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 the P2 at the latest.

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

Personal information	
Name	**Elena Macedo Dauzacker**
Student number	4688449

Studio		
Name / Theme	Glass Giants	
Main mentor	Dr. Charalampos Andriotis	Computational Structural Optimization
Second mentor	Dr. Faidra Oikonomopoulou	Structural Cast Glass

Argumentation of choice of the studio	I was inspired by the previous Glass Giants theses, which created a cast glass-specific algorithm for topology optimization based on methods that have worked well for other materials, and added checks for manufacturability and time efficiency of glass. During my masters, I learnt about using glass as a structural material, and basic computational methods that can be used for structural design. I want to challenge myself to learn and implement novel computational methods (machine learning) to further specify the topological optimization for structural glass as an extension of the exploration done in the previous Glass Giants theses. Those students had pointed out that the method they used (SIMP) required extensive post processing due to the grey-scale nature of the results. Additionally, they mentioned that machine learning might be applicable here and generate alternative results. They also mentioned other possibilities for the objective function. They did a volume minimization with a stress constraint. In literature there are also examples where the stress is taken as part of the objective function. Given that glass is very sensitive to peak stresses (in tension), it might be interesting to explore the results of an optimization procedure that minimises stress as well as volume, and to gain insight into how the stress minimization affects the results compared to only minimising the volume. I am curious to find out if indeed a different workflow can significantly decrease the post-processing time and to implement machine learning for this task. Since stress is a local quantity, including it in the optimization means that more computational time is needed to find results. Thus a method where machine learning takes over the FEA might provide an advantage when compared to more traditional methods like SIMP. Stress-based optimization (i.e. an optimization where the minimization of stress is present in the objective function) is notoriously difficult and computationally intensive. This is due to the local nature of stress (i.e. small local changes have a large effect on the values of stress in that area), the singularity problem that affects optimizations that use pseudo-densities for the FEs (e.g. SIMP) where elements with low density appear to be greatly overstressed and this is usually solved by applying a relaxation technique on the stress (where one re-defines the stress based on the density of the element), and computational costs of performing the

	FEA enough times to achieve a result due to the non-linearity of stress. An additional difficulty particular to optimizations with cast glass are the manufacturing constraints which require the cross section to be between specific values to ensure that residual stress stays within the allowable limit after cooling, that the cooling time is not too long, and that the minimum gap size (i.e. area of non-material surrounded by area of material) be large enough to allow for the production of the mould. The brittle nature of glass means that it performs better in topologies with rounded corners and transitions (which are less susceptible to peak stress concentrations during use). This project is an attempt at redefining the optimization process with those challenges in mind. A new definition of topology is proposed. Using this definition, one can generate many topologies which fulfil the material manufacturing constraints: cross section within a defined range, minimum gap size, continuity, rounded edges and transitions. Machine learning in the form of a Variational Autoencoder is trained to become a generative model not only for topologies (which will actually be defined implicitly from the following), but for their stress and displacement distributions, alleviating the computational cost of repeated FEA calculations during optimization and making use of its ability to encode information to generate unseen topologies and their stress fields.

Graduation project

Title of the graduation project	Glass Giants: Stress-Based Topology Optimization using a Variational Autoencoder Glass Giants: using Generative Design for a Stress-Based Optimization of Structural Cast Glass Topologies. Generative Glass Giants undergo Stress-Based Optimization Less Stress for Glass Giants

	Generative Model for Glass Giants' Stress Field
Goal	
Location:	Pedestrian bridge in the Great Court of the British Museum
The posed problem,	Create a 2D topology definition that can be used by a machine learning method to find an optimal design of a cast glass massive indoor structure that is manufacturable and time efficient while minimising stress.
research questions and	Research question: How can a (two-dimensional finite element model) stress-based optimization algorithm be set up for designing massive cast glass structural elements which are time and cost efficient? Sub questions: 1) Case Study What have the previous explorations of this Case Study found? What are the **boundary conditions** of the structural element? 2) Glass Which **material properties** of glass are relevant for this project? What are the **manufacturing constraints** of structural glass components? 3) Structural Calculations How can **structural calculations (stress, displacement**) happen efficiently within an algorithm? What are the possible **dimensions** of each finite element? 4) Optimization What are the **types** of structural optimization? What is the most suitable **combination of "objective" and "constraints"** for this project? And how do they relate to each other?

	What is **stress**? How can it be quantified in the context of structural topology optimization? What are the **challenges** specific to stress-based optimizations? How are **material distributions** usually defined for optimization? Is there a material distribution definition that could be particularly suited to cast glass elements? What are the **traditional topology optimization methods** found in literature? What **machine learning** algorithms can be used for topology optimization and how? Could machine learning be an alternative to traditional methods for topology optimization of structural cast glass? 5) Workflow How can the ingredients mentioned above come together in a **workflow** that outputs optimised cast glass structures? 6) Reflection How does the optimised topology **perform** structurally and visually? How well did the algorithm perform? What are the possible areas for **future research**?
design assignment in which these result.	The design assignment consists of: (1) Designing a workflow that combines material constraints, topology definition, and optimization algorithm. (2) Designing the material distribution definition and optimization algorithms. (3) Using the above to inform the design of an indoor cast glass pedestrian bridge.

Process

Method description

The project starts by conducting research in four areas, as well as their intersection. These areas are:

1) Case Study: Pedestrian Bridge at the British Museum

2) Material: Structural Cast Glass

    a) Material properties
    b) Manufacturing constraints

3) Structural Calculations: Finite Element Method

4) Optimization: algorithms

    a) Types
    b) Material distribution method
    c) Objectives and constraints
    d) Optimization method
        i) Traditional methods (e.g. SIMP)
        ii) Machine learning

This literature research includes the previous Glass Giants theses, structural glass applications, FEA methodology, a multitude of papers on structural topology optimization with different methodologies and/or objectives, as well as information on various kinds of machine learning algorithms.

From the literature research conducted up to now, the following methods and techniques are proposed for implementation in this project (these are also representative of the chapters of the report):

1) Case Study: learn from the experience of the previous thesis by Koniari (2022) and Schoenmaker (2023) for the Case Study of the pedestrian bridge at the British Museum. How did they perform the optimization? Which challenges did they encounter? Define the boundary conditions: support conditions, and loads applied, as well as the dimensions of the design space.

2) Material: gather information on the material properties of structural glass, manufacturing possibilities, and the manufacturing constraints associated with large glass structures. Quantify them as stress and displacement optimization constraints, plus constraint on element dimensions derived from the manufacturing process.

3) Structural Calculations: learn how the Finite Element Method (FEM) works, and how to code it. Use Finite Element Analysis (FEA) to calculate the stress and deflection throughout the structure for each given topology. It uses a 2D square mesh, with sides of 1cm, to approximate the continuous structure. This can be used either to check topologies at each optimization iteration, or to create a set

of topology-stress pairs (given previously generated topologies) for training a machine learning model.

3) Optimization:

   a) Type: topology
   b) Material distribution method: data-set of discrete topologies
   c) Objectives and constraints: stress + volume, displacement
   d) Method: exploration of the latent space of a Variational Autoencoder (VAE)

One of the key aspects in the methodology is creating a suitable workflow where the different method components come together.

The workflow starts with topology data generation. Followed by the calculation of their accompanying stress and displacement using the FEM. This data is used to train a VAE model. This model is used by an optimizer to search for the best results in the latent space.

Topology data generation will be done in the form of a reliable algorithm that can output many (i.e. at least 10,000) different topologies that fulfil the manufacturing and time efficiency requirement for cast glass: the cross section everywhere should fall within a certain admissible range, structural continuity (no islands or checkerboard patterns), minimum gap size large enough for mould production, rounded edges and transitions. One possibility for this algorithm which has been used for some preliminary exploration is inspired by the level-set method and uses a parametric Gaussian Landscape as the function to be cut by the plane(s).

The topology data is then assessed by a 2d square grid Finite Element Analysis (FEA) to output the stresses (tension and compression) and displacement distributions. The FEA code should be validated by comparing the results with those obtained by commercial software (ANSYS) for a baseline example before creating the dataset from the topology generator. The FEA is coded in MATLAB.

The data generated contains three channels (these contain one value per FE of the topology) : tensile stress, compressive stress, displacement. The data also contains a single value per topology for the volume ratio. These three channels are used in an analogy with RGB channels to train a VAE model to encode the information contained in the data in the latent space through dimensionality reduction, which can later be explored to predict those three channels for previously unseen topologies. The layers, architecture, and training of the Machine Learning model will take place in TensorFlow.

The objective function is to minimise a weighted sum of volume ratio and stress. Volume ratio is translated into area ratio, since this is a 2D optimization space, and is an easily computable global value (number of FE with material divided by the total number of FEs in the design space). Stress will be translated into a global variable by using the p-norm. The maximum tensile and compressive stresses of each element will first be combined by using the Drucker-Prager Criteria. In other words, the Drucker-Prager criterion combines tension and compression into one value per element, and then the p-norm combines all the values from the individual elements into one global value. The maximum displacement is used as a constraint.

An optimizer is responsible for performing this last step of exploring the latent space of the trained VAE model and finding the optimised topology based on the objective function.

The results will be evaluated and compared to results obtained by the previous thesis who worked on this same Case Study: an indoor pedestrian bridge at the British Museum with different methodologies. It will also be post processed for smooth, curved edges.

The logical organisation and chapters are as follows:

1) Introduction

A brief introduction into the topic.
Chapters 2 and 3 set the stage of the optimization, containing boundary conditions and the material-specific objectives and constraints to be used.
Chapters 4 and 5 contain research about the algorithms that each perform a specific task in the process of translating the boundary conditions into an optimised topology.
Chapter 6 Links those algorithms together in a workflow.
Chapter 7 Codes the algorithms.
Chapters 8 and 9 evaluate and refine the results.
Chapter 10 and 11 conclude and reflect on the project.

2) Case Study
3) Glass

The properties of glass as a structural material are outlined, such as its stress limits and manufacturing constraints.

4) Structural calculations

This chapter contains the steps for calculating stress and displacement given different topologies.

5) Optimization

This chapter takes a look into types of structural optimization, the relationships between objectives and constraints, and specific challenges related to stress-based optimization.

   a) Type
   b) Material distribution method
   c) Objectives and constraints:

i) Stress, quantify stress for the optimization process

d) Optimization method

i) Traditional methods (e.g. SIMP)

ii) Machine learning

Different machine learning algorithms are explored, as well as where they could be useful in the structural topology optimization process.

6) Workflow

Here the ingredients of the previous chapters come together to form the workflow used for the design of the case study in this project.

7) Algorithm

This is where the building of the algorithm for the different sections of the project (1) structural calculation, 2) material distribution method, 3) machine learning, 4) optimization) takes place.

8) Results
9) Post processing
10) Conclusion
11) Reflection
12) Bibliography

Literature and general practical references

Bristogianni, T., Nijsse, R., Oikonomopoulou, F., & Veer, F. (2019). The effect of manufacturing flaws in the meso-structure of cast glass on the structural performance. *Advances in Engineering Materials, Structures and Systems: Innovations, Mechanics and Applications - Proceedings of the 7th International Conference on Structural Engineering, Mechanics and Computation, 2019*, 1703–1708. https://doi.org/10.1201/9780429426506-294

Bruggi, M., & Duysinx, P. (2012). Topology optimization for minimum weight with compliance and stress constraints. *Structural and Multidisciplinary Optimization*, *46*(3), 369–384. https://doi.org/10.1007/s00158-012-0759-7

Cang, R., Yao, H., & Ren, Y. (2019). One-shot generation of near-optimal topology through theory-driven machine learning. *CAD Computer Aided Design*, *109*, 12–21. https://doi.org/10.1016/j.cad.2018.12.008

Chandrupatla, T. R. (2002). *Introduction to Finite Elements in Engineering*.

Damen, W. (2019). *Topologically Optimised Cast Glass Grid Shell Nodes Exploring Topology Optimisation as a design tool for Structural Cast Glass elements with reduced annealing time*.

Drucker, D. C., & Prager, W. (1952). Soil mechanics and plastic analysis or limit design. *Quart Appl Math*, *10*, 157–165.

Duysinx, P. (1999). *Topology Optimization with Different Stress Limits in Tension and Compression*.

Duysinx, P., & Bendsøe, M. P. (1998). Topology optimization of continuum structures with local stress constraints. *International Journal for Numerical Methods in Engineering*, *43*(8), 1453–1478. https://doi.org/10.1002/(SICI)1097-0207(19981230)43:8<1453::AID-NME480>3.0.CO;2-2

Duysinx, P., Van Miegroet, L., Lemaire, E., Brüls, O., & Bruyneel, M. (2008). Topology and generalized shape optimization: Why stress constraints are so important? *International Journal for Simulation and Multidisciplinary Design Optimization*, *2*(4), 253–258. https://doi.org/10.1051/ijsmdo/2008034

Grover, A. (2023). *Deep Generative Models*. Https://Deepgenerativemodels.Github.Io/Notes/Introduction/.

Harish, B., Eswara Sai Kumar, K., & Srinivasan, B. (2020). Topology optimization using convolutional neural network. *Lecture Notes in Mechanical Engineering*, 301–307. https://doi.org/10.1007/978-981-15-5432-2_26

Hoyer, S., Sohl-Dickstein, J., & Greydanus, S. (2019). *Neural reparameterization improves structural optimization*. http://arxiv.org/abs/1909.04240

Ishrat, T. Z. (2024). *Generative Design of Catalan Vaults for Multi-Storey Seismic Construction*.

Jeong, H., Batuwatta-Gamage, C., Bai, J., Xie, Y. M., Rathnayaka, C., Zhou, Y., & Gu, Y. T. (2023). A complete Physics-Informed Neural Network-based framework for structural topology optimization. *Computer Methods in Applied Mechanics and Engineering*, *417*. https://doi.org/10.1016/j.cma.2023.116401

Kingma, D. P., & Welling, M. (2013). *Auto-Encoding Variational Bayes*. http://arxiv.org/abs/1312.6114

Koniari, A. M. (2022). *Development of a Topology Optimization Algorithm for a Mass-Optimized Cast Glass Component*.

Le, C., Norato, J., Bruns, T., Ha, C., & Tortorelli, D. (2010). Stress-based topology optimization for continua. *Structural and Multidisciplinary Optimization*, *41*(4), 605–620. https://doi.org/10.1007/s00158-009-0440-y

Lee, S., Kim, H., Lieu, Q. X., & Lee, J. (2020). CNN-based image recognition for topology optimization. *Knowledge-Based Systems*, *198*. https://doi.org/10.1016/j.knosys.2020.105887

Lee, S. M., Park, S. Y., & Choi, B. H. (2022). Application of domain-adaptive convolutional variational autoencoder for stress-state prediction. *Knowledge-Based Systems*, *248*. https://doi.org/10.1016/j.knosys.2022.108827

Lew, A. J., & Buehler, M. J. (2021). Encoding and exploring latent design space of optimal material structures via a VAE-LSTM model. *Forces in Mechanics*, *5*. https://doi.org/10.1016/j.finmec.2021.100054

Mazé, F., & Ahmed, F. (2022). *Diffusion Models Beat GANs on Topology Optimization*. http://arxiv.org/abs/2208.09591

Nie, Z., Lin, T., Jiang, H., & Kara, L. B. (2020). *TopologyGAN: Topology Optimization Using Generative Adversarial Networks Based on Physical Fields Over the Initial Domain*. http://arxiv.org/abs/2003.04685

Oh, S., Jung, Y., Kim, S., Lee, I., & Kang, N. (2019). Deep generative design: Integration of topology optimization and generative models. *Journal of Mechanical Design*, *141*(11). https://doi.org/10.1115/1.4044229

Oikonomopoulou, F. (2019). *Unveiling the third dimension of glass Solid cast glass components and assemblies for structural applications*.

París, J., Navarrina, F., Colominas, I., & Casteleiro, M. (2009). Topology optimization of continuum structures with local and global stress constraints. *Structural and Multidisciplinary Optimization*, *39*(4), 419–437. https://doi.org/10.1007/s00158-008-0336-2

París, J., Navarrina, F., Colominas, I., & Casteleiro, M. (2010). Block aggregation of stress constraints in topology optimization of structures. *Advances in Engineering Software*, *41*(3), 433–441. https://doi.org/10.1016/j.advengsoft.2009.03.006

Pereira, J. T., Fancello, E. A., & Barcellos, C. S. (2004). Topology optimization of continuum structures with material failure constraints. In *Structural and Multidisciplinary Optimization* (Vol. 26, Issues 1–2, pp. 50–66). https://doi.org/10.1007/s00158-003-0301-z

Querin, O. M., Steven, G. P., & Xie, Y. M. (1998). *Evolutionary structural optimisation (ESO) using a bidirectional algorithm*.

Schoenmaker, E. (2023). *Adding a New Dimension to Glass Giants Development of a Three-Dimensional Topology Optimization Algorithm for Mass-Optimized Cast Glass Components*.

Shin, S., Shin, D., & Kang, N. (2023). Topology optimization via machine learning and deep learning: a review. In *Journal of Computational Design and Engineering* (Vol. 10, Issue 4, pp. 1736–1766). Oxford University Press. https://doi.org/10.1093/jcde/qwad072

Steift, P. S. (1983). Ductile versus brittle behaviour of amorphous metals. In *I. Mech. Phys. Solids* (Vol. 31, Issue 5).

Ulyanov, D., Vedaldi, A., & Lempitsky, V. (2018). *Deep Image Prior*. http://www.cs.tut.fi/

White, D. A., Arrighi, W. J., Kudo, J., & Watts, S. E. (2019). Multiscale topology optimization using neural network surrogate models. *Computer Methods in Applied Mechanics and Engineering*, *346*, 1118–1135. https://doi.org/10.1016/j.cma.2018.09.007

Xiang, C., Chen, A., & Wang, D. (2022). Real-time stress-based topology optimization via deep learning. *Thin-Walled Structures*, *181*. https://doi.org/10.1016/j.tws.2022.110055

Xie, Y. M., & Steven, G. P. (1997). Basic Evolutionary Structural Optimization. In Y. M. Xie & G. P. Steven (Eds.), *Evolutionary Structural Optimization* (pp. 12–29). Springer London. https://doi.org/10.1007/978-1-4471-0985-3_2

Yang, R. J., & Chen, C. J. (1996). Stress-based topology optimization. *Structural Optimization*, *12*(2–3), 98–105. https://doi.org/10.1007/BF01196941

Zhang, Y., Peng, B., Zhou, X., Xiang, C., & Wang, D. (2019). *A deep Convolutional Neural Network for topology optimization with strong generalization ability*.

Reflection

1. What is the relation between your graduation (project) topic, the studio topic (Glass Giants), your master track (BT), and your master programme (MSc AUBS)?

Starting with the broadest and zooming in:

The master programme (AUBS) is broadly about buildings (their architectural concept, their relationship to each other and their urban environment, their technical details, materiality, and structural scheme).

Building technology (BT) focuses on the technical aspect (this mostly means the materials and structural forms in which they are composed) of buildings in respect to many subjects: thermal comfort, structural soundness and efficiency, acoustics, and architectural expression. It also integrates at least some level of computational tool in the process (e.g. thermal simulation, structural optimization, data analysis).

The studio (Glass Giants) narrows it down to one material: glass, and the challenge of applying a structural optimization method. It also offers inspiration from the students who previously researched this area, their results, and their insights into the next steps.

My thesis topic aims to expand on two of the challenges encountered by those who worked on this before me: (1) that the SIMP optimization method they used gives a result that requires considerable time and effort in the post-processing phase, and (2) that there might be interesting results that could be obtained from applying newer methodologies in the field of machine learning (ML) to this problem.

Now quickly zooming out:

This project attempts to use novel machine learning techniques to structurally optimise an indoor pedestrian bridge made entirely of glass. The studio (Glass Giants) provides inspirational previous work on this project, and insightful, experienced mentors. The knowledge sharpened during the Building Technology courses informs the choice and evaluation of performance indicators, as well as the methods used in the workflow. The realm of AUBS contextualises the structural piece within the Built Environment.

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

Machine learning (ML) has been exploding in the past decade. This project explores possibilities on how to employ novel methodologies to solve problems which lie at the intersection of material and structure. How can material configurations be modelled? Can machine learning be used to play within that environment to find an optimal design?