GENERATIVE DESIGN OF CATALAN VAULTS FOR MULTI-STOREY SEISMIC CONSTRUCTION

P5 PRESENTATION
GRADUATION STUDIO AR3B0A25
21/06/24

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DELEGATE OF THE BOARD OF EXAMINERS
OLINDO CASO

Tahir Zahid Ishrat

LET'S KEEP IT SIMPLE

If ŷ is Buckling Load Factor, then

$$\hat{y} = -(1-b)^2$$

$$\frac{\partial \hat{y}}{\partial z} = -2(1-b) \times \frac{db}{dz} \qquad \text{(Equation I)}$$

If ŷ is Utilization, then

$$\hat{y} = (u-1)^2$$

$$\frac{\partial \hat{y}}{\partial z} = 2(u-1) \times \frac{du}{dz} \qquad \text{(Equation II)}$$

If ŷ is Interstorey Drift Ratio, then

$$\hat{y} = (i-0.010)^2$$

$$\frac{\partial \hat{y}}{\partial z} = 2(i-0.010) \times \frac{di}{dz} \qquad \text{(Equation III)}$$

Failure conditions are taken into account in each performance metric and ŷ is calculated accordingly.

$$\textit{Buckling Load Factor} < 1$$

$$\textit{Utilization} > 1$$

$$\textit{Interstorey Drift Ratio} > 0.010h \text{ (as specified in Eurocode 8)}$$

$$\text{ELBO}(\varphi) = \text{E}_{q\varphi(z|x)}[\log p_\theta(x \mid z)] - \text{D}_{KL}(q_\varphi(z \mid x) \,||\, p(z)).$$

$$z = \mu + \sigma \odot \epsilon$$

where $\epsilon \sim N(0, 1)$, and μ and σ are the mean and the standard deviation of $q_\varphi(z \mid x)$. ϵ is a standard Gaussian variable that plays a role of introducing noise, and $\odot$ denotes an element-wise product (Zhang et al., 2016).

$$\hat{y} = -(1-b)^2$$

$$z = z - learning\_rate \times - \frac{\partial \hat{y}}{\partial z}$$

$$z = z + learning\_rate \times \frac{\partial \hat{y}}{\partial z} \qquad \text{(Equation V)}$$

Furthermore, it becomes unnecessary to try to decrease (Utilization, Interstorey Drift Ratio) or increase (Buckling Load Factor) that metric if the metric is already under acceptable limits (no failure). To account for such conditions, the gradient update is configured accordingly by adding additional conditions.

If $(u-1) > 0$, perform the update; otherwise, do nothing.

If $(1-b) > 0$, perform the update; otherwise, do nothing.

If $(i-0.010) > 0$, perform the update; otherwise, do nothing.

(Equation VI)

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

In order to constrain the optimized meshes to be within a certain height threshold and to minimize material usage by minimizing mass, the gradient function was altered to account for multiple objectives instead of a single objective.

For single objective optimizations, the gradient function was as mentioned below:

$$y'(z) = \frac{\partial \hat{y}}{\partial z}$$

To consider multiple objectives, the different gradients were aggregated to form the overall gradient. Weights were included for each gradient to allow the user to optimize specific metrics over others.

$$y'(z) = W_1\left(\frac{\partial \hat{y}_1}{\partial z}\right) + W_2\left(\frac{\partial \hat{y}_2}{\partial z}\right) + W_3\left(\frac{\partial \hat{y}_3}{\partial z}\right)$$

where,
y' = *aggregated gradient*
$\hat{y}_1$ = *Height*
$\hat{y}_2$ = *Mass*
$\hat{y}_3$ = *Performance metric*
z = *latent space*
W_1, W_2, W_3 = *Weightage for respective gradients*

(Equation VII)

$$p(x, z, y) = p(x \mid z, y)p(z \mid y)$$

The conditional VAE tries to maximize:

$$\log p\theta(x \mid y) = \int_z \log(p(x \mid z, y)p(z \mid y))dz$$

while the loss function to minimize is:

$$\text{ELBO}(\varphi) = \text{E}_{q\varphi(z|x,y)}[\log p(x \mid z, y)] - \text{D}_{KL}(q_\varphi(z \mid x, y) \,||\, p(z \mid y)).$$

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$Buckling\ Load\ Factor < 1$

$Utilization > 1$

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Furthermore, it becomes unnecessary to try to decrease (Utilization, Interstorey Drift Ratio) or increase (Buckling Load Factor) that metric if the metric is already under acceptable limits (no failure). To account for such conditions, the gradient update is configured accordingly by adding additional conditions.

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PROBLEM

By 2050

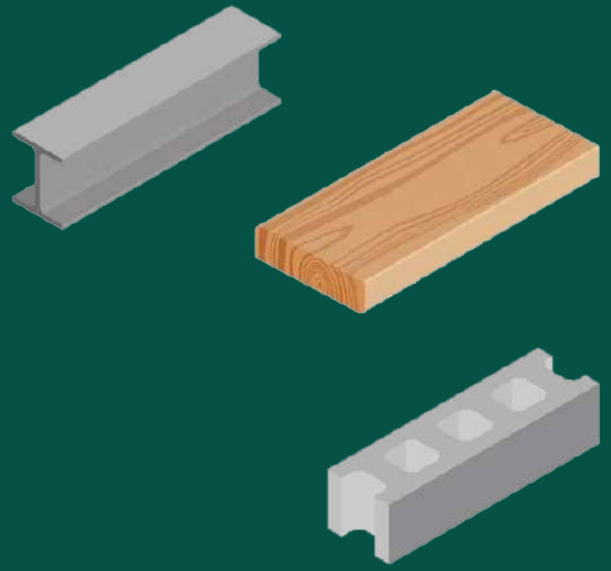
8.8-10 billion

PROBLEM

By 2050

8.8-10 billion

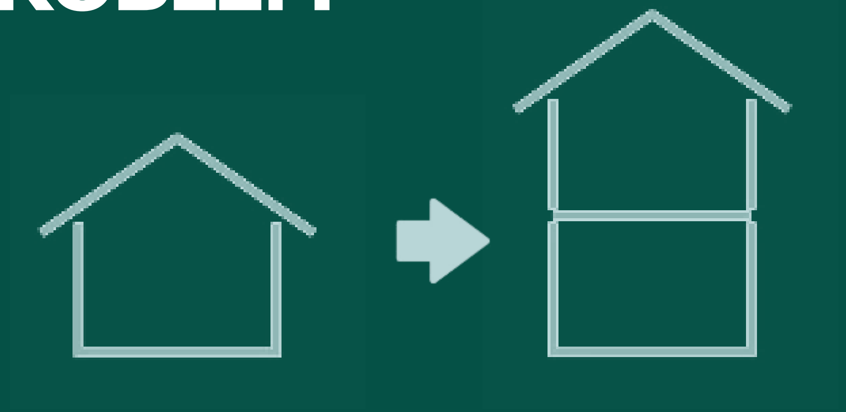
PROBLEM

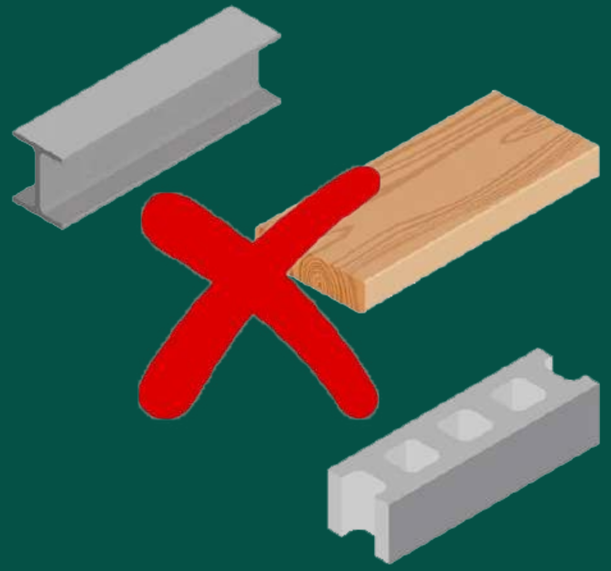


By 2050

8.8-10 billion

PROBLEM



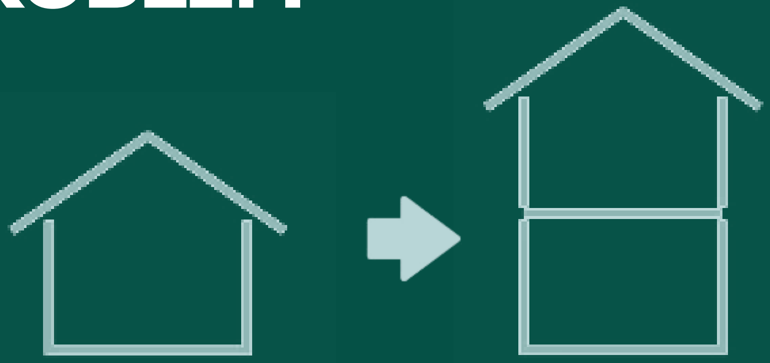


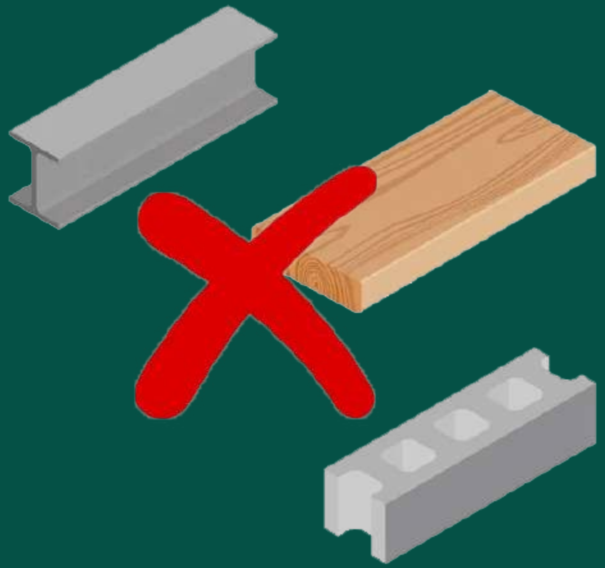
NOT AVAILABLE NEARBY

By 2050

8.8-10 billion

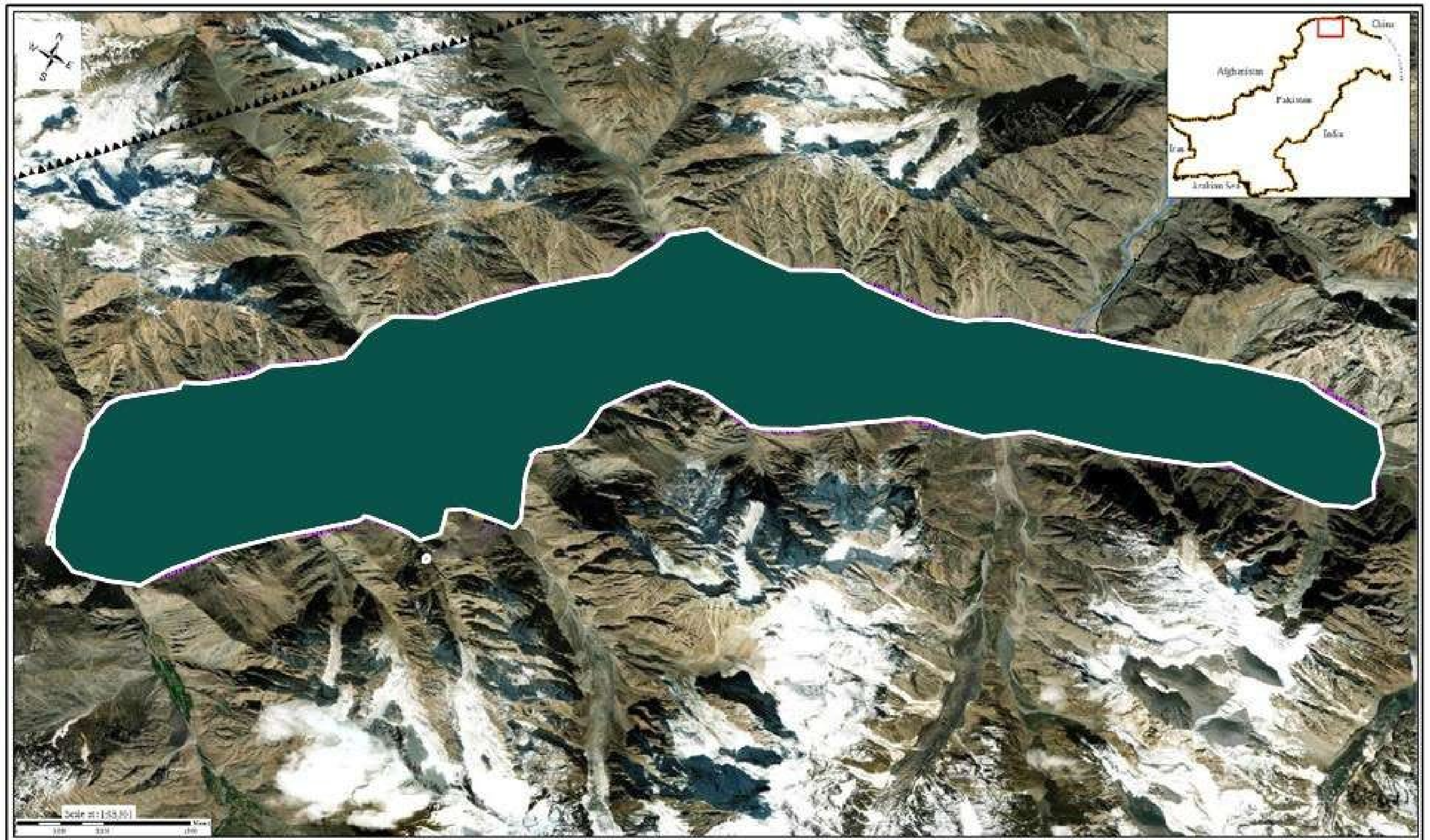
PROBLEM





NOT AVAILABLE NEARBY

Lower Yarkhun Valley, Chitral, Pakistan

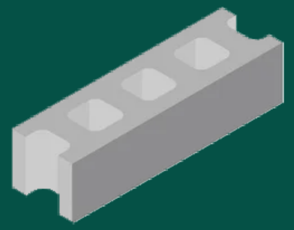


PROBLEM

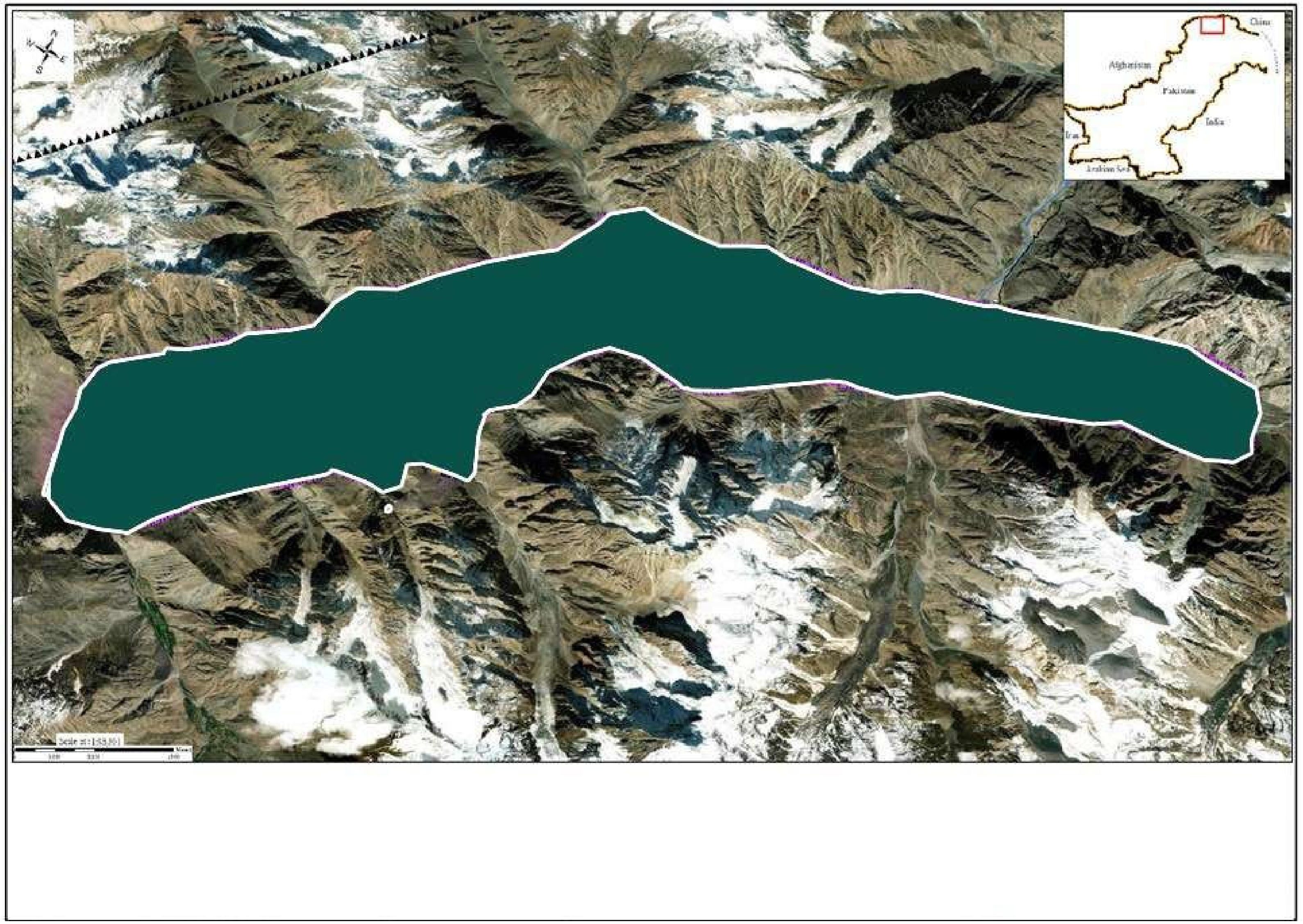
Carbon Cost

Material Cost

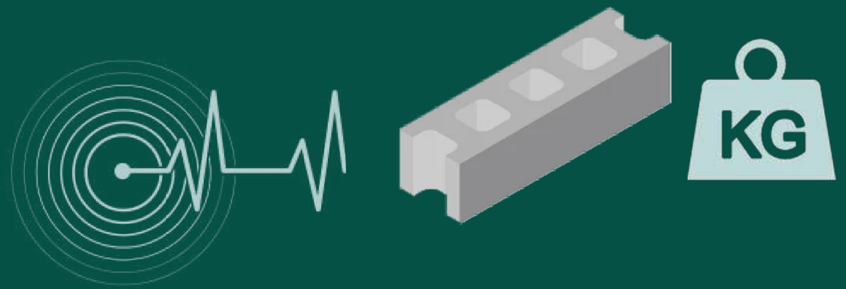
Transport Cost



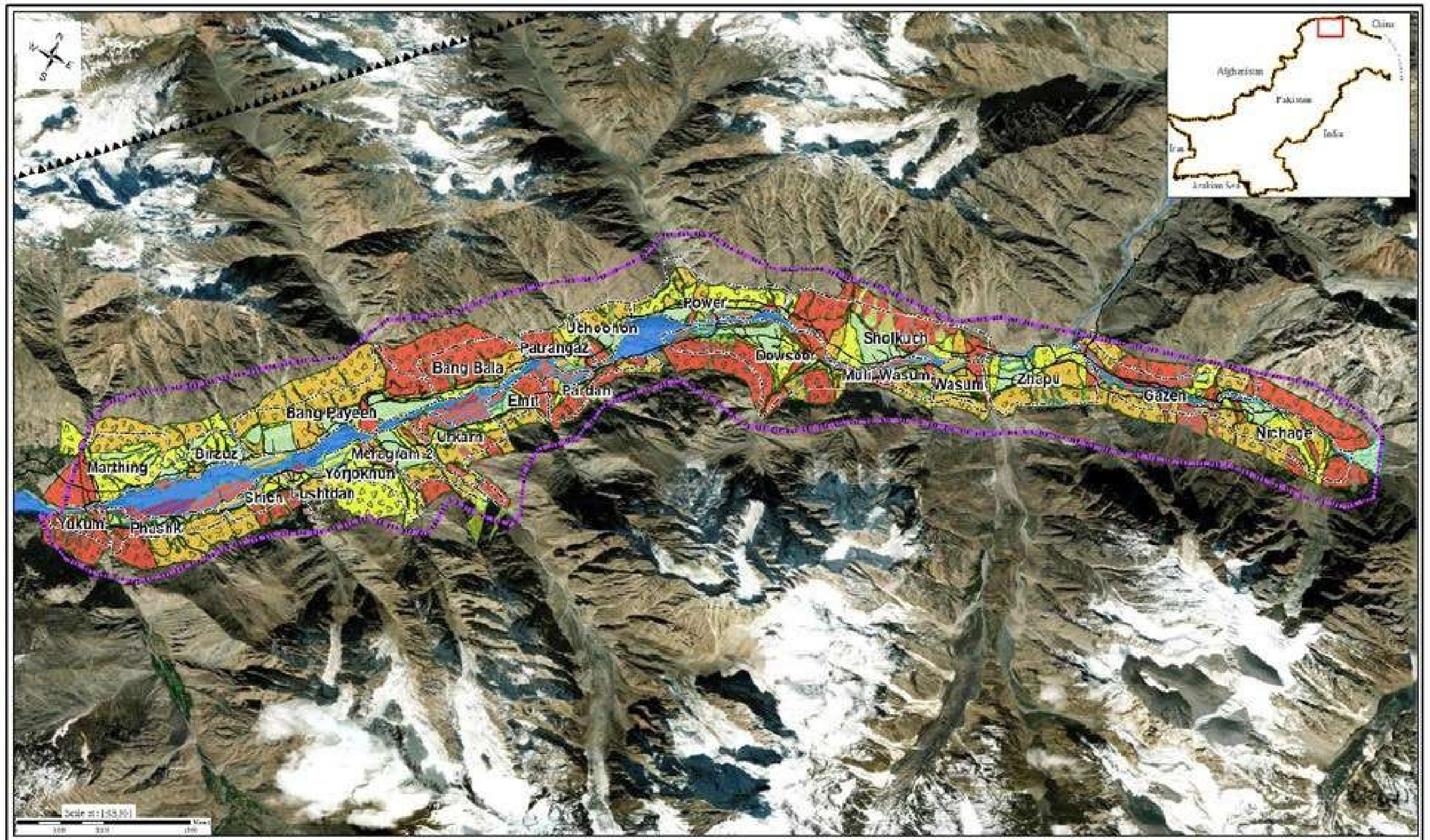
Lower Yarkhun Valley, Chitral, Pakistan



PROBLEM



Lower Yarkhun Valley, Chitral, Pakistan



HAZARD VULNERABILITY RISK ASSESSMENT MAP

high risk | medium risk | low risk | safe

FIGURE 01: Hazard Vulnerability map of Lower Yarkhun Valley, Chitral.- showing high risk areas in red, medium risk in orange, low risk in yellow, and safe in green. Ishrat & Baig (2022). AKAH Model Home Report: Country Analysis. [unpublished NGO Report]

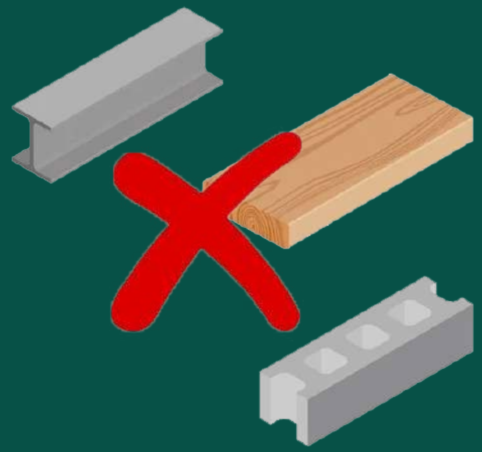
SOLUTION

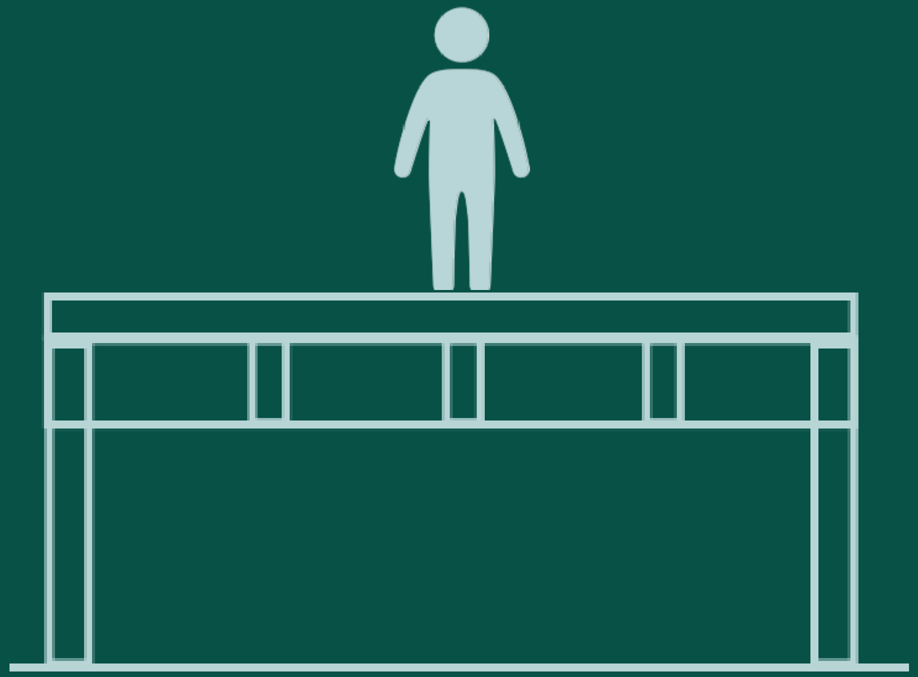
CHEAPER

SUSTAINABLE

RESILIENT

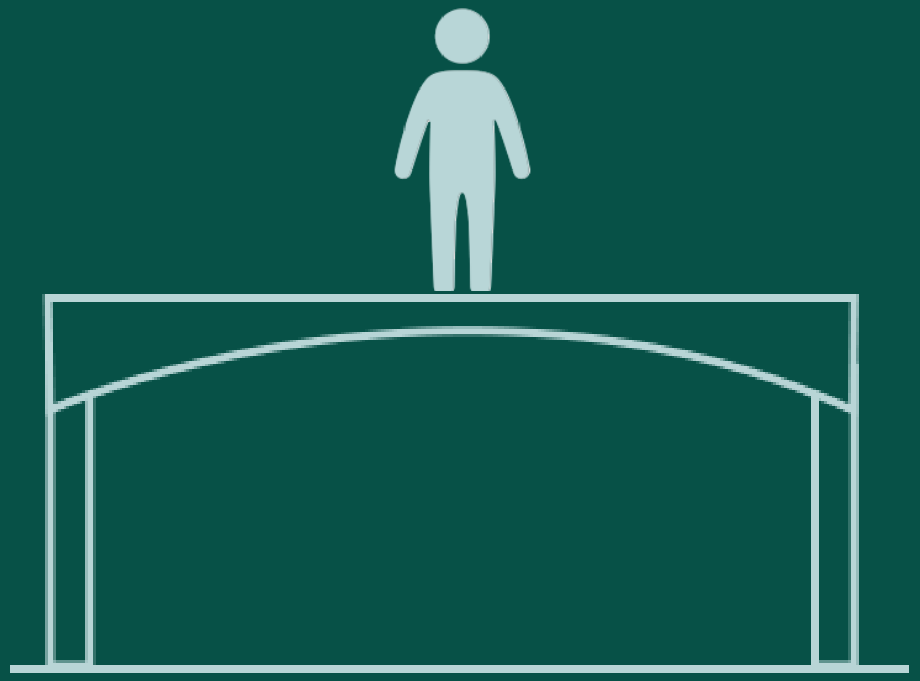
SOLUTION





SOLUTION

LOCAL



CATALAN VAULT

CATALAN VAULT

WHAT IS A CATALAN VAULT?

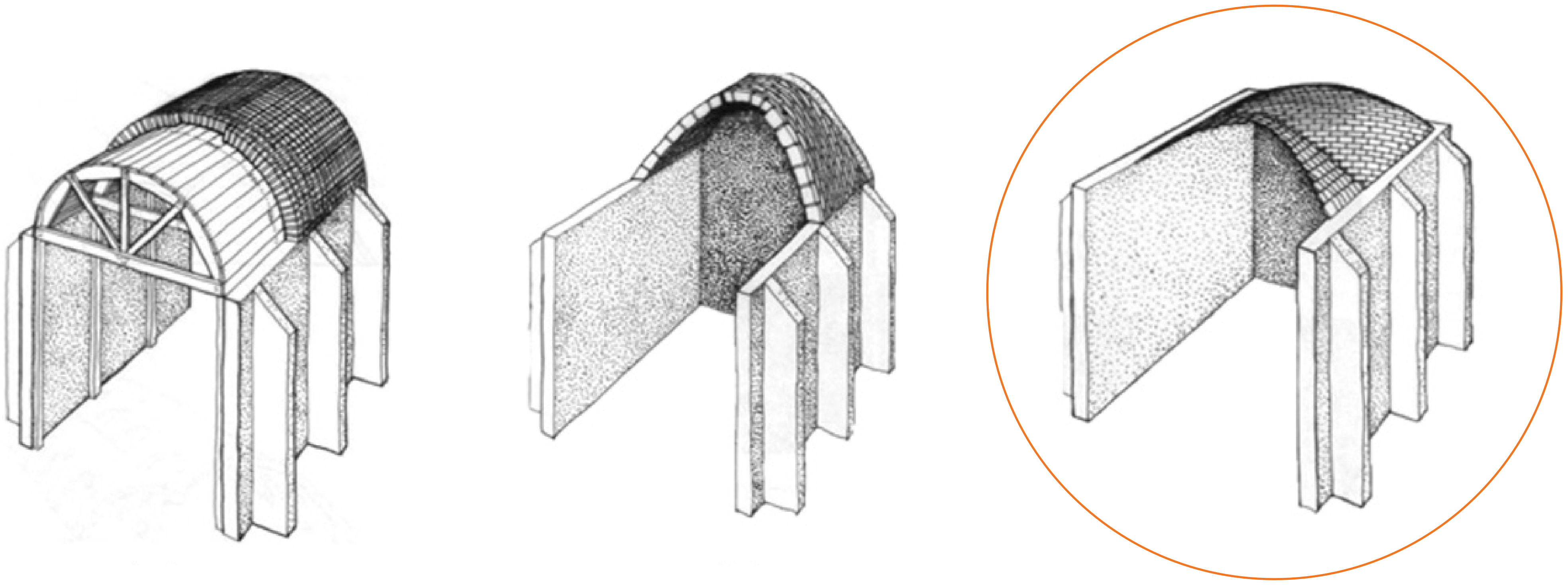
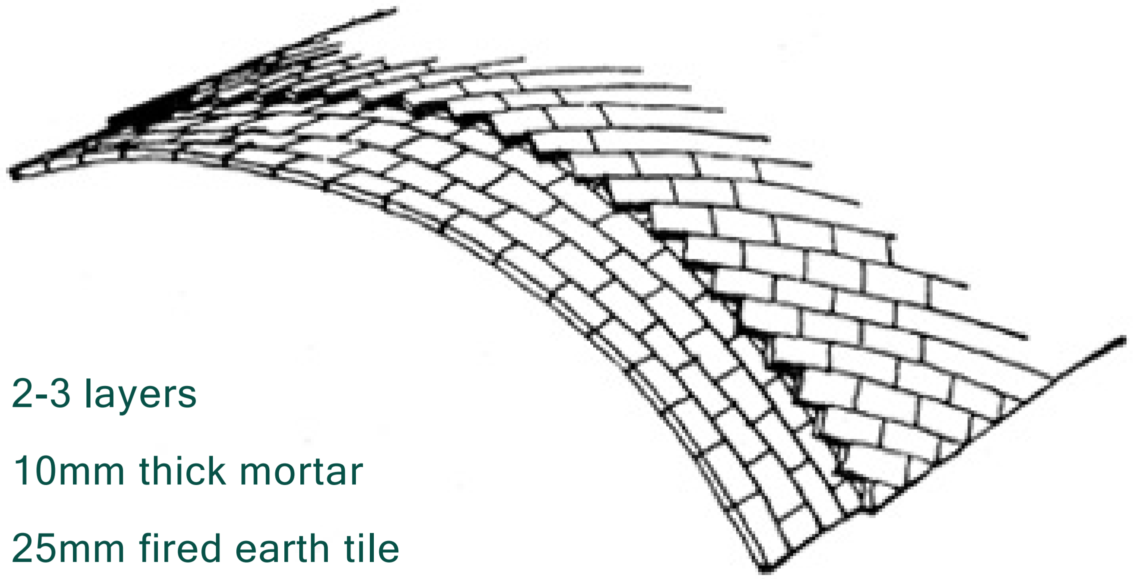


FIGURE 02: Types of vaults: a) Roman (semi-circular section built using formwork),b) Nubian (catenary section, no formwork), c) Catalan Vaulting (catenary section, can also be shallow, no formwork). Image retrieved from Chichester: John Wiley and Sons. Form and aage/catalan-vaulting/

CATALAN VAULT

WHAT IS A CATALAN VAULT?



2-3 layers

10mm thick mortar

25mm fired earth tile

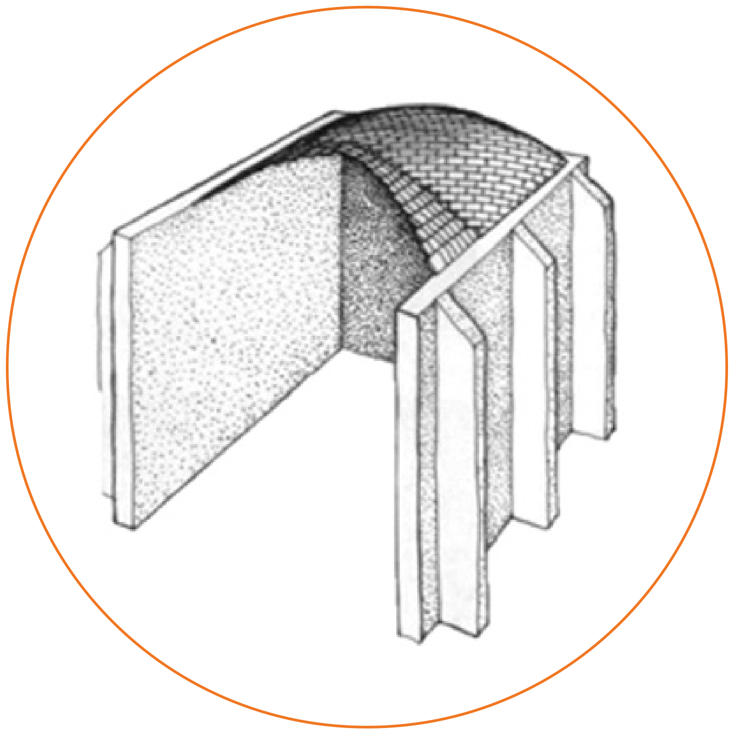


FIGURE 03: Catalan vault made from layers of thin tiles. The second layer is angled at 45 degrees to avoid continuous seams causing instability. Image retrieved from Moya, L. (1957). Archweb. https://www.archweb.com/en/design/page/catalan-vaulting/

CATALAN VAULT

USE AS A FLOOR SLAB

FIGURE 04: Catalan vault floor slab at SUDU project, Ethiopia with lightweight stiffening walls. Image retrieved from López López, D., Van Mele, T., & Block, P. (2016). Tile vaulting in the 21st century. Informes de La Construcción, 68(544), 162. https://doi.org/10.3989/ic.15.169.m15

CATALAN VAULT
SEISMIC STABILITY

REINFORCEMENT

FIGURE 05: Geogrid embedded in between mortar layers and tiles, for reinforcement against seismic loads, in the Bowls Centre, Yerba Buena Centre for the Arts, in San Francisco, USA. Image retrieved from Ramage, M. H., & Dejong, M. J. (n.d.). Design and Construction of Geogrid-reinforced Thin-shell Masonry.

DOUBLE CURVATURE

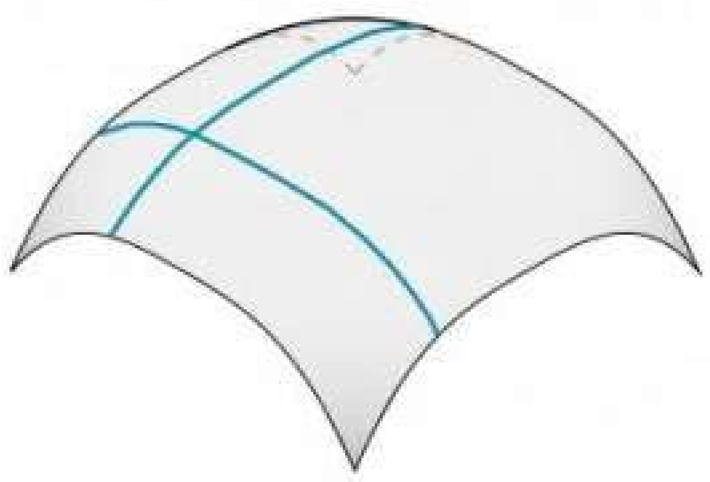


FIGURE 06: Double Curvature. Image retreived from Studio9. https://www.studio9.arch.kth.se/author/olgavoisnis/

STIFFENING WALLS OR/AND FILL

FIGURE 07: Catalan vault floor slab at SUDU project, Ethiopia, with lightweight stiffening walls and compacted fill. Image retrieved from López López, D., Van Mele, T., & Block, P. (2016). Tile vaulting in the 21st century. Informes de La Construcción, 68(544), 162. https://doi.org/10.3989/ic.15.169.m15

SOLUTION

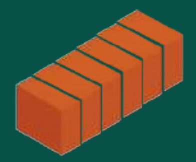
DESIGN FREEDOM

LOCAL

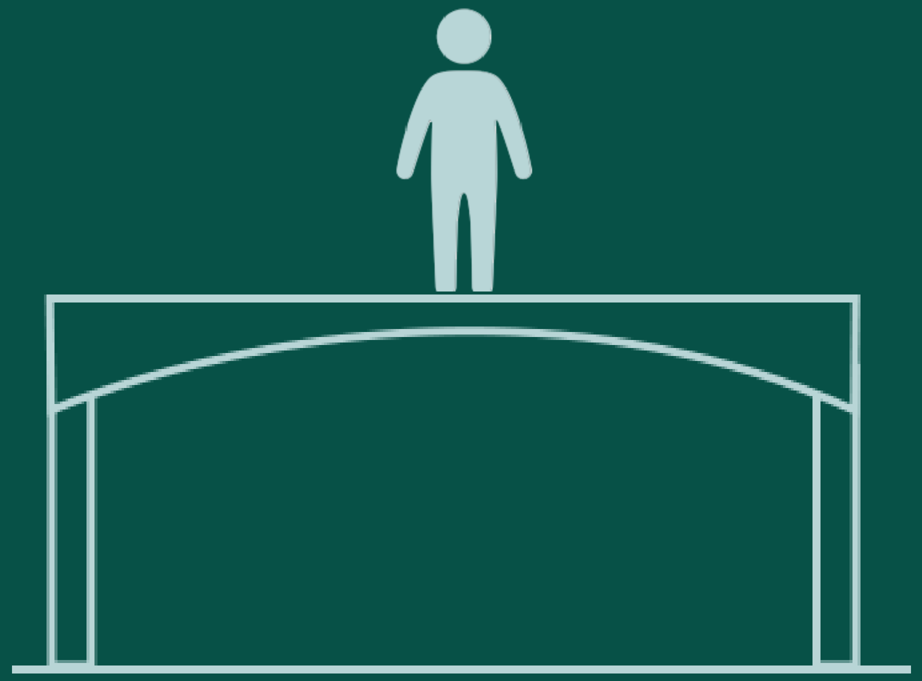
CATALAN VAULT

LONG TIME

SOLUTION



LOCAL



CATALAN VAULT

DESIGN FREEDOM

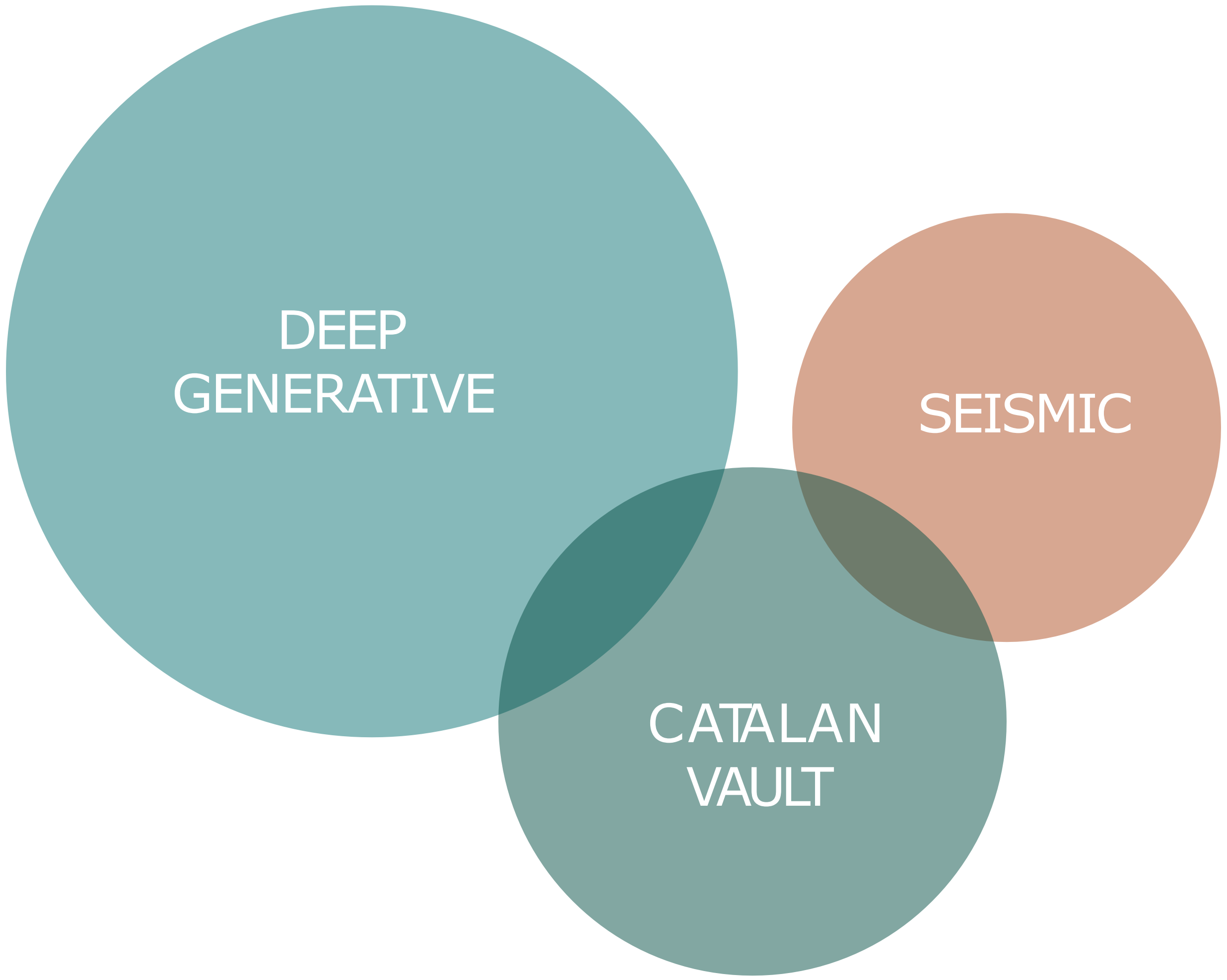
AI FRAMEWORK

REDUCE TIME

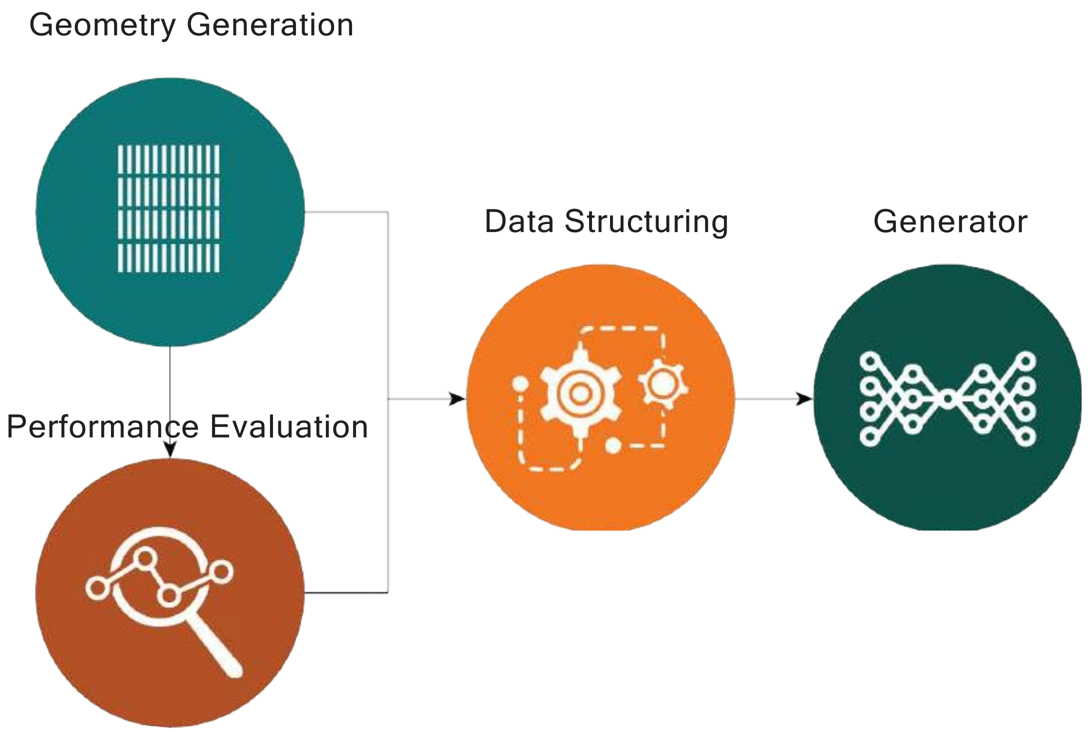
MAIN RESEARCH QUESTION

Can an AI based **generative framework** generate **new Catalan vaults** for **optimized seismic performance** for use as a floor slab?

RESEARCH DOMAINS



WHAT IS THE AI FRAMEWORK?



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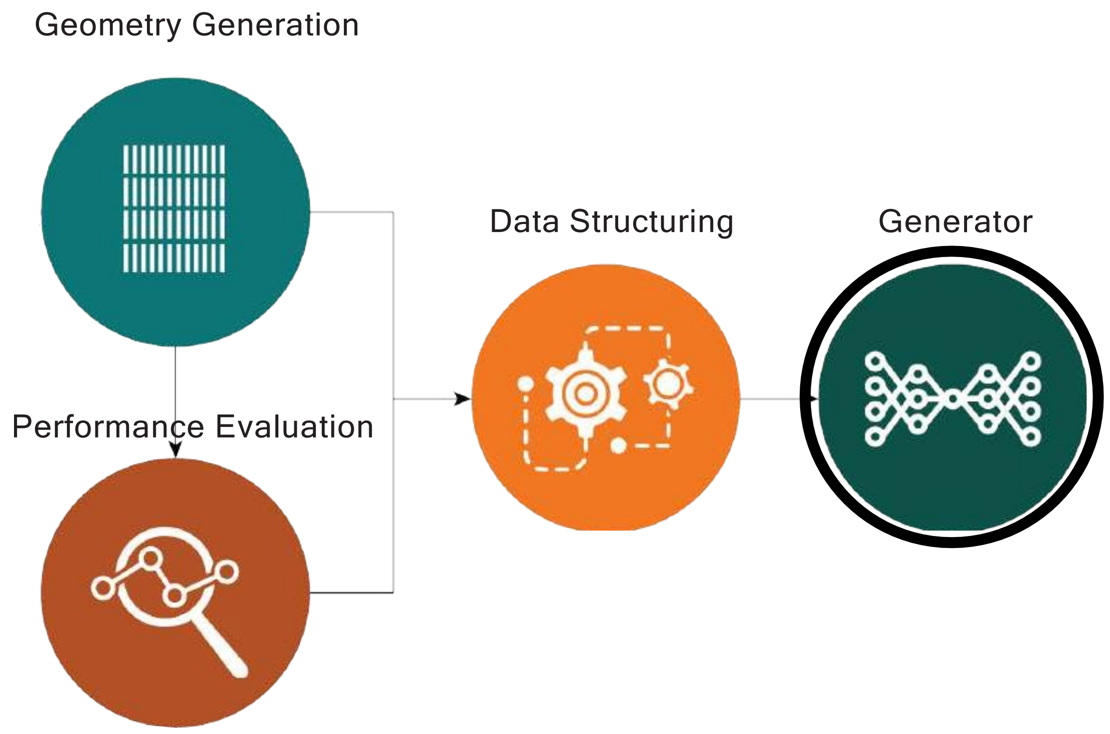


De afbeelding kan niet worden weergegeven.

BEHIND THE BLACKBOX

GENERATOR

OVERALL WORKLOW

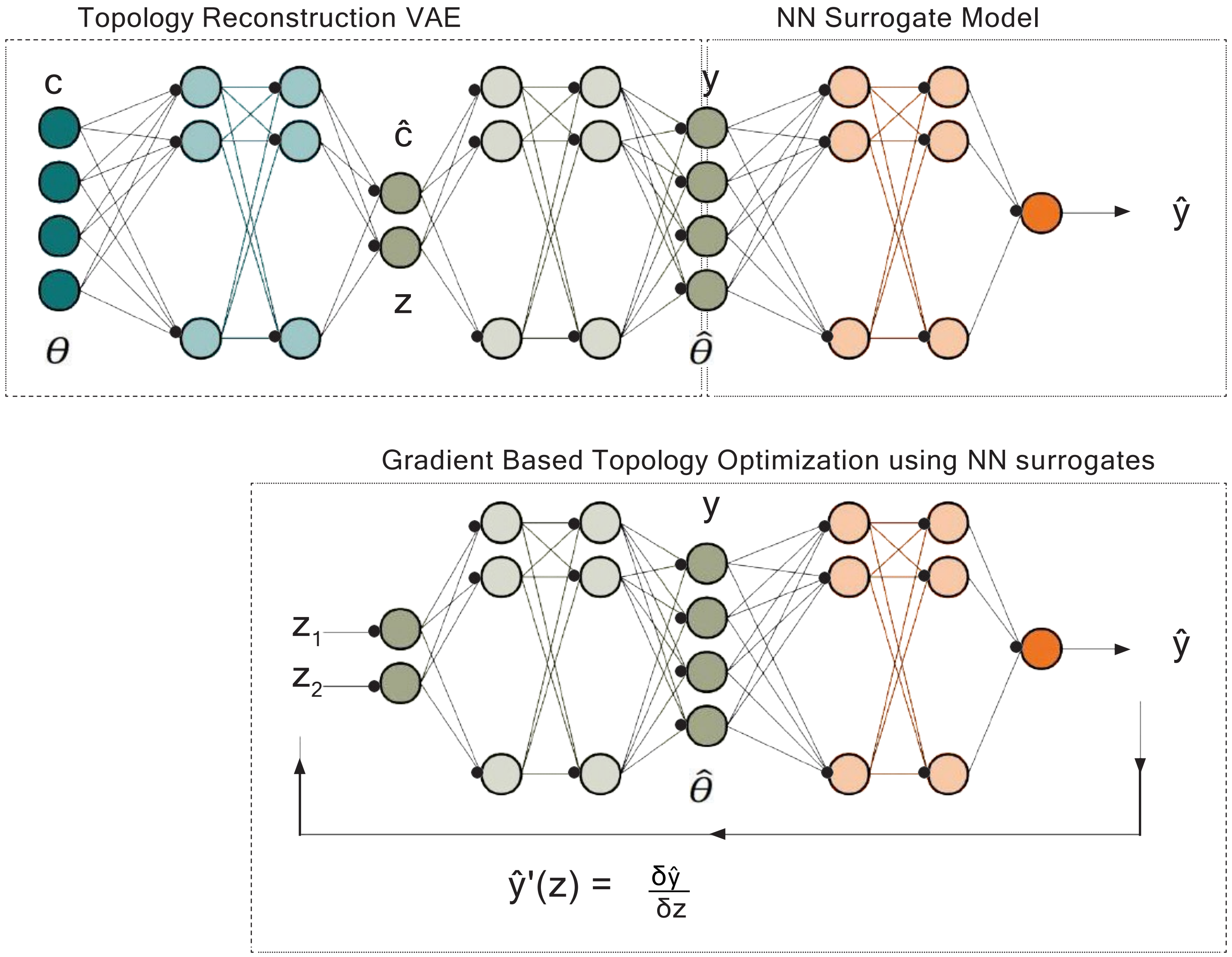
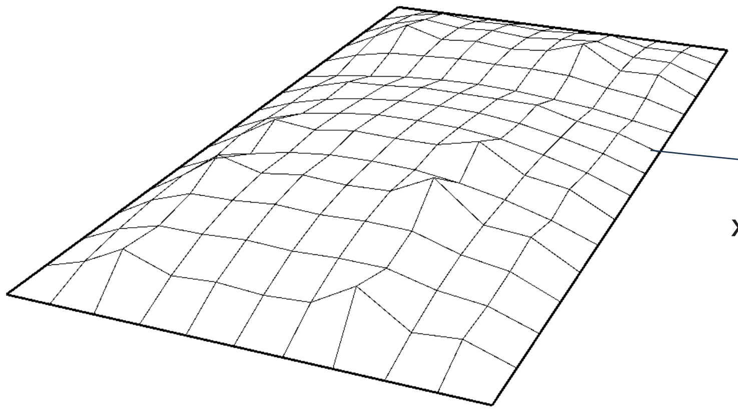


FIGURE 08: Overall Workflow connecting the VAE to the surrogate model and optimization through Gradient Descent. Inspired by Gladstone, R. J., Nabian, M. A., Keshavarzzadeh, V., & Meidani, H. (2021). Robust Topology Optimization Using Variational Autoencoders (arXiv:2107.10661). arXiv. http://arxiv.org/abs/2107.10661

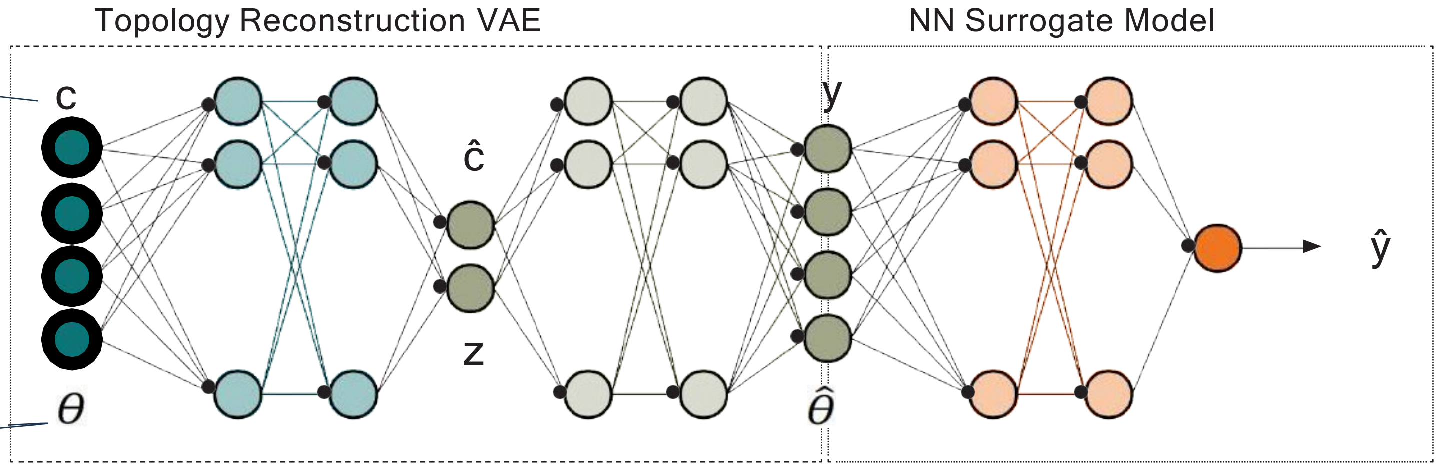
GENERATOR

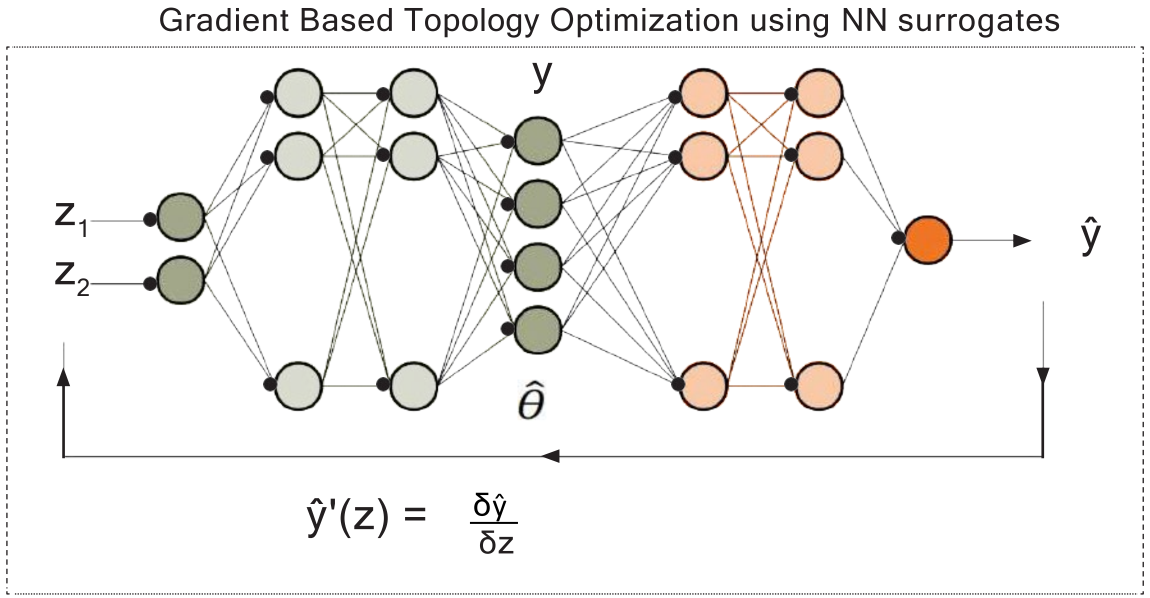
OVERALL WORKLOW

HEIGHT (c)



x 10,000

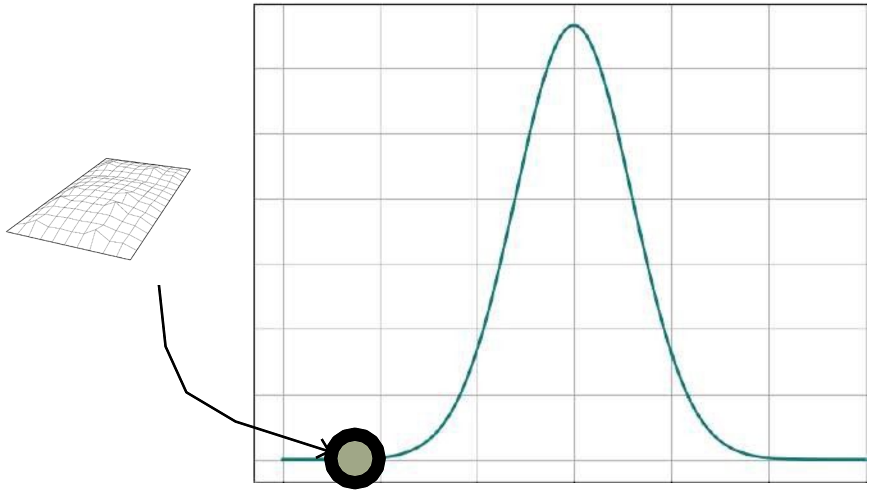




GENERATOR

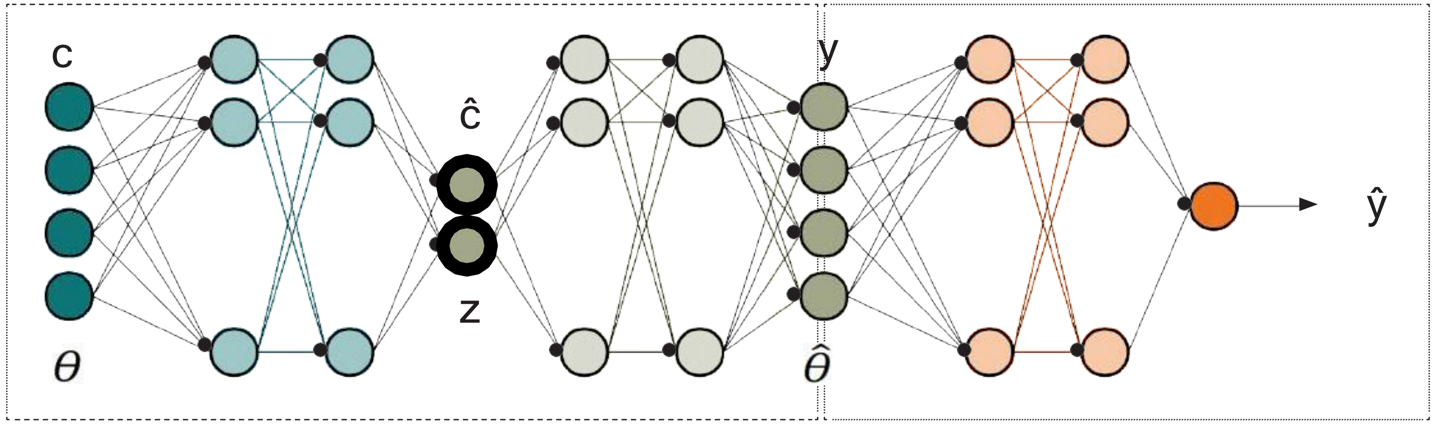
OVERALL WORKLOW

encoder

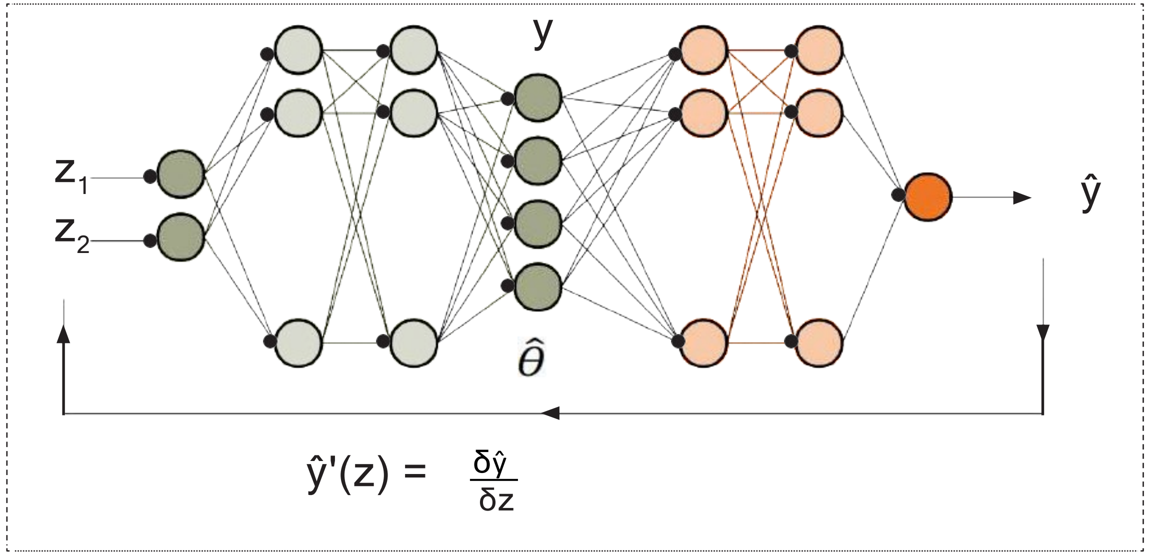


Topology Reconstruction VAE

NN Surrogate Model



Gradient Based Topology Optimization using NN surrogates

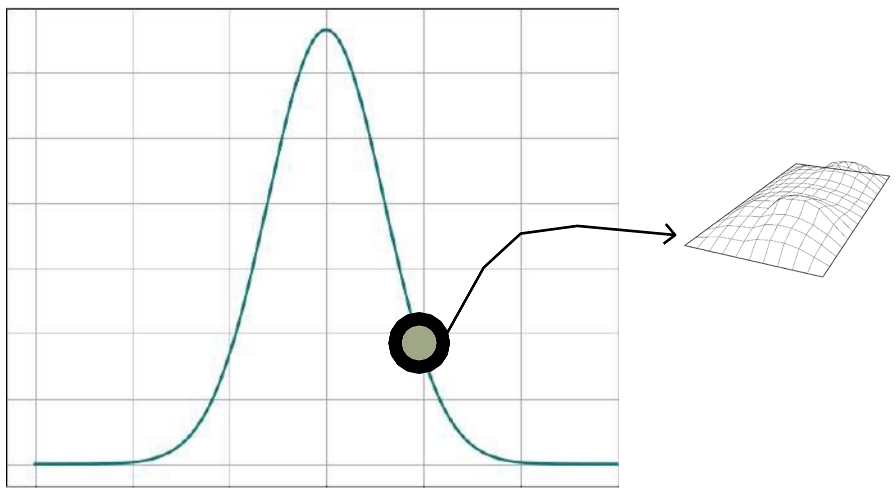


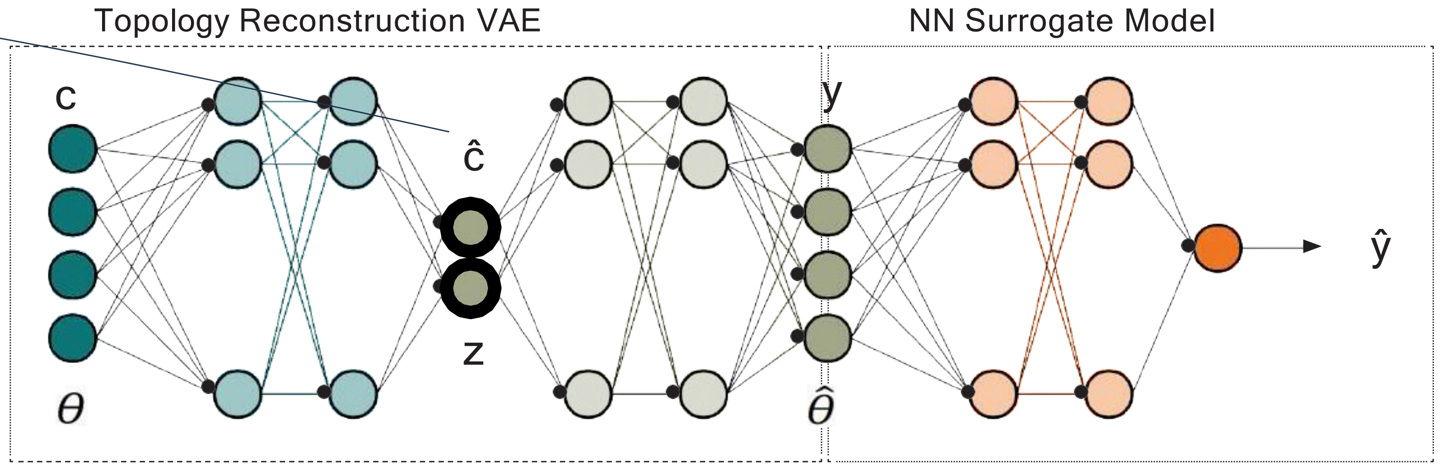
GENERATOR

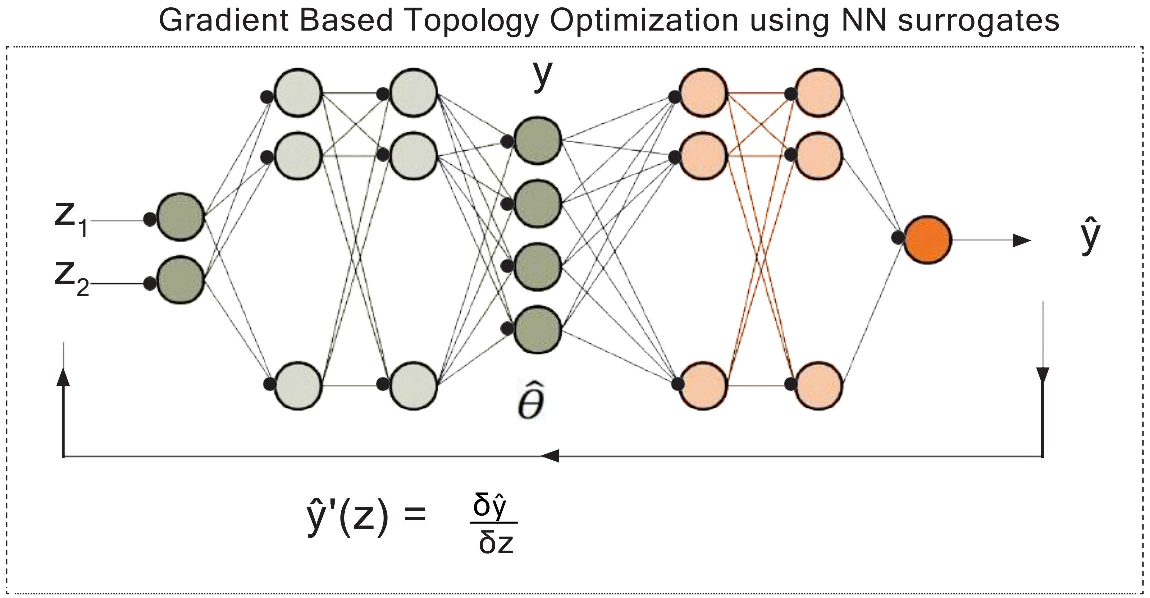
OVERALL WORKLOW

new meshes sampled

DESIRED HEIGHT ($\hat{c}$)



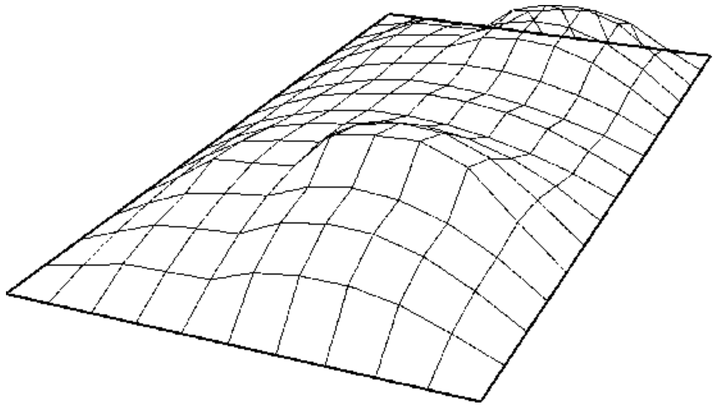


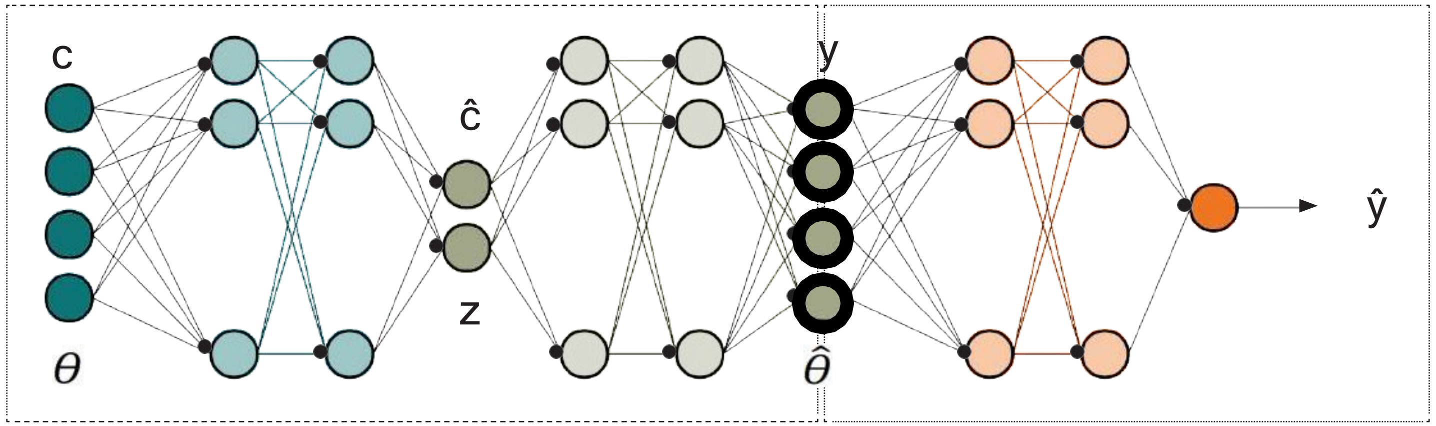


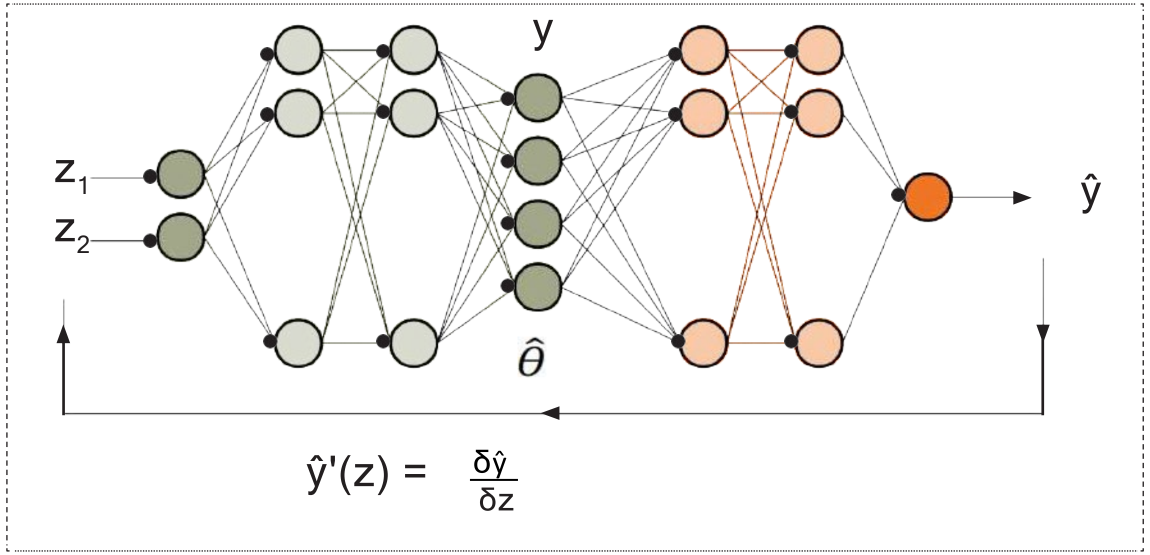
GENERATOR

OVERALL WORKLOW

decoder



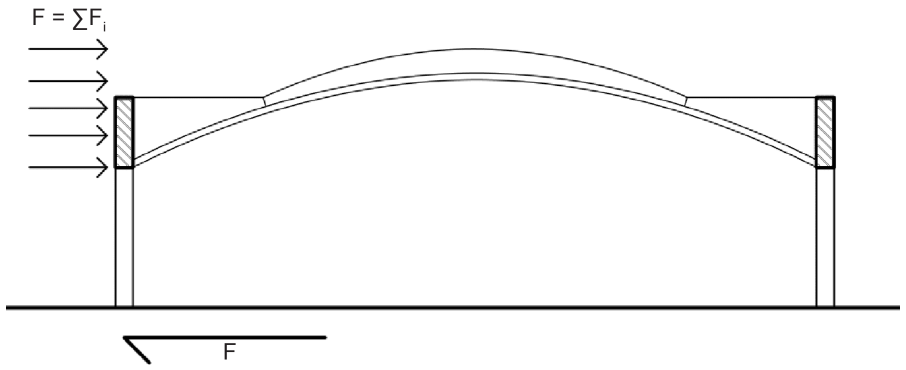


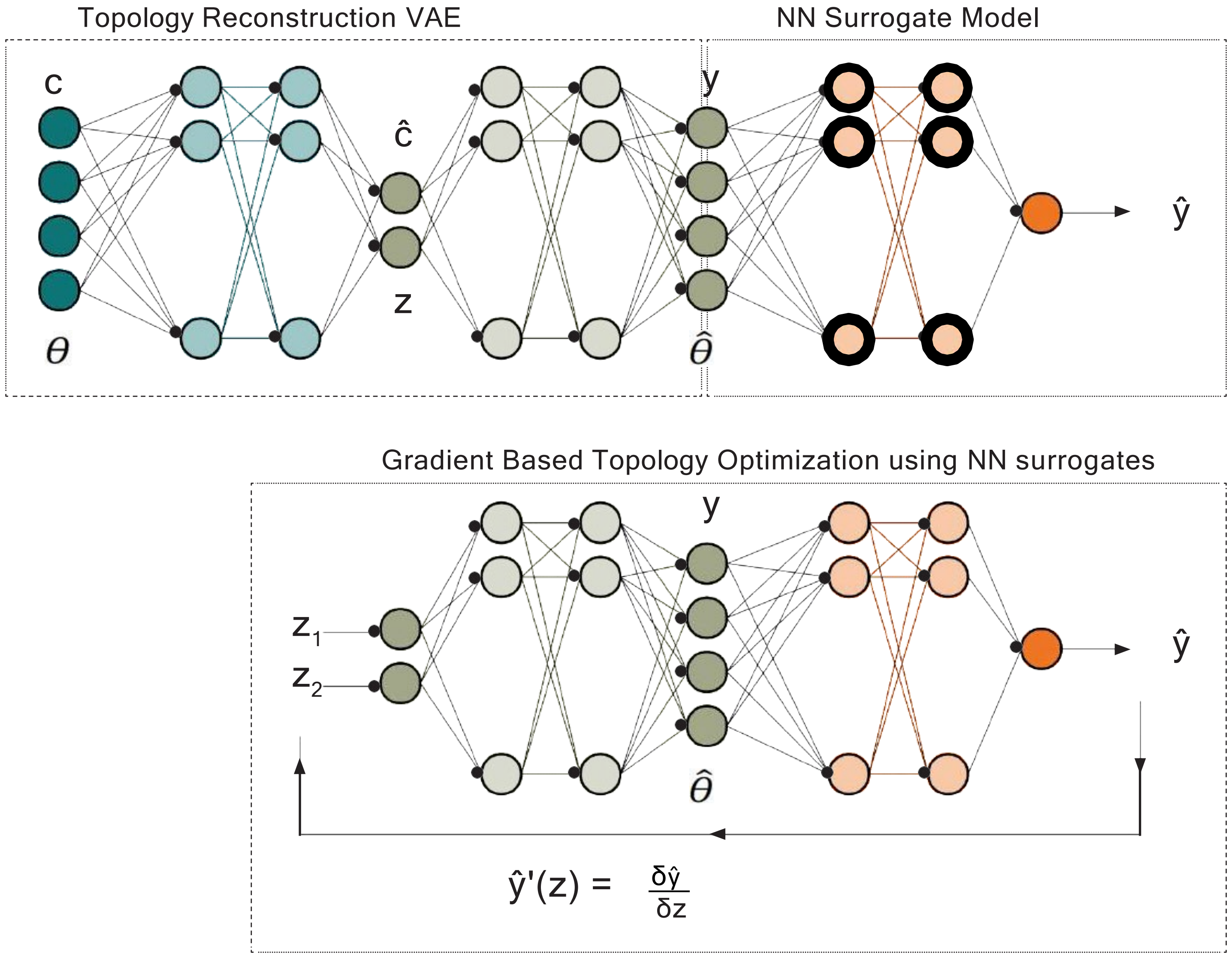


GENERATOR

OVERALL WORKLOW

prediction on seismic analysis

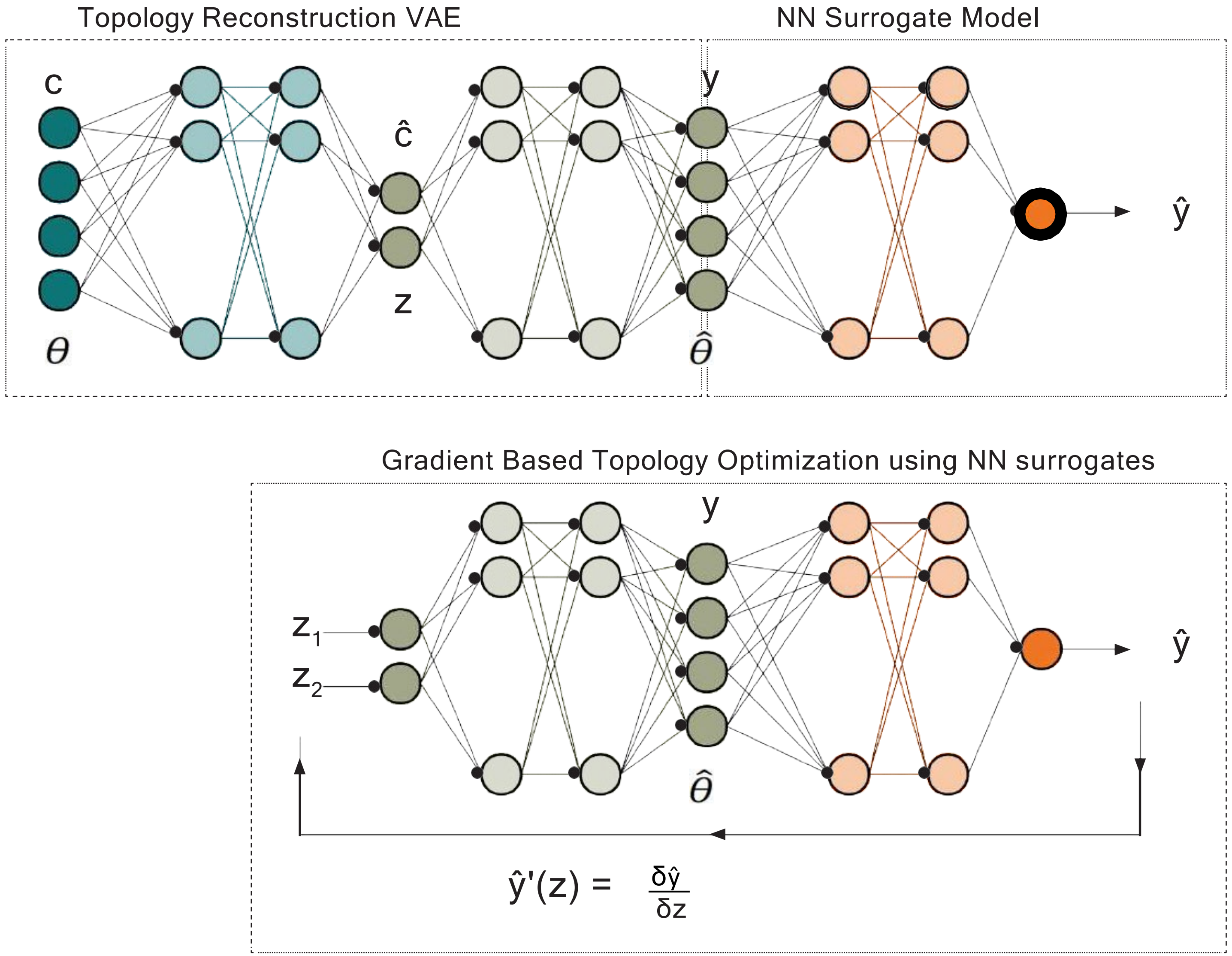




GENERATOR

OVERALL WORKLOW

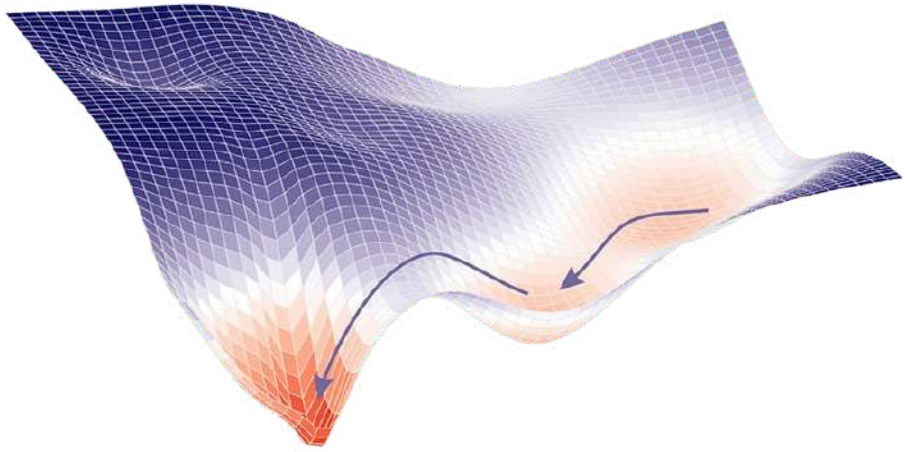
PERFORMANCE
SCORE
OF SURROGATE MODEL

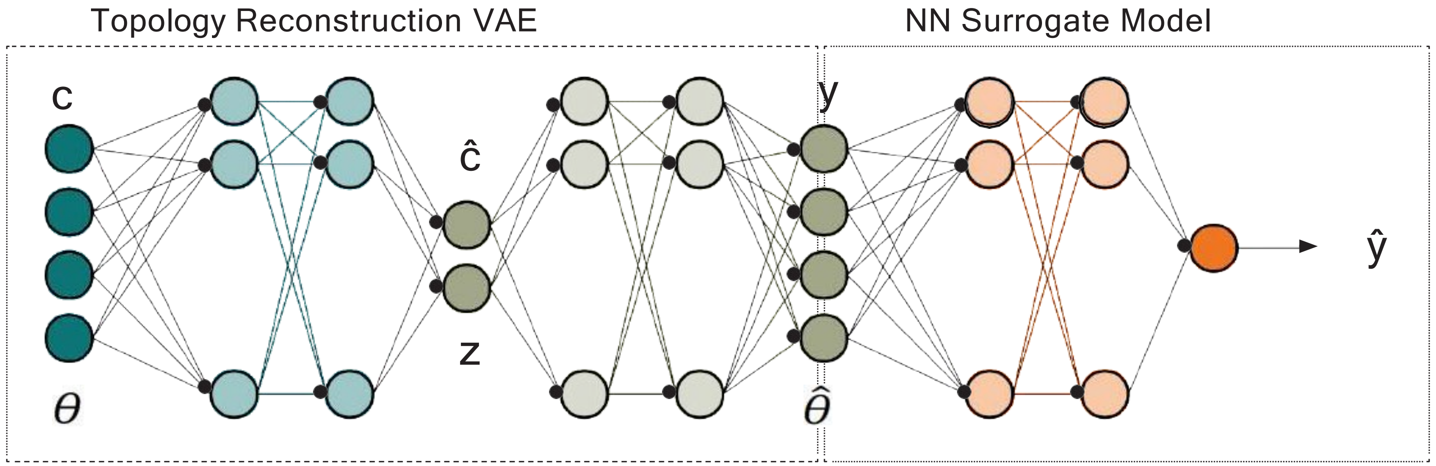


GENERATOR

OVERALL WORKLOW

optimization of mesh





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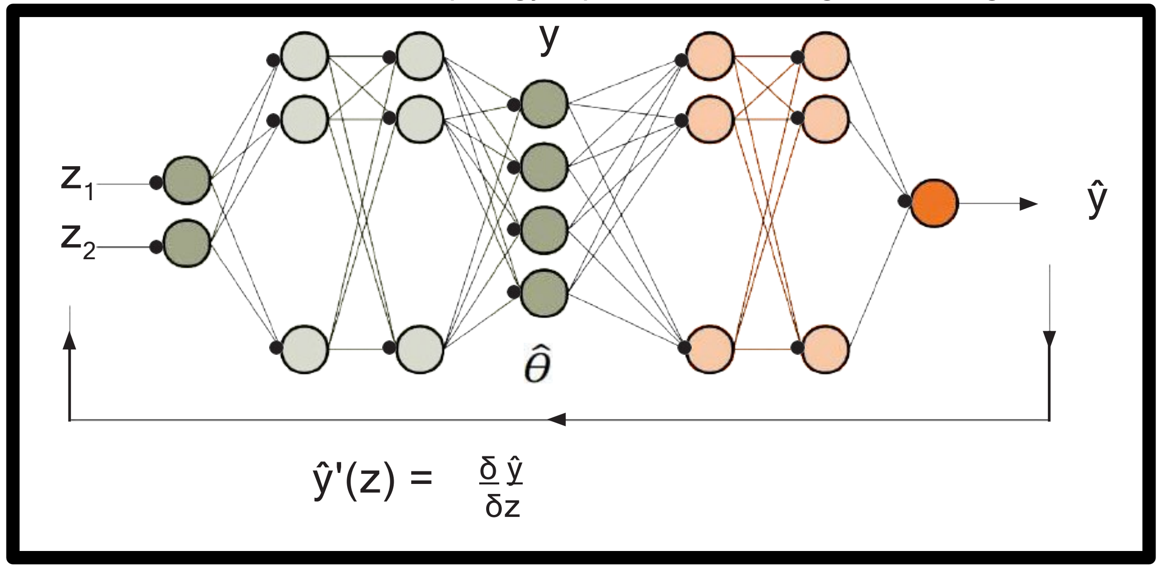
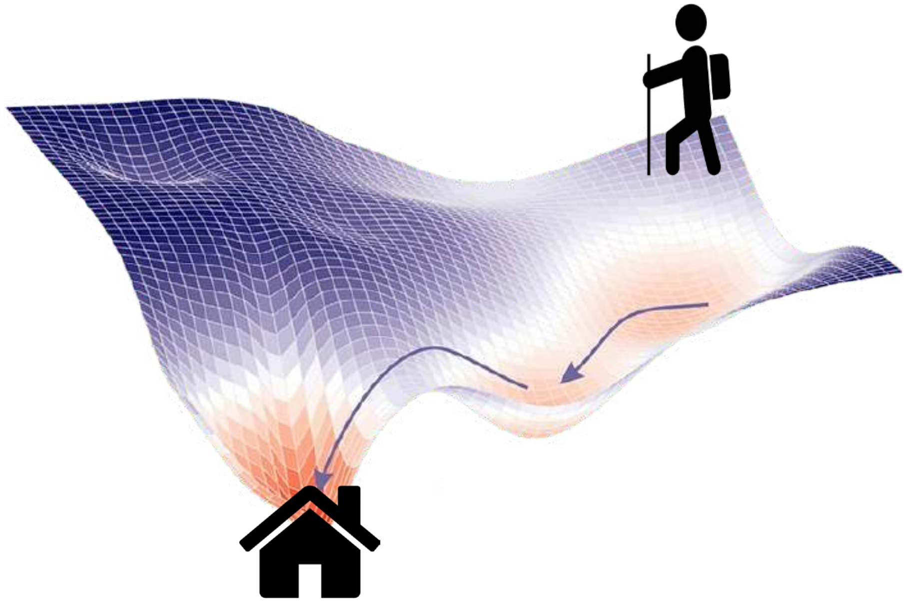


GENERATOR

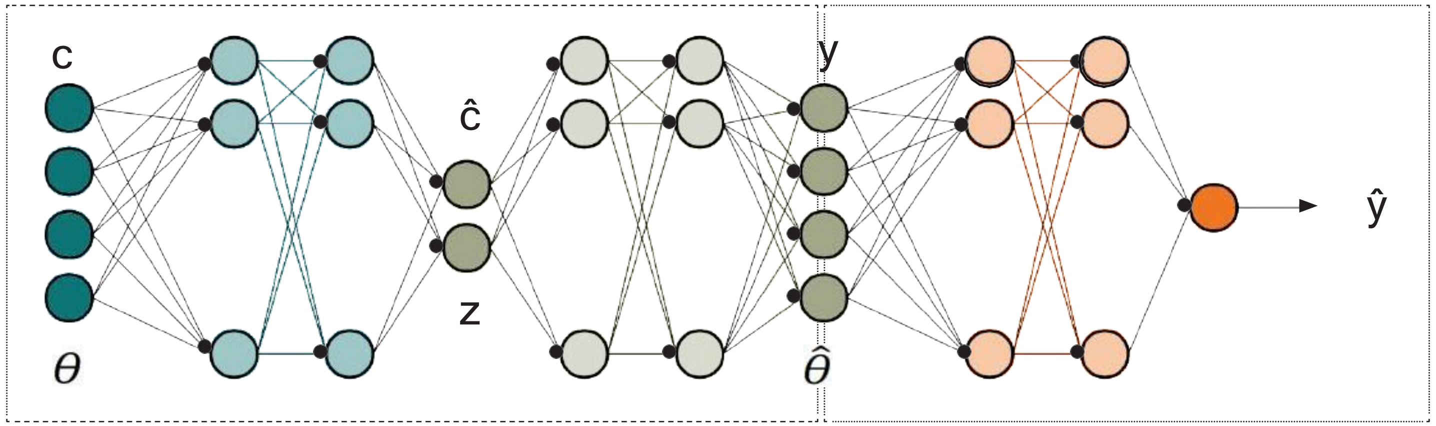
OVERALL WORKLOW

optimization of mesh

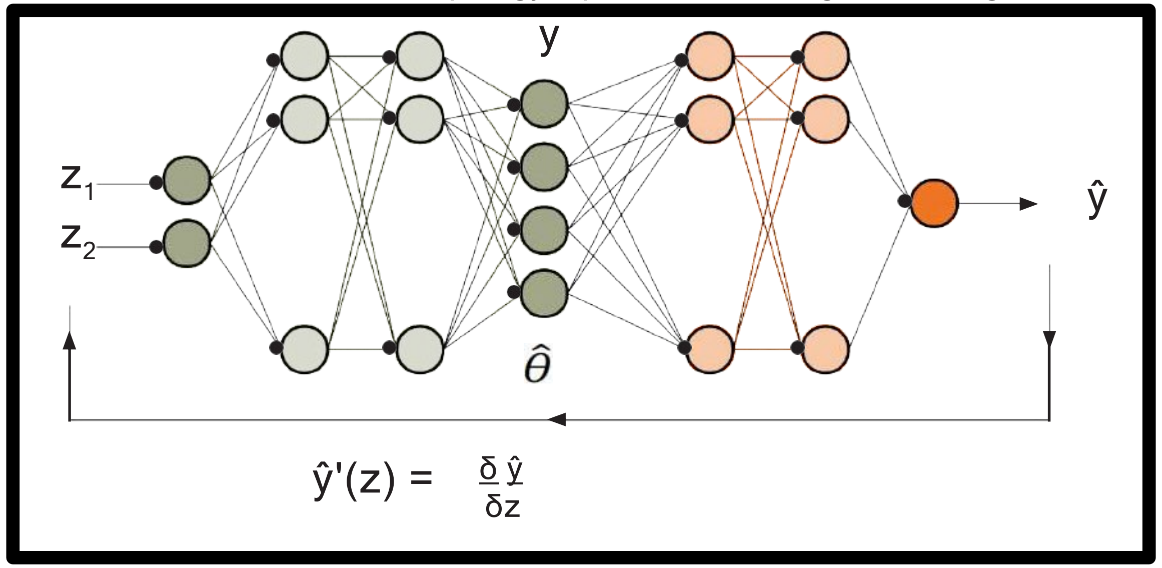


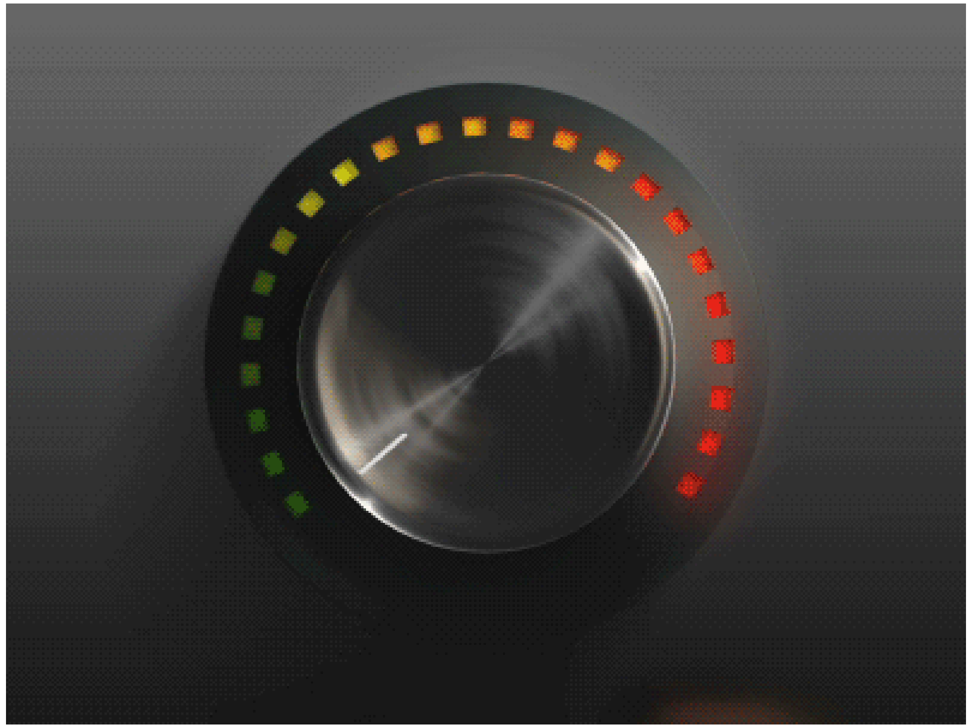
Topology Reconstruction VAE

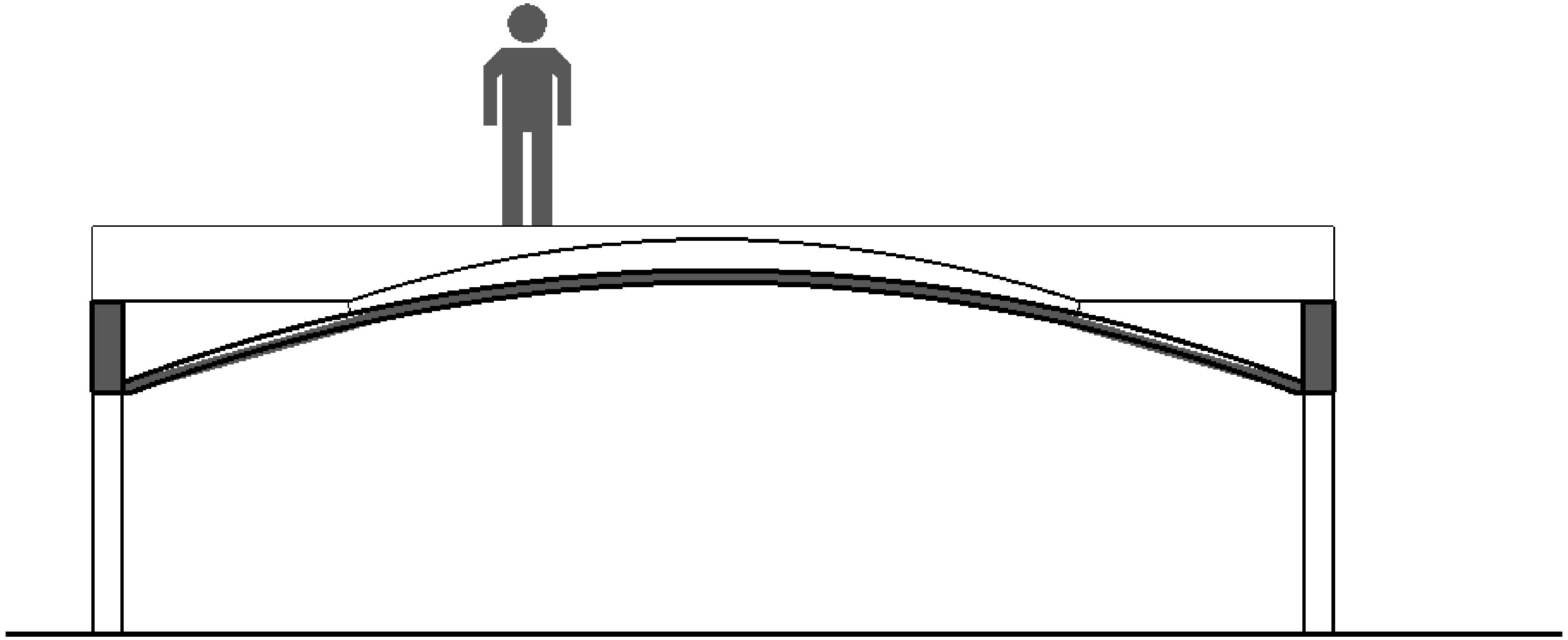
NN Surrogate Model



Gradient Based Topology Optimization using NN surrogates







GEOMETRY GENERATION

GEOMETRY GENERATION

Force Density Method

Particle Spring Systems

Dynamic Relaxation

Natural Shape Finding

Thrust Network Analysis

Surface Stress Density Method

GEOMETRY GENERATION

Force Density Method

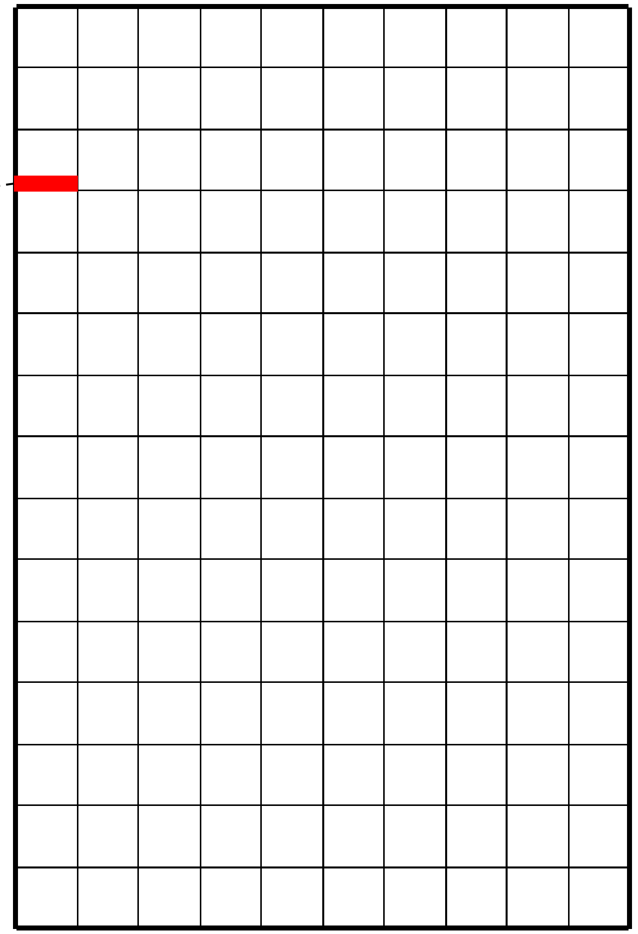
$$q = \frac{F}{L}$$

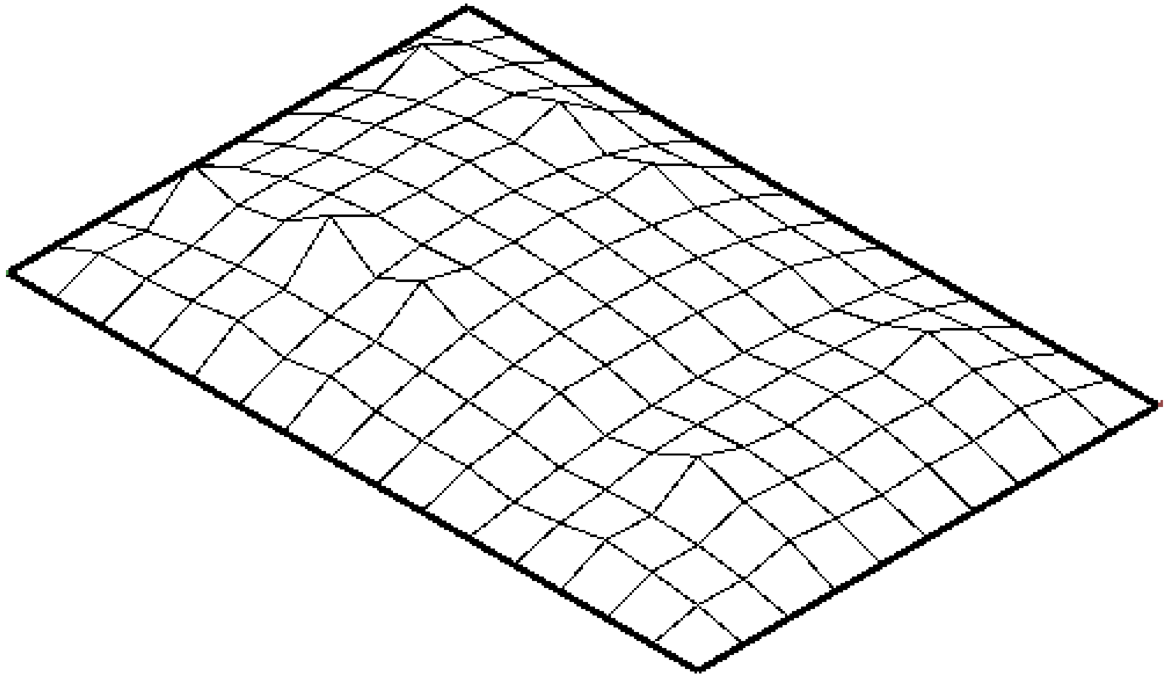
where,

$q = \mathit{Force\ Density}$

$F = \mathit{Force}$

$L = \mathit{length}$



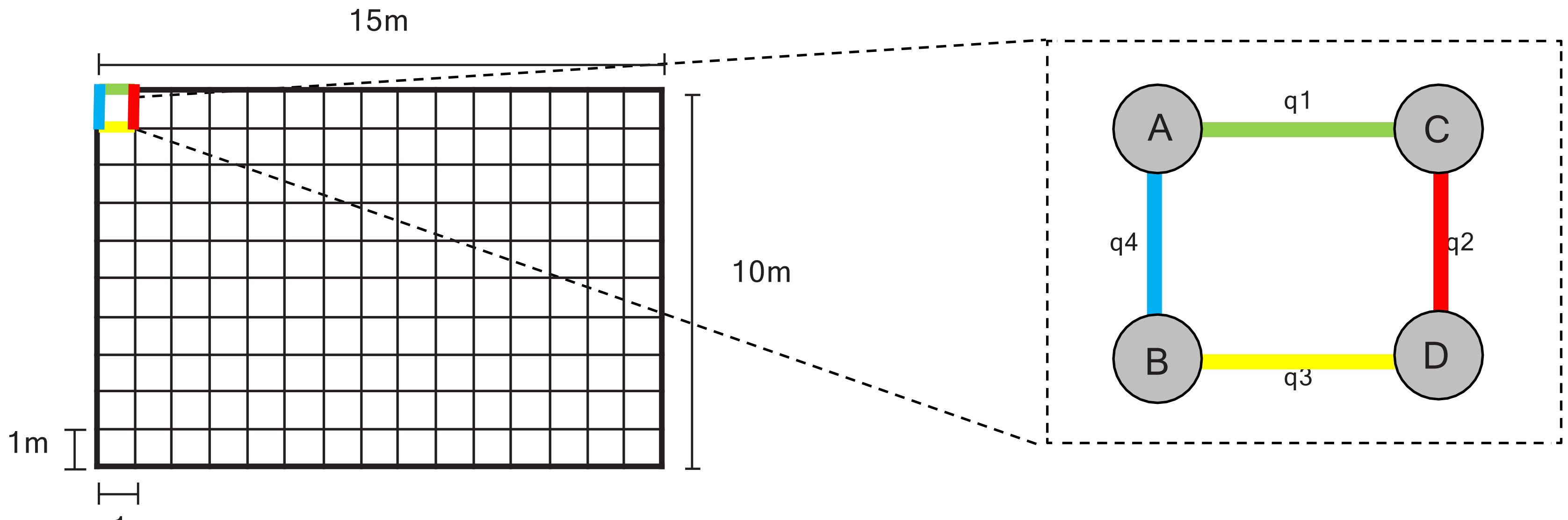


De afbeelding kan niet worden weergegeven.

HOW CAN A NEURAL NETWORK READ GEOMETRY?

DATA STRUCTURING

initial approach: ADJACENCY MATRIX



plan view of a mesh

dataset size= 10,000

176 values

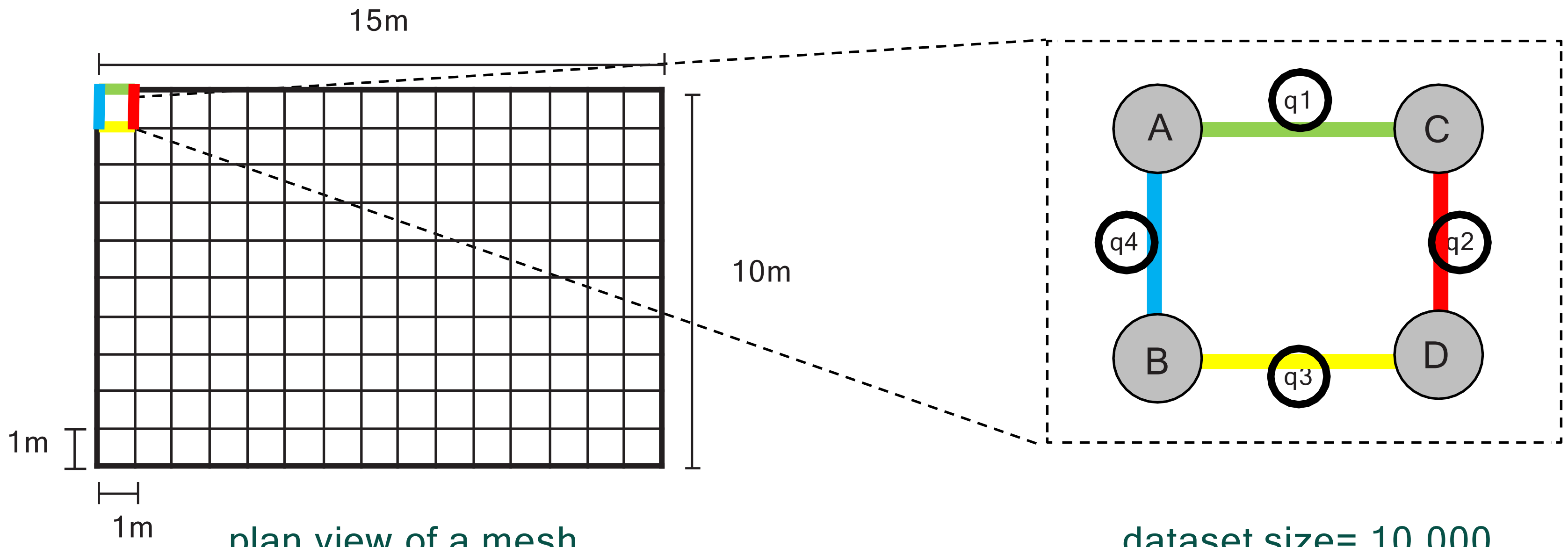
176 values

(only 4 values shown)

	A	B	C	D
A	0	q4	q1	0
B	q4	0	0	q3
C	q1	0	0	q2
D	0	q3	q2	0

DATA STRUCTURING

initial approach: ADJACENCY MATRIX



plan view of a mesh

dataset size= 10,000

176 values

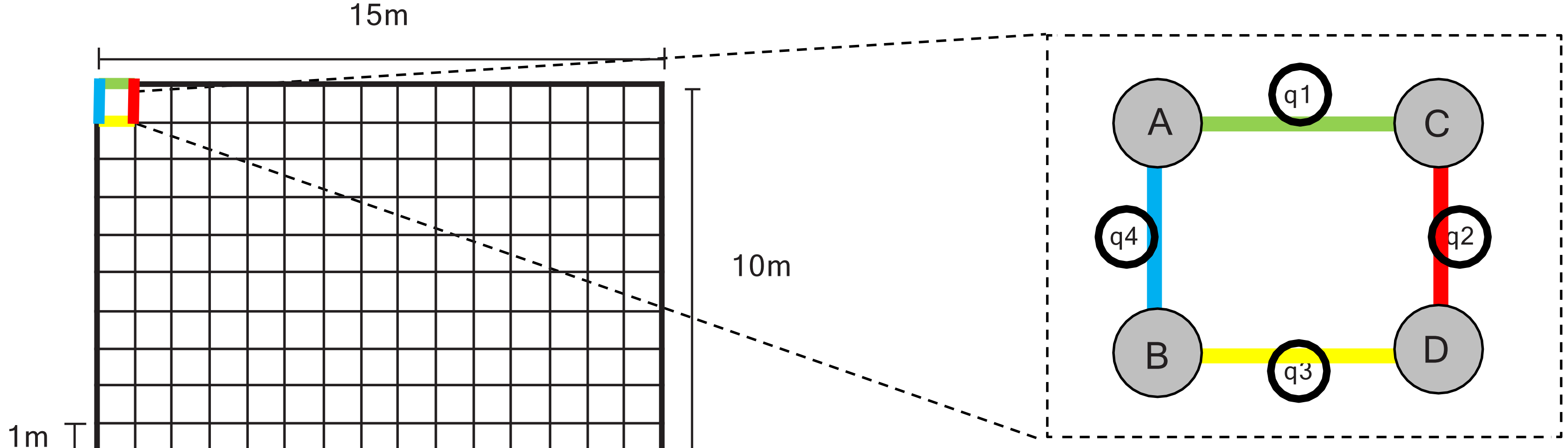
176 values

(only 4 values shown)

	A	B	C	D
A	0	q4	q1	0
B	q4	0	0	q3
C	q1	0	0	q2
D	0	q3	q2	0

DATA STRUCTURING

initial approach: ADJACENCY MATRIX



plan view of a mesh

dataset size= 10,000

176 values

176 values

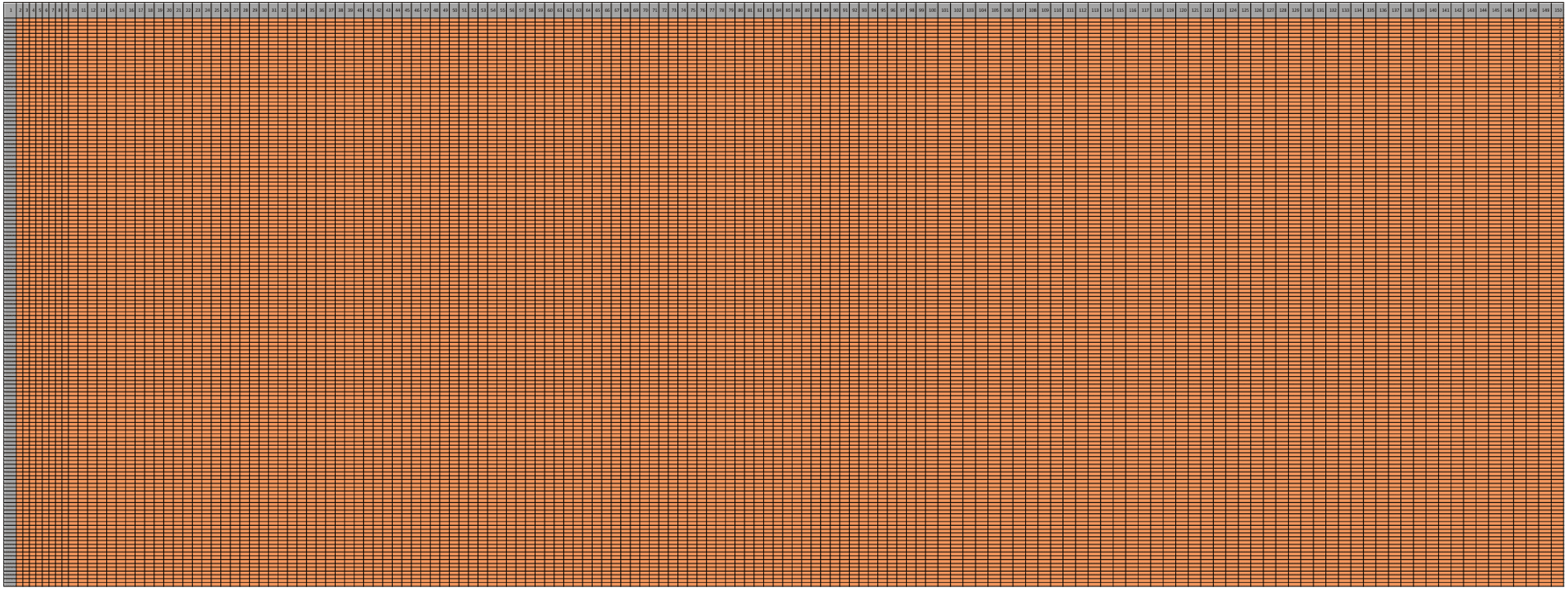
(only 4 values shown)

	A	B	C	D
A	0	q4	q1	0
B	q4	0	0	q3
C	q1	0	0	q2
D	0	q3	q2	0

DATA STRUCTURING

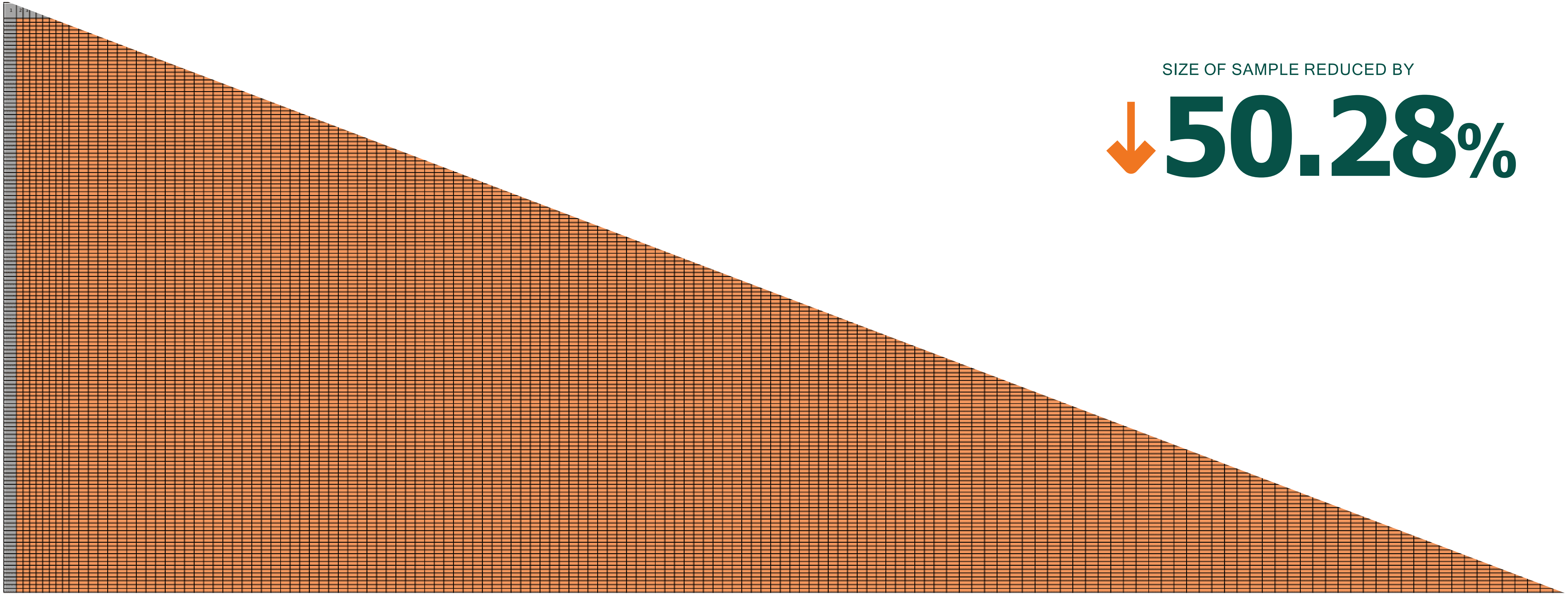
176x176 MATRIX

30,976 VALUES PER MESH



DATA STRUCTURING

15,400 VALUES PER MESH



SIZE OF SAMPLE REDUCED BY

↓50.28%

De afbeelding kan niet worden weergegeven.

27 VALUES PER MESH

SIZE OF SAMPLE REDUCED BY

↓99.82%

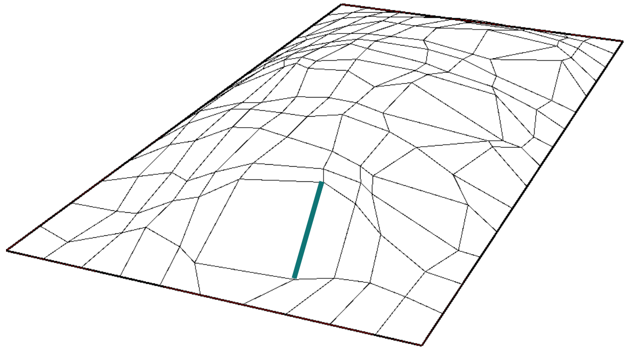
DATA STRUCTURING

polyedge = column **polyedge = row**

$$[\ [q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8, q_9, q_{10}, q_{11}],\ [q_{12}, q_{13}, q_{14}, q_{15}, q_{16}, q_{17}, q_{18}, q_{19}, q_{20}, q_{21}, q_{22}, q_{23}, q_{24}, q_{25}, q_{26}, q_{27}]\ ]$$

where,
Each value is a force density for that polyedge

1 force density value
per edge



1 force density value
per polyedge

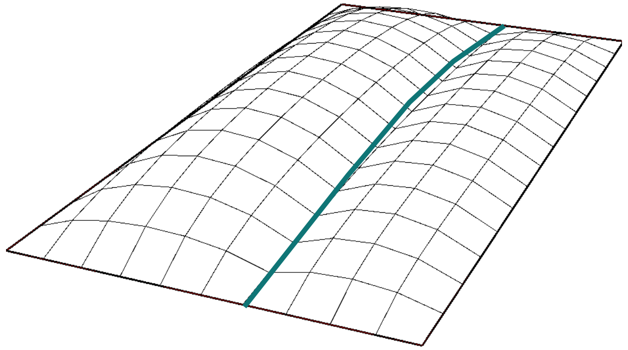
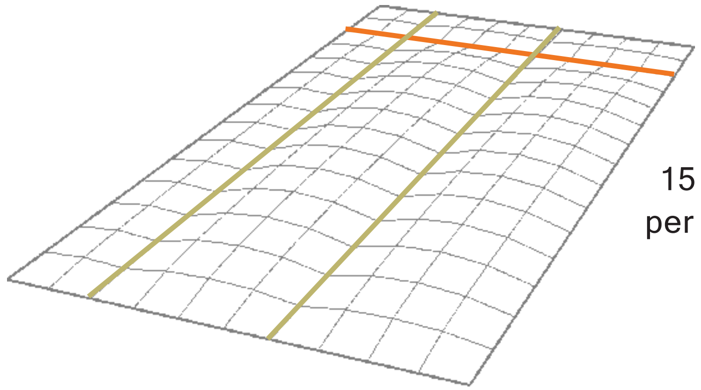


FIGURE 01: Representation of polyedges and their relationship to force densities in a creased dataset. (Own Work)

DATA STRUCTURING

polyedge = column | **polyedge = row**

$$[\ [\ q_1,\ q_2,\ q_3, q_4, q_5, q_6, q_7, q_8,\ q_9,\ q_{10},\ q_{11}]\ ,\ [q_{12}, q_{13}, q_{14},\ q_{15},\ q_{16}, q_{17}, q_{18}, q_{19}, q_{20},\ q_{21},\ q_{22},\ q_{23},\ q_{24},\ q_{25},\ q_{26},\ q_{27}\ ]\ ]$$



15 edges per column

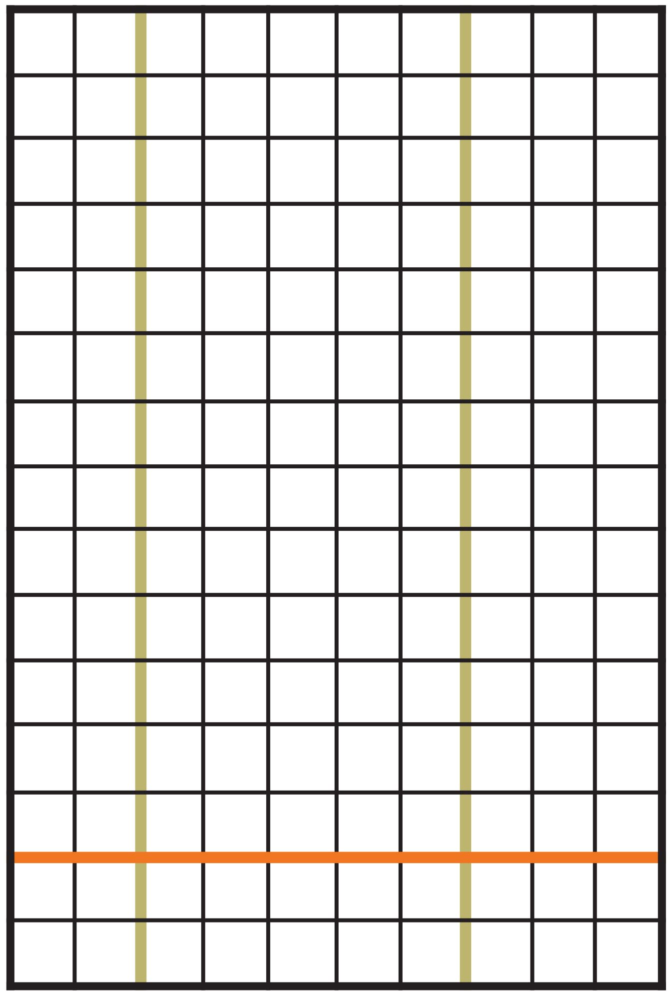
COLUMN
Individual Edge number

1	2	3	4	5	6	7	8	9	10	11
1	31	62	93	124	155	186	217	248	279	310
3	33	64	95	126	157	188	219	250	281	311
5	35	66	97	128	159	190	221	252	283	312
7	37	68	99	130	161	192	223	254	285	313
9	39	70	101	132	163	194	225	256	287	314
11	41	72	103	134	165	196	227	258	289	315
13	43	74	105	136	167	198	229	260	291	316
15	45	76	107	138	169	200	231	262	293	317
17	47	78	109	140	171	202	233	264	295	318
19	49	80	111	142	173	204	235	266	297	319
21	51	82	113	144	175	206	237	268	299	320
23	53	84	115	146	177	208	239	270	301	321
25	55	86	117	148	179	210	241	272	303	322
27	57	88	119	150	181	212	243	274	305	323
29	59	90	121	152	183	214	245	276	307	324

10 edges per row

ROW
Individual Edge number

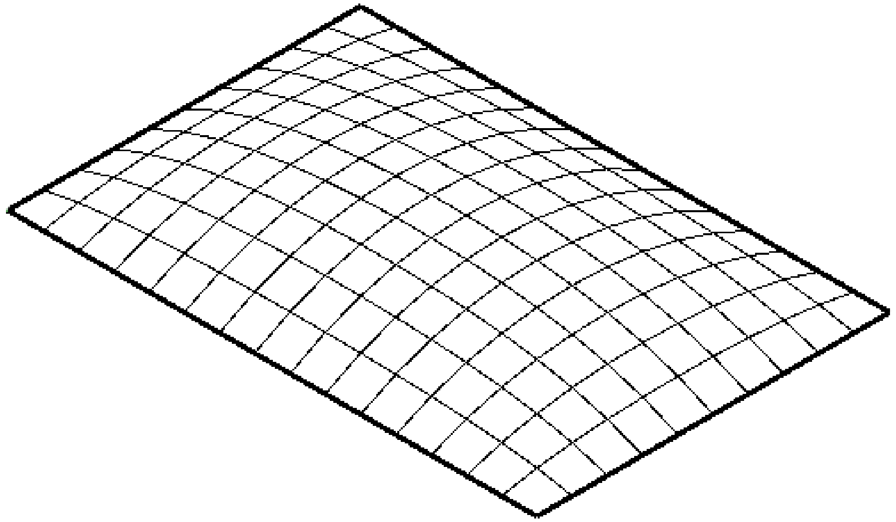
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30
32	34	36	38	40	42	44	46	48	50	52	54	56	58	60	61
63	65	67	69	71	73	75	77	79	81	83	85	87	89	91	92
94	96	98	100	102	104	106	108	110	112	114	116	118	120	122	123
125	127	129	131	133	135	137	139	141	143	145	147	149	151	153	154
156	158	160	162	164	166	168	170	172	174	176	178	180	182	184	185
187	189	191	193	195	197	199	201	203	205	207	209	211	213	215	216
218	220	222	224	226	228	230	232	234	236	238	240	242	244	246	247
249	251	253	255	257	259	261	263	265	267	269	271	273	275	277	278



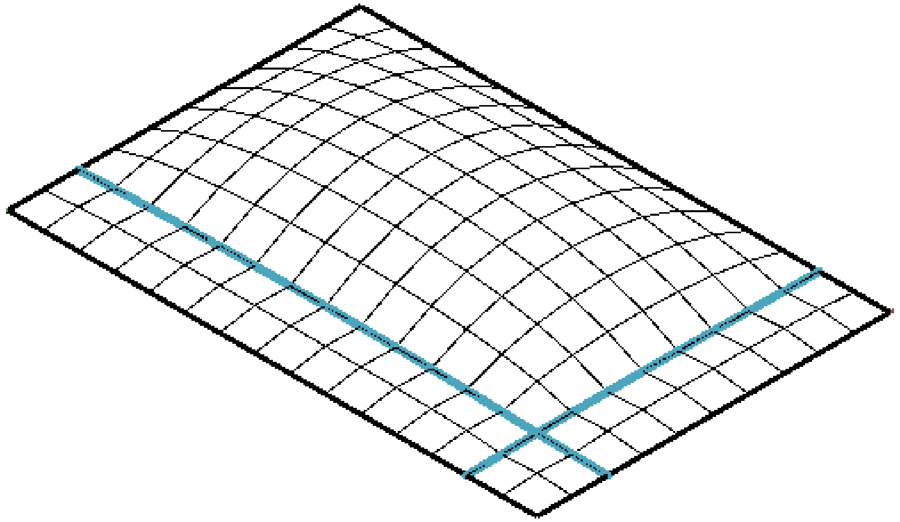
DATA STRUCTURING

DATASETS

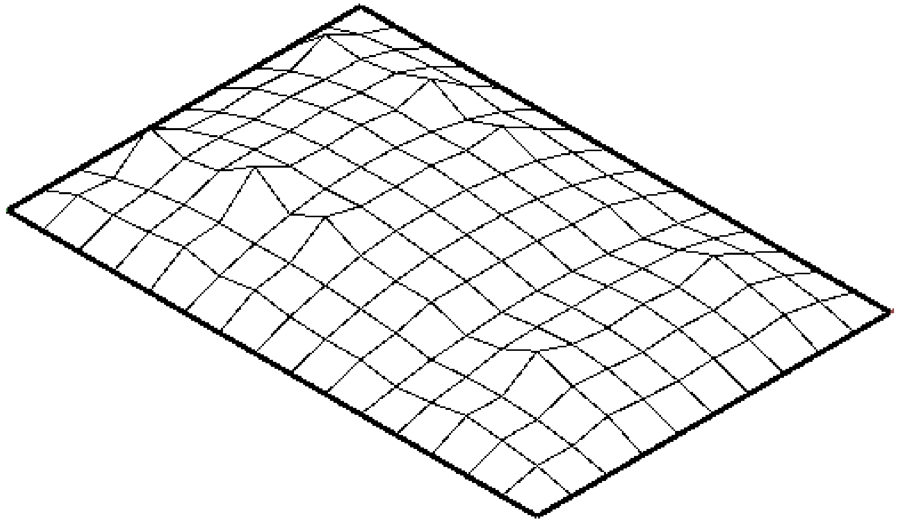
UNIFORM FORCE DENSITIES



CREASED



RANDOMIZED



WHAT IS THE EFFECT OF VARYING FORCE DENSITY?

DATA STRUCTURING

DATASET: UNIFORM FORCE DENSITIES

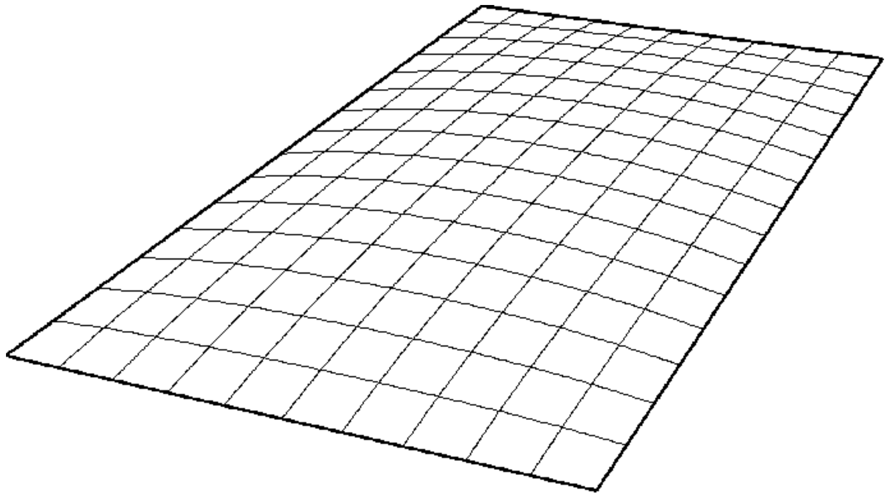
Polyedge number	Force density (q)
column_1	5
column_2	5
column_4	5
column_5	5
column_6	5
column_7	5
column_8	5
column_9	5
column_10	5
column_11	5
row_1	5
row_2	5
row_3	5
row_4	5
row_5	5
row_6	5
row_7	5
row_8	5
row_9	5
row_10	5
row_11	5
row_12	5
row_13	5
row_14	5
row_15	5
row_16	5
row_17	5

q_1
q_2
q_3
q_4
q_5
q_6
q_7
q_8
q_9
q_{10}
q_{11a}

polyedge = column

q_{12}
q_{13}
q_{14}
q_{15}
q_{16}
q_{17}
q_{18}
q_{19}
q_{20}
q_{21}
q_{22}
q_{23}
q_{24}
q_{25}
q_{26}
q_{27}
a

polyedge = row

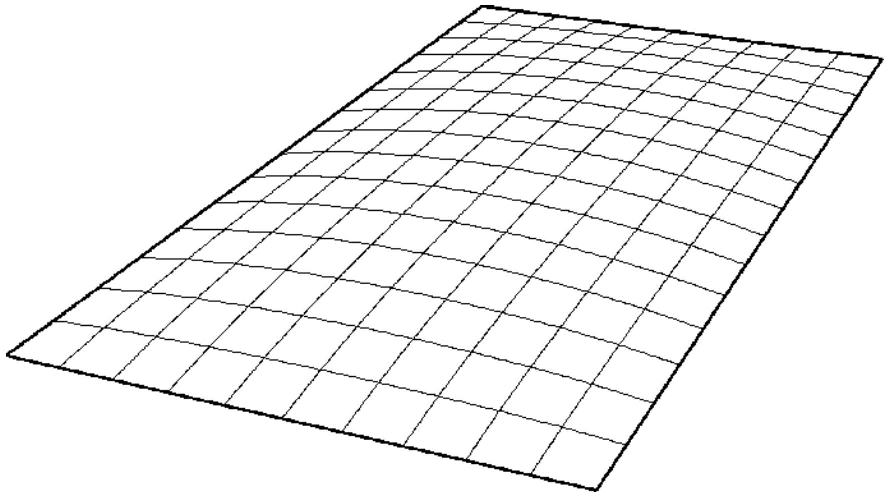


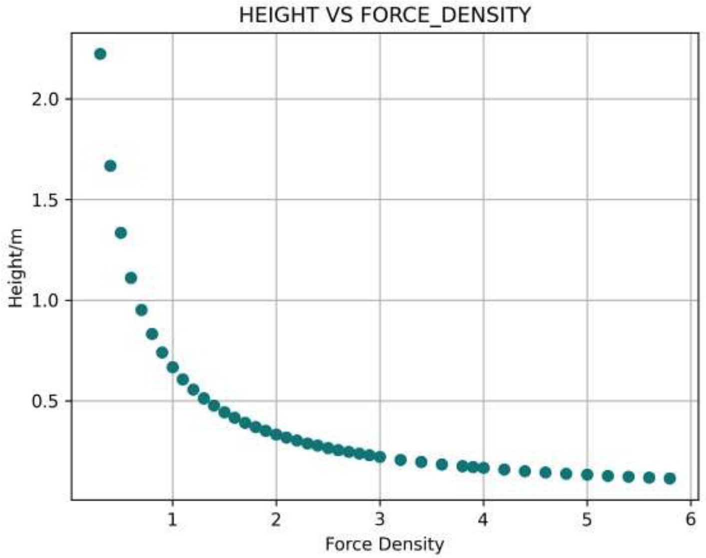
DATA STRUCTURING

DATASET: UNIFORM FORCE DENSITIES

DATASET: uniform force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	5	3	2	1	0.6	0.3
column_2	5	3	2	1	0.6	0.3
column_4	5	3	2	1	0.6	0.3
column_5	5	3	2	1	0.6	0.3
column_6	5	3	2	1	0.6	0.3
column_7	5	3	2	1	0.6	0.3
column_8	5	3	2	1	0.6	0.3
column_9	5	3	2	1	0.6	0.3
column_10	5	3	2	1	0.6	0.3
column_11	5	3	2	1	0.6	0.3
row_1	5	3	2	1	0.6	0.3
row_2	5	3	2	1	0.6	0.3
row_3	5	3	2	1	0.6	0.3
row_4	5	3	2	1	0.6	0.3
row_5	5	3	2	1	0.6	0.3
row_6	5	3	2	1	0.6	0.3
row_7	5	3	2	1	0.6	0.3
row_8	5	3	2	1	0.6	0.3
row_9	5	3	2	1	0.6	0.3
row_10	5	3	2	1	0.6	0.3
row_11	5	3	2	1	0.6	0.3
row_12	5	3	2	1	0.6	0.3
row_13	5	3	2	1	0.6	0.3
row_14	5	3	2	1	0.6	0.3
row_15	5	3	2	1	0.6	0.3
row_16	5	3	2	1	0.6	0.3
row_17	5	3	2	1	0.6	0.3

FORCE DENSITY = 5



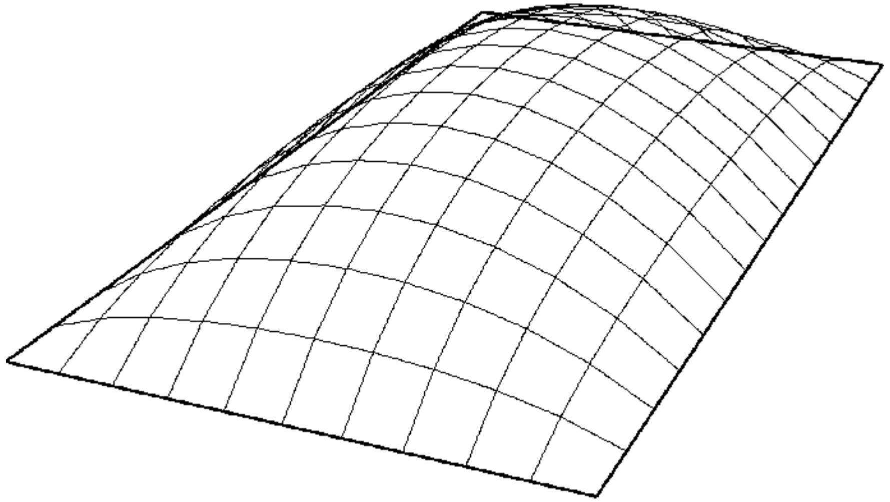


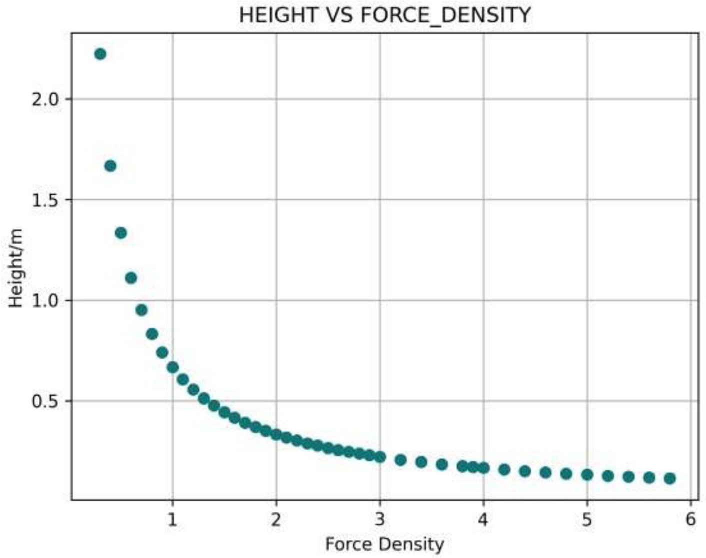
DATA STRUCTURING

DATASET: UNIFORM FORCE DENSITIES

DATASET: uniform force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	5	3	2	1	0.6	0.3
column_2	5	3	2	1	0.6	0.3
column_4	5	3	2	1	0.6	0.3
column_5	5	3	2	1	0.6	0.3
column_6	5	3	2	1	0.6	0.3
column_7	5	3	2	1	0.6	0.3
column_8	5	3	2	1	0.6	0.3
column_9	5	3	2	1	0.6	0.3
column_10	5	3	2	1	0.6	0.3
column_11	5	3	2	1	0.6	0.3
row_1	5	3	2	1	0.6	0.3
row_2	5	3	2	1	0.6	0.3
row_3	5	3	2	1	0.6	0.3
row_4	5	3	2	1	0.6	0.3
row_5	5	3	2	1	0.6	0.3
row_6	5	3	2	1	0.6	0.3
row_7	5	3	2	1	0.6	0.3
row_8	5	3	2	1	0.6	0.3
row_9	5	3	2	1	0.6	0.3
row_10	5	3	2	1	0.6	0.3
row_11	5	3	2	1	0.6	0.3
row_12	5	3	2	1	0.6	0.3
row_13	5	3	2	1	0.6	0.3
row_14	5	3	2	1	0.6	0.3
row_15	5	3	2	1	0.6	0.3
row_16	5	3	2	1	0.6	0.3
row_17	5	3	2	1	0.6	0.3

FORCE DENSITY = 1



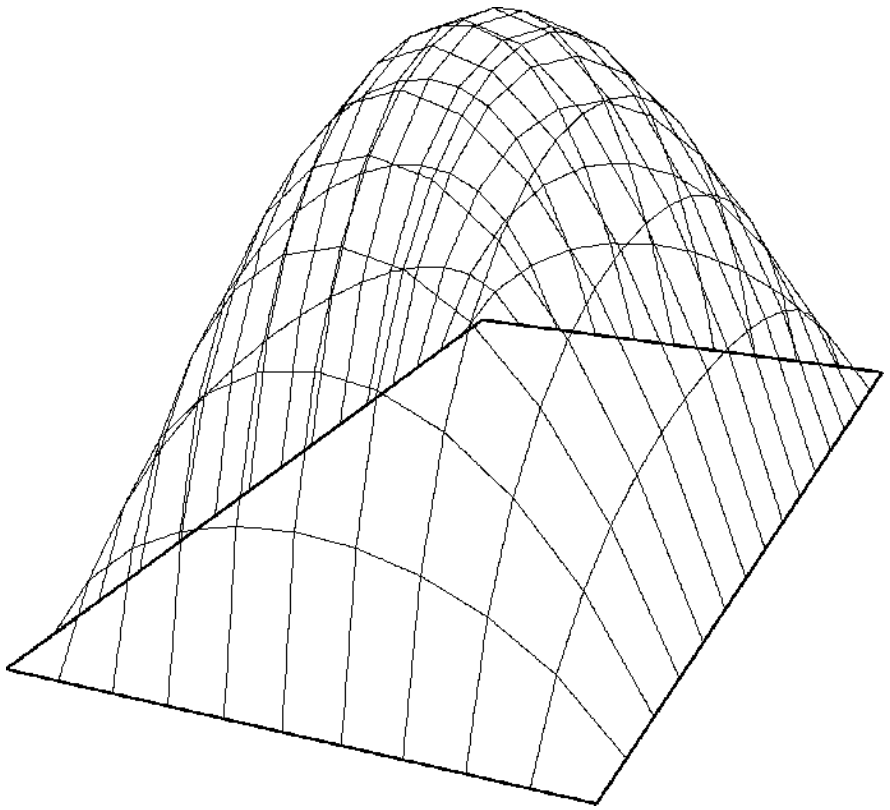


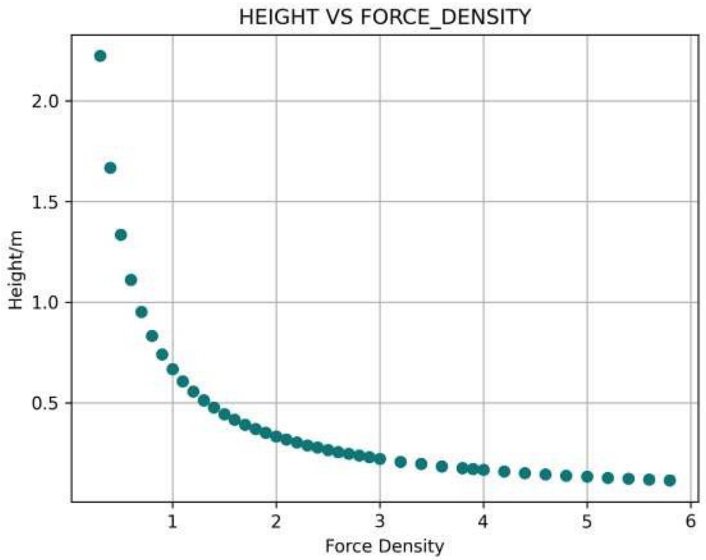
DATA STRUCTURING

DATASET: UNIFORM FORCE DENSITIES

DATASET: uniform force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	5	3	2	1	0.6	0.3
column_2	5	3	2	1	0.6	0.3
column_4	5	3	2	1	0.6	0.3
column_5	5	3	2	1	0.6	0.3
column_6	5	3	2	1	0.6	0.3
column_7	5	3	2	1	0.6	0.3
column_8	5	3	2	1	0.6	0.3
column_9	5	3	2	1	0.6	0.3
column_10	5	3	2	1	0.6	0.3
column_11	5	3	2	1	0.6	0.3
row_1	5	3	2	1	0.6	0.3
row_2	5	3	2	1	0.6	0.3
row_3	5	3	2	1	0.6	0.3
row_4	5	3	2	1	0.6	0.3
row_5	5	3	2	1	0.6	0.3
row_6	5	3	2	1	0.6	0.3
row_7	5	3	2	1	0.6	0.3
row_8	5	3	2	1	0.6	0.3
row_9	5	3	2	1	0.6	0.3
row_10	5	3	2	1	0.6	0.3
row_11	5	3	2	1	0.6	0.3
row_12	5	3	2	1	0.6	0.3
row_13	5	3	2	1	0.6	0.3
row_14	5	3	2	1	0.6	0.3
row_15	5	3	2	1	0.6	0.3
row_16	5	3	2	1	0.6	0.3
row_17	5	3	2	1	0.6	0.3

FORCE DENSITY = 0.3

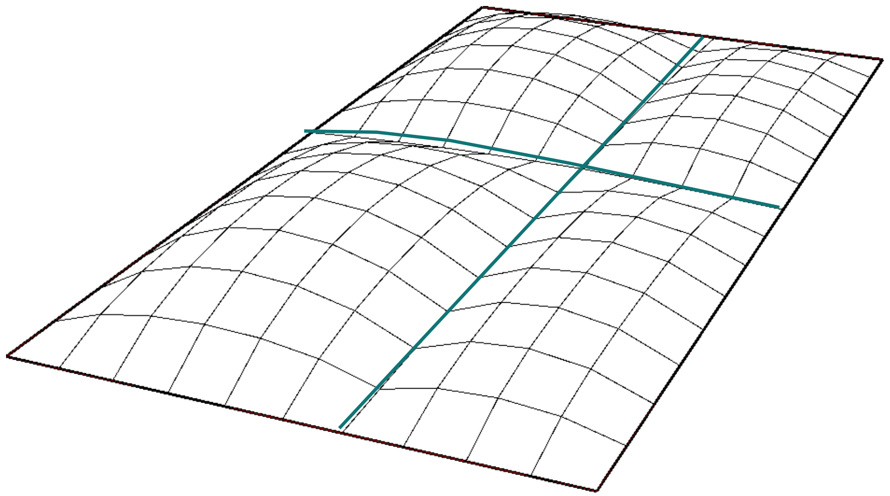




DATA STRUCTURING

DATASET: CREASED FORCE DENSITIES

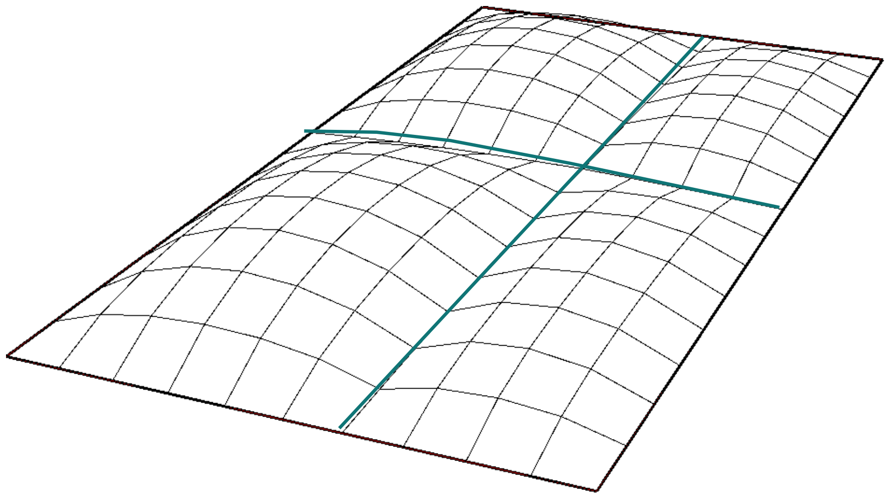
DATASET: creased force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	1	1	1	1	1	1
column_2	1	1	1	1	1	1
column_4	1	1	1	137	137	170
column_5	1	1	1	1	1	1
column_6	1	1	94	1	1	1
column_7	118	100	1	1	1	1
column_8	1	1	1	127	1	1
column_9	1	120	1	1	147	1
column_10	1	1	1	1	1	140
column_11	1	1	1	1	1	1
row_1	1	1	1	1	1	1
row_2	1	1	1	1	1	1
row_3	1	1	1	1	1	1
row_4	1	1	93	1	198	93
row_5	1	1	1	1	1	1
row_6	1	1	1	1	1	1
row_7	1	1	1	1	1	1
row_8	95	131	1	1	1	1
row_9	1	1	1	1	1	1
row_10	1	1	1	1	1	1
row_11	1	1	1	1	1	1
row_12	1	1	1	217	1	1
row_13	1	1	1	1	1	1
row_14	1	96	1	1	1	1
row_15	1	1	1	1	1	1
row_16	1	1	1	1	1	1
row_17	1	1	1	1	1	1



DATA STRUCTURING

DATASET: CREASED FORCE DENSITIES

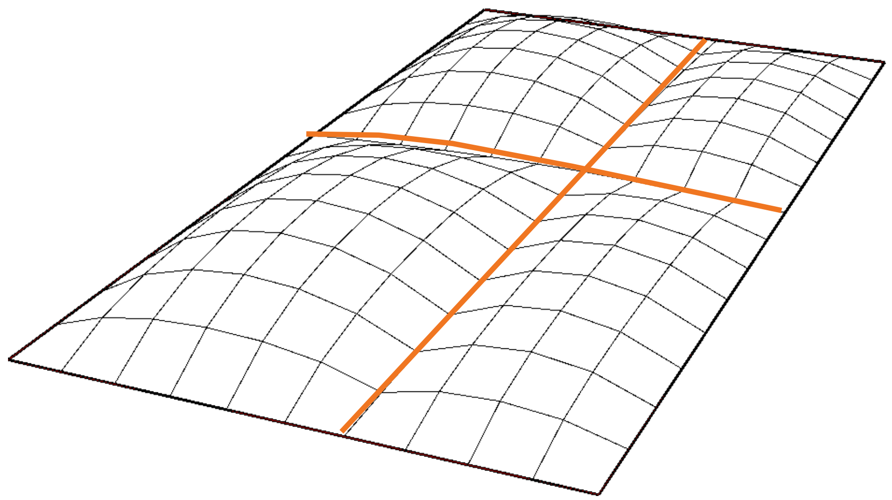
DATASET: creased force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	1	1	1	1	1	1
column_2	1	1	1	1	1	1
column_4	1	1	1	137	137	170
column_5	1	1	1	1	1	1
column_6	1	1	94	1	1	1
column_7	118	100	1	1	1	1
column_8	1	1	1	127	1	1
column_9	1	120	1	1	147	1
column_10	1	1	1	1	1	140
column_11	1	1	1	1	1	1
row_1	1	1	1	1	1	1
row_2	1	1	1	1	1	1
row_3	1	1	1	1	1	1
row_4	1	1	93	1	198	93
row_5	1	1	1	1	1	1
row_6	1	1	1	1	1	1
row_7	1	1	1	1	1	1
row_8	95	131	1	1	1	1
row_9	1	1	1	1	1	1
row_10	1	1	1	1	1	1
row_11	1	1	1	1	1	1
row_12	1	1	1	217	1	1
row_13	1	1	1	1	1	1
row_14	1	96	1	1	1	1
row_15	1	1	1	1	1	1
row_16	1	1	1	1	1	1
row_17	1	1	1	1	1	1



DATA STRUCTURING

DATASET: CREASED FORCE DENSITIES

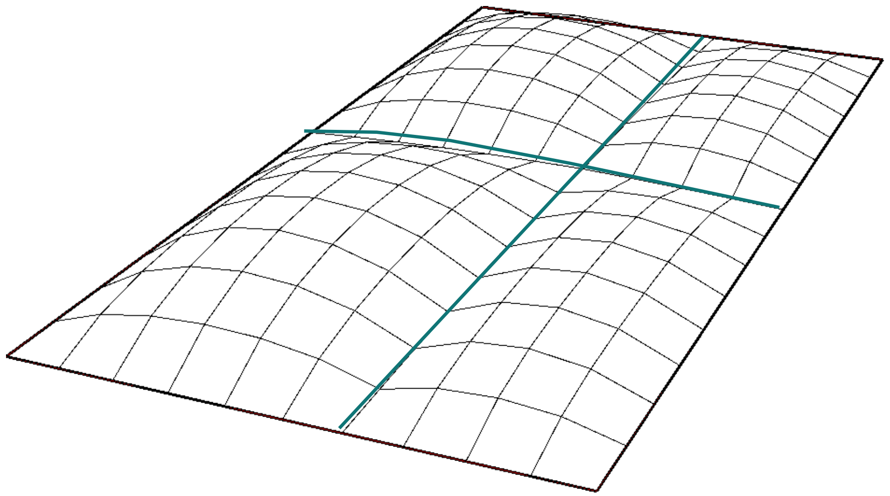
DATASET: creased force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	1	1	1	1	1	1
column_2	1	1	1	1	1	1
column_4	1	1	1	137	137	170
column_5	1	1	1	1	1	1
column_6	1	1	94	1	1	1
column_7	118	100	1	1	1	1
column_8	1	1	1	127	1	1
column_9	1	120	1	1	147	1
column_10	1	1	1	1	1	140
column_11	1	1	1	1	1	1
row_1	1	1	1	1	1	1
row_2	1	1	1	1	1	1
row_3	1	1	1	1	1	1
row_4	1	1	93	1	198	93
row_5	1	1	1	1	1	1
row_6	1	1	1	1	1	1
row_7	1	1	1	1	1	1
row_8	95	131	1	1	1	1
row_9	1	1	1	1	1	1
row_10	1	1	1	1	1	1
row_11	1	1	1	1	1	1
row_12	1	1	1	217	1	1
row_13	1	1	1	1	1	1
row_14	1	96	1	1	1	1
row_15	1	1	1	1	1	1
row_16	1	1	1	1	1	1
row_17	1	1	1	1	1	1

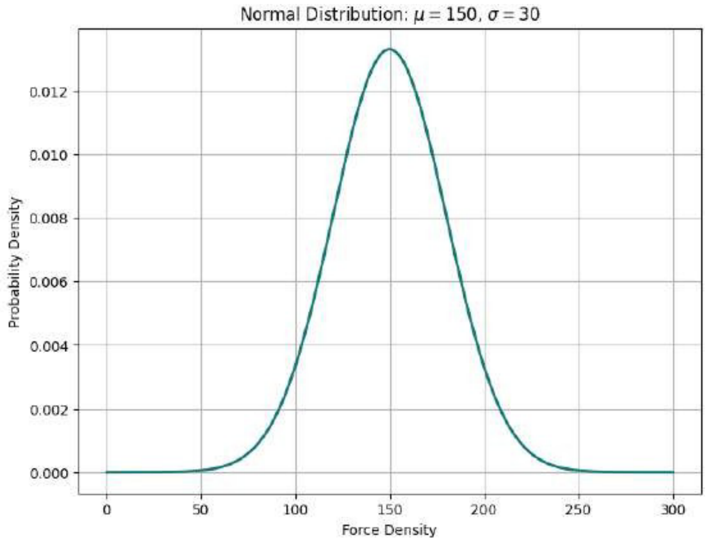


DATA STRUCTURING

DATASET: CREASED FORCE DENSITIES

DATASET: creased force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	1	1	1	1	1	1
column_2	1	1	1	1	1	1
column_4	1	1	1	137	137	170
column_5	1	1	1	1	1	1
column_6	1	1	94	1	1	1
column_7	118	100	1	1	1	1
column_8	1	1	1	127	1	1
column_9	1	120	1	1	147	1
column_10	1	1	1	1	1	140
column_11	1	1	1	1	1	1
row_1	1	1	1	1	1	1
row_2	1	1	1	1	1	1
row_3	1	1	1	1	1	1
row_4	1	1	93	1	198	93
row_5	1	1	1	1	1	1
row_6	1	1	1	1	1	1
row_7	1	1	1	1	1	1
row_8	95	131	1	1	1	1
row_9	1	1	1	1	1	1
row_10	1	1	1	1	1	1
row_11	1	1	1	1	1	1
row_12	1	1	1	217	1	1
row_13	1	1	1	1	1	1
row_14	1	96	1	1	1	1
row_15	1	1	1	1	1	1
row_16	1	1	1	1	1	1
row_17	1	1	1	1	1	1



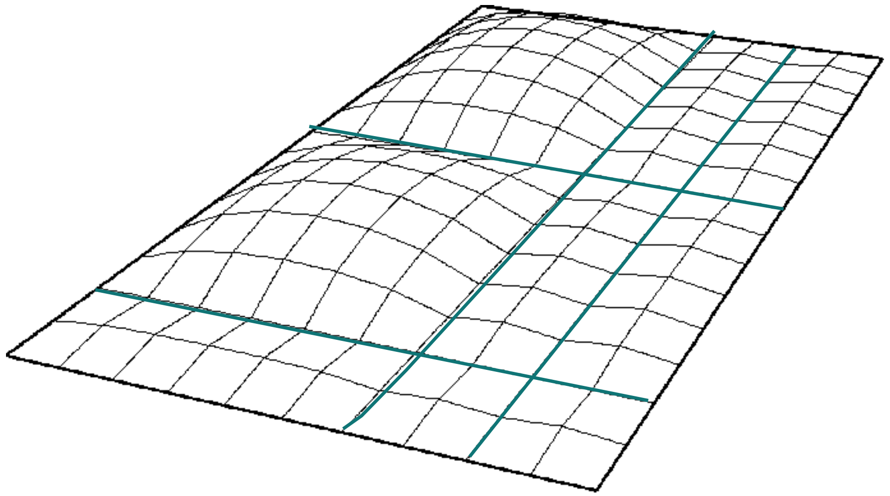


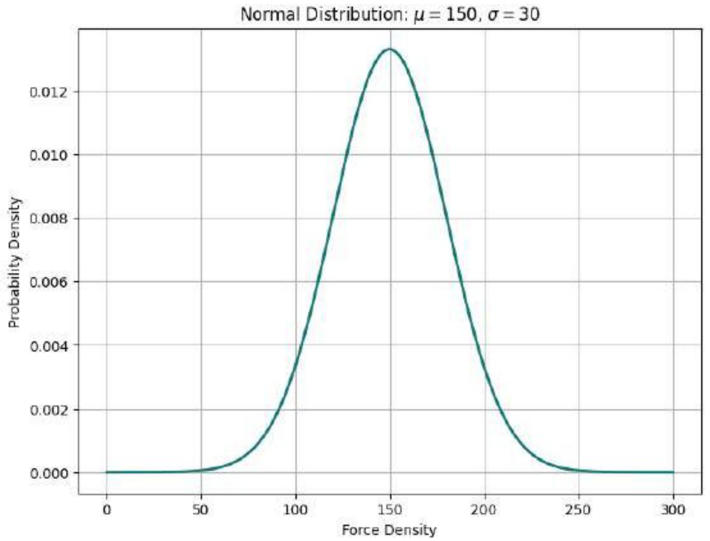
load = 35.0
μ = 150
σ = 30

DATA STRUCTURING

DATASET: CREASED FORCE DENSITIES

DATASET: creased force densities						
Edge number	mesh number					
	0	1	2	3	4	5
column_1	1	1	1	1	1	1
column_2	1	1	1	1	1	1
column_4	1	1	1	137	137	170
column_5	1	1	1	1	1	1
column_6	1	1	94	1	1	1
column_7	118	100	1	1	1	1
column_8	1	1	1	127	1	1
column_9	1	120	1	1	147	1
column_10	1	1	1	1	1	140
column_11	1	1	1	1	1	1
row_1	1	1	1	1	1	1
row_2	1	1	1	1	1	1
row_3	1	1	1	1	1	1
row_4	1	1	93	1	198	93
row_5	1	1	1	1	1	1
row_6	1	1	1	1	1	1
row_7	1	1	1	1	1	1
row_8	95	131	1	1	1	1
row_9	1	1	1	1	1	1
row_10	1	1	1	1	1	1
row_11	1	1	1	1	1	1
row_12	1	1	1	217	1	1
row_13	1	1	1	1	1	1
row_14	1	96	1	1	1	1
row_15	1	1	1	1	1	1
row_16	1	1	1	1	1	1
row_17	1	1	1	1	1	1



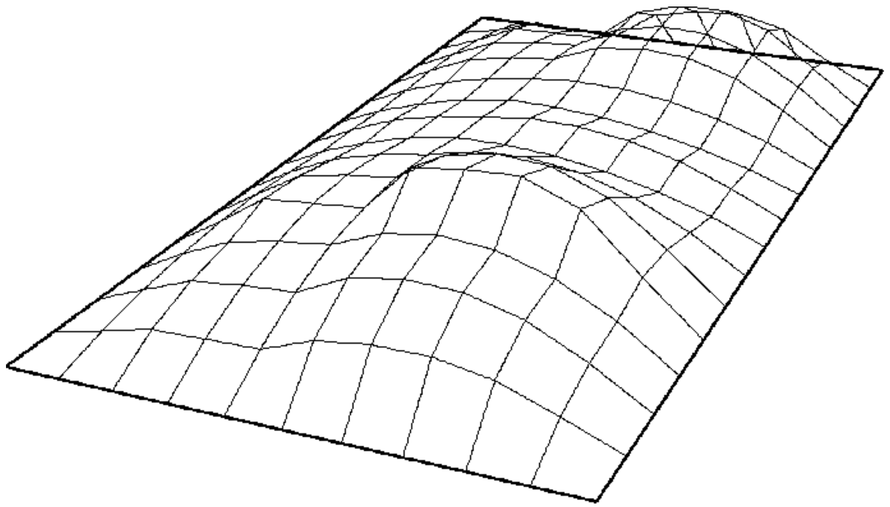


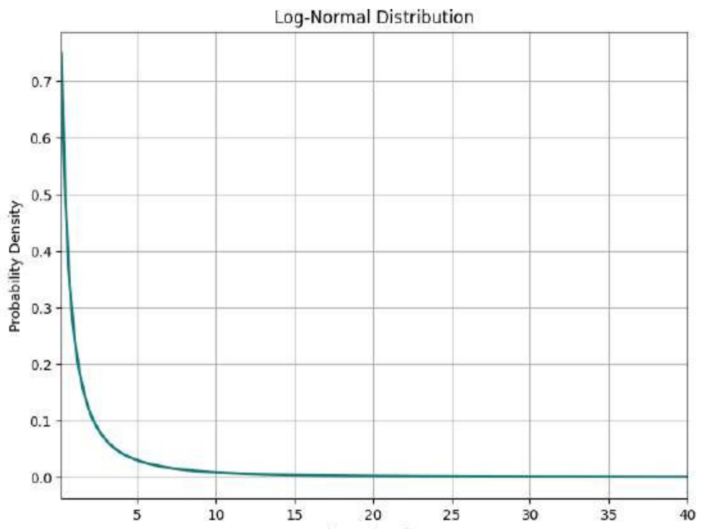
load = 35.0
μ = 150
σ = 30

DATA STRUCTURING

DATASET: RANDOMIZED FORCE DENSITIES

DATASET: randomized force densities						
Edge number	mesh number					
	6	10	12	20	30	40
column_1	0.1	6.3	2.6	2.1	0.5	0.2
column_2	1.1	0.8	0.1	1.3	2	0.1
column_4	0.2	0.6	1.1	0.2	1.7	1.4
column_5	0.2	0.5	0.5	0.3	9.9	5.5
column_6	0.3	3.1	1	0.1	0.5	4.4
column_7	0.2	6	0.3	1.5	7	1
column_8	4.6	0.4	1	0.2	8	10
column_9	1.9	1.3	0.4	2.9	2.2	0.3
column_10	0.6	4.1	1	1.4	0.9	8.5
column_11	4.3	3.7	0.6	0.1	0.2	1.4
row_1	10	1.7	12.3	3.9	0.8	6.6
row_2	1.9	0.9	3	0.5	3	1.7
row_3	0.3	0.3	0.2	1.4	0.7	2.3
row_4	0.4	0.4	0.1	0.6	1	1.6
row_5	1	6.5	0.4	3.3	0.7	0.8
row_6	0.8	1.6	1.2	0.1	0.1	0.1
row_7	3.2	0.6	1.1	0.2	4.9	0.3
row_8	5.3	1	0.8	0.5	0.3	0.1
row_9	1.4	0.9	12.1	0.3	5.2	0.6
row_10	4.7	0.4	0.4	1.3	0.2	0.8
row_11	1.6	2.2	4.2	0.9	0.9	0.4
row_12	0.6	0.1	7.1	2.1	1.2	0.1
row_13	0.1	0.2	1.2	0.1	0.4	0.2
row_14	1.6	0.1	0.2	0.6	1.2	14.5
row_15	0.8	2	3.6	0.2	1.4	2.5
row_16	0.8	1	1	0.1	2.8	0.6
row_17	0.1	2.2	0.7	1.5	1.1	0.9





load = 40.0

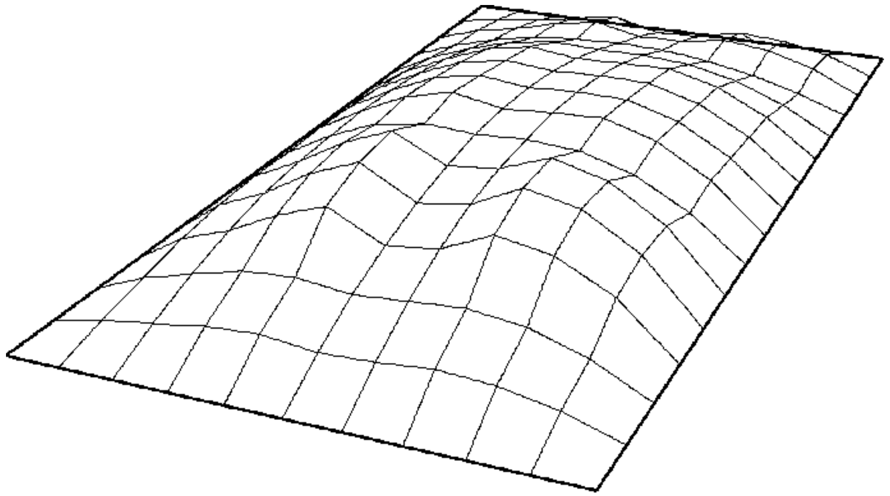
$\mu = \log(1)$

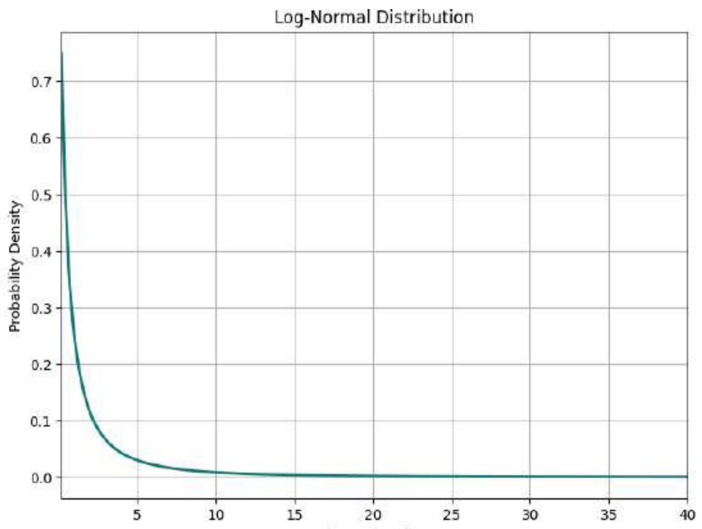
$\sigma = (\log(100) - \log(0.2)) / 4$

DATA STRUCTURING

DATASET: RANDOMIZED FORCE DENSITIES

DATASET: randomized force densities						
Edge number	mesh number					
	6	10	12	20	30	40
column_1	0.1	6.3	2.6	2.1	0.5	0.2
column_2	1.1	0.8	0.1	1.3	2	0.1
column_4	0.2	0.6	1.1	0.2	1.7	1.4
column_5	0.2	0.5	0.5	0.3	9.9	5.5
column_6	0.3	3.1	1	0.1	0.5	4.4
column_7	0.2	6	0.3	1.5	7	1
column_8	4.6	0.4	1	0.2	8	10
column_9	1.9	1.3	0.4	2.9	2.2	0.3
column_10	0.6	4.1	1	1.4	0.9	8.5
column_11	4.3	3.7	0.6	0.1	0.2	1.4
row_1	10	1.7	12.3	3.9	0.8	6.6
row_2	1.9	0.9	3	0.5	3	1.7
row_3	0.3	0.3	0.2	1.4	0.7	2.3
row_4	0.4	0.4	0.1	0.6	1	1.6
row_5	1	6.5	0.4	3.3	0.7	0.8
row_6	0.8	1.6	1.2	0.1	0.1	0.1
row_7	3.2	0.6	1.1	0.2	4.9	0.3
row_8	5.3	1	0.8	0.5	0.3	0.1
row_9	1.4	0.9	12.1	0.3	5.2	0.6
row_10	4.7	0.4	0.4	1.3	0.2	0.8
row_11	1.6	2.2	4.2	0.9	0.9	0.4
row_12	0.6	0.1	7.1	2.1	1.2	0.1
row_13	0.1	0.2	1.2	0.1	0.4	0.2
row_14	1.6	0.1	0.2	0.6	1.2	14.5
row_15	0.8	2	3.6	0.2	1.4	2.5
row_16	0.8	1	1	0.1	2.8	0.6
row_17	0.1	2.2	0.7	1.5	1.1	0.9





load = 40.0

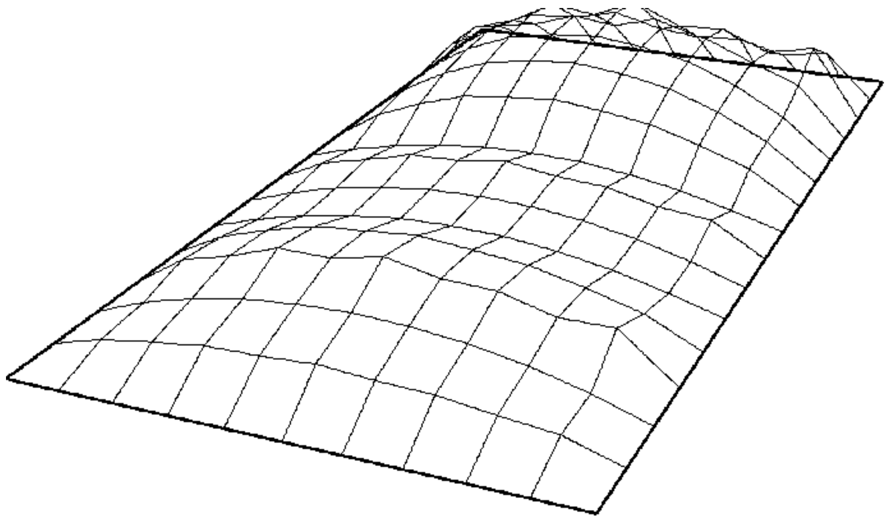
$\mu = \log(1)$

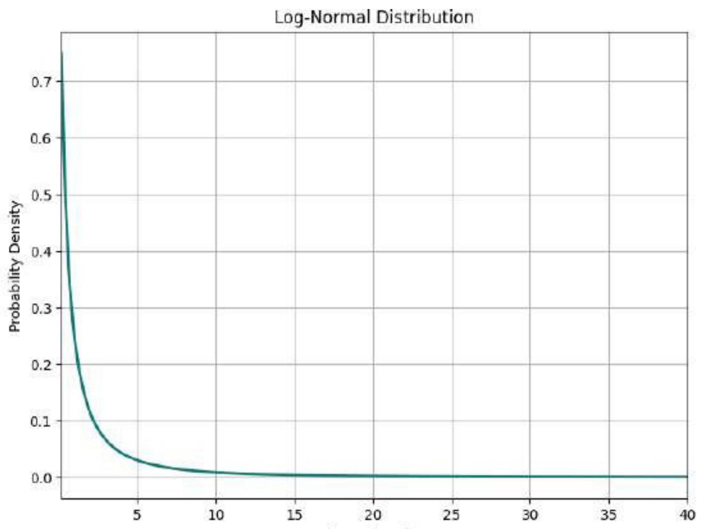
$\sigma = (\log(100) - \log(0.2)) / 4$

DATA STRUCTURING

DATASET: RANDOMIZED FORCE DENSITIES

DATASET: randomized force densities						
Edge number	mesh number					
	6	10	12	20	30	40
column_1	0.1	6.3	2.6	2.1	0.5	0.2
column_2	1.1	0.8	0.1	1.3	2	0.1
column_4	0.2	0.6	1.1	0.2	1.7	1.4
column_5	0.2	0.5	0.5	0.3	9.9	5.5
column_6	0.3	3.1	1	0.1	0.5	4.4
column_7	0.2	6	0.3	1.5	7	1
column_8	4.6	0.4	1	0.2	8	10
column_9	1.9	1.3	0.4	2.9	2.2	0.3
column_10	0.6	4.1	1	1.4	0.9	8.5
column_11	4.3	3.7	0.6	0.1	0.2	1.4
row_1	10	1.7	12.3	3.9	0.8	6.6
row_2	1.9	0.9	3	0.5	3	1.7
row_3	0.3	0.3	0.2	1.4	0.7	2.3
row_4	0.4	0.4	0.1	0.6	1	1.6
row_5	1	6.5	0.4	3.3	0.7	0.8
row_6	0.8	1.6	1.2	0.1	0.1	0.1
row_7	3.2	0.6	1.1	0.2	4.9	0.3
row_8	5.3	1	0.8	0.5	0.3	0.1
row_9	1.4	0.9	12.1	0.3	5.2	0.6
row_10	4.7	0.4	0.4	1.3	0.2	0.8
row_11	1.6	2.2	4.2	0.9	0.9	0.4
row_12	0.6	0.1	7.1	2.1	1.2	0.1
row_13	0.1	0.2	1.2	0.1	0.4	0.2
row_14	1.6	0.1	0.2	0.6	1.2	14.5
row_15	0.8	2	3.6	0.2	1.4	2.5
row_16	0.8	1	1	0.1	2.8	0.6
row_17	0.1	2.2	0.7	1.5	1.1	0.9



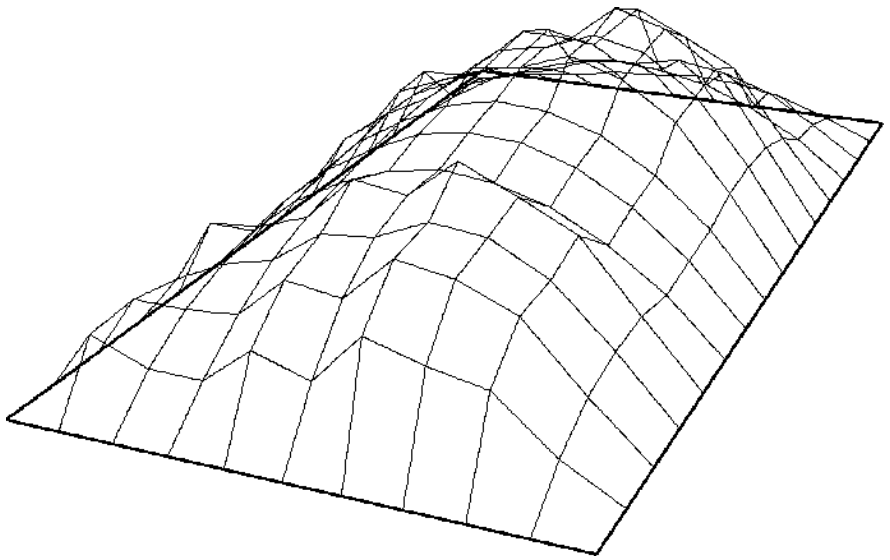


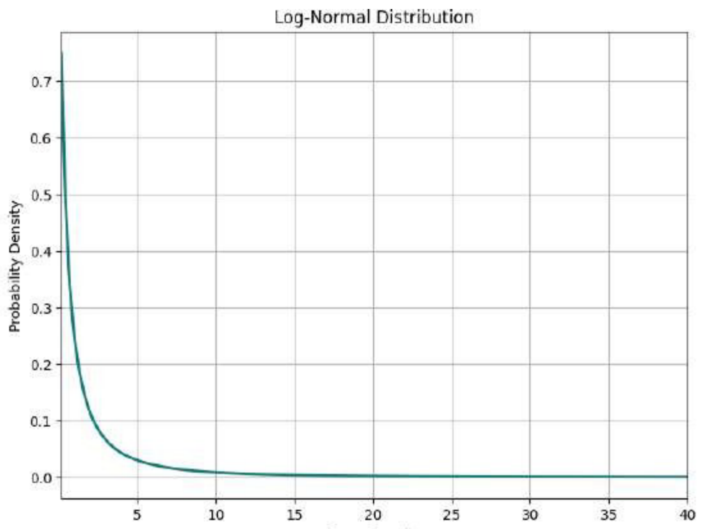
load = 40.0
μ = log(1)
σ = (log(100) - log(0.2)) / 4

DATA STRUCTURING

DATASET: RANDOMIZED FORCE DENSITIES

DATASET: randomized force densities						
Edge number	mesh number					
	6	10	12	20	30	40
column_1	0.1	6.3	2.6	2.1	0.5	0.2
column_2	1.1	0.8	0.1	1.3	2	0.1
column_4	0.2	0.6	1.1	0.2	1.7	1.4
column_5	0.2	0.5	0.5	0.3	9.9	5.5
column_6	0.3	3.1	1	0.1	0.5	4.4
column_7	0.2	6	0.3	1.5	7	1
column_8	4.6	0.4	1	0.2	8	10
column_9	1.9	1.3	0.4	2.9	2.2	0.3
column_10	0.6	4.1	1	1.4	0.9	8.5
column_11	4.3	3.7	0.6	0.1	0.2	1.4
row_1	10	1.7	12.3	3.9	0.8	6.6
row_2	1.9	0.9	3	0.5	3	1.7
row_3	0.3	0.3	0.2	1.4	0.7	2.3
row_4	0.4	0.4	0.1	0.6	1	1.6
row_5	1	6.5	0.4	3.3	0.7	0.8
row_6	0.8	1.6	1.2	0.1	0.1	0.1
row_7	3.2	0.6	1.1	0.2	4.9	0.3
row_8	5.3	1	0.8	0.5	0.3	0.1
row_9	1.4	0.9	12.1	0.3	5.2	0.6
row_10	4.7	0.4	0.4	1.3	0.2	0.8
row_11	1.6	2.2	4.2	0.9	0.9	0.4
row_12	0.6	0.1	7.1	2.1	1.2	0.1
row_13	0.1	0.2	1.2	0.1	0.4	0.2
row_14	1.6	0.1	0.2	0.6	1.2	14.5
row_15	0.8	2	3.6	0.2	1.4	2.5
row_16	0.8	1	1	0.1	2.8	0.6
row_17	0.1	2.2	0.7	1.5	1.1	0.9





load = 40.0

$\mu = \log(1)$

$\sigma = (\log(100) - \log(0.2)) / 4$

PERFORMANCE EVALUATION

PERFORMANCE EVALUATION

WORKFLOW

Start

Modal Analysis

- Seismic weight
- Check mass participation of dominant modes
- Time period of structure
- Spectral Accelerations

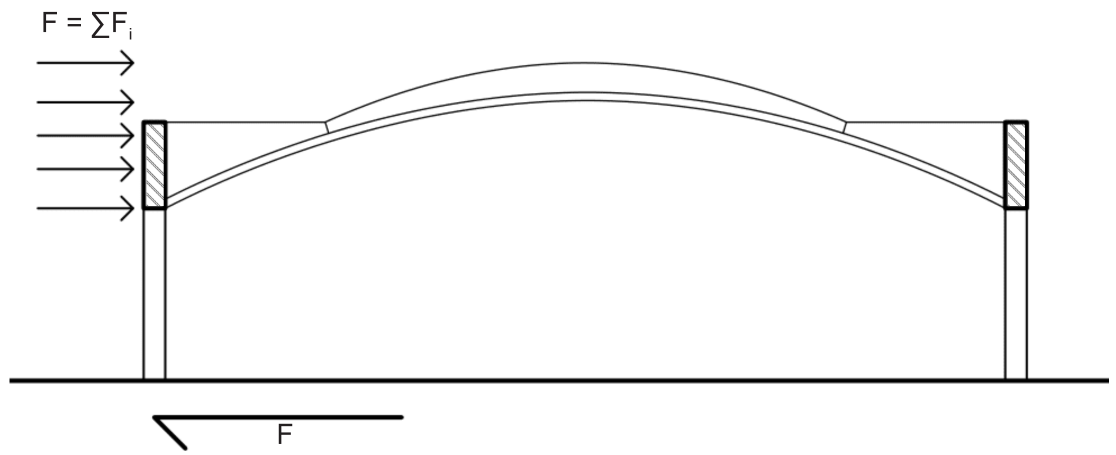
Response Spectrum Analysis

- Base Shear
- SRSS
- Vertical Distribution of forces
- Apply Seismic Loads to FEA Model
- Calculate Interstorey Drift and get other internal reactions

10,000 simulations completed?

yes → Stop

no → Modal Analysis



PERFORMANCE EVALUATION

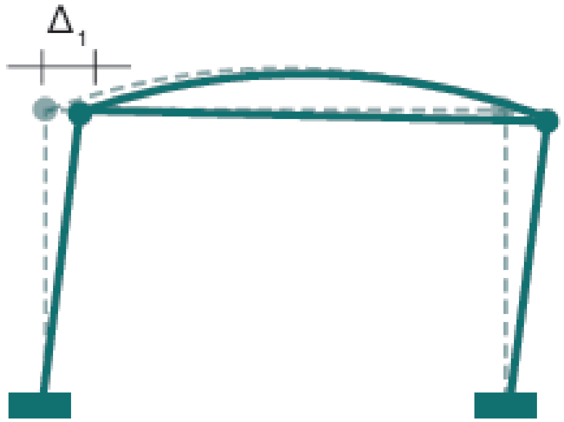
BUCKLING LOAD FACTOR

STABILITY

UTILIZATION

STRENGTH

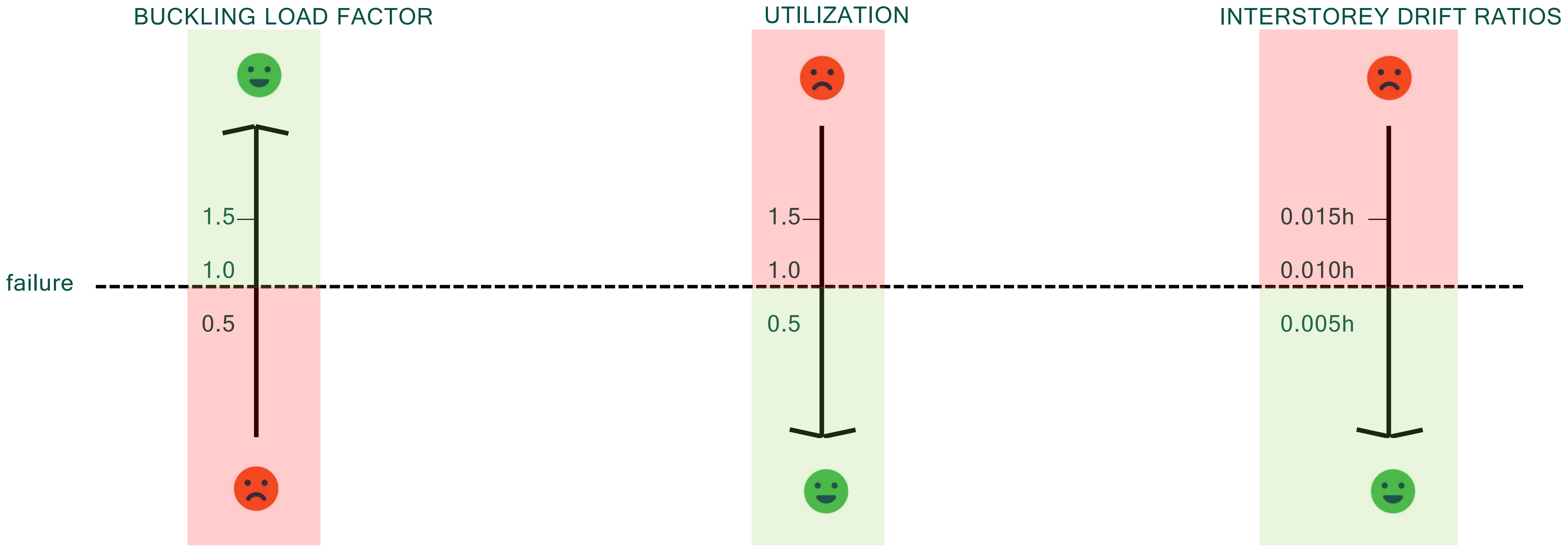
INTERSTOREY DRIFT RATIOS



STIFFNESS

PERFORMANCE EVALUATION

PERFORMANCE METRICS



PERFORMANCE EVALUATION

SEISMIC REGION

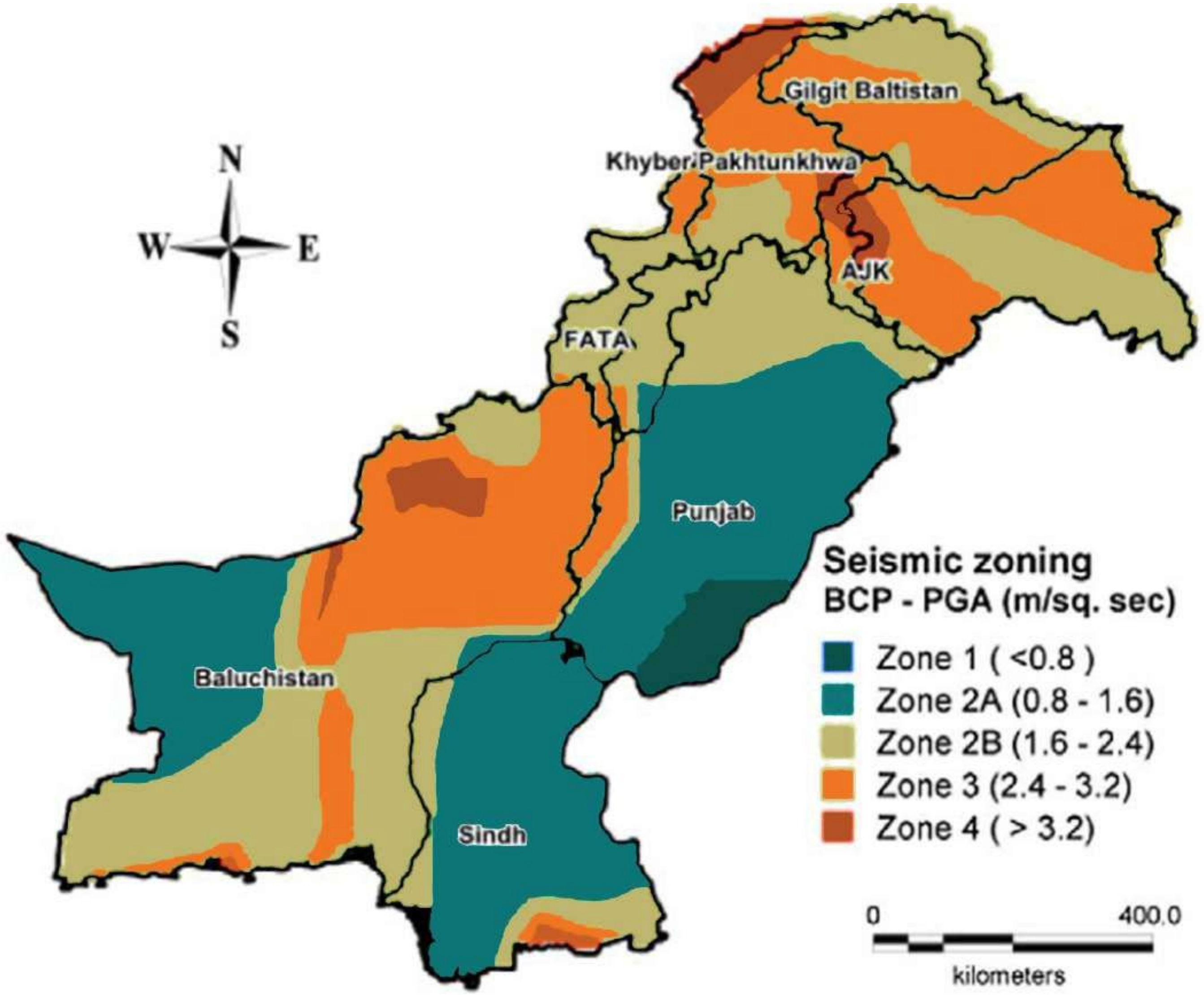


FIGURE 01: Sesimic Zoning map of Pakistan according to Building Code of Pakistan (BCP). Edited by Author. Image Taken from Siddique, M. S., & Schwarz, J. (2015). Elaboration of Multi-Hazard Zoning and Qualitative Risk Maps of Pakistan. Earthquake Spectra, 31(3), 1371-1395. https://doi.org/10.1193/042913EQS114M

PERFORMANCE EVALUATION

SEISMIC REGION

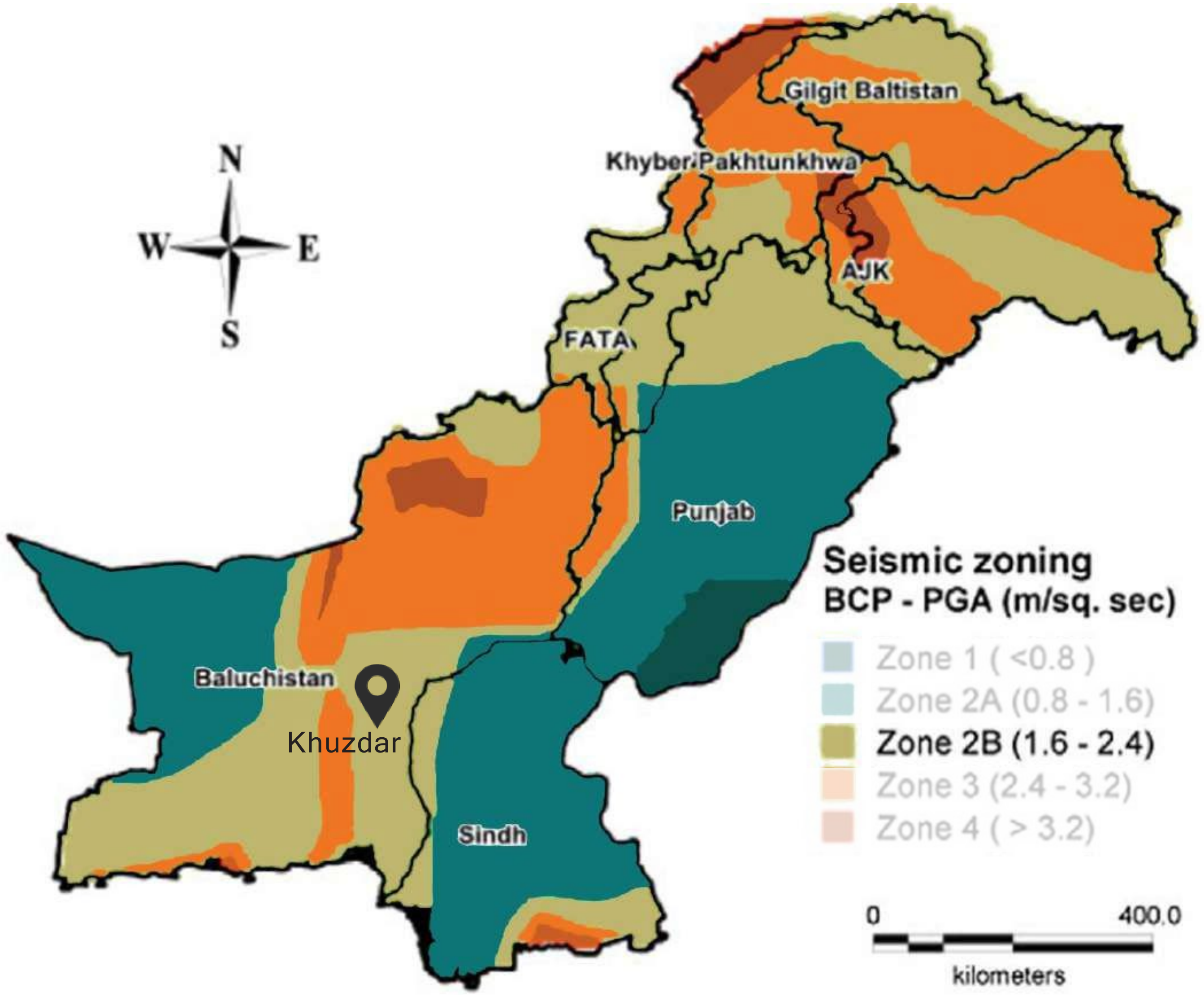
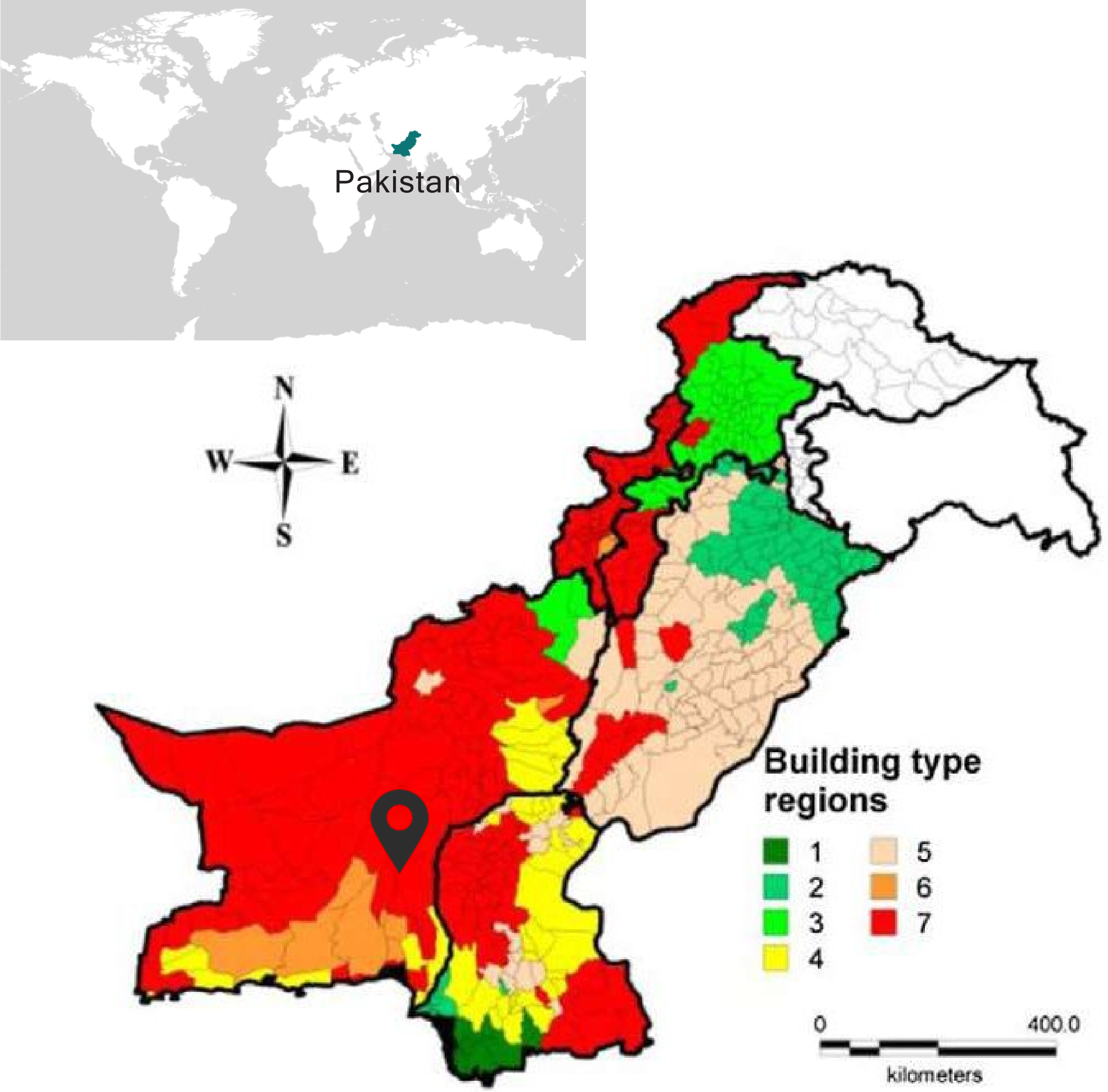


FIGURE 12: Sesimic Zoning map of Pakistan according to Building Code of Pakistan (BCP). Edited by Author. Image Taken from Siddique, M. S., & Schwarz, J. (2015). Elaboration of Multi-Hazard Zoning and Qualitative Risk Maps of Pakistan. Earthquake Spectra, 31(3), 1371-1395. https://doi.org/10.1193/042913EQS114M

PERFORMANCE EVALUATION

BUILDING TYPE REGION



Region	Building type	Comments
1	A SM CBM BM T	Predominantly timber structures with all the other building types in "few" range.
2	A SM CBM BM T	Predominantly brick masonry and all other building types in "few" range.
3	A SM CBM BM T	Adobe, stone masonry and brick masonry in almost equal proportions.
4	A SM CBM BM T	Predominantly adobe and timber structures.
5	A SM CBM BM T	Predominantly adobe and brick masonry with all others in "few" range.
6	A SM CBM BM T	Predominantly adobe along with timber in "many" range.
7	A SM CBM BM T	Predominantly adobe structures with all the other building types in "few" range.

FIGURE 13: Building type region map of Pakistan. Image taken from Siddique, M. S., & Schwarz, J. (2015). Elaboration of Multi-Hazard Zoning and Qualitative Risk Maps of Pakistan. Earthquake Spectra, 31(3), 1371-1395. https://doi.org/10.1193/042913EQS114M

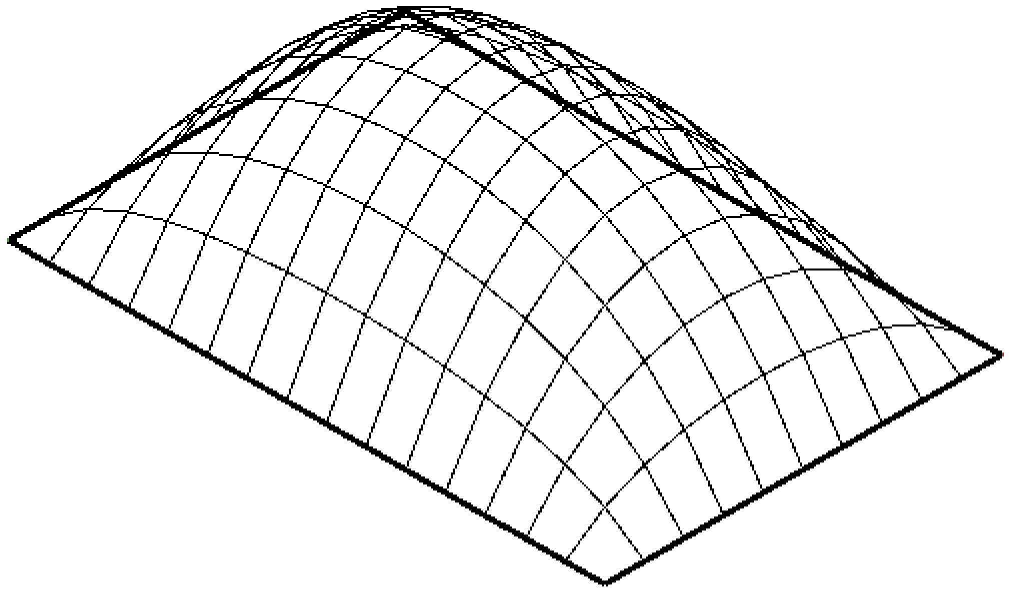
PERFORMANCE EVALUATION

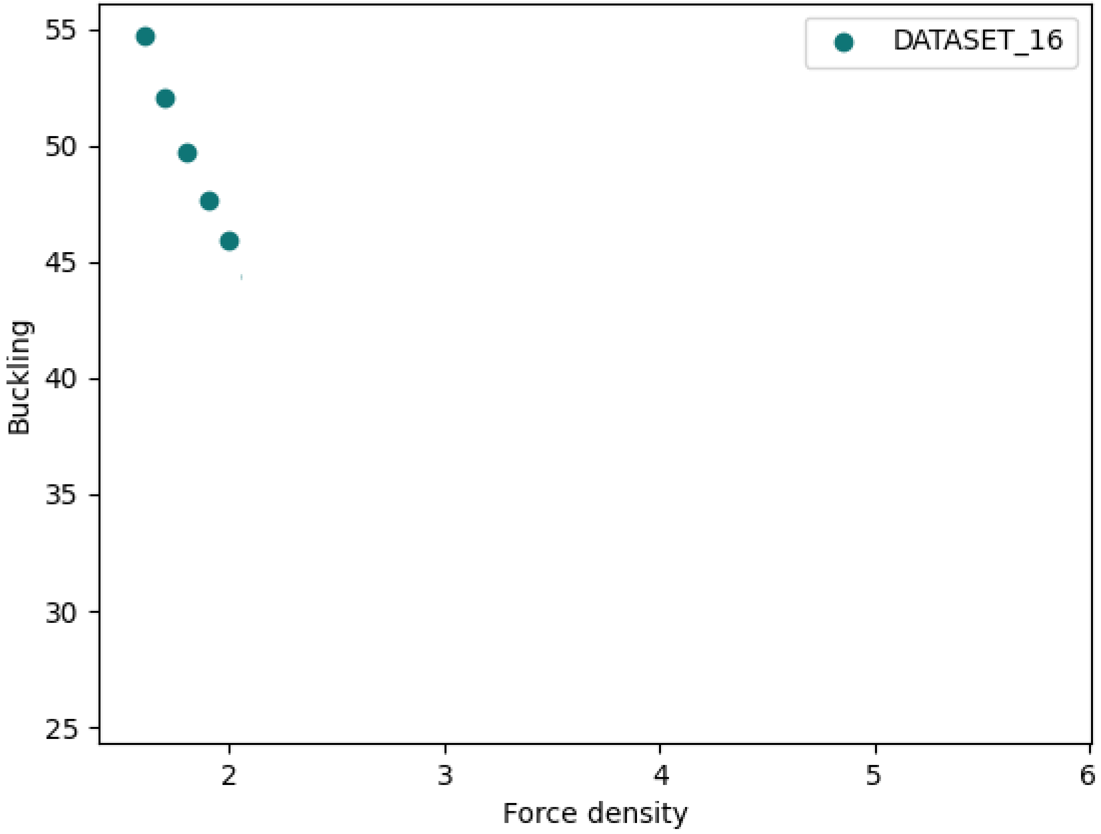
VARIATION IN FORCE DENSITIES

a) uniform force densities dataset

BUCKLING LOAD FACTOR

DATASET 16





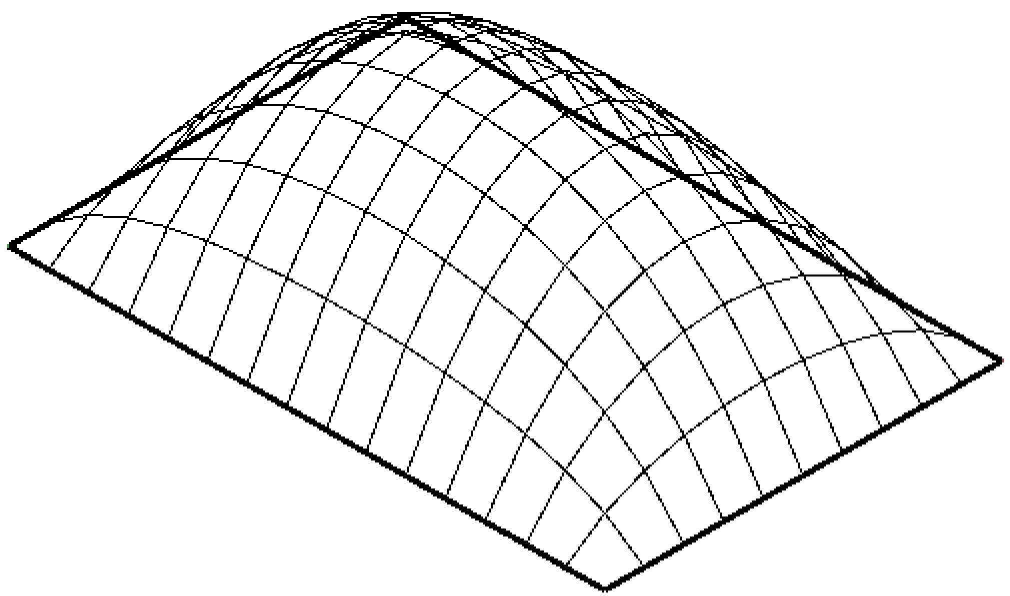
PERFORMANCE EVALUATION

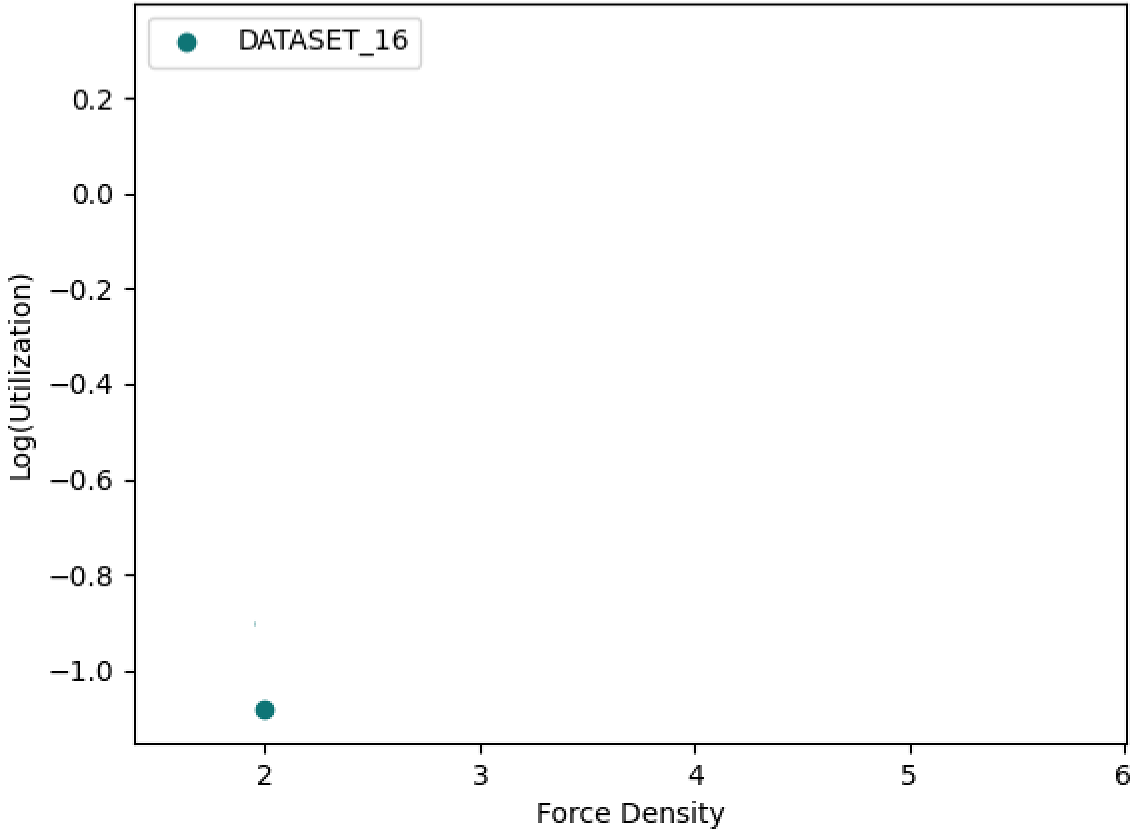
VARIATION IN FORCE DENSITIES

a) uniform force densities dataset

UTILIZATION

DATASET 16



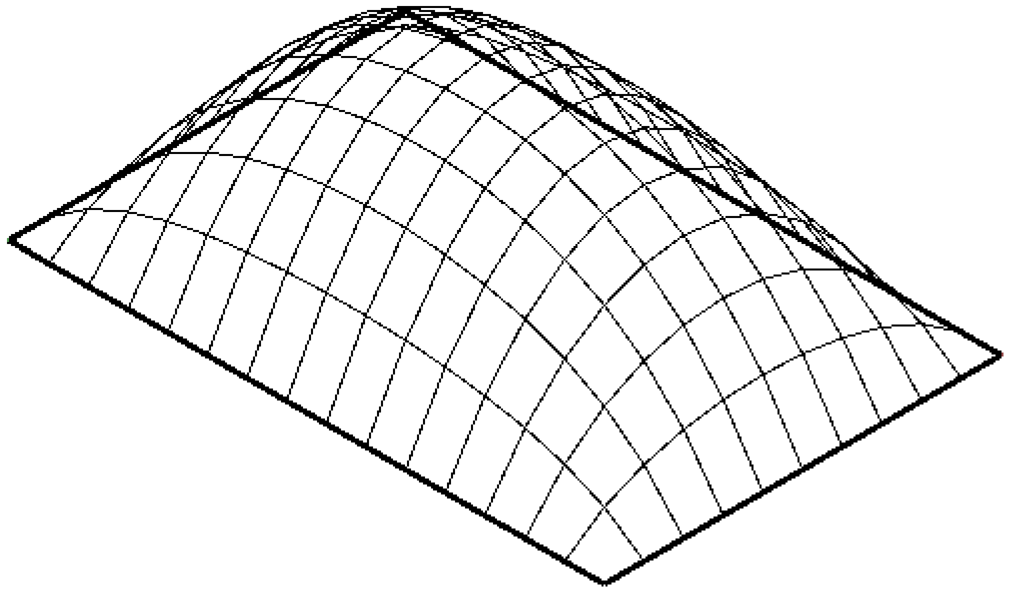


PERFORMANCE EVALUATION

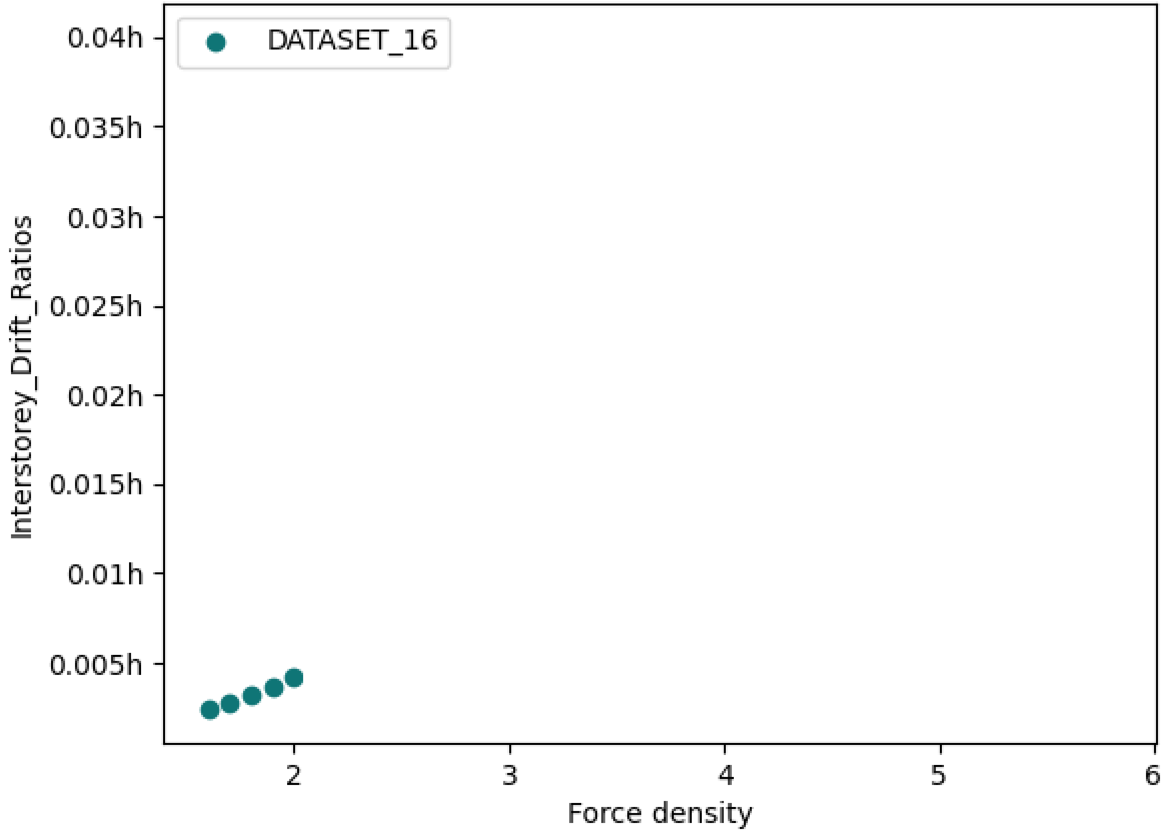
VARIATION IN FORCE DENSITIES

a) uniform force densities dataset

DATASET 16



INTERSTOREY DRIFT RAITIOS

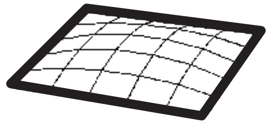


PERFORMANCE EVALUATION

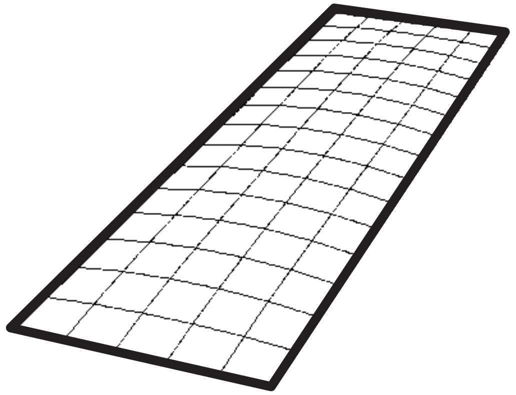
VARIATION IN DATASET STRATEGIES

Performance improves

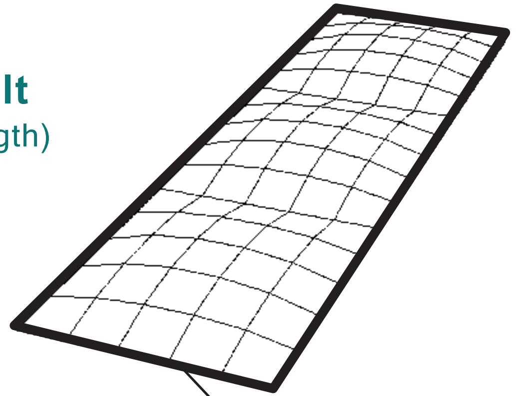
small vault
(1/3 original length)



uniform force densities

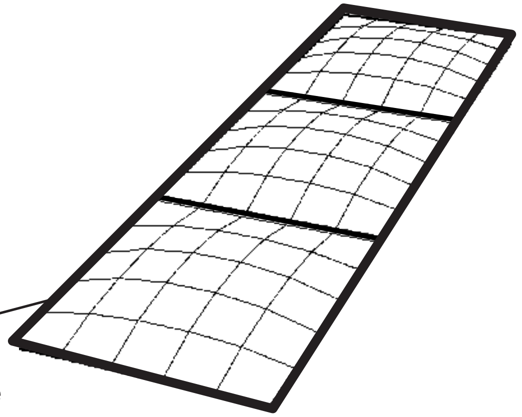


creased vault
(1/3 original length)



supports at outer perimeter

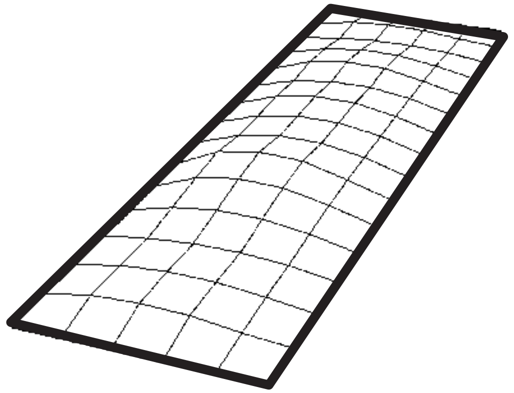
segmented vaults
(1/3 original length)
suppported separately



supports also along the whole perimeter of each segmented vault

30 samples per dataset

randomized force densities

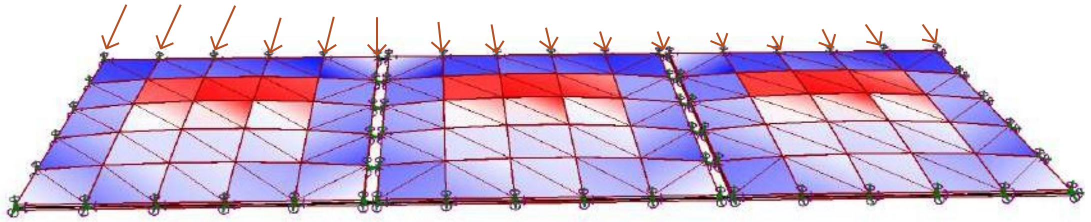


PERFORMANCE EVALUATION

VARIATION IN DATASET STRATEGIES

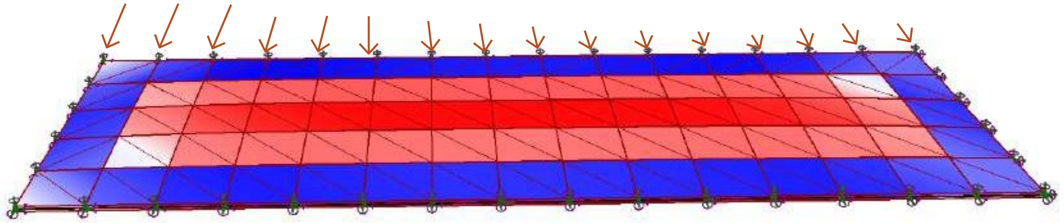
segmented vaults
(1/3 original length)
suppported separately

seismic load



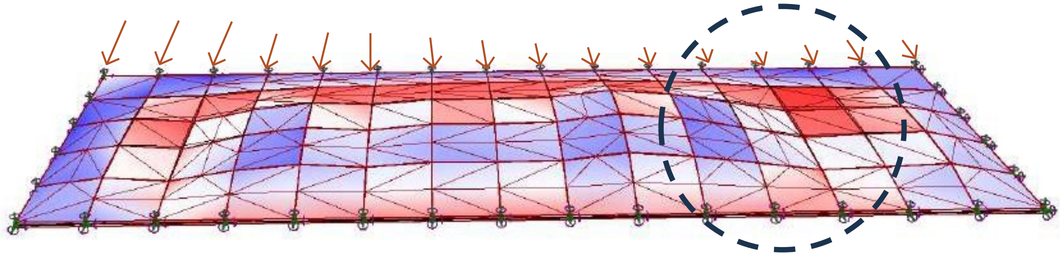
uniform force densities

seismic load



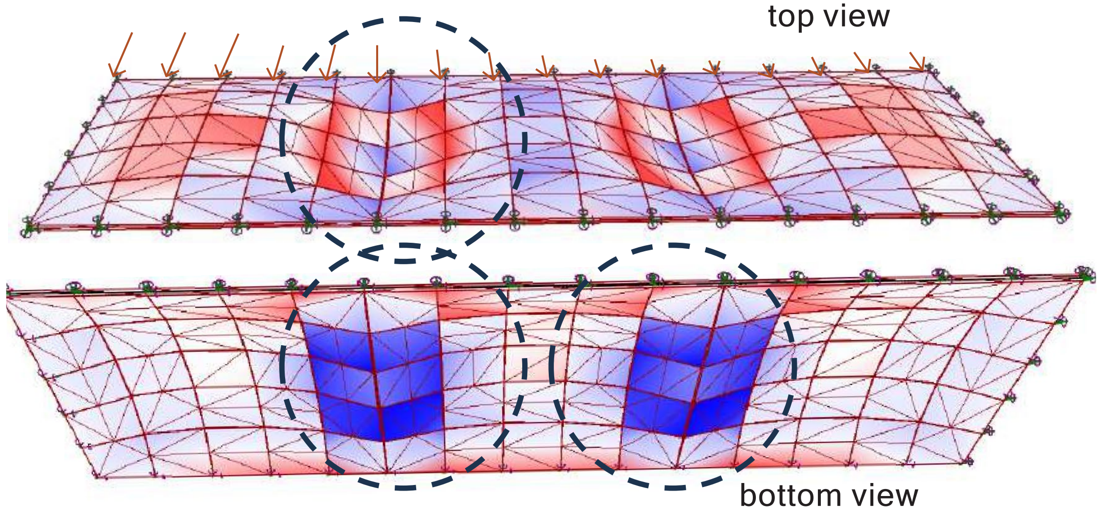
randomized force densities

seismic load



creased vault
(1/3 original length)

seismic load



PERFORMANCE EVALUATION

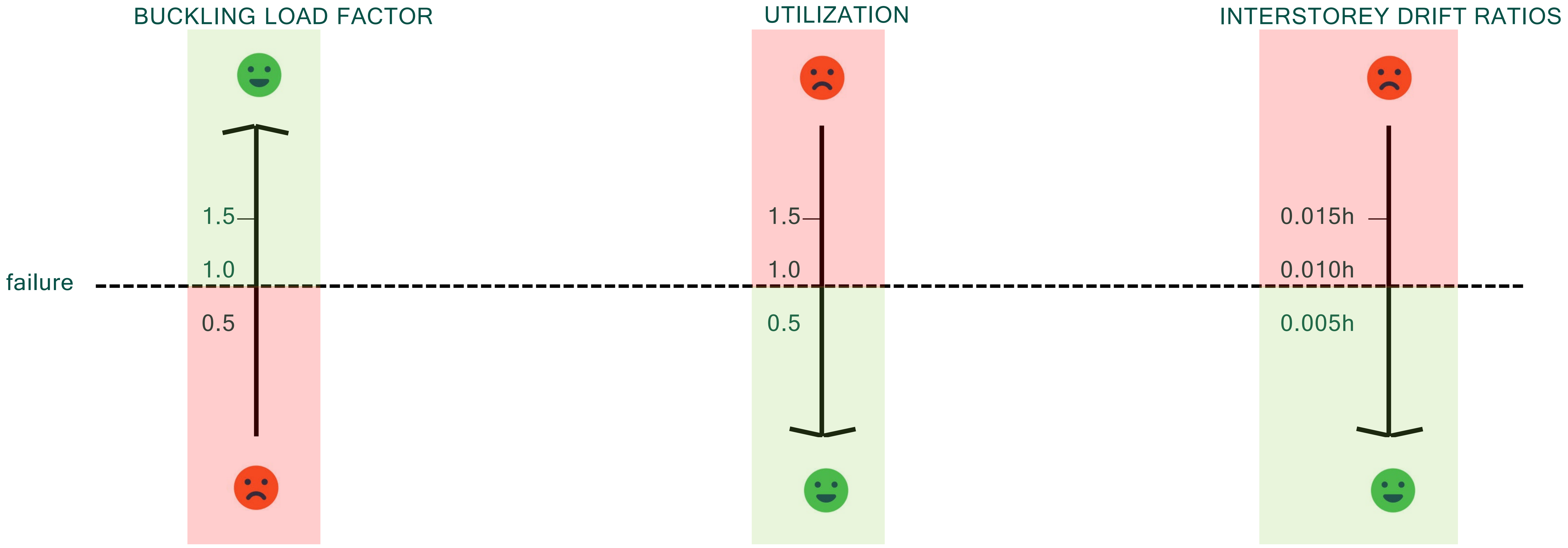
10,000 **samples** = **9,950** **samples** + **50** **samples**

randomized force densities

uniform force densities

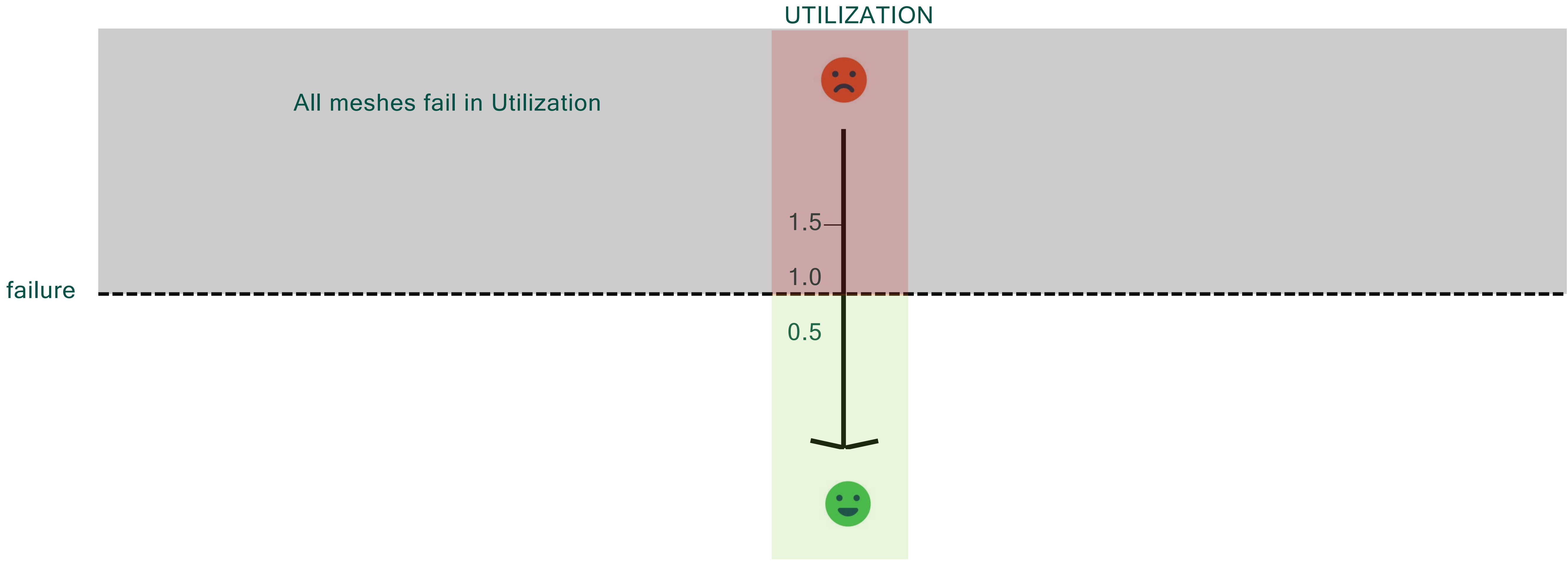
PERFORMANCE EVALUATION

PERFORMANCE METRICS



PERFORMANCE EVALUATION

PERFORMANCE OF RANDOMIZED DATASET



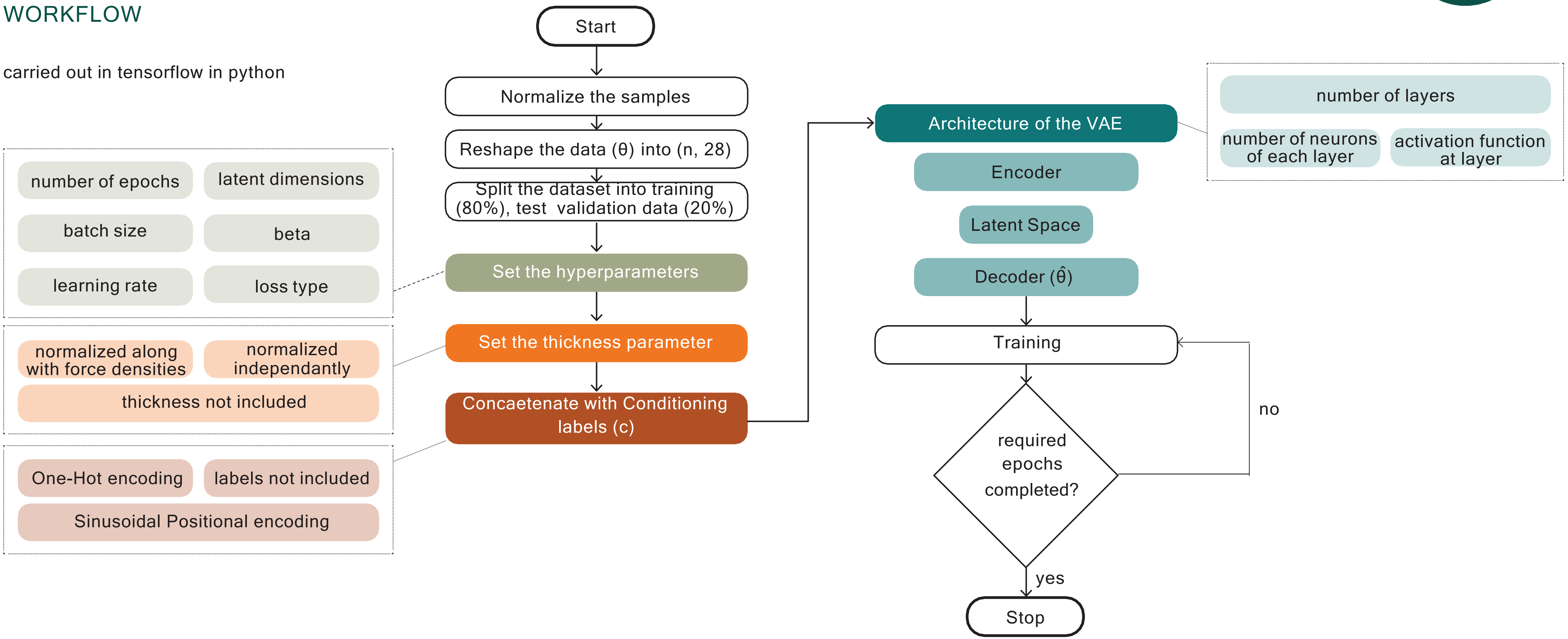
GENERATOR

GENERATOR

VAE

WORKFLOW

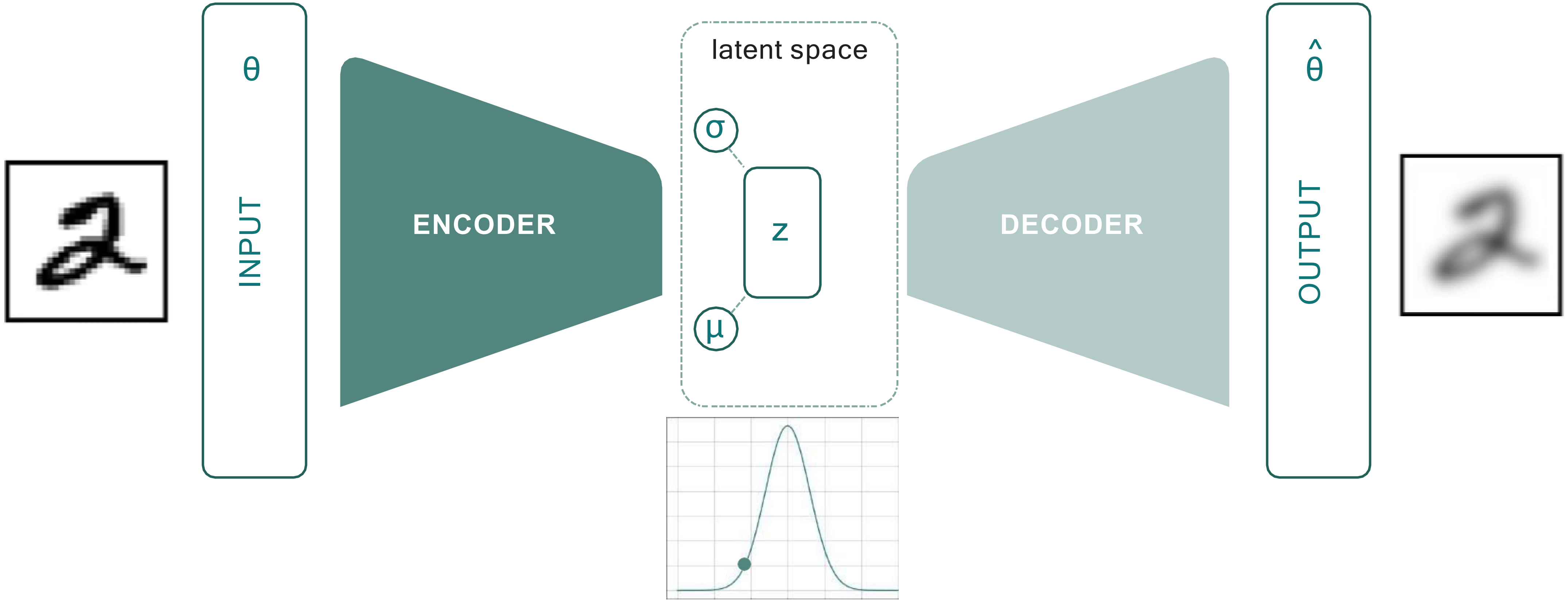
carried out in tensorflow in python



GENERATOR

VAE

CONCEPT



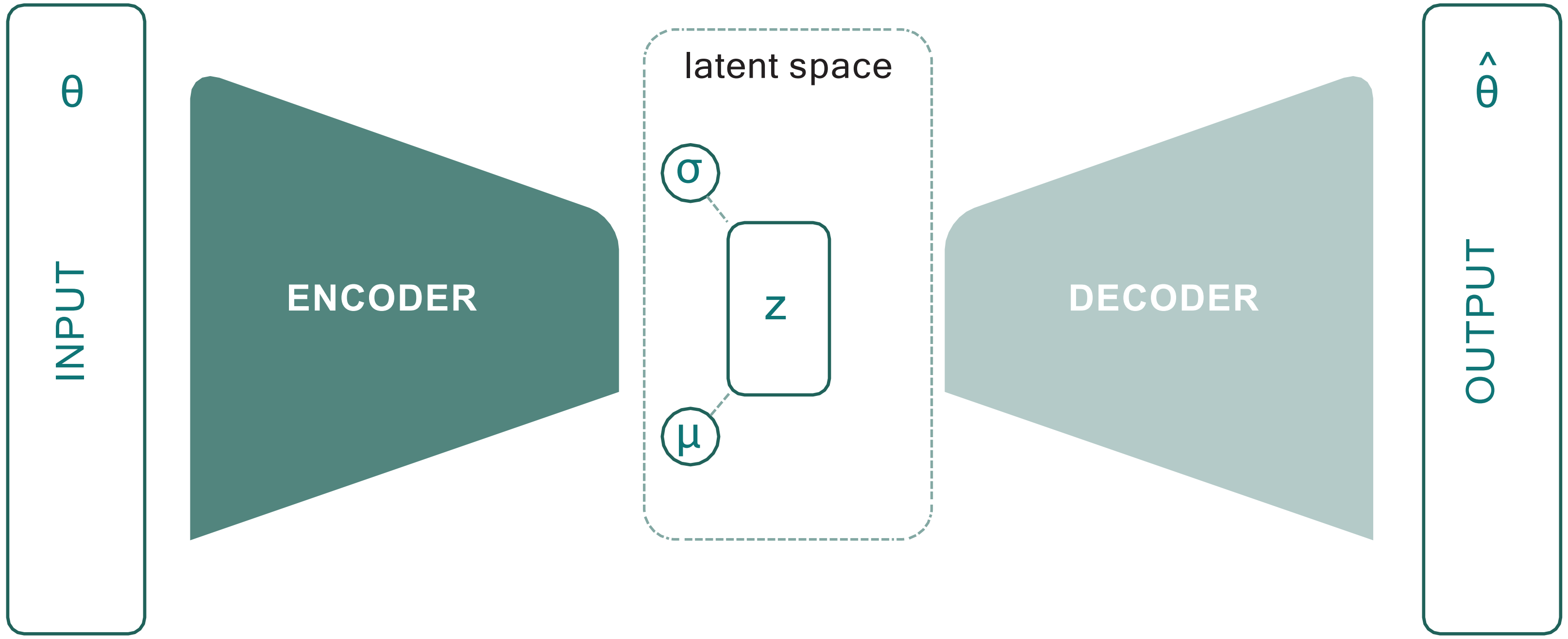
GENERATOR

VAE

CONCEPT

Force densities

$[\ [q_1,\ q_2,\ q_3, q_4, q_5, q_6, q_7, q_8,\ q_9,\ q_{10},\ q_{11}]\ \ ,\ \ [q_{12}, q_{13}, q_{14},\ q_{15},\ q_{16}, q_{17}, q_{18}, q_{19}, q_{20},\ q_{21},\ q_{22},\ q_{23},\ q_{24},\ q_{25},\ q_{26},\ q_{27}\ ]\ ]$

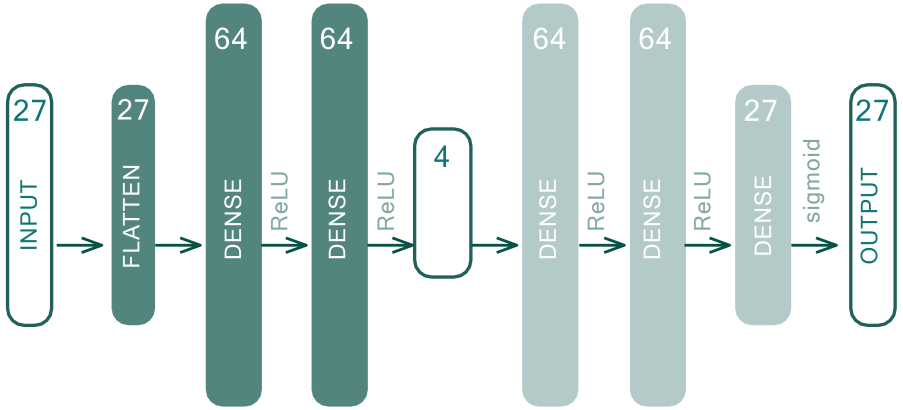


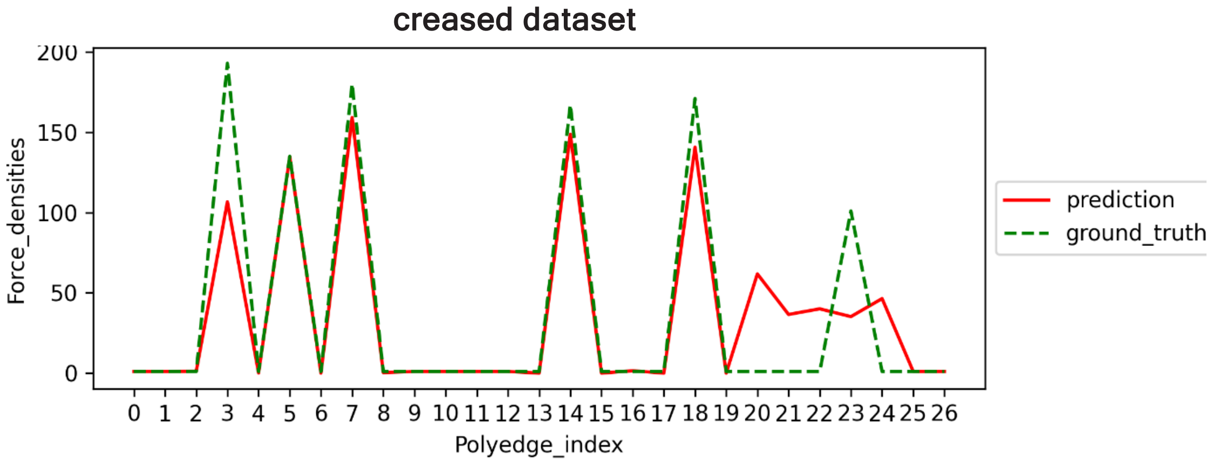
GENERATOR

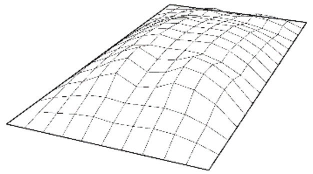
VAE

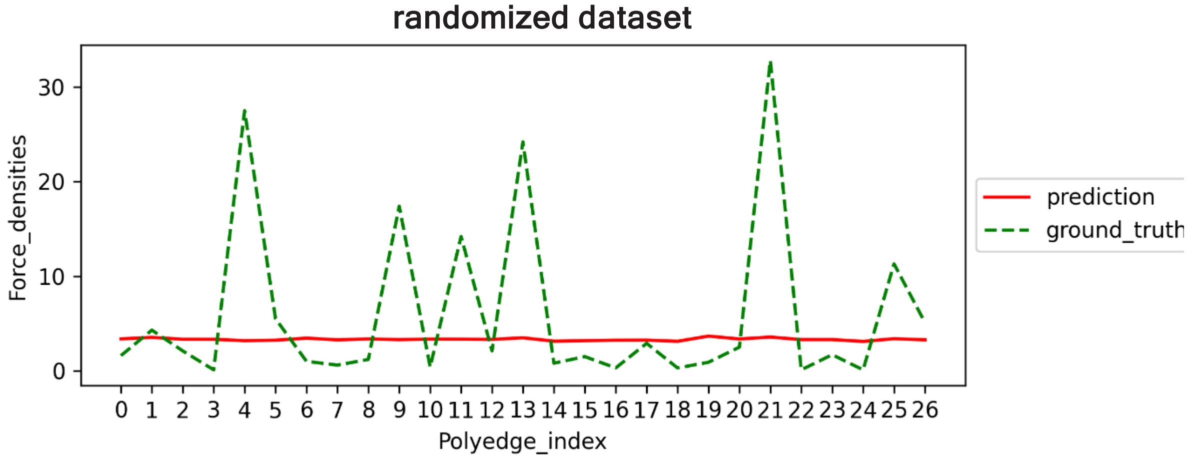
PREDICTION OF SAMPLE FORCE DENSITIES

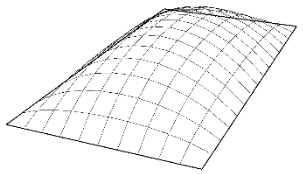
HYPERPARAMETERS: latent_dimension = 4, **beta** = 0.2, **epochs** = 600, **batch_size** = 64, **learning_rate** = 1E-03











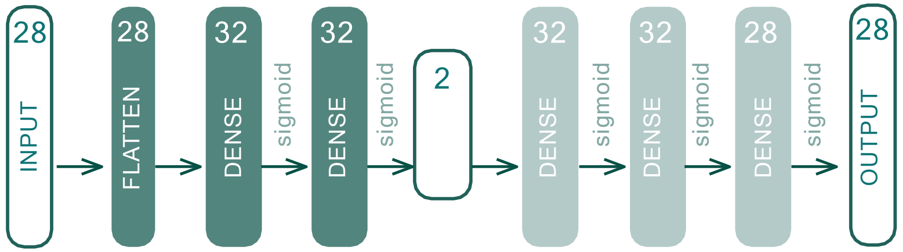
uniform force densities are better in performance

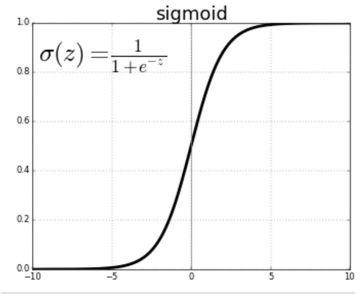
GENERATOR

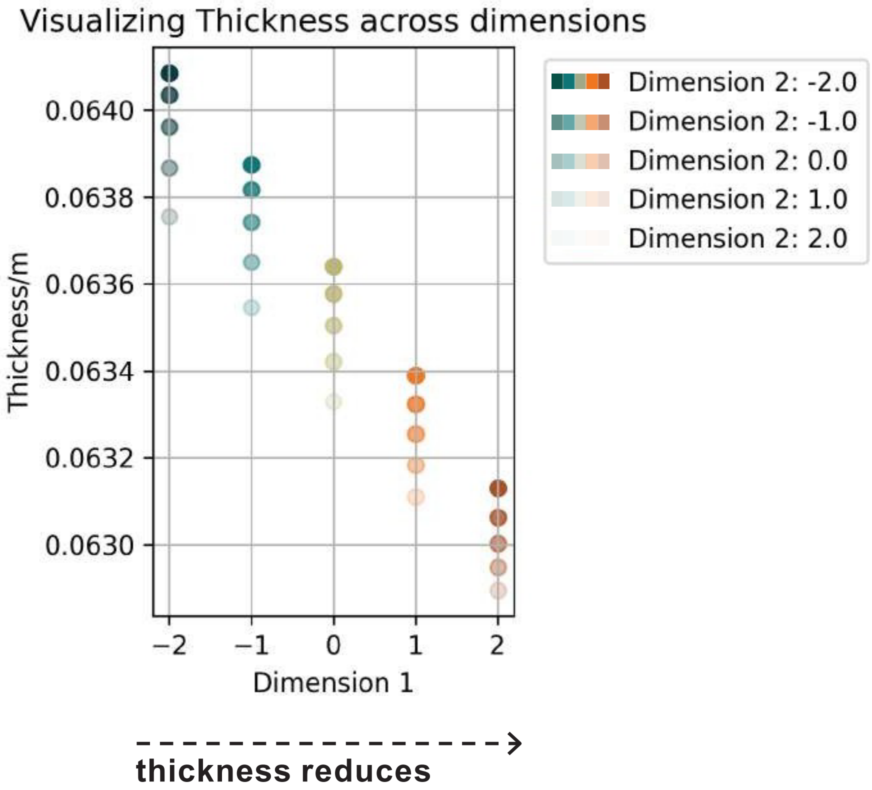
VAE

ACTIVATION FUNCTION = sigmoid

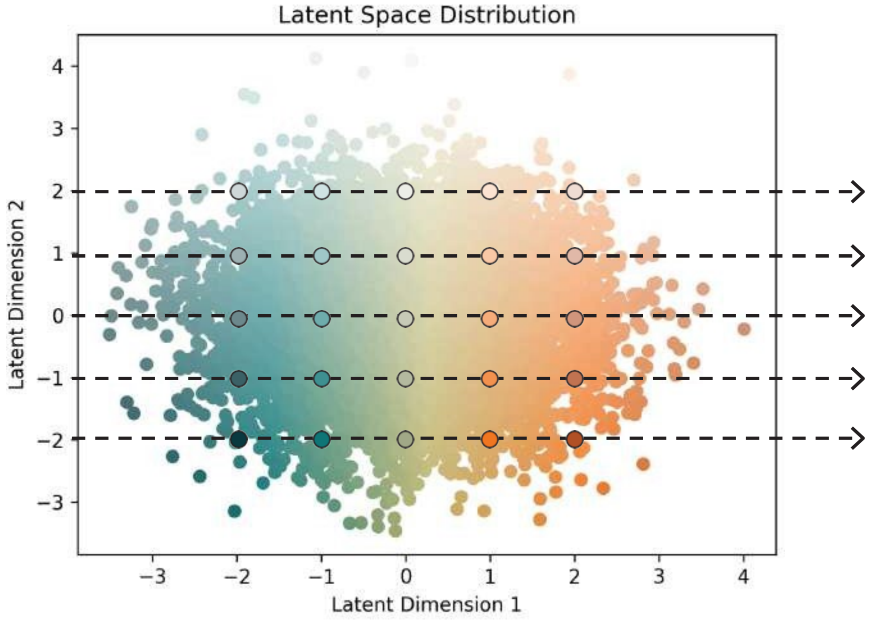
HYPERPARAMETERS: latent_dimension = 2, **beta** = 0.2, **epochs** = 600, **batch_size** = 128, **learning_rate** = 1E-05







Across Dimension 1

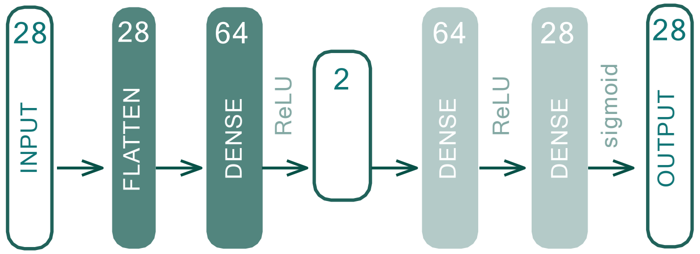


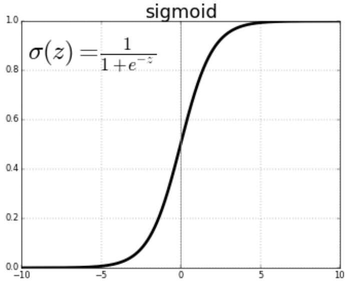
GENERATOR

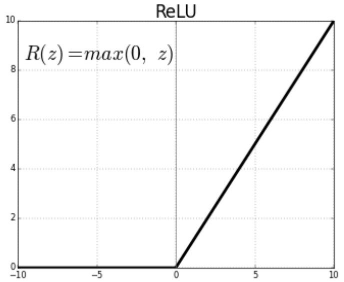
VAE

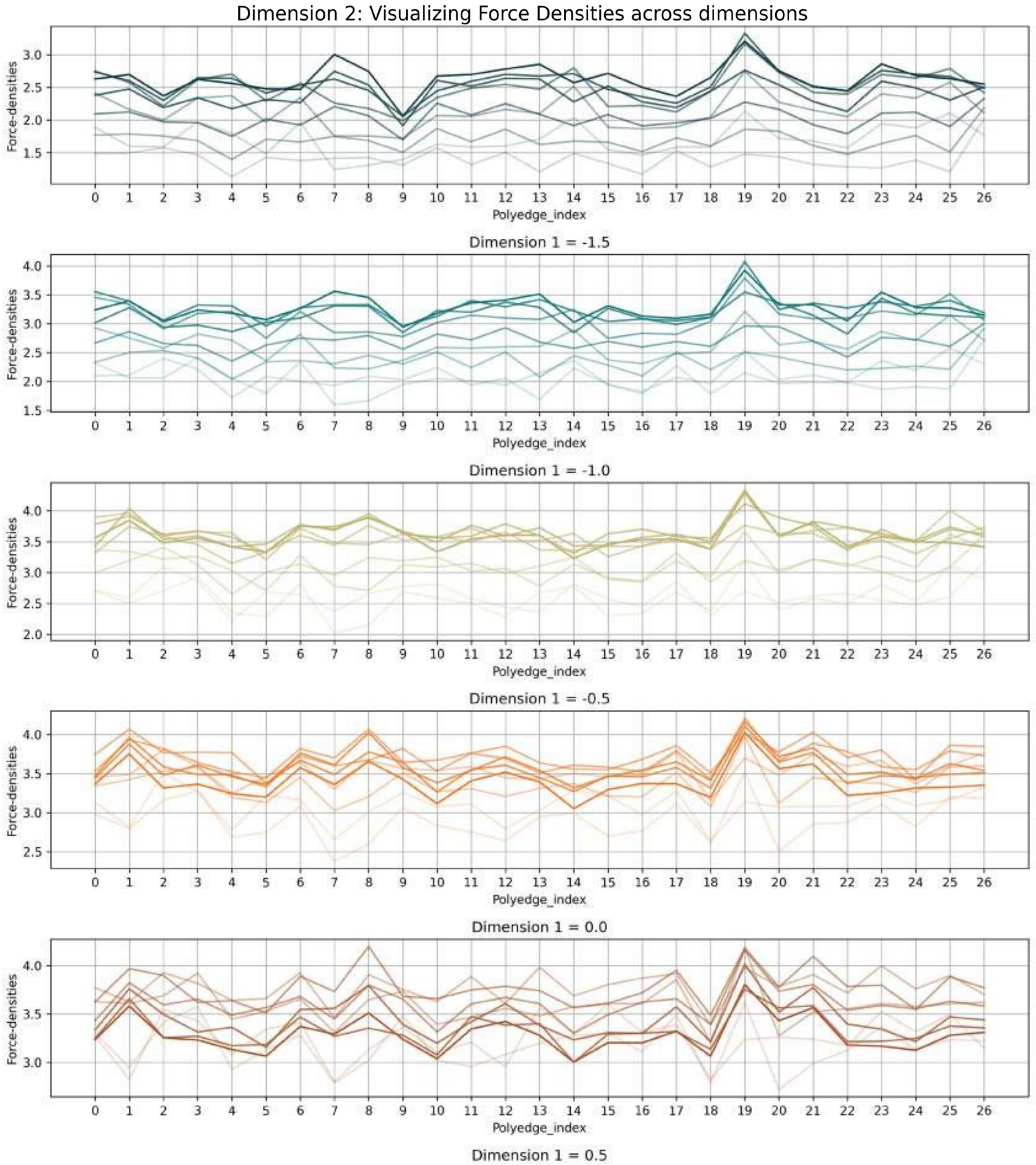
ACTIVATION FUNCTION = sigmoid + ReLU

HYPERPARAMETERS: latent_dimension = 2, **beta** = 0.2, **epochs** = 600, **batch_size** = 128, **learning_rate** = 1E-04

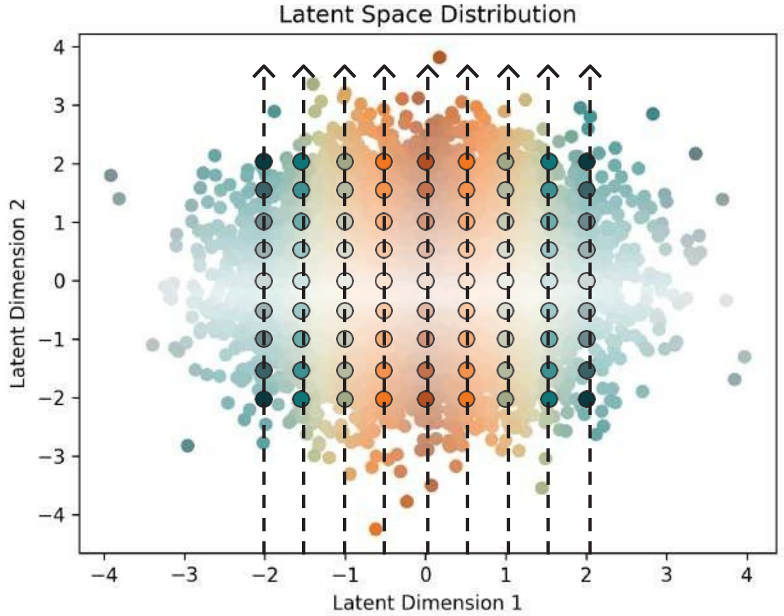


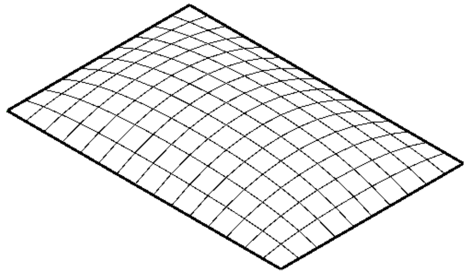






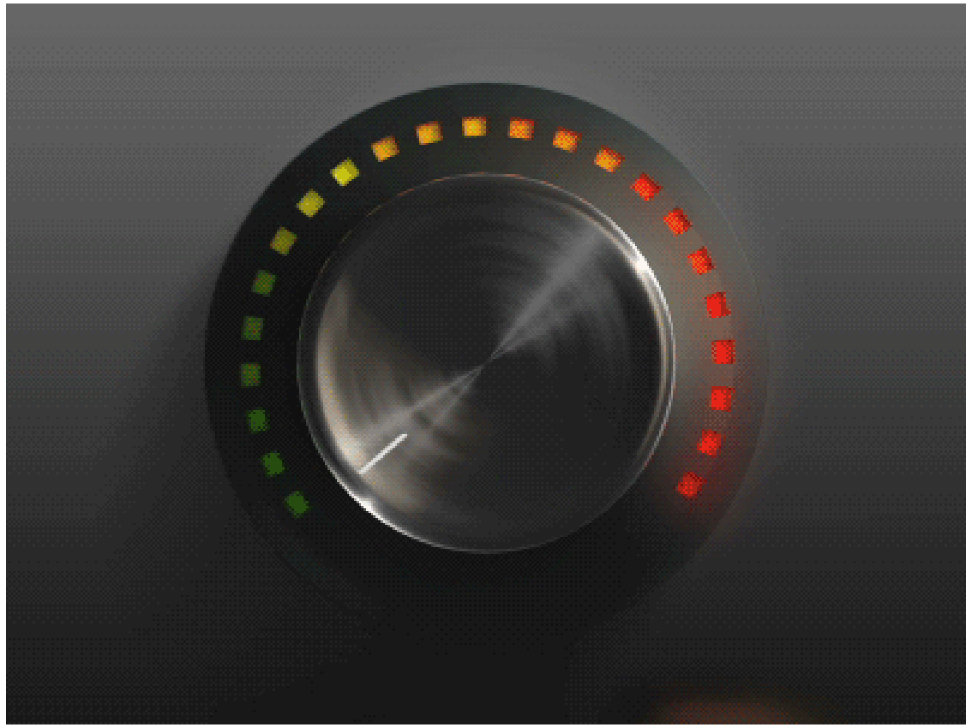
Across Dimension 2

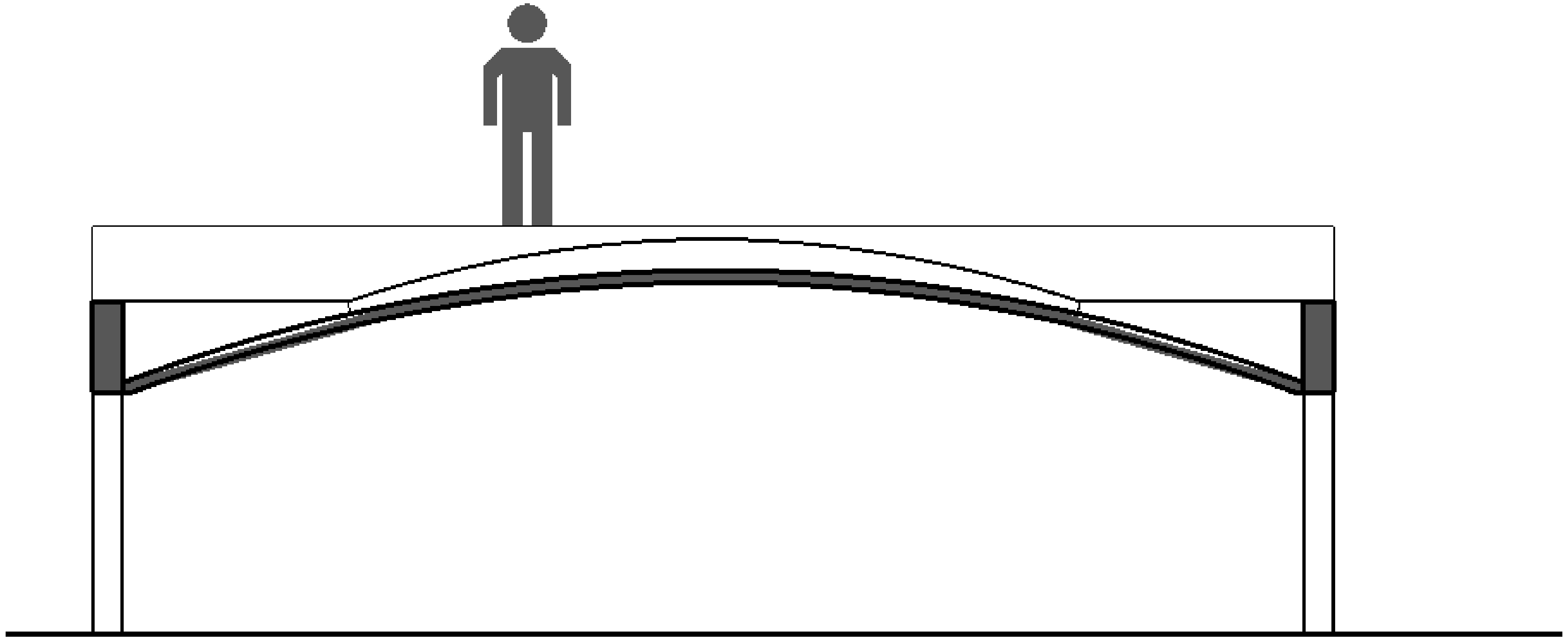




GENERATOR

CONDITIONAL VAE

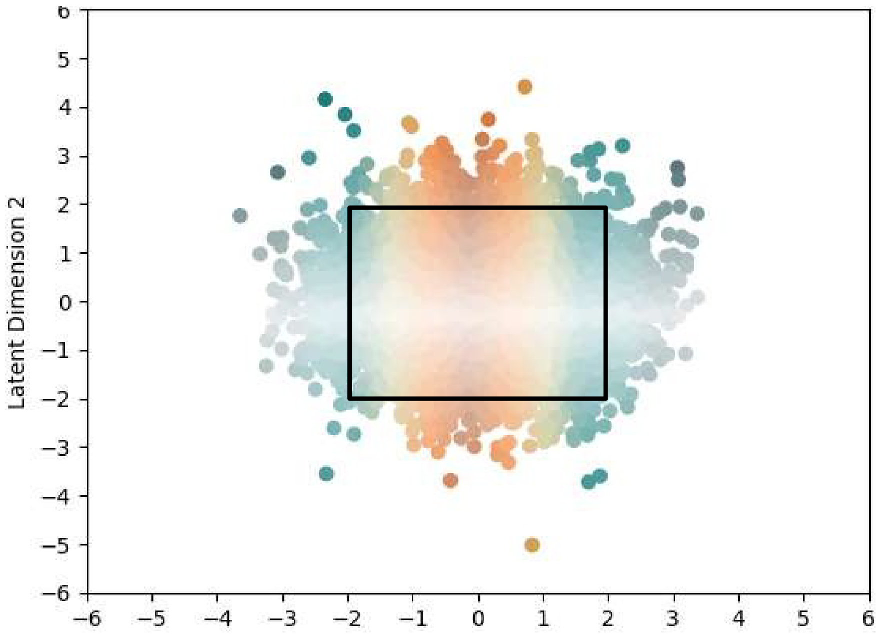




GENERATOR

CONDITIONAL VAE

Small dense latent space



Sinusoidal positional encoding

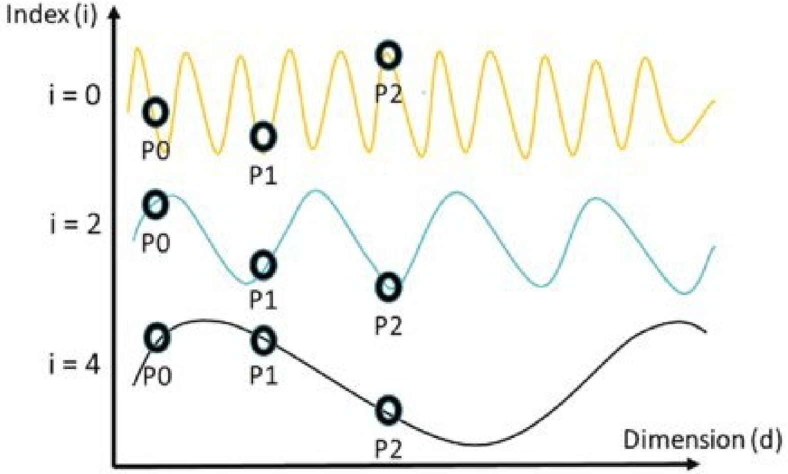


FIGURE:https://www.researchgate.net/publication/372249718_Vision_transformer_architecture_and_applications_in_digital_health_a_tutorial_and_survey/figures?lo=1

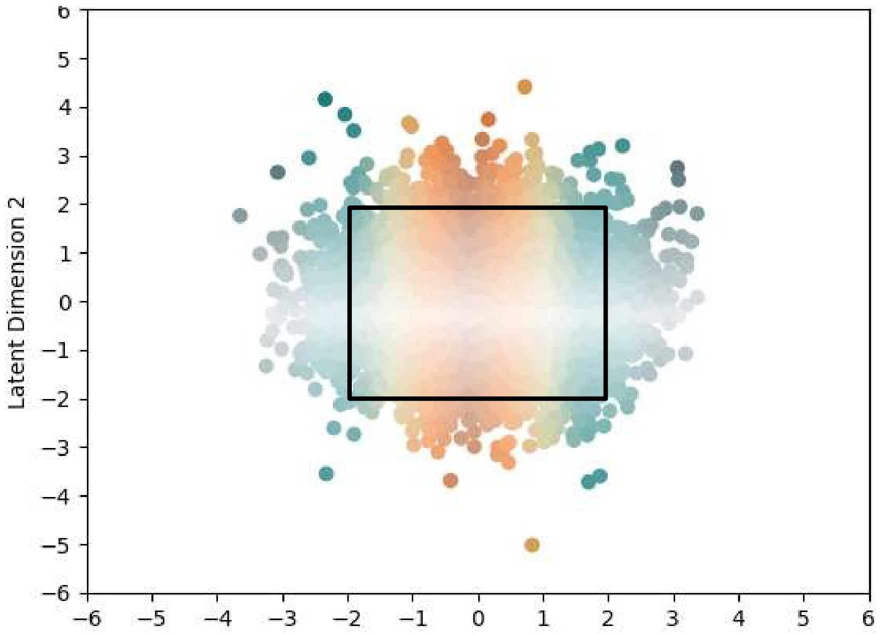
One Hot vector encoding

'New York'	= 1	0	0
'London'	= 0	1	0
'Dublin'	= 0	0	1

GENERATOR

CONDITIONAL VAE

Small dense latent space



Sinusoidal positional encoding

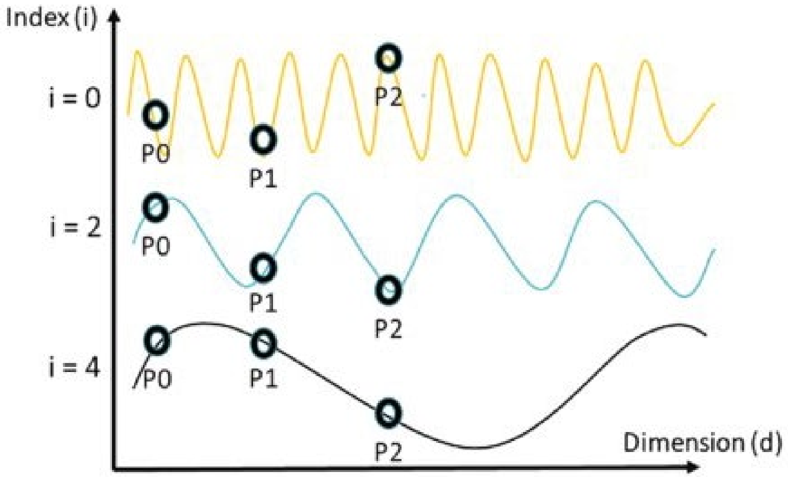


FIGURE:https://www.researchgate.net/publication/372249718_Vision_transformer_architecture_and_applications_in_digital_health_a_tutorial_and_survey/figures?lo=1

One Hot vector encoding

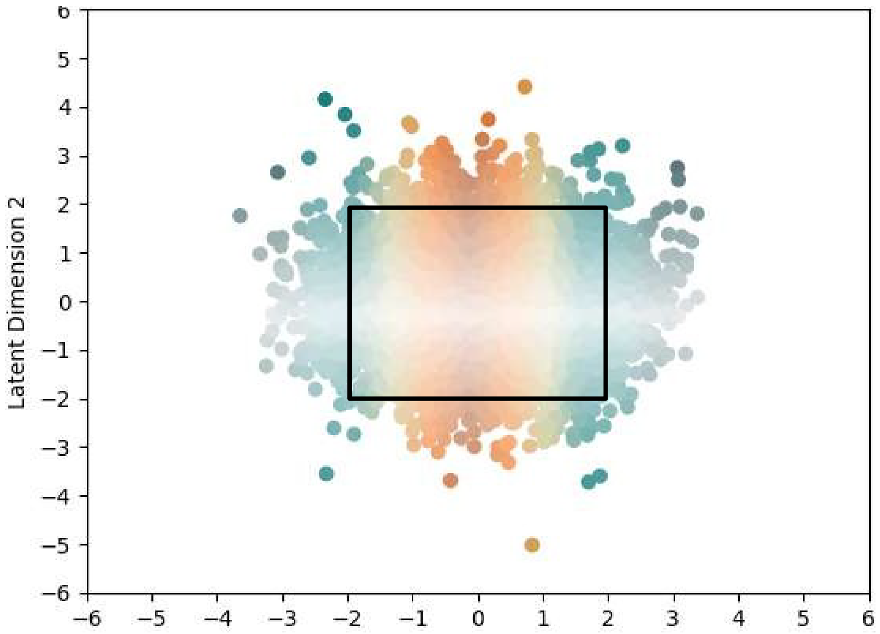
'New York'	=	1	0	0
'London'	=	0	1	0
'Dublin'	=	0	0	1

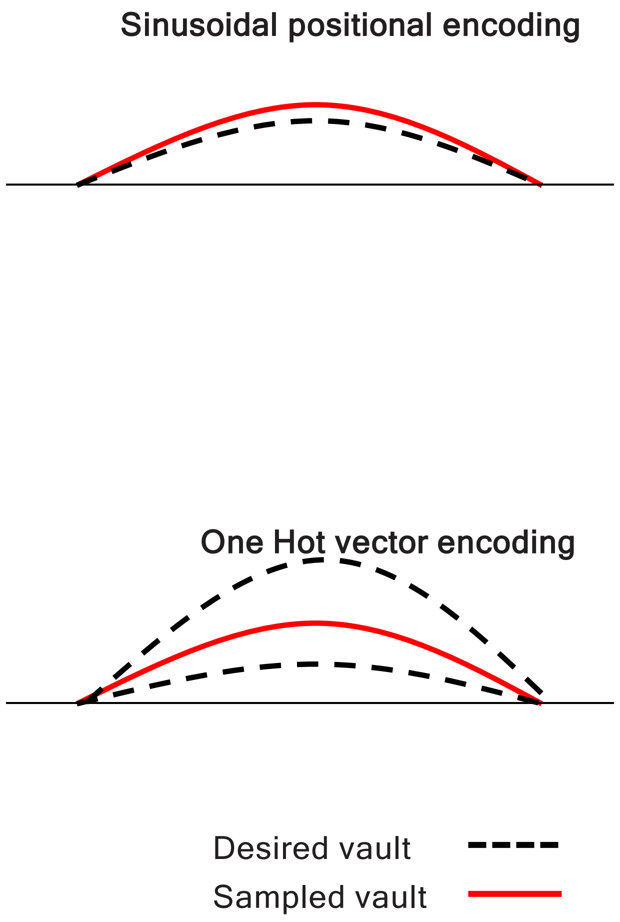
GIVE ME A NEW VAULT OF HEIGHT 0.8 METERS

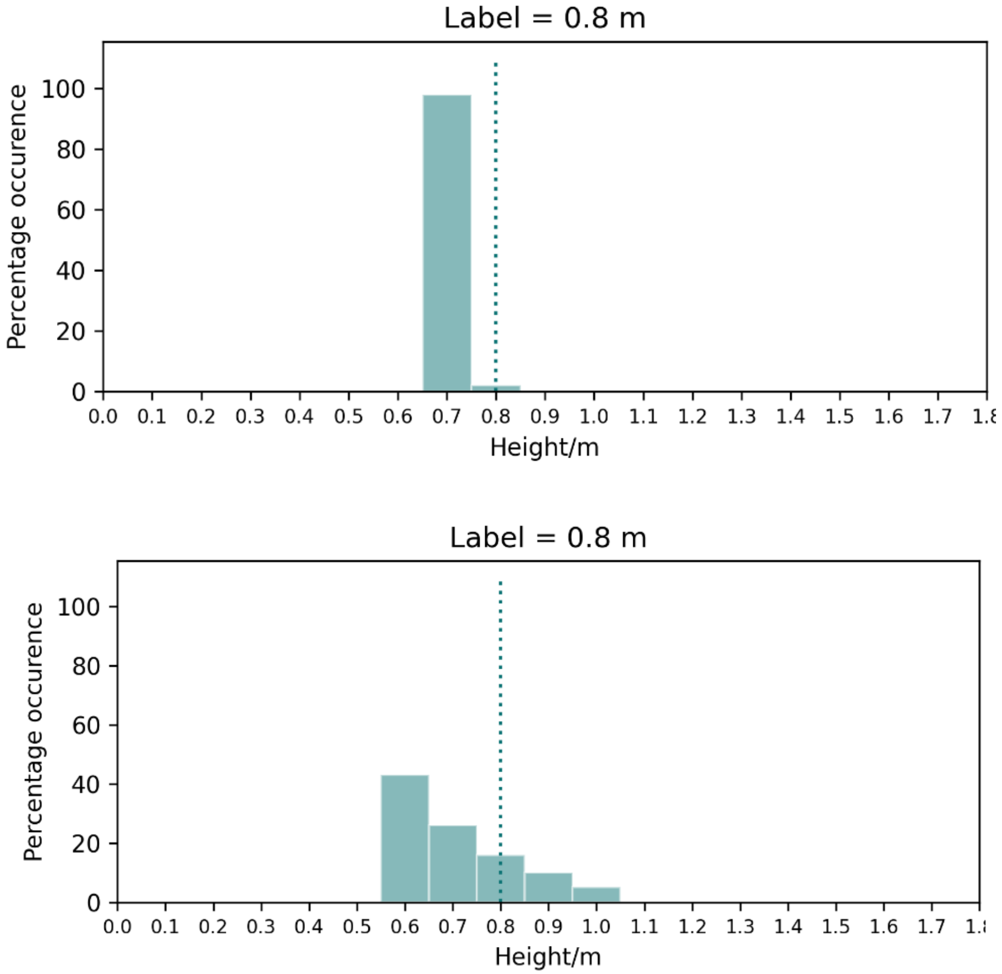
GENERATOR

CONDITIONAL VAE

Small dense latent space



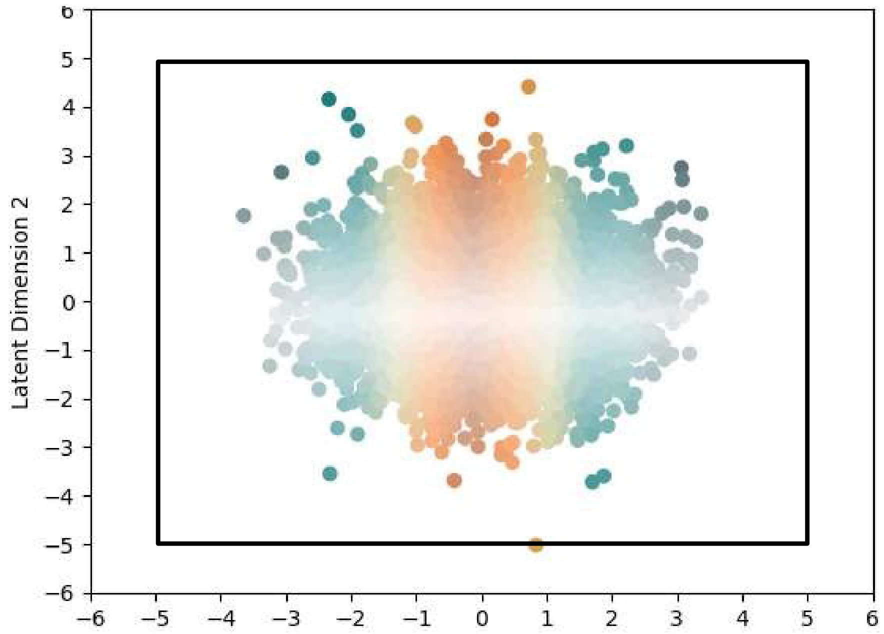


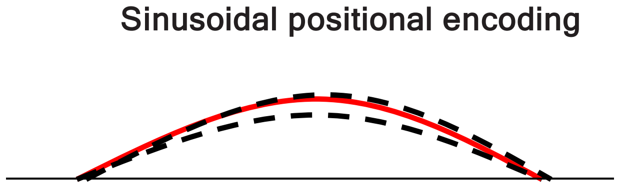


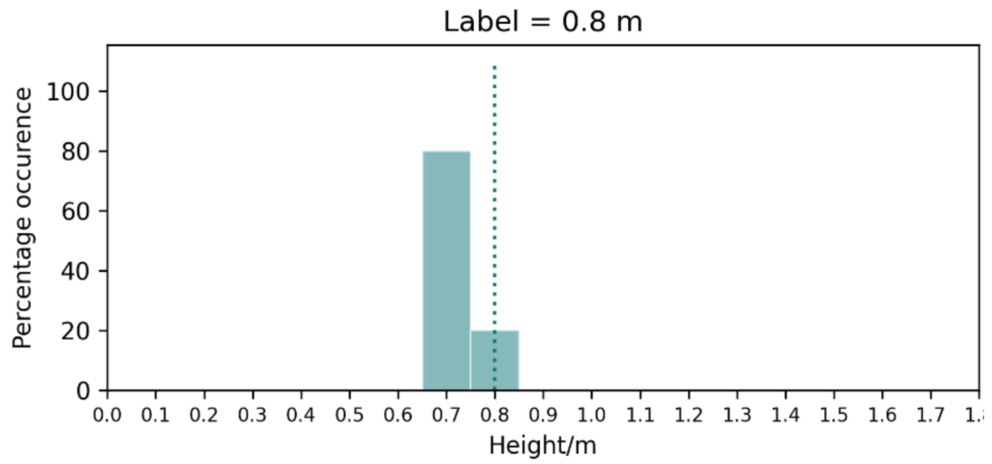
GENERATOR

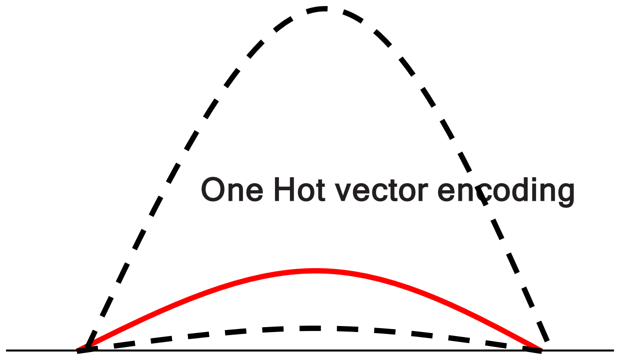
CONDITIONAL VAE

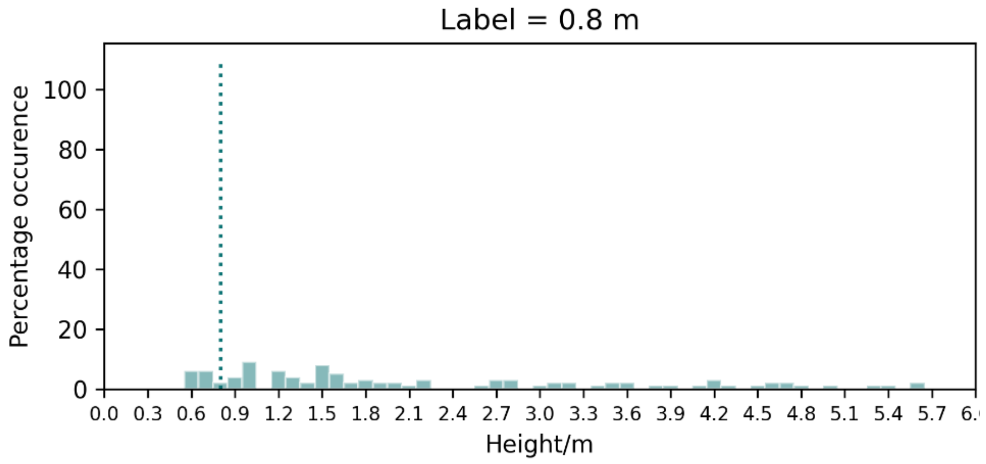
Large sparse latent space











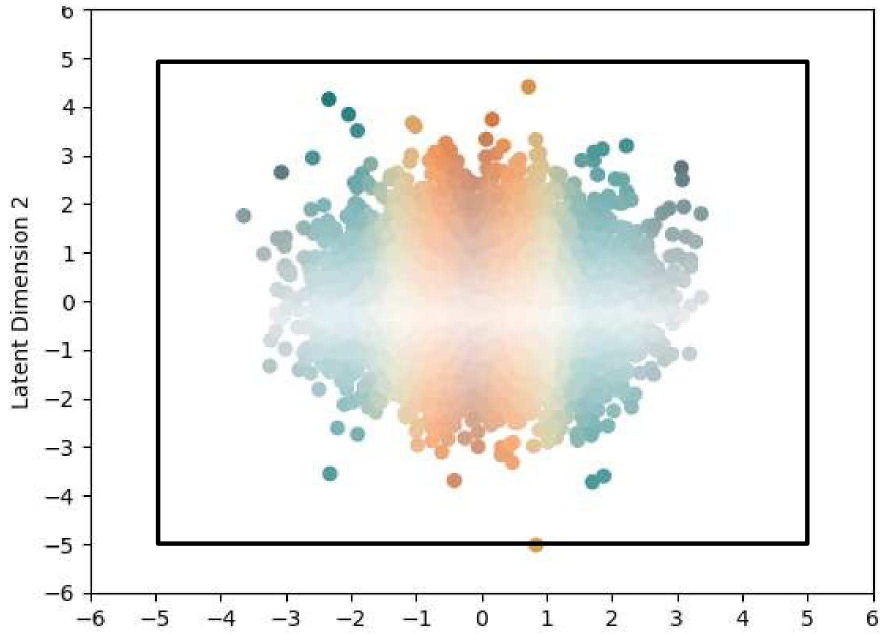
Desired vault

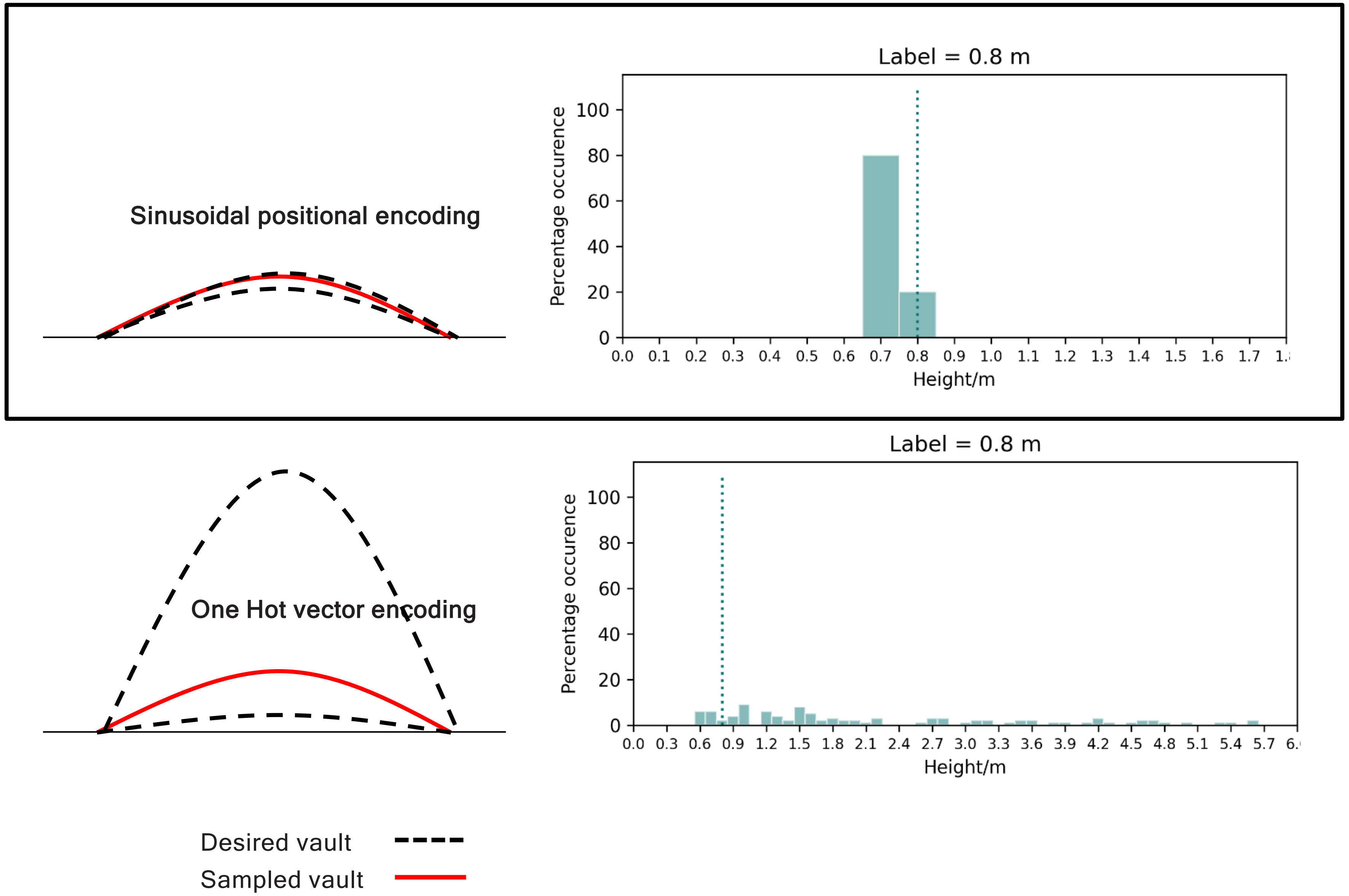
Sampled vault

GENERATOR

CONDITIONAL VAE

Large sparse latent space

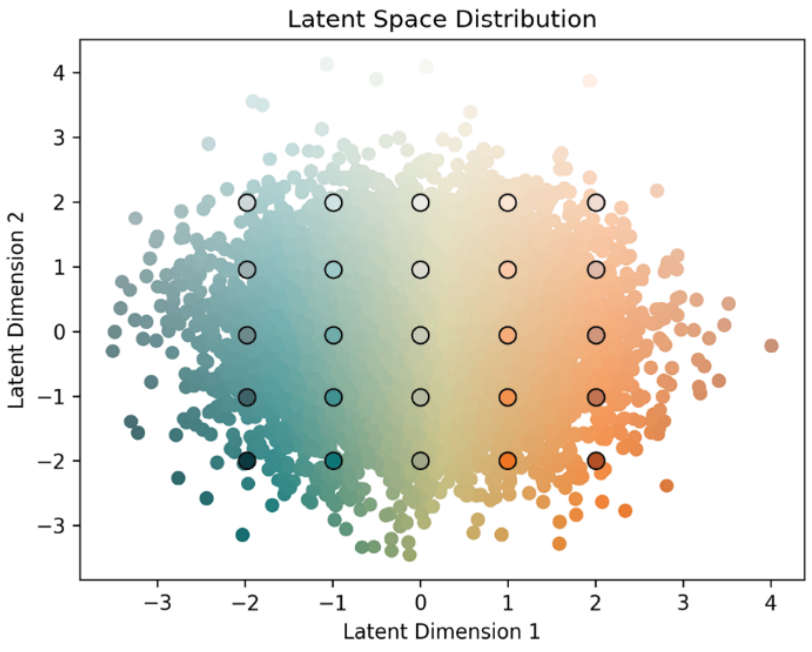


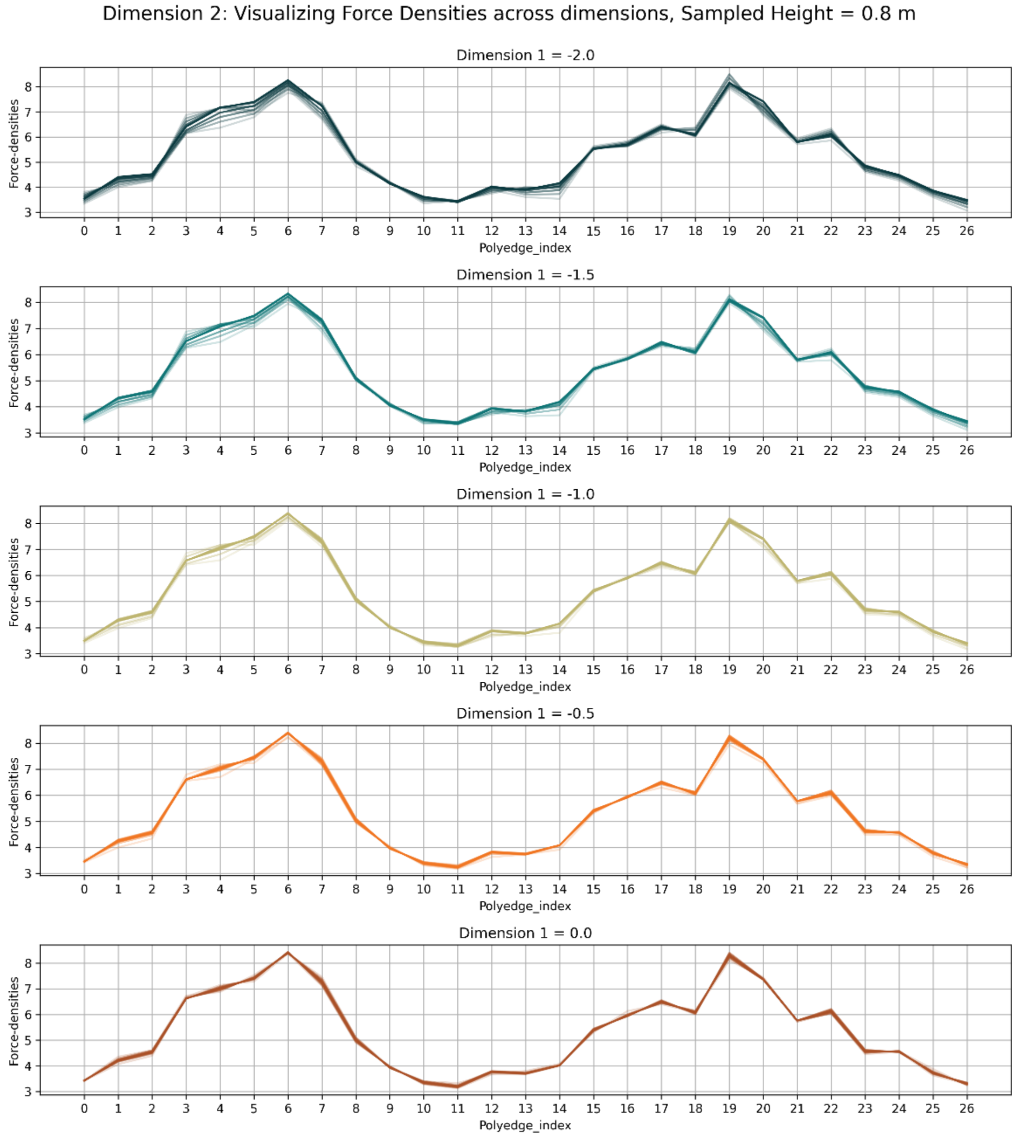


GENERATOR

CONDITIONAL VAE

Large sparse latent space

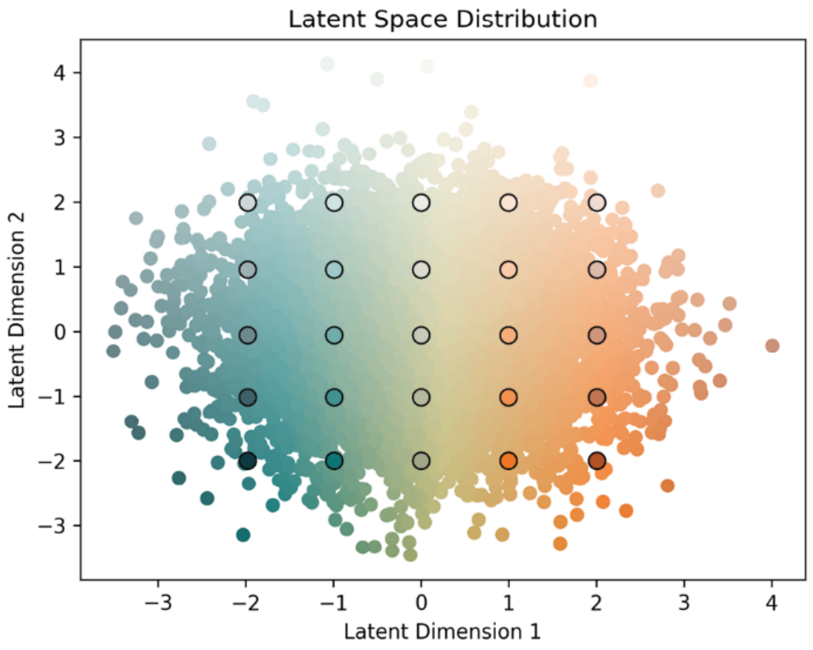


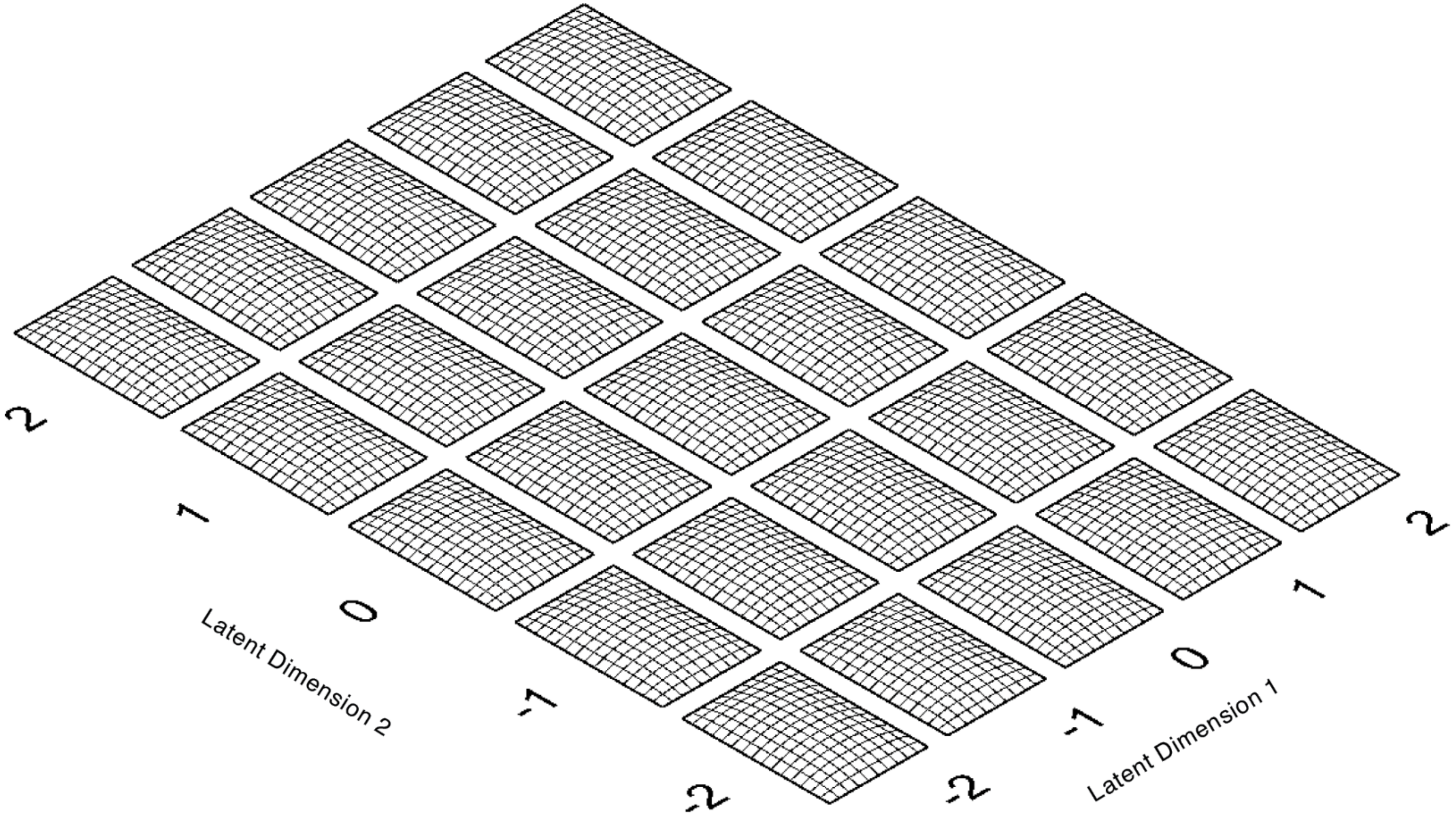


GENERATOR

CONDITIONAL VAE

Large sparse latent space



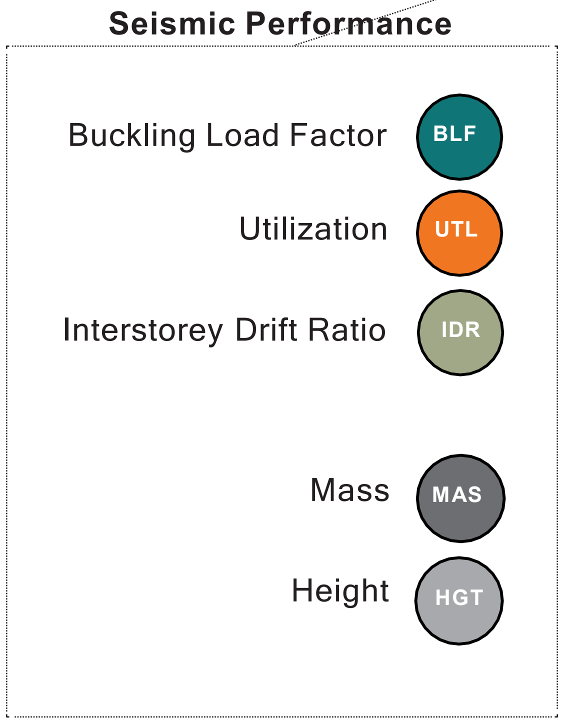


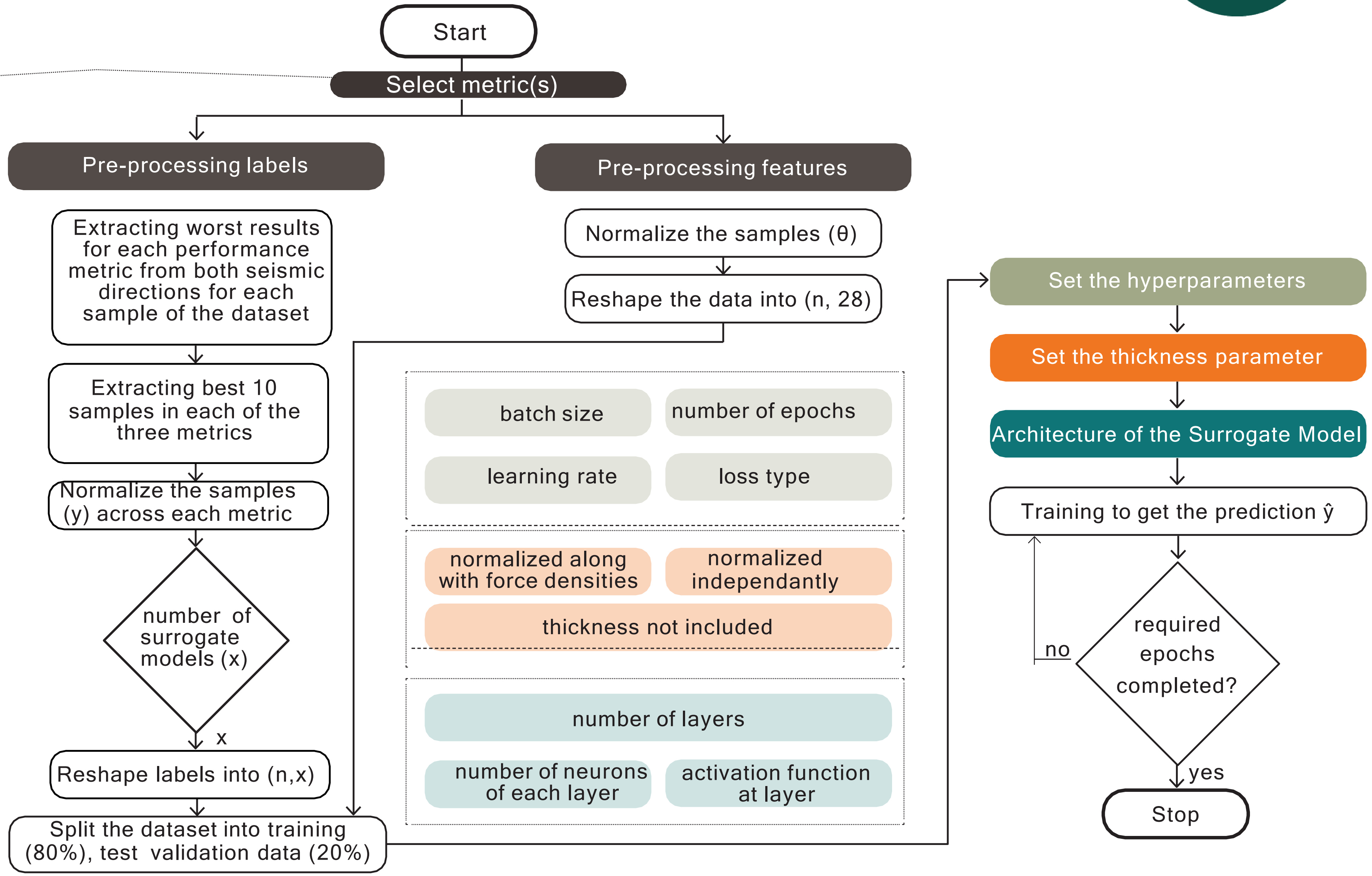
GENERATOR

SURROGATE MODEL

WORKFLOW

carried out in tensorflow in python

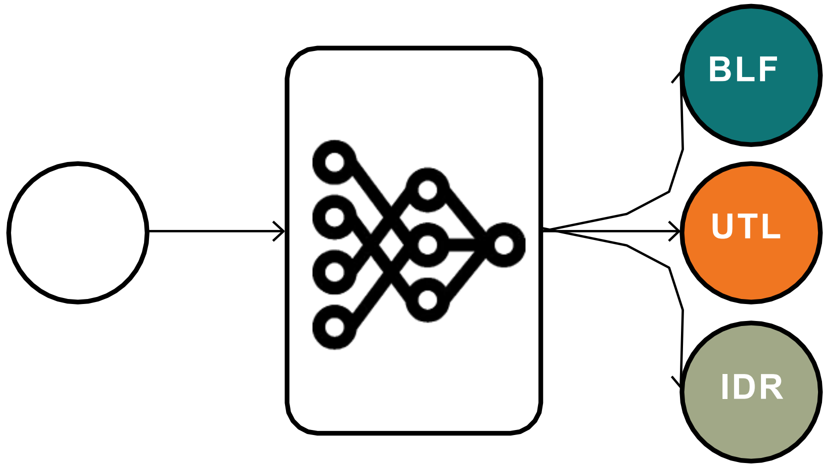




GENERATOR

SURROGATE MODEL

One surrogate model

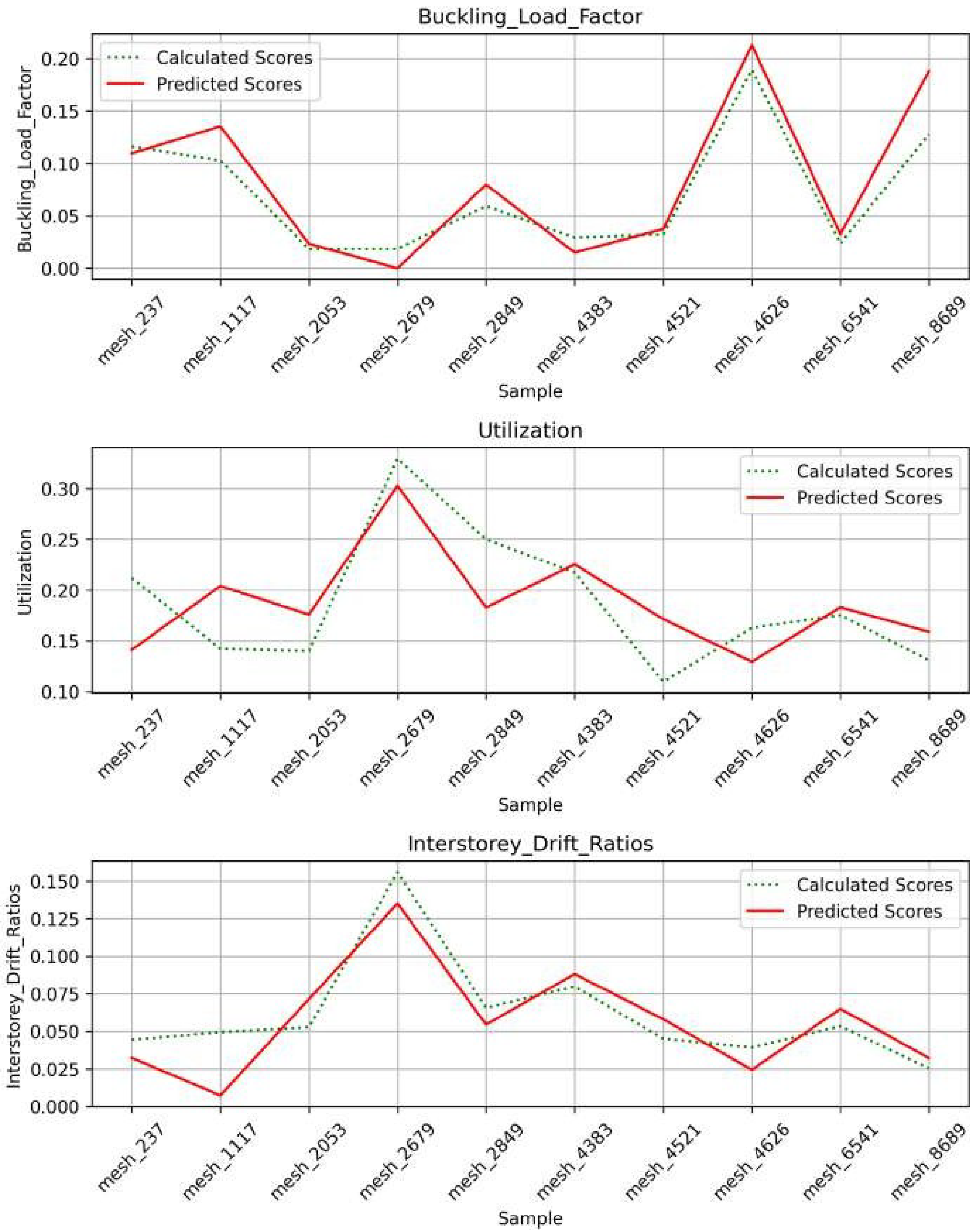


1 surrogate model would unite them all.
1 model would guide them
1 would be connected to the VAE
And, through gradient descent,
optimize them

GENERATOR

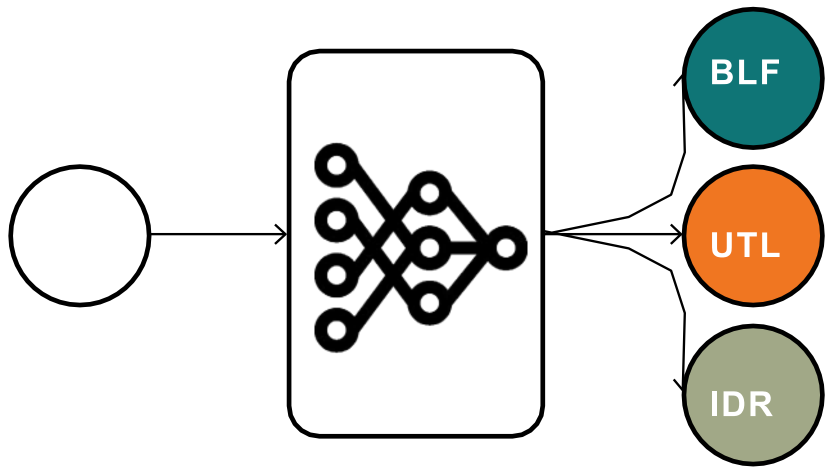
HYPERPARAMETERS: epochs = 3000, **batch_size** = 128, **learning_rate** = 1E-06

SURROGATE MODEL



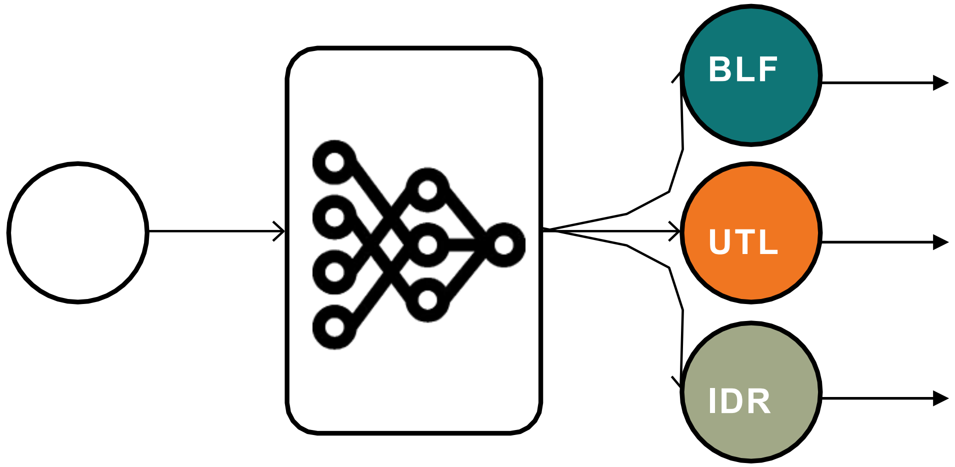
GENERATOR

SURROGATE MODEL



GENERATOR

SURROGATE MODEL



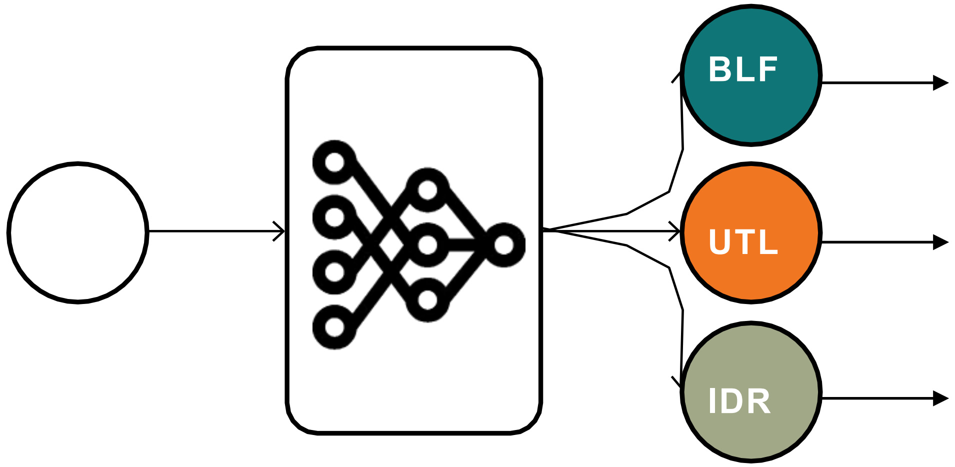
$$loss_1 = \frac{1}{n} \sum_{i=1}^{n} \left(y_{1,i} - y_{1,true,i}\right)^2$$

$$loss_2 = \frac{1}{n} \sum_{i=1}^{n} \left(y_{2,i} - y_{2,true,i}\right)^2$$

$$loss_3 = \frac{1}{n} \sum_{i=1}^{n} \left(y_{3,i} - y_{3,true,i}\right)^2$$

GENERATOR

SURROGATE MODEL



$$loss_1 = \frac{1}{n}\sum_{i=1}^{n}\left(y_{1,i} - y_{1,true,i}\right)^2$$

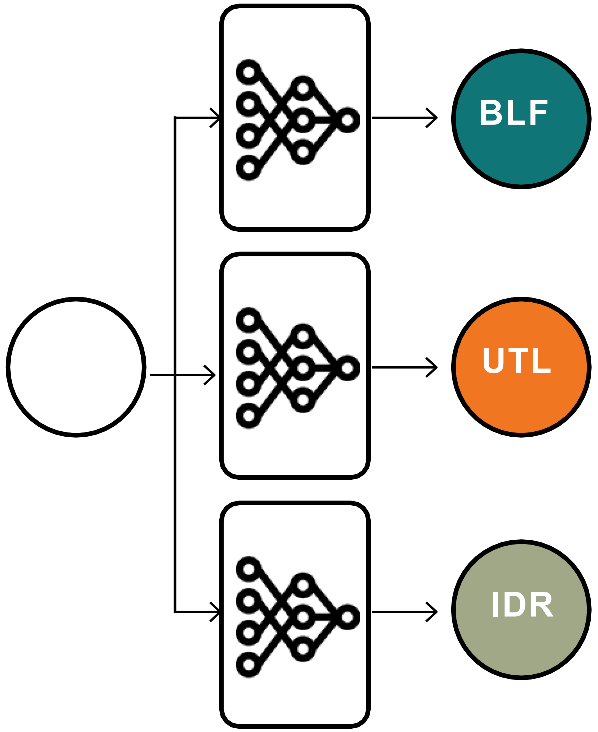
$$loss_2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_{2,i} - y_{2,true,i}\right)^2$$

$$loss_3 = \frac{1}{n}\sum_{i=1}^{n}\left(y_{3,i} - y_{3,true,i}\right)^2$$

$$loss_{total} = w_1 . loss_1 + w_2 . loss_2 + w_3 . loss$$

GENERATOR

SURROGATE MODEL

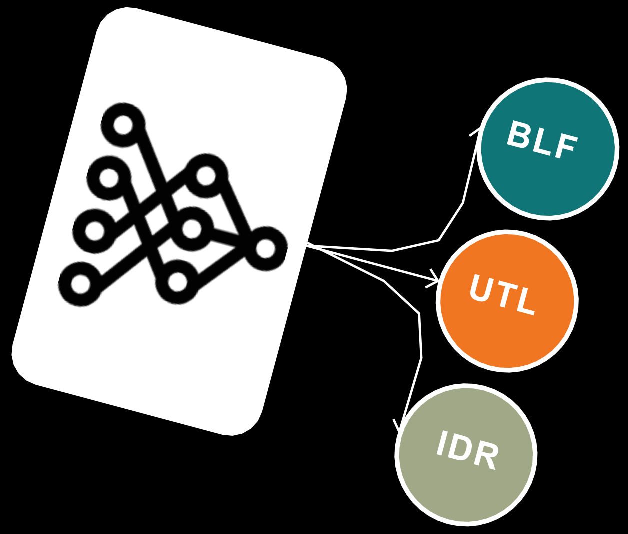


$$loss_1 = \frac{1}{n} \sum_{i=1}^{n} \left(y_{1,i} - y_{1,true,i}\right)^2$$

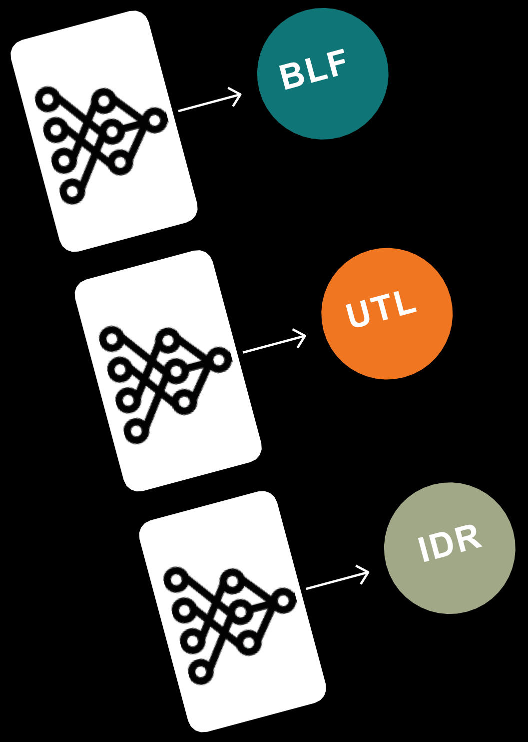
$$loss_2 = \frac{1}{n} \sum_{i=1}^{n} \left(y_{2,i} - y_{2,true,i}\right)^2$$

$$loss_3 = \frac{1}{n} \sum_{i=1}^{n} \left(y_{3,i} - y_{3,true,i}\right)^2$$

Is it really that PRECIOUS?



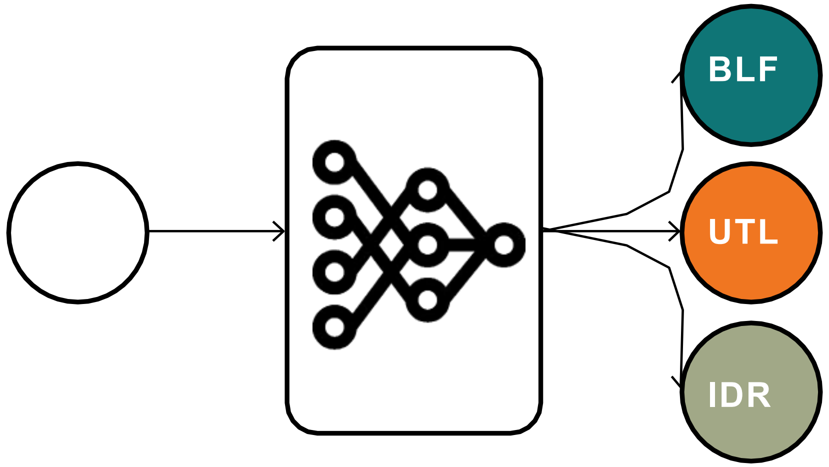
Or is there a surrogate PRECIOUS-er?



GENERATOR

SURROGATE MODEL

Single Surrogate Model

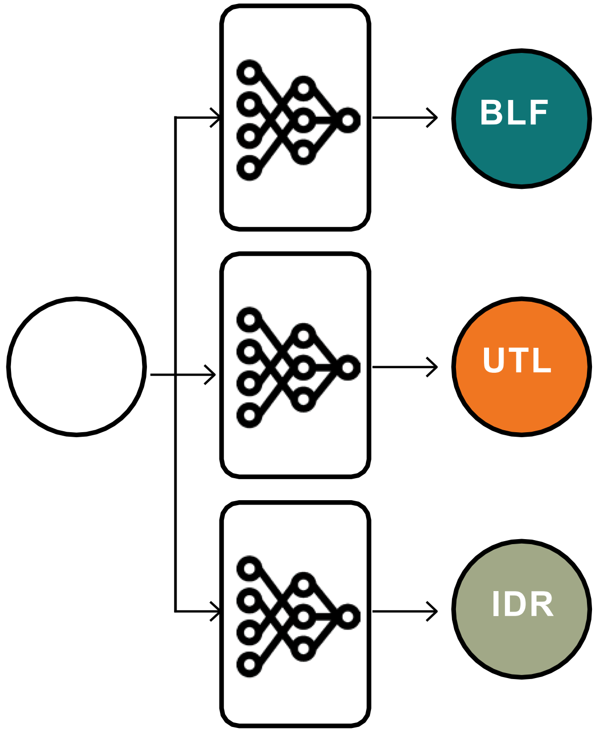


BUCKLING LOAD FATOR

UTILIZATION

INTERSTOREY DRIFT RATIOS

3 separate surrogate models



GENERATOR

SURROGATE MODEL

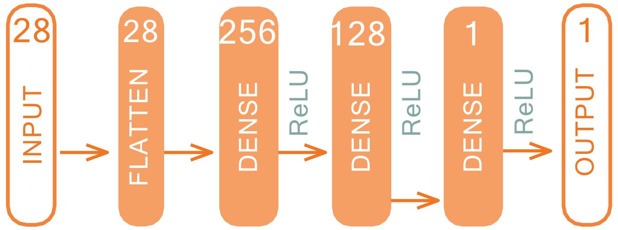
Single Surrogate Model

3 separate surrogate models

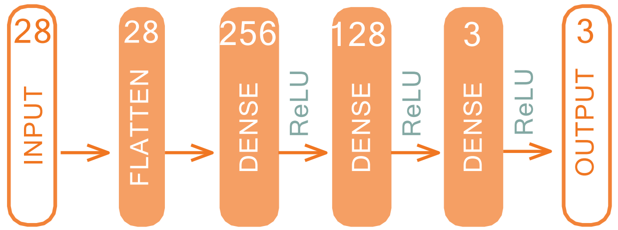
NMRSE OF
14.74%

BUCKLING LOAD FATOR

NMRSE OF
7.27%



HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06

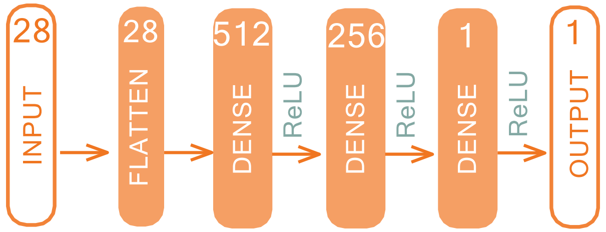


HYPERPARAMETERS: epochs = 3000, **batch_size** = 128, **learning_rate** = 1E-06

NMRSE OF
20.92%

UTILIZATION

NMRSE OF
9.18%

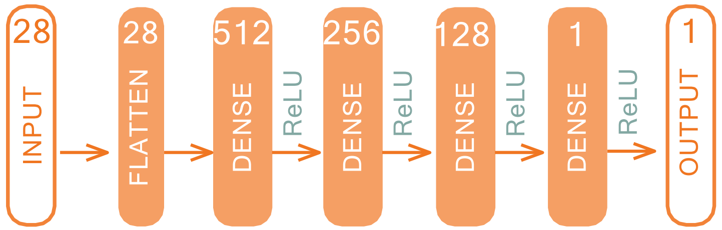


HYPERPARAMETERS: epochs = 3000, **batch_size** = 256, **learning_rate** = 5E-06

NMRSE OF
14.26%

INTERSTOREY DRIFT RATIOS

NMRSE OF
9.81%

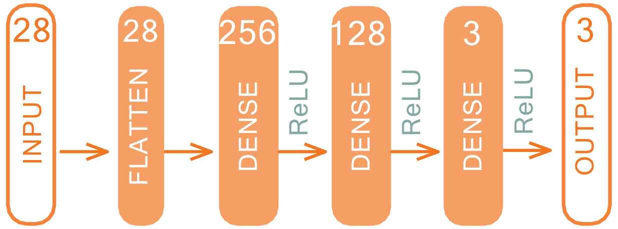


HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06

GENERATOR

SURROGATE MODEL

Single Surrogate Model



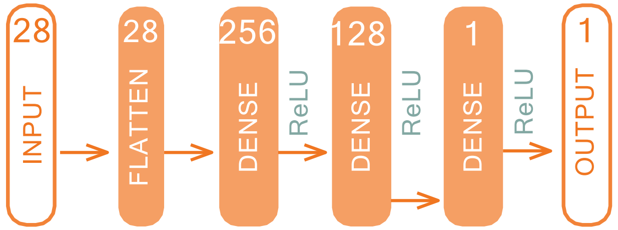
HYPERPARAMETERS: epochs = 3000, **batch_size** = 128, **learning_rate** = 1E-06

3 separate surrogate models

BUCKLING LOAD FATOR

NMRSE OF **14.74%**

REDUCTION OF ↓ **50.7%**

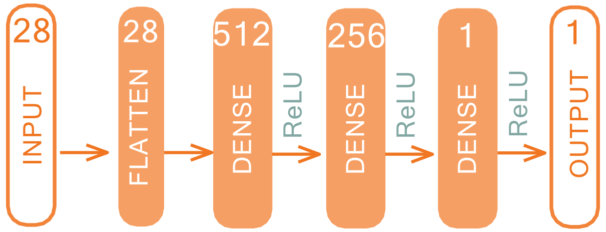


HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06

UTILIZATION

NMRSE OF **20.92%**

REDUCTION OF ↓ **56.1%**

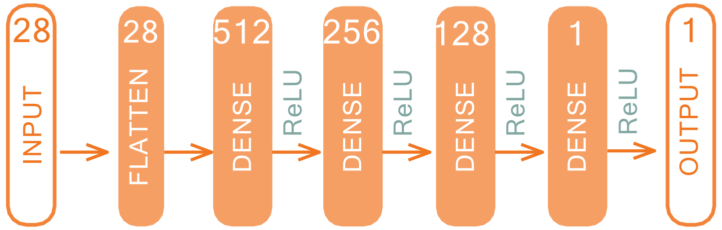


HYPERPARAMETERS: epochs = 3000, **batch_size** = 256, **learning_rate** = 5E-06

INTERSTOREY DRIFT RATIOS

NMRSE OF **14.26%**

REDUCTION OF ↓ **31.2%**

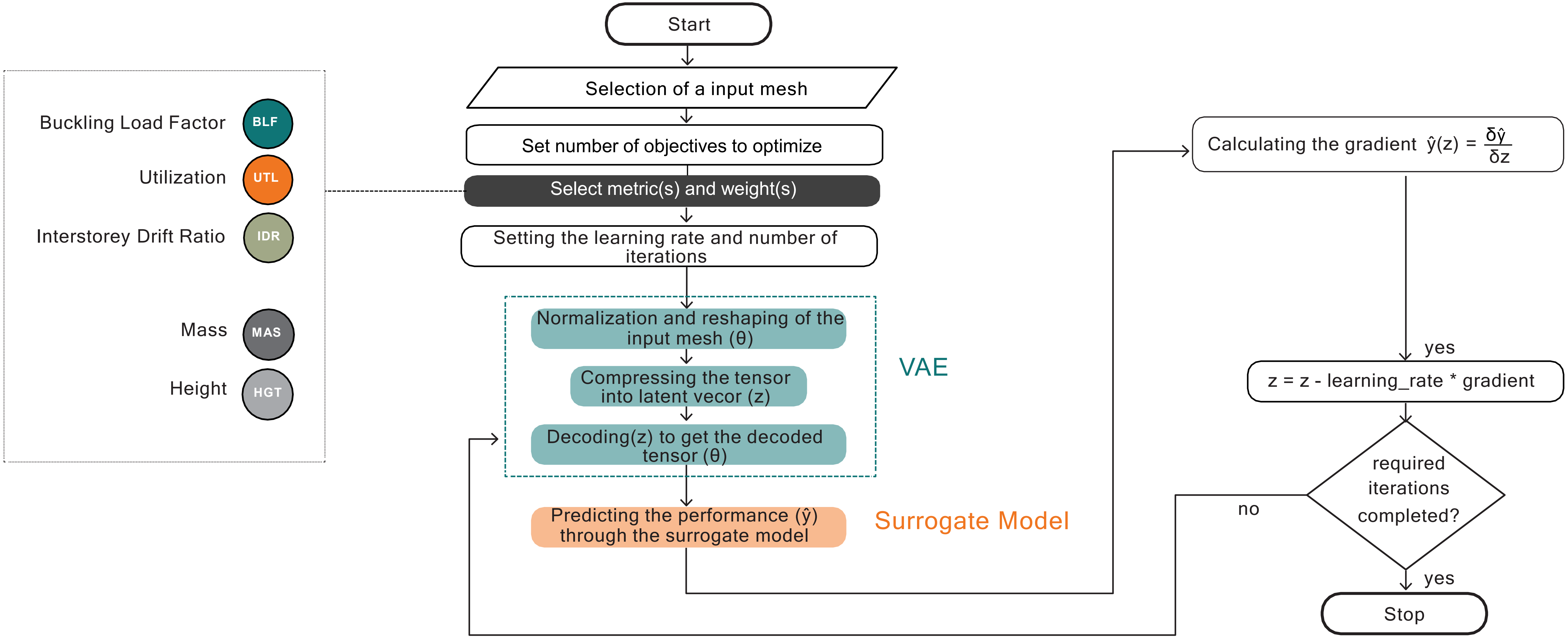


HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06

GENERATOR

OPTIMIZATION

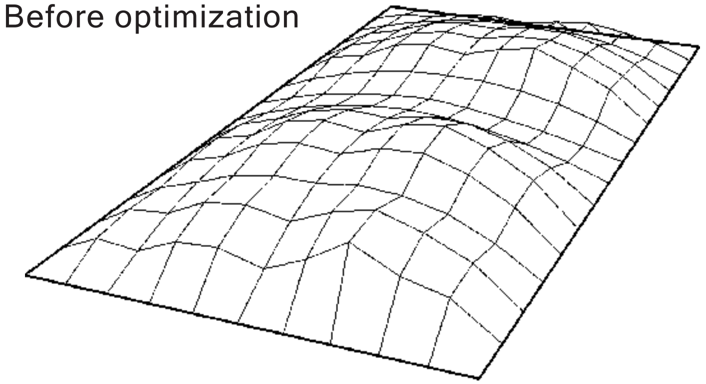
WORKFLOW



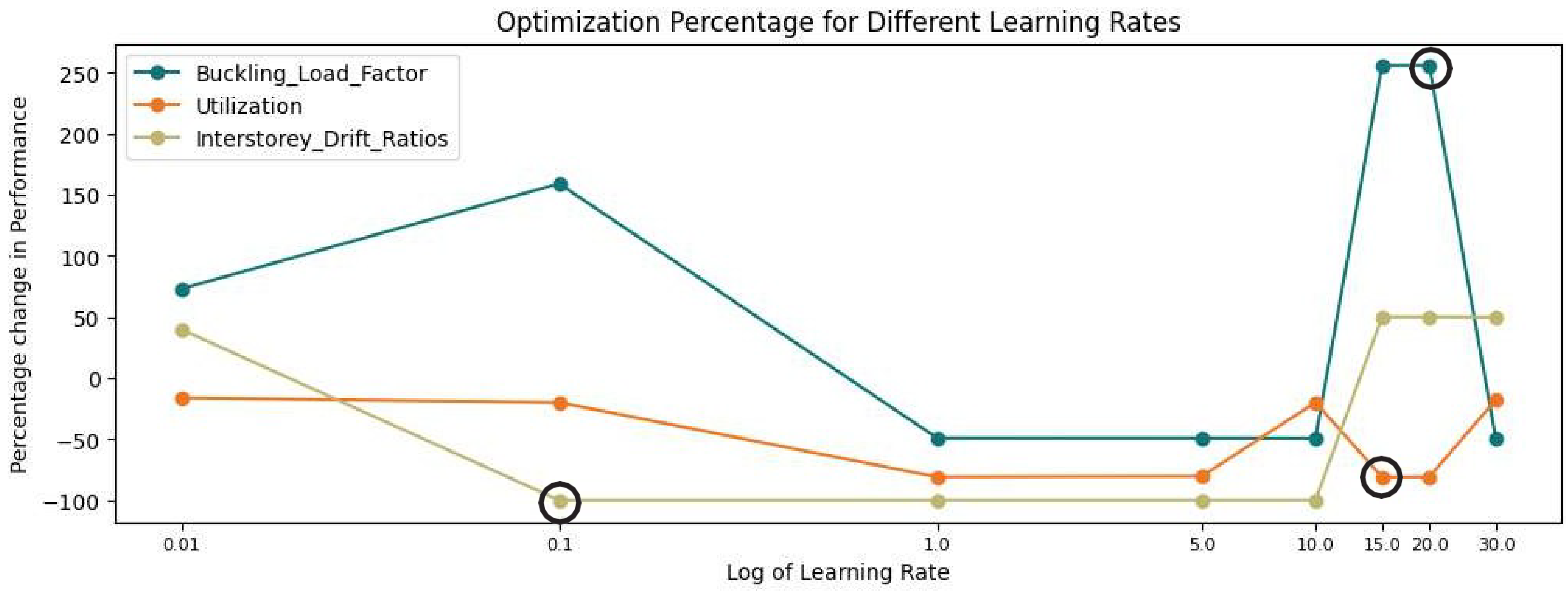
GENERATOR

OPTIMIZATION

Before optimization



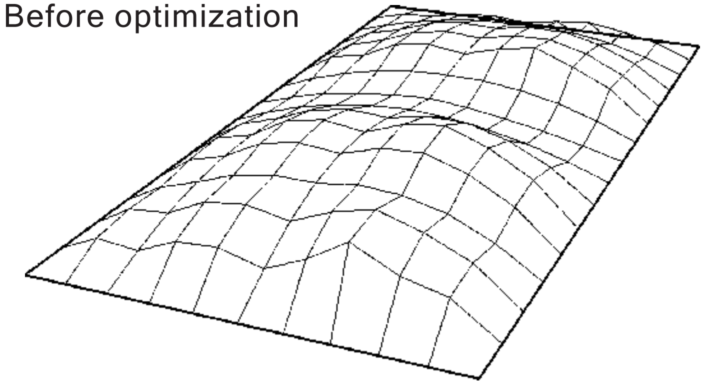
DATASET: randomized	
Metric	Values before Optimization
Buckling Load Factor	12.6
Utilization	10.6
Interstorey Drift Ratio	2.83E-03h
Thickness	0.06m



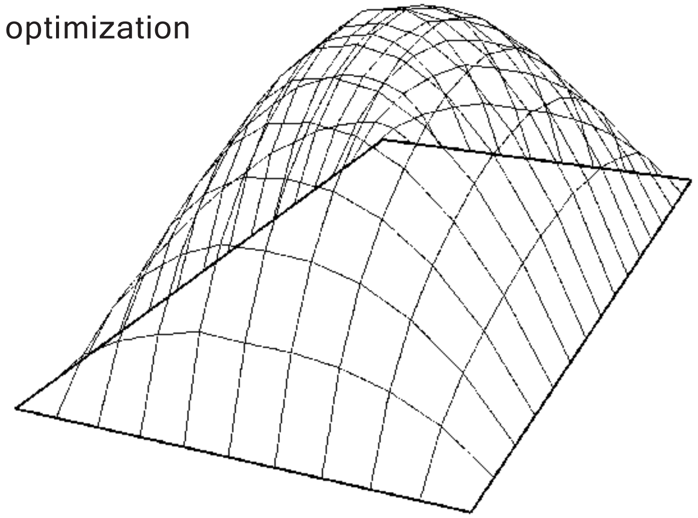
GENERATOR

SINGLE OJECTIVE OPTIMIZATION

Before optimization



After optimization



DATASET: randomized	
Metric	Values before Optimization
Buckling Load Factor	12.6
Utilization	10.6
Interstorey Drift Ratio	2.83E-03h
Thickness	0.06m

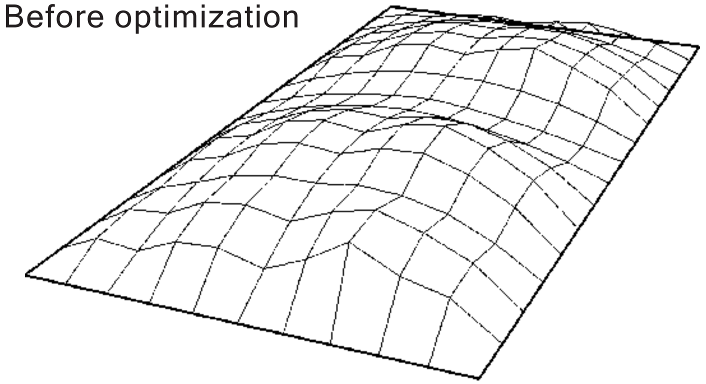
Force densities

Interstorey Drift Ratio
0.6
0.3
0.3
0.4
0.4
0.6
0.3
0.5
0.4
0.4
0.3
0.5
0.4
0.3
0.5
0.4
0.3
0.5
0.3
0.5
0.4
0.4
0.5
0.5
0.4
0.4
0.4

GENERATOR

SINGLE OJECTIVE OPTIMIZATION

Before optimization



DATASET: randomized	
Metric	**Values before Optimization**
Buckling Load Factor	12.6
Utilization	10.6
Interstorey Drift Ratio	2.83E-03h
Thickness	0.06m

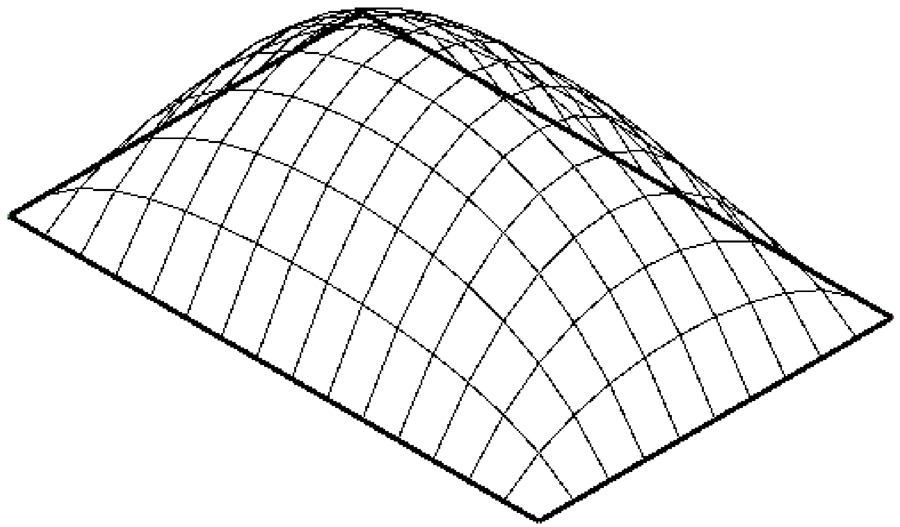
Edge number	Force densities of Initial Mesh	Force densities of Optimized mesh in		
		Buckling Load Factor	Utilization	Interstorey Drift Ratio
column_1	0.2	Near zero	Near zero	0.6
column_2	0.3	Near zero	Near zero	0.3
column_4	0.4	Near zero	Near zero	0.3
column_5	0.1	Near zero	Near zero	0.4
column_6	0.5	Near zero	Near zero	0.4
column_7	3.3	Near zero	Near zero	0.6
column_8	0.5	Near zero	Near zero	0.3
column_9	0.5	Near zero	Near zero	0.5
column_10	4.2	Near zero	Near zero	0.4
column_11	0.6	Near zero	Near zero	0.4
row_1	1.3	Near zero	Near zero	0.3
row_2	7.5	Near zero	Near zero	0.5
row_3	0.8	Near zero	Near zero	0.4
row_4	3.4	Near zero	Near zero	0.3
row_5	1.0	Near zero	Near zero	0.5
row_6	1.0	Near zero	Near zero	0.4
row_7	0.3	Near zero	Near zero	0.3
row_8	3.4	Near zero	Near zero	0.5
row_9	9.6	Near zero	Near zero	0.3
row_10	4.9	Near zero	Near zero	0.5
row_11	0.8	Near zero	Near zero	0.4
row_12	0.4	Near zero	Near zero	0.4
row_13	0.6	Near zero	Near zero	0.5
row_14	1.9	Near zero	Near zero	0.5
row_15	0.4	Near zero	Near zero	0.4
row_16	0.1	Near zero	Near zero	0.4
row_17	0.5	Near zero	Near zero	0.4

INVALID MESHES

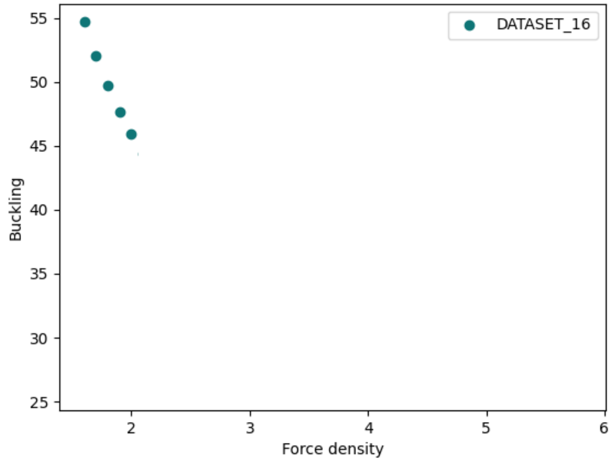
GENERATOR

SINGLE OJECTIVE OPTIMIZATION

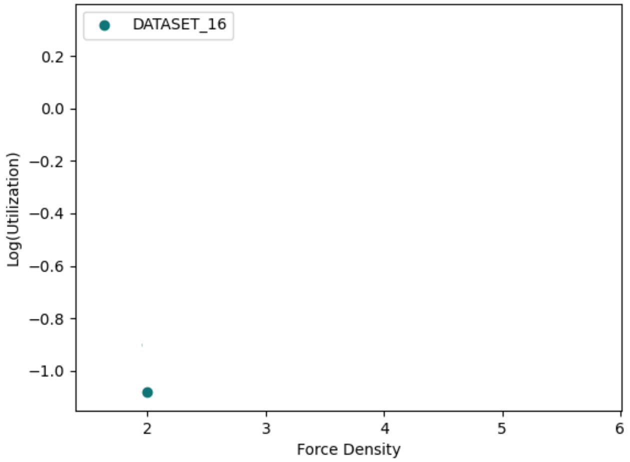
uniform force densities dataset



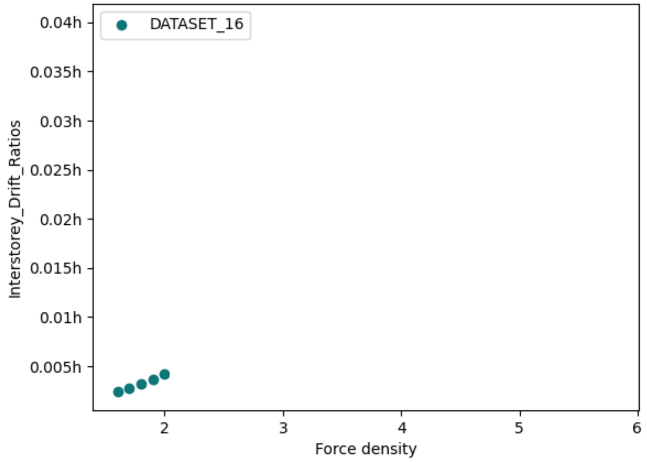
BUCKLING LOAD FACTOR



UTILIZATION



INTERSTOREY DRIFT RATIOS

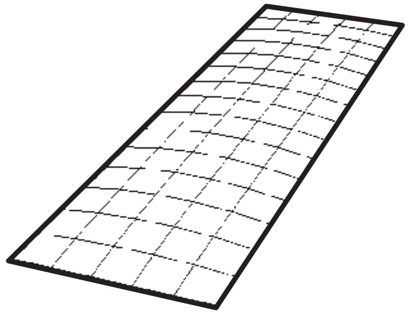


GENERATOR

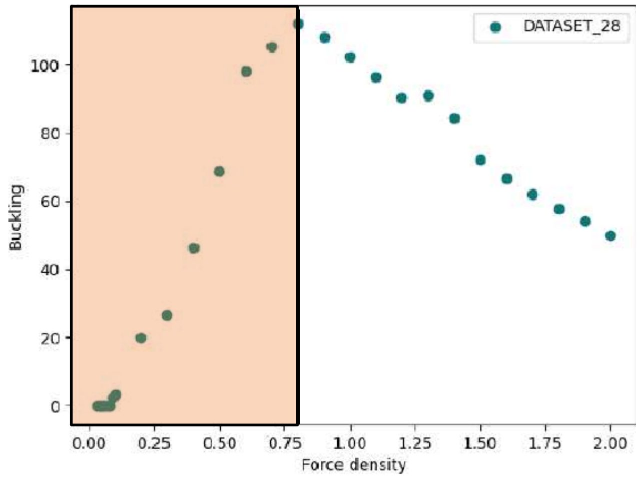
SINGLE OJECTIVE OPTIMIZATION

uniform force densities dataset

DATASET 16



BUCKLING LOAD FACTOR

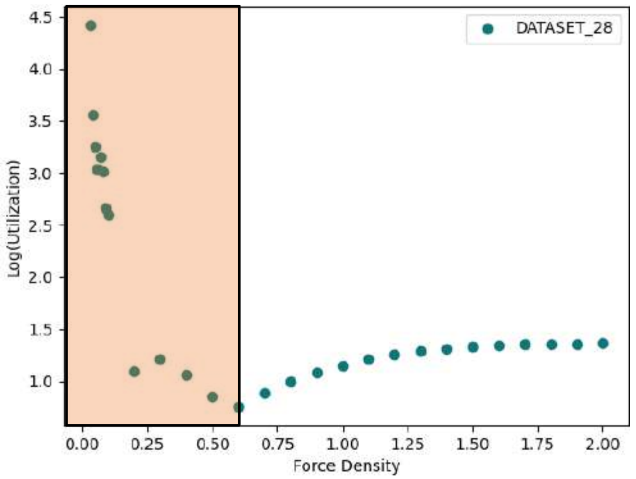


fd = 0.8

0.15%

OF DATASET

UTILIZATION

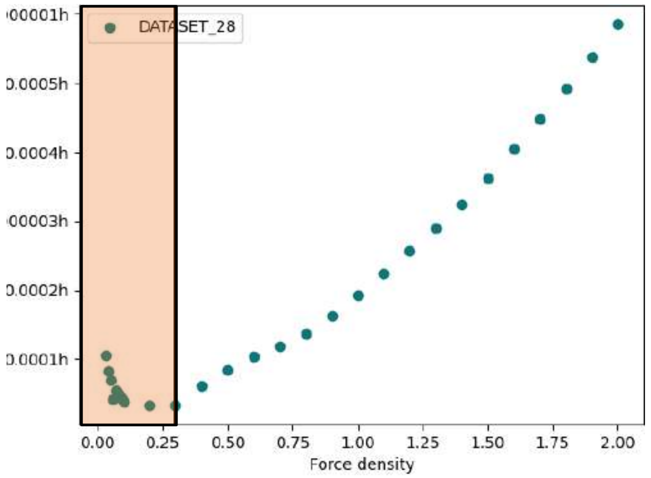


fd = 0.6

0.05%

OF DATASET

INTERSTOREY DRIFT RATIOS



fd = 0.3

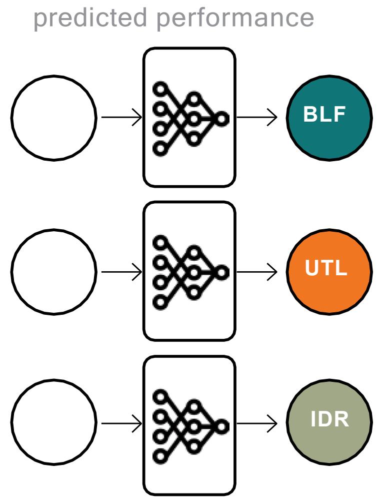
0.00%

OF DATASET

GENERATOR

SINGLE OBJECTIVE OPTIMIZATION

$$\hat{y}'(z) = \left(\frac{\delta \hat{y}}{\delta z}\right)$$

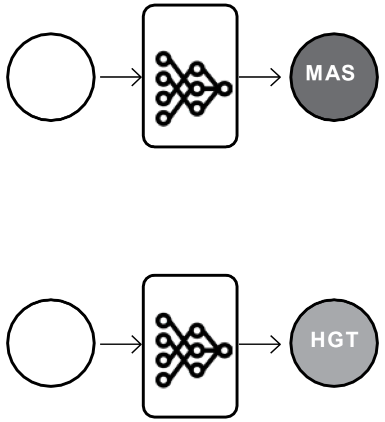


GENERATOR

MULTI OBJECTIVE OPTIMIZATION

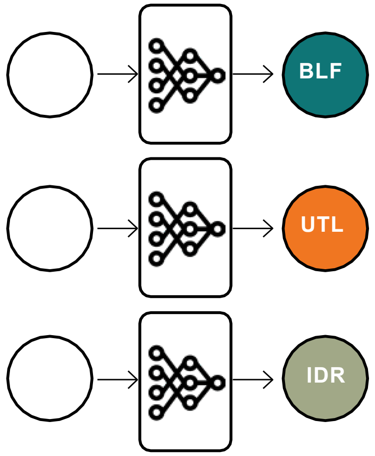
MASS

HEIGHT



$$\hat{y}'(z) = W_1\left(\frac{\delta \hat{y}_1}{\delta z}\right) + W_2\left(\frac{\delta \hat{y}_2}{\delta z}\right) + W_3\left(\frac{\delta \hat{y}_3}{\delta z}\right)$$

predicted performance



GENERATOR

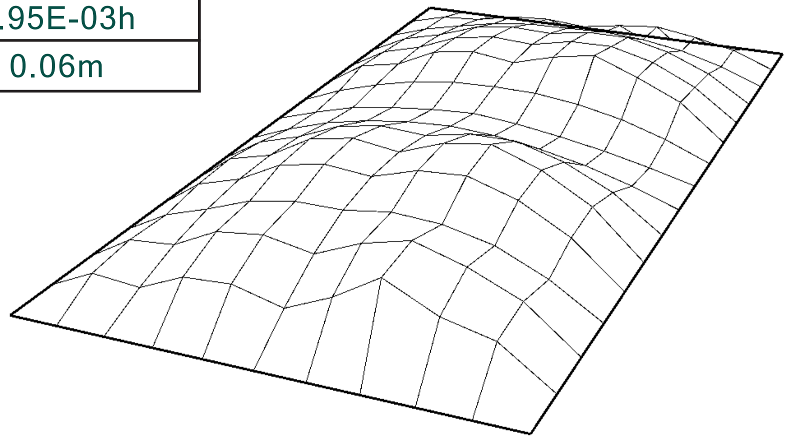
MULTI-OBJECTIVE OPTIMIZATION

UTILIZATION + INTERSTOREY DRIFT RATIO + HEIGHT

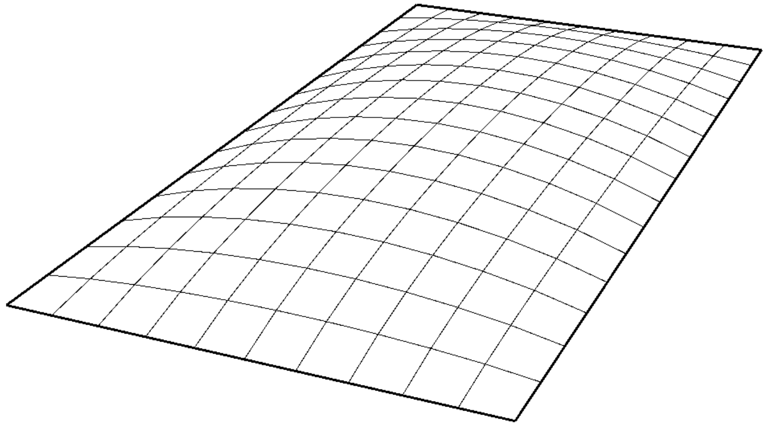
When initial mesh is sampled from dataset

Metric	Values before Optimization	Values before Optimization
Height	2.0m	1.29m
Utilization	10.6	7.3
Interstorey Drift Ratio	2.83E-03h	2.95E-03h
Thickness	0.06m	0.06m

Before optimization



After optimization

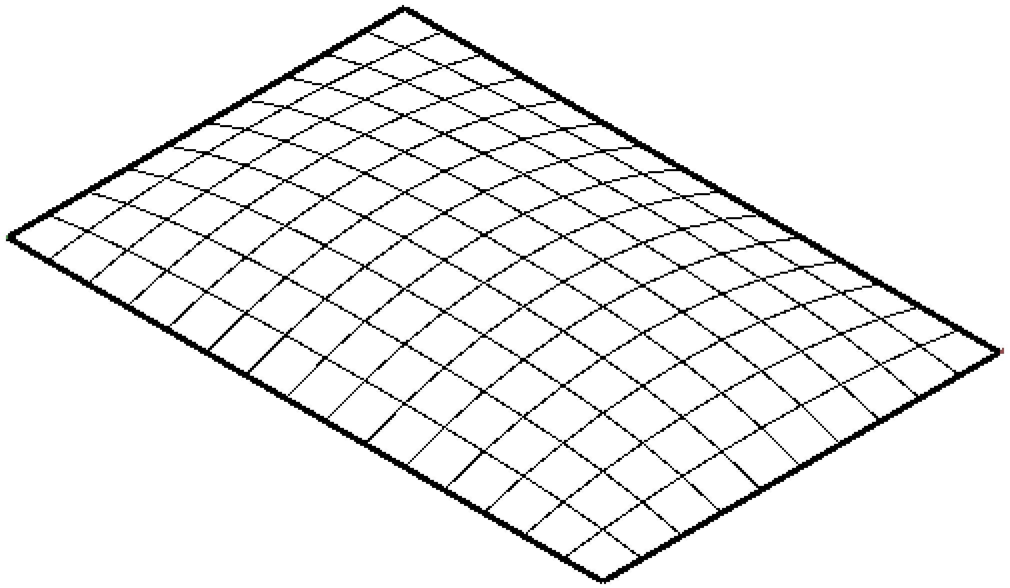


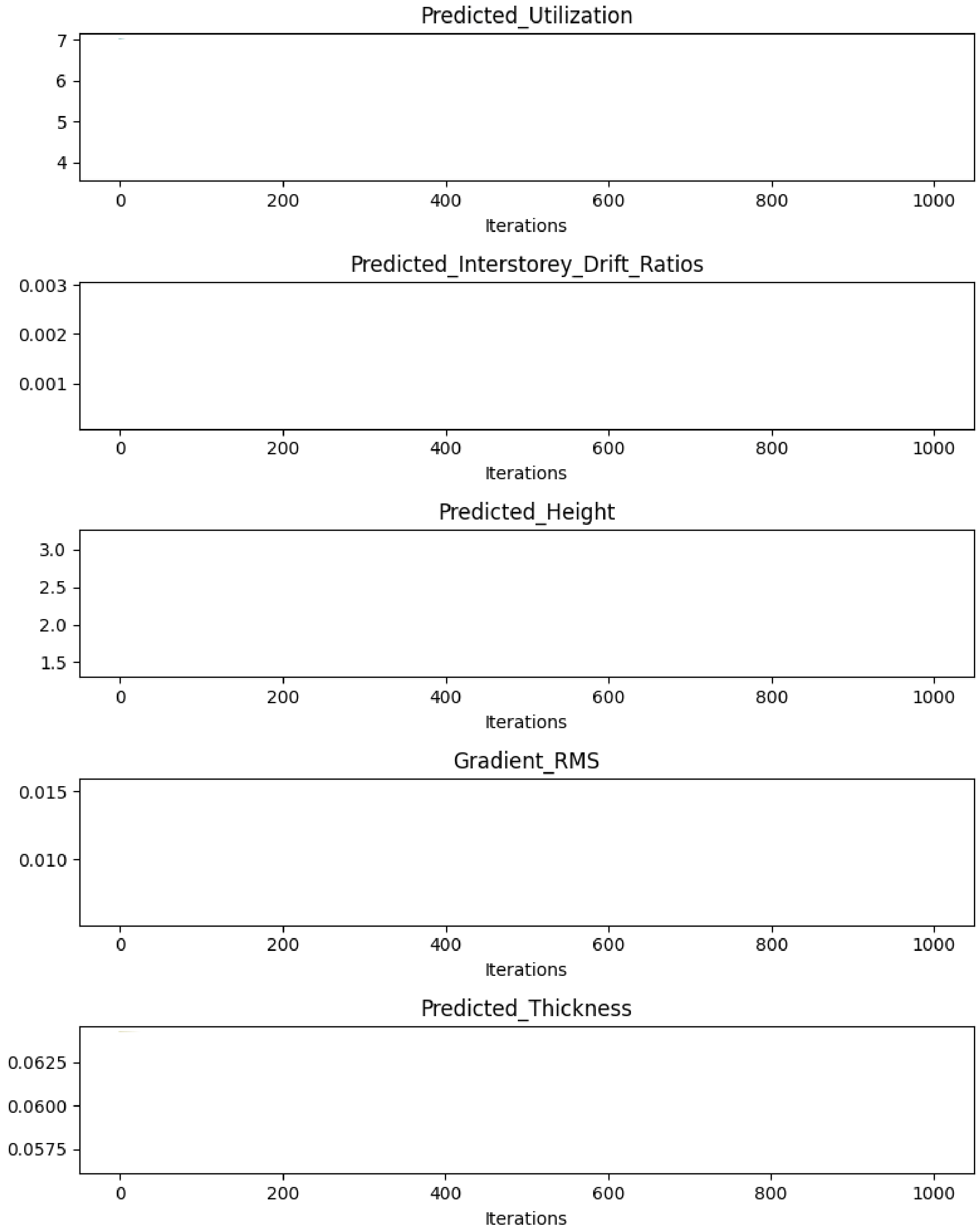
GENERATOR

MULTI-OBJECTIVE OPTIMIZATION

UTILIZATION + INTERSTOREY DRIFT RATIO + HEIGHT

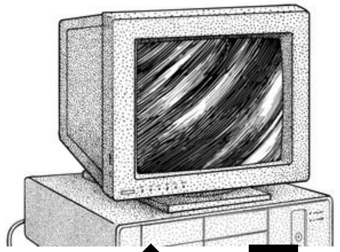
When initial mesh is sampled from latent space





De afbeelding kan niet worden weergegeven.

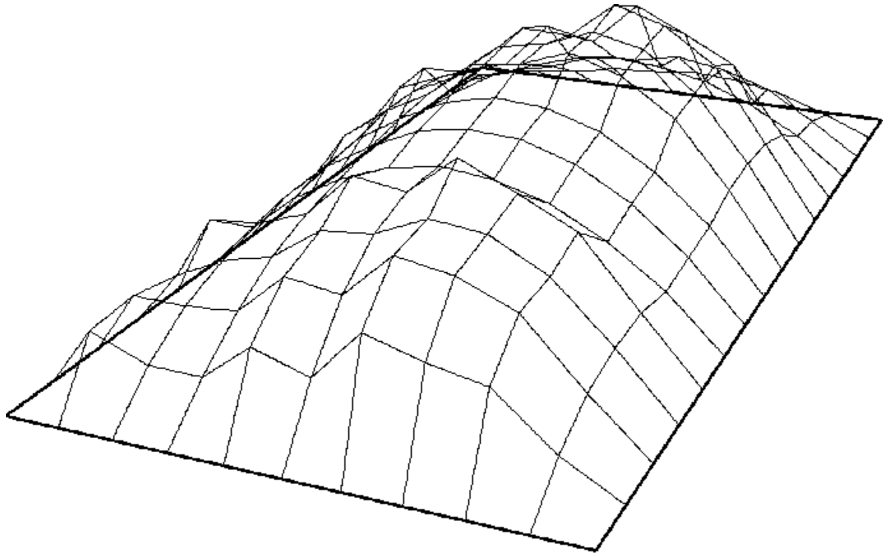
De afbeelding kan niet worden weergegeven.

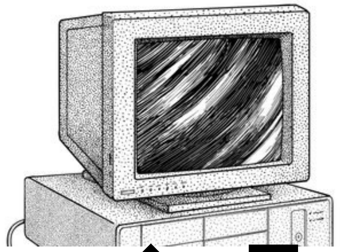


IN

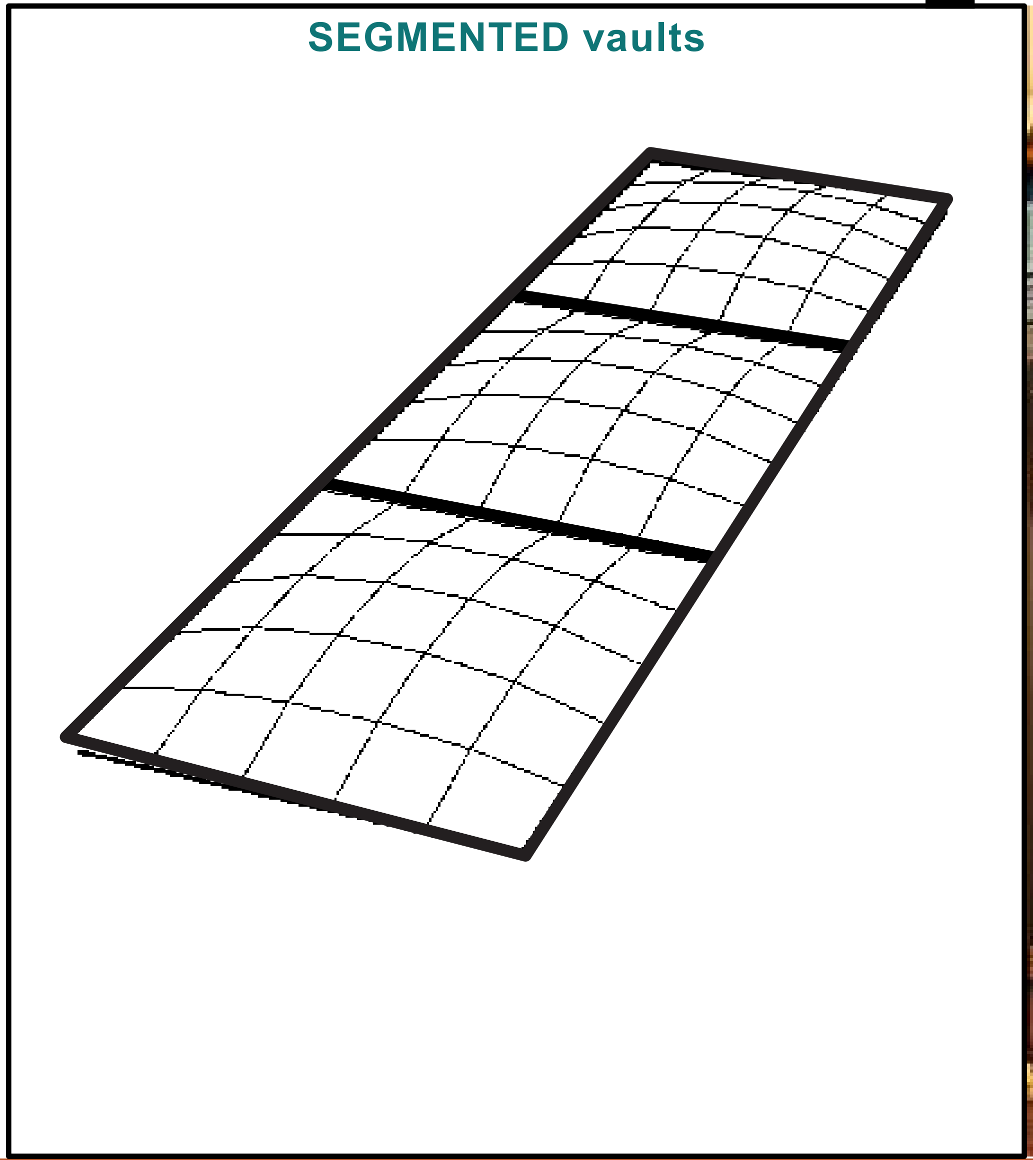
OUT

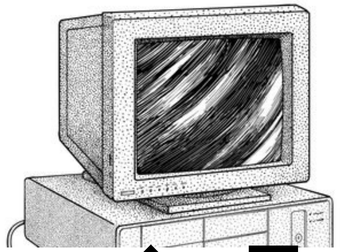
RANDOMIZED vaults





IN OUT

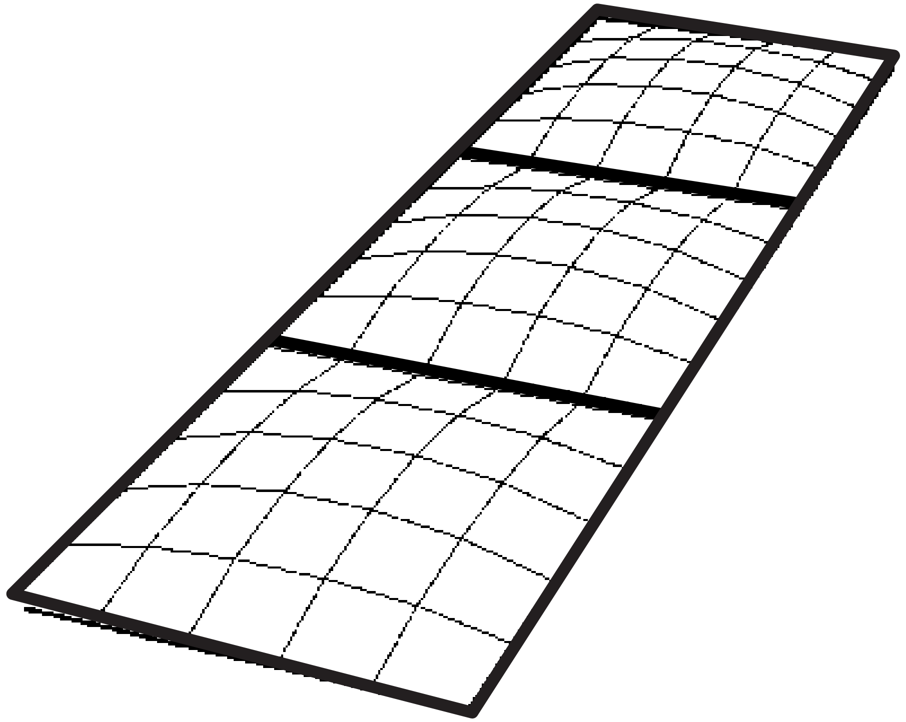




IN

OUT

SEGMENTED vaults



polyedge = column

polyedge = row

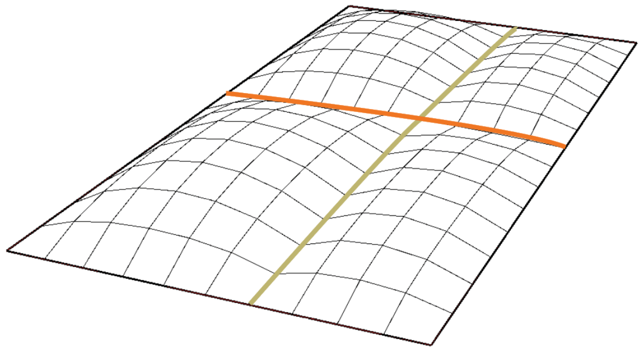
force density

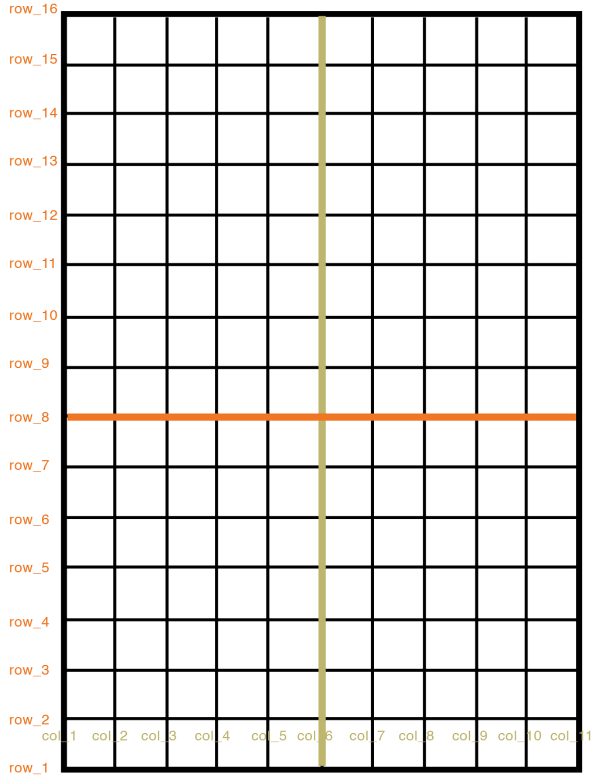
[[0,0,0,0,0,0,1,0,0,0,0] , [0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0] , [q]]

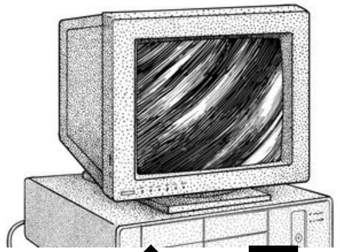
1.0 = support

0.0= not support

float value (eg1.2) = force density
of all polyedges of mesh



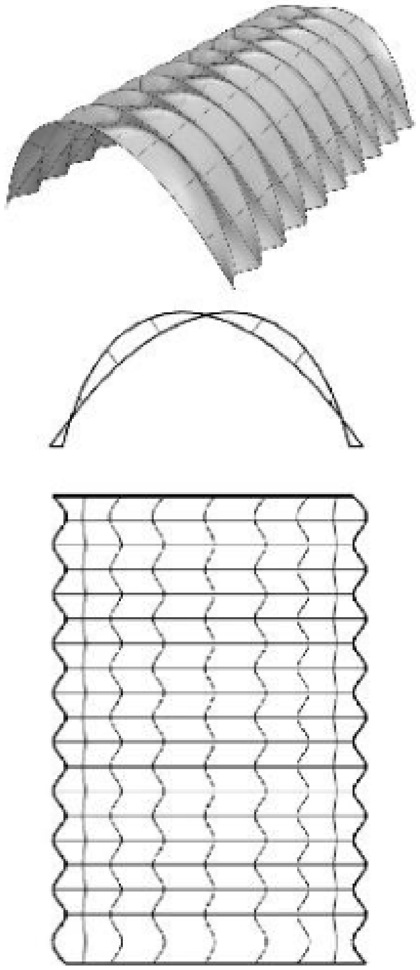




IN

OUT

CORRUGATED vaults

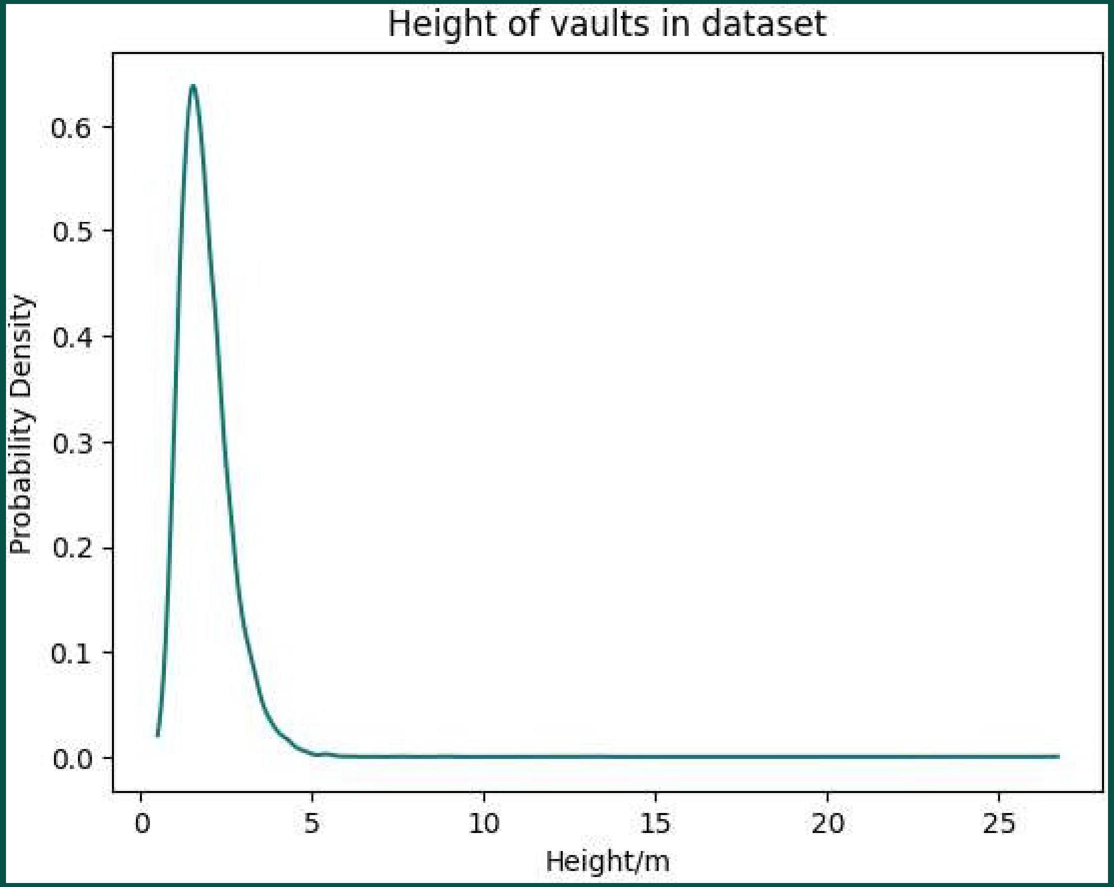


FUTURE POTENTIAL

1. Dataset revision for
    a) Better performing meshes under seismic loads

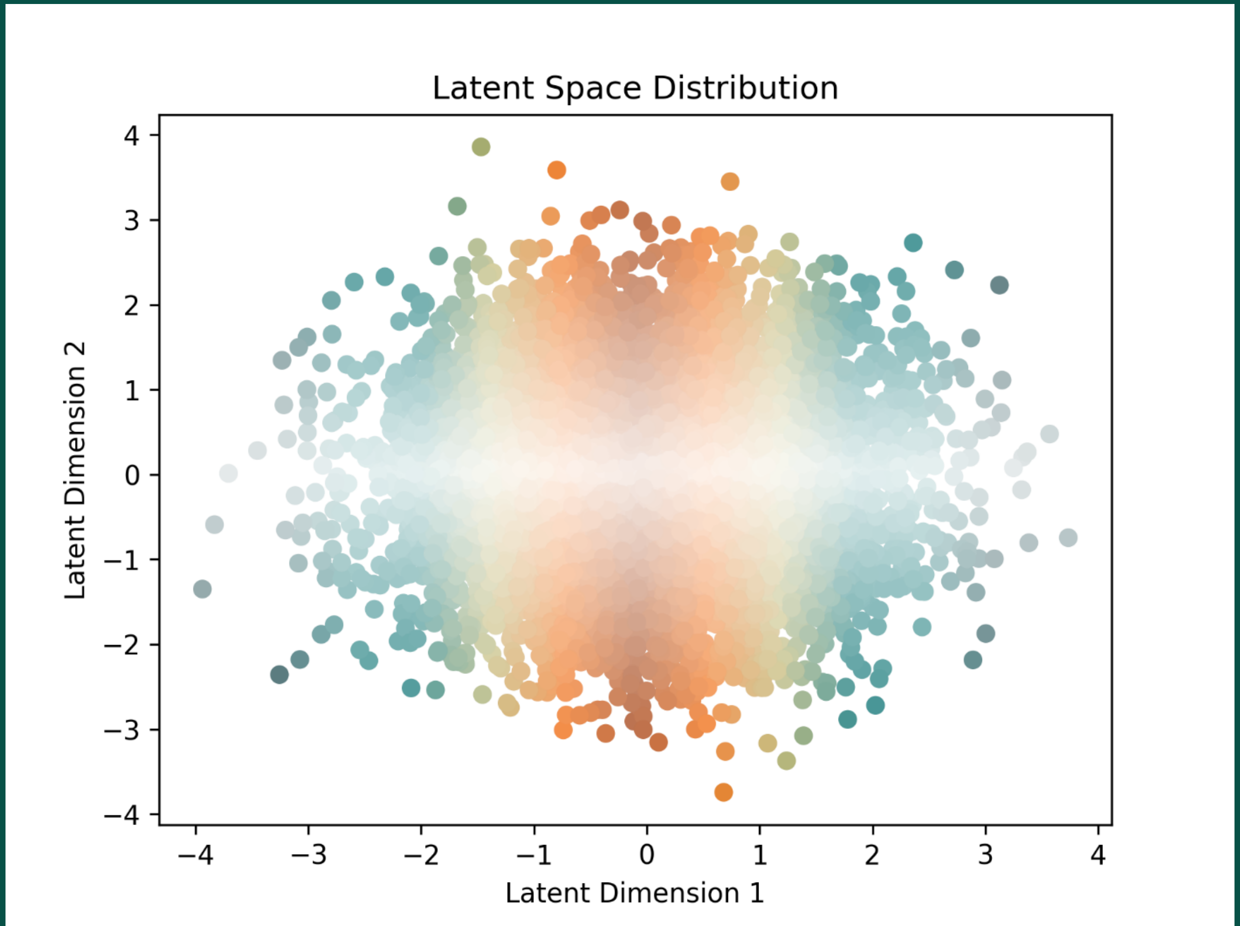
FUTURE POTENTIAL

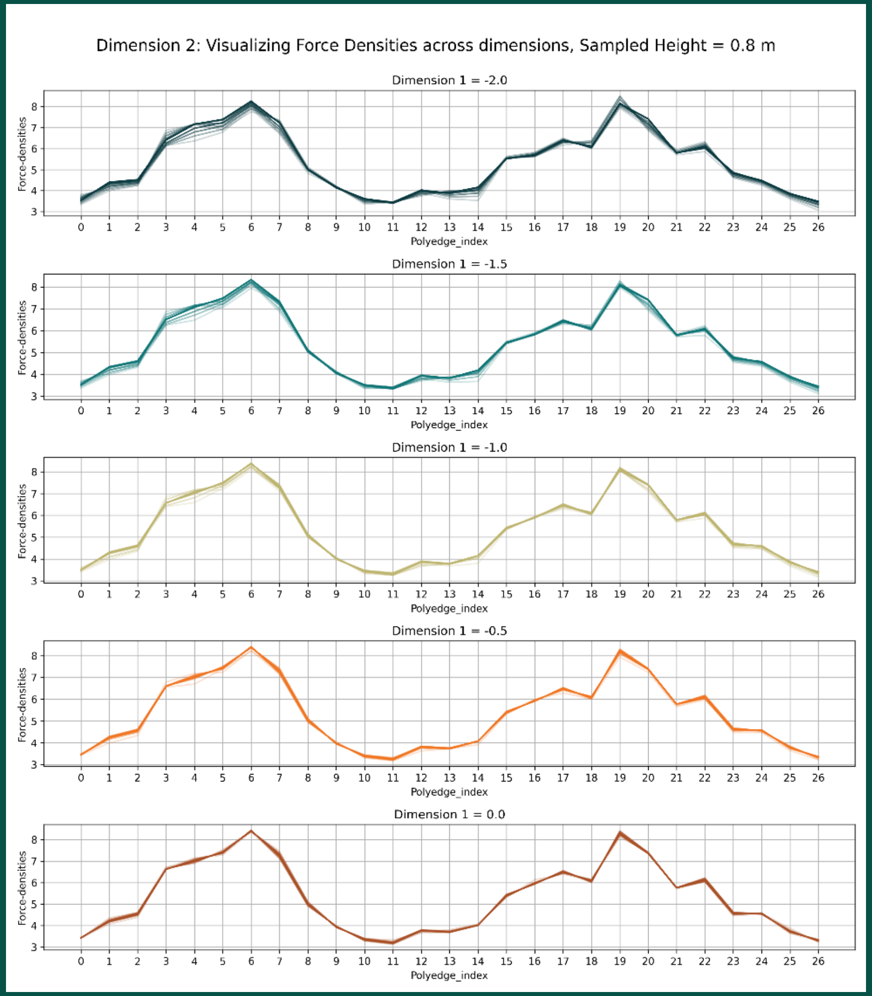
1. Dataset revision for
   a) Better performing meshes under seismic loads
   b) More accurate conditioning of the Conditional VAE



FUTURE POTENTIAL

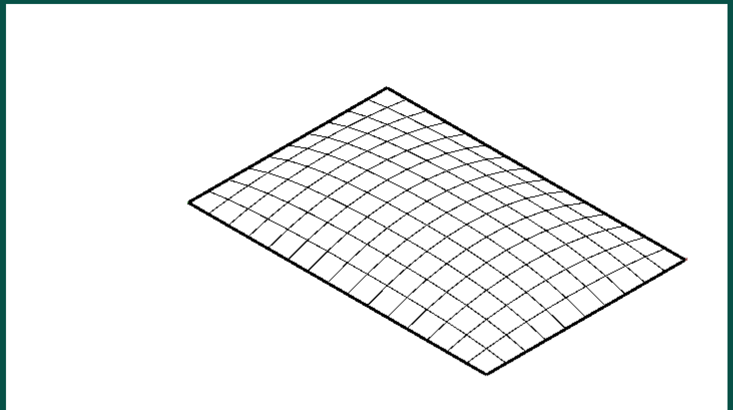
1. Dataset revision for
   a) Better performing meshes under seismic loads
   b) More accurate conditioning of the Conditional VAE
   c) Better latent space representation for multi-objective optimization of conflicting objectives

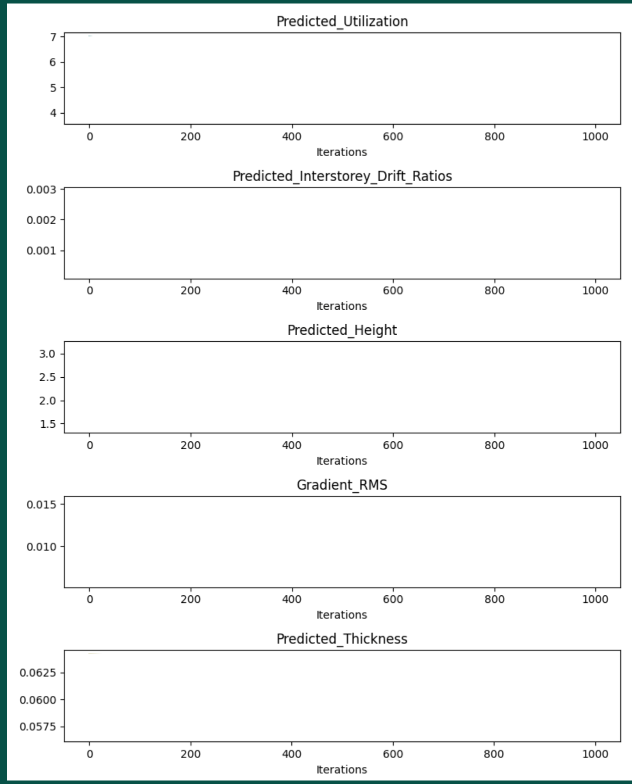


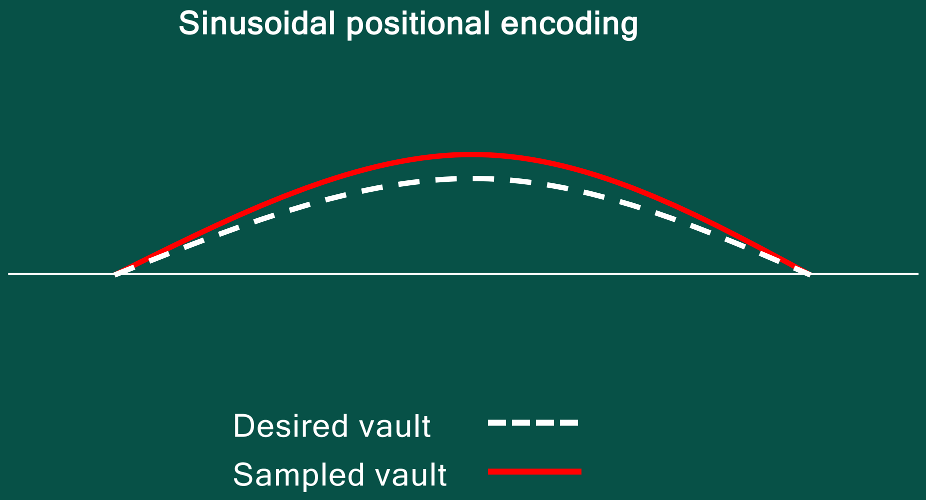


FUTURE POTENTIAL

1. Dataset revision for
    a) Better performing meshes under seismic loads
    b) More accurate conditioning of the Conditional VAE
    c) Better latent space representation for multi-objective optimization of conflicting objectives
2. How to constrain the latent space so that during optimization conditioned samples are within label limits





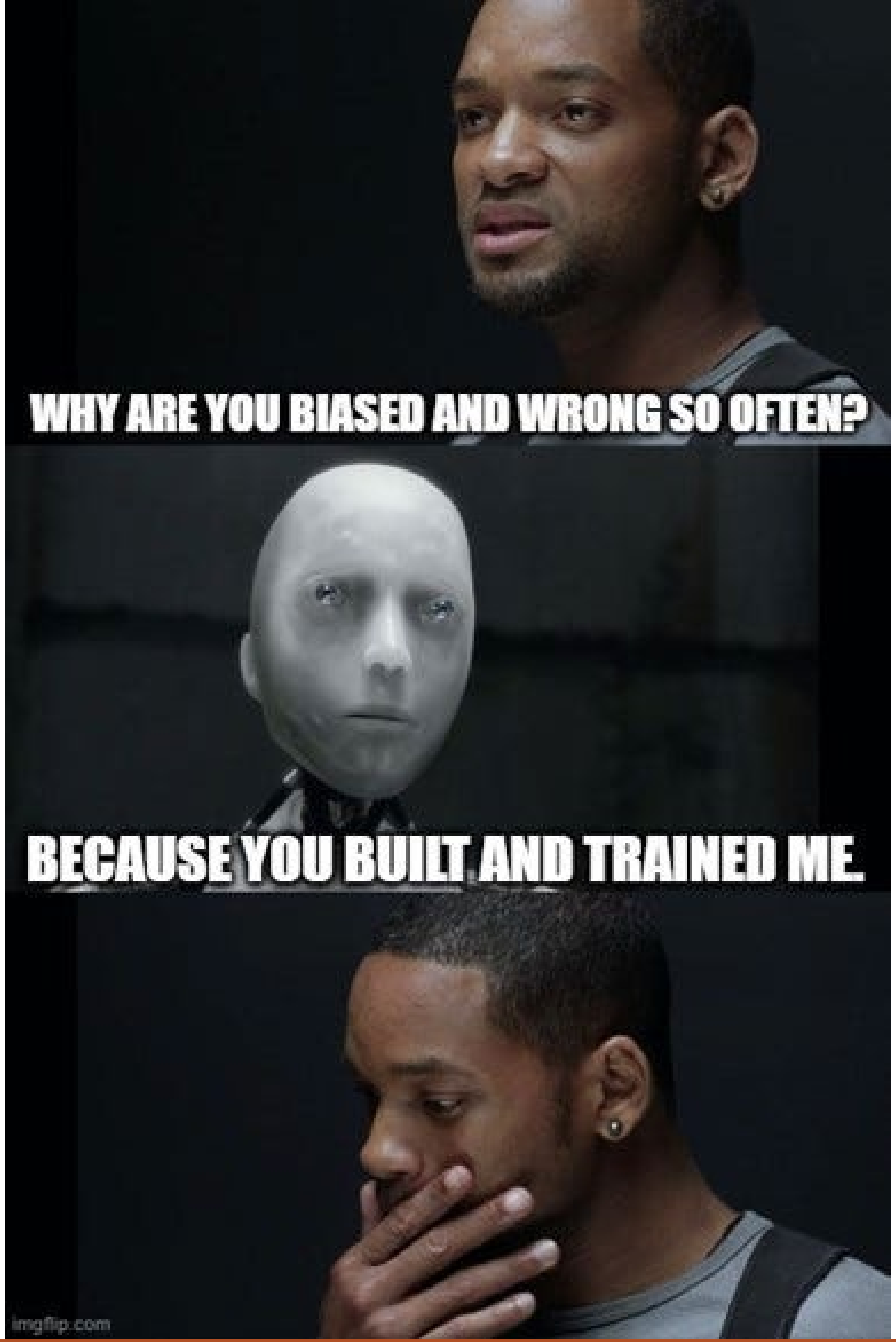


FUTURE POTENTIAL

1. Dataset revision for
   a) Better performing meshes under seismic loads
   b) More accurate conditioning of the Conditional VAE
   c) Better latent space representation for multi-objective optimization of conflicting objectives
2. How to constrain the latent space so that during optimization conditioned samples are within label limits
3. Other generative models

FUTURE POTENTIAL

1. Dataset revision for
   a) Better performing meshes under seismic loads
   b) More accurate conditioning of the Conditional VAE
   c) Better latent space representation for multi-objective optimization of conflicting objectives
2. How to constrain the latent space so that during optimization conditioned samples are within label limits
3. Other generative models
4. Potential for heavier FEA models

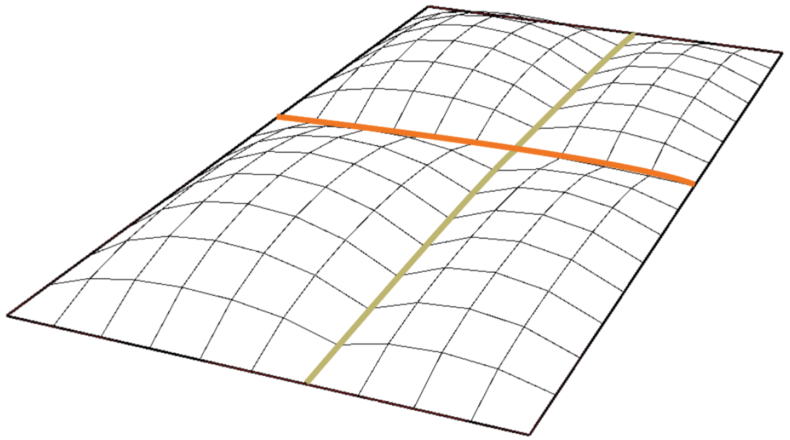

WHY ARE YOU BIASED AND WRONG SO OFTEN?
BECAUSE YOU BUILT AND TRAINED ME.
imgflip.com

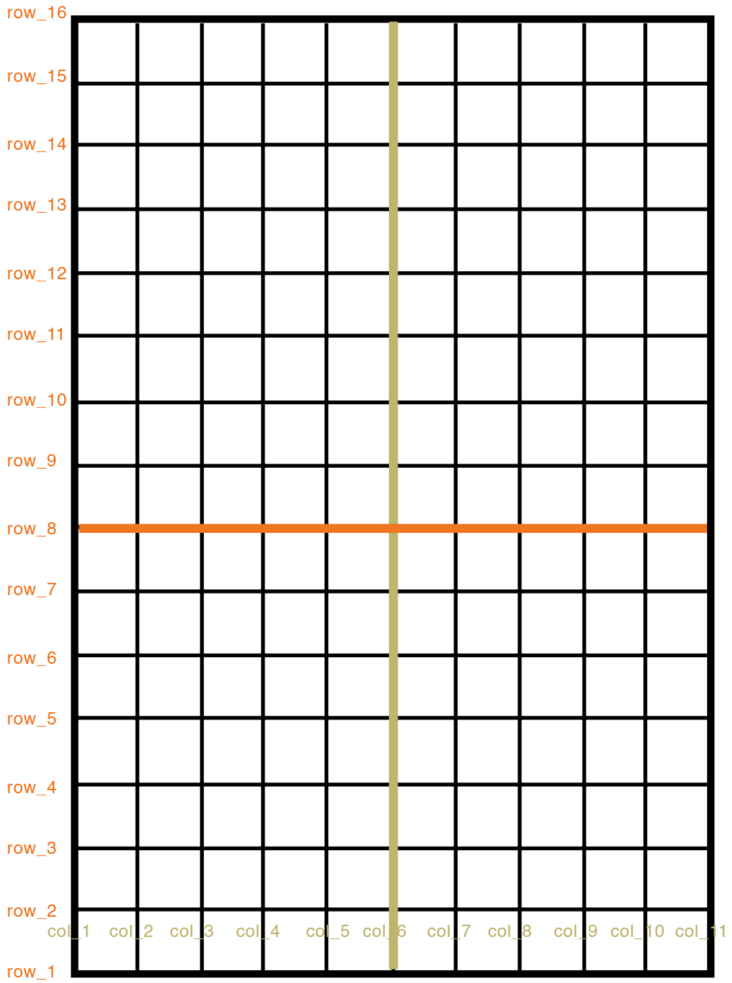
THANK YOU!

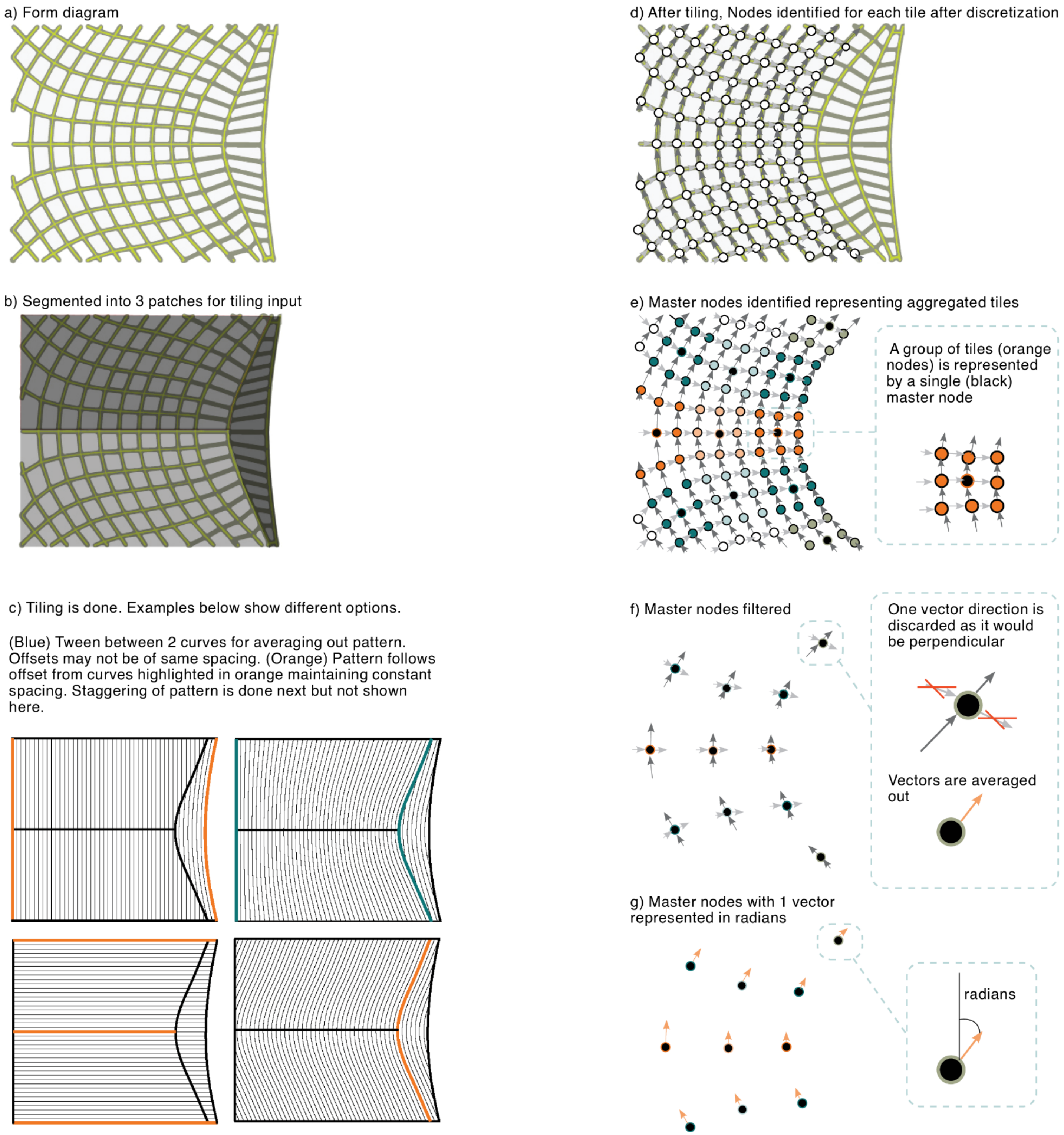
polyedge = column　　polyedge = row　　force density

[[0,0,0,0,0,0,1,0,0,0,0] , [0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0] , [q]]

1.0 = support　　0.0= not support　　float value (eg1.2) = force density of all polyedges of mesh






a) Form diagram
b) Segmented into 3 patches for tiling input
c) Tiling is done. Examples below show different options.
(Blue) Tween between 2 curves for averaging out pattern. Offsets may not be of same spacing. (Orange) Pattern follows offset from curves highlighted in orange maintaining constant spacing. Staggering of pattern is done next but not shown here.
d) After tiling, Nodes identified for each tile after discretization
e) Master nodes identified representing aggregated tiles
A group of tiles (orange nodes) is represented by a single (black) master node
f) Master nodes filtered
One vector direction is discarded as it would be perpendicular
Vectors are averaged out
g) Master nodes with 1 vector represented in radians
radians

If ŷ is Buckling Load Factor, then

$$\hat{y} = -(1-b)^2$$

$$\frac{\partial \hat{y}}{\partial z} = -2(1-b) \times \frac{db}{dz} \qquad \text{(Equation I)}$$

If ŷ is Utilization, then

$$\hat{y} = (u-1)^2$$

$$\frac{\partial \hat{y}}{\partial z} = 2(u-1) \times \frac{du}{dz} \qquad \text{(Equation II)}$$

If ŷ is Interstorey Drift Ratio, then

$$\hat{y} = (i-0.010)^2$$

$$\frac{\partial \hat{y}}{\partial z} = 2(i-0.010) \times \frac{di}{dz} \qquad \text{(Equation III)}$$

Failure conditions are taken into account in each performance metric and ŷ is calculated accordingly.

$Buckling\ Load\ Factor < 1$

$Utilization > 1$

$Interstorey\ Drift\ Ratio > 0.010h$ (as specified in Eurocode 8)

(Equation IV)

$$\text{ELBO}(\varphi) = \text{E}_{q\varphi(z|x)}[\log p_\theta(x \mid z)] - \text{D}_{KL}(q_\varphi(z \mid x) \mid\mid p(z)).$$

$$z = \mu + \sigma \odot \epsilon$$

where $\epsilon \sim N(0, 1)$, and μ and σ are the mean and the standard deviation of $q_\varphi(z \mid x)$. ϵ is a standard Gaussian variable that plays a role of introducing noise, and $\odot$ denotes an element-wise product (Zhang et al., 2016).

$$\hat{y} = -(1-b)^2$$

$$z = z - learning\_rate \times - \frac{\partial \hat{y}}{\partial z}$$

$$z = z + learning\_rate \times \frac{\partial \hat{y}}{\partial z} \qquad \text{(Equation V)}$$

Furthermore, it becomes unnecessary to try to decrease (Utilization, Interstorey Drift Ratio) or increase (Buckling Load Factor) that metric if the metric is already under acceptable limits (no failure). To account for such conditions, the gradient update is configured accordingly by adding additional conditions.

If $(u-1) > 0$, perform the update; otherwise, do nothing.

If $(1-b) > 0$, perform the update; otherwise, do nothing.

If $(i-0.010) > 0$, perform the update; otherwise, do nothing.

(Equation VI)

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

In order to constrain the optimized meshes to be within a certain height threshold and to minimize material usage by minimizing mass, the gradient function was altered to account for multiple objectives instead of a single objective.

For single objective optimizations, the gradient function was as mentioned below:

$$y'(z) = \frac{\partial \hat{y}}{\partial z}$$

To consider multiple objectives, the different gradients were aggregated to form the overall gradient. Weights were included for each gradient to allow the user to optimize specific metrics over others.

$$y'(z) = W_1\left(\frac{\partial \hat{y}_1}{\partial z}\right) + W_2\left(\frac{\partial \hat{y}_2}{\partial z}\right) + W_3\left(\frac{\partial \hat{y}_3}{\partial z}\right)$$

where,

$y' = aggregated\ gradient$

$\hat{y}_1 = Height$

$\hat{y}_2 = Mass$

$\hat{y}_3 = Performance\ metric$

$z = latent\ space$

$W_1, W_2, W_3 = Weightage\ for\ respective\ gradients$

(Equation VII)

$$p(x, z, y) = p(x \mid z, y)p(z \mid y)$$

The conditional VAE tries to maximize:

$$\log p\theta(x \mid y) = \int_z \log(p(x \mid z, y)p(z \mid y))dz$$

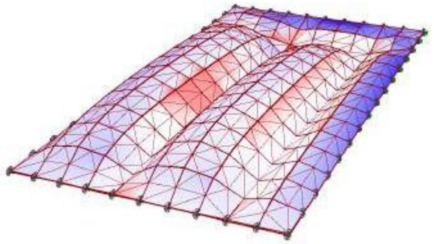
while the loss function to minimize is:

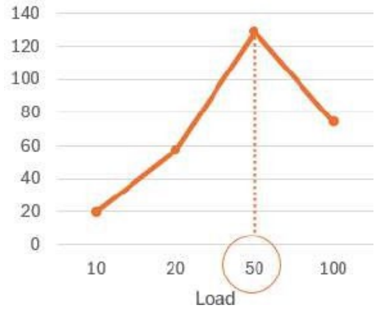
$$\text{ELBO}(\varphi) = \text{E}_{q\varphi(z|x,y)}[\log p(x \mid z, y)] - \text{D}_{KL}(q_\varphi(z \mid x, y) \mid\mid p(z \mid y)).$$

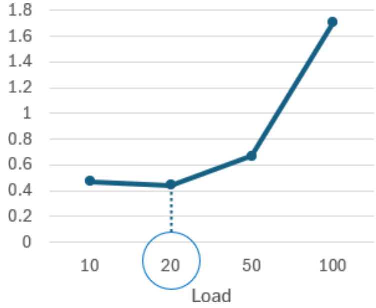
PERFORMANCE EVALUATION

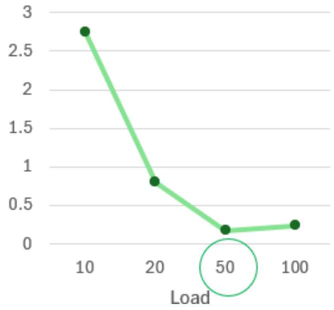
VARIATION IN STOREY HEIGHT

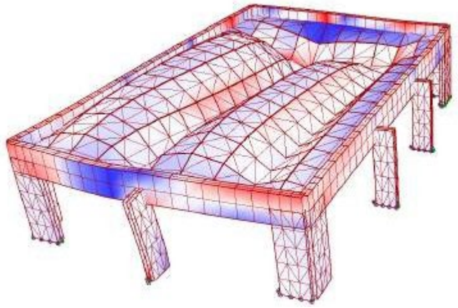
BUCKLING LOAD FACTOR | UTILIZATION | INTERSTOREY DRIFT RATIOS

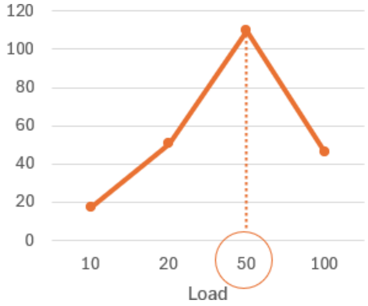


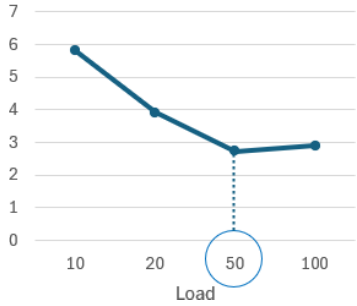


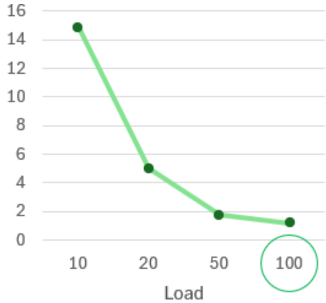


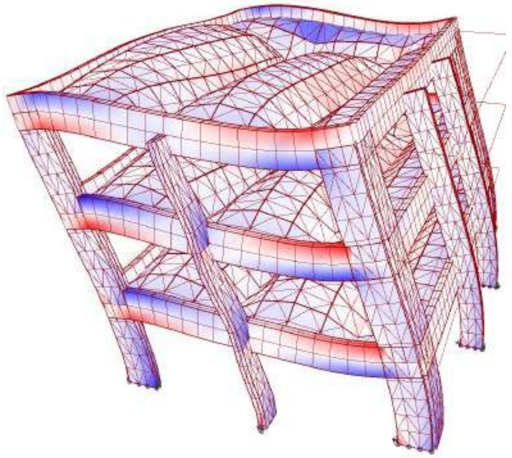


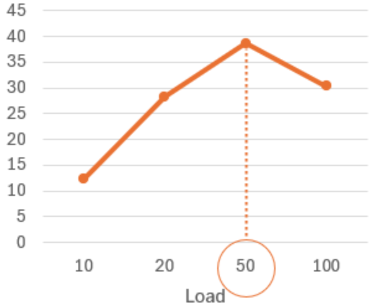


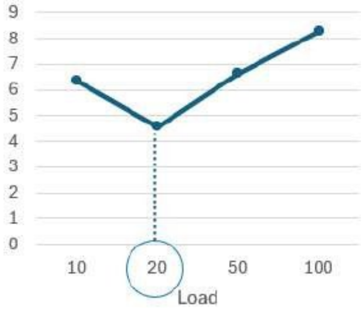


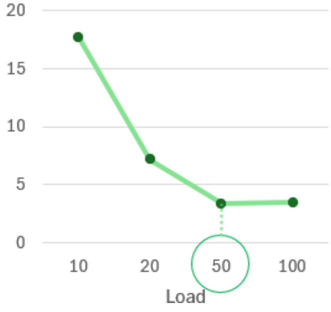






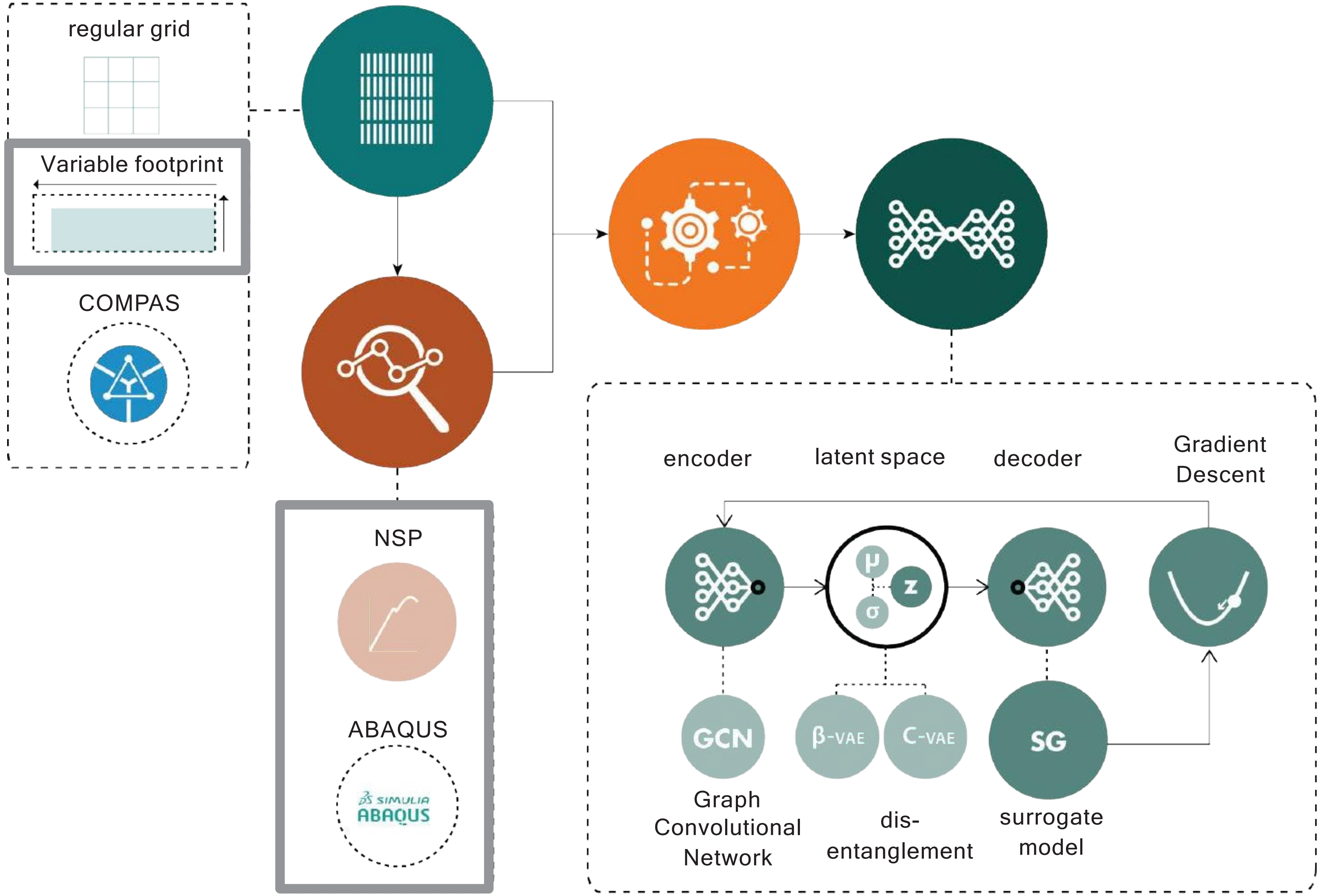


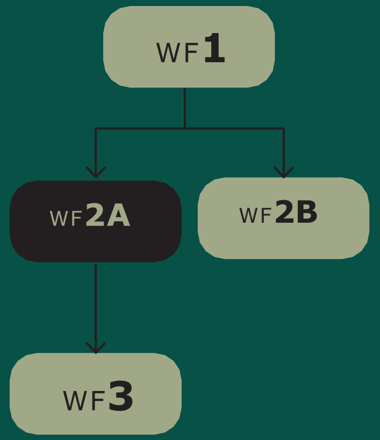




RESEARCH WORKFLOW

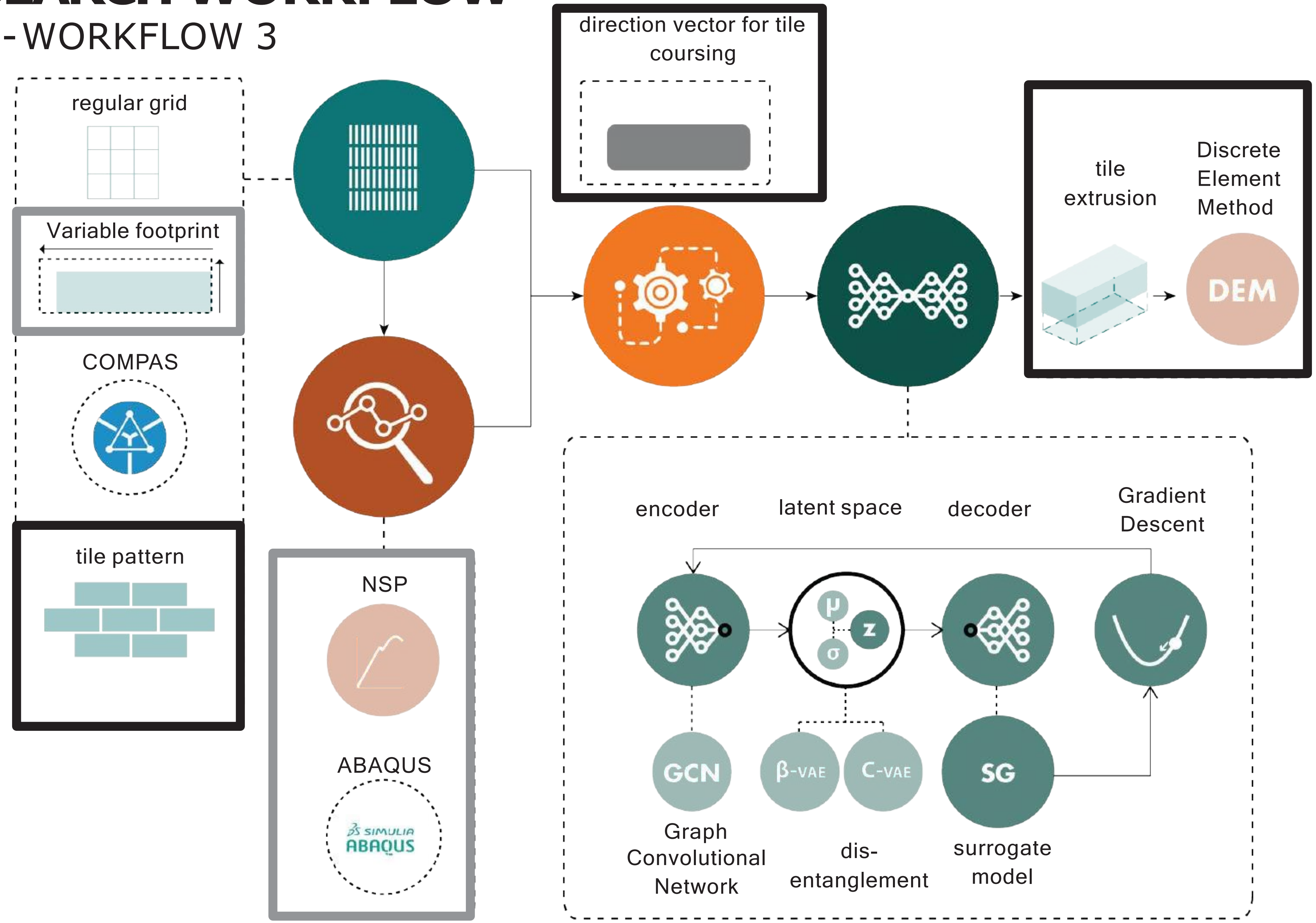
WF**2A** -WORKFLOW 2A

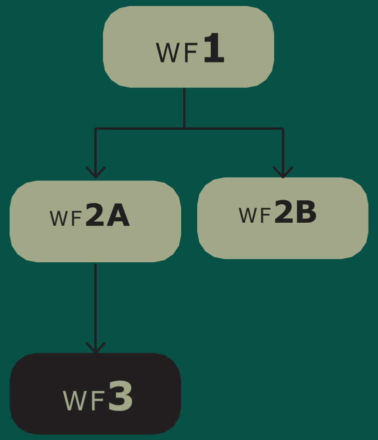




RESEARCH WORKFLOW

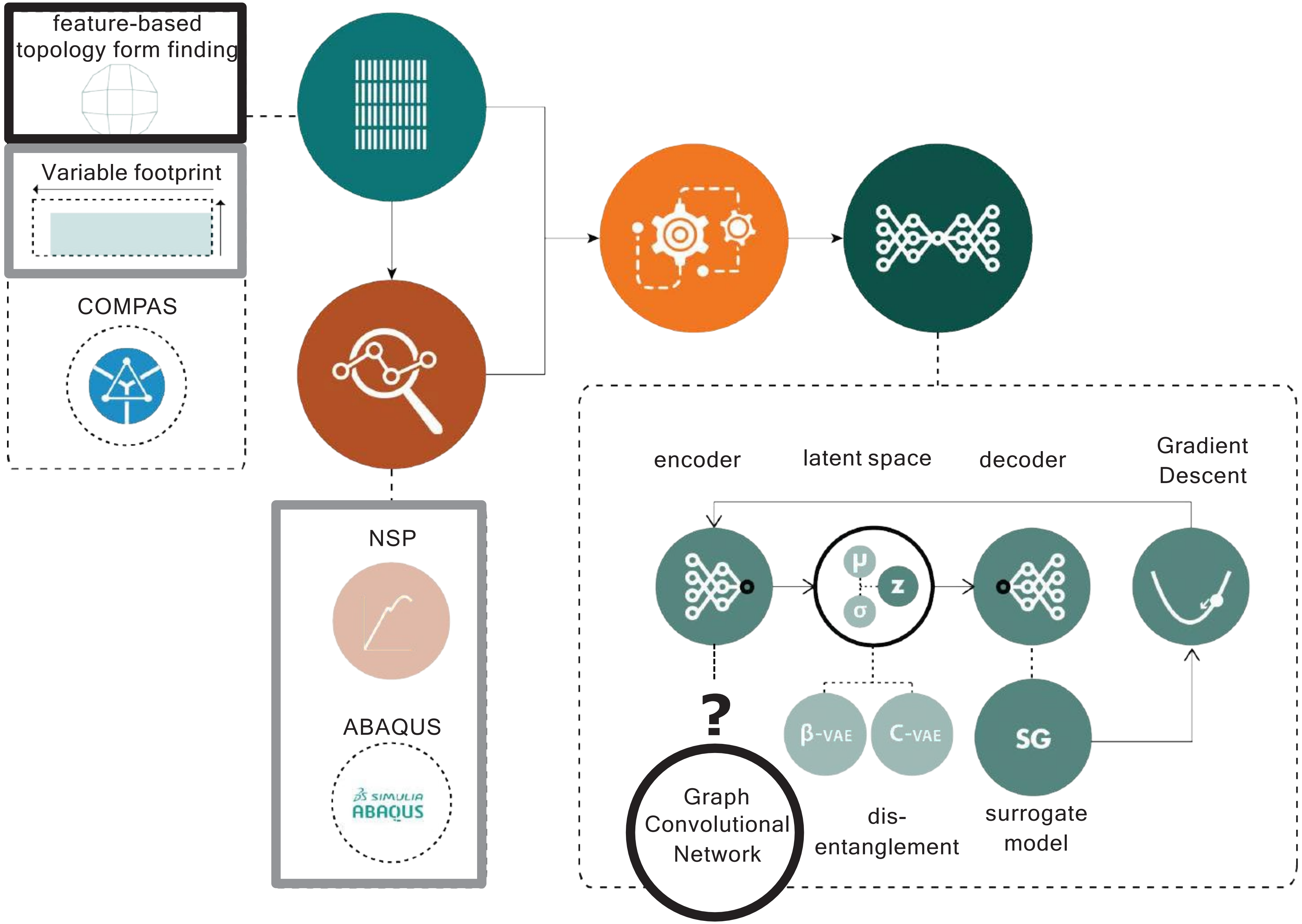
WF**3** - WORKFLOW 3

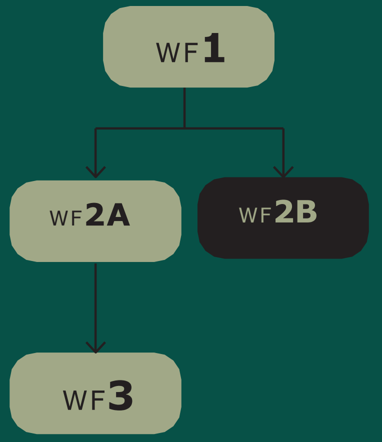




RESEARCH WORKFLOW

WF2B - WORKFLOW 2B

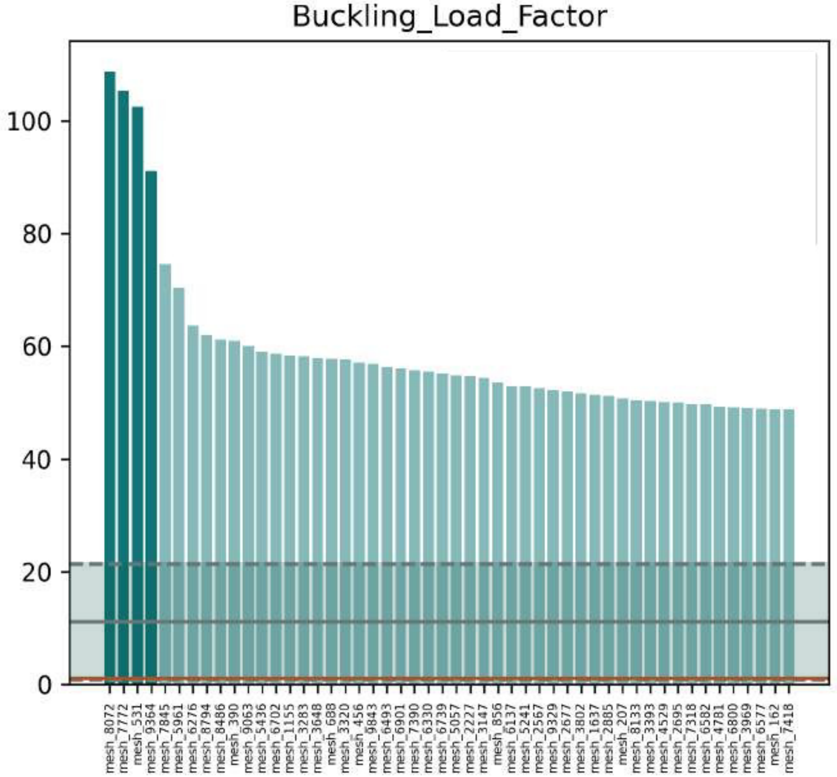




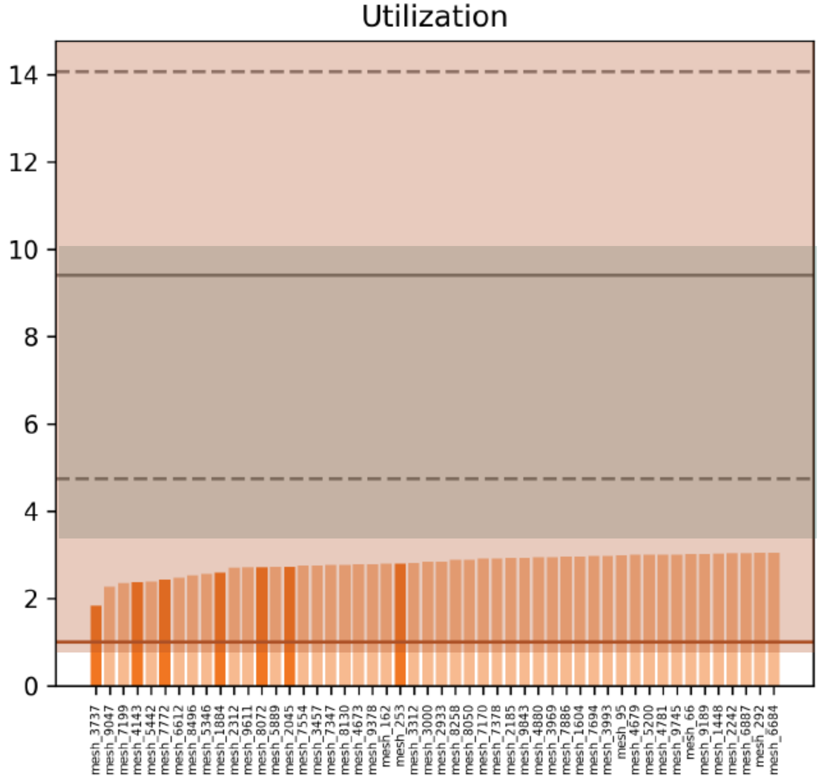
PERFORMANCE EVALUATION

BEST PERFORMING SAMPLES IN THE MAIN DATASET

BUCKLING LOAD FACTOR

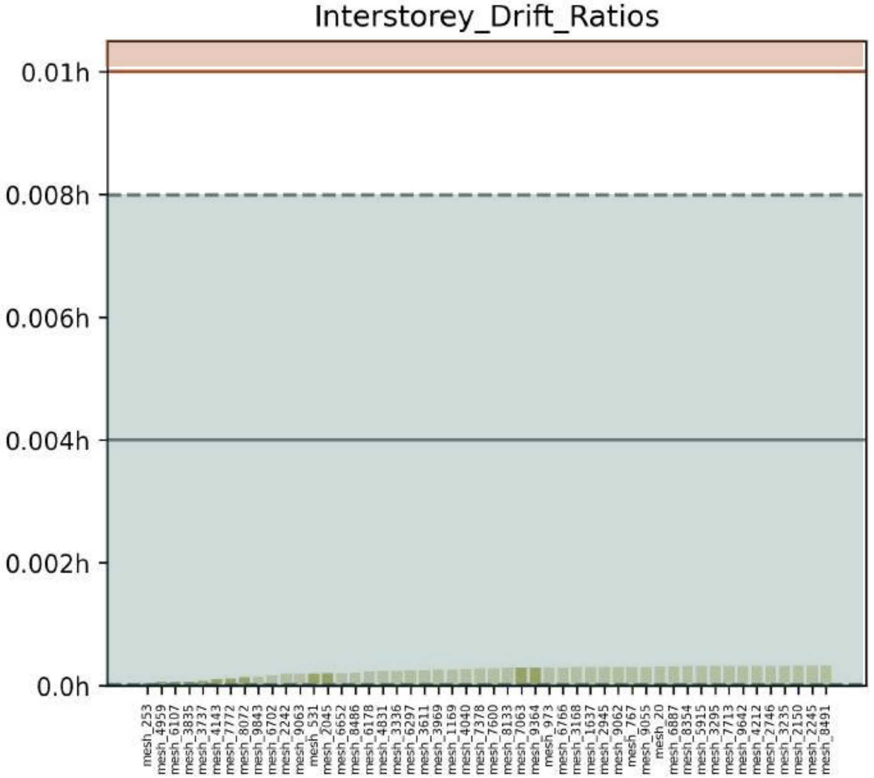


UTILIZATION



even the best samples fail in utilization

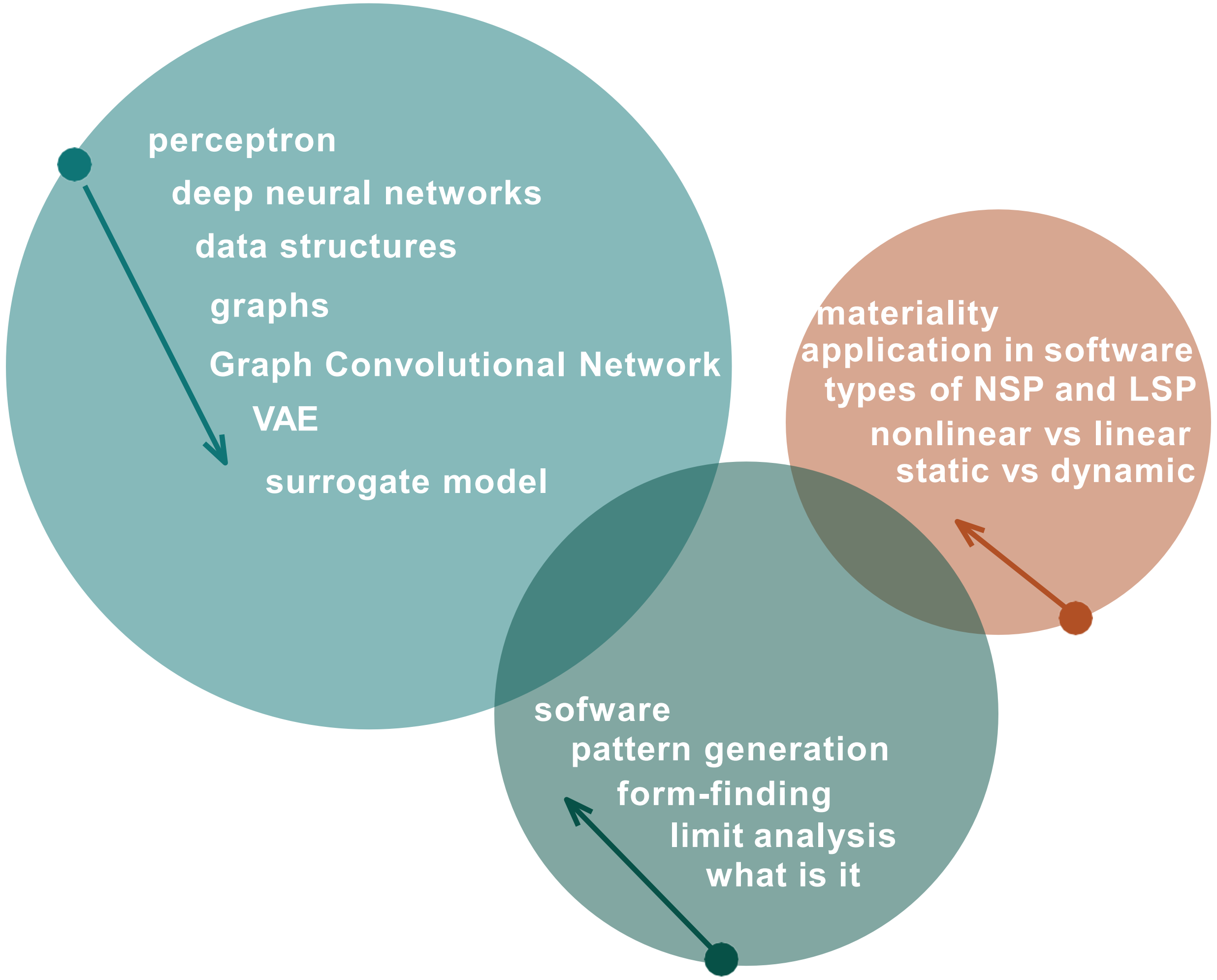
INTERSTOREY DRIFT RATIOS



no failure of any sample within 1 standard deviation from the mean

- Mean
- Standard Deviation
- Failure
- Random force densities
- Uniform force densities

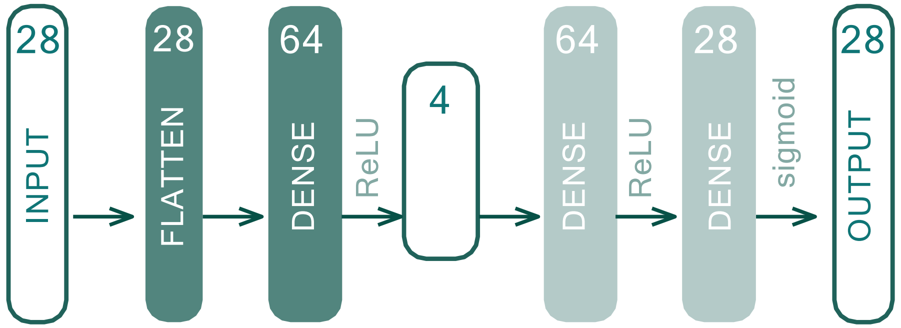
RESEARCH DOMAINS



GENERATOR

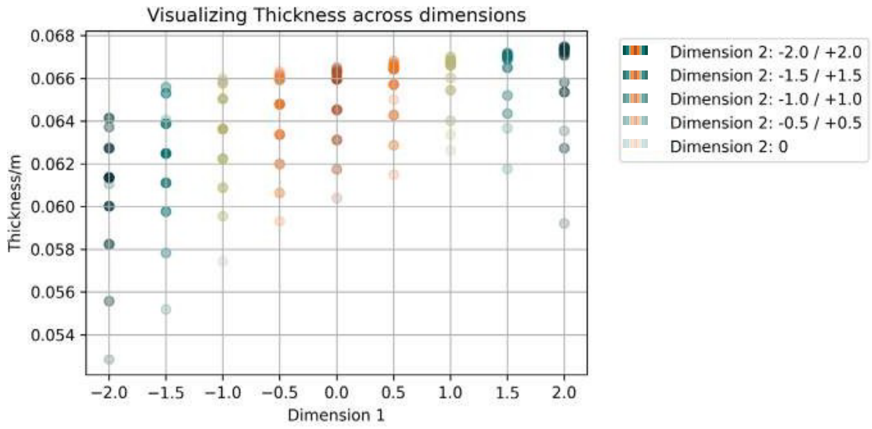
SAMPLING ACROSS LATENT DIMENSIONS

HYPERPARAMETERS: latent_dimension = 2, **beta** = 0.2, **epochs** = 600, **batch_size** = 64, **learning_rate** = 1E-04

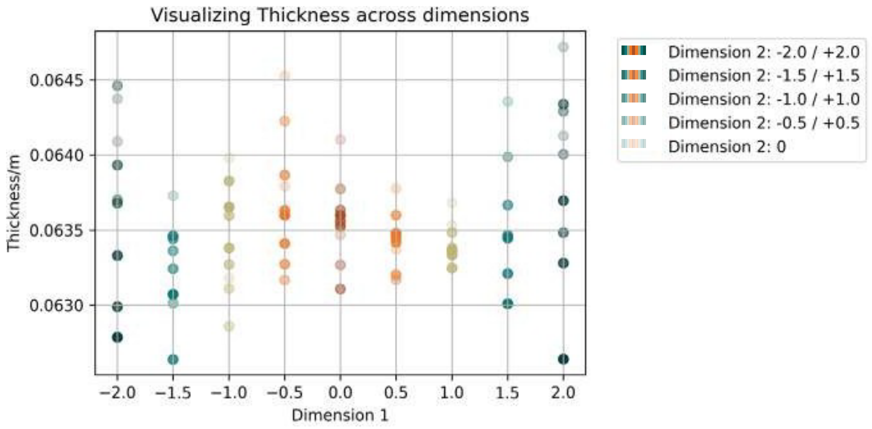


VAE

Thickness normalization along with force densities



thickness normalized independantly



SUBQUESTIONS

Deep generative + Vault

1. Can unique **latent dimension** of the VAE represent **unique features** representing the geometry of the vault? If yes, what features are represented?

Deep generative + Seismic + Vault

2. Can vaults with **variable footprints** be generated that are **structurally optimized** for seismic performance?

Seismic + Vault

3. How does the **depth** of the Catalan vault floor slab get affected by **varying input footprint** size?
4. What effect does varying the **force densities** have on overall structural **performance**?
5. Is there a favourable **pattern** in terms of **force densities** for **seismic performance?**

PERFORMANCE EVALUATION

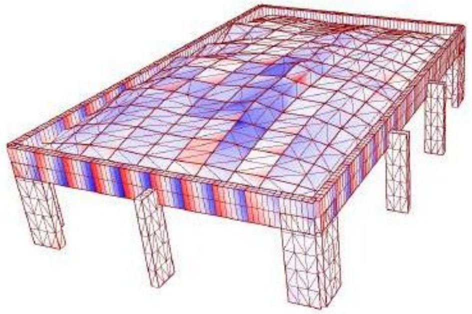
MODAL ANALYSIS

DATASET: randomized							
Mesh number	Modal Analysis Metrics						
	Mass Participation total cumulative (x,y,z) / %	Time Period / s	Mass Participation total / %	Mode	Mass Participation for dominant modes / %	Base shear / KN	Eurocode satsisfied?
mesh_1	[82.75, 115.82, 48.92]	[0.11]	100.91	[3]	[100.91]	130.37	yes
mesh_2	[55.04, 48.52, 19.79]	[0.09]	36.6	[9]	[16.52]	85	no
mesh_4	[119.89, 106.52, 59.73]	[0.11]	92.07	[5]	[60.81]	137.12	yes
mesh_5	[111.76, 68.48, 50.2]	[0.11]	54.5	[3]	[27.85]	130.74	no
mesh_6	[69.42, 66.21, 21.63]	[0.1, 0.08]	48.3	[8, 11]	[19.52, 11.76]	123.3	no
mesh_11	[98.56, 75.71, 23.59]	[0.1, 0.08]	48.09	[7, 11]	[21.09, 13.04]	128.79	no

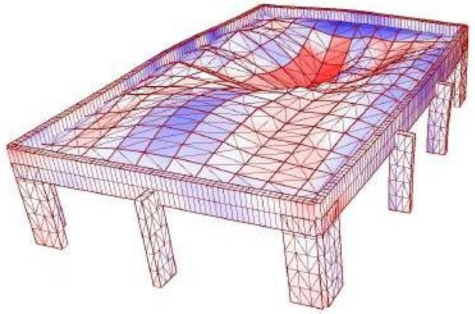
> 90%

min = 50%

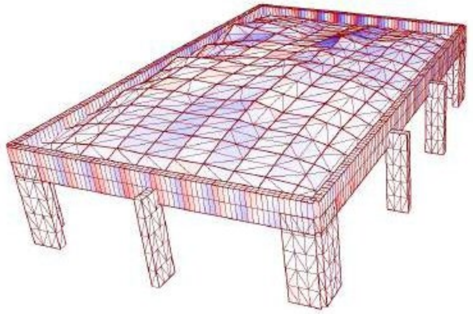
Mode 1



Mode 2



Mode 3



PERFORMANCE EVALUATION

VARIATION IN SEISMICITY

Seismic zoning BCO - PGA (g)

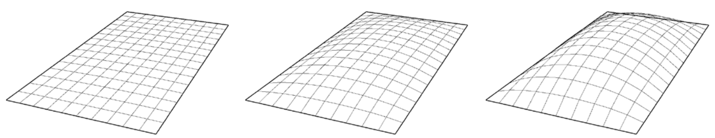
- Zone 2A (0.08g - 0.16g) - low
- Zone 2B (0.16g - 0.25g) - medium
- Zone 3 (0.25g - 0.33g) - high

FIGURE 15: Sesimic Zoning map of Pakistan according to Building Code of Pakistan (BCP). Edited by Author. Image Taken from Siddique, M. S., & Schwarz, J. (2015). Elaboration of Multi-Hazard Zoning and Qualitative Risk Maps of Pakistan. Earthquake Spectra, 31(3), 1371-1395. https://doi.org/10.1193/042913EQS114M

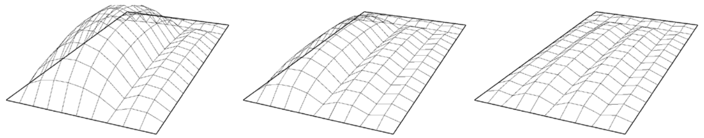
PERFORMANCE EVALUATION

VARIATION IN SEISMICITY

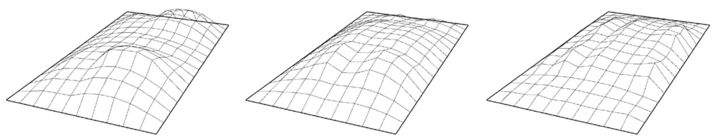
a) uniform force densities dataset

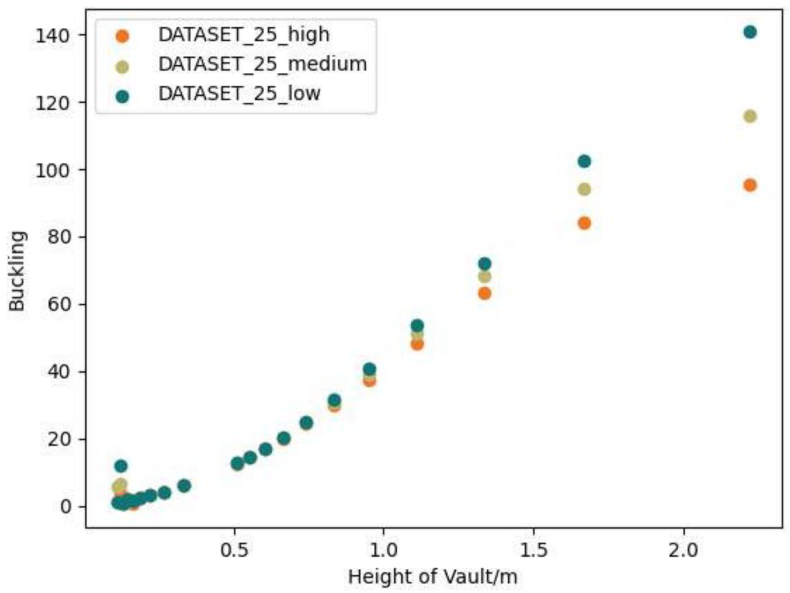


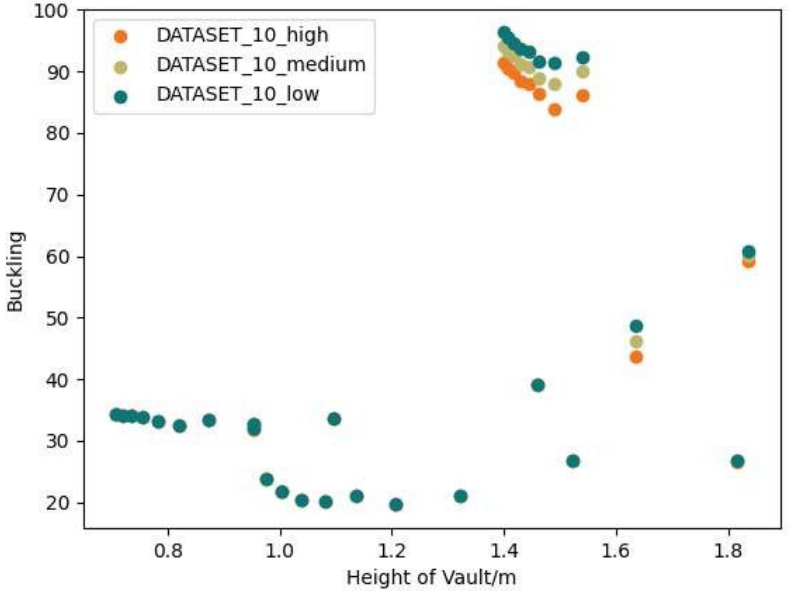
b) creased dataset

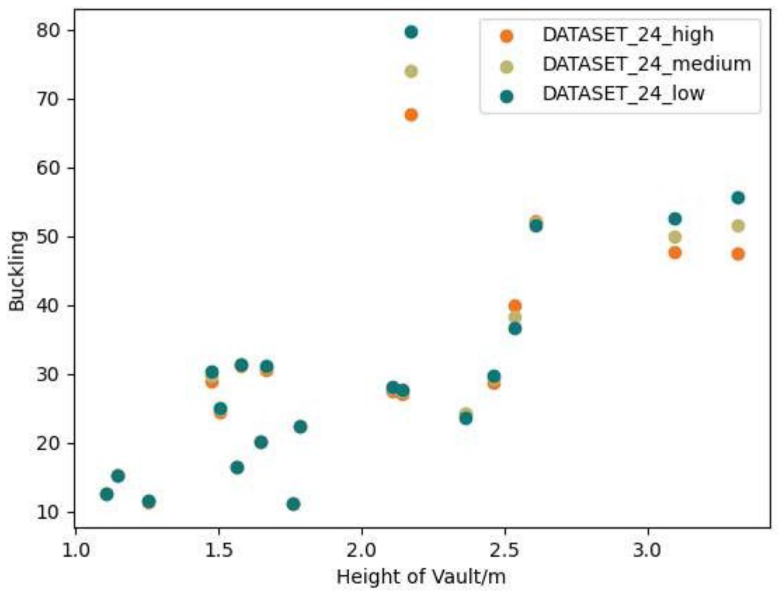


c) randomized dataset









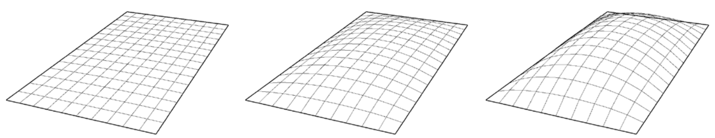
- High (PGA = 2.8)
- Medium (PGA = 1.8)
- Low (PGA = 0.8)

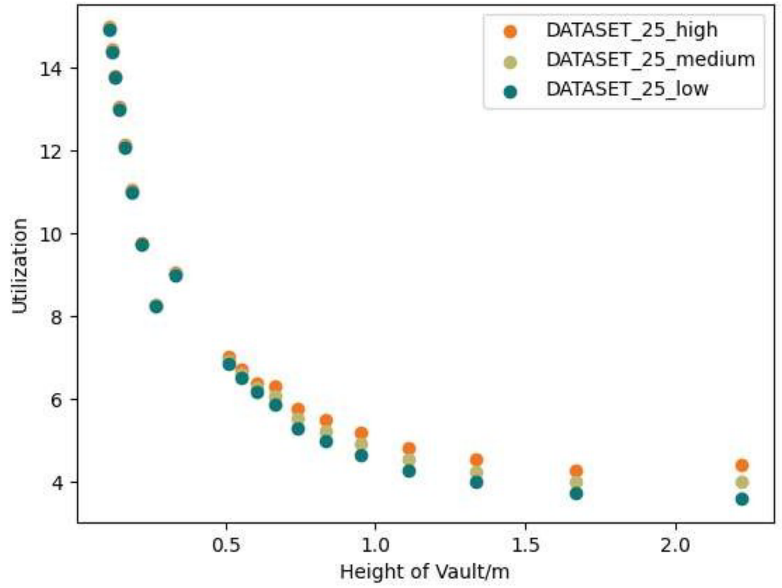
BUCKLING LOAD FACTOR

PERFORMANCE EVALUATION

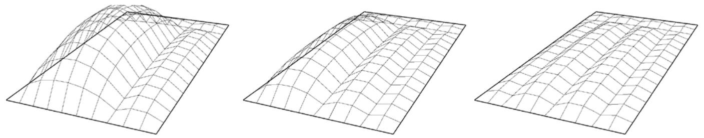
VARIATION IN SEISMICITY

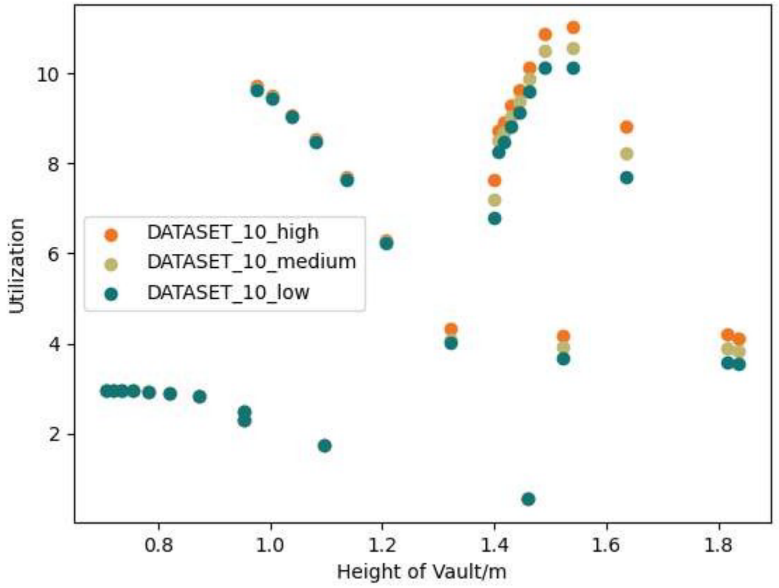
a) uniform force densities dataset



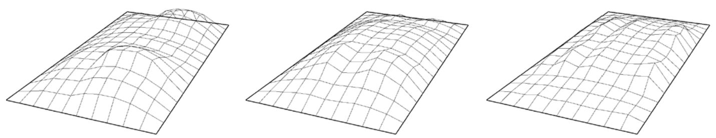


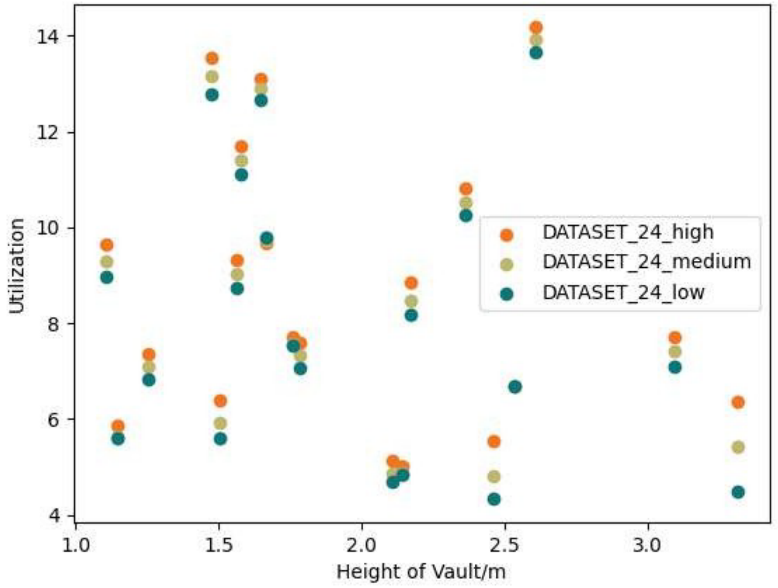
b) creased dataset





c) randomized dataset





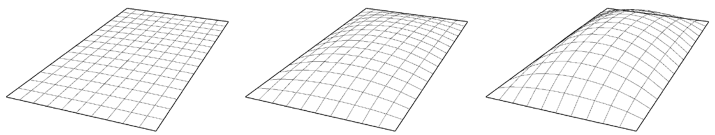
- High (PGA = 2.8)
- Medium (PGA = 1.8)
- Low (PGA = 0.8)

UTILIZATION

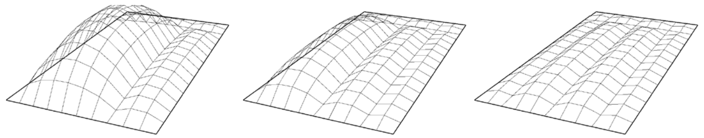
PERFORMANCE EVALUATION

VARIATION IN SEISMICITY

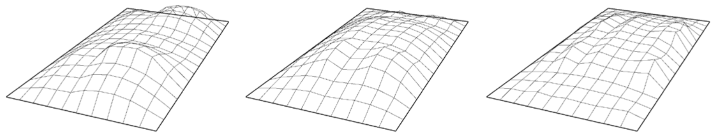
a) uniform force densities dataset

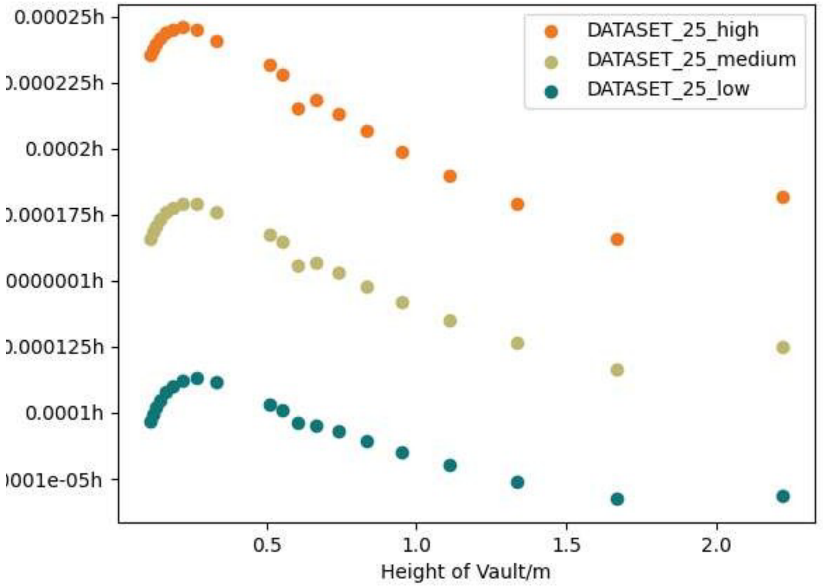


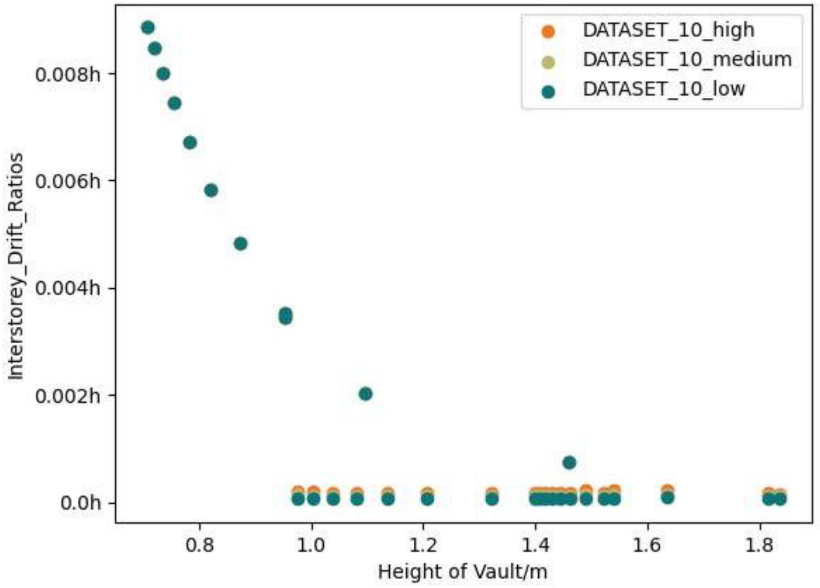
b) creased dataset

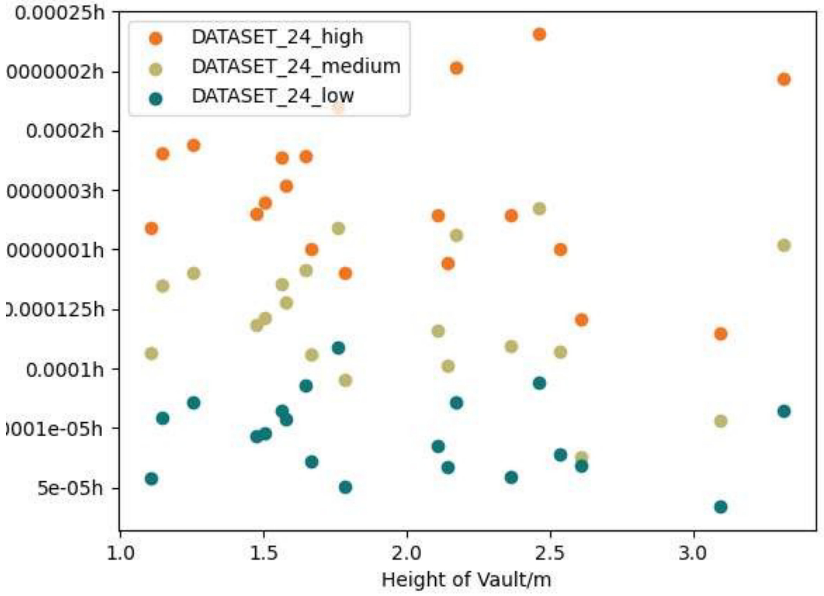


c) randomized dataset









High (PGA = 2.8)

Medium (PGA = 1.8)

Low (PGA = 0.8)

INTERSTOREY DRIFT RATIOS

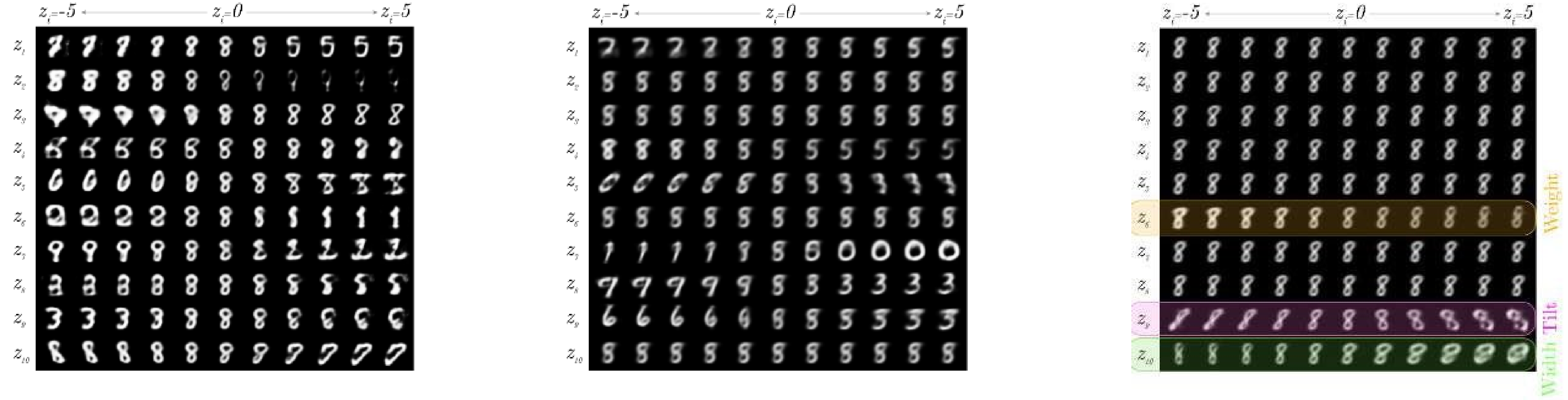
GENERATOR

DISENTANGLEMENT

a) standard (vanilla) VAE

b) β-VAE, β=10

c) C-VAE + β-VAE, β=10



loss function

↓

Reconstruction loss

+

β. Regularization term

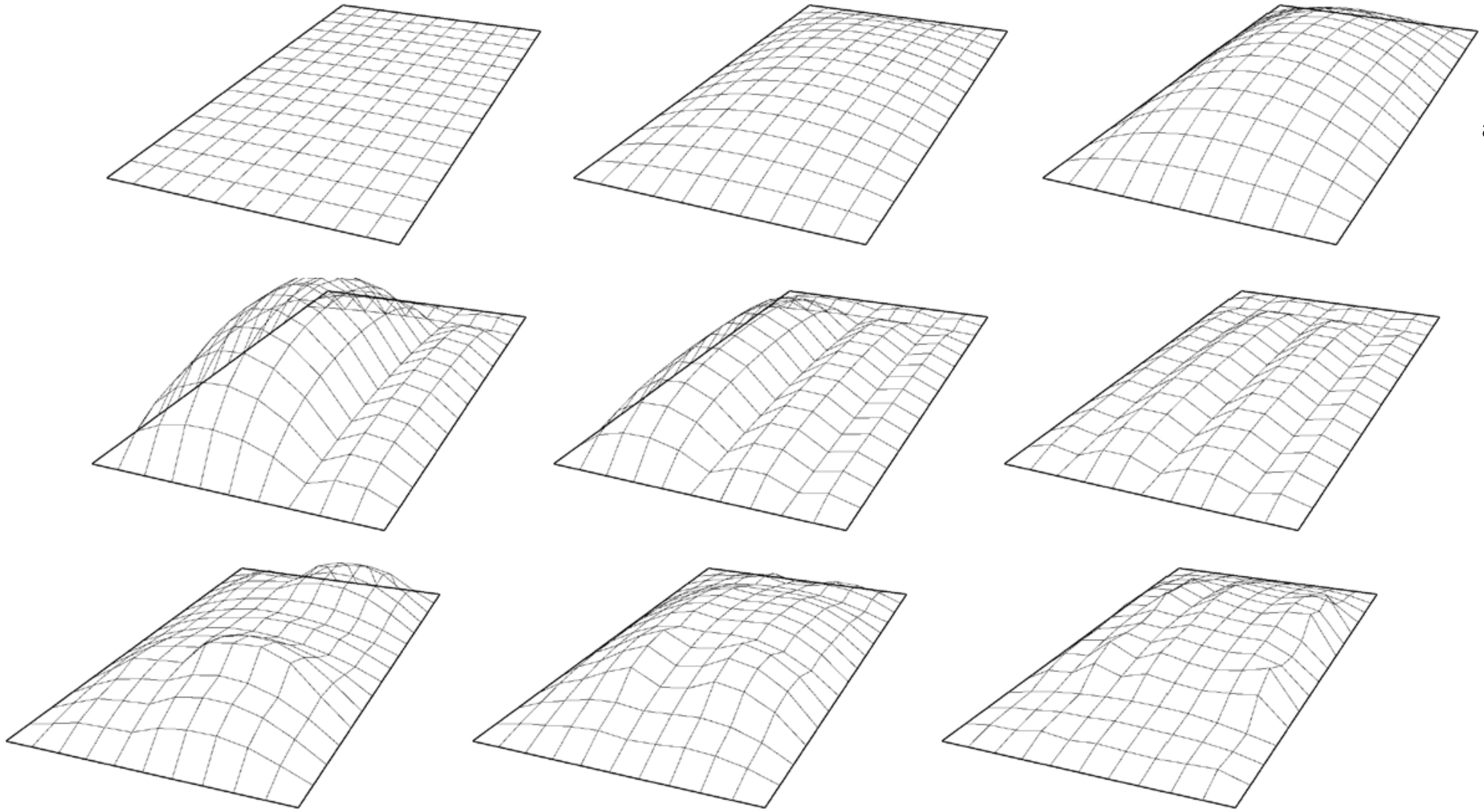
FIGURE 09: A disentangled latent space with distinguishable features is represented only in c) where a conditional β-VAE is used. The features learnt are weight, tilt, and width. Image retrieved from Pastrana, R. (2022). Disentangling Variational Autoencoders. https://doi. org/10.48550/arxiv.2211.07700

PERFORMANCE EVALUATION

SUPPORT CONDITIONS

Pinned Supports

Fixed Supports



a) uniform force densities dataset

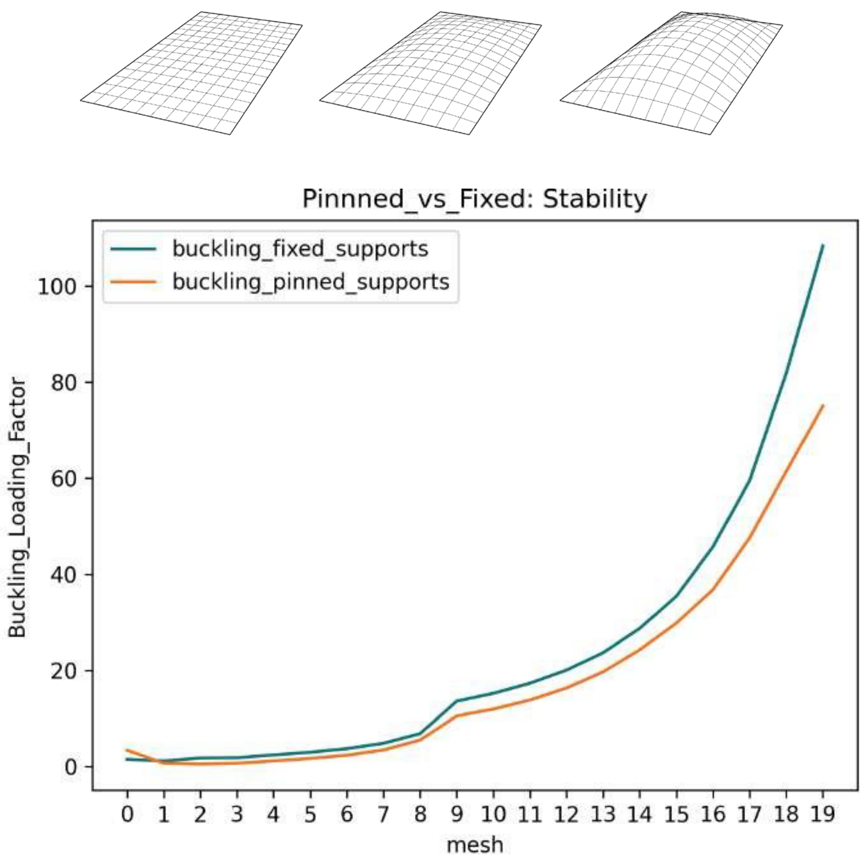
b) creased dataset

c) randomized dataset

PERFORMANCE EVALUATION

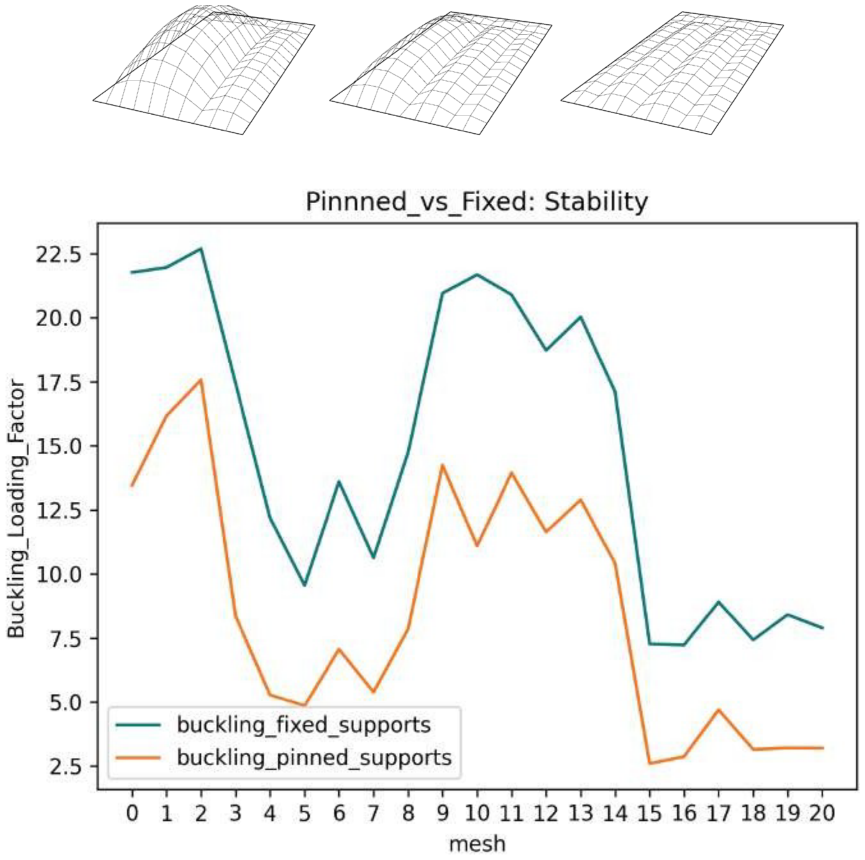
SUPPORT CONDITIONS

a) uniform force densities dataset



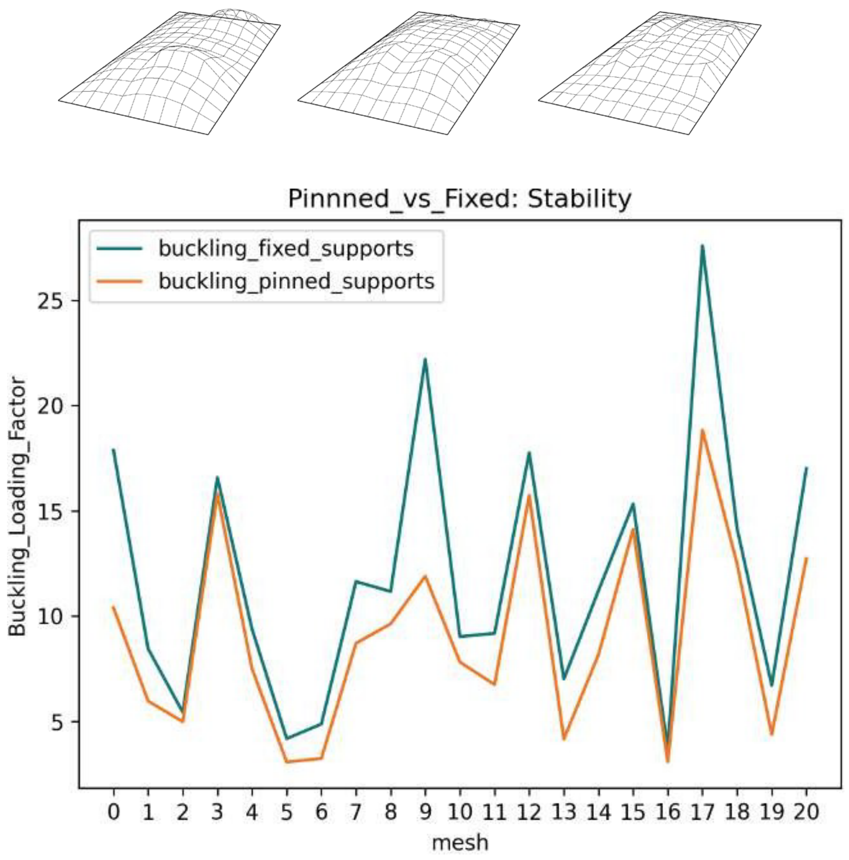
26.0% CHANGE

b) creased dataset



53.4% CHANGE

c) randomized dataset



27.2% CHANGE

Pinned Supports

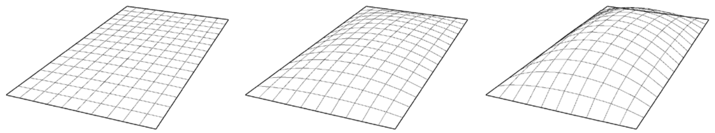
Fixed Supports

BUCKLING LOAD FACTOR

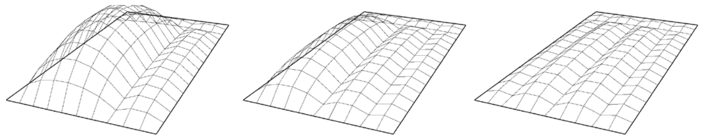
PERFORMANCE EVALUATION

SUPPORT CONDITIONS

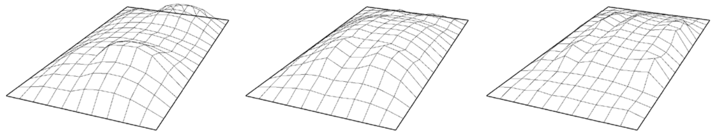
a) uniform force densities dataset

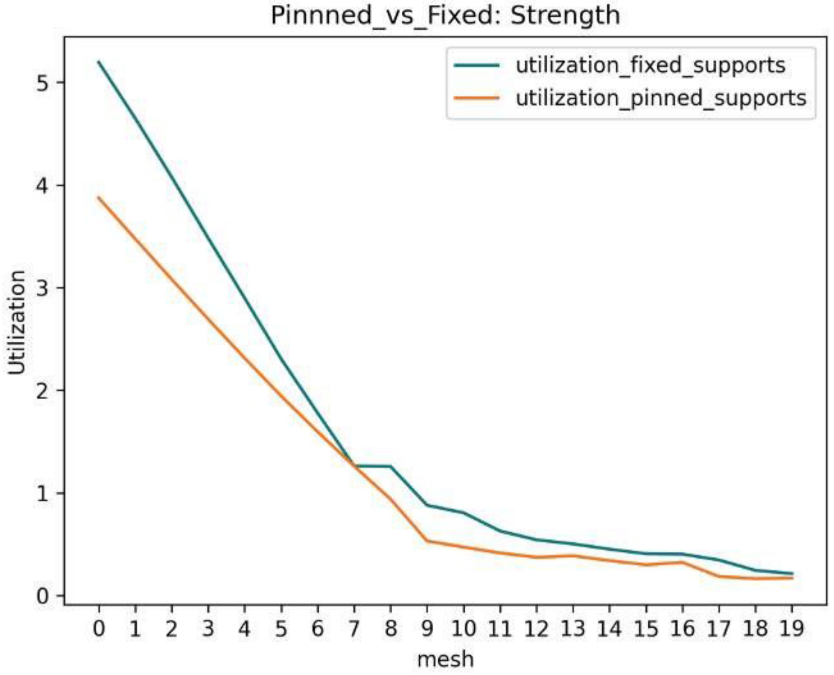


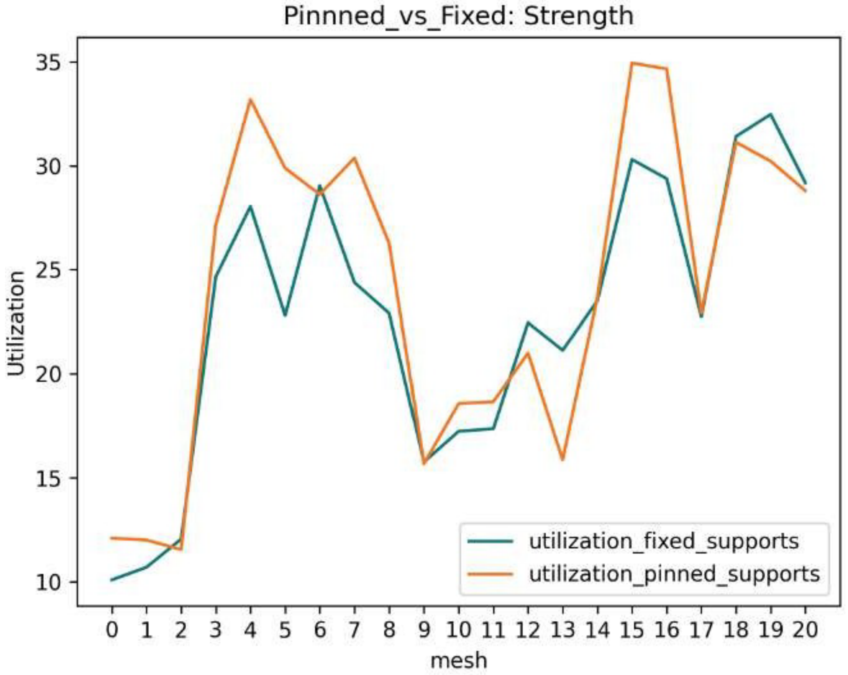
b) creased dataset

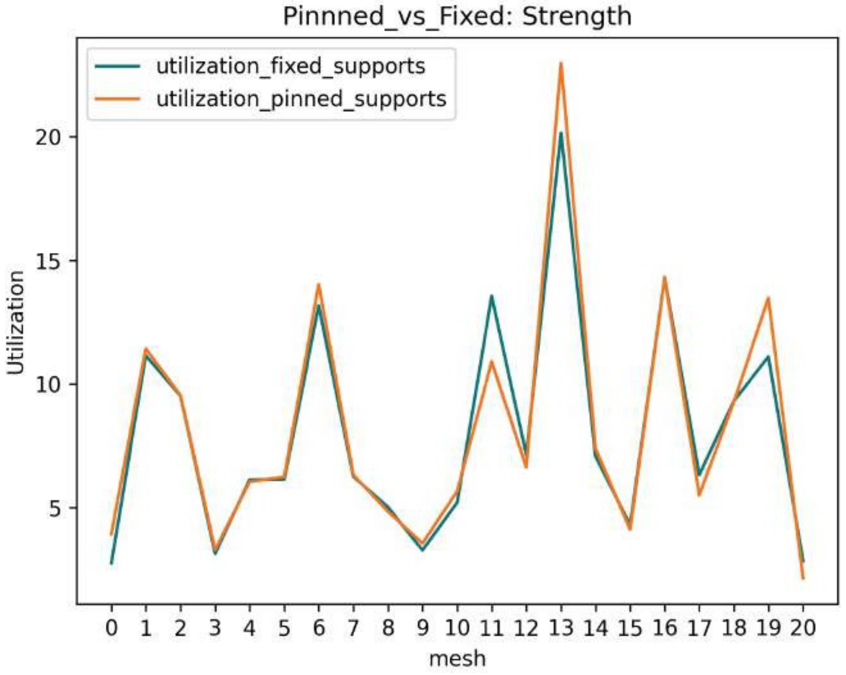


c) randomized dataset









26.2% CHANGE

Pinned Supports

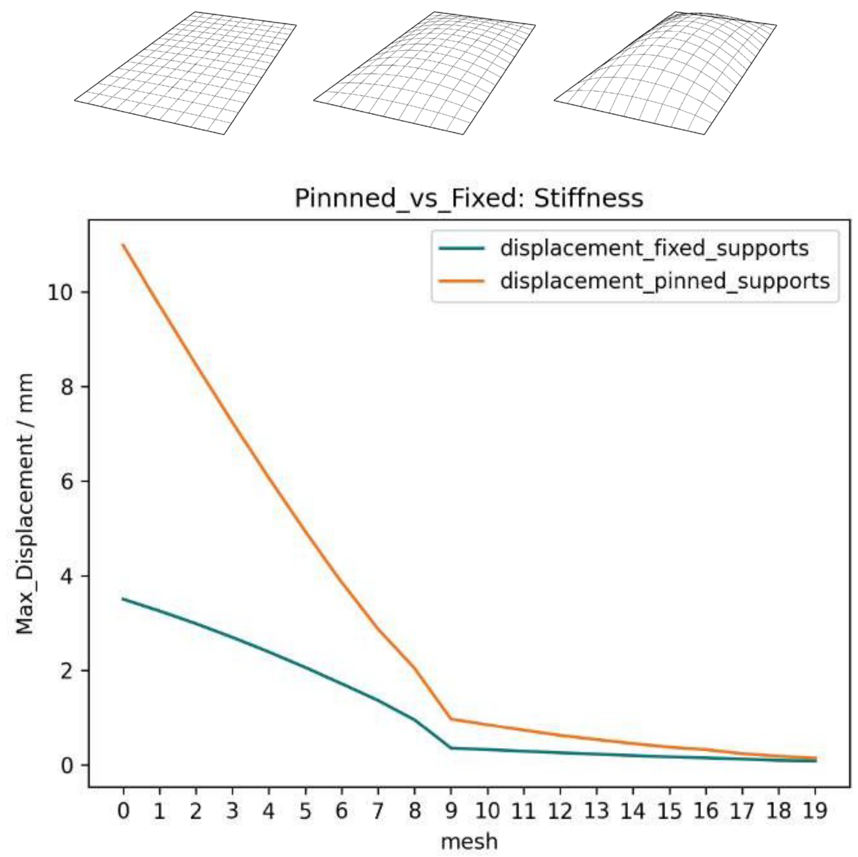
Fixed Supports

UTILIZATION

PERFORMANCE EVALUATION

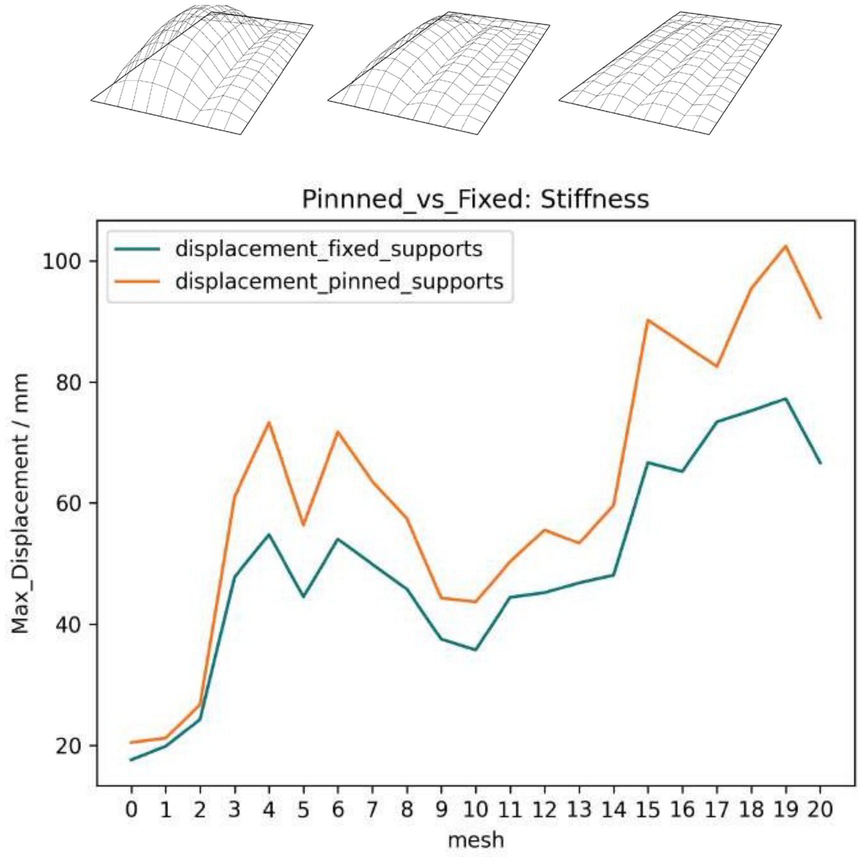
SUPPORT CONDITIONS

a) uniform force densities dataset



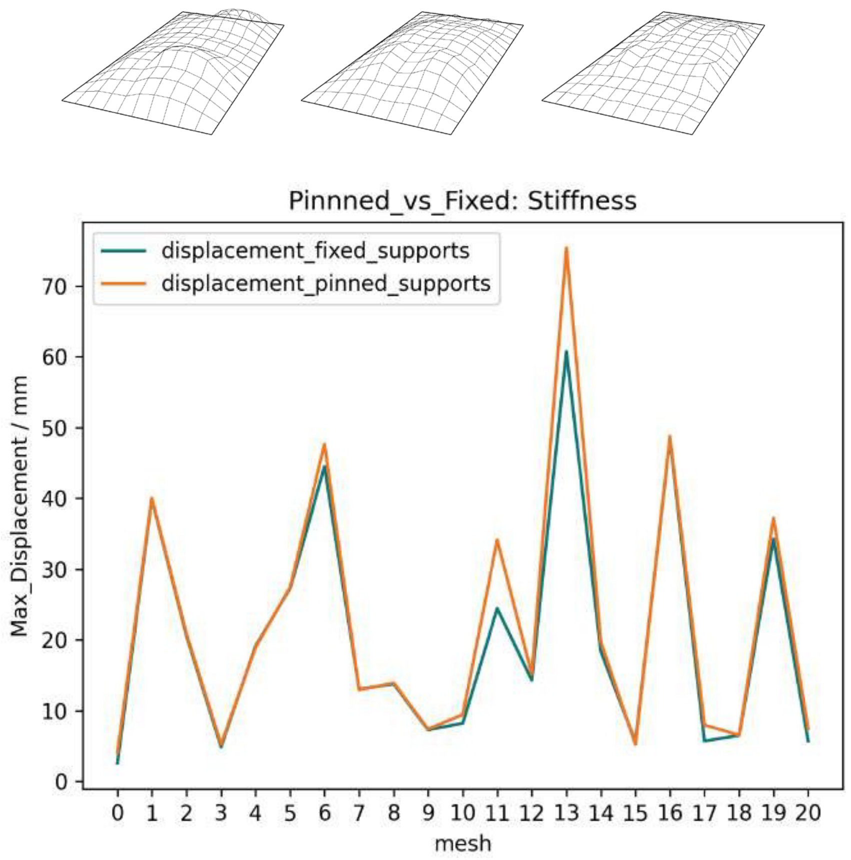
90.7% CHANGE

b) creased dataset

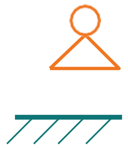


22.6% CHANGE

c) randomized dataset



9.1% CHANGE



Pinned Supports

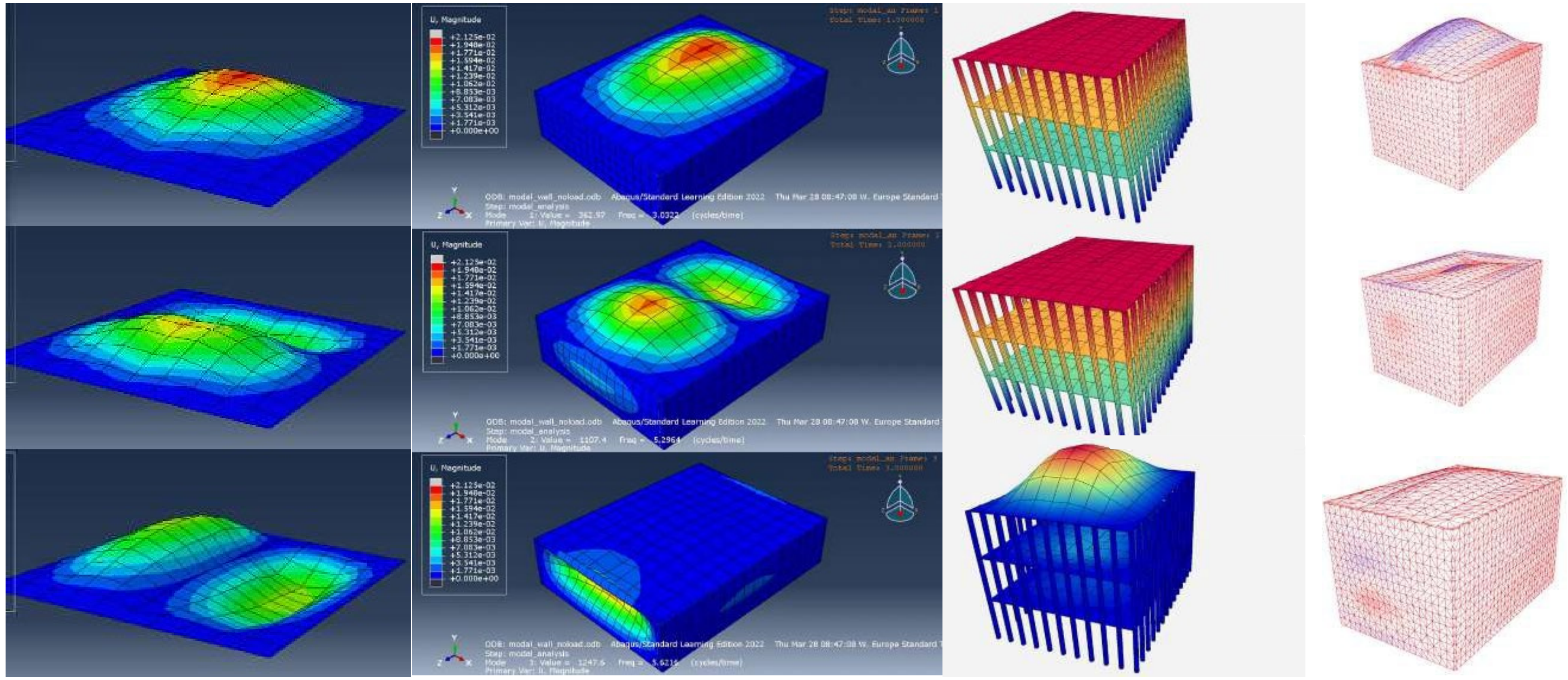
Fixed Supports

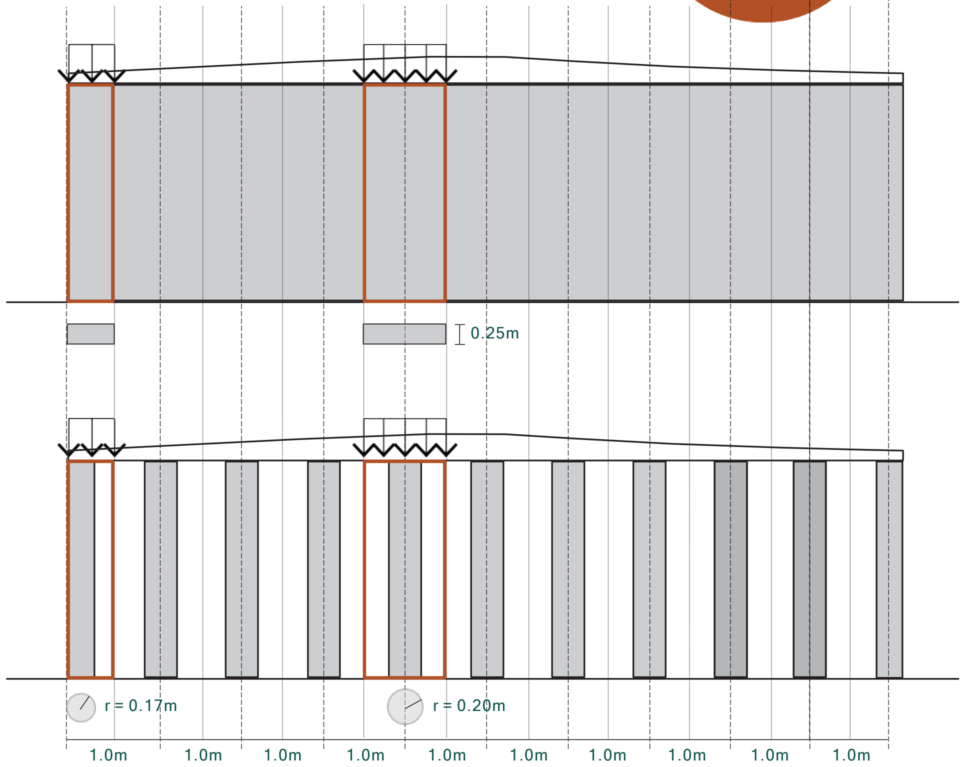
MAXIMUM DISPLACEMENT

REST OF THE STRUCTURE

Macromodel			
		Units	Unit (mortar+masonry)
Young's Modulus	*E*	GPa	3.2
Possion ratio	*v*	-	0.15
Density	*ρ*	kg/m3	1219.4
Tension	*Gfl*	N/mm	0.14
	ft	MPa	0.24
Compression	*Gfc*	N/mm	9.44
	fc	MPa	5.9
Shear	*fflex*	MPa	0.46

FIGURE 14: Material property for Macromodel and Discrete model. Material properties for the macromodel are retrieved from López, L., Rodríguez, D., & Fernández, P. (n.d.). Using a Construction Technique to Understand it: Thin-Tile Vaulting. Material properties of the discrete model are retrieved from Oktiovan, Y. P., Davis, L., Wilson, R., Dell'Endice, A., Mehrotra, A., Pulatsu, B., & Malomo, D. (2023). Simplified Micro-Modeling of a Masonry Cross-Vault for Seismic Assessment Using the Distinct Element Method. International Journal of Architectural Heritage, 1-34. https://doi.org/10.1080/15583058.2023.2277328



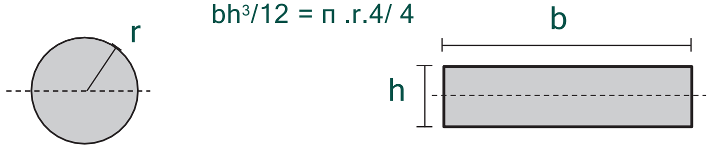


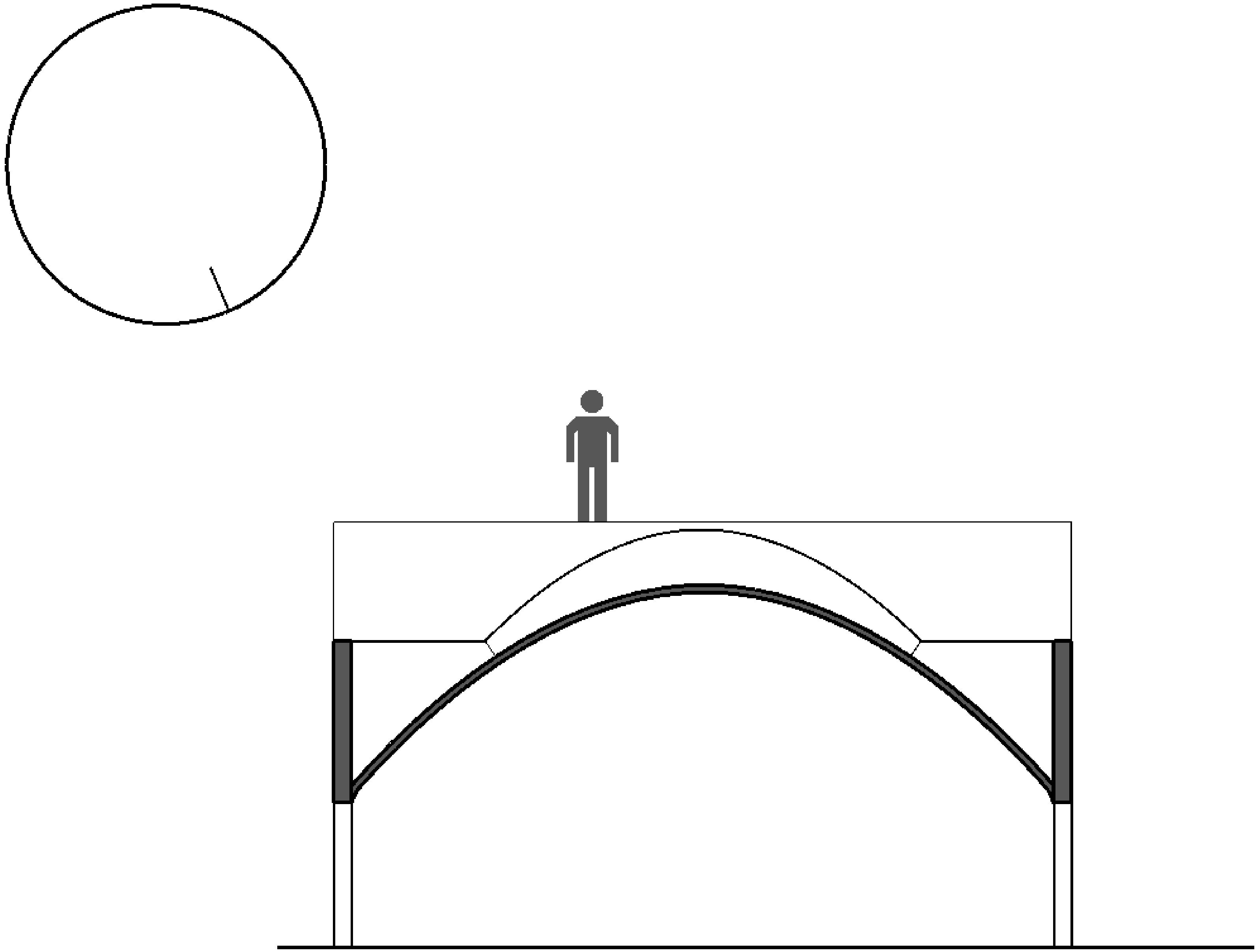
stiffness of column section = stiffness of equivalent wall section

$EI_{wall} = EI_{column}$

$I_{wall} = I_{column}$

$bh^3/12 = \pi .r.4/ 4$

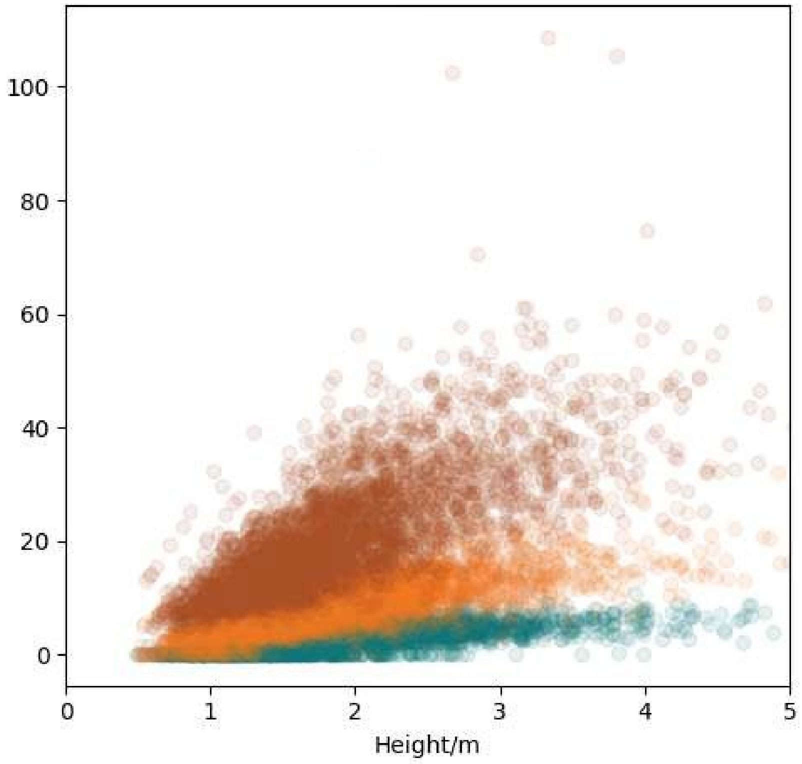




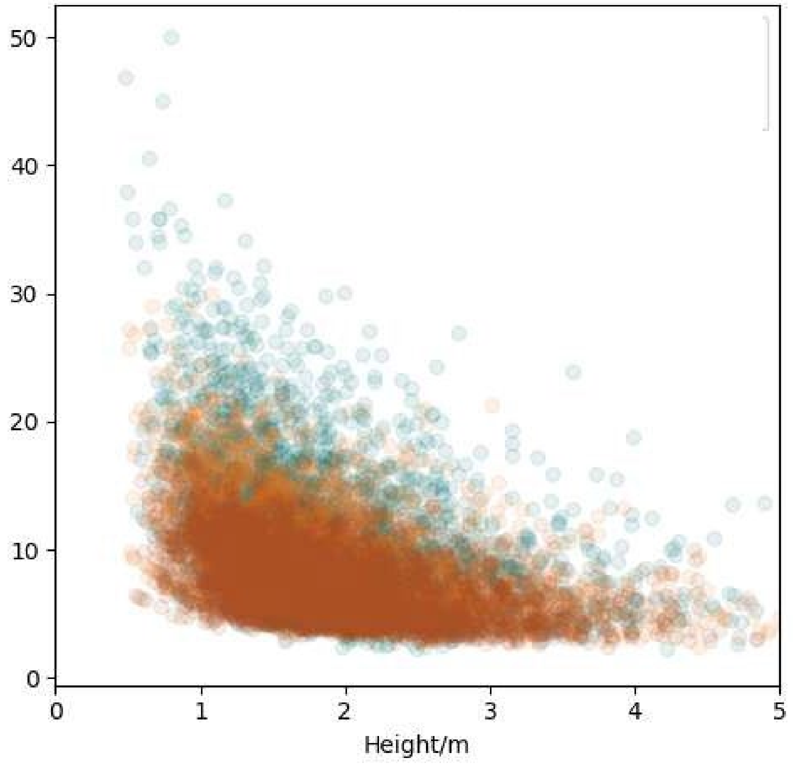
PERFORMANCE EVALUATION

VARIATION IN THICKNESS/ NUMBER OF LAYERS OF TILES

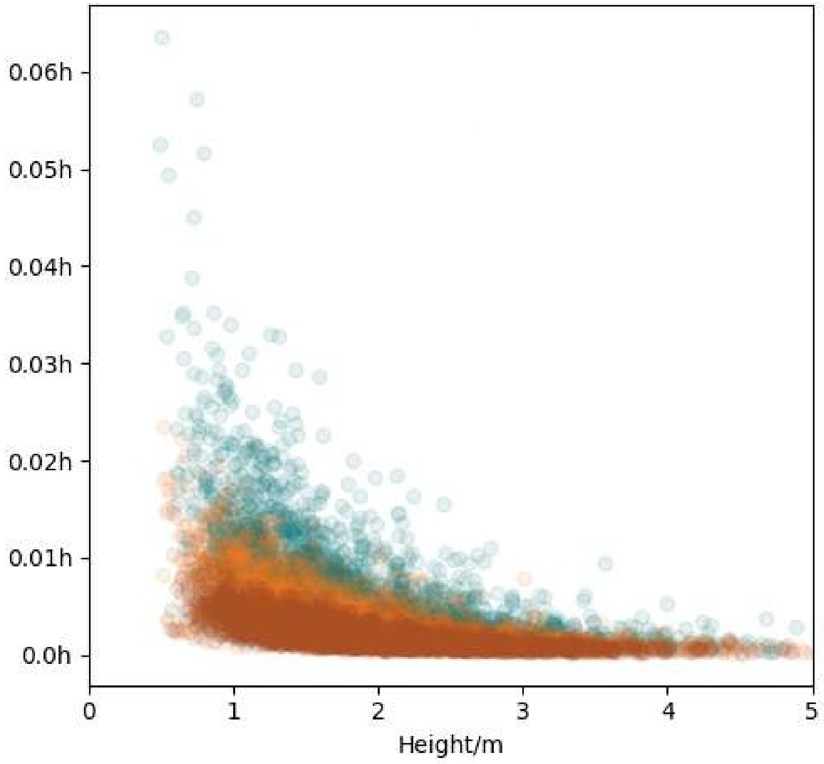
BUCKLING LOAD FACTOR



UTILIZATION



INTERSTOREY DRIFT RATIOS



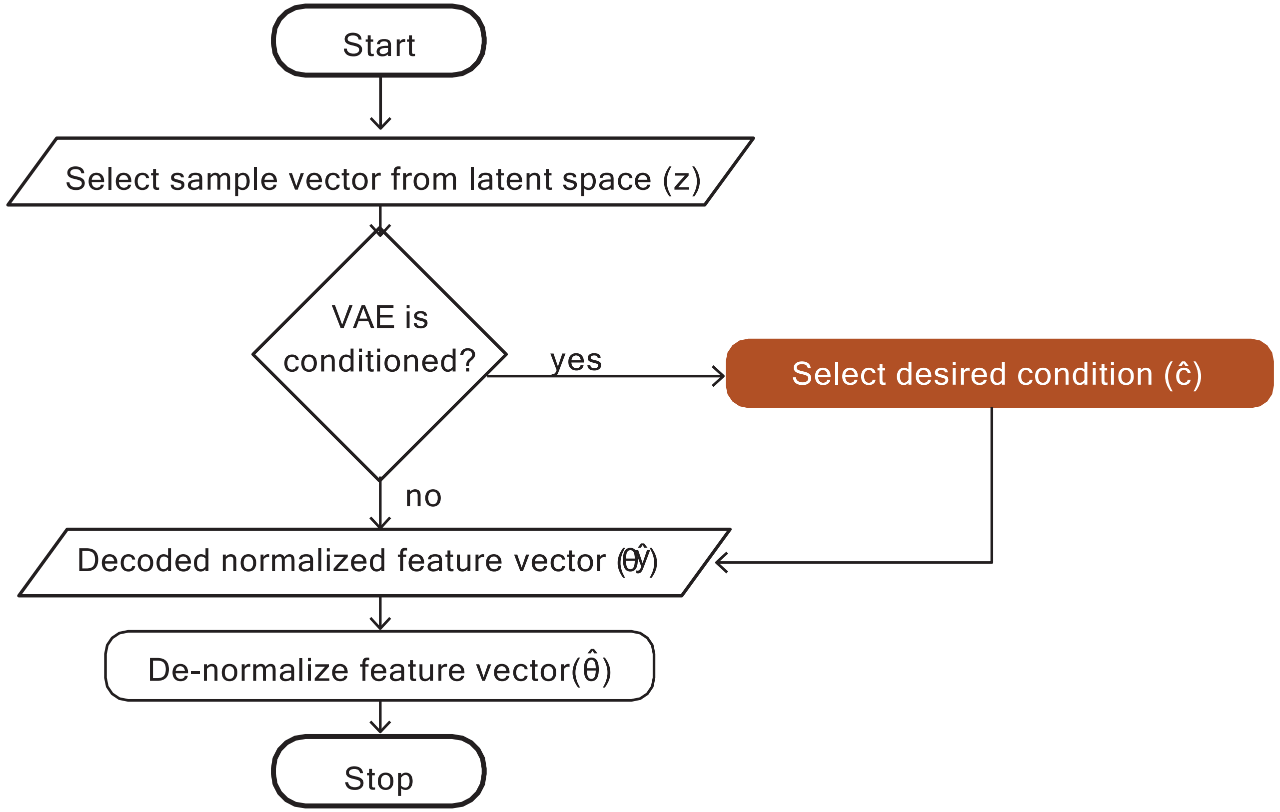
- thickness = 0.095m
- thickness = 0.060m
- thickness = 0.035m

DATASET: randomized		
Performance metric	Number of layers of tiles	
	single layer to double layer tiles	double layer tiles to triple layer tiles
Buckling_Load_Factor	213.4% increase	59.1% increase
Utilization	16.3% reduction	26.6% reduction
Interstorey_Drift_Ratios	38.5% reduction	62.3% reduction

GENERATOR

VAE

WORKFLOW

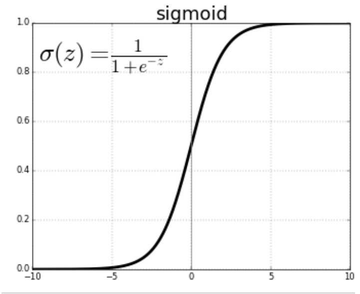


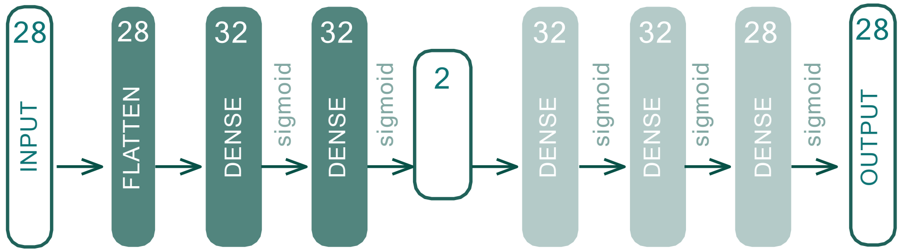
GENERATOR

VAE

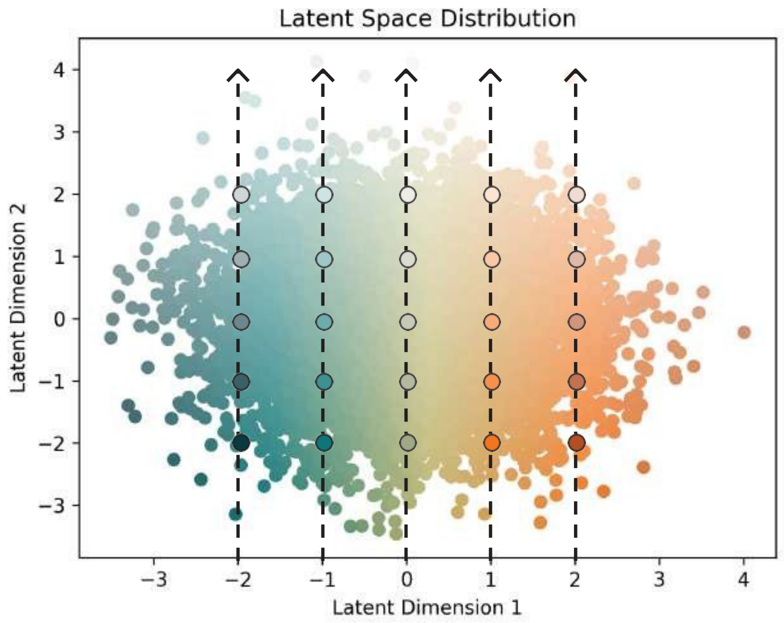
ACTIVATION FUNCTION = sigmoid

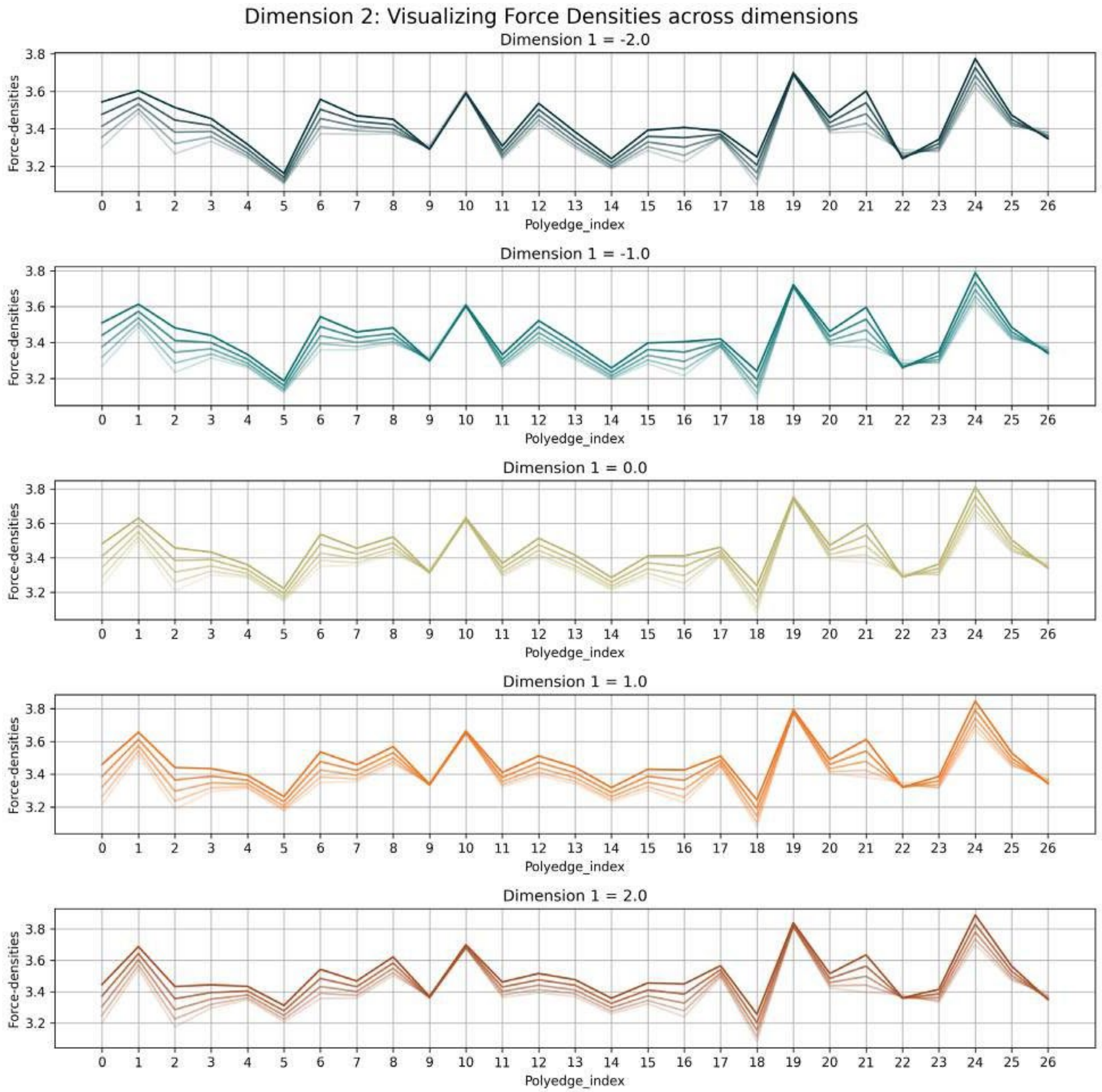
HYPERPARAMETERS: latent_dimension = 2, **beta** = 0.2, **epochs** = 600, **batch_size** = 128, **learning_rate** = 1E-05





Across Dimension 2



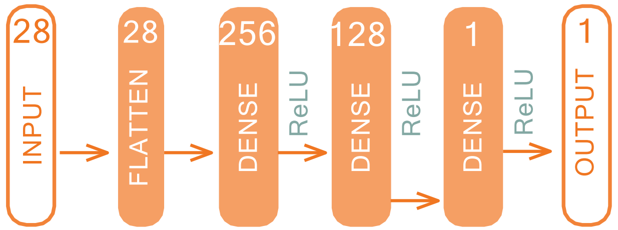


GENERATOR

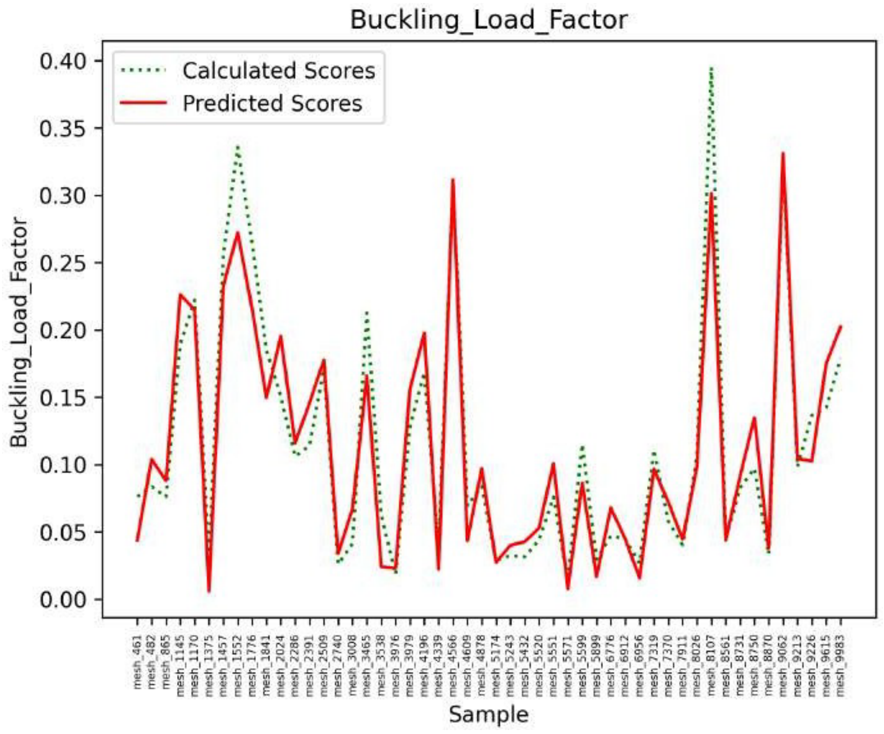
SURROGATE MODEL

BUCKLING LOAD FACTOR

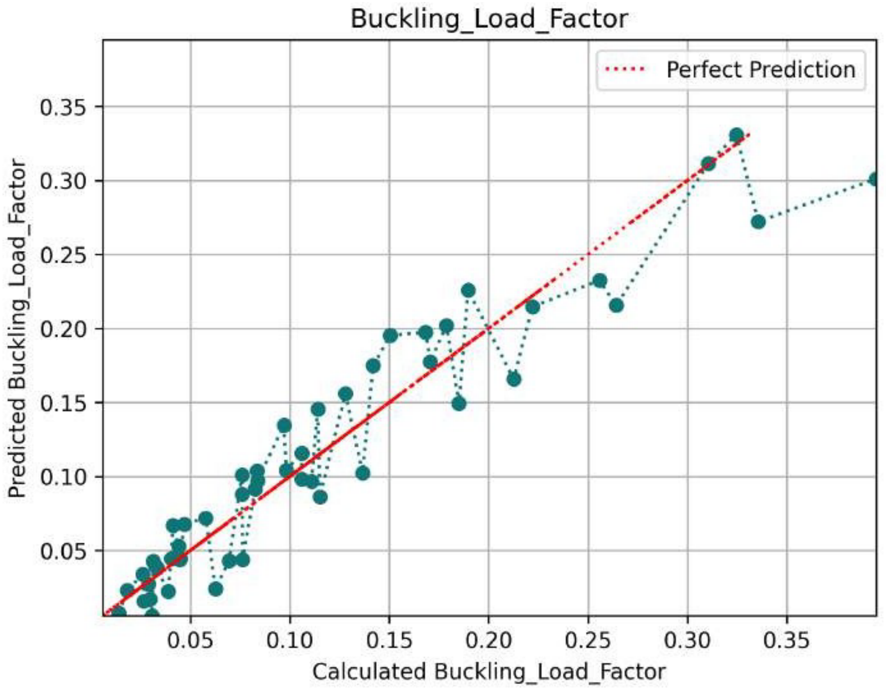
HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06



Predictions on Test Data



Prediction Pattern



Absolute in crease for notmalization along with force densities 14.25%

NMRSE OF

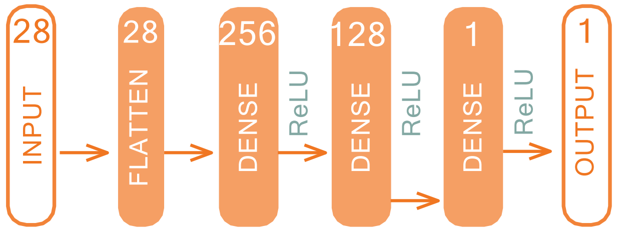
7.2%

GENERATOR

SURROGATE MODEL

BUCKLING LOAD FACTOR

HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06



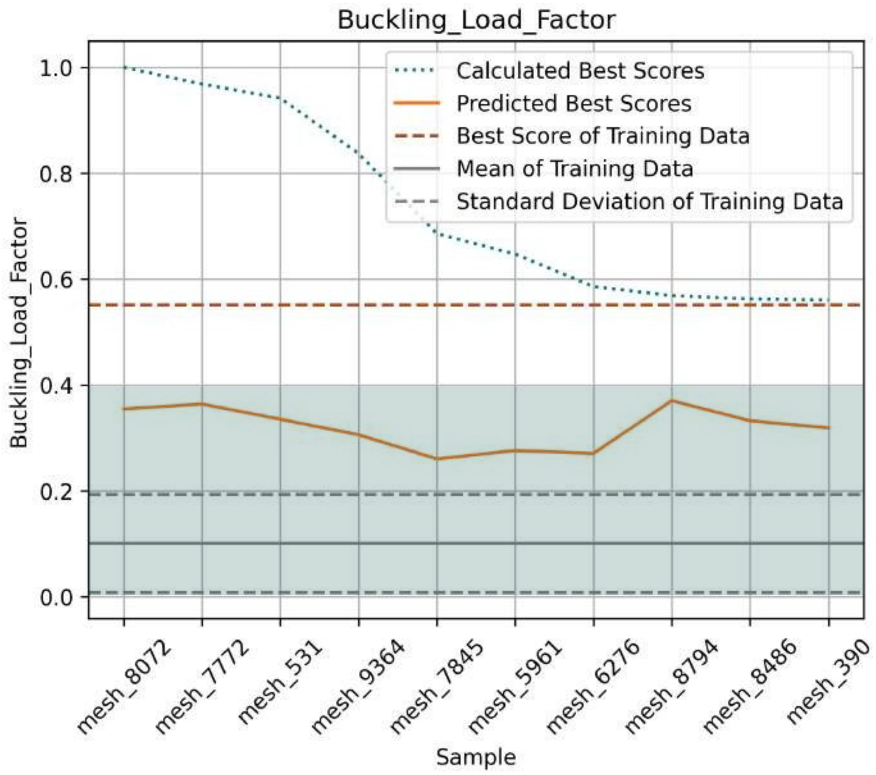
Absolute in crease for normalization along with force densities

14.25%

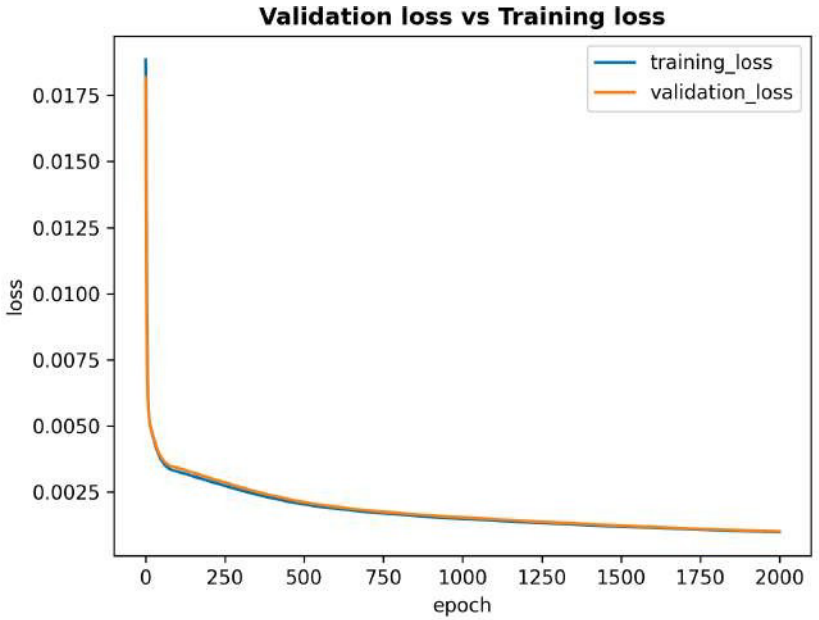
NMRSE OF

7.2%

Predictions on 10 best samples in Buckling Load Factor



Training and Validation Losses

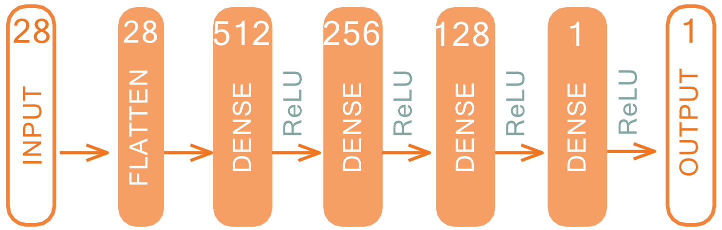


GENERATOR

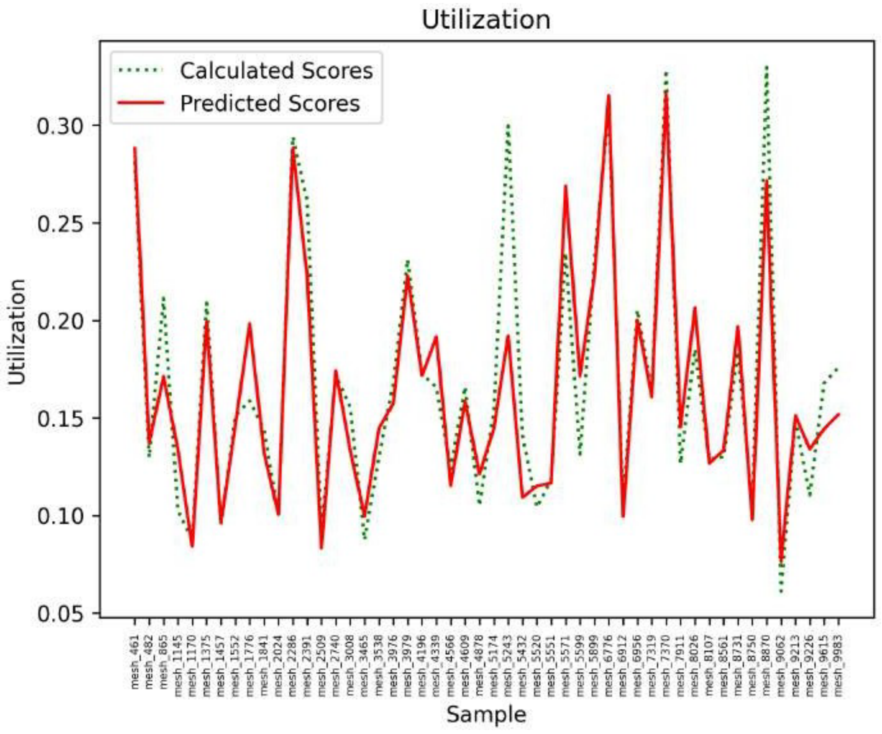
SURROGATE MODEL

UTILIZATION

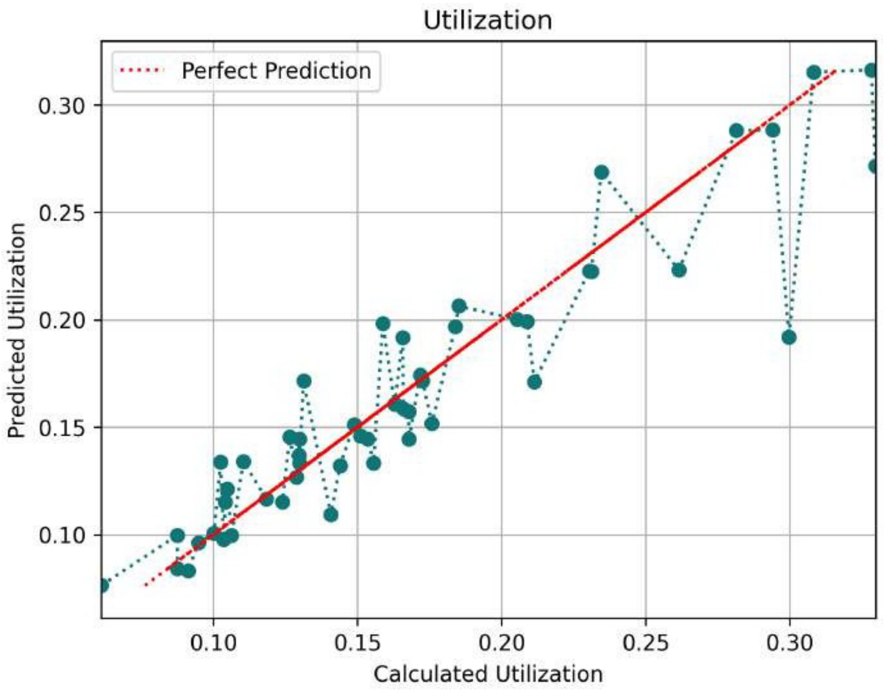
HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06



Predictions on Test Data



Prediction Pattern



NMRSE OF

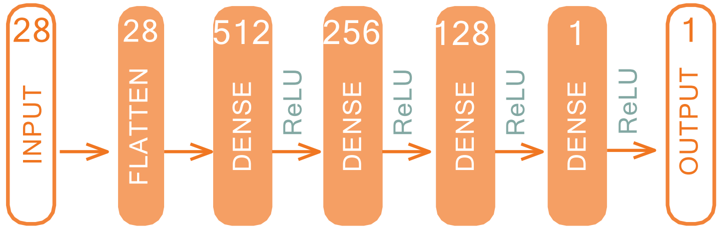
9.18%

GENERATOR

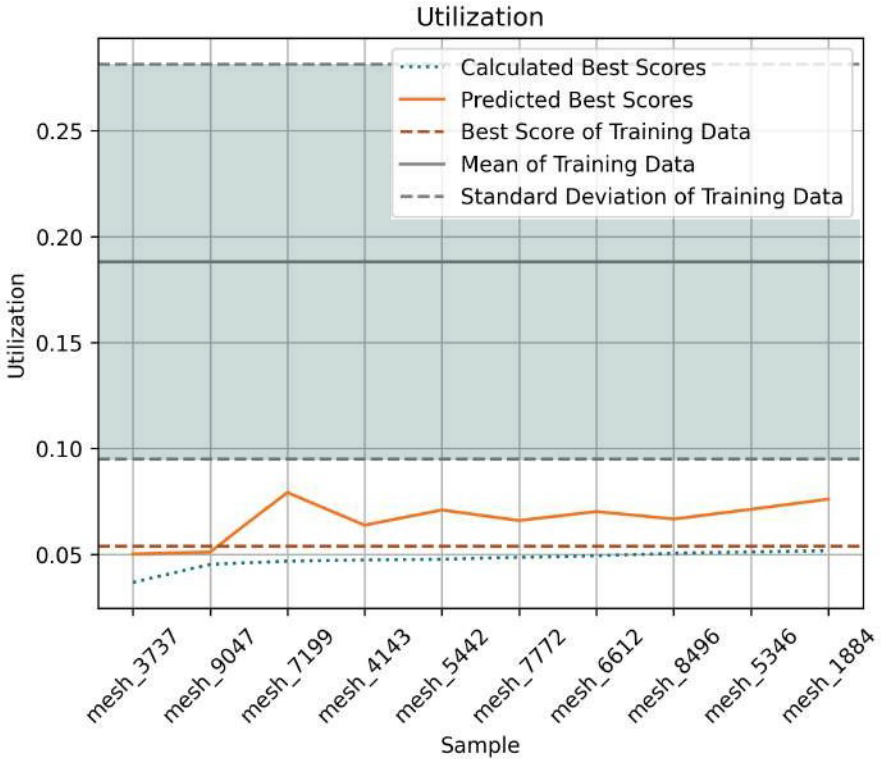
SURROGATE MODEL

UTILIZATION

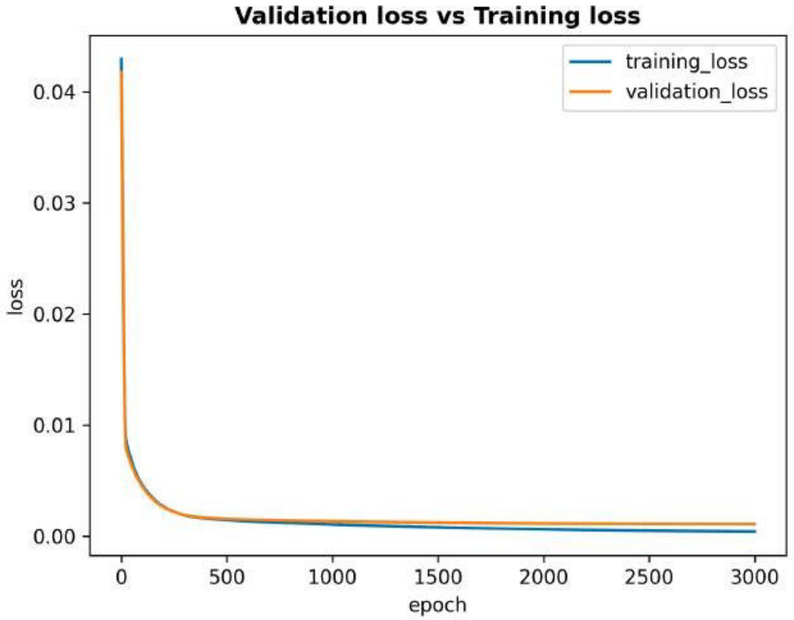
HYPERPARAMETERS: epochs = 2000, **batch_size** = 256, **learning_rate** = 5E-06



Predictions on Test Data



Prediction Pattern



NMRSE OF

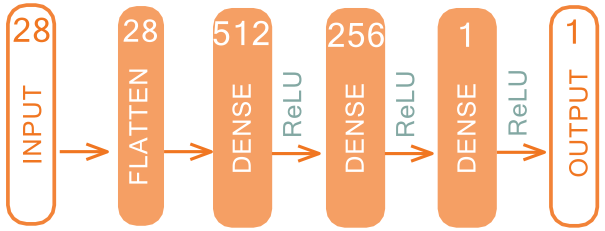
9.18%

GENERATOR

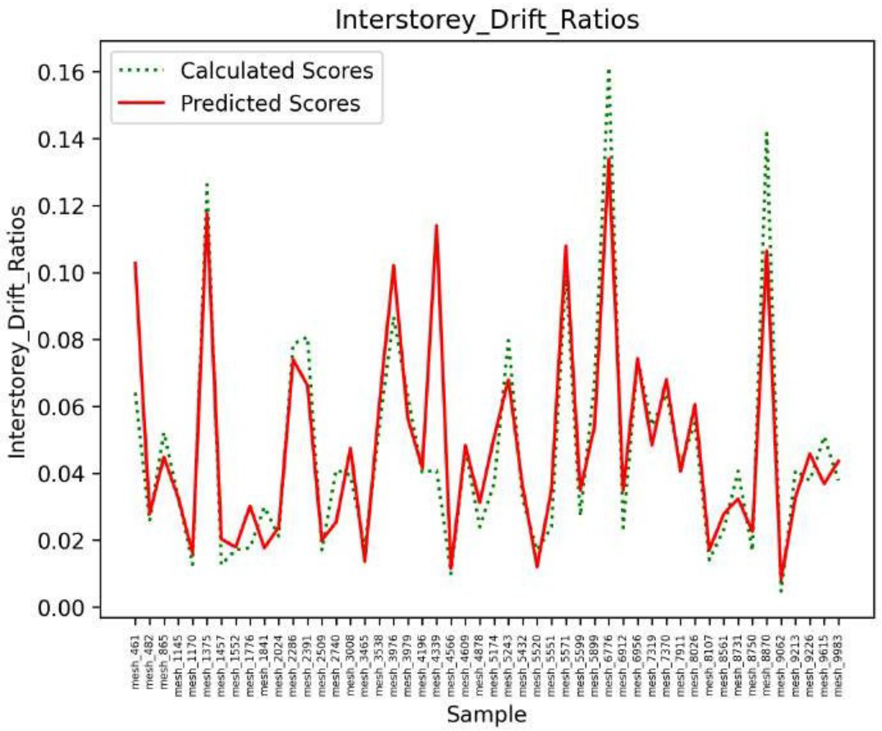
SURROGATE MODEL

INTERSTOREY DRIFT RATIOS

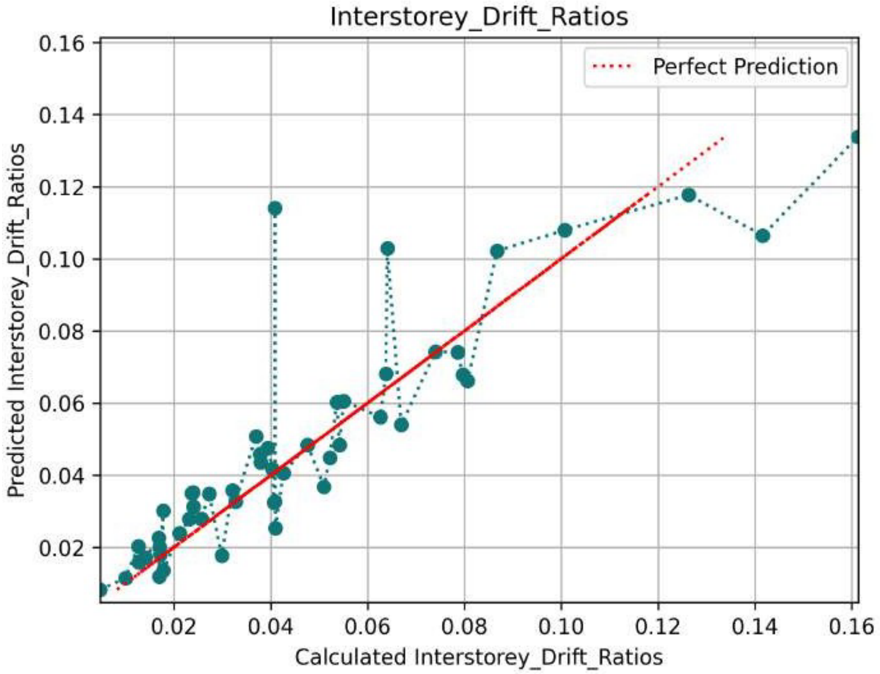
HYPERPARAMETERS: epochs = 3000, **batch_size** = 256, **learning_rate** = 5E-06



Predictions on Test Data



Prediction Pattern



NMRSE OF

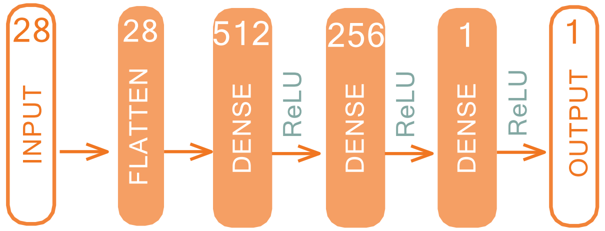
9.81%

GENERATOR

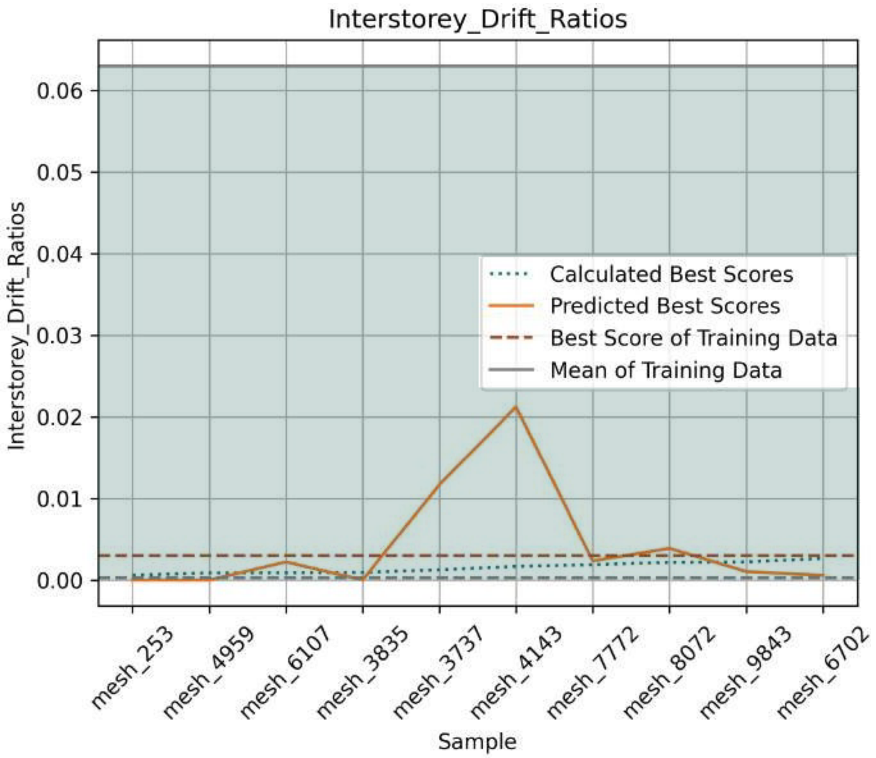
SURROGATE MODEL

INTERSTOREY DRIFT RATIOS

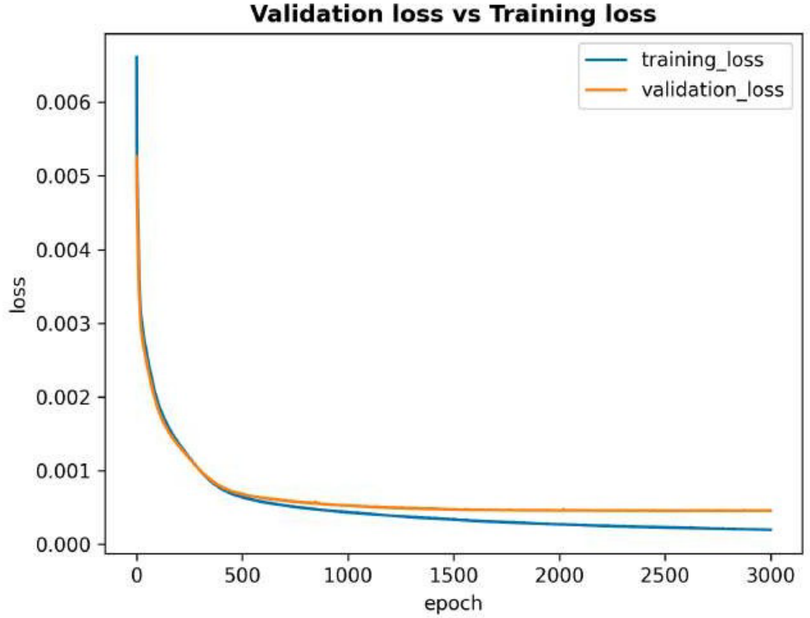
HYPERPARAMETERS: epochs = 3000, **batch_size** = 256, **learning_rate** = 5E-06



Predictions on Test Data



Prediction Pattern



NMRSE OF

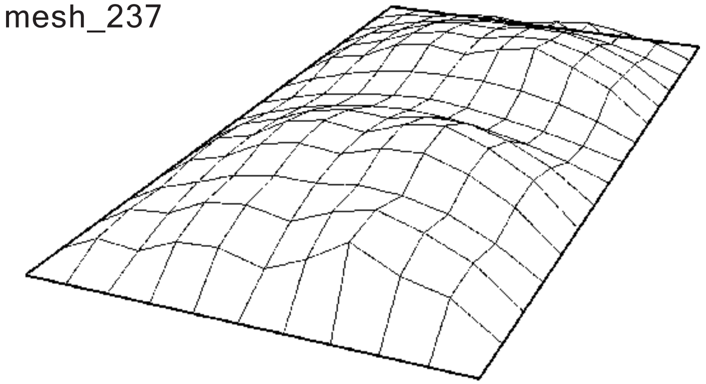
9.81%

GENERATOR

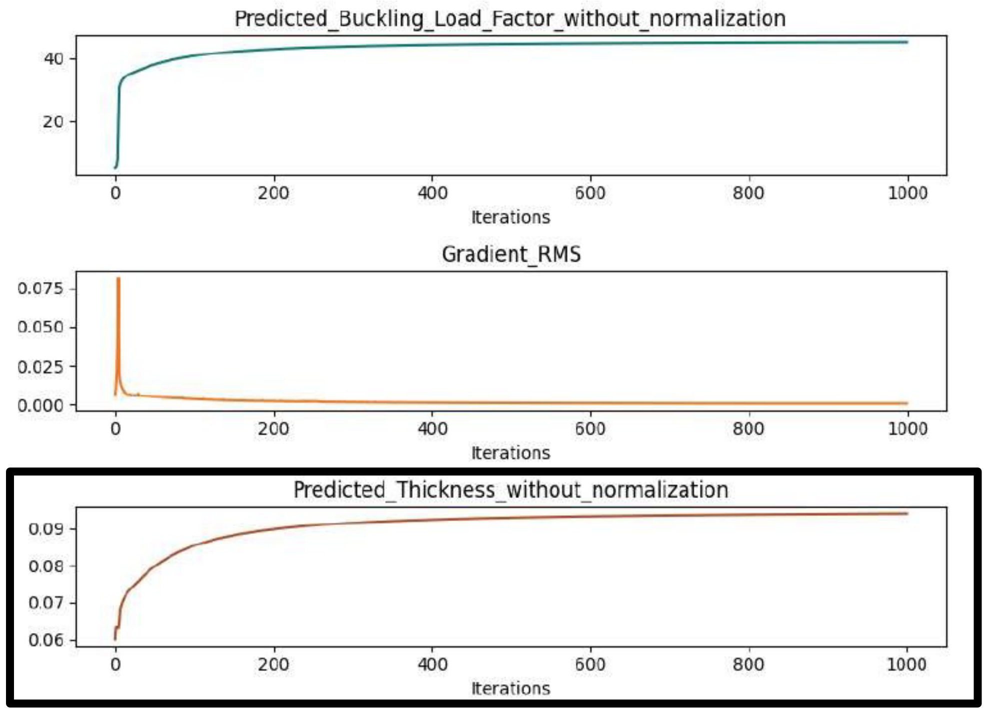
SINGLE OJECTIVE OPTIMIZATION

BUCKLING LOAD FACTOR

mesh_237



DATASET: randomized	
Metric	**Values before Optimization**
Buckling Load Factor	12.6452
Utilization	10.6016
Interstorey Drift Ratio	2.83E-03h
Thickness	0.060m



Learning rate = 20
Iterations = 1000

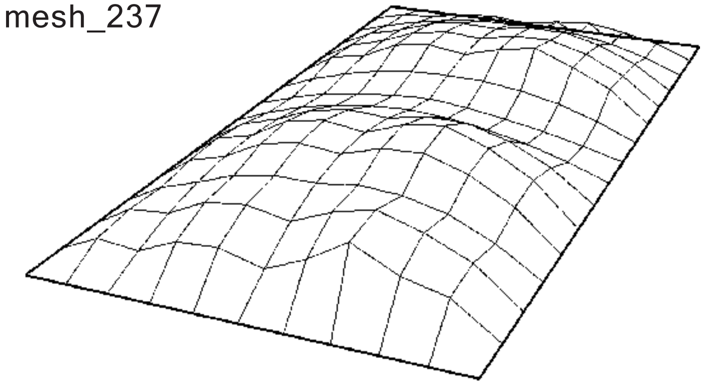
#	Gradient Descent: Buckling Load Factor			
	Learning Rate	**Percentage change**	**Final Thickness / m**	**Final Performance score**
1	20	256.05%	0.094	45.0239
2	15	255.97%	0.094	45.0139
3	0.1	159.13%	0.0702	32.768
4	0.01	72.99%	0.0646	21.8748
5	1	-49.14%	0.0637	6.4318
6	5	-49.19%	0.0637	6.4251
7	10	-49.27%	0.0637	6.4149
8	30	-49.61%	0.0637	6.3714

GENERATOR

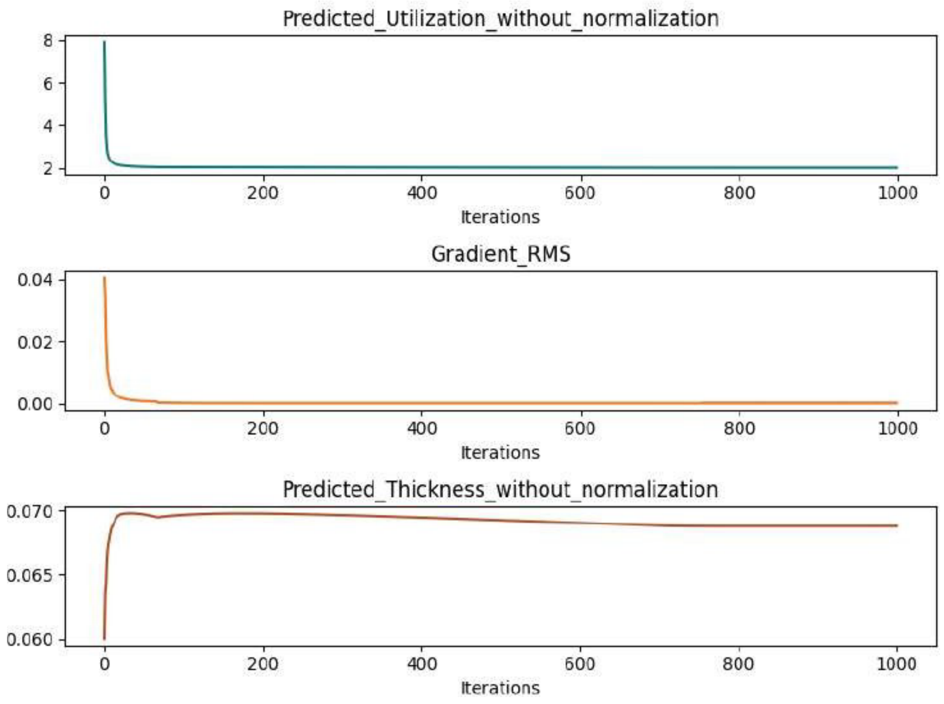
SINGLE OJECTIVE OPTIMIZATION

UTILIZATION

mesh_237



DATASET: randomized	
Metric	**Values before Optimization**
Buckling Load Factor	12.6452
Utilization	10.6016
Interstorey Drift Ratio	2.83E-03h
Thickness	0.060m



Learning rate = 15
Iterations = 1000

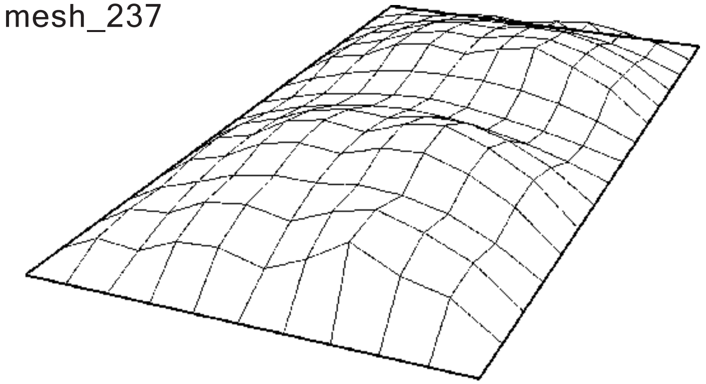
#	Gradient Descent: Utilization			
	Learning Rate	Percentage change	Final Thickness / m	Final Performance score
1	15	-81.02%	0.0688	2.0123
2	20	-81.02%	0.0688	2.0123
3	1	-80.95%	0.068	2.0197
4	5	-80.43%	0.0718	2.0750
5	0.1	-19.99%	0.0637	8.4822
6	10	-19.85%	0.0637	8.4973
7	30	-17.53%	0.0634	8.7430
8	0.01	-16.04%	0.0637	8.9007

GENERATOR

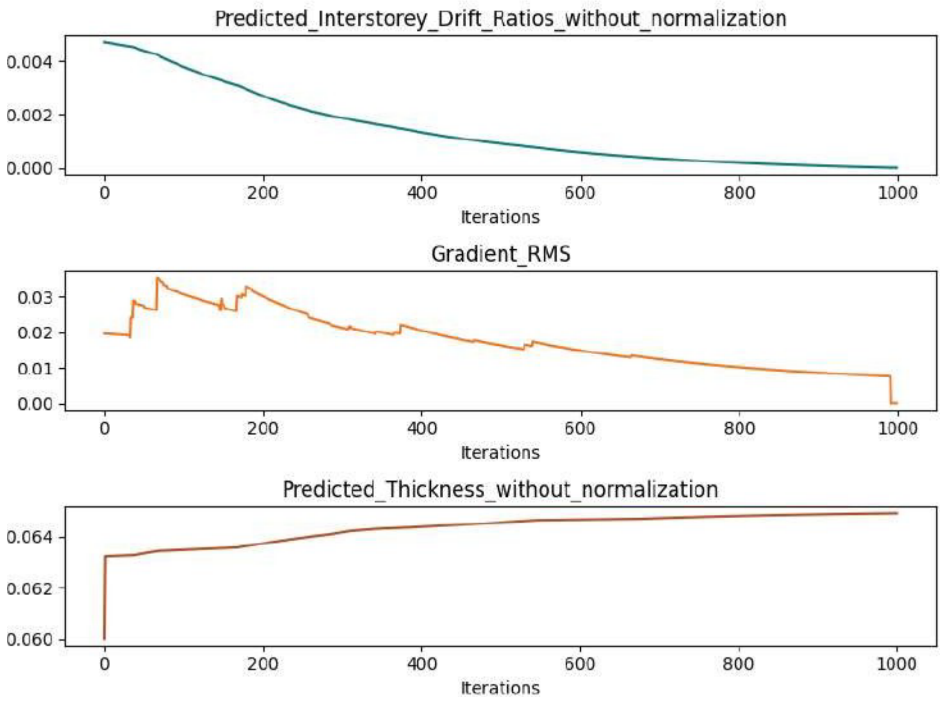
SINGLE OJECTIVE OPTIMIZATION

INTERSTOREY DRIFT RATIOS

mesh_237



DATASET: randomized	
Metric	**Values before Optimization**
Buckling Load Factor	12.6452
Utilization	10.6016
Interstorey Drift Ratio	2.83E-03h
Thickness	0.060m



Learning rate = 0.1
Iterations = 1000

#	Gradient Descent: Interstorey Drift Ratios			
	Learning Rate	**Percentage change**	**Final Thickness / m**	**Final Performance score**
1	0.1	-100%	0.0649	0.00E+00h
2	10	-100%	0.0668	0.00E+00h
3	1	-100%	0.0654	0.00E+00h
4	5	-100%	0.0654	0.00E+00h
5	0.01	39.99%	0.0636	3.96E-03h
6	30	49.89%	0.0636	4.24E-03h
7	15	50.03%	0.0636	4.24E-03h
8	20	50.12%	0.0636	4.24E-03h

PERFORMANCE EVALUATION

PERFORMANCE METRICS

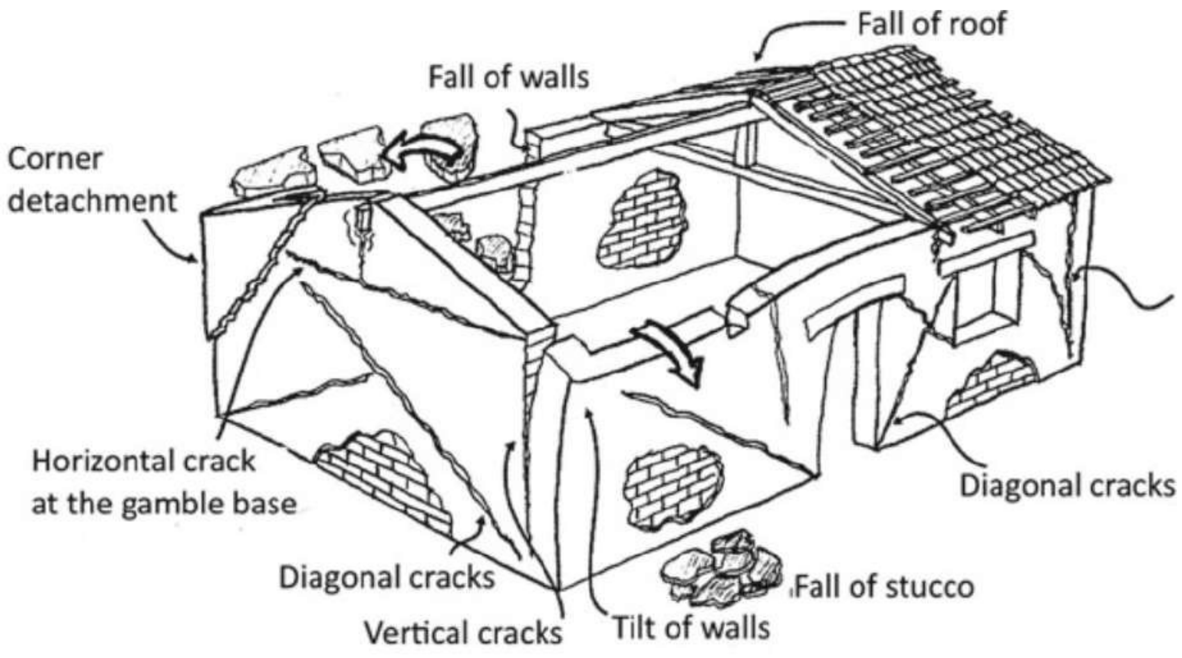
DATASET: randomized					
Performance metric	Mesh number				
	mesh_1	mesh_2	mesh_3	mesh_4	mesh_5
Buckling_Load_Factor	20.384	2.468	20.807	17.458	21.273
Utilization	12.469	11.034	5.908	10.041	9.830
Interstorey_Drift_Ratios	0.0033542h	0.00841904h	0.00197305h	0.00251683h	0.00287915h
Avg_Displacement/mm	10.051	21.939	6.192	9.438	8.500
Max_Displacement/mm	30.015	76.820	17.778	26.988	26.866
Avg_Shear_Force/KN	1.233	0.370	1.249	1.568	1.368
Max_Shear_Force/KN	12.666	3.052	9.481	13.098	16.628
Avg_Bending_Moment/KNm	0.614	0.092	0.469	0.722	0.559
Max_Bending_Moment/KNm	5.055	0.580	2.278	3.965	4.088
Max_Compresive_Stress/MPa	-0.996	-1.551	-0.315	-0.804	-0.802
Max_Tensile_Stress/MPa	3.314	3.222	1.492	2.719	2.615
Max_Principal_Stress/MPa	0.022	0.035	0.017	0.019	0.020

ULS

SLS

PERFORMANCE EVALUATION

REST OF THE STRUCTURE



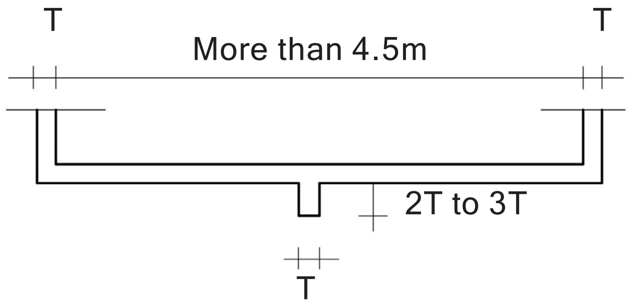
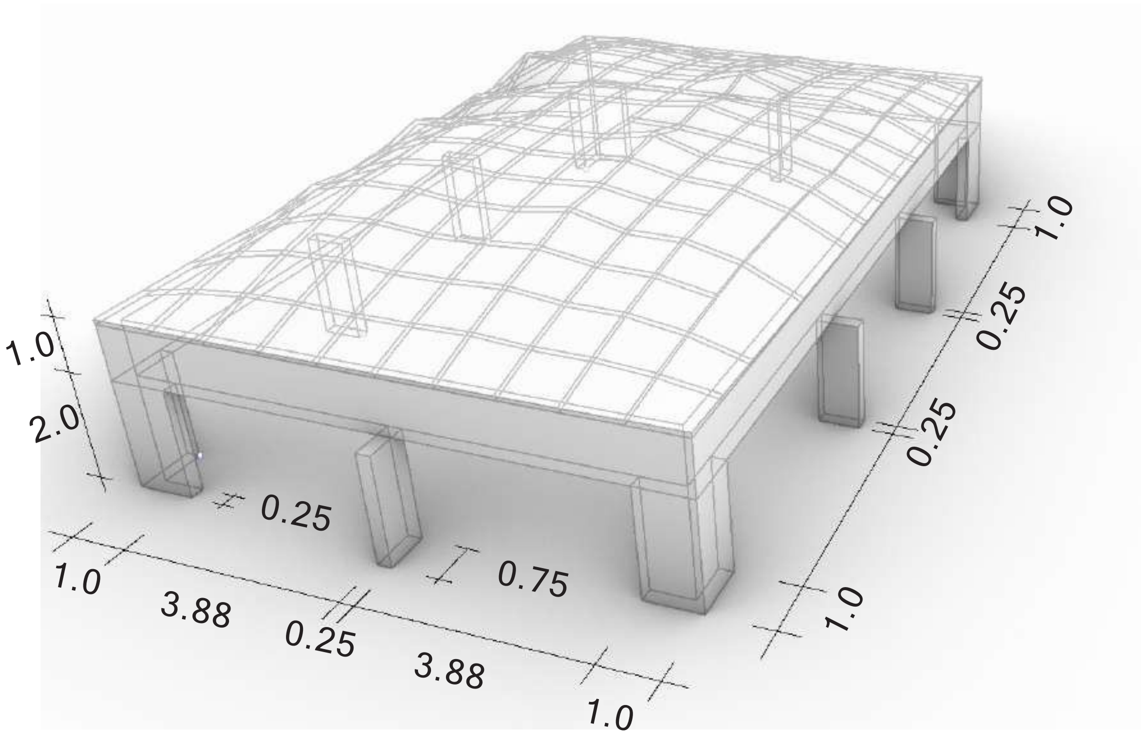


FIGURE 10: Vulnerability of Adobe Structures in Seismic events. Tarque, N., Sayın, E., Rafi, M.M., Tolles, E.L. (2021). Behaviour of Adobe Construction in Recent Earthquakes. In: Varum, H., Parisi, F., Tarque, N., Silveira, D. (eds) Structural Characterization and Seismic Retrofitting of Adobe Constructions. Building Pathology and Rehabilitation, vol 20. Springer, Cham. https://doi.org/10.1007/978-3-030-74737-4_2

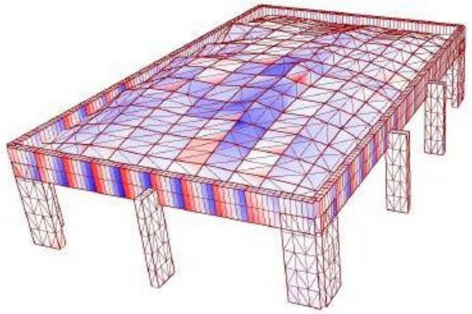
FIGURE 11: Butressing / Crosswalls needed for unreinforced masonyry walls greater than 4.5m. https://dev.earth-auroville.com/

PERFORMANCE EVALUATION

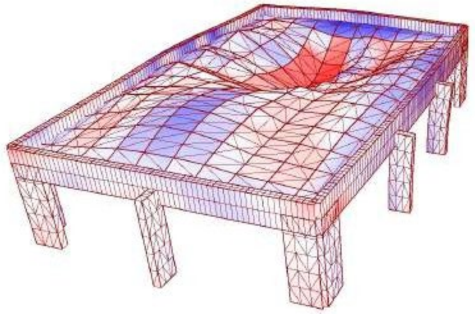
REST OF THE STRUCTURE



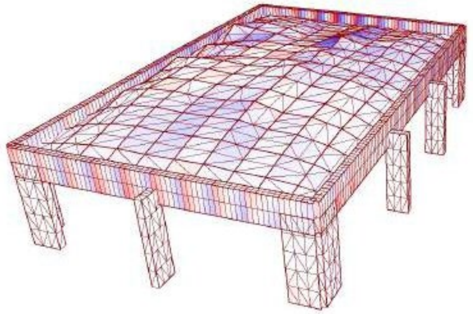
Mode 1



Mode 2



Mode 3



GENERATOR

OVERALL WORKLOW

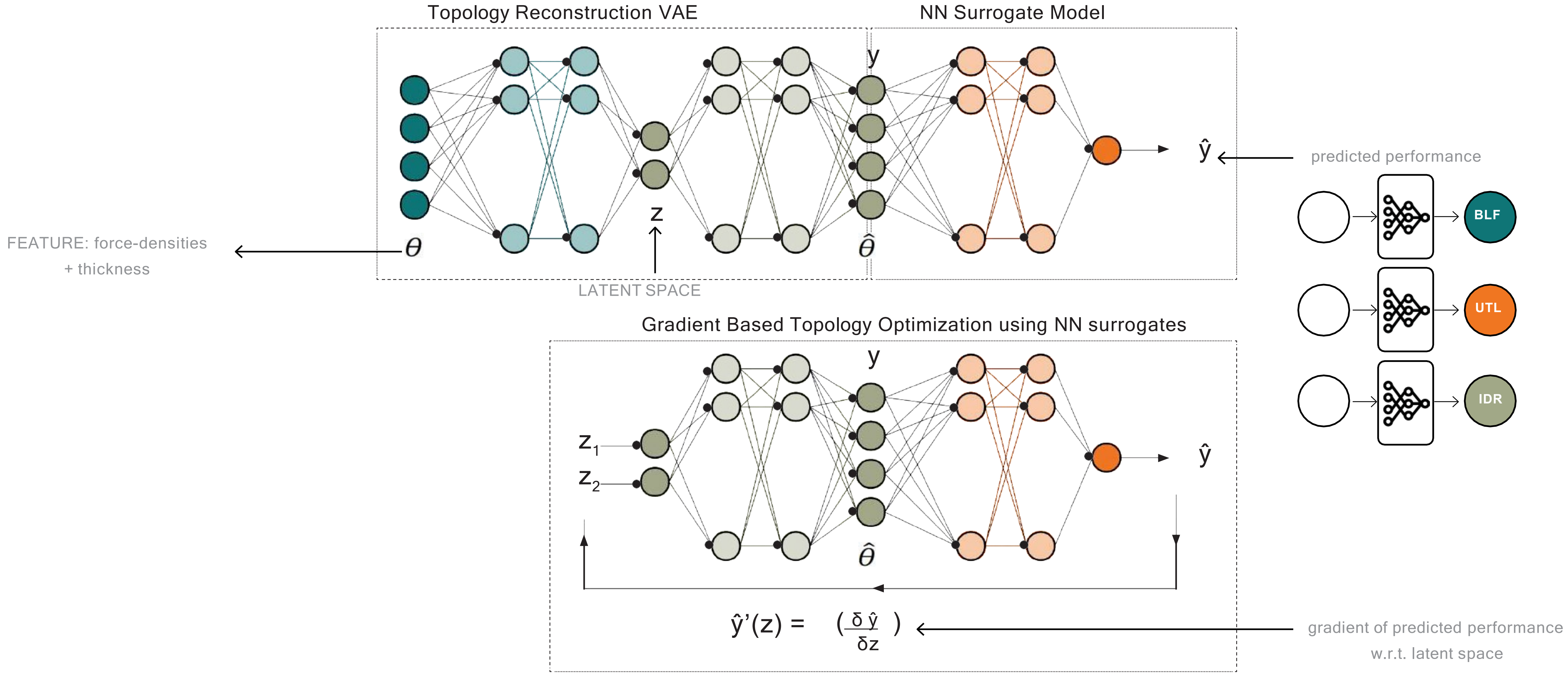
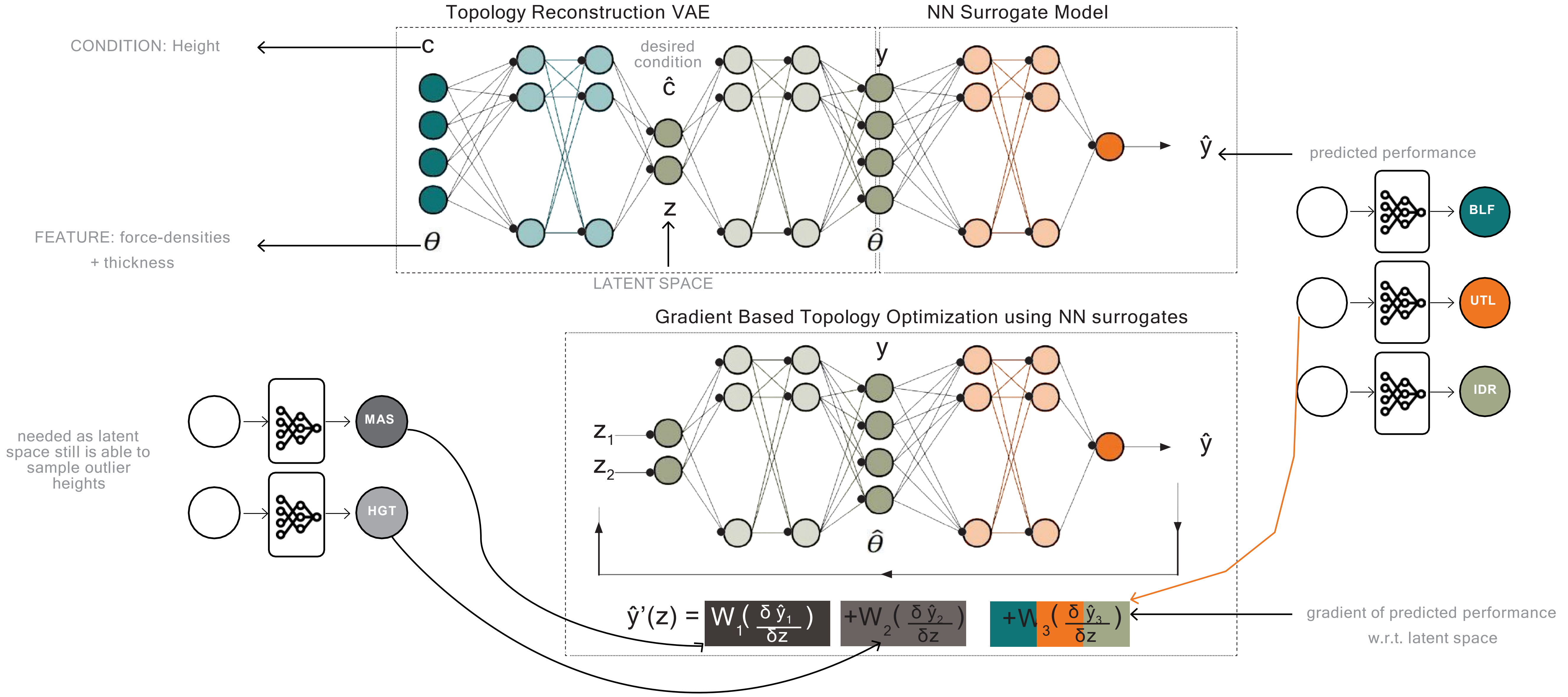


FIGURE 01: Overall Workflow connecting the VAE to the surrogate model and optimization through Gradient Descent. Inspired by Gladstone, R. J., Nabian, M. A., Keshavarzzadeh, V., & Meidani, H. (2021). Robust Topology Optimization Using Variational Autoencoders (arXiv:2107.10661). arXiv. http://arxiv.org/abs/2107.10661

GENERATOR

OVERALL WORKLOW



GENERATOR

VAE

ADDING THICKNESS AS FEATURE

index number		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	
1 sample	[	0.7	9.3	0.1	9.3	0.1	0.6	0.1	0.6	1.1	7.3	6.3	0.4	2.6	0.1	3.5	3.4	3.6	0.3	0.3	1.2	2.1	0.1	2.2	1.7	0.9	0.1	0.1	]
	[	0.6	7.6	3.7	3.9	0.5	0.1	1.1	0.7	1.2	0.6	0.8	1.4	0.1	1.7	0.4	1.0	0.9	0.4	0.5	11.4	1.3	1.8	0.8	11.0	0.1	13.8	10.6	]
	[	5.5	3.4	0.2	0.2	26.8	7.6	0.2	309.7	4.9	0.4	0.6	0.1	1.1	10.2	6.7	2.6	7.3	0.6	0.4	0.6	0.2	1.0	2.0	7.0	3.4	0.3	0.1	]
	[	0.1	0.1	0.6	1.4	2.5	0.9	0.2	1.9	1.0	19.7	0.5	1.1	0.5	1.5	0.4	0.3	1.2	7.2	0.1	6.5	0.3	0.9	0.4	3.8	10.5	1.0	1.5	]
	[	1.9	0.5	6.6	0.5	5.0	0.7	0.3	0.7	18.1	0.5	3.1	0.3	1.0	6.9	1.1	0.2	0.3	0.2	0.8	10.6	0.1	2.3	1.9	0.2	11.0	10.2	0.9	]
	[	3.3	1.0	20.9	1.6	0.1	2.5	0.2	0.3	0.1	7.2	6.0	0.4	0.3	11.1	8.4	0.9	0.5	16.0	2.2	1.4	1.5	15.7	3.1	0.6	0.8	0.1	0.1	]
	[	1.4	1.1	0.8	0.3	0.1	0.2	4.6	3.1	1.8	1.1	0.4	0.2	1.0	4.4	4.0	0.7	1.0	1.0	0.6	0.8	0.2	16.8	0.2	0.3	2.0	0.1	0.4	]
	[	2.9	0.6	1.6	1.0	0.1	0.6	1.9	0.1	1.2	0.1	1.3	0.2	0.4	0.3	0.2	0.8	0.6	0.5	2.6	1.1	2.9	0.6	24.4	1.8	1.6	0.1	0.7	]

force densities

GENERATOR

VAE

ADDING THICKNESS AS FEATURE

index number		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	
1 sample	[	0.7	9.3	0.1	9.3	0.1	0.6	0.1	0.6	1.1	7.3	6.3	0.4	2.6	0.1	3.5	3.4	3.6	0.3	0.3	1.2	2.1	0.1	2.2	1.7	0.9	0.1	0.1	0.095	]
	[	0.6	7.6	3.7	3.9	0.5	0.1	1.1	0.7	1.2	0.6	0.8	1.4	0.1	1.7	0.4	1.0	0.9	0.4	0.5	11.4	1.3	1.8	0.8	11.0	0.1	13.8	10.6	0.060	]
	[	5.5	3.4	0.2	0.2	26.8	7.6	0.2	309.7	4.9	0.4	0.6	0.1	1.1	10.2	6.7	2.6	7.3	0.6	0.4	0.6	0.2	1.0	2.0	7.0	3.4	0.3	0.1	0.095	]
	[	0.1	0.1	0.6	1.4	2.5	0.9	0.2	1.9	1.0	19.7	0.5	1.1	0.5	1.5	0.4	0.3	1.2	7.2	0.1	6.5	0.3	0.9	0.4	3.8	10.5	1.0	1.5	0.035	]
	[	1.9	0.5	6.6	0.5	5.0	0.7	0.3	0.7	18.1	0.5	3.1	0.3	1.0	6.9	1.1	0.2	0.3	0.2	0.8	10.6	0.1	2.3	1.9	0.2	11.0	10.2	0.9	0.095	]
	[	3.3	1.0	20.9	1.6	0.1	2.5	0.2	0.3	0.1	7.2	6.0	0.4	0.3	11.1	8.4	0.9	0.5	16.0	2.2	1.4	1.5	15.7	3.1	0.6	0.8	0.1	0.1	0.035	]
	[	1.4	1.1	0.8	0.3	0.1	0.2	4.6	3.1	1.8	1.1	0.4	0.2	1.0	4.4	4.0	0.7	1.0	1.0	0.6	0.8	0.2	16.8	0.2	0.3	2.0	0.1	0.4	0.095	]
	[	2.9	0.6	1.6	1.0	0.1	0.6	1.9	0.1	1.2	0.1	1.3	0.2	0.4	0.3	0.2	0.8	0.6	0.5	2.6	1.1	2.9	0.6	24.4	1.8	1.6	0.1	0.7	0.060	]

force densities

thickness

GENERATOR

VAE

ADDING THICKNESS AS FEATURE

index number		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	
1 sample	[	0.7	9.3	0.1	9.3	0.1	0.6	0.1	0.6	1.1	7.3	6.3	0.4	2.6	0.1	3.5	3.4	3.6	0.3	0.3	1.2	2.1	0.1	2.2	1.7	0.9	0.1	0.1	0.095	]
	[	0.6	7.6	3.7	3.9	0.5	0.1	1.1	0.7	1.2	0.6	0.8	1.4	0.1	1.7	0.4	1.0	0.9	0.4	0.5	11.4	1.3	1.8	0.8	11.0	0.1	13.8	10.6	0.060	]
	[	5.5	3.4	0.2	0.2	26.8	7.6	0.2	309.7	4.9	0.4	0.6	0.1	1.1	10.2	6.7	2.6	7.3	0.6	0.4	0.6	0.2	1.0	2.0	7.0	3.4	0.3	0.1	0.095	]
	[	0.1	0.1	0.6	1.4	2.5	0.9	0.2	1.9	1.0	19.7	0.5	1.1	0.5	1.5	0.4	0.3	1.2	7.2	0.1	6.5	0.3	0.9	0.4	3.8	10.5	1.0	1.5	0.035	]
	[	1.9	0.5	6.6	0.5	5.0	0.7	0.3	0.7	18.1	0.5	3.1	0.3	1.0	6.9	1.1	0.2	0.3	0.2	0.8	10.6	0.1	2.3	1.9	0.2	11.0	10.2	0.9	0.095	]
	[	3.3	1.0	20.9	1.6	0.1	2.5	0.2	0.3	0.1	7.2	6.0	0.4	0.3	11.1	8.4	0.9	0.5	16.0	2.2	1.4	1.5	15.7	3.1	0.6	0.8	0.1	0.1	0.035	]
	[	1.4	1.1	0.8	0.3	0.1	0.2	4.6	3.1	1.8	1.1	0.4	0.2	1.0	4.4	4.0	0.7	1.0	1.0	0.6	0.8	0.2	16.8	0.2	0.3	2.0	0.1	0.4	0.095	]
	[	2.9	0.6	1.6	1.0	0.1	0.6	1.9	0.1	1.2	0.1	1.3	0.2	0.4	0.3	0.2	0.8	0.6	0.5	2.6	1.1	2.9	0.6	24.4	1.8	1.6	0.1	0.7	0.060	]

force densities

thickness

Independant Normalization of thickness feature $= \dfrac{0.060}{\text{thickness}_{max}}$

GENERATOR

VAE

ADDING THICKNESS AS FEATURE

index number		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	
1 sample	[	0.7	9.3	0.1	9.3	0.1	0.6	0.1	0.6	1.1	7.3	6.3	0.4	2.6	0.1	3.5	3.4	3.6	0.3	0.3	1.2	2.1	0.1	2.2	1.7	0.9	0.1	0.1	0.095	]
	[	0.6	7.6	3.7	3.9	0.5	0.1	1.1	0.7	1.2	0.6	0.8	1.4	0.1	1.7	0.4	1.0	0.9	0.4	0.5	11.4	1.3	1.8	0.8	11.0	0.1	13.8	10.6	0.060	]
	[	5.5	3.4	0.2	0.2	26.8	7.6	0.2	1038.8	4.9	0.4	0.6	0.1	1.1	10.2	6.7	2.6	7.3	0.6	0.4	0.6	0.2	1.0	2.0	7.0	3.4	0.3	0.1	0.095	]
	[	0.1	0.1	0.6	1.4	2.5	0.9	0.2	1.9	1.0	19.7	0.5	1.1	0.5	1.5	0.4	0.3	1.2	7.2	0.1	6.5	0.3	0.9	0.4	3.8	10.5	1.0	1.5	0.035	]
	[	1.9	0.5	6.6	0.5	5.0	0.7	0.3	0.7	18.1	0.5	3.1	0.3	1.0	6.9	1.1	0.2	0.3	0.2	0.8	10.6	0.1	2.3	1.9	0.2	11.0	10.2	0.9	0.095	]
	[	3.3	1.0	20.9	1.6	0.1	2.5	0.2	0.3	0.1	7.2	6.0	0.4	0.3	11.1	8.4	0.9	0.5	16.0	2.2	1.4	1.5	15.7	3.1	0.6	0.8	0.1	0.1	0.035	]
	[	1.4	1.1	0.8	0.3	0.1	0.2	4.6	3.1	1.8	1.1	0.4	0.2	1.0	4.4	4.0	0.7	1.0	1.0	0.6	0.8	0.2	16.8	0.2	0.3	2.0	0.1	0.4	0.095	]
	[	2.9	0.6	1.6	1.0	0.1	0.6	1.9	0.1	1.2	0.1	1.3	0.2	0.4	0.3	0.2	0.8	0.6	0.5	2.6	1.1	2.9	0.6	24.4	1.8	1.6	0.1	0.7	0.060	]

force densities

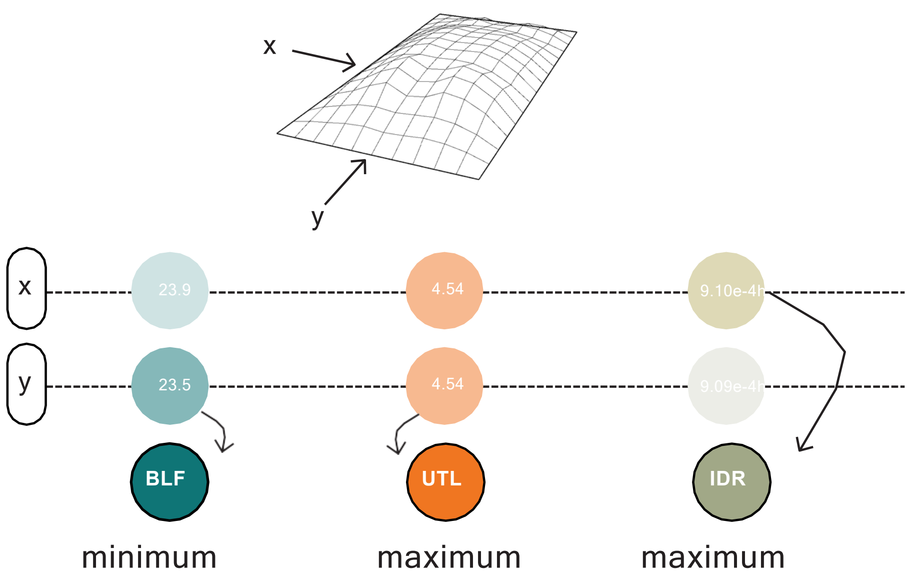
thickness

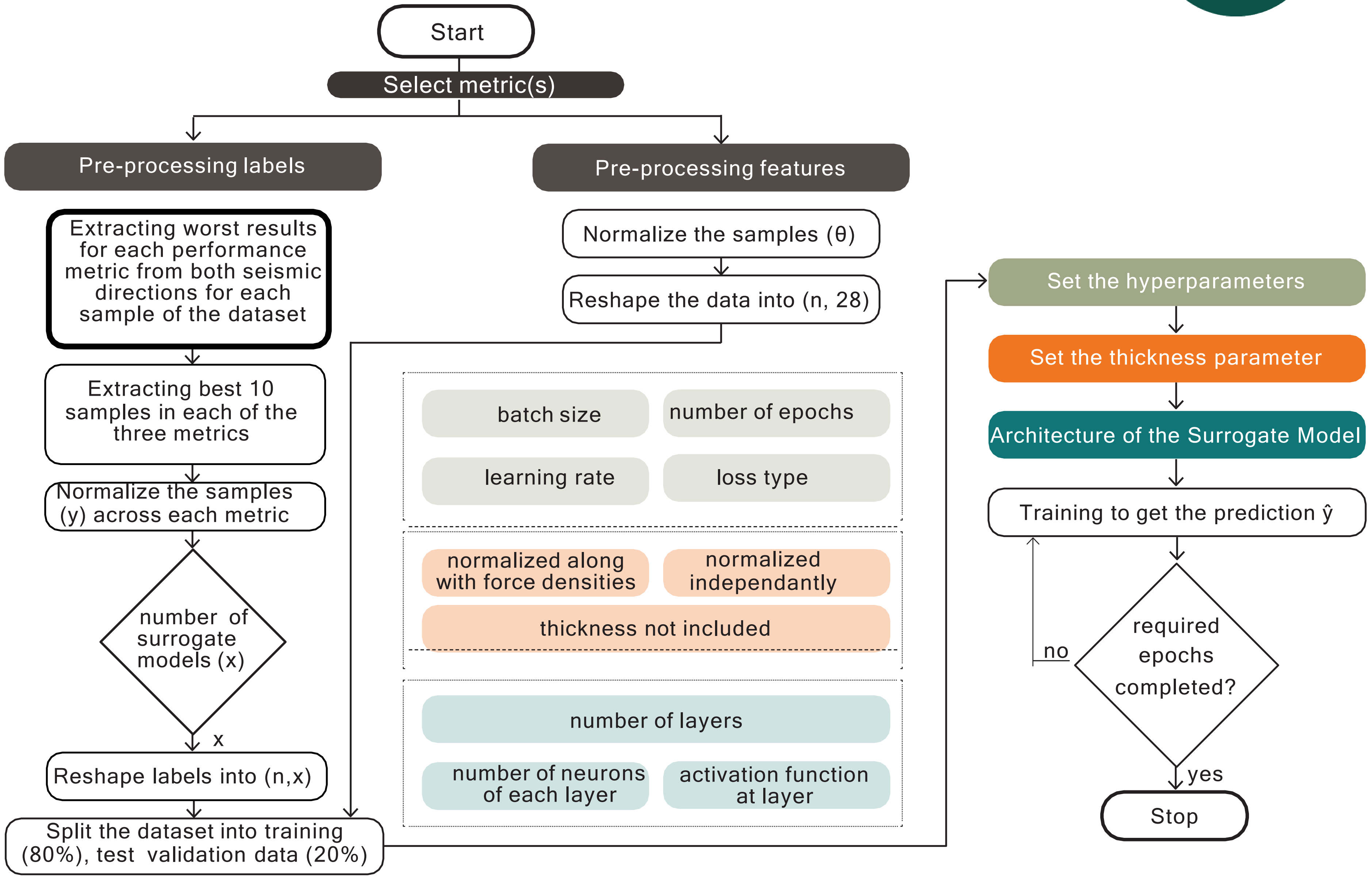
Normalization of thickness feature along with force densities $= \frac{0.060}{q_{max}}$

GENERATOR

SURROGATE MODEL

WORKFLOW

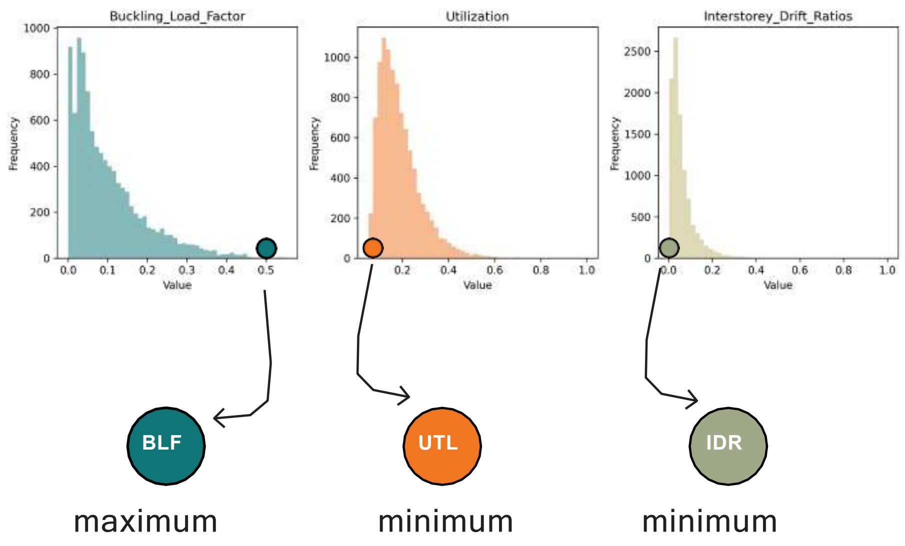


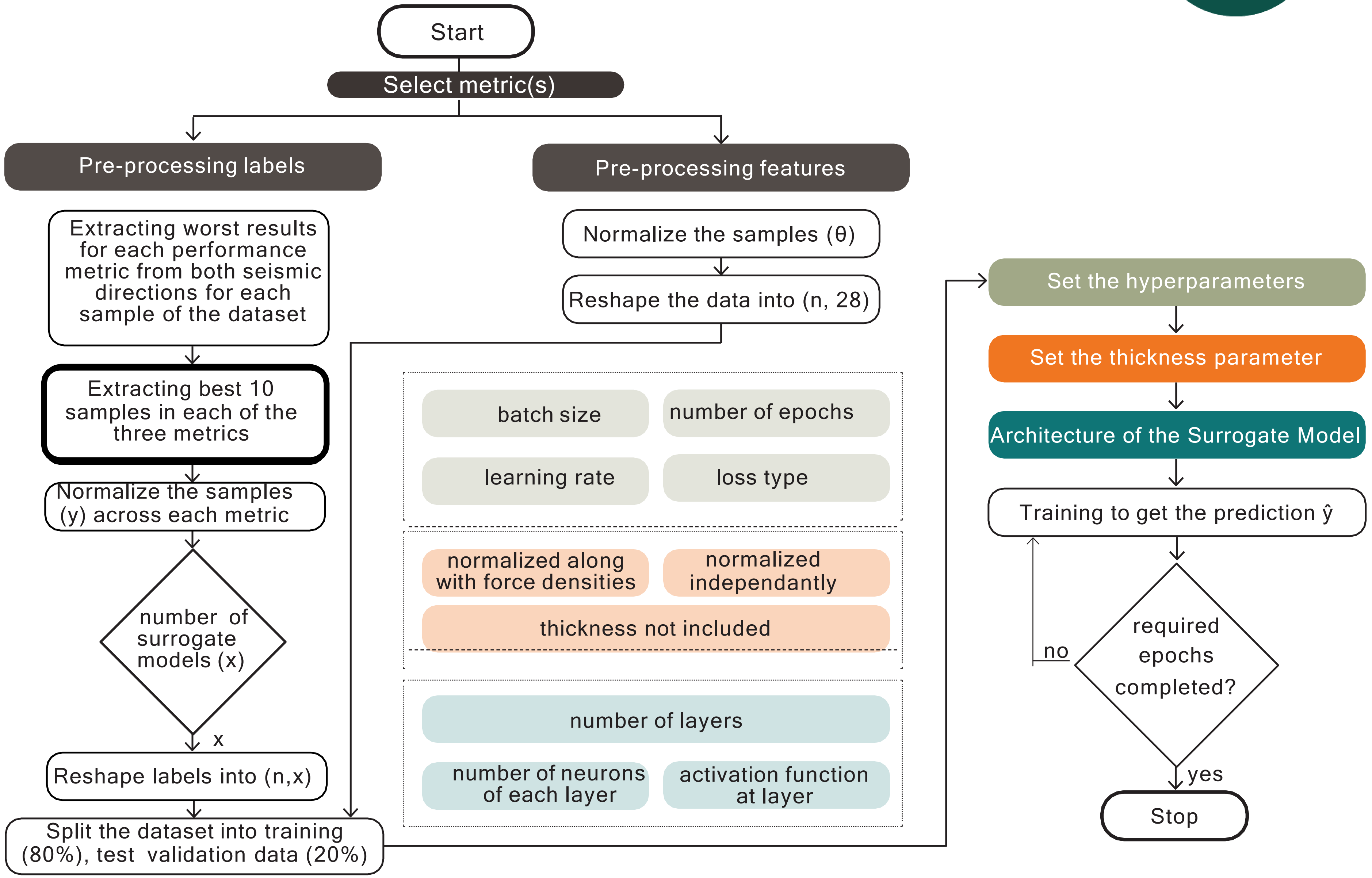


GENERATOR

SURROGATE MODEL

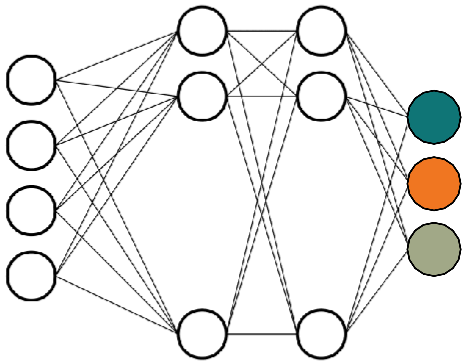
WORKFLOW



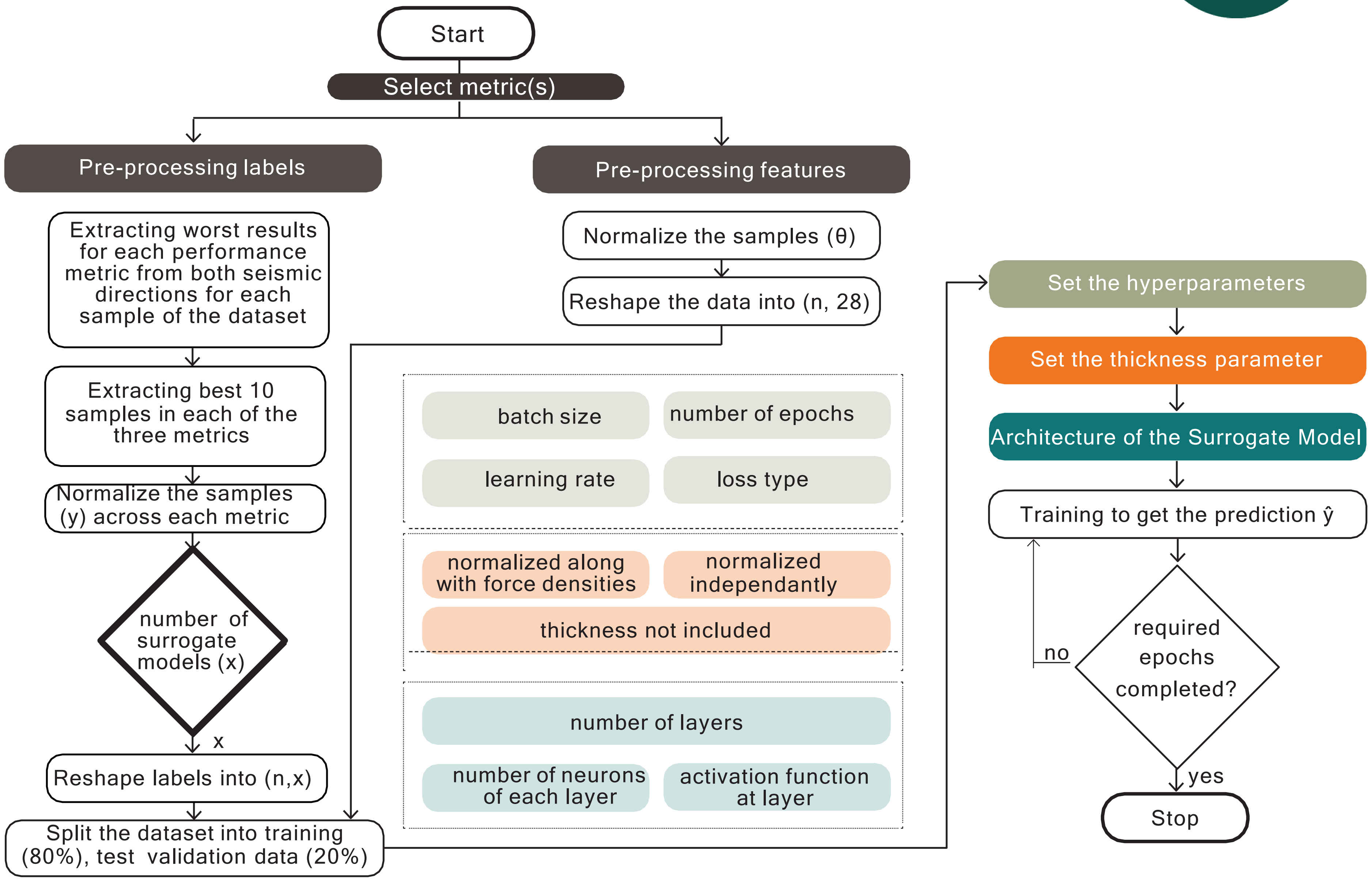


GENERATOR

WORKFLOW

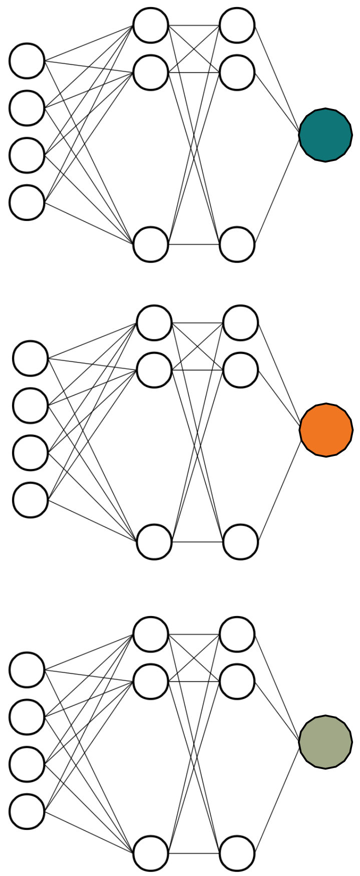


SURROGATE MODEL

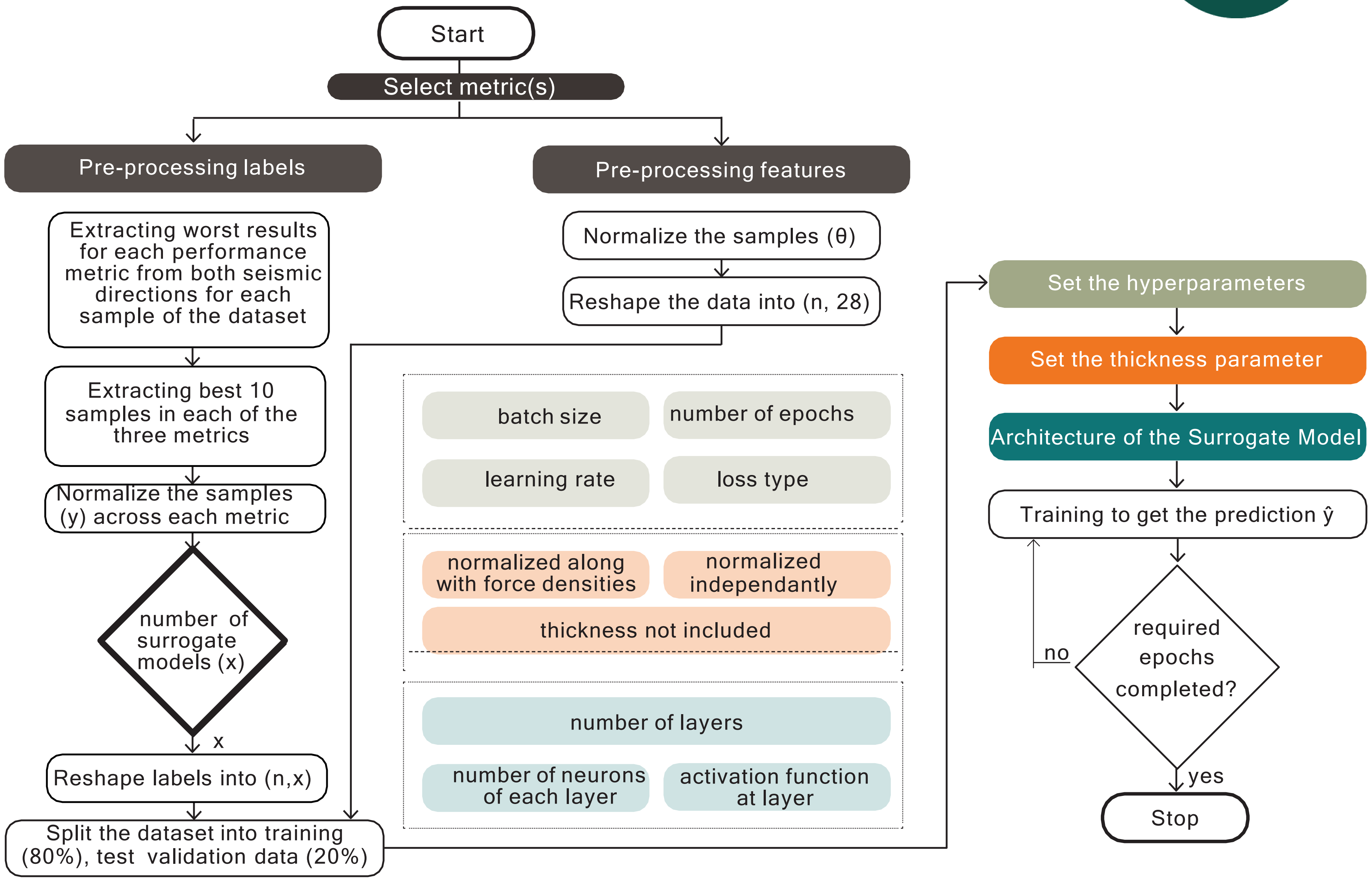


GENERATOR

WORKFLOW



SURROGATE MODEL



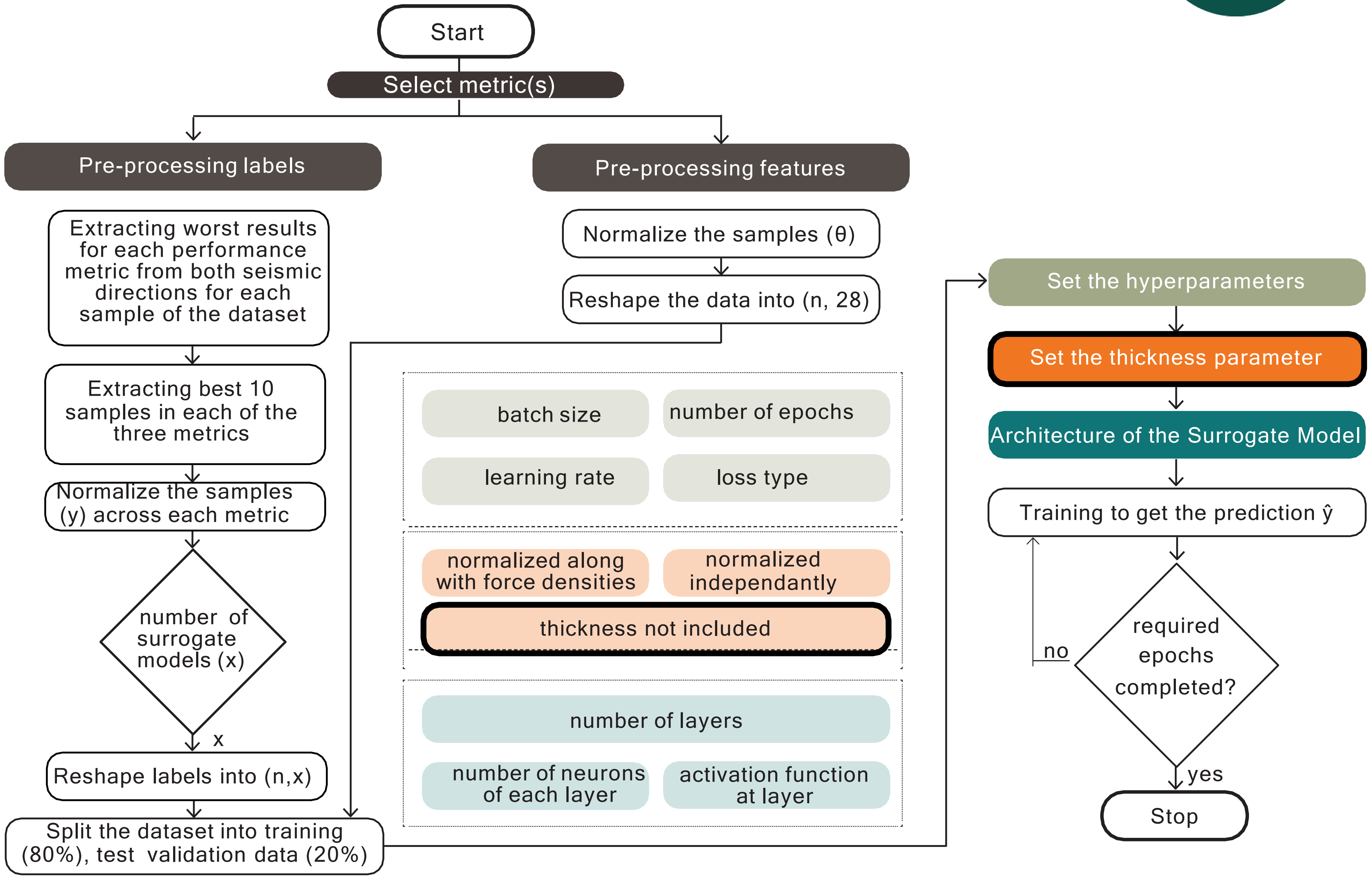
GENERATOR

SURROGATE MODEL

WORKFLOW

[	0.7	9.3	0.1	9.3	0.1	0.6	0.1	0.6	1.1	7.3	6.3	0.4	2.6	0.1	3.5	3.4	3.6	0.3	0.3	1.2	2.1	0.1	2.2	1.7	0.9	0.1	0.1	]
[	0.6	7.6	3.7	3.9	0.5	0.1	1.1	0.7	1.2	0.6	0.8	1.4	0.1	1.7	0.4	1.0	0.9	0.4	0.5	11.4	1.3	1.8	0.8	11.0	0.1	13.8	10.6	]
[	5.5	3.4	0.2	0.2	26.8	7.6	0.2	1038.8	4.9	0.4	0.6	0.1	1.1	10.2	6.7	2.6	7.3	0.6	0.4	0.6	0.2	1.0	2.0	7.0	3.4	0.3	0.1	]
[	0.1	0.1	0.6	1.4	2.5	0.9	0.2	1.9	1.0	19.7	0.5	1.1	0.5	1.5	0.4	0.3	1.2	7.2	0.1	6.5	0.3	0.9	0.4	3.8	10.5	1.0	1.5	]
[	1.9	0.5	6.6	0.5	5.0	0.7	0.3	0.7	18.1	0.5	3.1	0.3	1.0	6.9	1.1	0.2	0.3	0.2	0.8	10.6	0.1	2.3	1.9	0.2	11.0	10.2	0.9	]
[	3.3	1.0	20.9	1.6	0.1	2.5	0.2	0.3	0.1	7.2	6.0	0.4	0.3	11.1	8.4	0.9	0.5	16.0	2.2	1.4	1.5	15.7	3.1	0.6	0.8	0.1	0.1	]
[	1.4	1.1	0.8	0.3	0.1	0.2	4.6	3.1	1.8	1.1	0.4	0.2	1.0	4.4	4.0	0.7	1.0	1.0	0.6	0.8	0.2	16.8	0.2	0.3	2.0	0.1	0.4	]
[	2.9	0.6	1.6	1.0	0.1	0.6	1.9	0.1	1.2	0.1	1.3	0.2	0.4	0.3	0.2	0.8	0.6	0.5	2.6	1.1	2.9	0.6	24.4	1.8	1.6	0.1	0.7	]

$\underbrace{\hphantom{xxxxxxxxxxxxxxxx}}_{\text{force densities}}$



GENERATOR

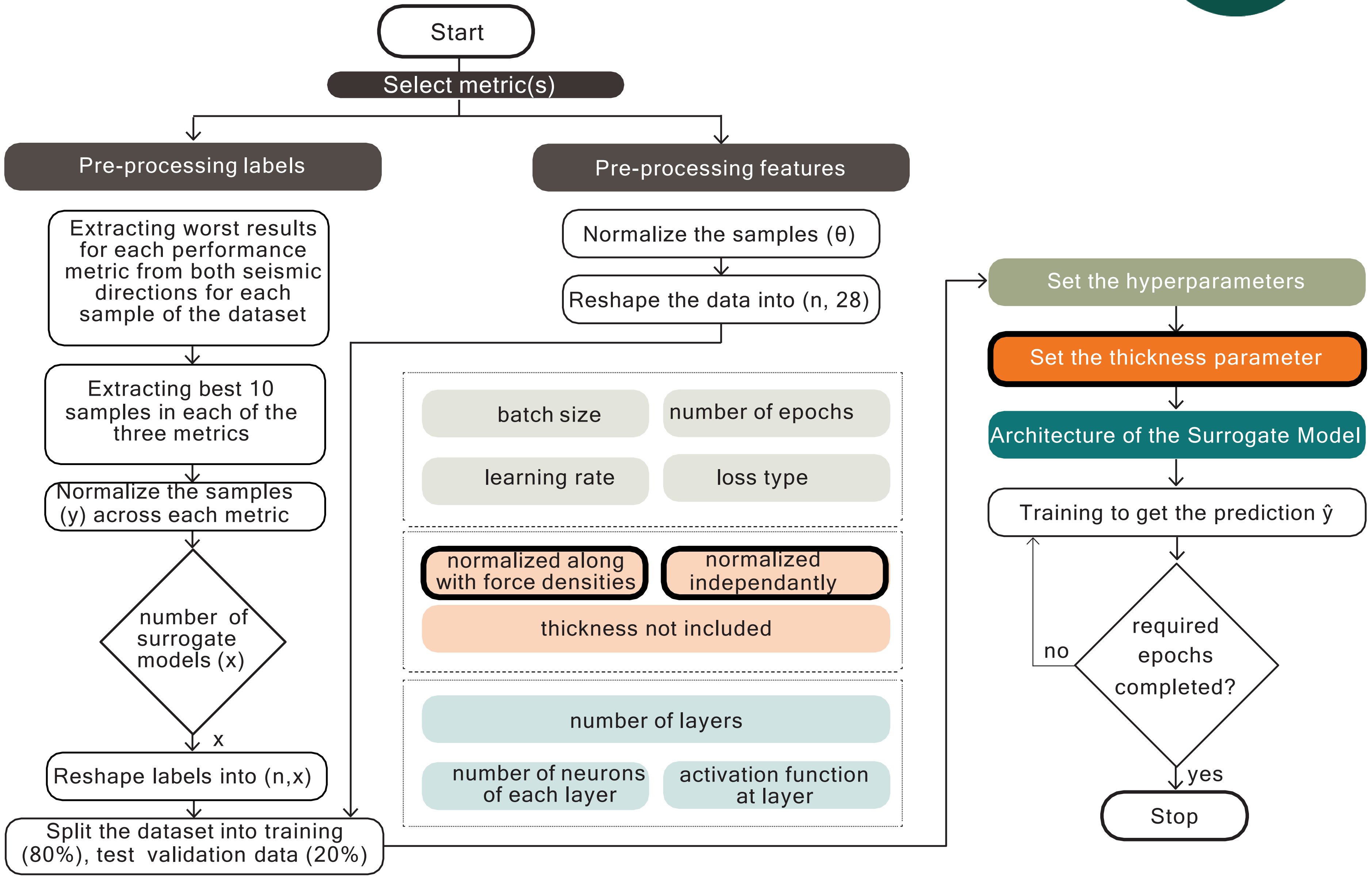
WORKFLOW

[	0.7	9.3	0.1	9.3	0.1	0.6	0.1	0.6	1.1	7.3	6.3	0.4	2.6	0.1	3.5	3.4	3.6	0.3	0.3	1.2	2.1	0.1	2.2	1.7	0.9	0.1	0.1	0.095	]
[	0.6	7.6	3.7	3.9	0.5	0.1	1.1	0.7	1.2	0.6	0.8	1.4	0.1	1.7	0.4	1.0	0.9	0.4	0.5	11.4	1.3	1.8	0.8	11.0	0.1	13.8	10.6	0.060	]
[	5.5	3.4	0.2	0.2	26.8	7.6	0.2	1038.8	4.9	0.4	0.6	0.1	1.1	10.2	6.7	2.6	7.3	0.6	0.4	0.6	0.2	1.0	2.0	7.0	3.4	0.3	0.1	0.095	]
[	0.1	0.1	0.6	1.4	2.5	0.9	0.2	1.9	1.0	19.7	0.5	1.1	0.5	1.5	0.4	0.3	1.2	7.2	0.1	6.5	0.3	0.9	0.4	3.8	10.5	1.0	1.5	0.035	]
[	1.9	0.5	6.6	0.5	5.0	0.7	0.3	0.7	18.1	0.5	3.1	0.3	1.0	6.9	1.1	0.2	0.3	0.2	0.8	10.6	0.1	2.3	1.9	0.2	11.0	10.2	0.9	0.095	]
[	3.3	1.0	20.9	1.6	0.1	2.5	0.2	0.3	0.1	7.2	6.0	0.4	0.3	11.1	8.4	0.9	0.5	16.0	2.2	1.4	1.5	15.7	3.1	0.6	0.8	0.1	0.1	0.035	]
[	1.4	1.1	0.8	0.3	0.1	0.2	4.6	3.1	1.8	1.1	0.4	0.2	1.0	4.4	4.0	0.7	1.0	1.0	0.6	0.8	0.2	16.8	0.2	0.3	2.0	0.1	0.4	0.095	]
[	2.9	0.6	1.6	1.0	0.1	0.6	1.9	0.1	1.2	0.1	1.3	0.2	0.4	0.3	0.2	0.8	0.6	0.5	2.6	1.1	2.9	0.6	24.4	1.8	1.6	0.1	0.7	0.060	]

force densities

thickness

SURROGATE MODEL



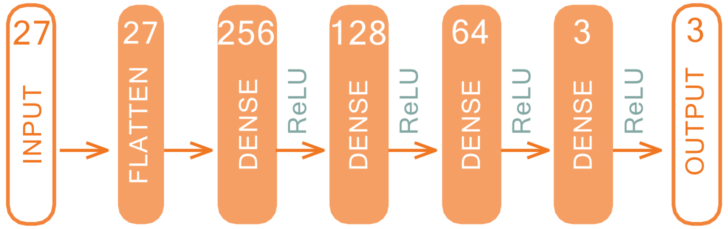
GENERATOR

SURROGATE MODEL

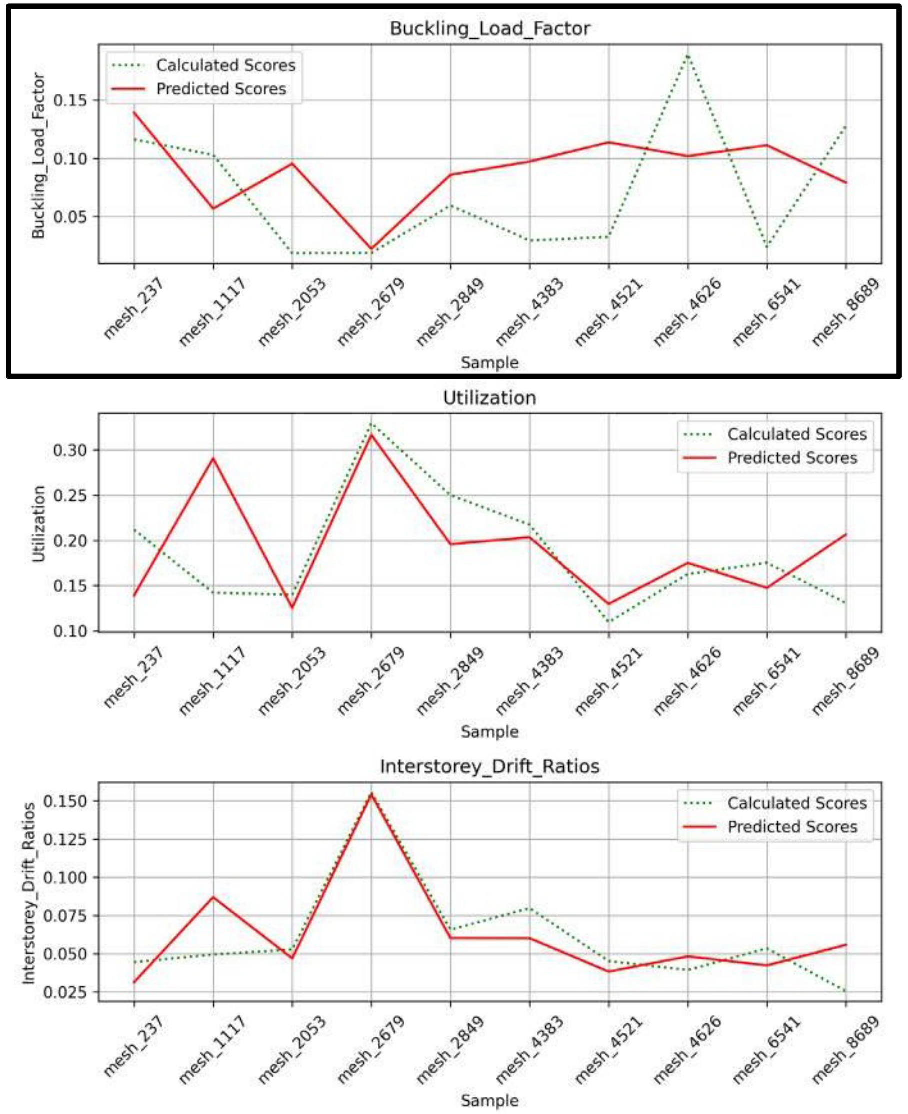
THICKNESS NOT INCLUDED

HYPERPARAMETERS: epochs = 600, **batch_size** = 128, **learning_rate** = 5E-06

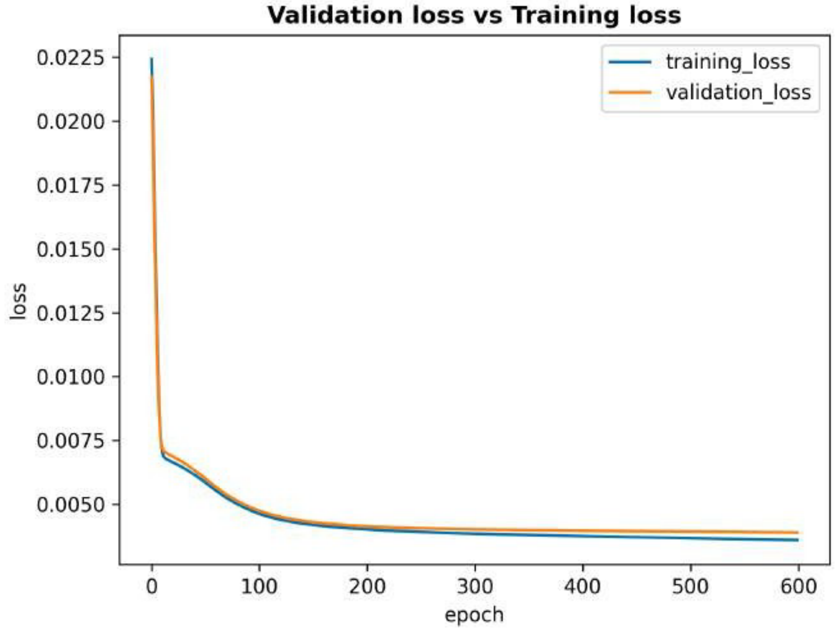
4 Dense Layers



Predictions on Test Data



Training and Validation Losses



GENERATOR

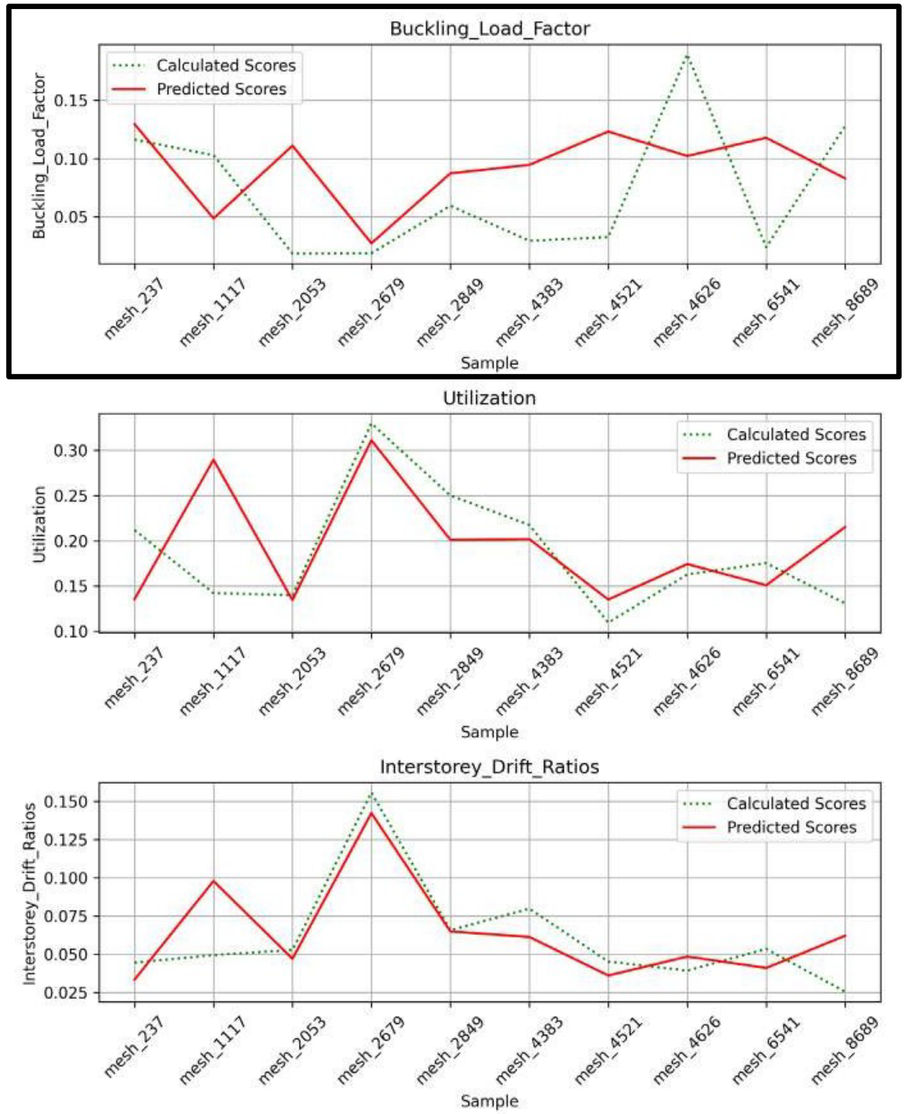
SURROGATE MODEL

THICKNESS NOT INCLUDED

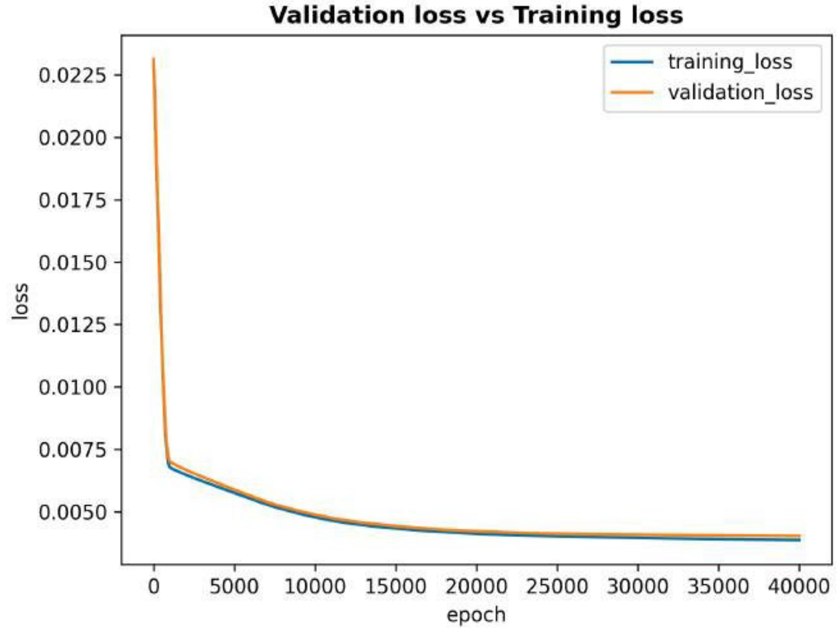
HYPERPARAMETERS: epochs = 4000, **batch_size** = 64, **learning_rate** = 1E-07

3 Dense Layers

Predictions on Test Data



Training and Validation Losses



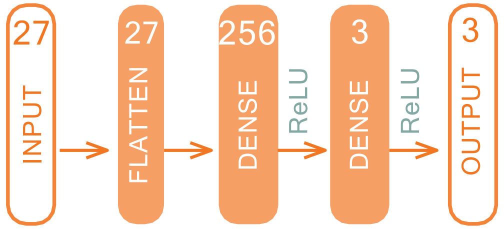
GENERATOR

SURROGATE MODEL

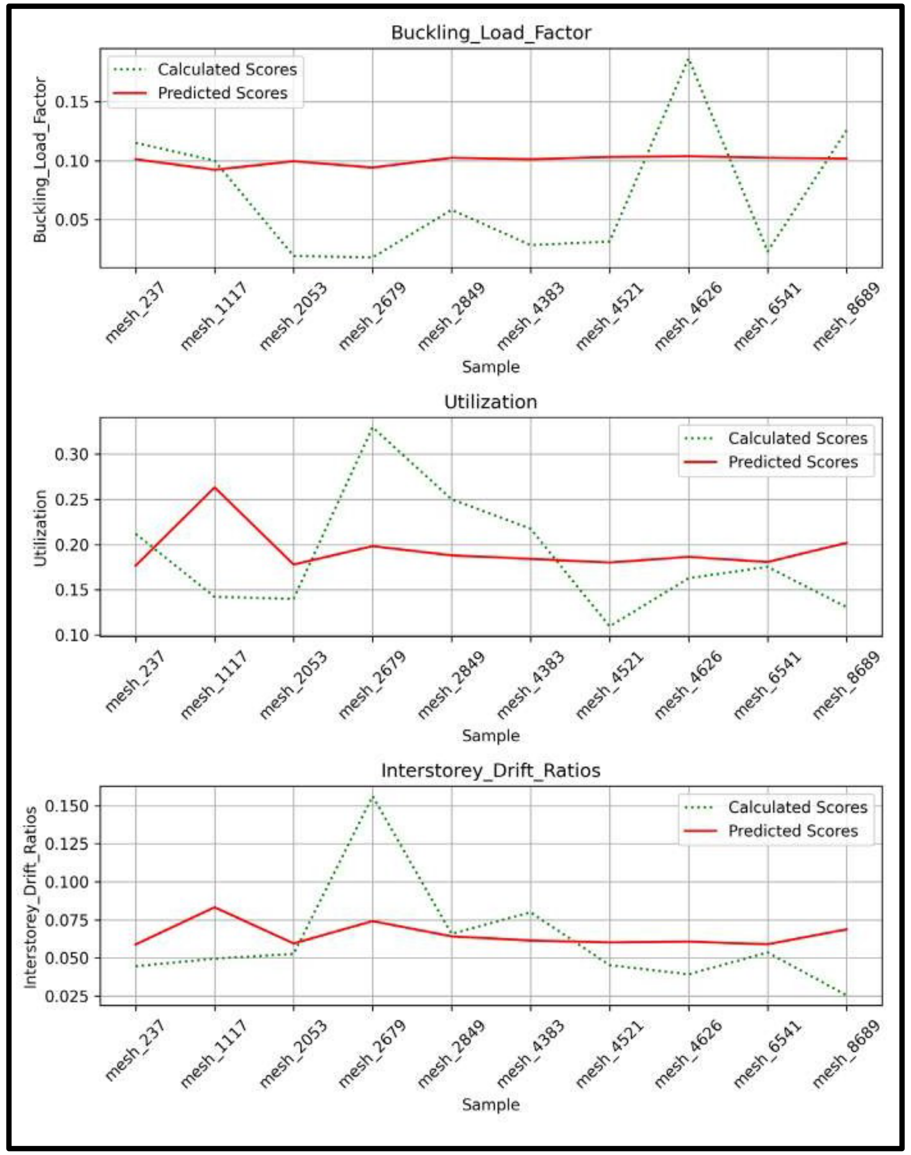
THICKNESS NOT INCLUDED

HYPERPARAMETERS: epochs = 4000, **batch_size** = 64, **learning_rate** = 1E-07

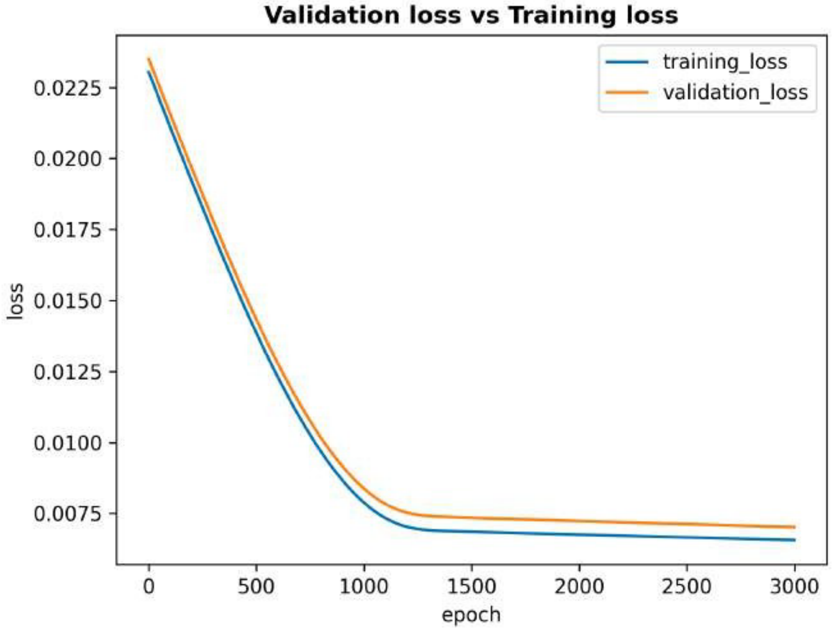
2 Dense Layers



Predictions on Test Data



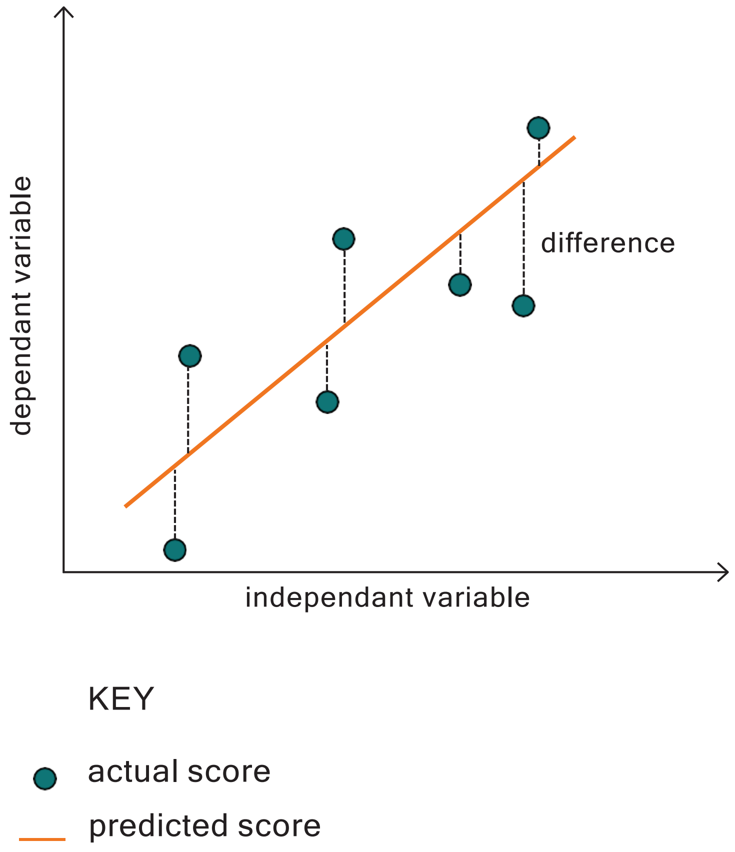
Training and Validation Losses



GENERATOR

SURROGATE MODEL

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{,i} - \hat{y}_{,i}\right)^2}}{y_{max} - y_{min}}$$



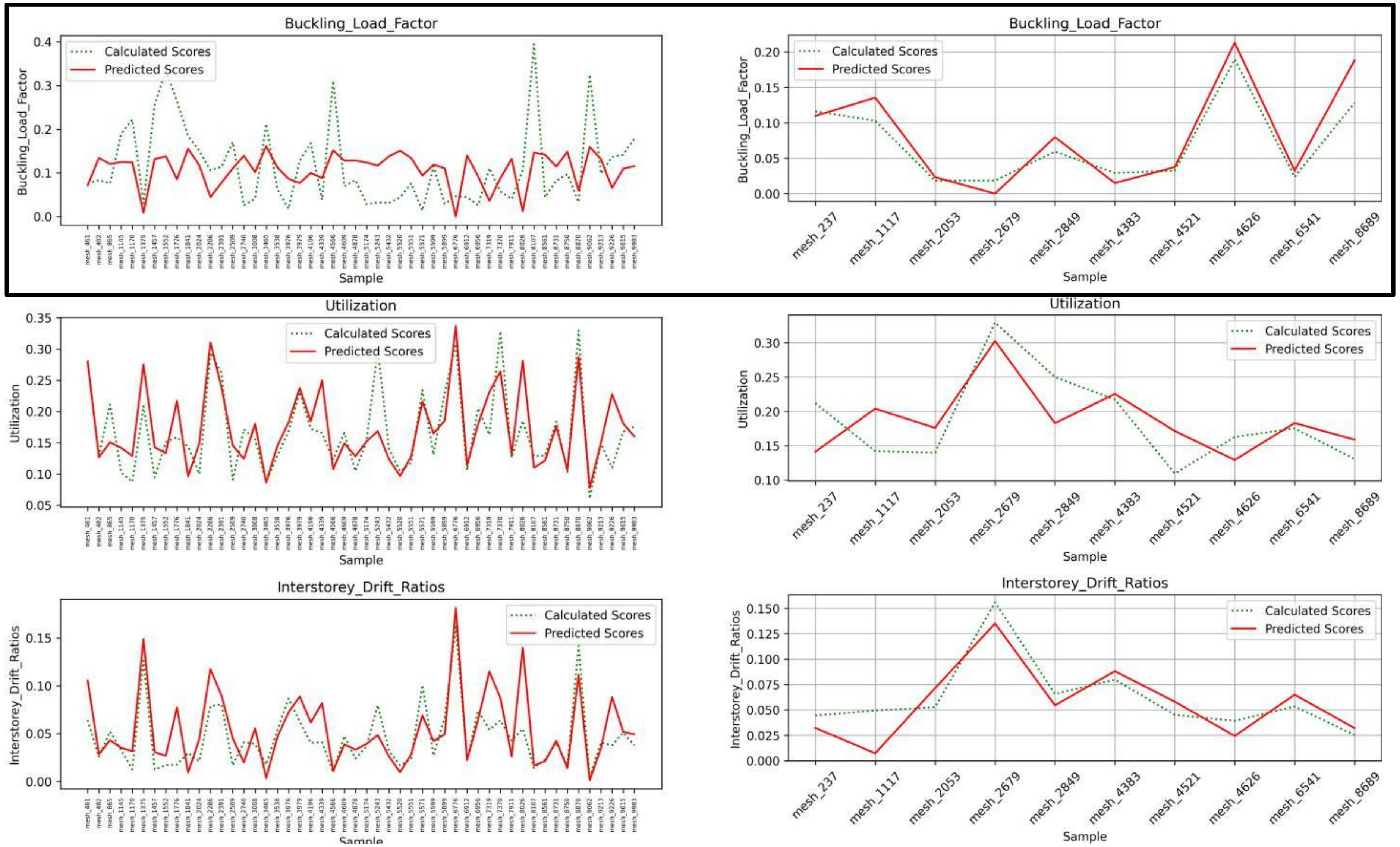
GENERATOR

SURROGATE MODEL

THICKNESS NORMALIZED ALONG WITH FORCE DENSTIES

THICKNESS NORMALIZED INDEPENDANTLY

HYPERPARAMETERS: epochs = 3000, **batch_size** = 128, **learning_rate** = 1E-06



MAX FORCE DENSITY 1038.8
MAX THICKNESS 0.095

FACTOR OF
10934
THICKNESS REDUCTION