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	Tahir Zahid Ishrat
Student number	5698928

Studio		
Name / Theme	Building Technology/ Deep Generative Design	
Main mentor	Charalampos Andriotis	AiDAPT Lab / Design Informatics
Second mentor	Simona Bianchi	Structural Design
Argumentation of choice of the studio	Deep generative design opens vast opportunities for design generation out of complex problems at the initial stage. This saves time and allows ideation of a vast array of optimized designs. The application for the main research is in the field of structural design in shape optimization which is usually very computationally expensive	

Graduation project	
Title of the graduation project	Generative Design of Catalan Vaults for Multi-storey Seismic Design
Goal	
Location:	Rural/peri-urban seismic areas in the developing world. An example is given of Chitral and Gilgit-Baltistan, Pakistan. Training of the model may be done on any area fitting the narrative.
The posed problem,	In (poorer) areas where concrete, steel, and timber are not readily available, multi-storey construction can be problematic leading to a high carbon footprint in addition to material and transport costs. Despite high material strength, poor construction practices can make heavy RC structures unsafe especially due to seismic activity. The cast-in-situ RC floor slab contributes a great deal to the overall building mass; therefore a cheaper, sustainable

	alternative is required that makes use of local materials. Utilizing local soil, the low compressive strength can be compensated by optimizing geometry of the slab for load transfer. There is potential for unreinforced/minimally reinforced floor construction using Catalan vaults where the absence of formwork further decreases costs. However, seismic loads induce bending stresses inside the compression-only vault that may lead to collapse. For this reason, the project involves the development of a computational tool that optimizes the structure of a Catalan vault slab for seismic loads. Topology and shape optimization simulations are computationally expensive. Furthermore, multiple simulations may be needed at the initial stages of design where, for greater design freedom, it is common to have variable inputs. An AI Artificial Intelligence) trained generative model may allow for greater design freedom and help generate designs and save on computational time.
research questions and	**Main research question:** Can an AI based generative framework generate new Catalan vaults for optimized seismic performance for use as a floor slab? **Sub-questions:** **Deep generative** 1) Can unique latent dimension of the Variational Autoencoder (VAE) represent unique features representing the geometry of the vault? If yes, what features are represented? **Deep generative + Seismic** 2) Can vaults with variable footprints be generated that are structurally optimized for seismic performance?

	3) Can information be extracted from the generated models that may be used to indicate reinforcement requirements **Seismic** 4) How does the depth of the Catalan vault floor slab get affected by varying input footprint size 5) What effect does varying the force densities have on overall structural performance.
design assignment in which these result.	The goal is to create a deep generative model based on the problem earlier highlighted. The project can be divided into largely a two-tiered approach. The first phase involves the formation of a workflow for the problem. It will consist of a Variational Autoencoder that is able to generate novel designs of Catalan vaults optimized for seismic loads in order to be used as floor-slabs. Baked earthen tiles are to be used as the material for the masonry vault as a low-cost alternative to more material-intensive, expensive, and carbon-intensive materials that are not accessible. The project can be divided into largely a two-tiered approach. The first phase involves the literature review which guides the formation of a workflow for the problem. In the second phase, the workflow is applied in the formation and testing of a generative model.

[This should be formulated in such a way that the graduation project can answer these questions.
The definition of the problem has to be significant to a clearly defined area of research and design.]

Process

Method description

A deep generative model is to be constructed for shape optimization. The main workflow has been categorized into 4 main phases: Geometry Generation, Performance Evaluation, Data Structuring, and Variational Autoencoder (VAE). The methodology for the workflow has been inspired by the work of Sterrenberg (2023) who had taken inspiration from Pavlidou (2022).

The workflow consists of tools, software, and concepts that are novel for the student. Therefore, for practical purposes considering time limitations and computational power, the approach has been structured in the form of a basic structure (Workflow 1) with incremental layers of complexity (Workflow 2A and 2B) introduced as the project develops. This aims to firstly establish a basic yet holistic framework, then works towards developing more complexity through prioritization of goals and realistic choices under the timeframe. This aims to keep alternative workflows available in case of possible bottlenecks caused by unforeseen delays instead of reformulation of the workflow altogether. They are highlighted in the form of holistic alternative workflows.

Workflow 1 will be carried out in all cases. After that, **either** Workflow 2A will be carried out or Workflow 2B. The main difference is that Workflow 2A uses a discrete model where each tile is modelled separately while Workflow 2B uses a continuous model. The Form-finding method will dictate which workflow is to be implemented. If enough design variations are found to be generated, then it may not be necessary to add further complexity with tile patterning in Workflow 2B.

WORKFLOW 1

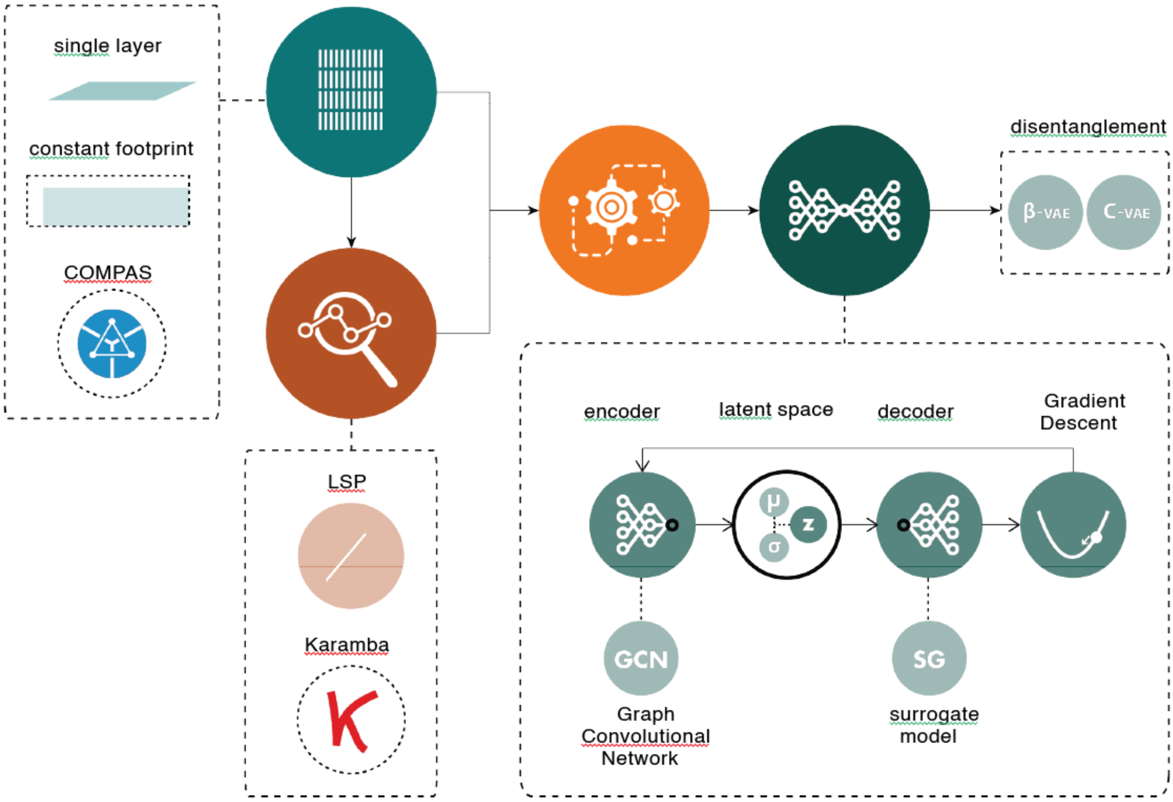
Geometry Generation: An input shape is to be defined in the initial step. This would form the perimeter of the floor slab. In the initial workflow, for simplification the footprint is to be kept as a rectangle with constant dimensions x and y. Form-finding is next done on the input footprint inside Grasshopper where multiple design variations are produced through the use of Thrust Network Analysis (TNA) through the software COMPAS. Each Catalan vault will be composed of a single layer structure.

Performance Evaluation: The geometry is then evaluated seismically through a Linear Static Procedure (LSP) in the software Karamba. Since this is also integrated inside Grasshopper, it will help ease into the workflow and gain familiarity with seismic analysis before introducing more complexity and moving into ABAQUS.

Data structuring: After this, the data is restructured in a form readable for the neural network.

VAE 1 : The structured dataset is then used to train a Variational Autoencoder. Graph convolutions (GCN) will be used inside the encoder layers to learn distinct features and for permutation invariance. A surrogate model will be used to reconstruct the output using backpropagation through a gradient descent optimization. Test data will be used to validate the training data.

VAE 2: Once the VAE has been trained and tested successfully generating new designs, disentanglement will be introduced to the VAE so a single latent dimension may correspond to a single controllable feature. The β term will be added to the KL divergence to change the VAE from a vanilla VAE to a β -VAE. Labels will be introduced to condition the dataset for better latent representation.



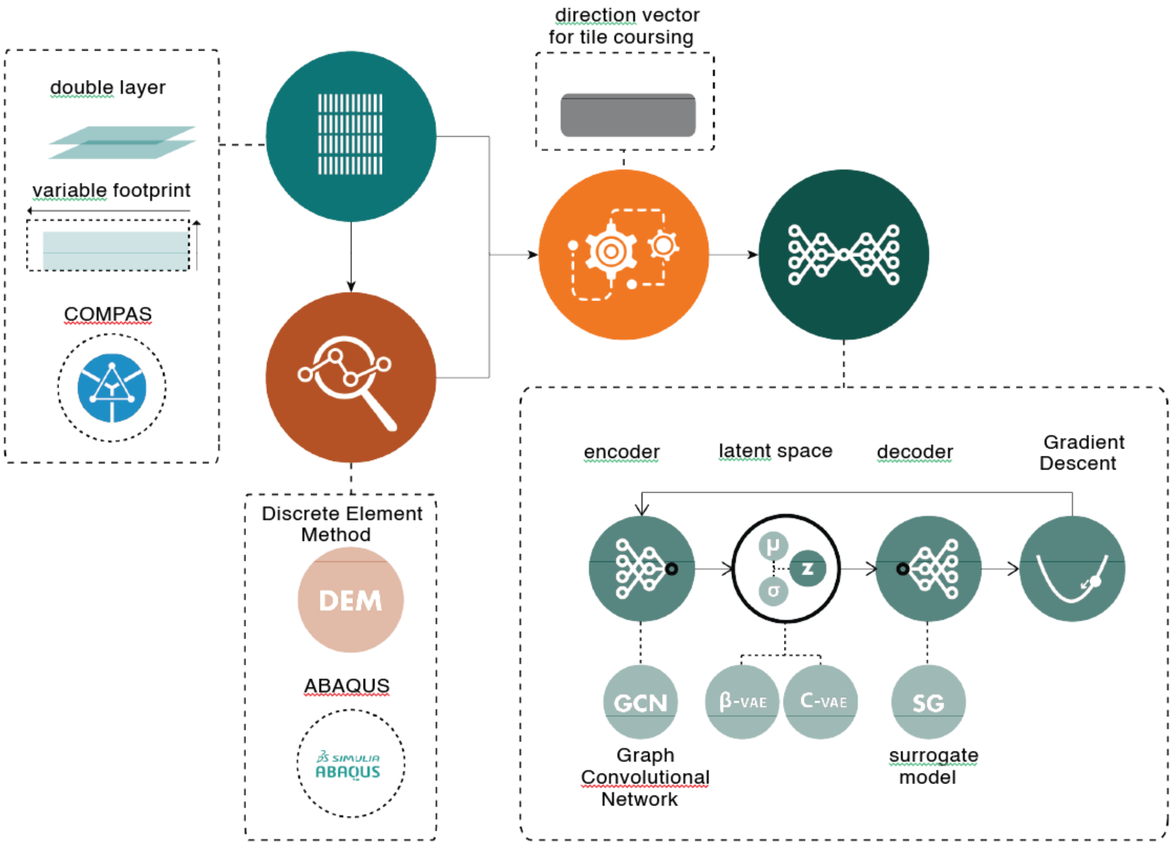
WORKFLOW 2A

Data Generation: A variable input rectangular footprint is generated of x and y dimensions. Form-finding is next done. After this, tiling is done. Each vault will be composed of a 2-layer structure.

Performance Evaluation: The geometry is then evaluated seismically through Discrete Element Method in the software ABAQUS.

Data Structuring: The data is then restructured similar to Workflow 1. However, this time, the tile geometry needs to be restructured as well.

VAE 2: The data will be used as an input dataset to VAE 2.



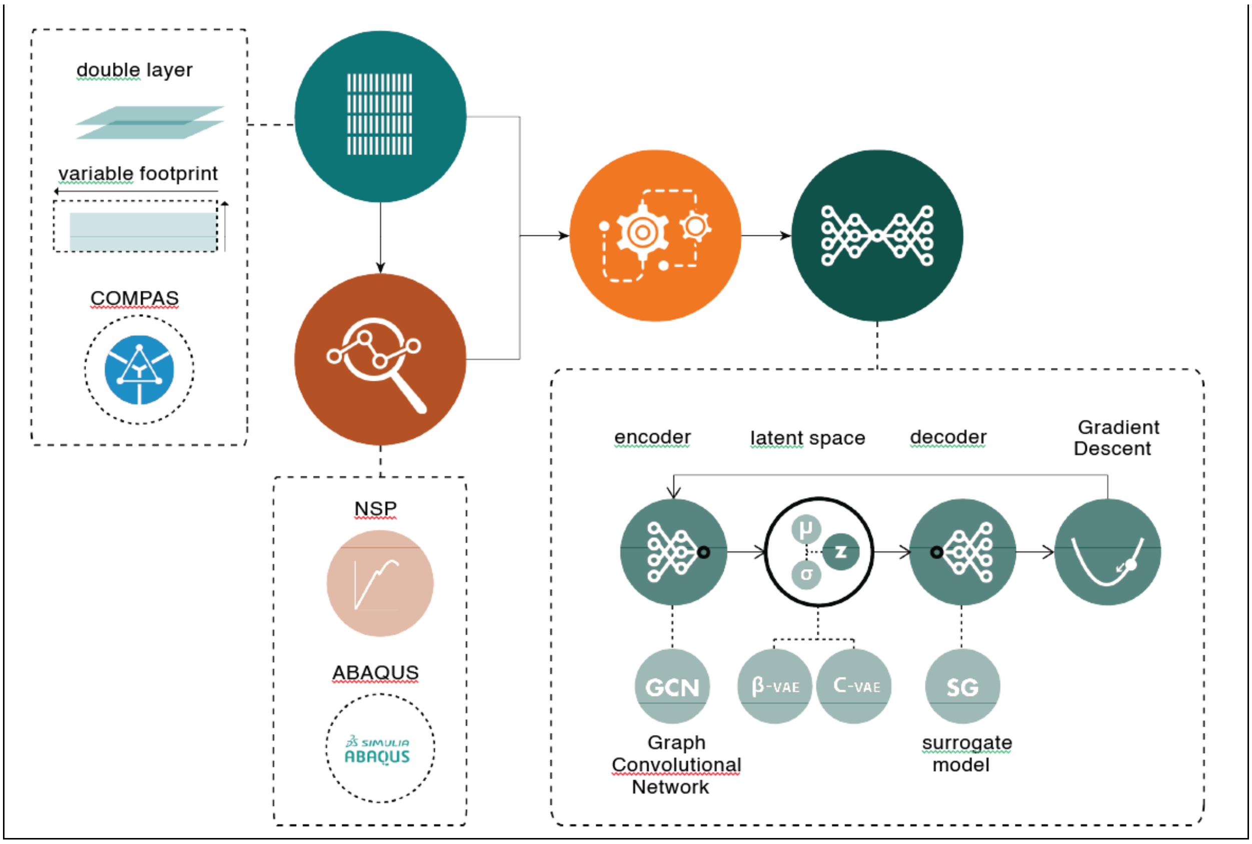
WORKFLOW 2B

Data Generation: Same as Workflow 1 but with a variable footprint.

Performance Evaluation: The geometry is then evaluated seismically through Non-linear Static Procedure (NSP) in ABAQUS.

Data Structuring: Same as Workflow 1.

VAE 2: Same as Workflow 2A.


double layer
variable footprint
COMPAS
NSP
ABAQUS
SIMULIA
ABAQUS
encoder
latent space
decoder
Gradient Descent
μ
z
σ
GCN
β-VAE
C-VAE
SG
Graph Convolutional Network
surrogate model

Literature and general practical references

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Reflection

1. 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 topic, 'Generative Design of Catalan Vaults for Multi-storey Seismic Design', combines two fields of the Building Technology Master Track – Design Informatics (DI) and Structural Design (SD). Within the two fields, it specifically delves into the field of Deep Generative Design due to which it is relevant to the AiDAPT Lab as well.

The topic builds up from the foundations laid by previous courses completed in the Masters Program. The field of Artificial Intelligence (AI) was introduced in the Computational Intelligence for Integrated Design (AR0202), Sustainable Architectural whilst CORE (AR30B12) established a background in python programming and provided an introduction to seismic design. Materials and Structures (AR1B023) and Technoledge Structural Design (AR0133) developed a foundation for understanding of structural mechanics.

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

In the broader context, the chosen case aims to serve as a test to determine whether the AI framework can generate reliable outputs. This aims to add to the state of the art. If the VAE learns to generate optimized solutions from a simpler dataset, it may be extrapolated that this means that there is also high potential for it to generate optimized solutions for more complex micromodels if the training dataset had been trained on that performance evaluation model as well. This would inform whether the case can serve as an application for the use of a VAE in shape optimization tasks which would otherwise be far too computationally expensive to perform. The project also aims to determine whether individual dimensions of the latent space of the VAE would learn to represent the same parameters that would be necessary for structural optimization. If this is the case then these dimensions would be interpretable, and thus, may be able to consciously tuned like control-knobs tweaked to generate novel and structurally sound solutions.

Generative design is a developing field and has great potential in several disciplines including engineering and architectural design. While there is some precedent research that deals with generative design of skeletal shells, there is a research gap in generative design for thin tiled shells. Disentanglement is a new field and there is further research to be conducted on the scope of disentanglement in topology optimization and shape optimization problems. Moreover, there is also a gap in research in the development of a generative framework for seismic design as well. This research aims to deal with these research gaps in the larger scientific framework.

The project targets a problem that is a growing concern in the present – the need to go vertical in an absence of conventional building materials. Due to a need for multistorey construction arising from rapid population growth, it may pose a much greater problem in the future.