Learning Frame-By-Frame

A material-first generative structural design assistant for repurposed bicycle frames

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For A4 Presentation for master thesis 'Learning Frame-by-frame'
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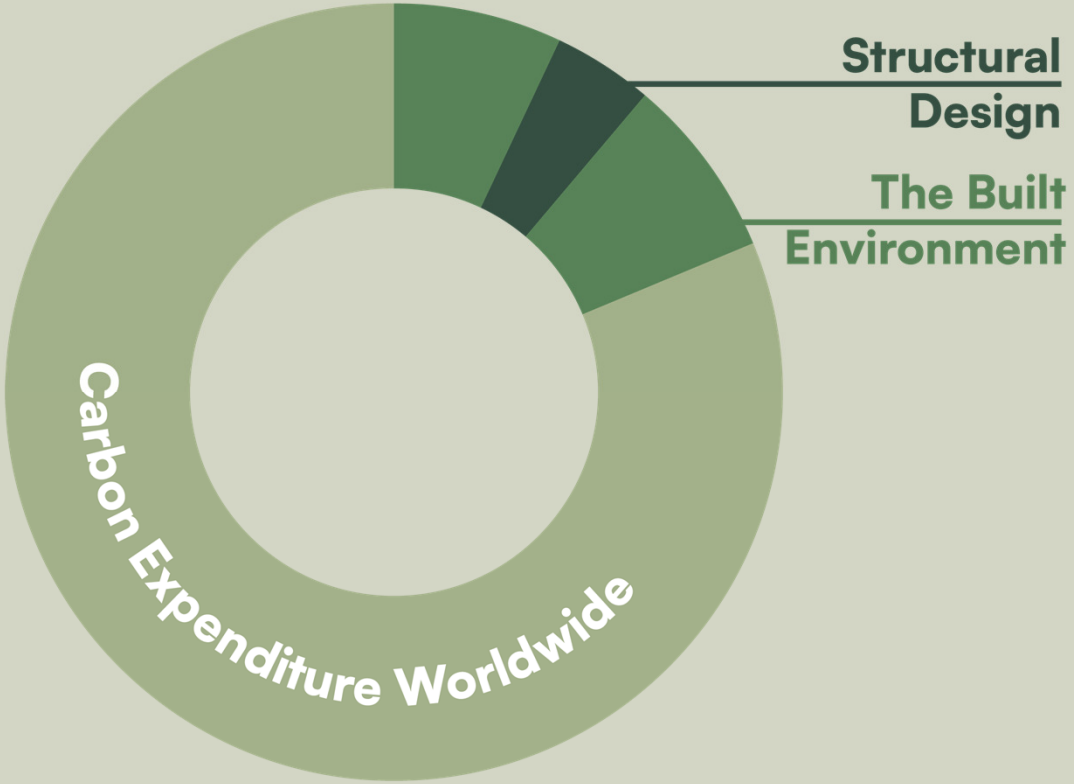
State of the Built Environment

20% OF CARBON EXPENDITURES WORLDWIDE

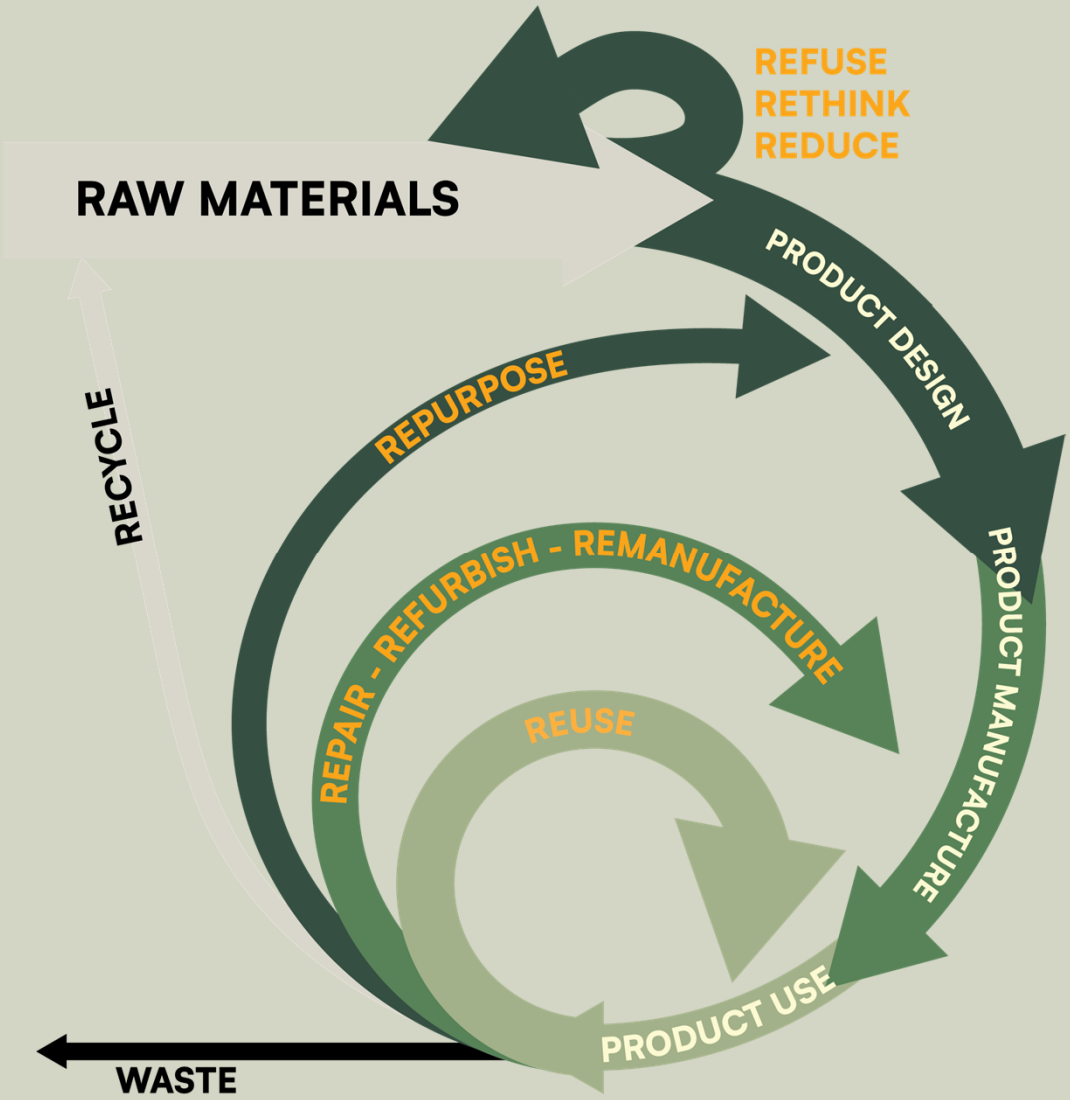
44% OF RAW MATERIAL CONSUMPTION WORLDWIDE

18% OF CARBON EXPENDITURE FROM CONCRETE AND STEEL PRODUCTION



Circular Economy

- First described in 1966
- Three Major Strategies:
  1. Narrowing
  2. Slowing
  3. Closing
- Closing destroys the material
- Focus: Slowing Strategies



Reuse Practice Barriers



TRANSPORTATION



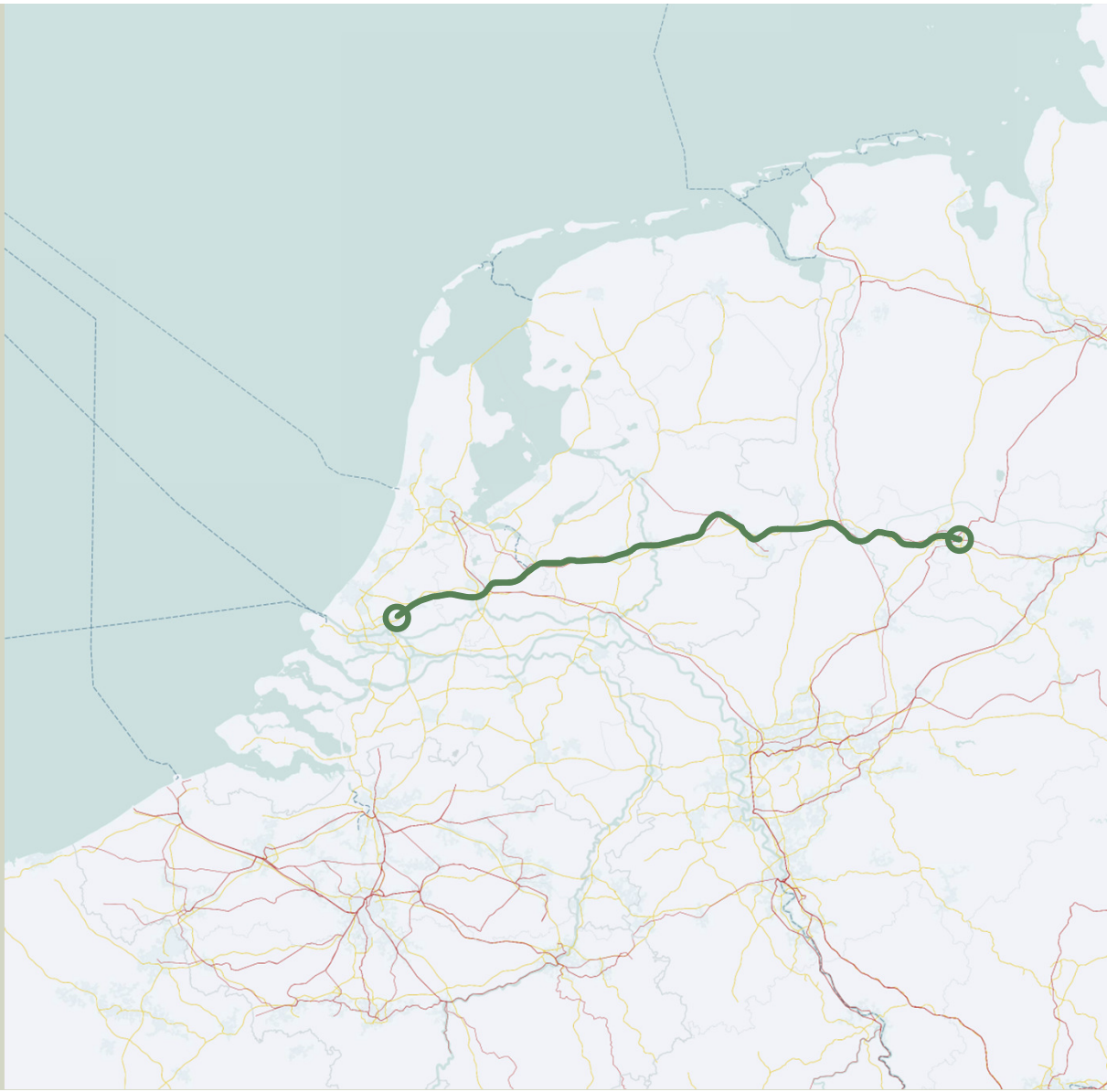
MODIFICATION



GENERALIZED PRACTICE

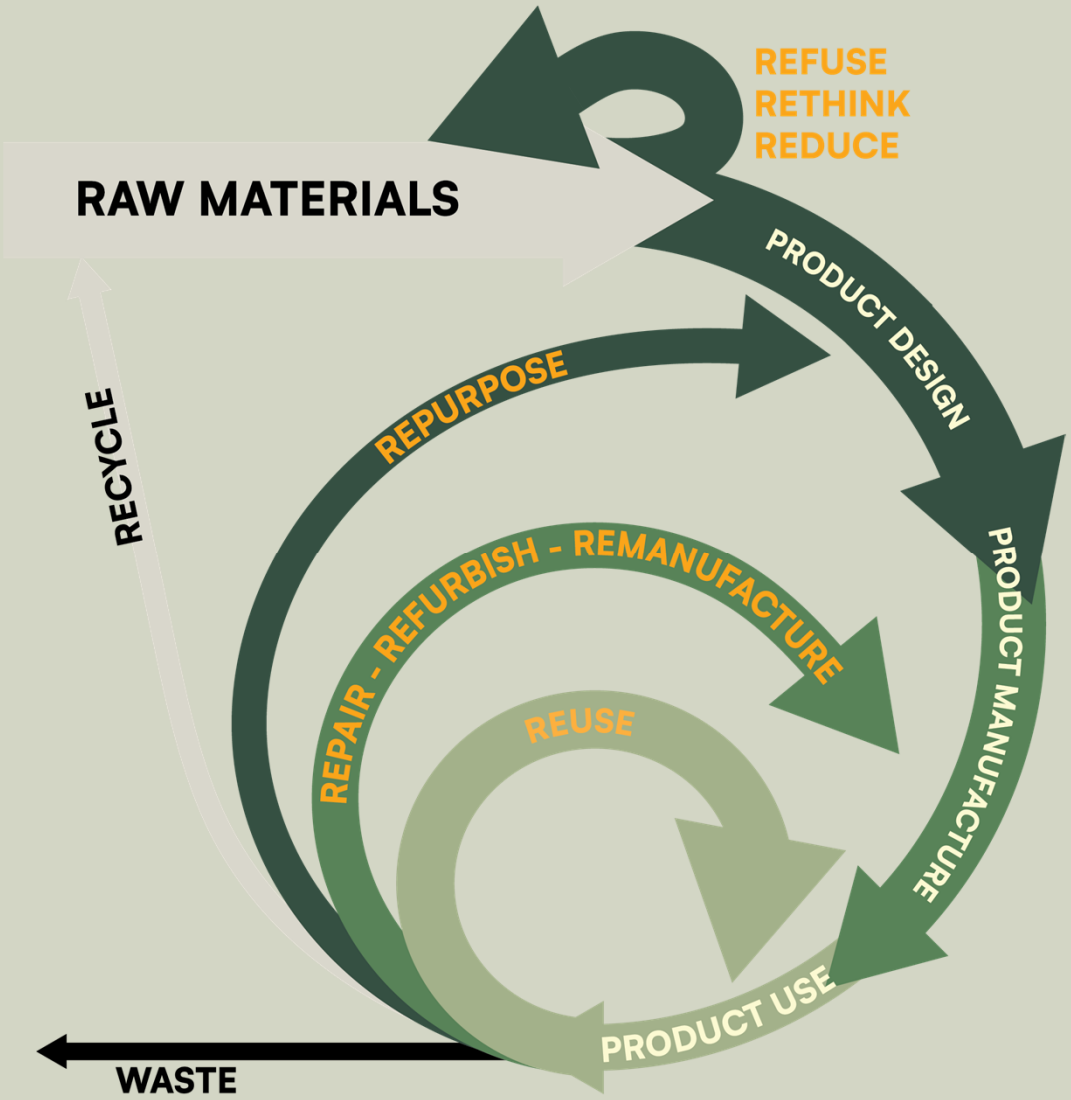
Transportation

- Success of reuse practices are dependent on local availability
- Insight into available reuse stock-piles often difficult to ascertain
- Overarching lack of waste-stream documentation



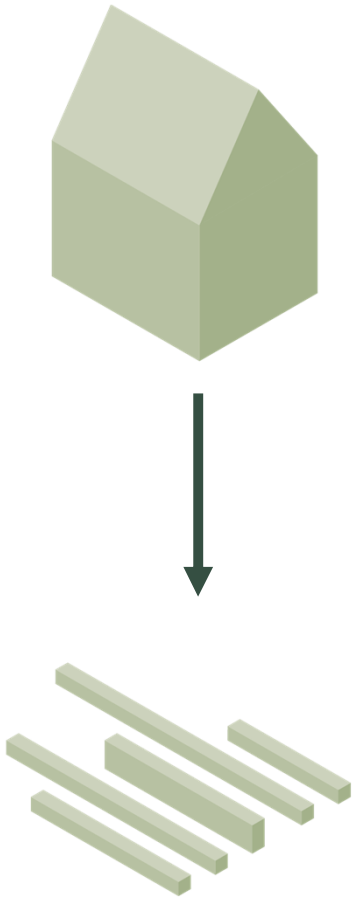
Repurposing: Value Proposition

By sourcing materials originally intended for other purposes but from closer locations, we can reduce the embodied carbon associated with our reuse practice.

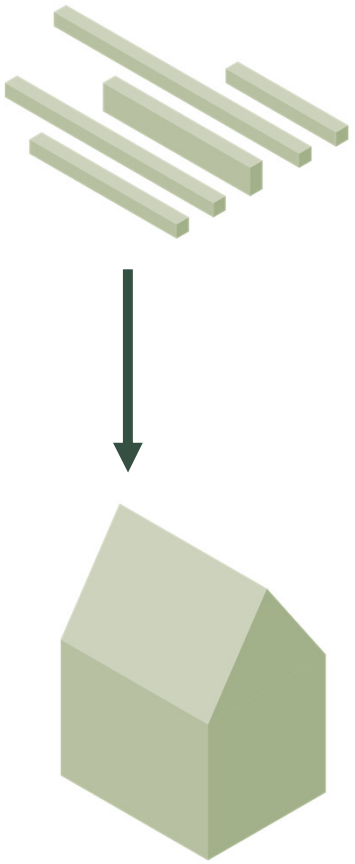


Modification

- Additional labour
- Additional storage
- Raw materials
- Longer transportation chains



Design -> Material



Material -> Design

Generalized Application

- Lack of generalized methods to design and construct with reused or repurposed materials

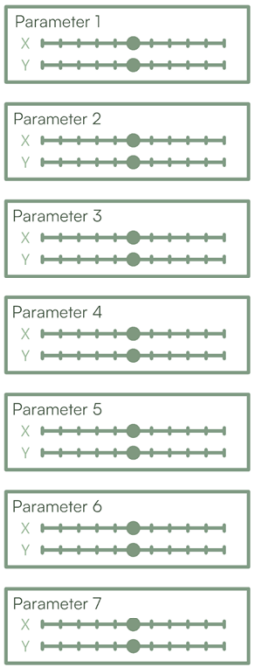
- Linear Economy:
  - Material stock is dependent, predictable & flexible
- Circular Economy:
  - Material stock becomes a design variable

- Common Approach: Computational Design

Parametric Design

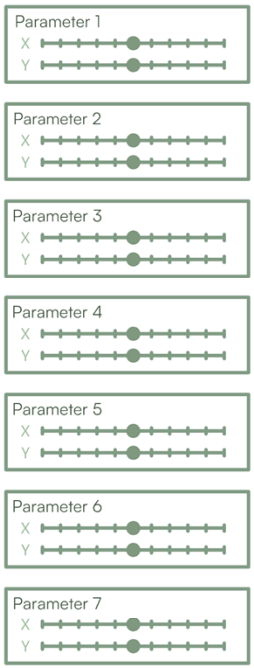


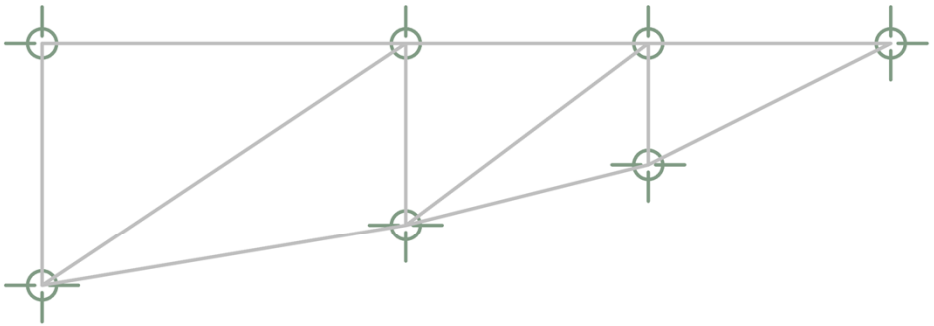
Parametric Design



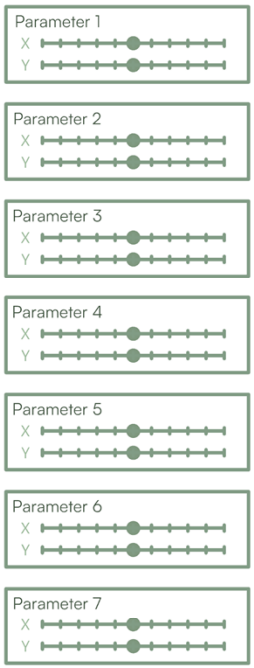


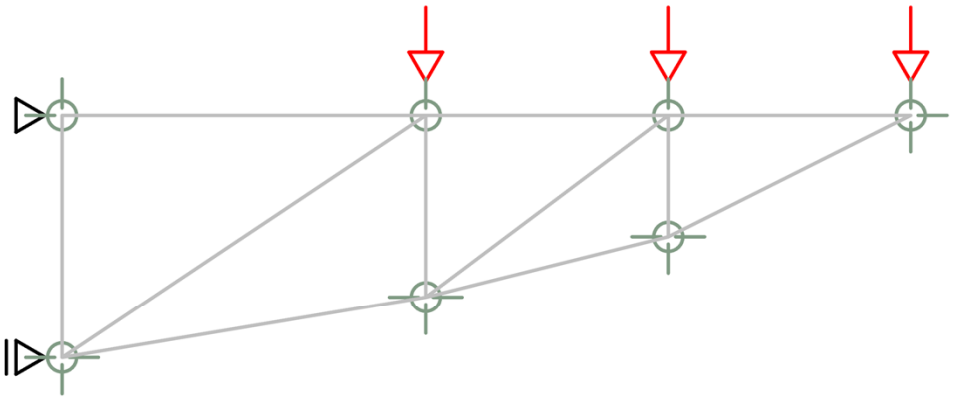
Parametric Design

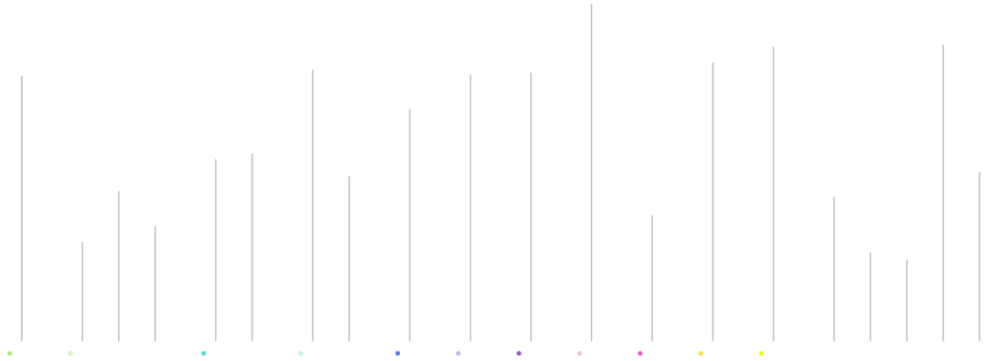




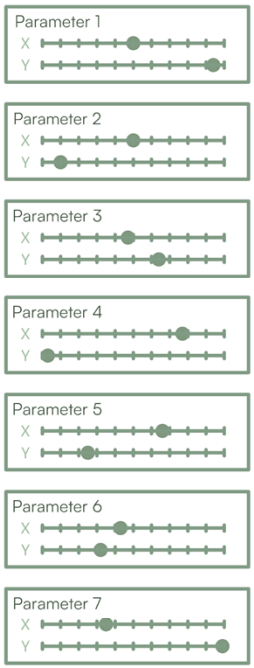
Parametric Design

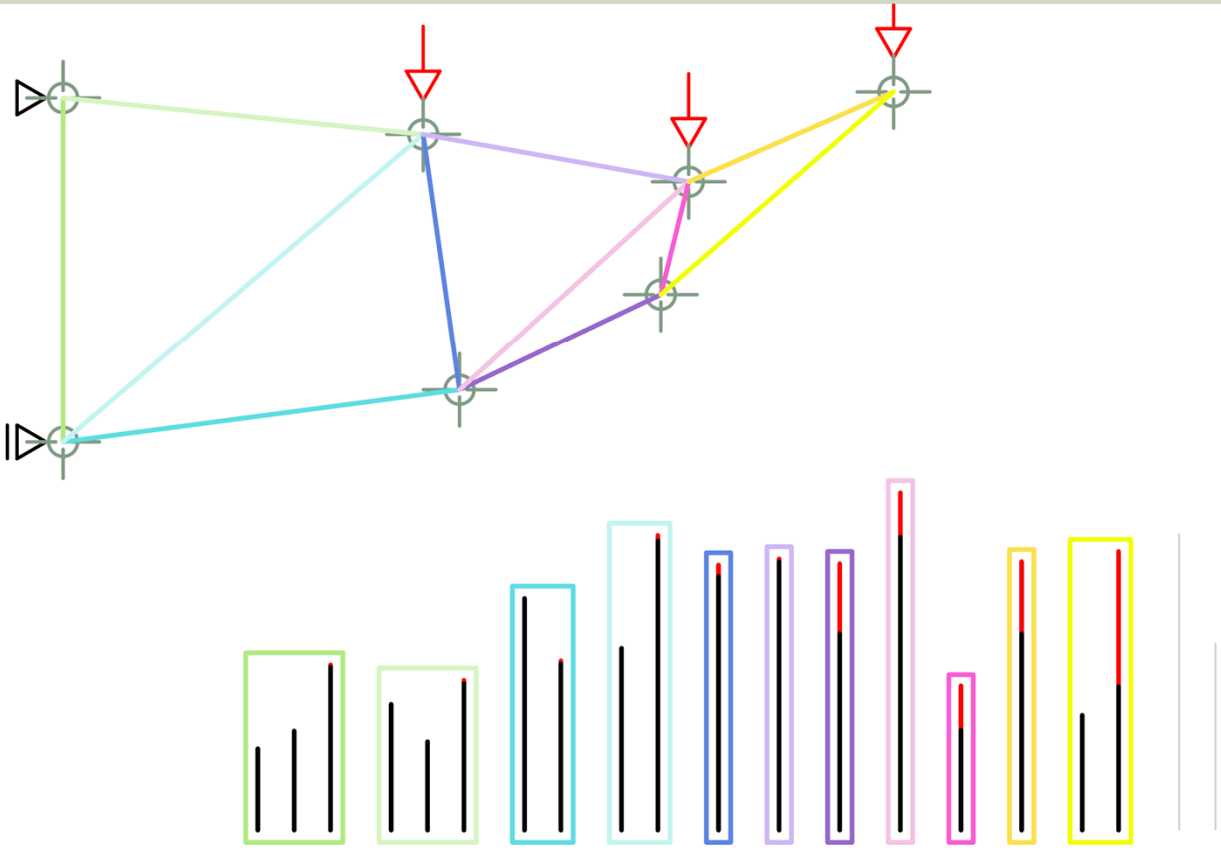






Parametric Design





Generative Design

- Iterative process
- Repeated set of instructions
- Output is generally more diverse



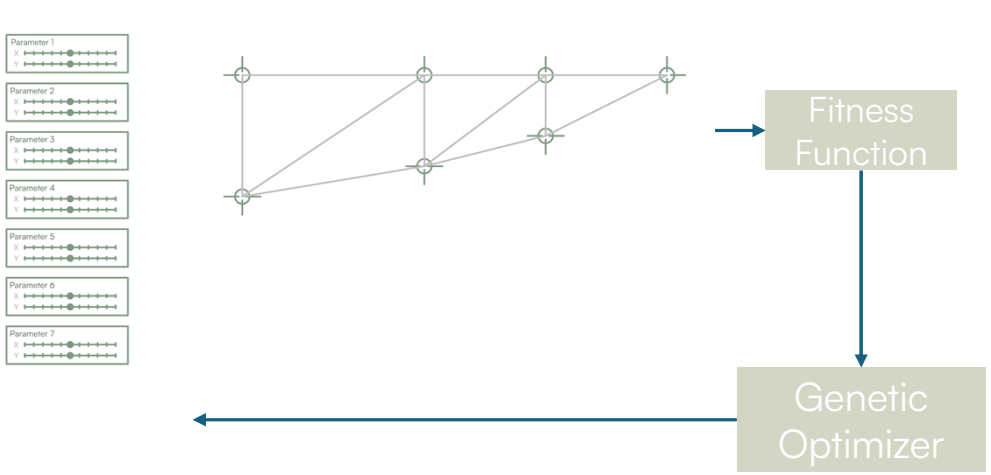


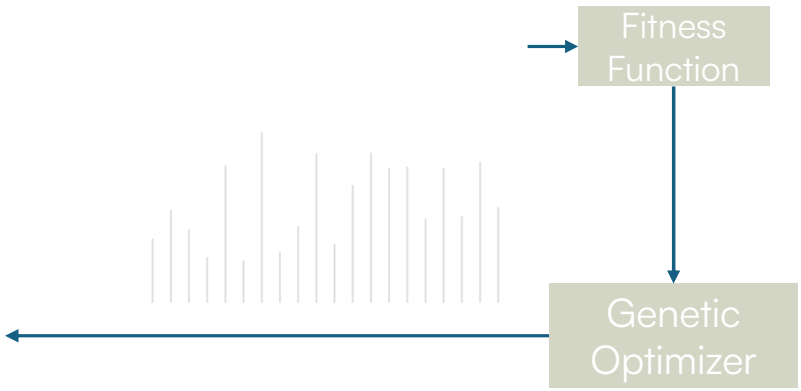


Optimization

- Traditional method: Genetic algorithms
- Does not work sequentially
- Performs worse in systems when parameters are interdependent

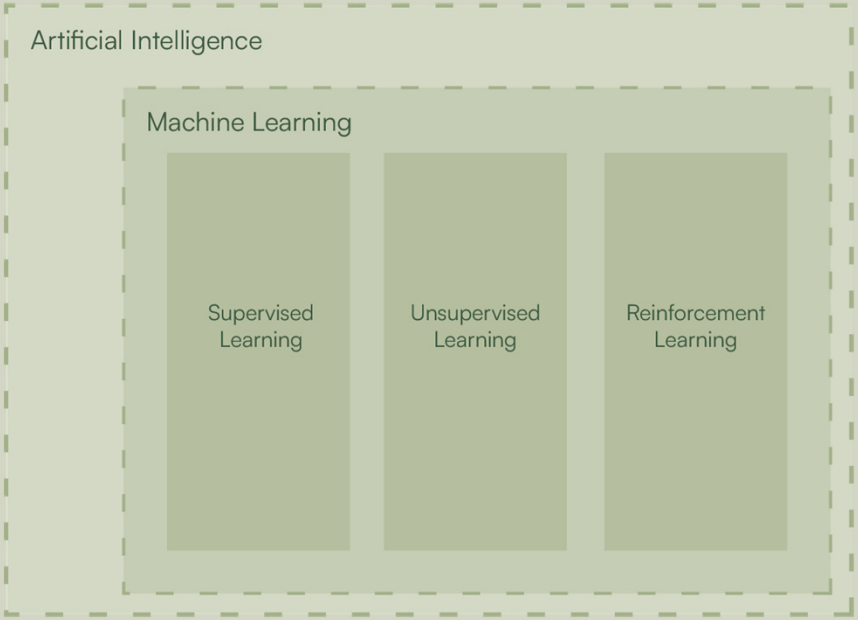
- How would you approach this?





Reinforcement Learning

- Learns step-by-step
- Learns based on an observation
- Fast acting in deployment
- Capacity for generalization



Case Study: Material Stock

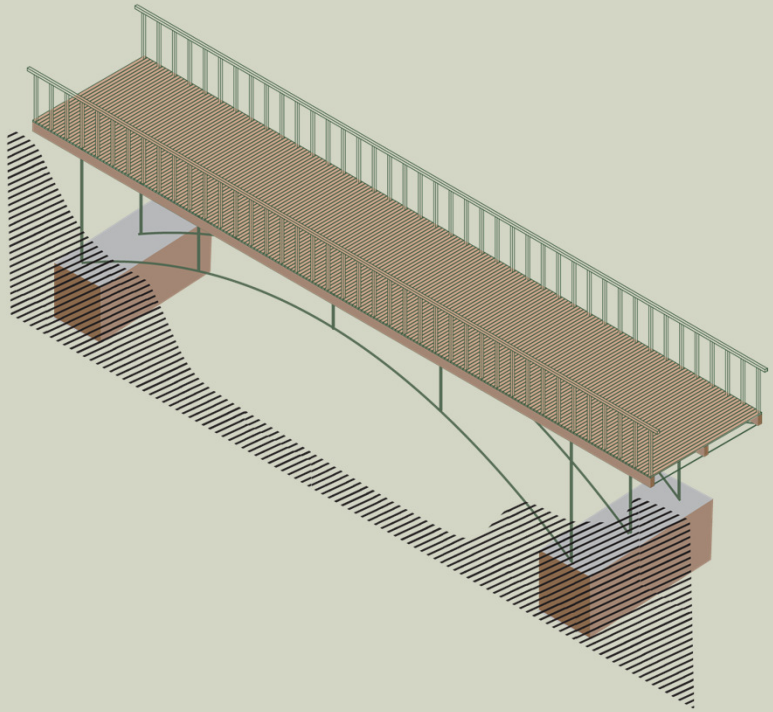
- Over 200.000 bicycles removed annually by municipalities
- Made from steel, aluminium or carbon fibre
- Rigid construction
- Demountable



Case Study: Design

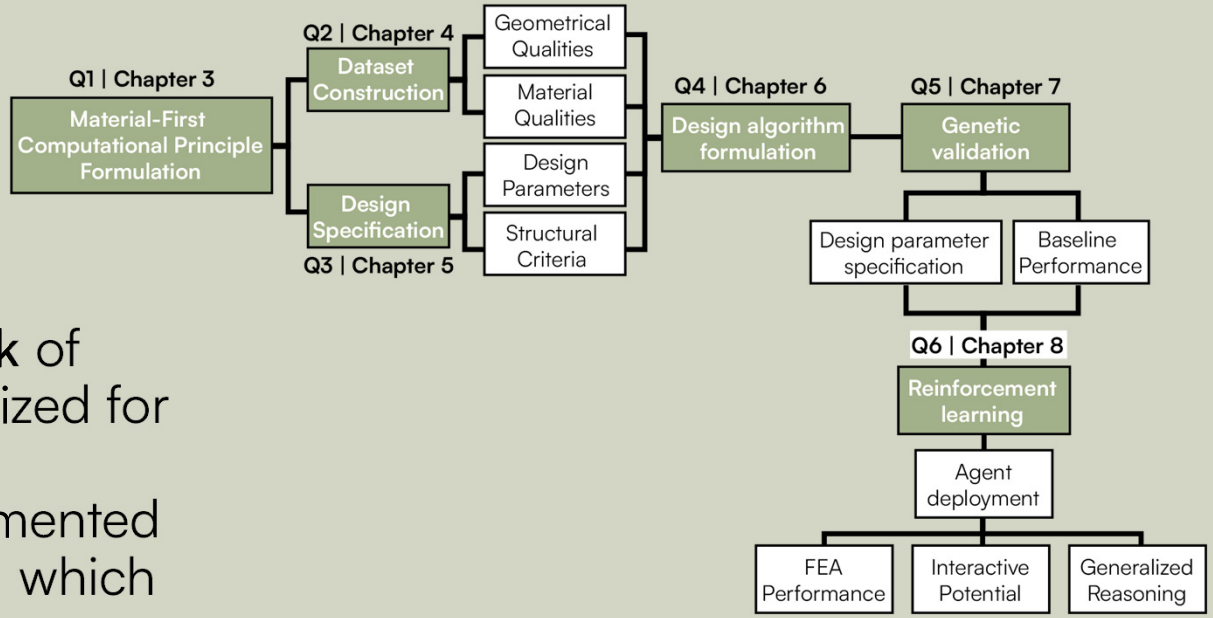
- Cycling bridges are typical to Dutch infrastructure
- Bridges offer interesting structural considerations

- It is a fun idea!



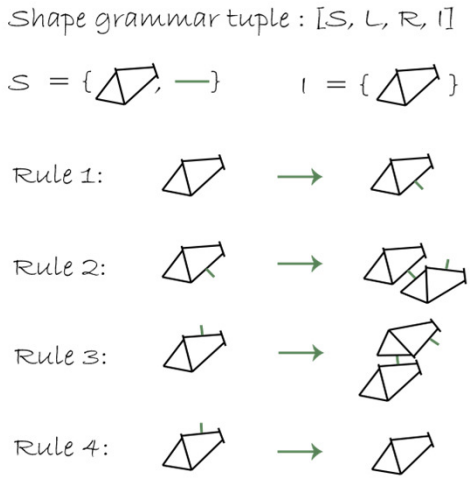
Research Question

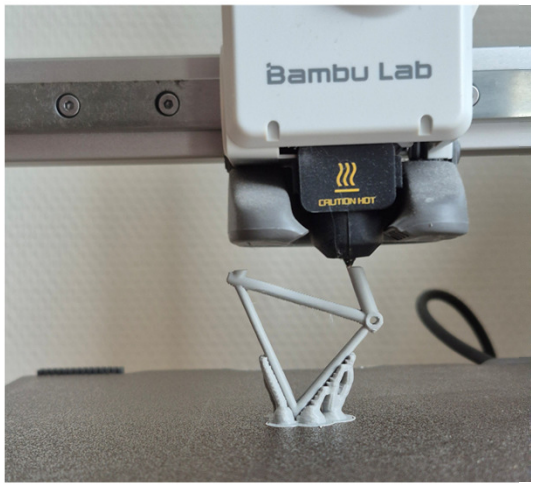
How can a **constrained stock** of **repurposed elements** be utilized for **structural designs** through a **generative algorithm**, implemented as an **interactive design tool** which enables **material-first design solutions**?

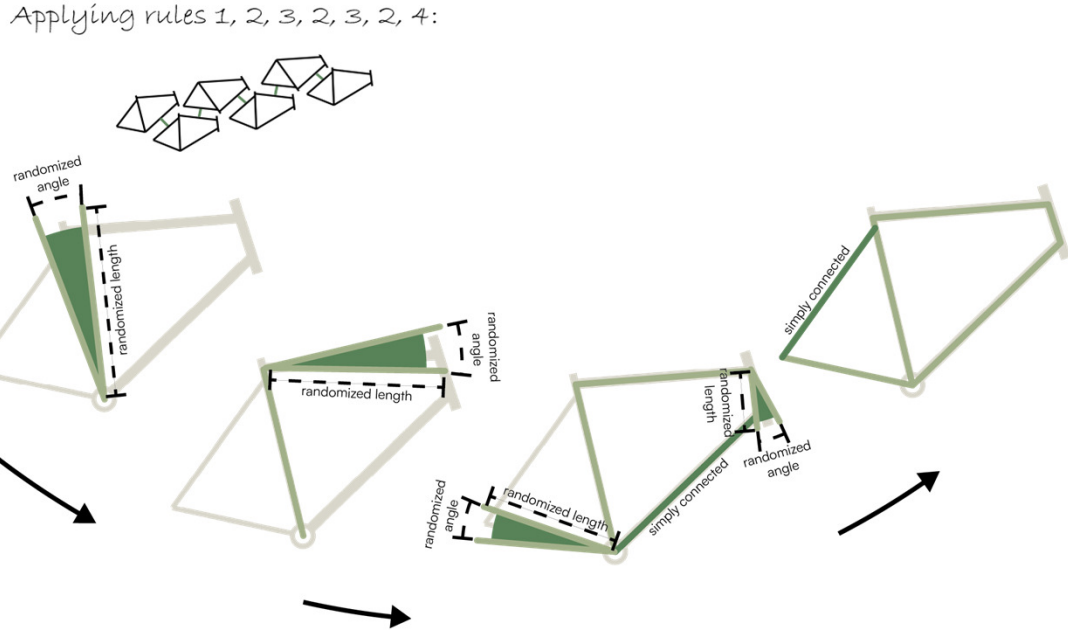


Design Games Setup

- Question: What to design?
- 3D printed 1:15 frames
- Dataset developed using randomization
- Connections between frames via printed clips

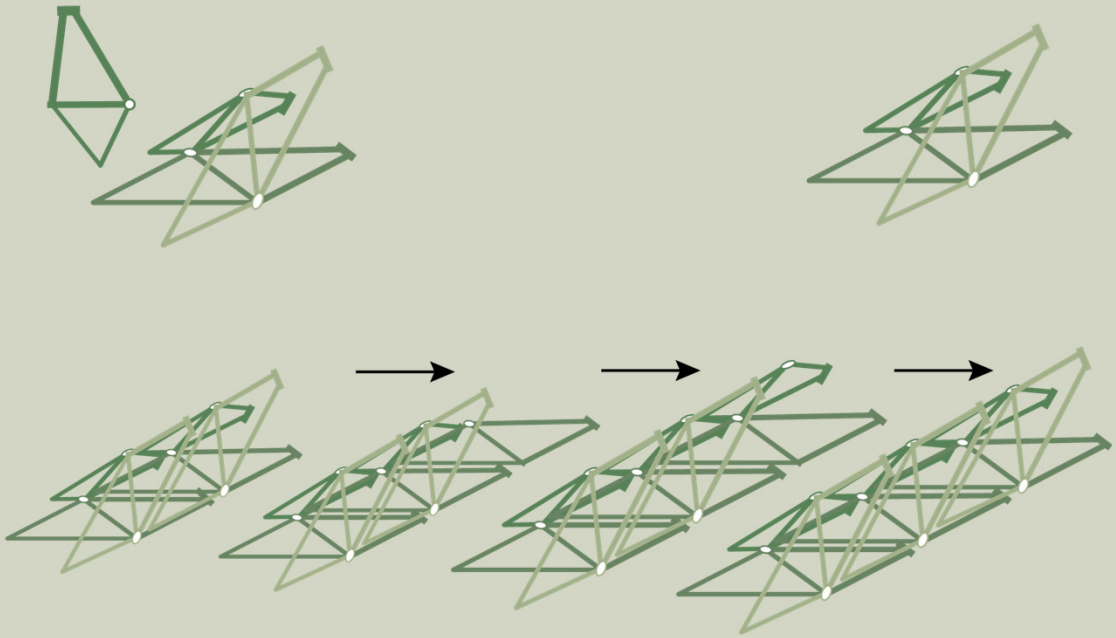


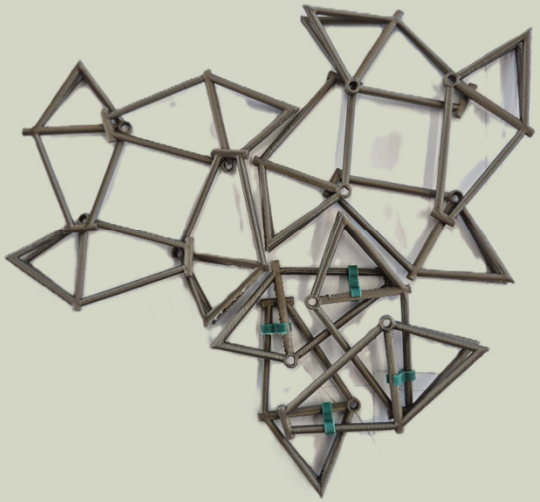


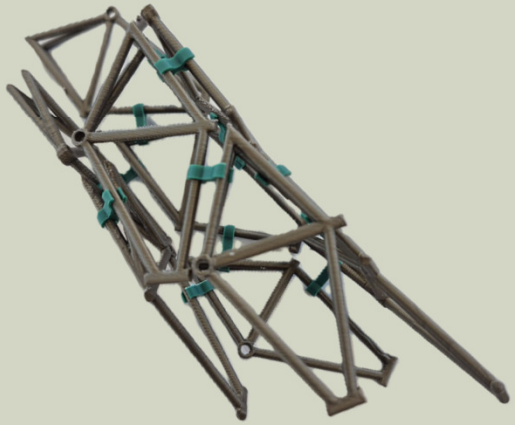


Design Games Experiments

- Proved interesting, but experiments were too complicated to realize inside the scope.







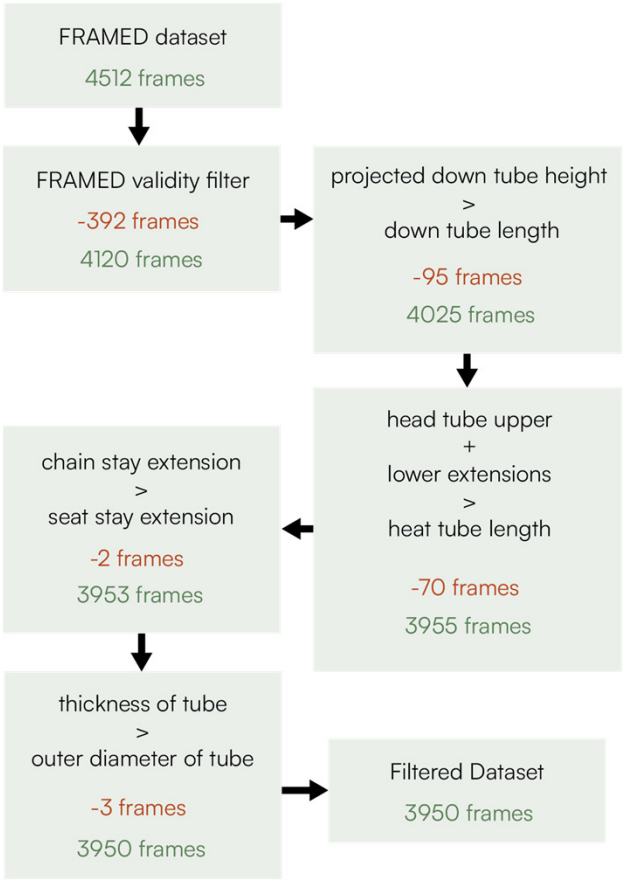
Constrained Stock Dataset Formulation

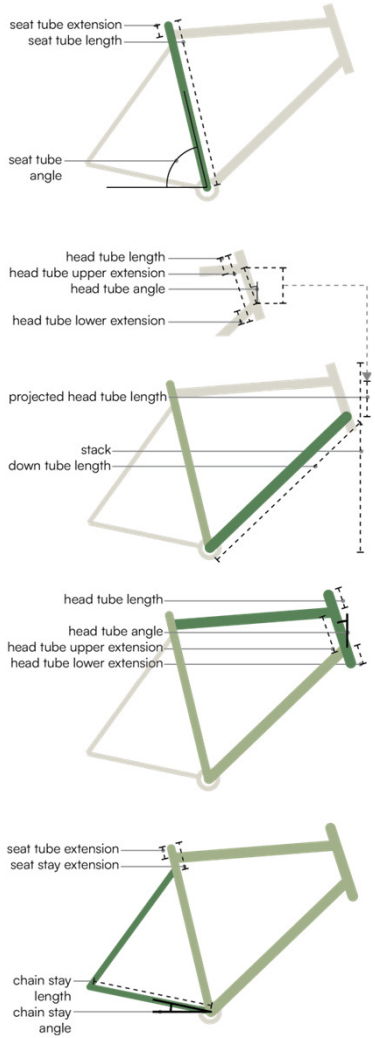
- Question: How to formulate a representative dataset?

- Using FRAMED by Regenwetter et al.
- From the MIT DeCodeLab
- Extracted from BikeCad opensource design software
- Eclectic but valuable data

Dataset Validation

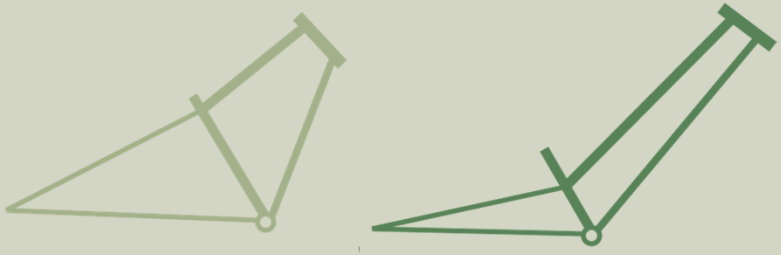
- Invalidated 572 frames based on geometrically unfeasible dimensions

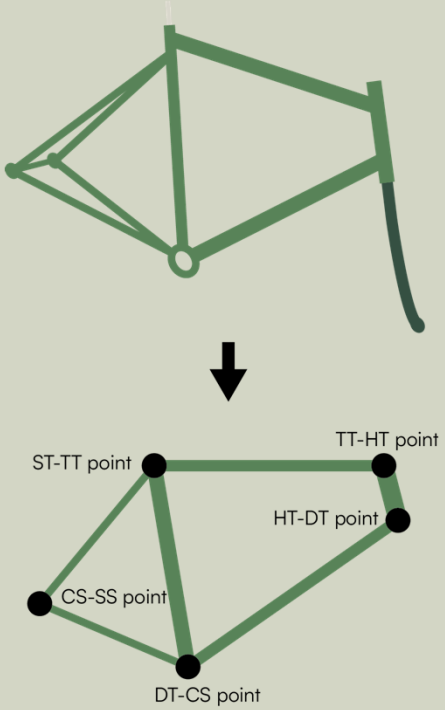


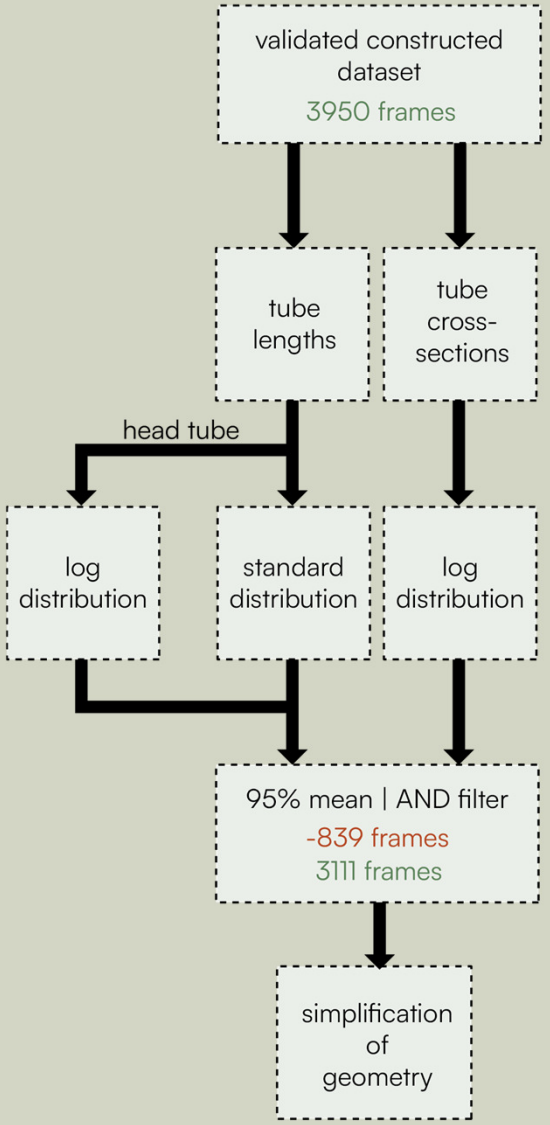


Dataset Filtering

- Removing any frames whose dimensions exceed the 95% mean
- Simplifying the representation to five points

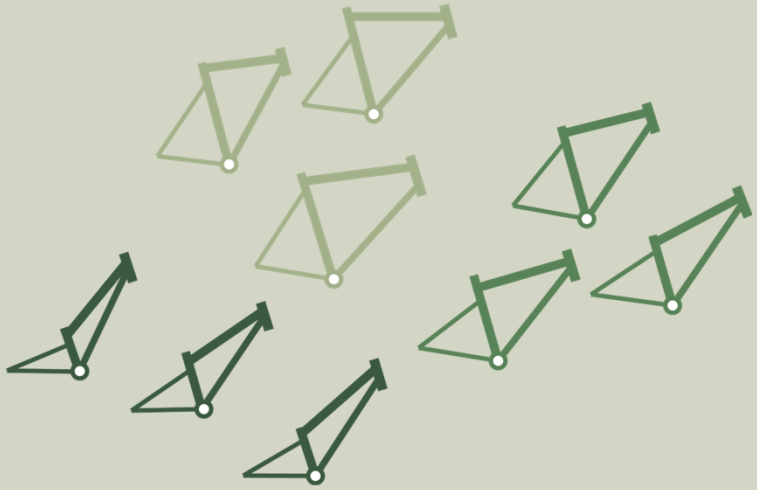


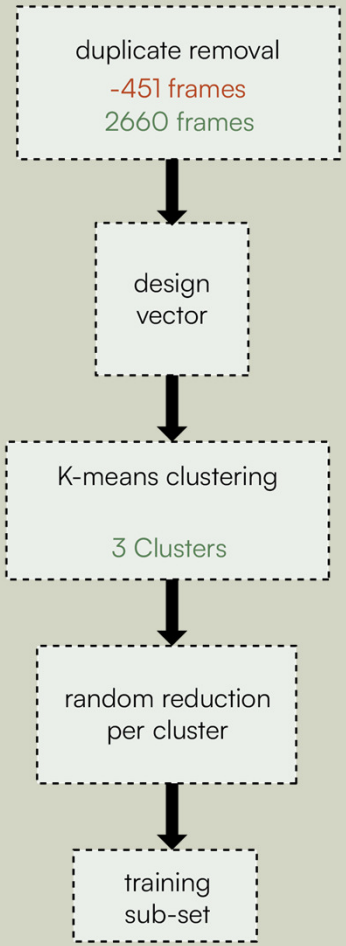




Dataset Extraction

- Using K-Means clustering to identify common geometrical typologies
- Randomly extracting frames on per-cluster basis
- 35 total frames in a given extraction





Design Case Study: Cycling Bridge

- Question: How to conceive of design requirements and parameters?

Structural Requirements of Cycling Bridges

- Live Loading: Crowd loading model from NEN-EN 1991-2

$$q_{\mathrm{fk}} = 2.0 + \frac{120}{L + 30}, \quad 2.5 \leq q_{\mathrm{fk}} \leq 5.0\,\mathrm{kN/m^2}$$

- Dead Load: Derived through structural analysis
- ULS safety factors:
  - 1.50 multiplication for dead loads
  - 1.35 multiplication for live loads

Case Study Selection



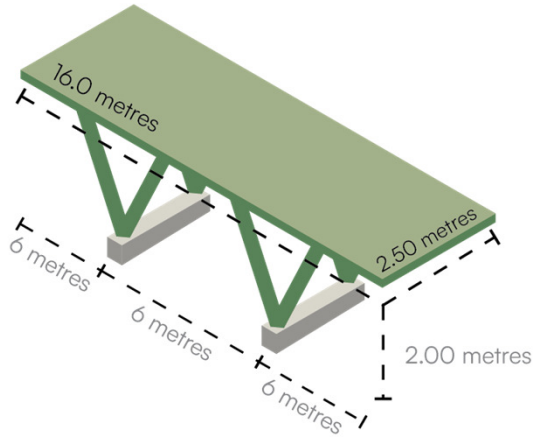
Zigzag Brug Arnhem

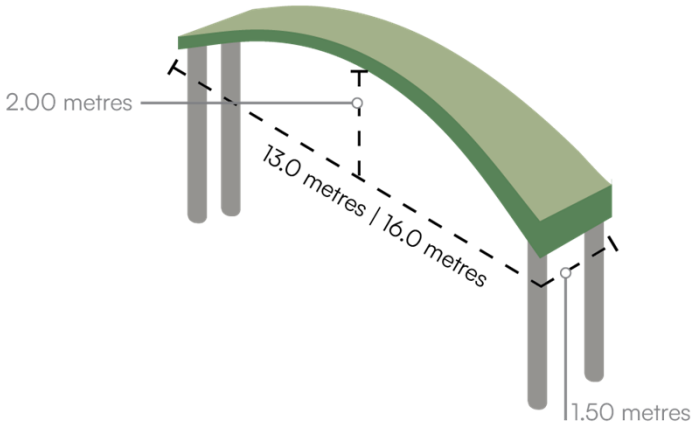


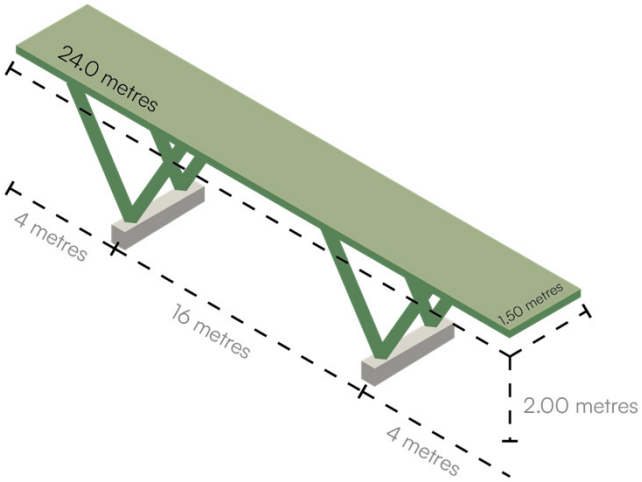
Footbridges Arsenaal Delft



Footbridge Almere Haven





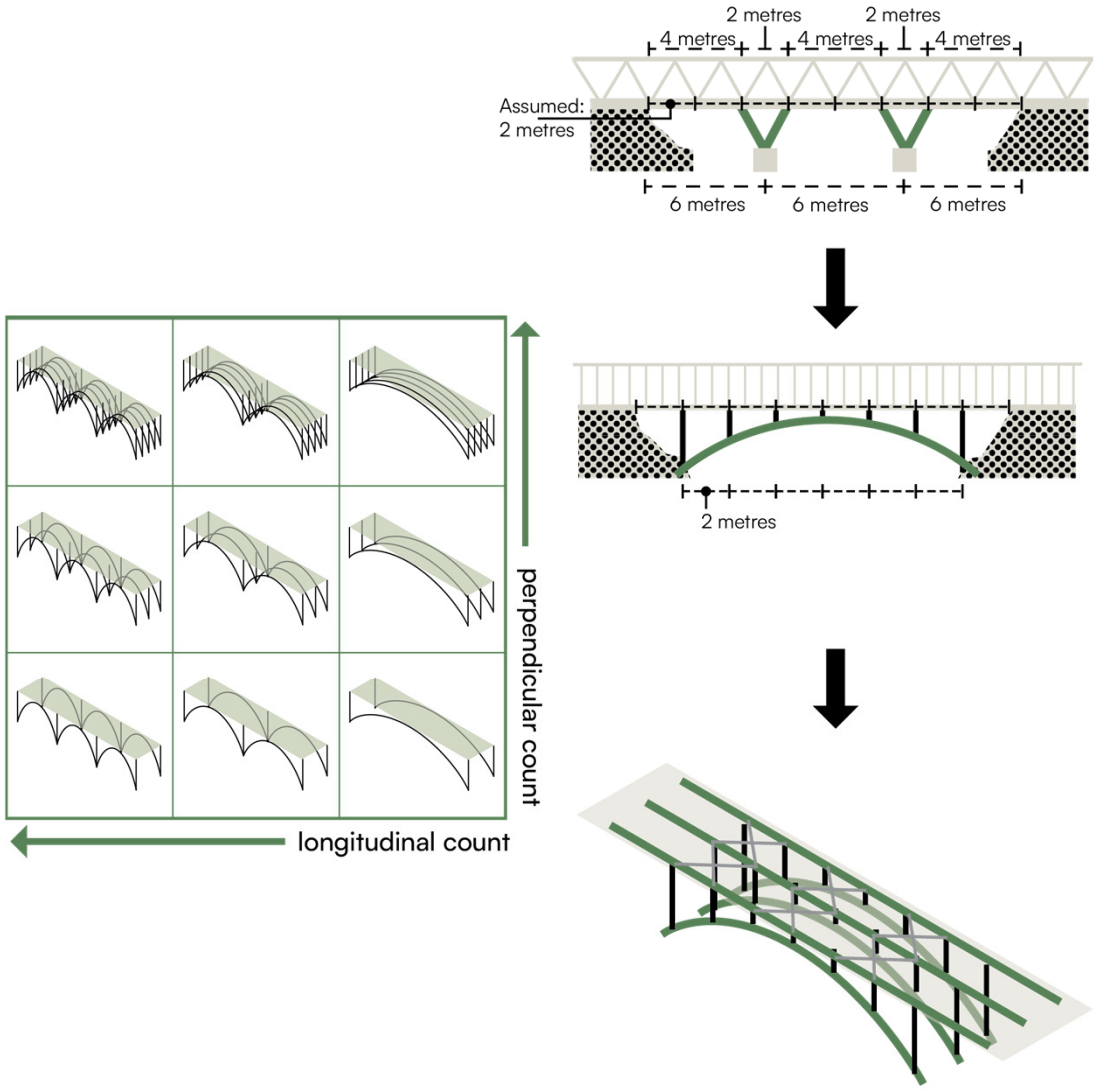


Known Size
Estimated Size

Design Intent & Parameters

- Replace existing support structure with an arch

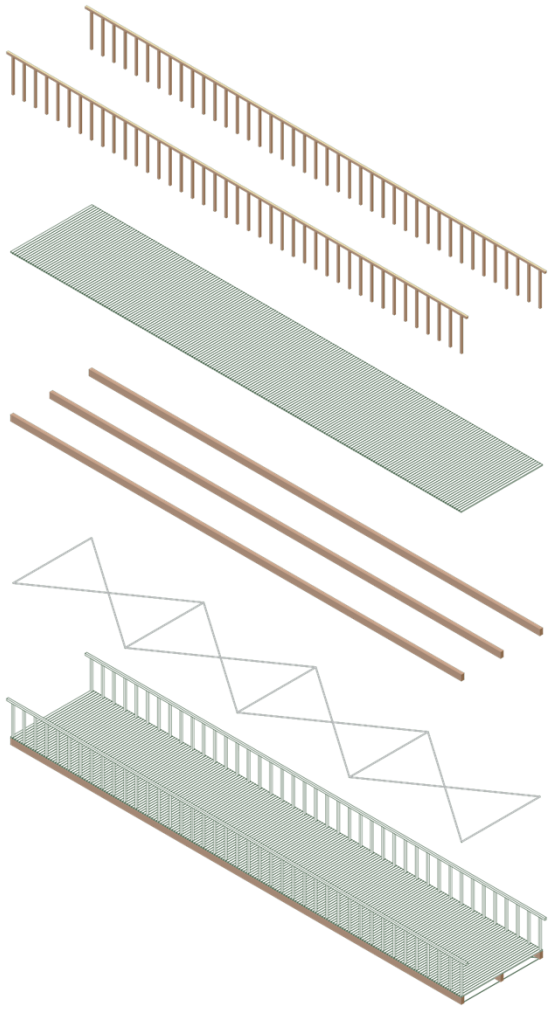
- Longitudinal Arch Count
- Perpendicular Arch Count



Loading Determination

- Derived via finite element analysis of the assumed deck composition
  - Beams
  - Slats
  - Crosses for horizontal loads
  - Railing

Action	SLS	ULS
Total Live Load	5.00 kN.m2	6.75 kN/m2
Total Dead Load	0.50 kN/m2	0.75 kN/m2



Structural Validation

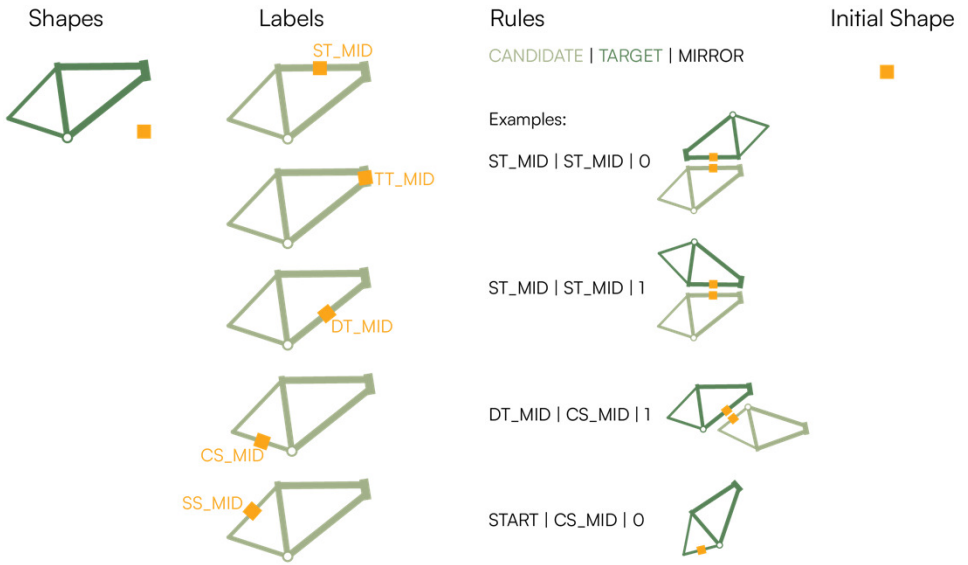
- Maximum Deformation
- Maximum Stress
- Partial check:
  - Total deformation
  - Stress on the frames
- Full check:
  - Connection stresses
  - Tension cable stresses

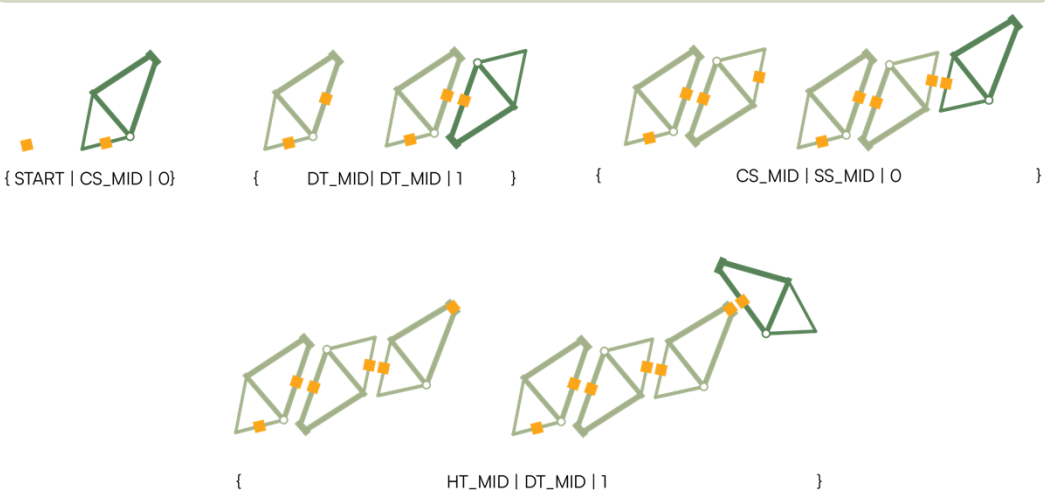
Metric	Condition	Partial FEA	Full FEA
Maximum Deformation	≤ 37.50 mm | 1 arch	Y	Y
	≤ 17.50 mm | 2 arches	Y	Y
	≤ 10.83 mm | 3 arches	Y	Y
Maximum Frame Tensile Stress	≤ 62.10 kN/cm^2	Y	Y
Maximum Frame Compressive Stress	≤ 48.30 kN/cm^2	Y	Y
Maximum Connection Tensile Stress	≤ 35.50 kN/cm^2	N	Y
Maximum Connection Compressive Stress	≤ 35.50 kN/cm^2	N	Y
Maximum Cable Tensile Stress	≤ 13.65 kN/cm^2	N	Y
Maximum Cable Compressive Stress	≤ 0.0 kN/cm^2	N	Y

Element	Sizing	E-Modulus	Shear Modulus	Tensile Strength	Compressive Strength
Bike frames	Variable	210000 N/mm2	8076.00 kN/cm2	62.10 kN/cm2	48.30 kN/cm2
Connections	30.00 mm outer diameter, 5 mm thickness	210000 N/mm2	8076.00 kN/cm2	35.50 kN/cm2	35.50 kN/cm2
Tension cables	18.00 mm diameter	127000 N/mm2	4884.00 kN/cm2	13.65 kN/cm2	0.00 kN/cm2

Design Algorithm Overview

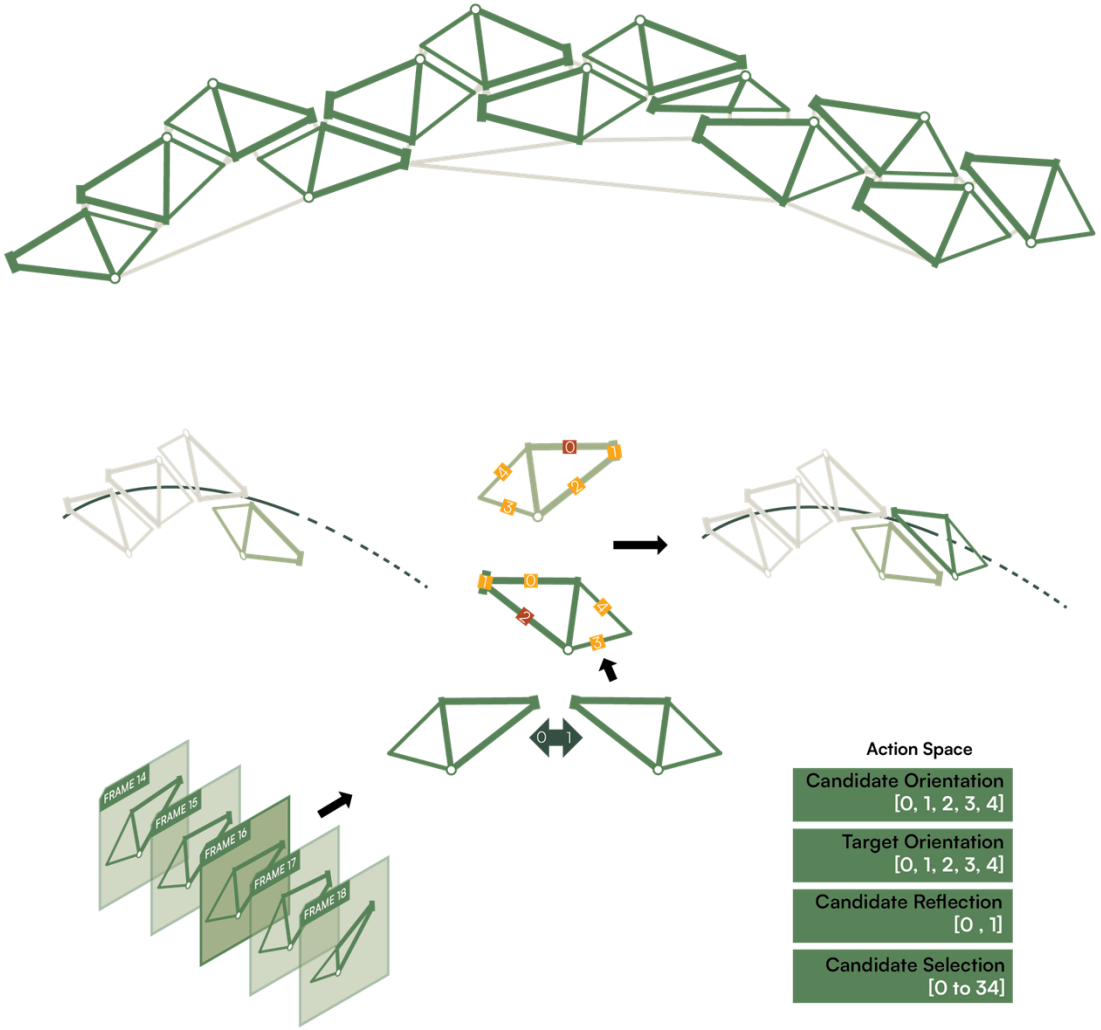
- Action space:
  - Frame selection
  - Target orientation
  - Candidate orientation
  - Mirroring





Design Algorithm Overview

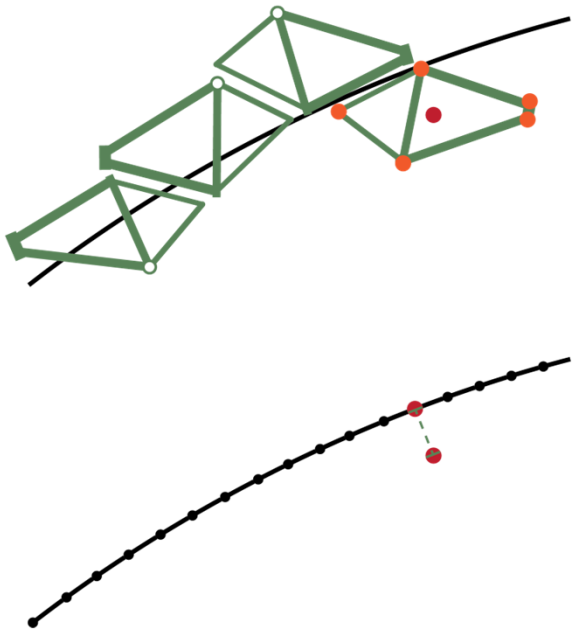
- Design Gesture:
  - Intended to guide the structure's development



Metrics

- Closeness to Design Gesture
  - Euclidean distance
- Progression
  - Measured over the curve itself
- Termination
  - Boolean condition

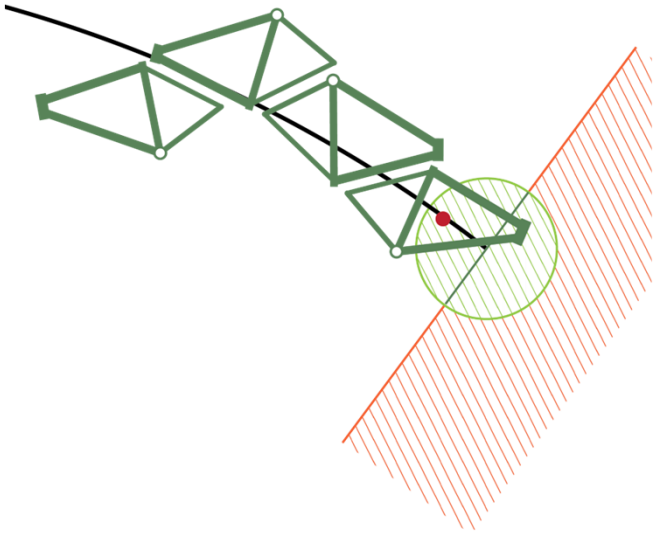
Distance Metric



$$\mathbf{dg}_s = \underset{i \in \{0,\ldots,N\}}{\arg\min} \|\mathbf{g}_i - \mathbf{c}_s\|$$

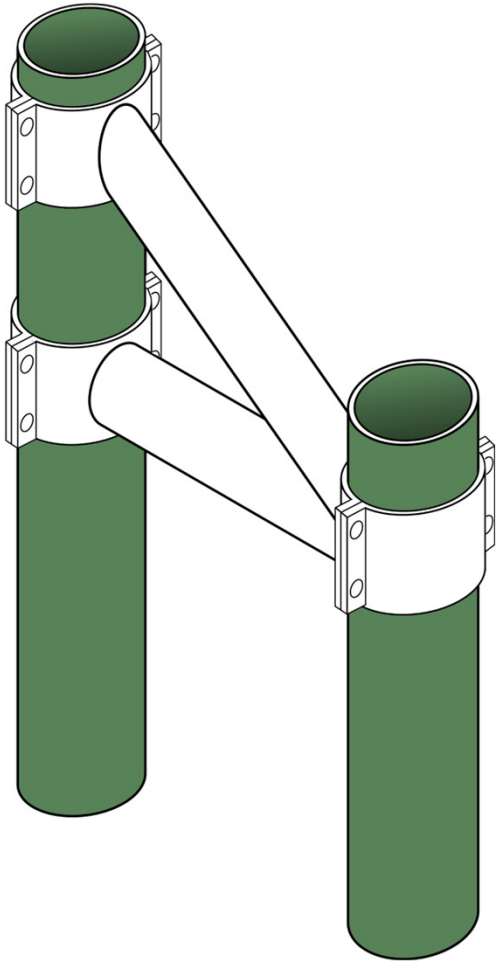
$$d_s = \sqrt{(x_{\mathrm{dg},s} - x_{\mathrm{c},s})^2 + (z_{\mathrm{dg},s} - z_{\mathrm{c},s})^2}$$

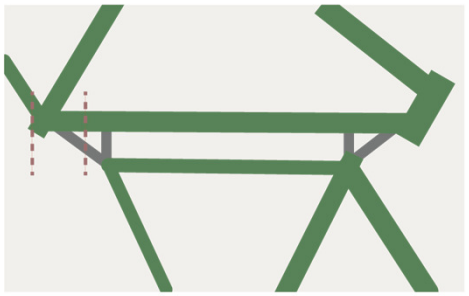
Termination



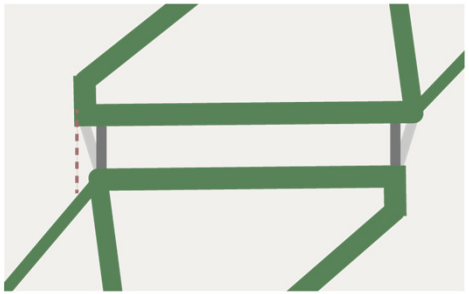
Connections

- Approached simply
- Two pronged to ensure minimal perpendicular forces
  - Disallowing too wide of a connection
  - Disallowing near-perpendicular two-pronged connections

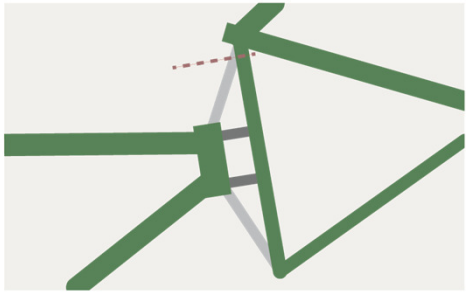




> minimum connection distance
< connection distance limit



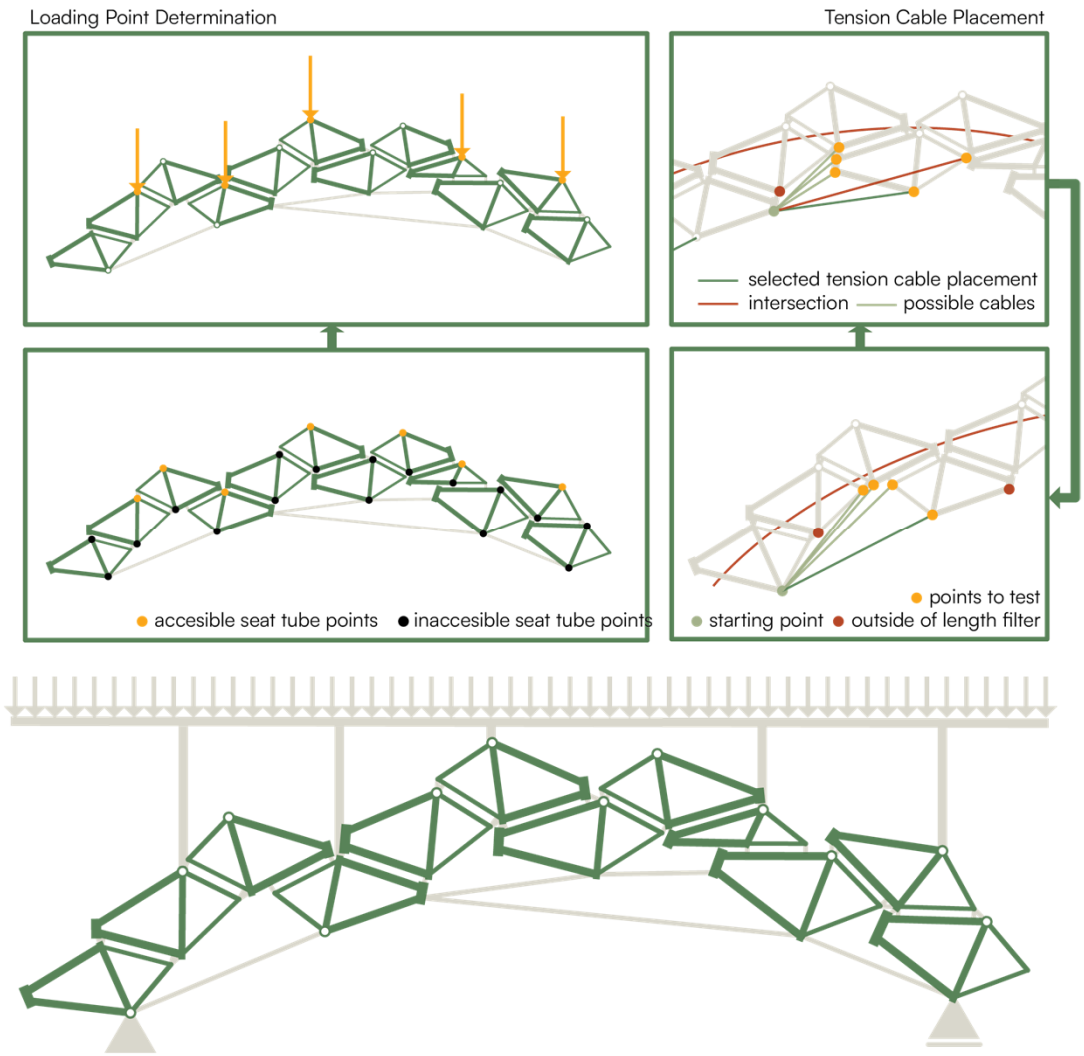
< minimum connection distance



> connection distance limit

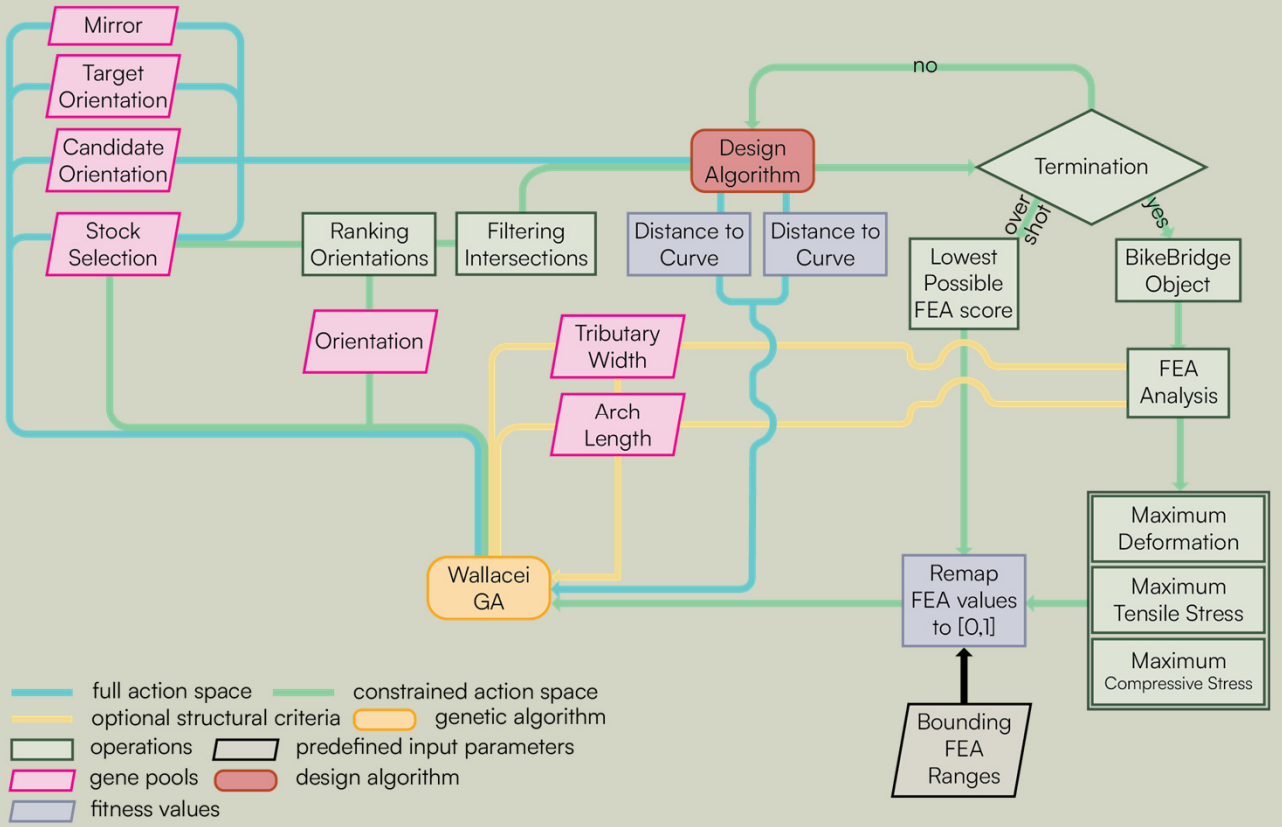
Tension Elements & Loading

- Loading points spread across available points as evenly as possible
- Tension cables placed via independent logic — the optimizer does not control this



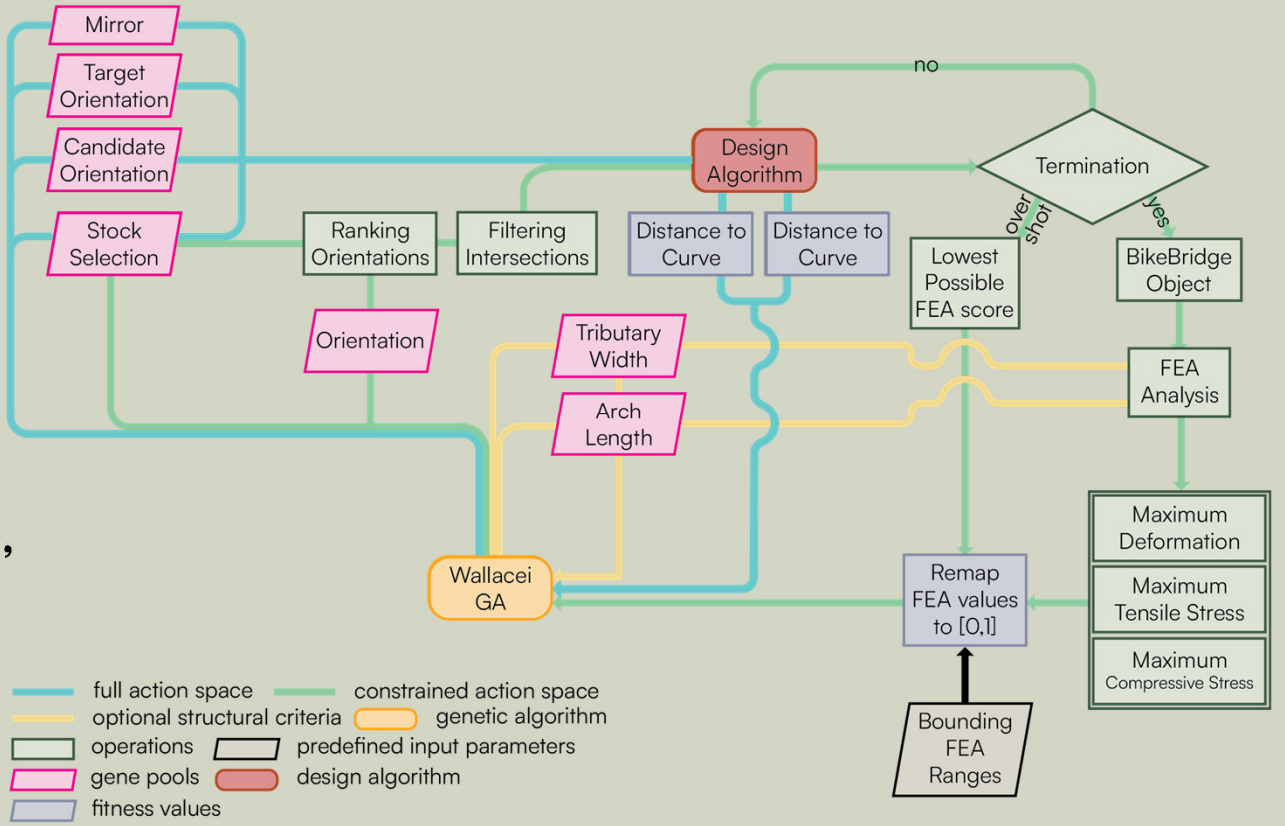
Genetic Validation

- Validate that the algorithm is able to generate complete designs
- Validate ability to optimize the design algorithm
- Assert baseline structural performance



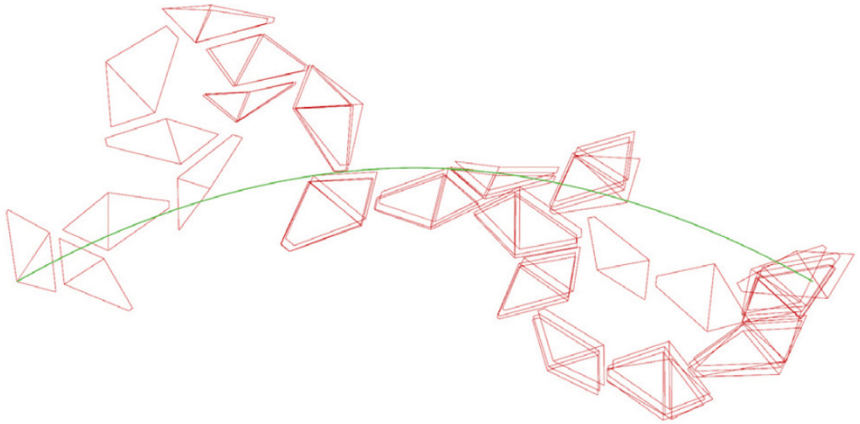
Full Action Space

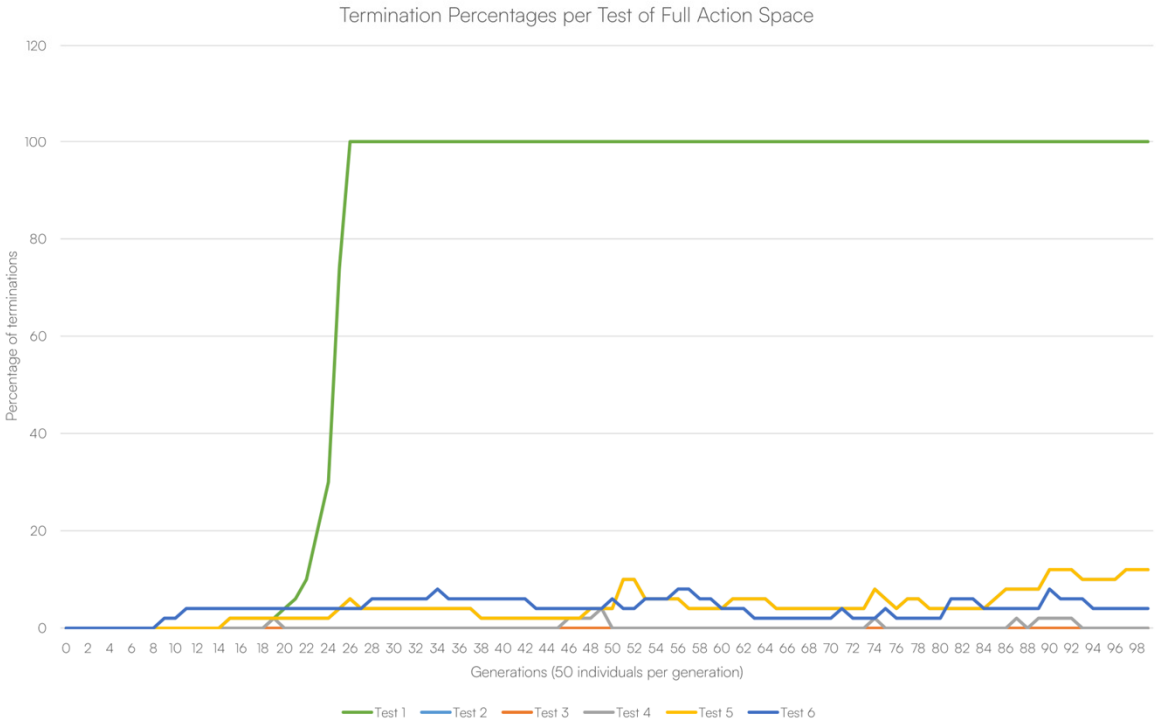
- Genetic optimizer selects stock, target, candidate and mirror actions
- 35 allowable steps
- Not yet tested for structural performance, only for ability to converge



Full Action Space

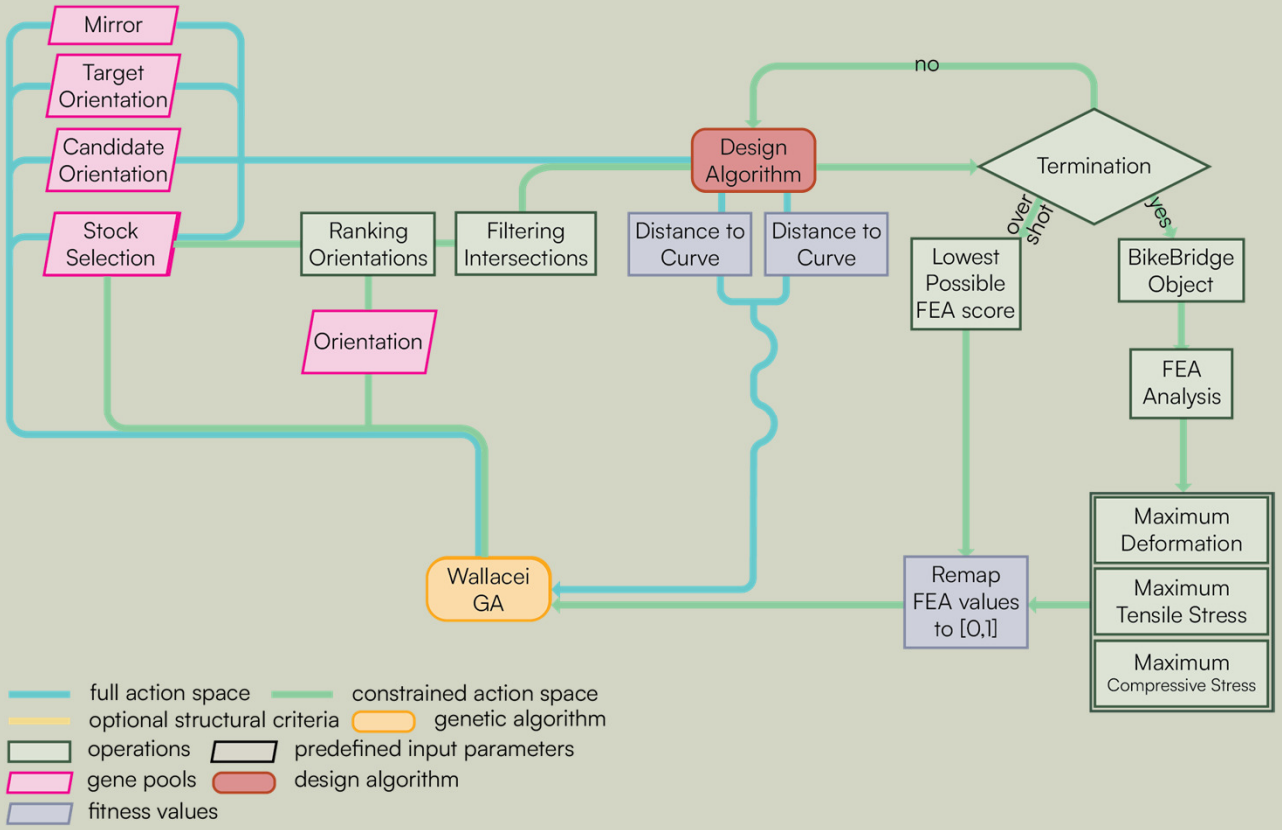
- Reward signal:
  - Closeness to design gesture
  - Progress across design gesture
  - Termination:
    - Replacement reward (1)
    - Flat reward (2,4)
    - Vicinity based reward(3,5)



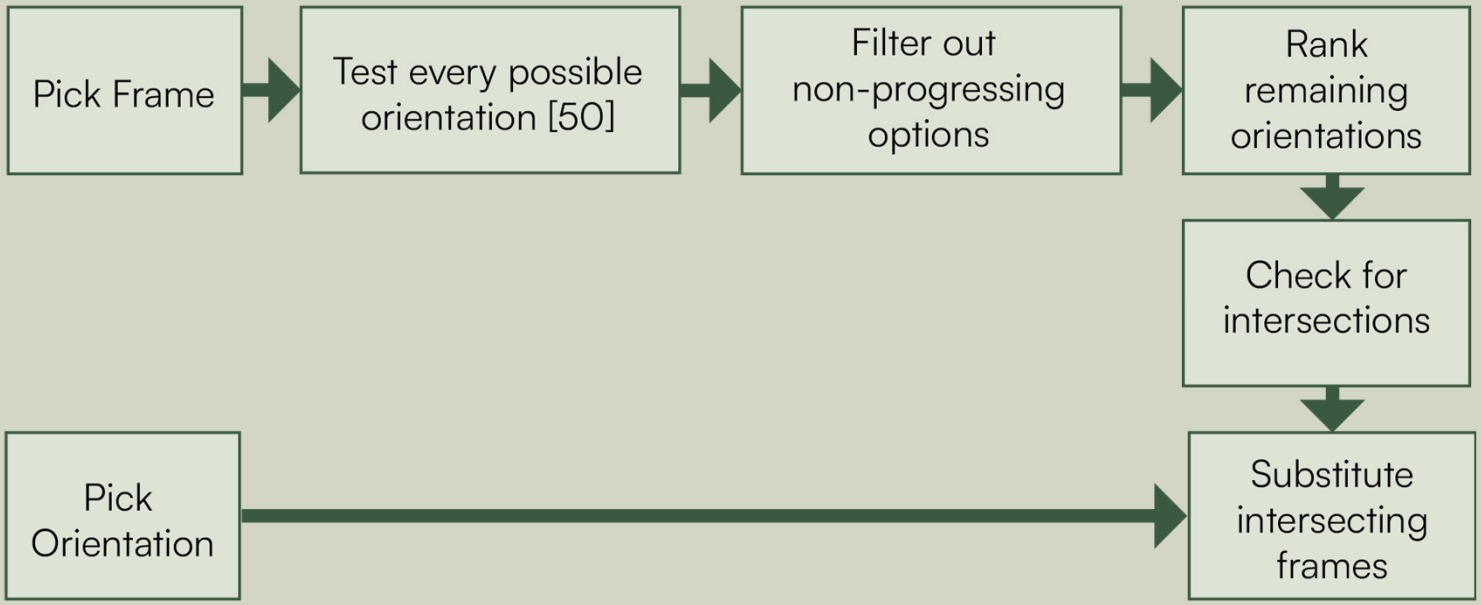


Partial Action Space

- Replaced candidate, target and mirror actions with a single action
- Genetic algorithm picks from preselected set of correct orientations



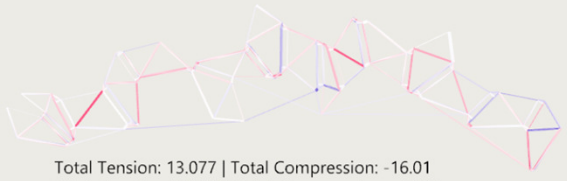
Partial Action Space



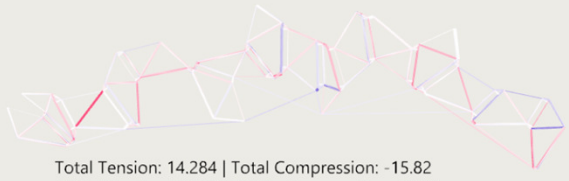
Constrained Action Space

- Reward signal:
  - Structural Performance
- Optional parameter:
  - Size of the ranked orientation pool

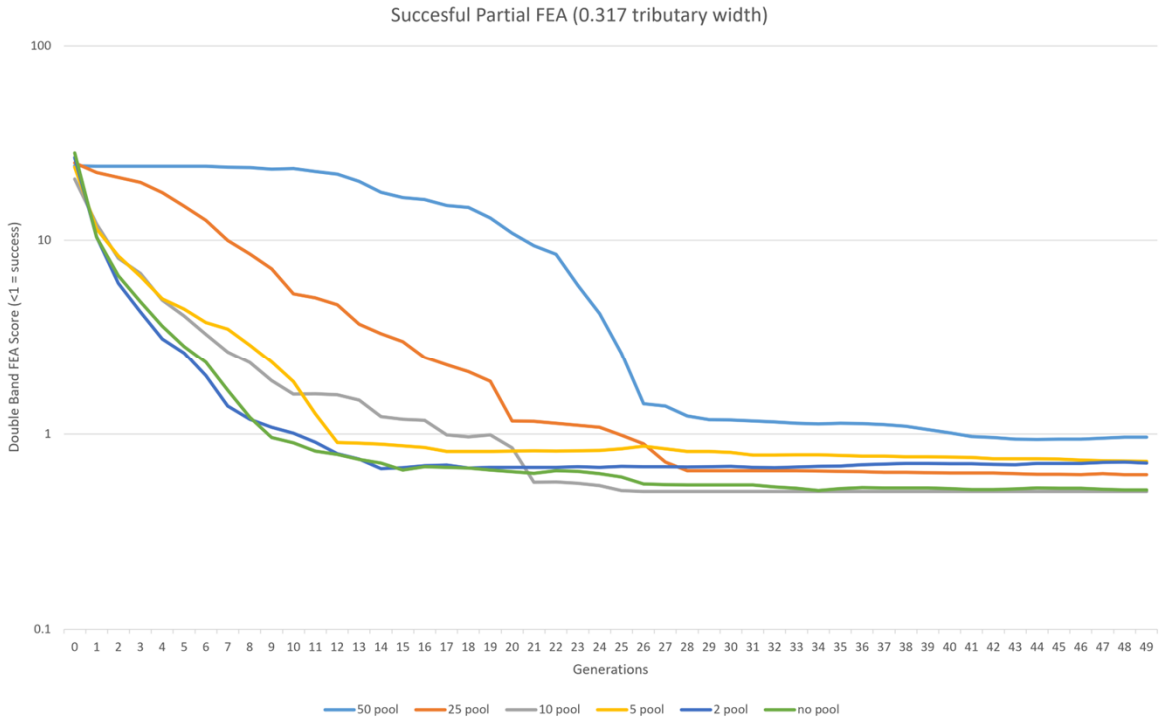
- Runtime ~15 minutes
- Low variance in solution space



Total Tension: 13.077 | Total Compression: -16.01
Cable Tension: 2.6804 | Cable Compression: -2.420
Conn. Tension: 10.745 | Conn. Compression: -13.01
Maximum Deformation: 0.4003



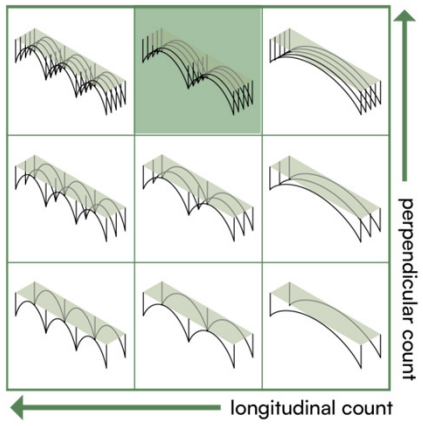
Total Tension: 14.284 | Total Compression: -15.82
Cable Tension: 2.6981 | Cable Compression: -2.543
Conn. Tension: 10.845 | Conn. Compression: -13.11
Maximum Deformation: 0.3755

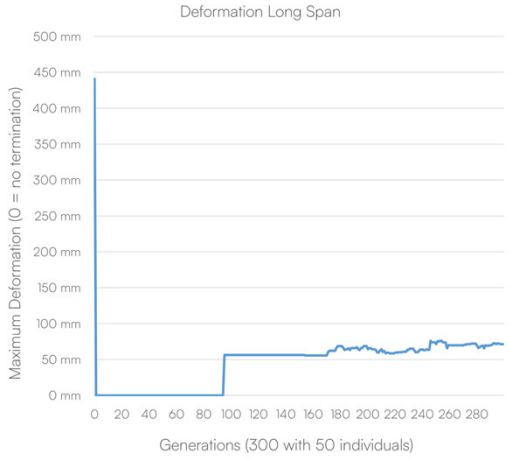


Baseline Structural Performance

- Long span arch of 15 metres proved unfeasible
- Minimum of two 7 metre longitudinal arches required
- Minimum of four perpendicular arches required

	50 pool	25 pool	10 pool	5 pool	2 pool	no pool	Total
2 arches	0	0	0	0	0	0	0
4 arches	0	0	295	667	0	131	1057
5 arches	0	0	1	0	0	161	162
6 arches	0	0	0	0	225	26	251
7 arches	0	449	431	738	0	572	2190
8 arches	0	0	0	0	0	0	0
9 arches	0	0	2	0	0	756	758
Total	0	449	729	1405	225	1886	





Fundaments for Reinforcement Learning



ACTIONS



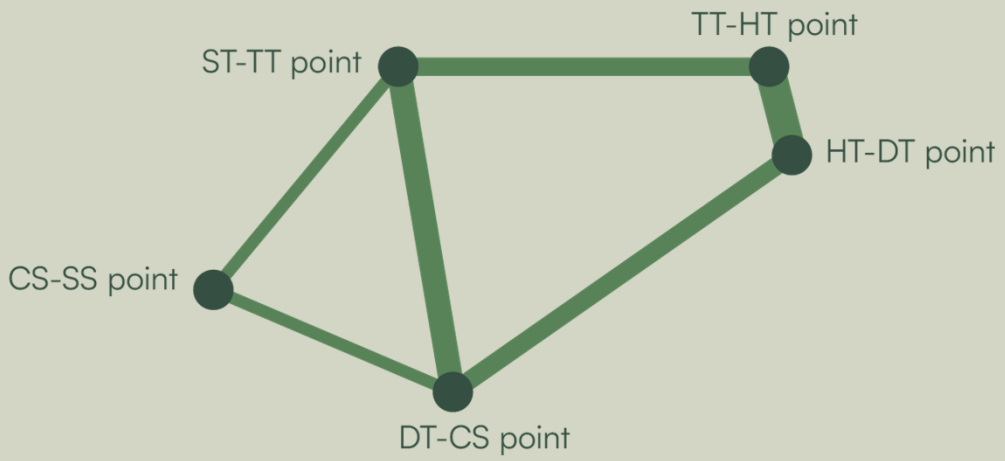
STATES

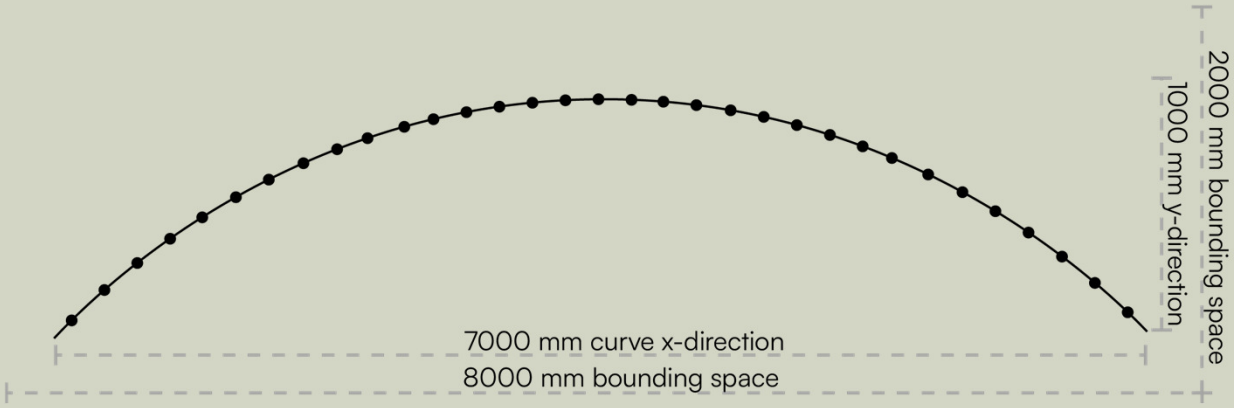


REWARDS

States

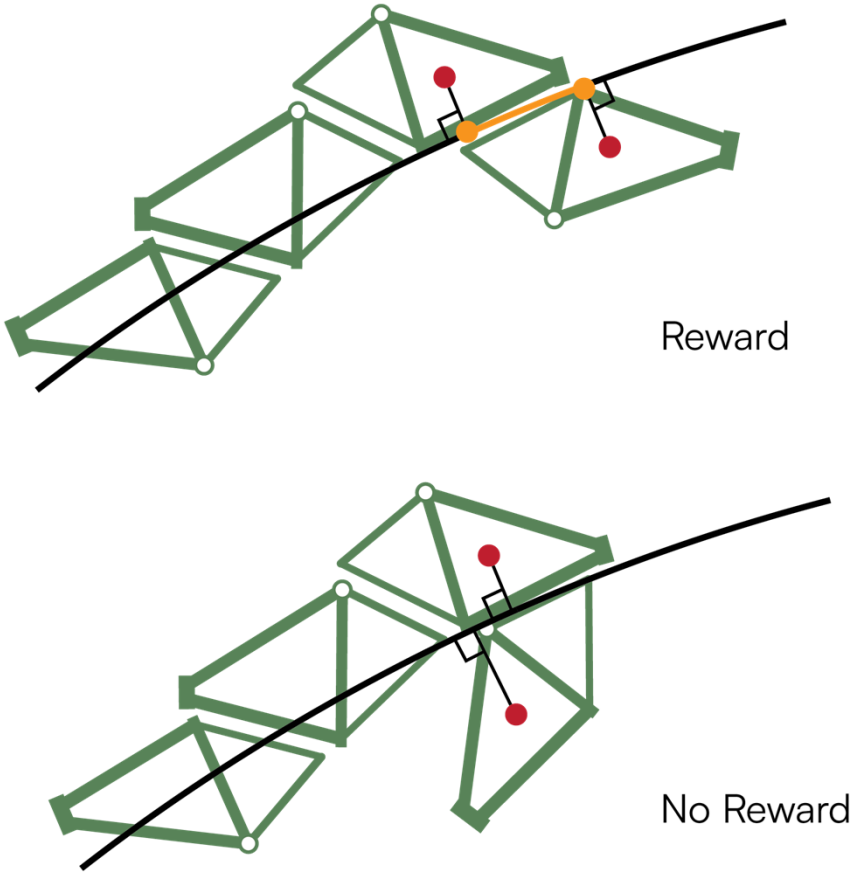
- Guide Gesture
  - Sampled in XY coordinates
- Frames
  - 5 points in XY coordinates
  - Tubes represented with cross-sectional areas
- Consumption mask
- Progression
  - Time step
  - Design gesture progress





Reward Functions

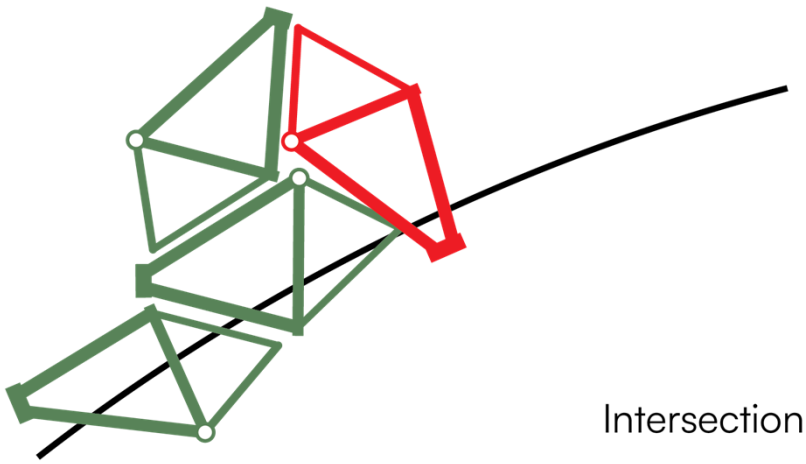
- Progress reward
  - Step based reward
  - Maximum of 1.0
  - Never negative
  - Only for true progress
- Distance reward
  - Approaches 1.0 the closer to the guide curve
  - Never lower than -1.0



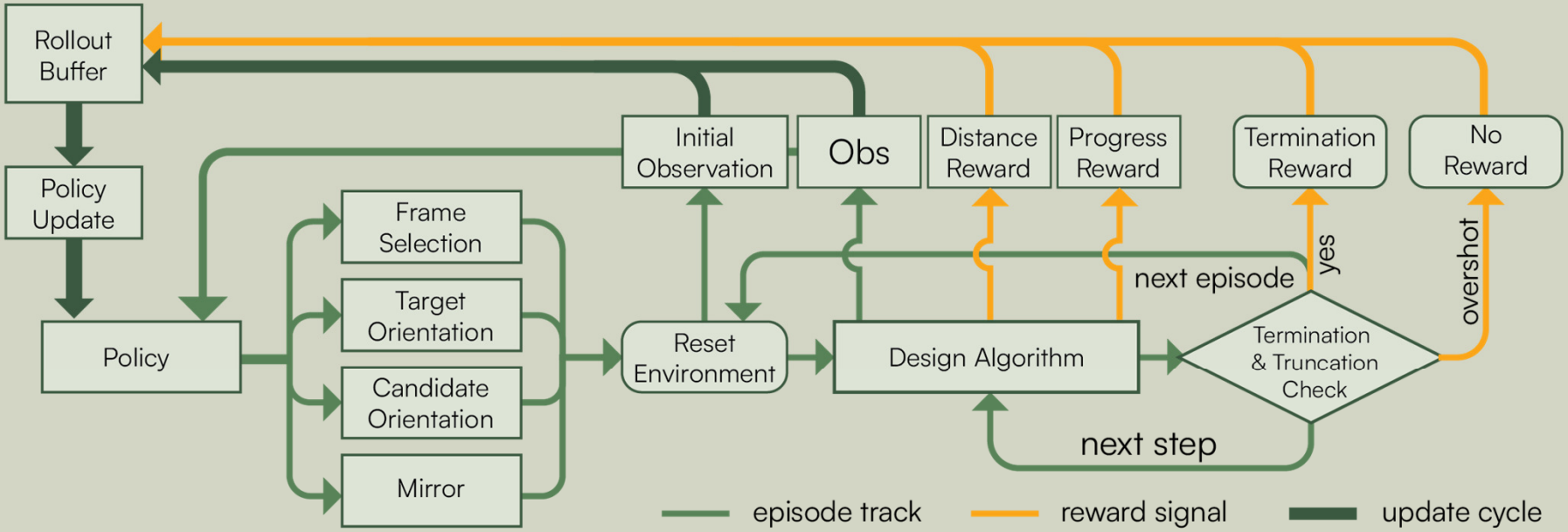
Progress reward

Reward Functions

- Termination
  - Flat reward of 3.0
- Structural Performance
  - Composed of sub-rewards for deformation, tension and compression
  - Never negative
  - Maximum of 30.0
- Intersection & Reselection of frame
  - Flat Penalty of -2.0
  - Action skipped

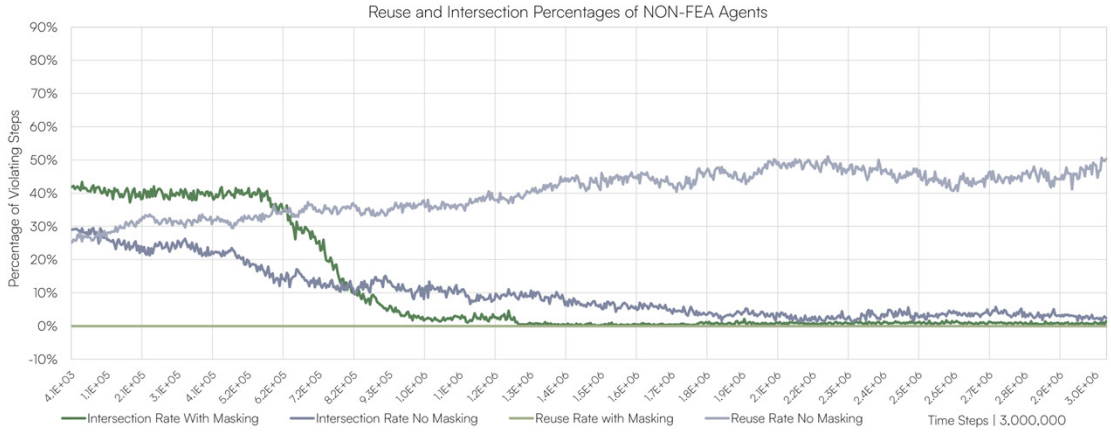


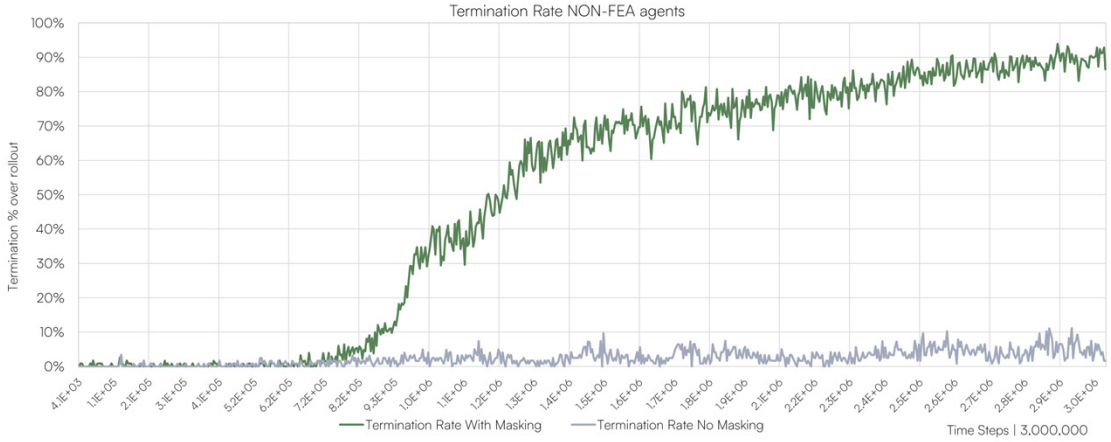
Training Setup



NON-FEA Agents

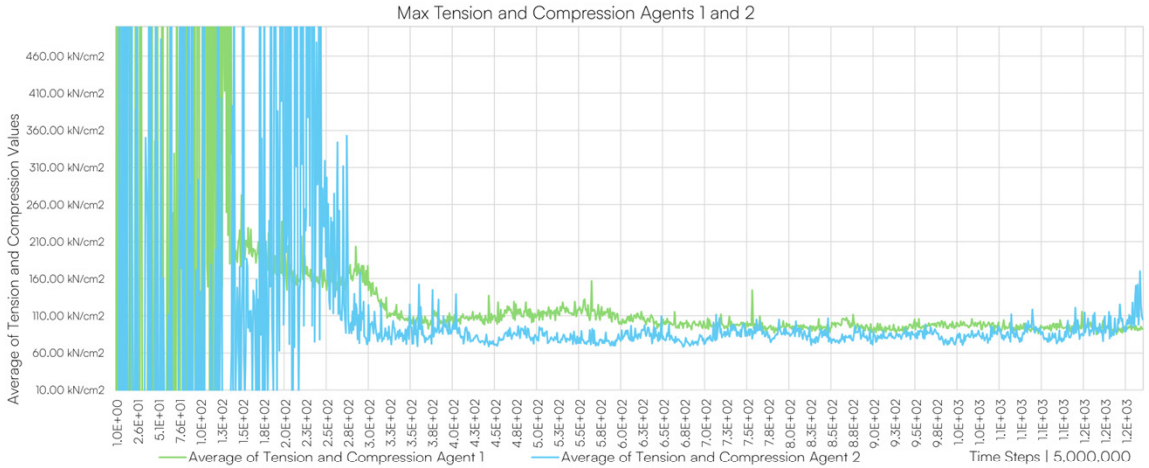
- Learning both the reuse and intersection penalty proved difficult
- Enabled the masking of actions, rather than observations

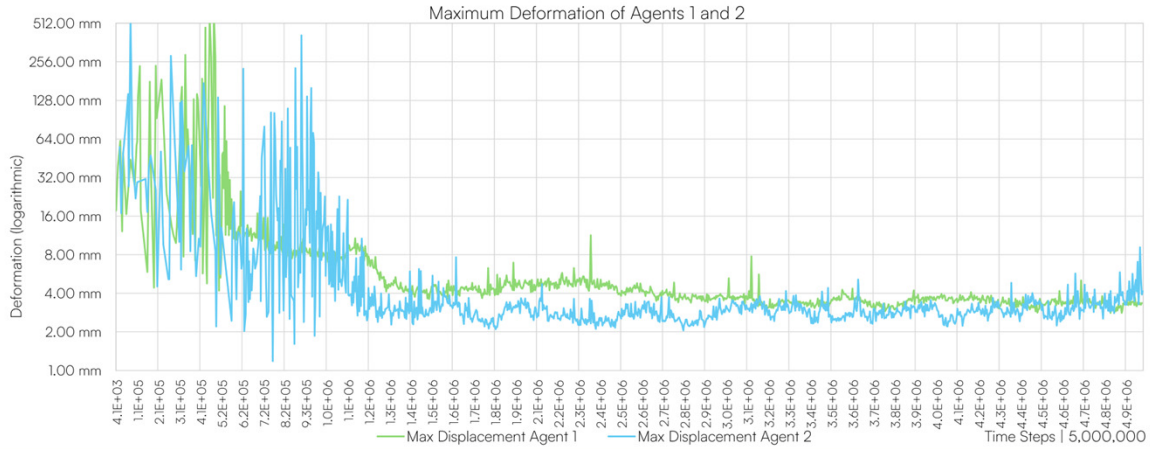




Structural Agents

- Initial strong improvements in structural performance
- Extended plateau
- Slight improvements with higher entropy (agent 2)

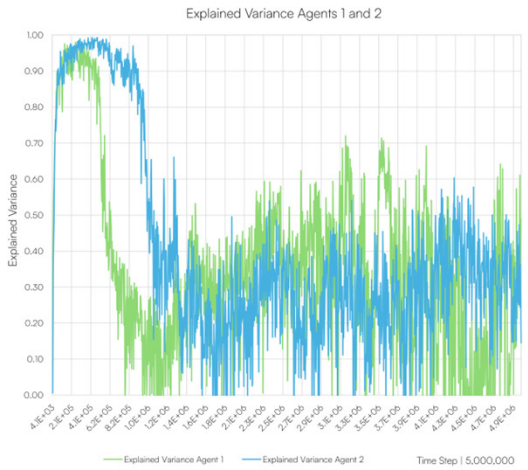


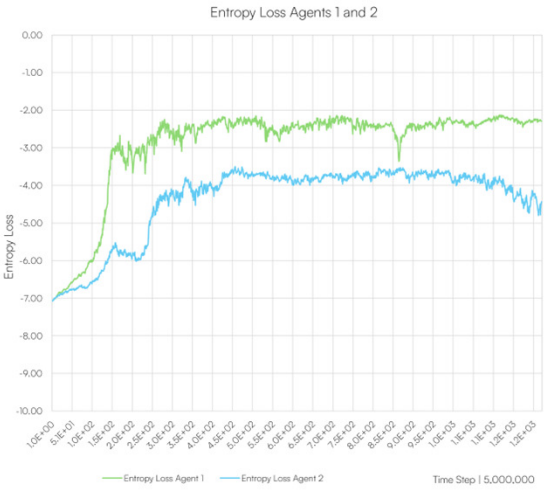


Structural Agents

- Six agents capable of generating valid design solutions
- Notable improvements with raised entropy
- Potential improvements with reward balancing

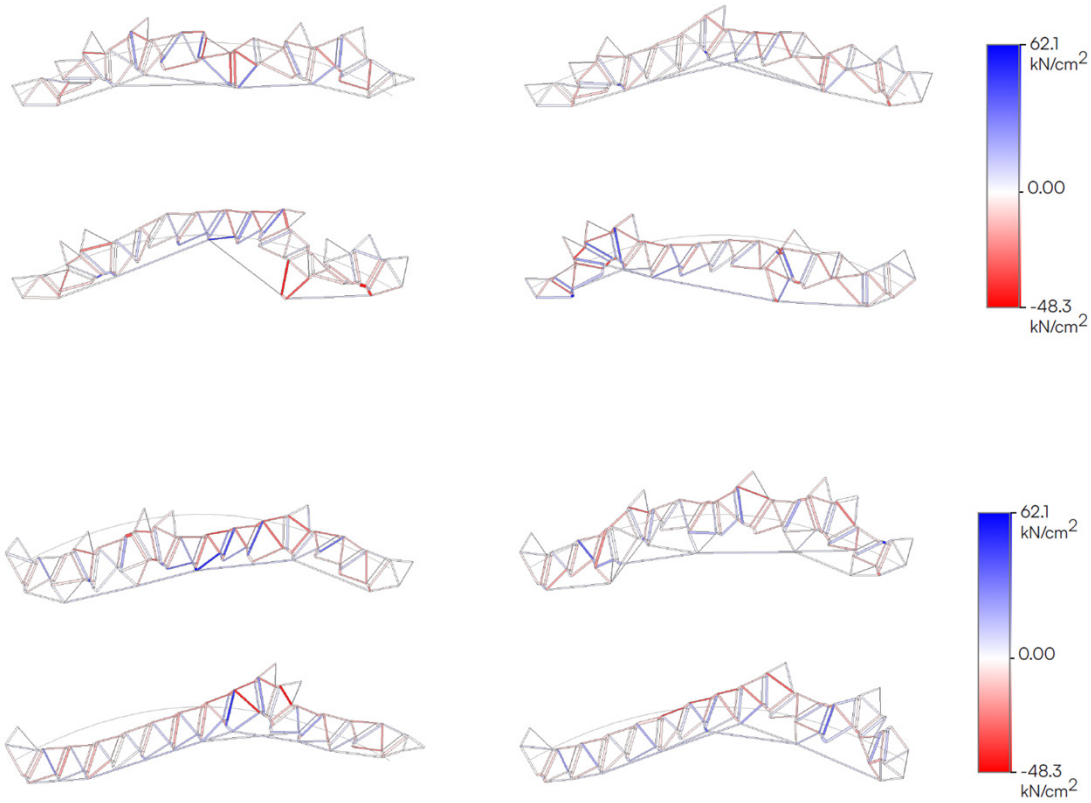
Agent	Settings	Termination Percentage	FULL FEA	PARTIAL FEA
Agent 1	Methodology Settings 5 million total steps	85.2%	0.0%	0.2%
Agent 2	Entropy coefficient of 0.010 5 million total steps	57.0%	4.7%	11.5%
Agent 3	FEA Maximum reward lowered (30>24) 3 million total steps*	68.2%	0.9%	1.3%
Agent 4	FEA Maximum reward lowered (30>24) Entropy coefficient of 0.015 5 million total steps	63.4%	1.1%	5.2%
Agent 5	Alternative seed of agent 4 8 million total steps	85.4%	4.4%	10.5%
Agent 6	Alternative seed of agent 4 8 million total steps	79.4%	0.2%	7.5%





Structural Agents

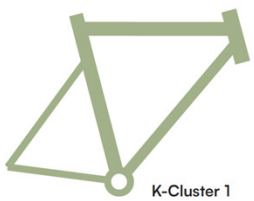
- Greater variety of design solutions
- Structural performance only acceptable at 6 perpendicular arches
- Genetic optimization managed 4 perpendicular arches
- Can generate high quantities of valid solutions in less than a minute

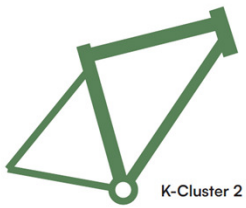


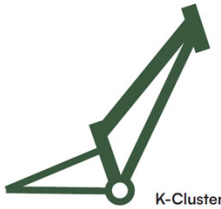
Generalization

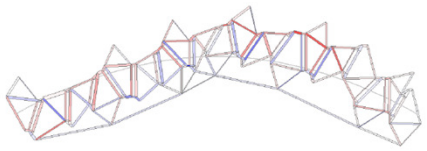
- Greater variety of design solutions
- Structural performance only acceptable at 6 perpendicular arches
- Genetic optimization managed 4 perpendicular arches

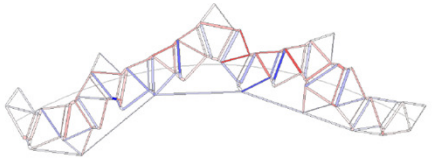
	% Terminated	Agent 2 Full FEA	Agent 2 Partial FEA	% Terminated	Agent 5 Full FEA	Agent 5 Partial FEA
Baseline	57.0%	4.7%	11.5%	85.4%	4.4%	10.5%
Alternate Seed 1	61.5%	8.8%	12.1%	86.4%	5.6%	12.7%
Alternate Seed 2	62.2%	4.2%	11.5%	85.0%	5.3%	11.7%
Cluster 1	69.9%	5.2%	8.5%	82.9%	8.2%	13.3%
Cluster 2	66.5%	2.5%	7.6%	92.3%	7.1%	17.8%
Cluster 3	2.1%	0.1%	0.2%	21.1%	0.0%	0.2%

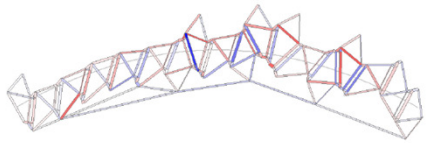

K-Cluster 1

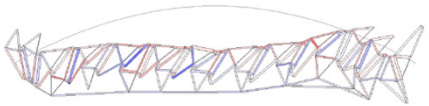

K-Cluster 2

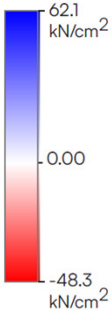

K-Cluster 3


Alternate Seeding 1


Cluster 1


Cluster 2

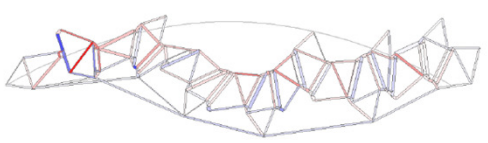

Cluster 3



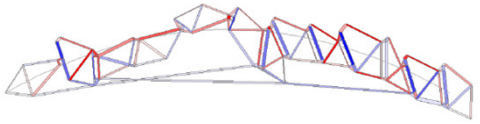
Interactivity

- Supplied a partial state from the genetic optimization
- Potential is visible but limited in current state

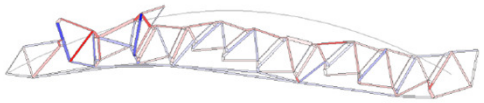
Agent	% Terminated	% Valid Partial FEA	% Valid Full FEA
Agent 1 3 Frames	57.2%	16.8%	5.6%
Agent 1 6 Frames	53.4%	4.7%	0.0%
Agent 5 3 Frames	0.40%	0.0%	0.0%
Agent 5 6 Frames	1.70%	0.0%	0.0%



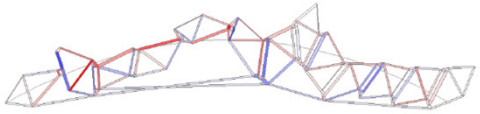
Agent 1 — Three Placed Frames



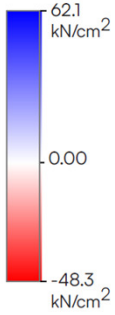
Agent 5 — Three Placed Frames



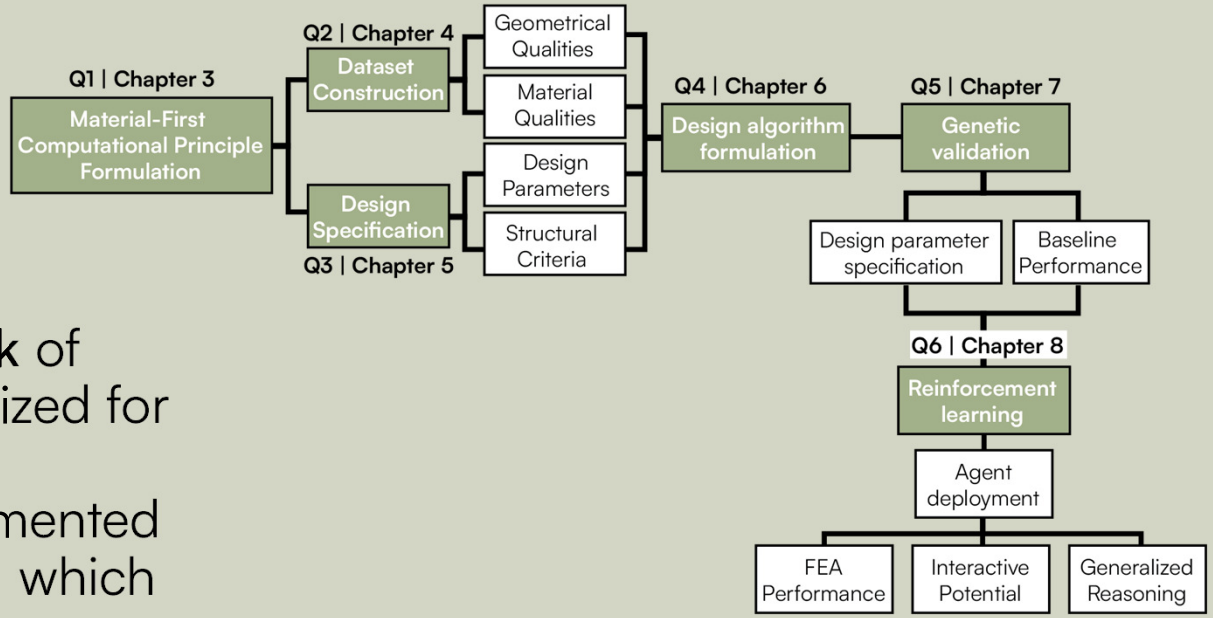
Agent 1 — Six Placed Frames



Agent 5 — Six Placed Frames



Conclusions



How can a **constrained stock** of **repurposed elements** be utilized for **structural designs** through a **generative algorithm**, implemented as an **interactive design tool** which enables **material-first design solutions**?

Conclusions

- Extracted a geometrically valid and simplified representation of bicycle frames from an existing dataset.
- Implemented K-Means clustering and 95% mean filtering to create a coherent subset to train reinforcement learning algorithm
- Formulated a design algorithm to sequentially place bicycle frames in 2D space along a design gesture
- Optimized the algorithm both genetically and via reinforcement learning to yield design outputs which can potentially be applied to the chosen design context

Conclusions

- Genetic optimization:
  - Could not be used on the design algorithm as is
  - Improved structural performance when using a more constrained action space
- Reinforcement learning:
  - Could be used on the complete design algorithm as is
  - Shown potential for application to a wider dataset
  - Shown potential for interactivity
  - Yielded valid solutions at much faster rates

Discussion

- Limitations:
  - Simplified 2D model
  - Connections are idealised
  - Buckling not accounted for
  - No horizontal loading
  - Database is mostly theoretical
- Performance barriers:
  - Structural performance plateau
  - Explained variance plateau
- Disconnects:
  - Design game investigations

Discussion

- Immediate next steps:
  - Feature Engineering
  - Alternative structural reward implementation

- Research continuation steps:
  - Realistic connection design
  - Fabrication and assembly pipeline
  - Life Cycle Analysis
  - Genuine interactive workflow

A Final Note

- Repurposing can be a valid practice
- There is real (creative) value in computational design

A Word of Thanks | Dankjewel

Dankjewel Opa, zonder jouw oneindige fascinaties was ik niet hier.