecture. I employed these techniques and increased my understanding of these subjects during my bachelor and master programmes, both within and beyond the provided courses. I was introduced to programming and its uses in various domains during the master programme. I developed a keen interest in this area while studying generative design as a method for design optimization during the EXTREME course. Python was introduced to me in the CORE course, along with its use in several facets of architectural design. I feel that my graduation project will deepen my understanding of computational design and enable me to investigate the potential for incorporating AI into this process, which I believe will result in promising, novel approaches to developing design solutions.	

Graduation project	
Title of the graduation project	Deep Generative Design for Optimized Spatial Truss Structures with Stock Constraints
Goal	
Location:	N/A (Simulation based design case study)
The posed problem,	The building sector is a major contributor to environmental problems, including energy consumption, CO2 emissions and waste production

(GlobalABC, 2020, Jin et al., 2019, Eurostat, 2022). Closing these material loops, as done in a circular economy, will reduce the demand for virgin materials, reduce waste and lower emissions and energy consumption caused by the mining and manufacturing of these resources. Steel production specifically plays a significant role in these problems (World Steel Association, 2021). To reduce the effects of these problems and increase the sector sustainability, remanufacturing and reuse of steel should be considered.

However, reuse strategies are not yet widely applied, as actors in the construction industry perceive barriers, which include time delays in the early stages of the design process. Still, reuse of structural steel elements (like those in truss structures) is seen as favourable by structural engineering, especially when the aforementioned barriers can be lifted (Dunant et al., 2017). However, tools that can aid this process are not yet developed. A deep generative design framework (generative design that integrates artificial intelligence and deep learning) can be developed to optimize for structural performance, material use and similarity to a defined material stock and therefore be a useful tool in early-stage architectural design exploration, especially with regards to circular design & reuse.

References for this section:

- Dunant, C. F., Drewniok, M. P., Sansom, M., Corbey, S., Allwood, J. M., & Cullen, J. M. (2017). Real and perceived barriers to steel reuse across the UK construction value chain. *Resources, Conservation and Recycling*, *126*, 118–131. https://doi.org/10.1016/j.resconrec.2017.07.036
- GlobalABC. (2020). *The 2020 Global Status Report for Buildings and Construction*. United Nations Environmental Programme.
- Jin, R., Yuan, H., & Chen, Q. (2019). Science mapping approach to assisting the review of construction and demolition waste management research published between 2009 and 2018. Resources, Conservation and Recycling, 140, 175-188.
- World Steel Association. (2021). *Climate change and the production of iron and steel*.

research questions and	In this thesis, the following research question will be answered: Can an artificial intelligence (AI) based generative design framework generate new spatial (3D) truss design solutions, with optimized structural performance, minimized material use and that consist of linear elements that closely match elements from a reusable material stock, in reference to the training dataset, and therefore be used as an effective tool for design exploration in early design stages of the materially circular architectural design process? The answer to this question provides insight into the effectiveness of AI as a tool to make successful integration of reused materials in the structural design process more feasible. The chosen simulated case study is that of a spatial truss. The details of this truss structure are defined in the “Method description” section of this Graduation Plan. Additionally, the following sub-questions will be discussed: ▪ What types of AI can be used in generative models? ▪ What form of data, describing spatial truss-like 3D geometry with variable-length linear members, could be used to train the AI generative framework to generate new design solutions with similar properties to this training dataset? ▪ How can a spatial truss-like 3D geometry be computationally evaluated on its structural performance, so that the outcome data can be used to train an AI generative framework? ▪ How can a spatial truss-like 3D geometry be computationally evaluated on its material use, so that the outcome data can be used to train an AI generative framework?

	▪ How can a restrictive, yet suitable stock library be defined for materially circular design of a spatial truss? ▪ How can a spatial truss-like 3D geometry be computationally evaluated on its similarity to a stock library, so that the outcome data can be used to train an AI generative framework? ▪ How can an AI generative framework be trained to generate new spatial truss-like 3D geometry with optimized structural performance, minimal material use and high similarity to the material stock? ▪ Can a surrogate model effectively predict the performance score of datasets describing a set of spatial truss-like 3D geometry, in its encoded and decoded forms? ▪ How can optimized solutions be found within the data generated by the AI generative framework? ▪ How does the proposed AI generative framework compare to conventional shape and topology optimization tools
design assignment in which these result.	Generative Models that integrate Artificial Intelligence can be integrated into the workflow mentioned in the design problem to optimize for structural performance and similarity to a given material stock, which introduces the design assignment, which is to gain insight into the application of AI as a tool in reuse-based design strategies by developing an AI based generative design framework that prescribes innovative designs for spatial truss-like 3D structures consisting of linear elements, based on a circular approach where material reuse is prioritized, with an integrated computational workflow using deep learning models like variational autoencoders. This will result in a designed computational framework and a set of generated designs for a spatial truss, of which the specific configuration is mentioned in the "Method Description" section of this Graduation Plan.

Process

Method description

This study consist of two parts: A literature review & a designing and training the deep learning generative design framework. In these section, both parts will be described.

Firstly, a literature review is done to explore AI models and their use in (structural) design optimization. This study includes the following terms: Artificial Intelligence (AI) and its subsets, Neural Networks (NN) and various types of NNs, Variational Autoencoders (VAE), Loss Function and Gradient Descent. Secondly, research is done on defining the spatial truss structures in a way that makes it suitable for training the neural network. This too done through literature review. The exact topics of this literature review are mentioned in the next section of this graduation plan.

Next, various computational tools that can be used in this process will be researched, evaluated and selected. After this, the computational framework will be designed, trained and optimized. The framework consists of the following four components:

- An input dataset describing a set of spatial (3D) truss structures and their performance
- A stock library, describing a realistic, limited material stock for re-use
- A variational autoencoder neural network (VAE)
- A surrogate model

The following flowchart (figure 1) shows the proposed set-up of the framework. The text below the figure offers further details based on this flowchart.

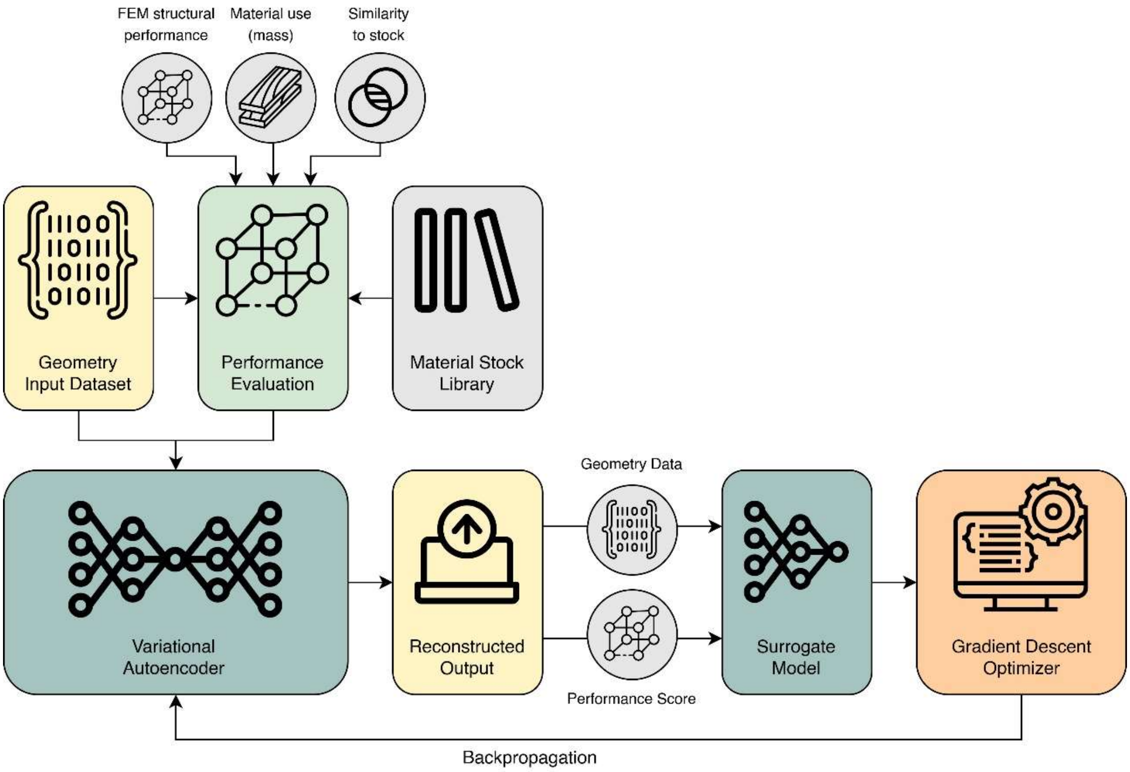

Figure 1. Diagram showing the proposed framework.
Source: Own Work with icons retrieved from (top to bottom, left to right):
Structure icons created by DinosoftLabs - Flaticon, from https://www.flaticon.com/free-icons/structure.

Wood icons created by winniwvinzence - Flaticon, from https://www.flaticon.com/free-icons/wood.
Transparency icons created by Freepik - Flaticon, from https://www.flaticon.com/free-icons/ transparency.
Matrix icons created by Freepik - Flaticon, from https://www.flaticon.com/free-icons/matrix.
Library icons created by inkubators - Flaticon, from https://www.flaticon.com/free-icons/library.
Neural network icons created by Freepik – Flaticon, from https://www.flaticon.com/free-icons/neural-network.
Output icons created by Peter Lakenbrink - Flaticon, from https://www.flaticon.com/free-icons/output.
Code icons created by Eucalyp - Flaticon, from https://www.flaticon.com/free-icons/code.

In the first step an input dataset is created. The input dataset consists of a 3D geometry representing a non-curved triangular spatial truss, consisting of two quadrilateral grids and an in-between structure. The chosen simulated case study is that of a spatial truss supporting a planar slab (roof, floor, etc.). Specifically, a spatial truss configuration as used in the Orange Hall (Oost Serre) and Model Hall (Zuid Serre) of the Architecture and the Built Environment Faculty of TU Delft are used. An exploded view of such a structure is shown in figure 2. This dataset is then evaluated, resulting in a performance score. Due to the limited timeframe and scope of this study, the design objectives used in this score are simplified. This dataset will be evaluated on three factors: (1) Structural performance, (2) material use/mass and (3) the similarity to the stock library. These factors will be translated into one performance score. Structural performance evaluation will be done using the Karamba3D Plugin in Rhinoceros Grasshopper, a parametric Finite Element Method (FEM) program (Karamba3D, n.d.).

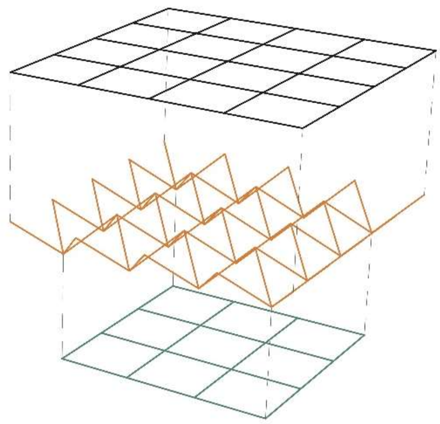

Figure 2. An exploded view of the spatial truss configuration used as a case study. Source: Own Work

To create the geometric definitions for the dataset, information found in the literature review mentioned previously is used. This literature review includes topics on mesh and wire-frame model definitions and transformations. This will result in a set of matrices that describe the geometry. In the following step, this dataset will be used to train a Variational Autoencoder (VAE). This neural network architecture was first introduced by Diederik Kingma and Max Welling in 2014 (Kingma & Welling, 2014). The VAE will generate a new set of data. This data will then be input into a surrogate model that can predict the structural performance of the spatial geometry it represents. Finally, the VAE and the surrogate model's outputs can be used for backpropagation. This process, using a gradient descent optimizer, locates the best solutions. These solutions and the framework can then be evaluated.

Note: This framework could still be slightly altered based on findings in further research and findings in the literature review will further specify these steps.

References for this section:
- Karamba3D. (n.d.). *Welcome to Karamba3D*. https://manual.karamba3d.com/
- Kingma, D. P., & Welling, M. (2014). Auto-encoding variational Bayes. 2nd international conference on learning representations (ICLR2014). *Preprint, submitted December*, *23*, 2013.

Literature and general practical preference

So far, literature review has been done on the following topics:
- Environmental Impacts of the Building and Construction Sector
- Circularity and Reuse of Metals (including Barriers to Reuse in Design)
- Generative Design
- Artificial Intelligence and its subsets (including Neural Networks, Variational Autoencoders and the Training of Neural Networks)
- Training of AI models
- Defining Geometry for AI processing
- Case-studies: AI Guided Generative Design Frameworks

The next steps include researching methods for creating the Training Dataset containing training geometry and performance indicators. At the same time, computational tools need to be researched and experimented with. These tools include:
- Rhinoceros Grasshopper
- Karamba3D Grasshopper Plug-in
- Python
- Python Libraries such as Tensorflow, Pytorch, Keras
- AI, Variational Autoencoders, Surrogate Models & Gradient Descent (Optimizers)

Notable References:
- Truss design through reuse:
  Brütting, J., Desruelle, J., Senatore, G., & Fivet, C. (2019). Design of Truss Structures Through Reuse. *Structures*, *18*, 128–137. https://doi.org/10.1016/j.istruc.2018.11.006
- Previously done thesis on this topic:
  Pavlidou S. (2022). *Deep Generative Design A Deep Learning Framework for Optimized Shell Structures*.
- Example of a VAE framework for Topology Optimization:
  Gladstone, R. J., Nabian, M. A., Keshavarzzadeh, V., & Meidani, H. (2021). *Robust Topology Optimization Using Variational Autoencoders*. http://arxiv.org/abs/2107.10661
- Example of a VAE framework for 3D Wire-frame Models:
  de Miguel Rodríguez, J., Villafañe, M. E., Piškorec, L., & Sancho Caparrini, F. (2020). Generation of geometric interpolations of building types with deep variational autoencoders. *Design Science*. https://doi.org/10.1017/dsj.2020.31

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 overall graduation topic of Deep Generative Design as described in the documentation for BT track graduation topics links strongly to the Building Technology master track and the AUBS master programme, as it combines architectural design and engineering. The design of a sustainable architectural structure forms the end design product and application of this graduation project. This product fits the theme of "Sustainable Structures" well. For this thesis specifically, the topic was refined as "Deep Generative Design for Optimized Spatial Truss Structures with Stock Constraints". This topic adds the theme of circularity and reuse to the graduation project too. Both of these topics are viewed as essential to making the building and construction sector more sustainable and therefore make the connection to the theme of sustainability even stronger than the original documentation states.

Moreover, the focus of the graduation thesis will be on the design process and the application of technological innovations within this process, demonstrating an even stronger link to both design and engineering. The intended workflow will contain innovations that incorporate AI, Deep Learning and Variational Autoencoders. These technologies are all part of "Design Informatics" and enable many new possibilities within the building technology. During the master track, various computational tools that augment the human designer have been introduced already. AI, however, also offers a new form of design exploration and can be used to build onto existing generative design principles. This allows designers to reach solutions that go beyond their own design imagination.

So, even though some of the mentioned topics are not (yet) explicitly part of the BT track courses, they are a logical extension of the principles explored during the master track courses. Additionally, it provides an interesting challenge and further development of my skills within the field of Structural Design and Design Informatics. Finally, generative models based on AI are tools that can innovate these fields overall, as they are not yet widely applied.

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

(The relevant scientific background of this works relevance was also summarized in the "The posed problem" section of this Graduation Plan. Though this section will elaborate further on this information first, the sections that specifically discusses the main relevance of the graduation work starts under "Main Relevance of the Graduation Work".)

The construction industry is vital to society. However, it is also a major contributor to environmental problems like climate change. The 2020 Global Status Report for Buildings and Construction from the Global Alliance for Buildings and Construction (GlobalABC) states that the building sector is responsible for 35% of the global energy consumption and 18% of global CO_2 emissions. (GlobalABC, 2020). To minimize and reverse these environmental impacts it is essential to work towards creating more sustainable design and construction. At the end-of-life stage of a structure, the environmental impacts include the effects from generation of construction and demolition waste (CDW). These impacts include land degradation, resource depletion and water pollution (Akanbi et al., 2018, Ding et al., 2016, Ruiz et al., 2020). CDW accounts for the most significant waste stream globally (Jin et al., 2019). Additionally, CDW production contributes to the aforementioned CO_2 emissions and high energy consumptions. Globally, only 20-30% of CWD is recycled or reused (World Economic Forum, 2016), even though many of the materials found in CWD waste are recyclable and reuseable. Closing these material loops, using a circular economy framework, will reduce the demand for virgin materials, reduce waste production and lower emissions and energy consumption caused by the mining and manufacturing of these resources.

Steel production specifically still accounts for a significant part of global anthropogenic CO_2 emissions - 7-9% in 2020 (World Steel Association, 2021). To reduce this, remanufacturing and reuse of the material should be considered. Though some case studies show successful integration of reused steel in structural designs, it is not yet widely applied. Part of the barriers perceived by structural engineers have to do with the accessibility of materials. Another problem that is often encountered is designing with a constantly changing and limited material stock, which creates time-pressure for designers.

Main Relevance of the Graduation Work

A computational framework can aid in and speed up the process of topology exploration and optimization, so that designers can better and more quickly assess feasibility of a project with the present material stocks. So, the suggested deep learning generative workflow can aid in making design for re-use more feasible and therefore accessible to architects, engineers and designers.

On top of this, this graduation project is also relevant to the use and development of computational tools such as AI, Deep Learning and Variational Autoencoders in architectural and/or structural design. These tools are all relatively new to the fields of Architecture, Urbanism and Building Sciences, but have proven to be promising in other fields, like computer science and industrial/product design (Cui & Tang, 2017, Jiang et al., 2022, Oh et al., 2018, Qian et al., 2022). Therefore studying these tools and transforming/adjusting them to further fit within the architectural design process has great relevance to the scientific framework of architecture, building technology and engineering.

The research in this graduation project builds onto the generative design methods first introduced in the 1970's by Frazer (Frazer, 2002), but since applied in various ways within architectural and structural design processes. For example, in generative tools and plug-ins in the Rhinoceros Grasshopper software, that provide easy ways to generate designs based on a parametrically defined model. In this graduation project, the concept of a variational autoencoder (VAE), a neural network architecture that was first introduced by Diederik Kingma and Max Welling in 2014, is also used. (Kingma & Welling, 2014).

In conclusion, the computational, AI generative workflow that will be developed during this project will provide insight into ways to incorporate AI into the architectural design process to achieve new goals. This work will describe a case that, if successful, can directly improve the feasibility of circular, sustainable design, which is currently limited.

*Part of these answers are taken from the "Introduction" chapter of the thesis draft.

References for this section:

- Akanbi, L. A., Oyedele, L. O., Akinade, O. O., Ajayi, A. O., Delgado, M. D., Bilal, M., & Bello, S. A. (2018). Salvaging building materials in a circular economy: A BIM-based whole-life performance estimator. Resources, Conservation and Recycling, 129, 175-186.
- Cui, J., & Tang, M. X. (2017). Towards generative systems for supporting product design. In *Int. J. Design Engineering* (Vol. 7, Issue 1).
- Ding, Z., Wang, Y., & Zou, P. X. (2016). An agent based environmental impact assessment of building demolition waste management: Conventional versus green management. Journal of Cleaner Production, 133, 1136-1153.
- Dunant, C. F., Drewniok, M. P., Sansom, M., Corbey, S., Allwood, J. M., & Cullen, J. M. (2017). Real and perceived barriers to steel reuse across the UK construction value chain. *Resources, Conservation and Recycling*, *126*, 118–131. https://doi.org/10.1016/j.resconrec.2017.07.036
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- Frazer, J. (2002). Creative design and the generative evolutionary paradigm. In Creative evolutionary systems (pp. 253-274). Morgan Kaufmann.
- Jiang, Z., Wen, H., Han, F., Tang, Y., & Xiong, Y. (2022). Data-driven generative design for mass customization: A case study. *Advanced Engineering Informatics*, *54*. https://doi.org/10.1016/j.aei.2022.101786
- Jin, R., Yuan, H., & Chen, Q. (2019). Science mapping approach to assisting the review of construction and demolition waste management research published between 2009 and 2018. Resources, Conservation and Recycling, 140, 175-188.
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- Oh, S., Jung, Y., Kim, S., Lee, I., Kang, N., Oh, K. †s, & Jung, Y. (2018). *Deep Generative Design: Integration of Topology Optimization and Generative Models*.
- Qian, C., Tan, R. K., & Ye, W. (2022). An adaptive artificial neural network-based generative design method for layout designs. *International Journal of Heat and Mass Transfer*, *184*. https://doi.org/10.1016/j.ijheatmasstransfer.2021.122313
- Ruiz, L. A. L., Ramón, X. R., & Domingo, S. G. (2020). The circular economy in the construction and demolition waste sector–A review and an integrative model approach. Journal of Cleaner Production, 248, 119238.
- World Steel Association. (2021). *Climate change and the production of iron and steel*.