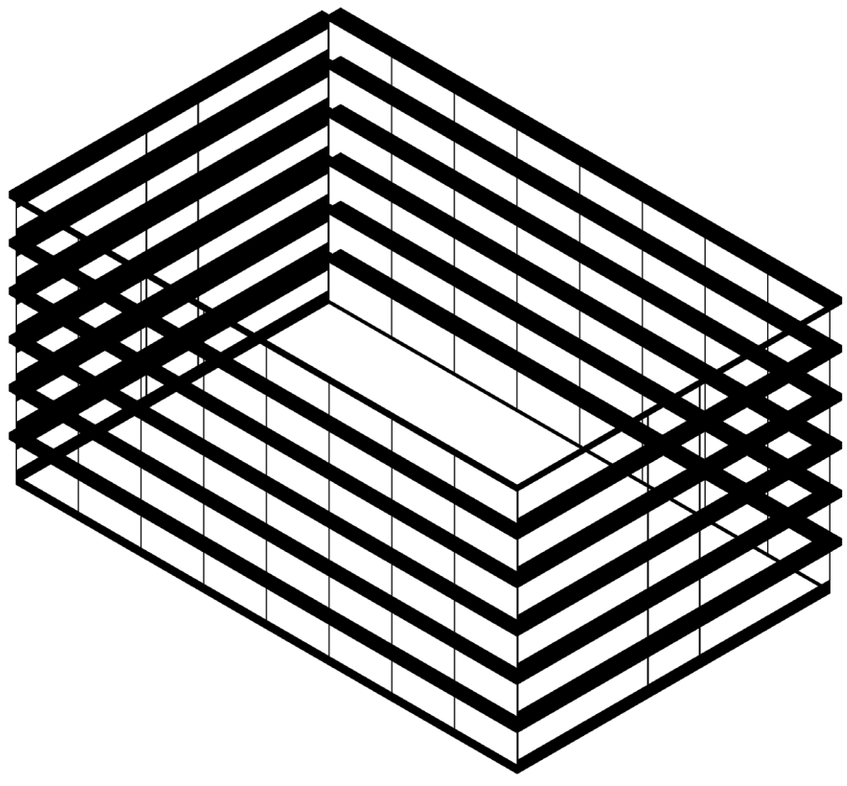
Multi Objective Optimization of Façade Geometry for Wind and Thermal Resilience

Graduation Project
Msc Building Technology Track
Delft University of Technology



By
Muhammad Rafif Cahyadi Agung

Wednesday, 24th of July 2026
11:30 CEST
Zaal D Bouwkunde TU Delft

Mentor
Simona Bianchi
Gabriele Mirra

TU Delft

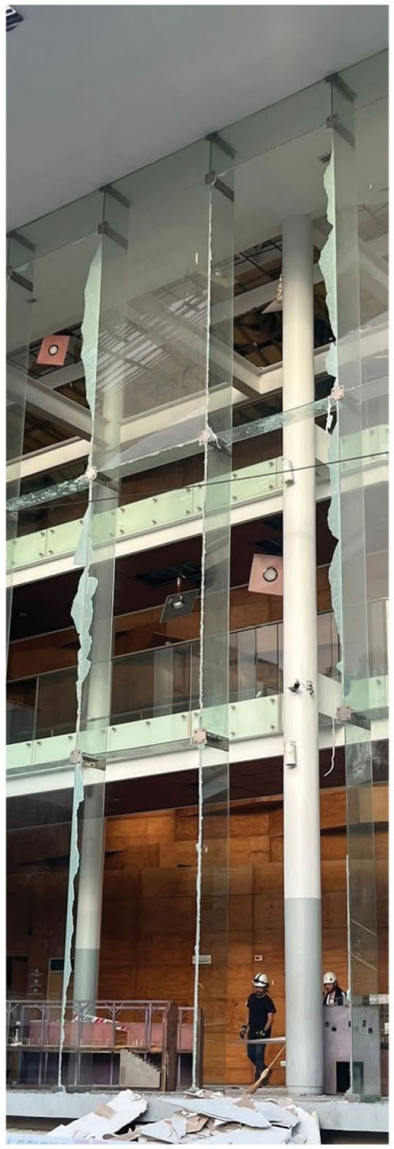


Image: AP Photo/David J. Phillip



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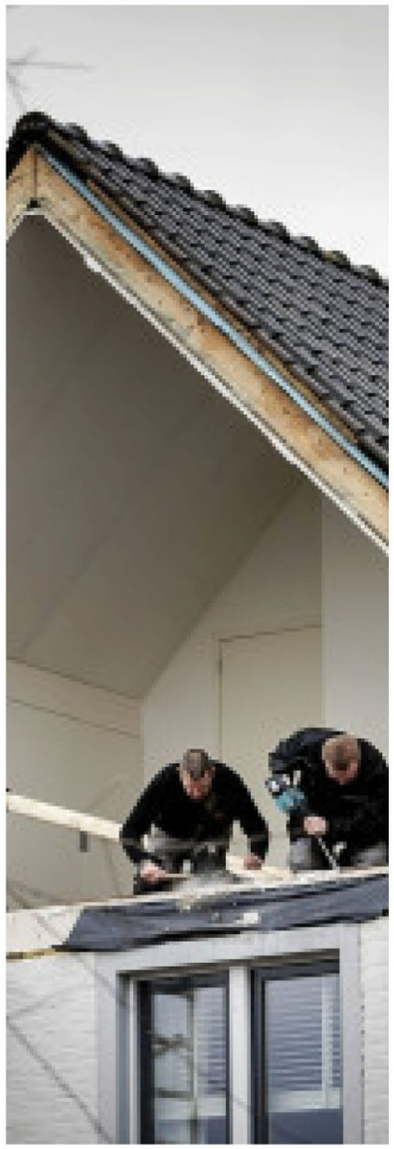

Image: Robin van Lonkhuijsen / AFP



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Image: Marcelo del Pozo / Bloomberg



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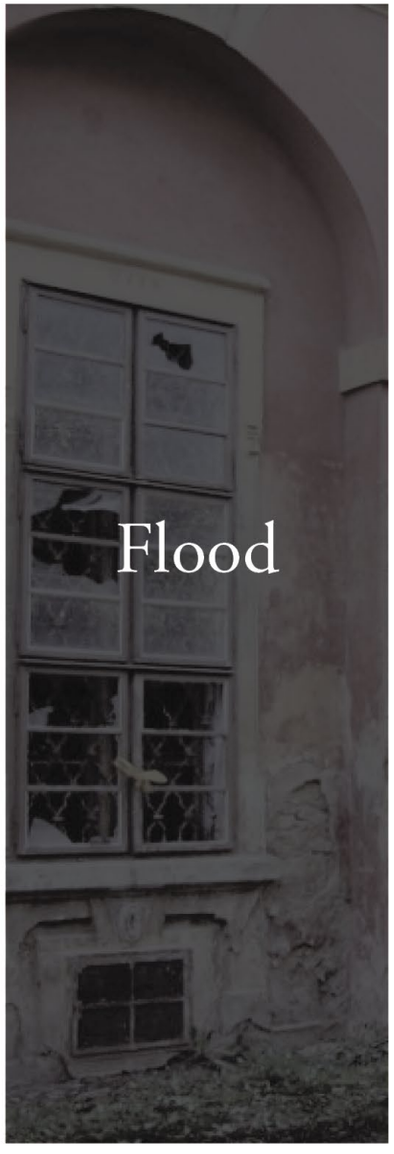

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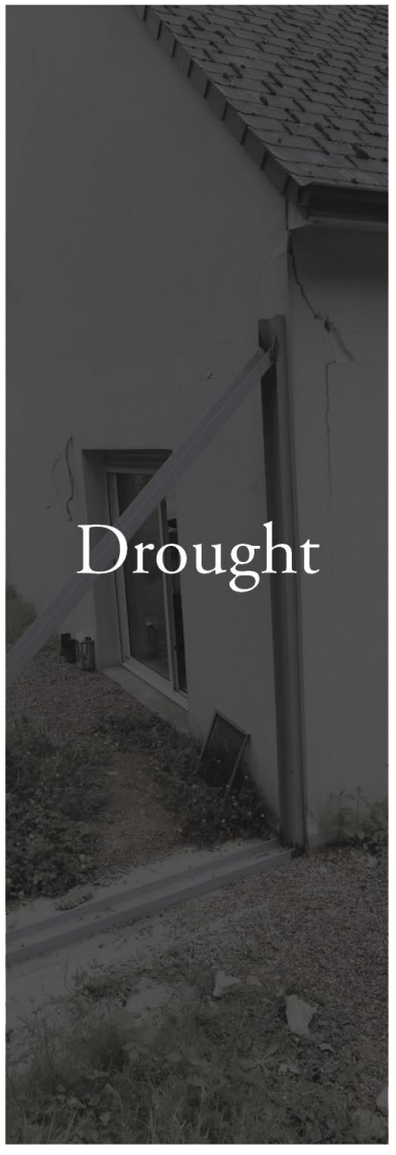

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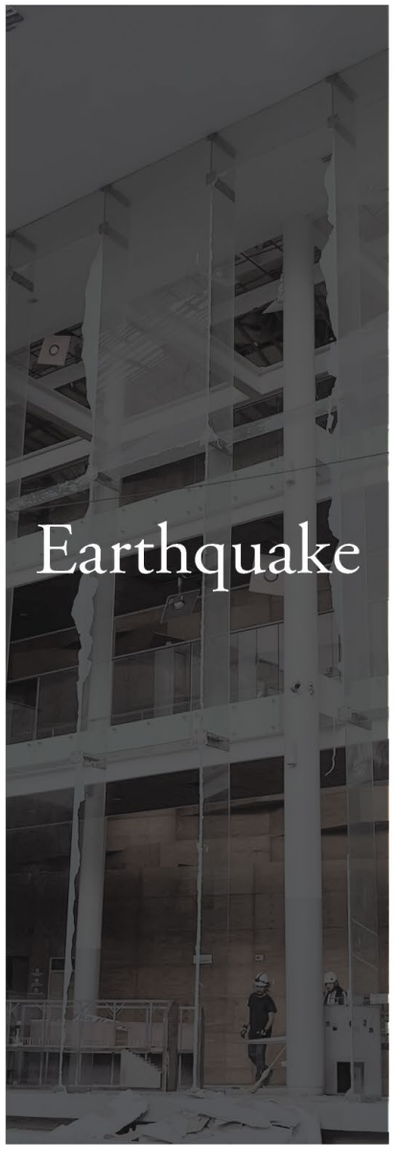

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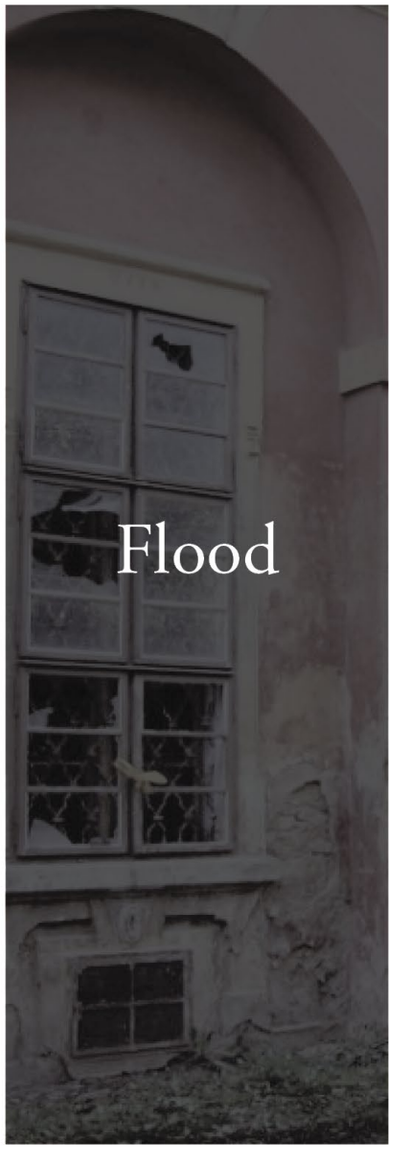

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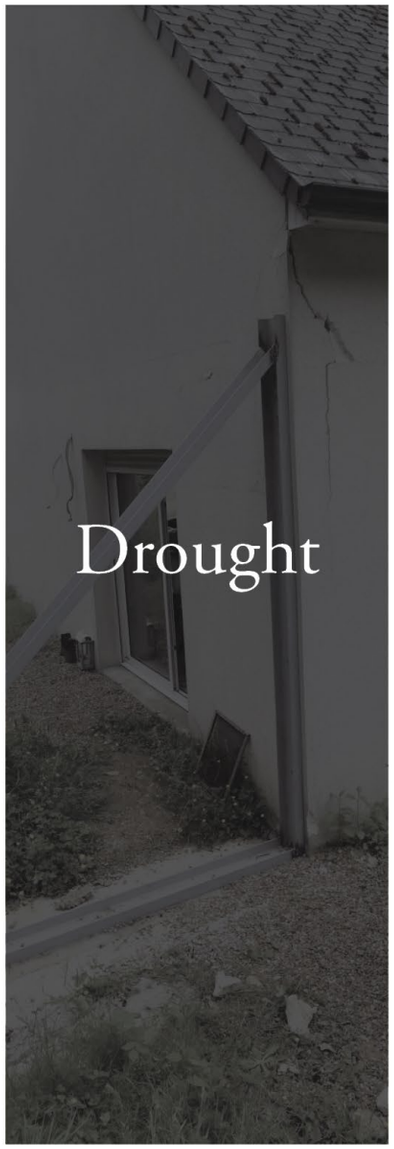

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Image: Marcelo del Pozo / Bloomberg

In 2007–2022, 10 out of the 20 most expensive natural hazard events in the Netherlands were related to windstorms.

(Verbond van Verzekeraars 2017, 2023)



Image: Robin van Lonkhuijsen / AFP

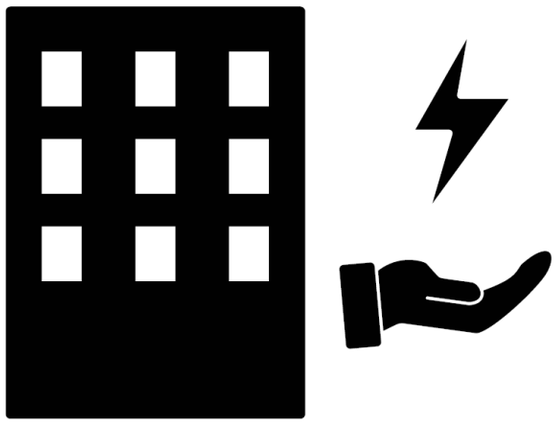
Past heatwaves in 2006 and 2019 caused hundreds of excess deaths in the Netherlands.

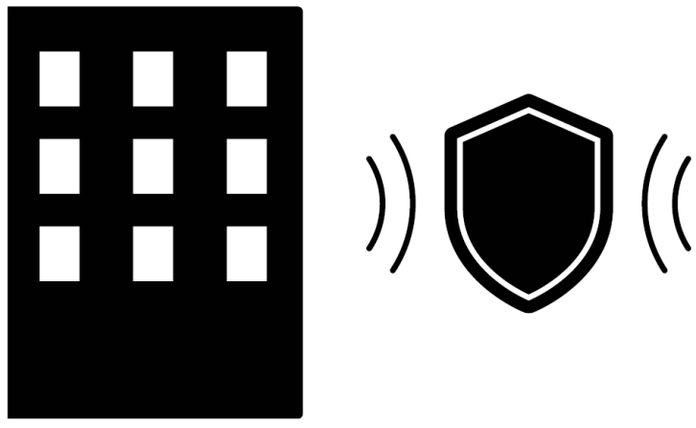
(Centraal Bureau voor de Statistiek [CBS], 2019; Klok and Kluck, 2018).



Image: Marcelo del Pozo / Bloomberg

From Policy Standpoint





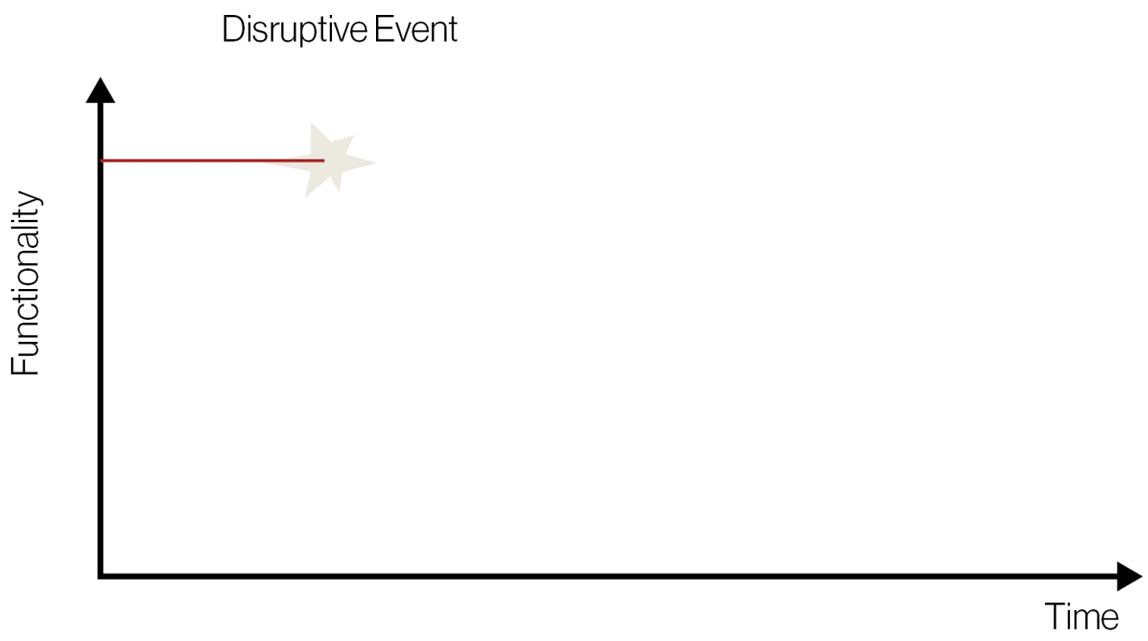
Recent resilience and codes work directly frames the “future EPBD” as evolving from energy-only compliance toward a multi-hazard resilience framework for buildings, citing Europe’s exposure to heatwaves, floods and other extremes.

Shady Attia. (2025, December 8). Future proofing the EPBD: Multi-Hazard resilience in Europe’s building energy codes [Video]. YouTube. https://www.youtube.com/watch?v=0uNE2KsrORk

What is Resilience?



What is Resilience?



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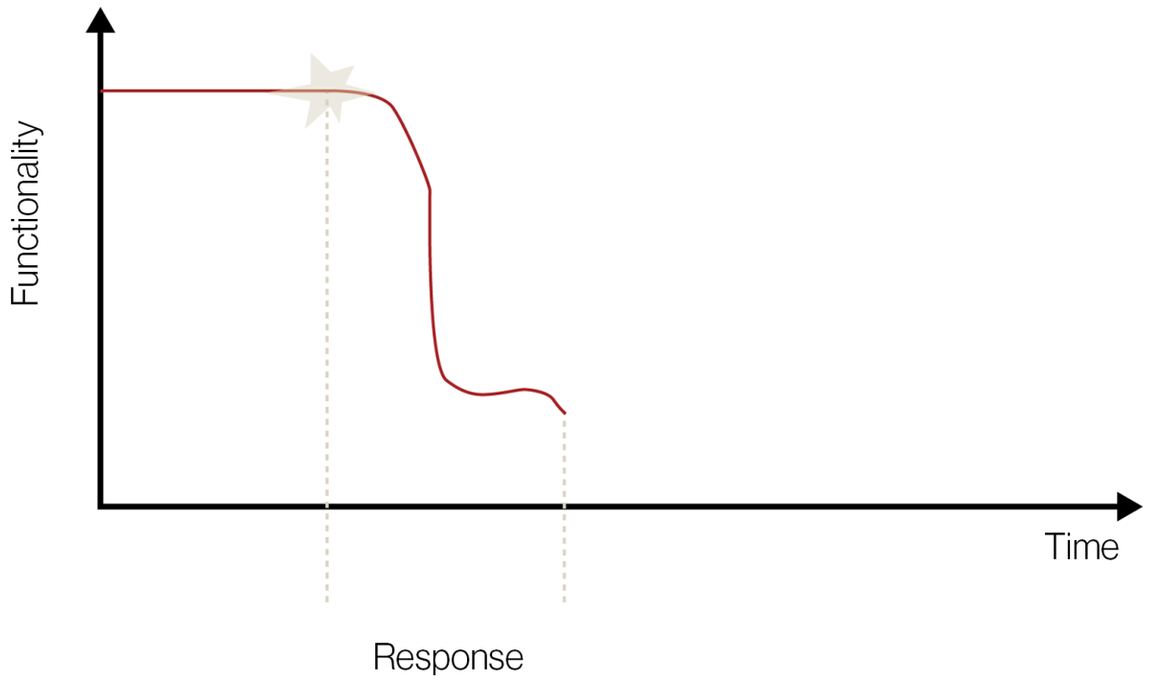

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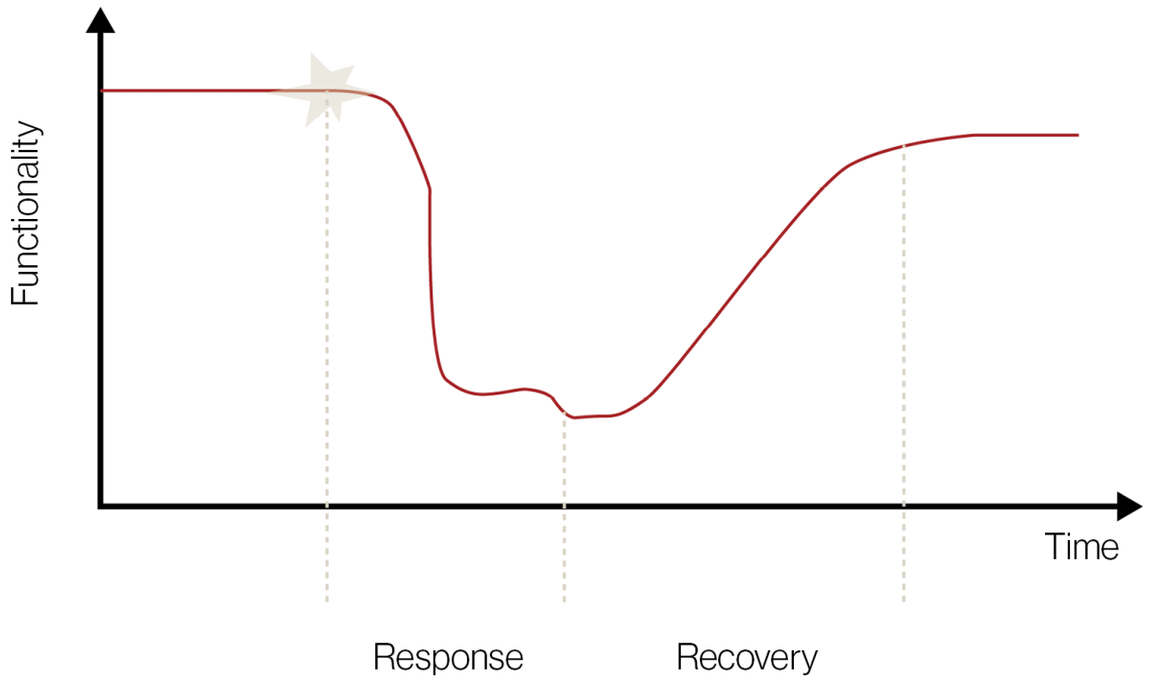

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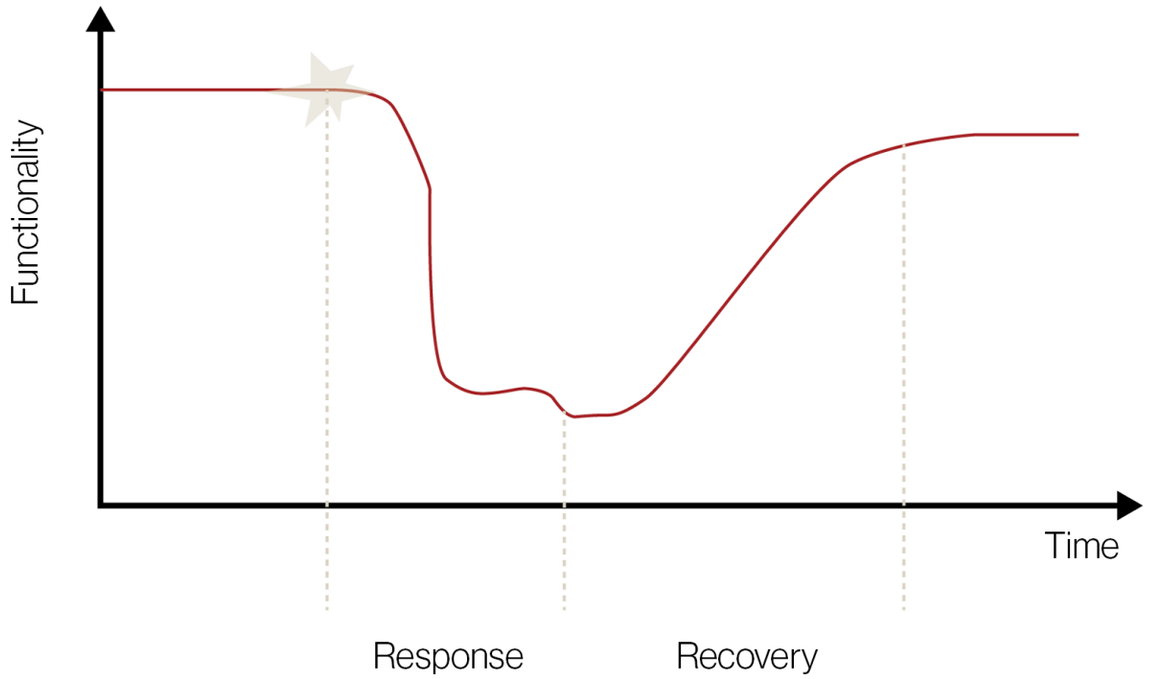



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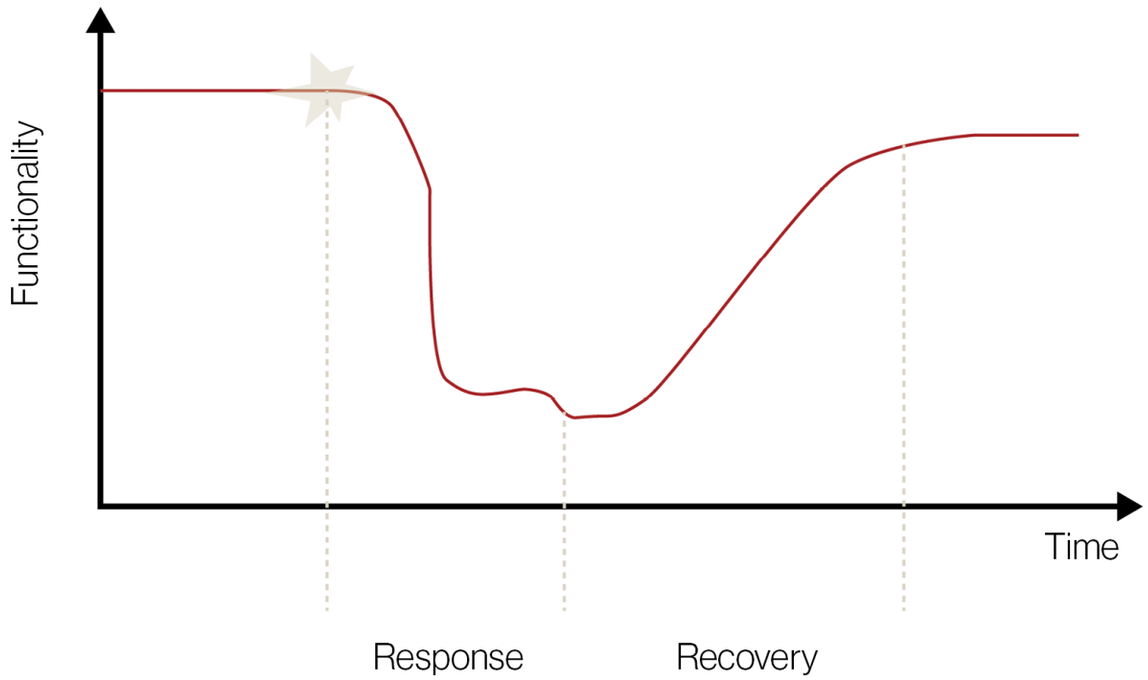

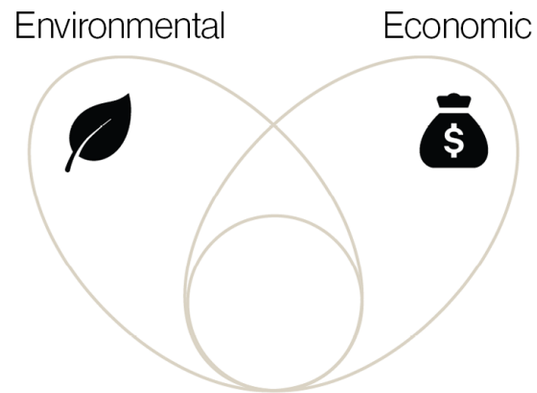

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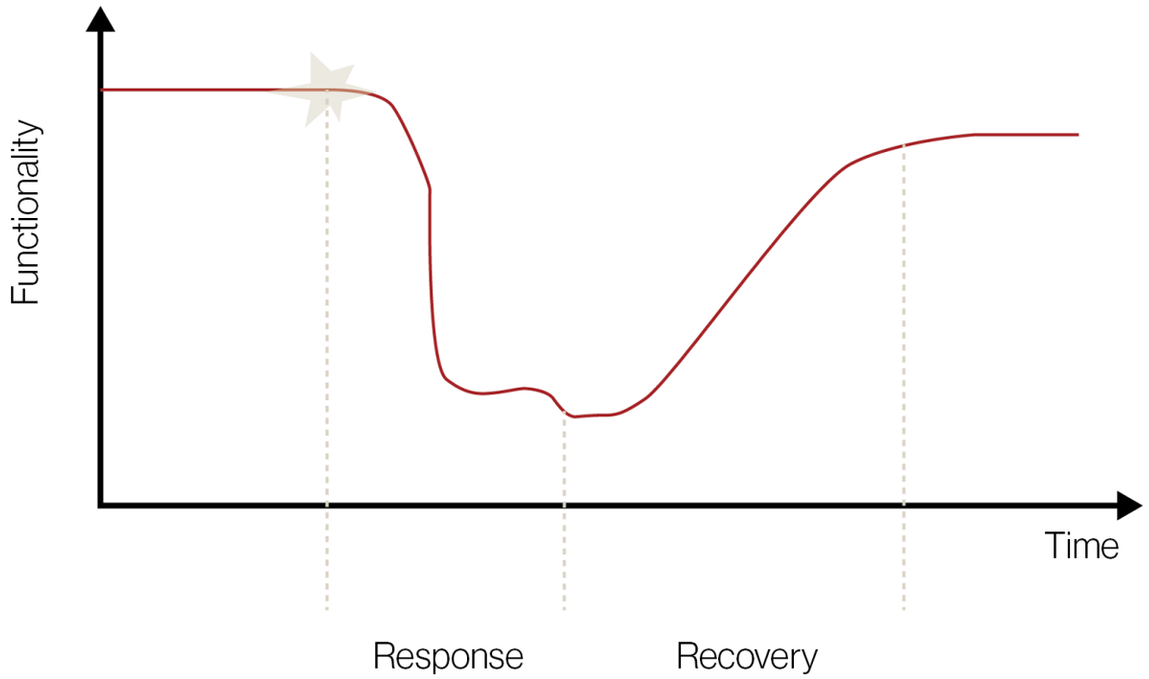

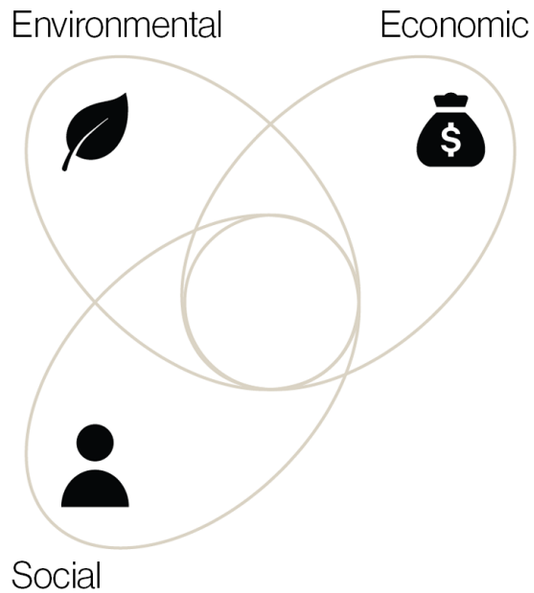

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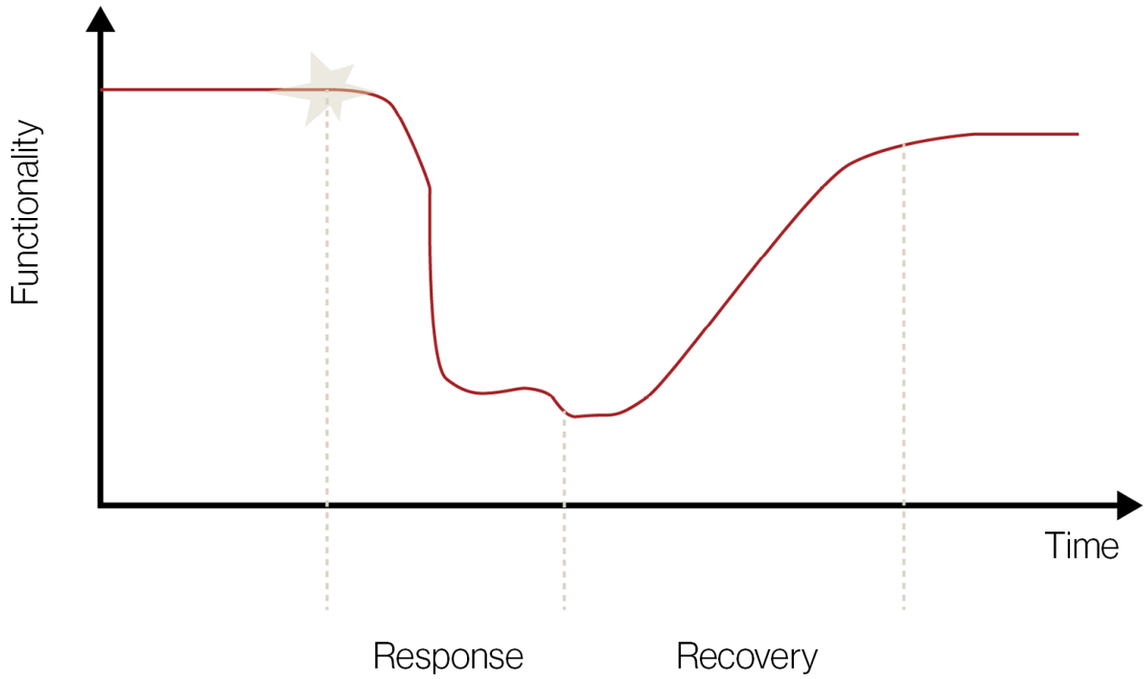
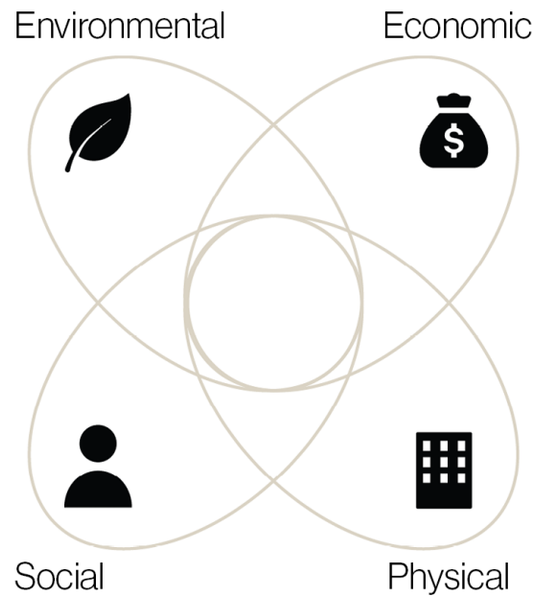
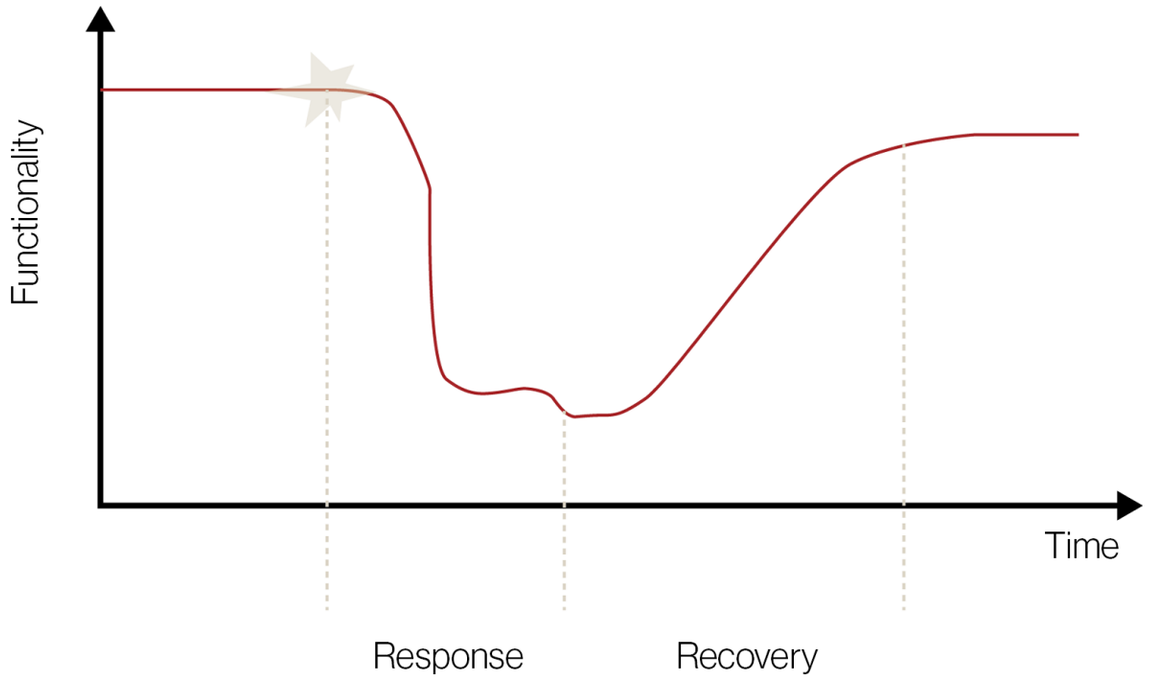


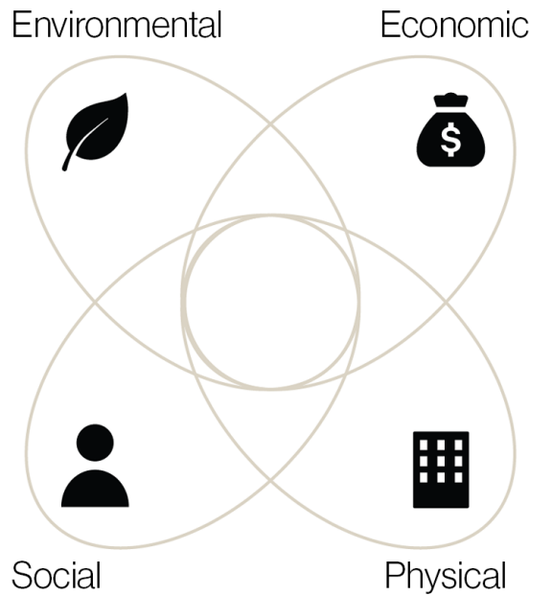


What is Resilience?

Resilience is defined by the ability of a building to “bounce back” to a new equilibrium within a recovery time after absorbing the impact of an external natural or man-made event.

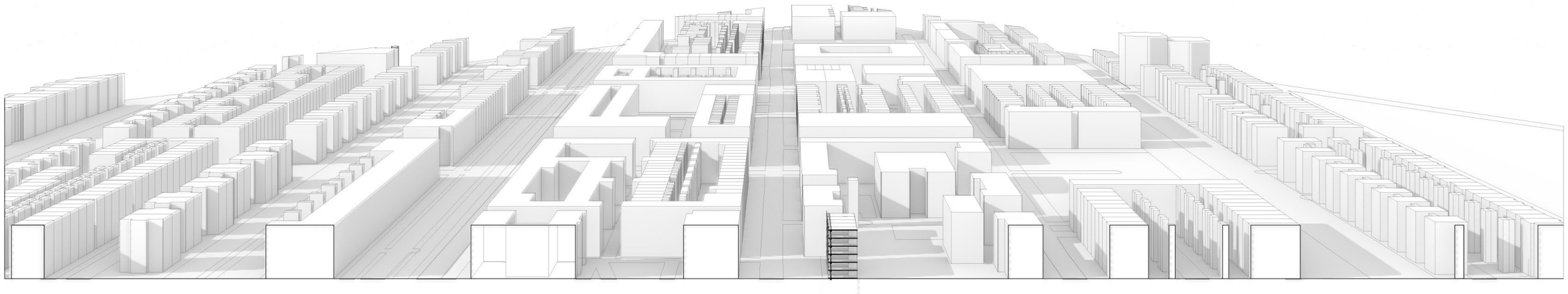
Bruneau et al., “A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities.”





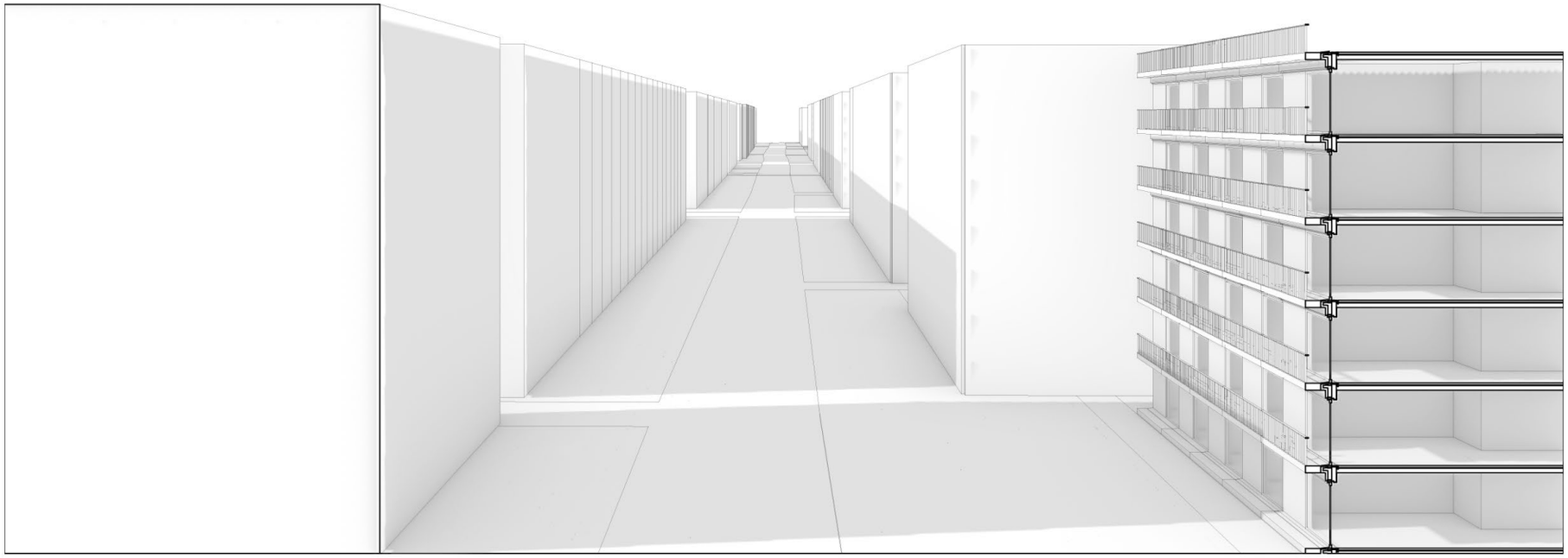
Where can it be applied to?

Urban Level

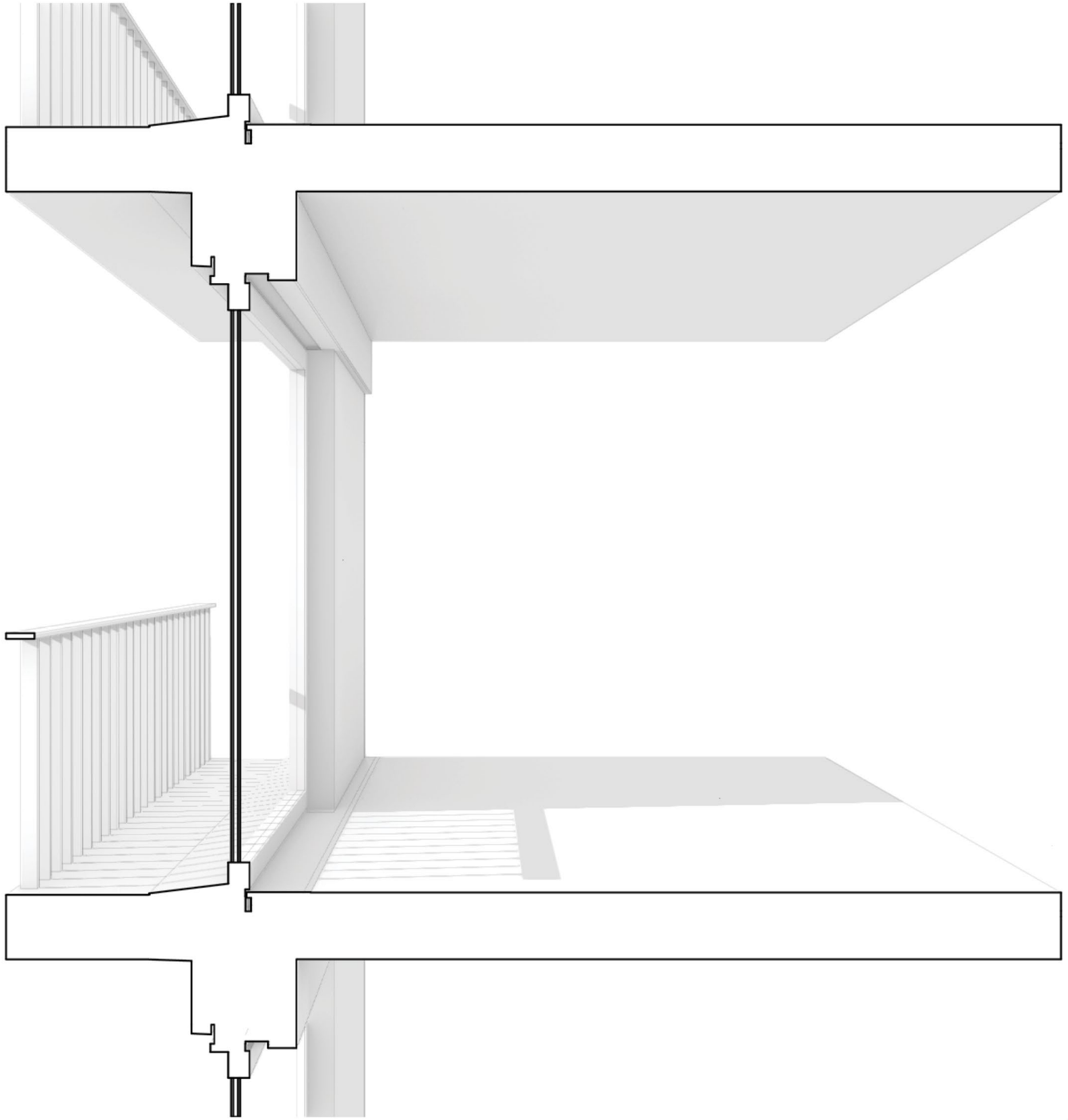


Where can it be applied to?

Building Level

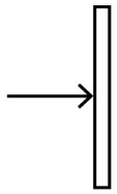


Facade Level

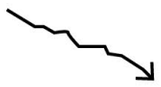


Why Facade Level?

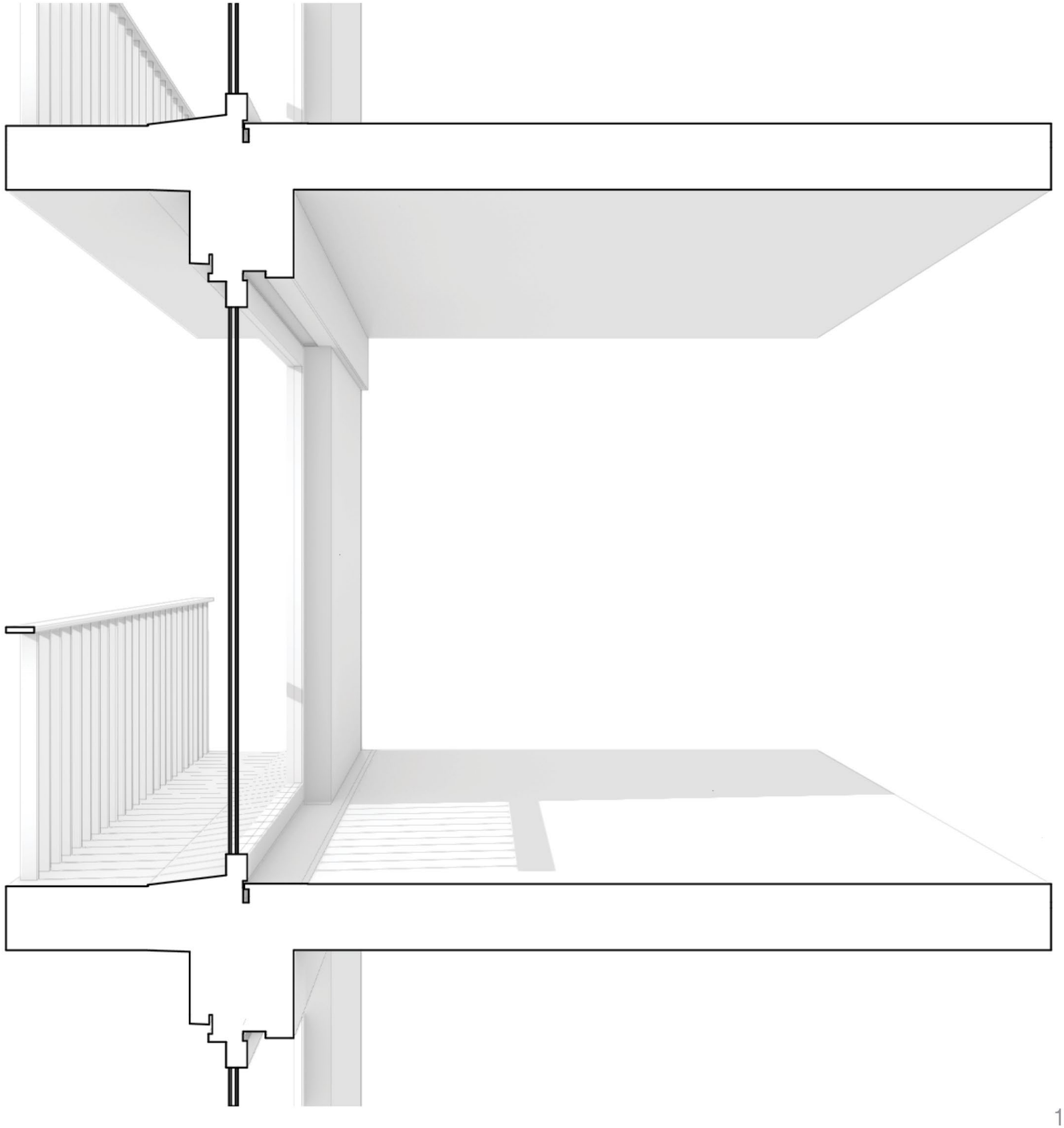
First Line of Contact



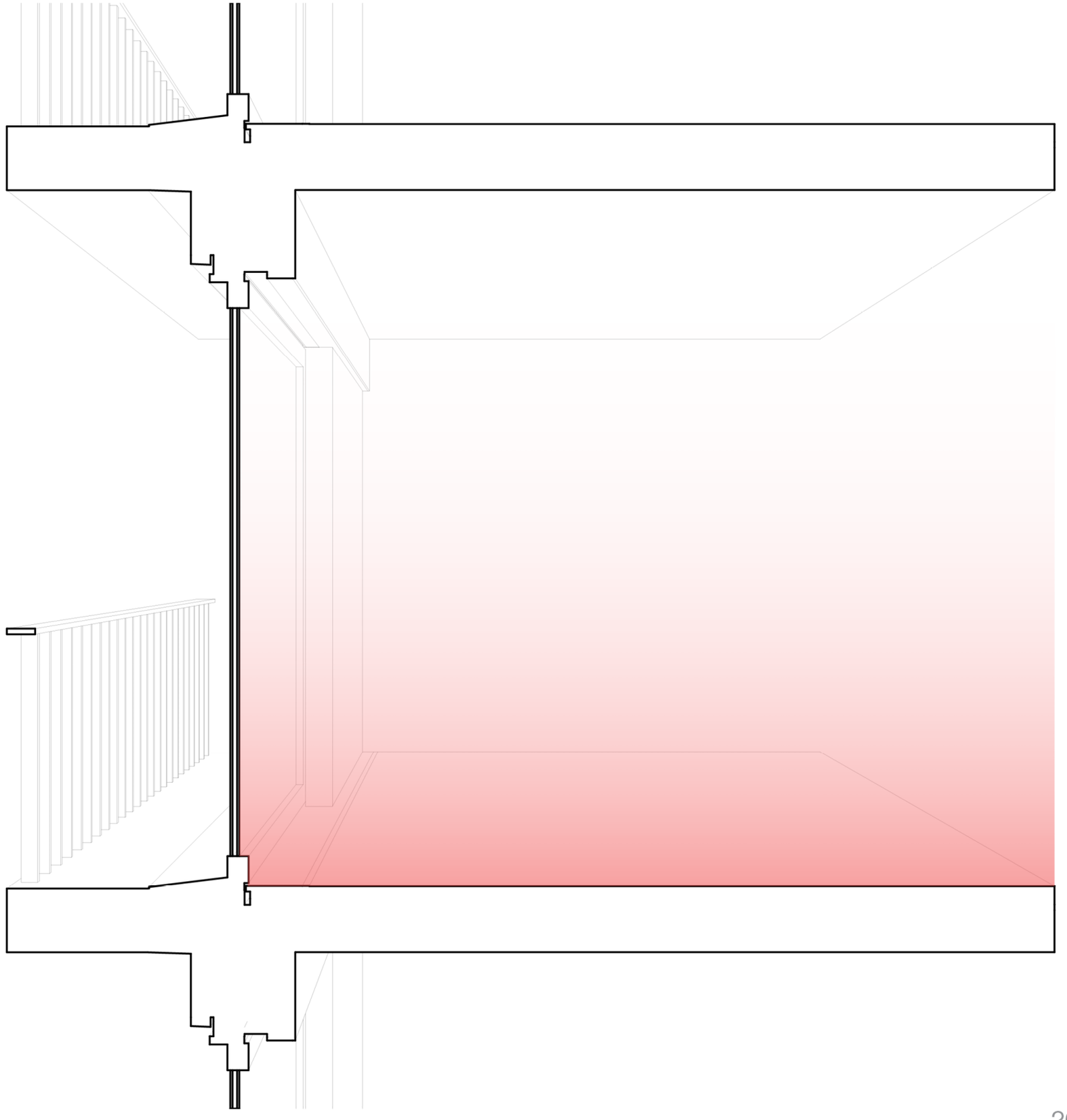
Small stresses,
large consequences



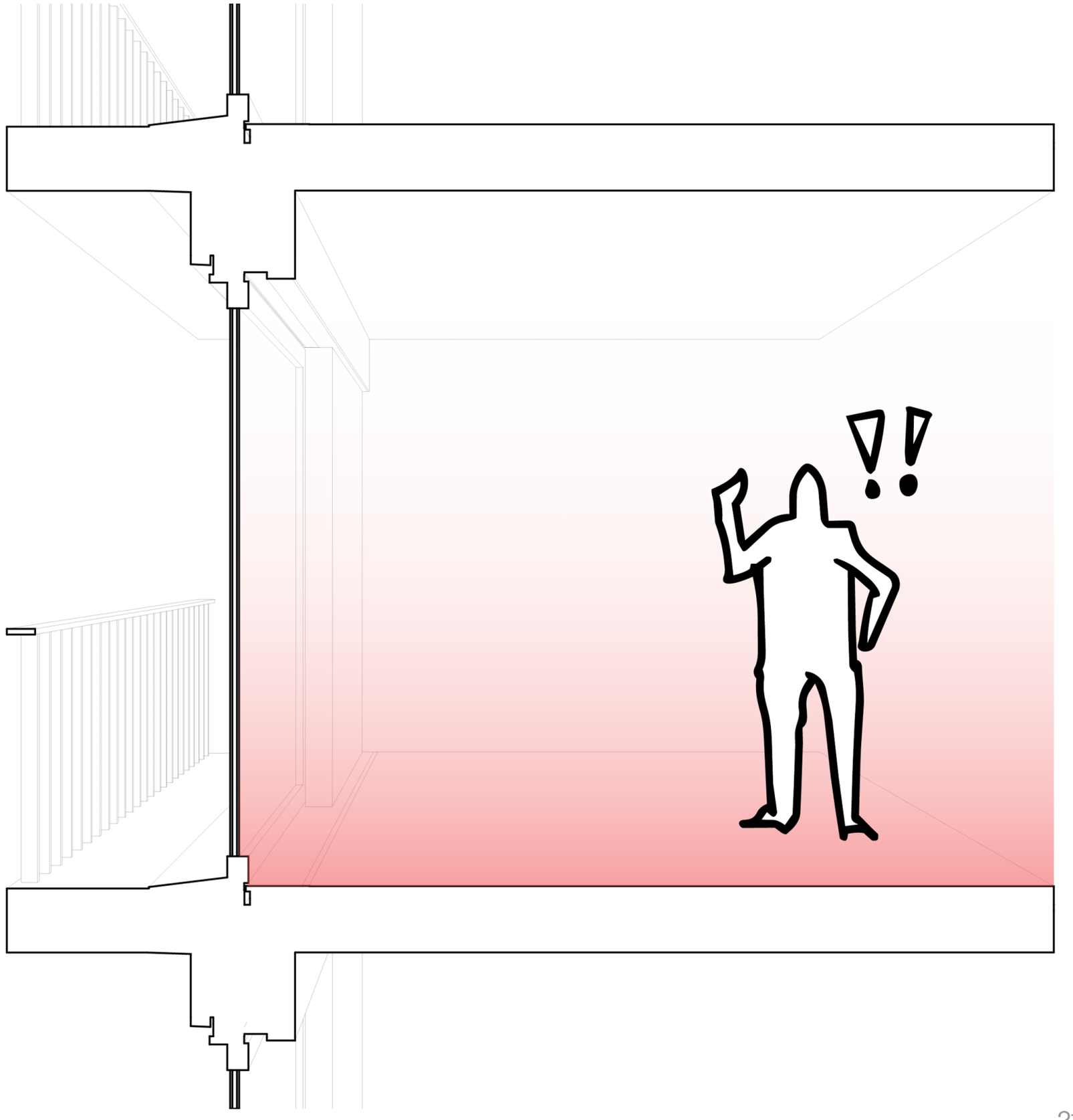
Single layer,
a system wide effect



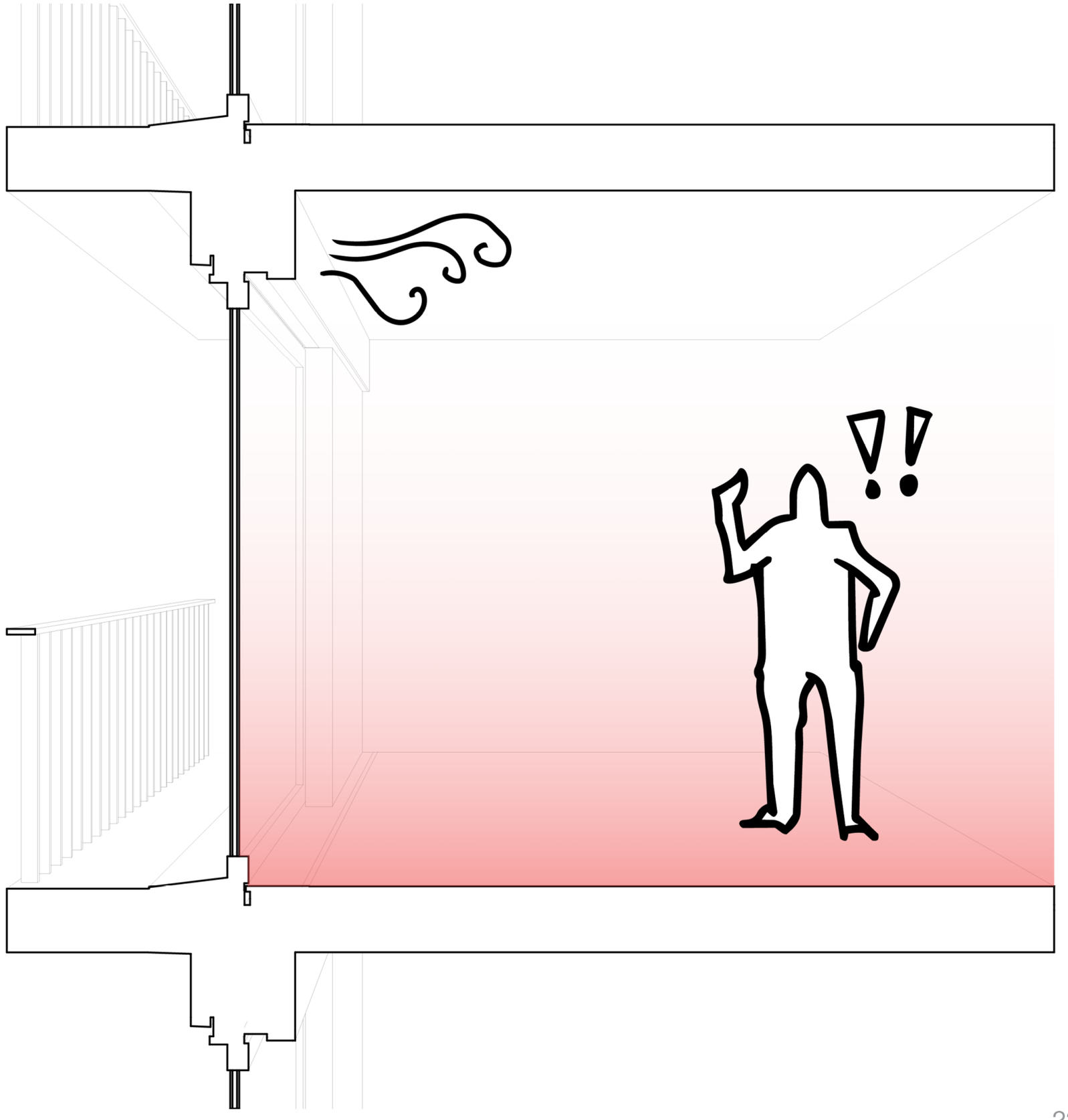
Extreme Heatwave causes



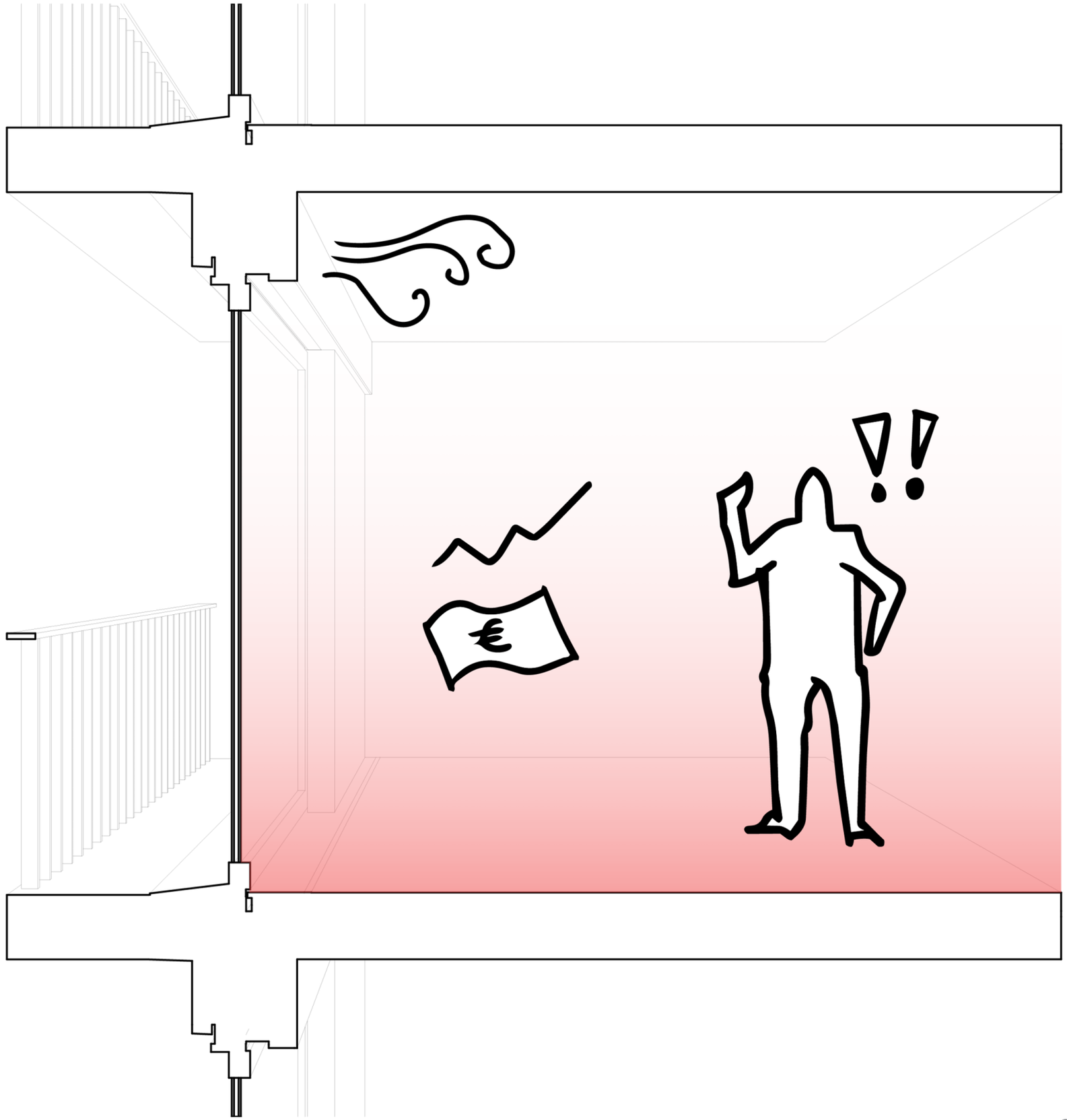
Discomfort



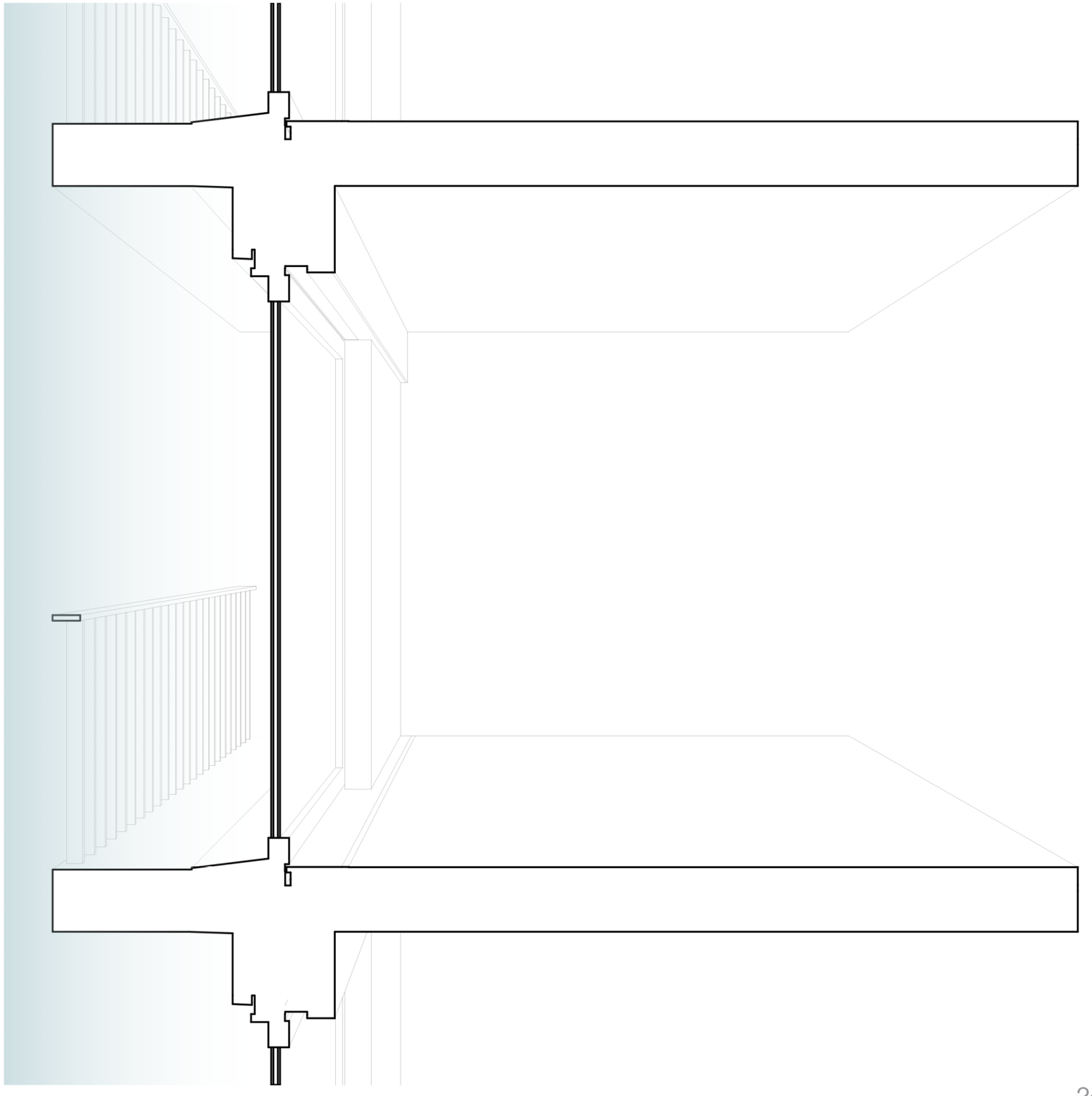
More Energy Consumption



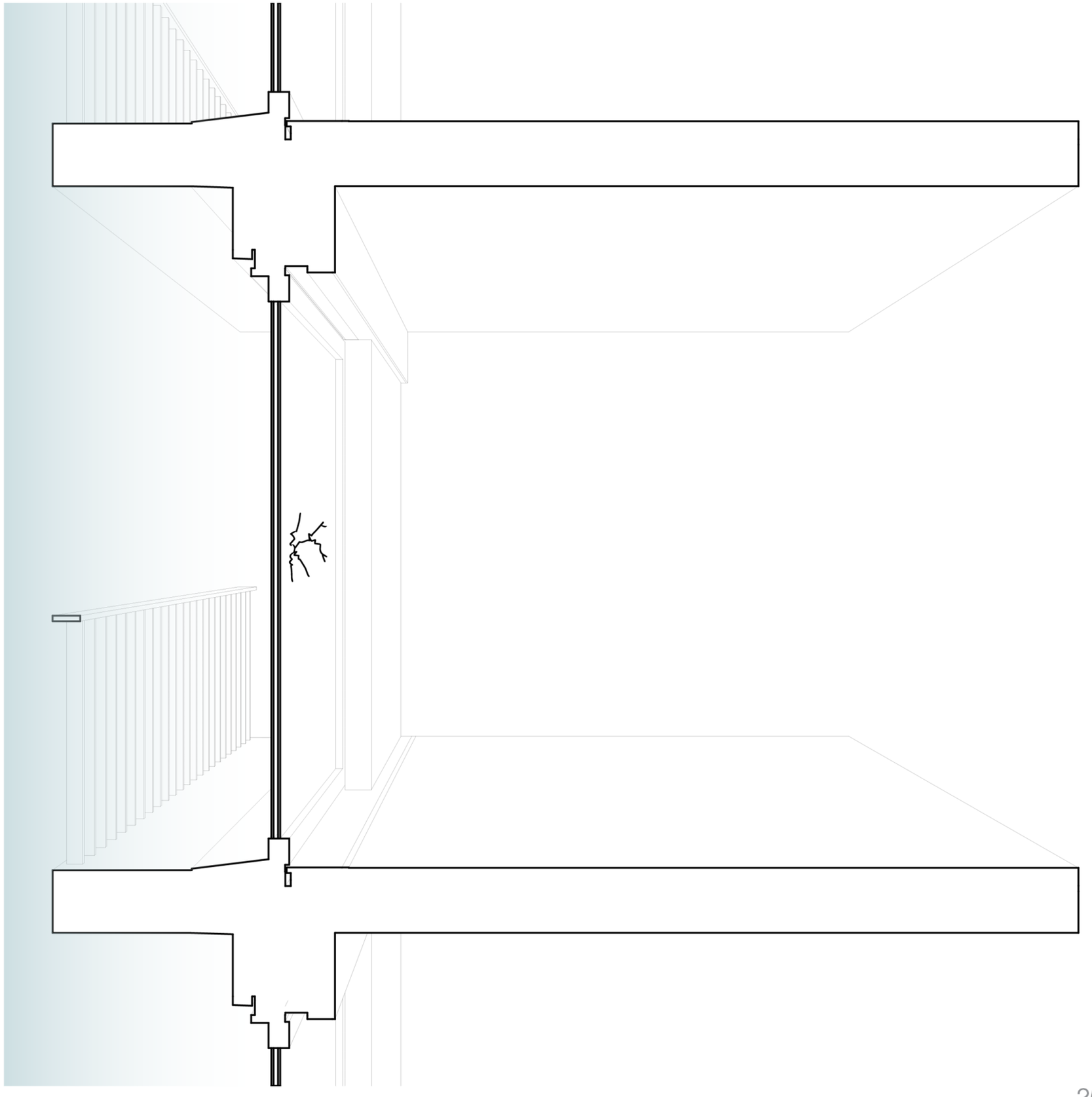
More Energy Cost



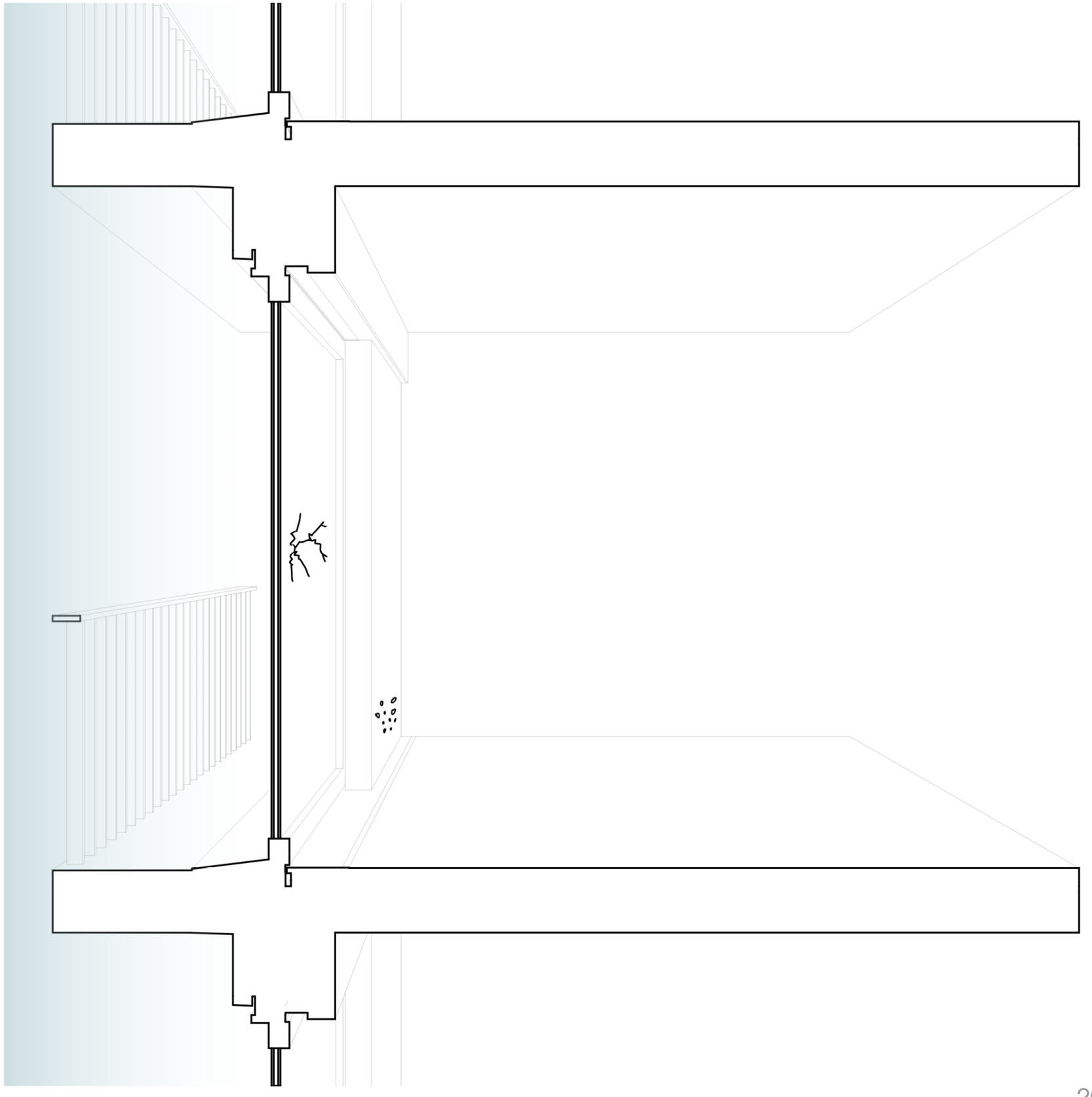
Extreme Wind Event causes



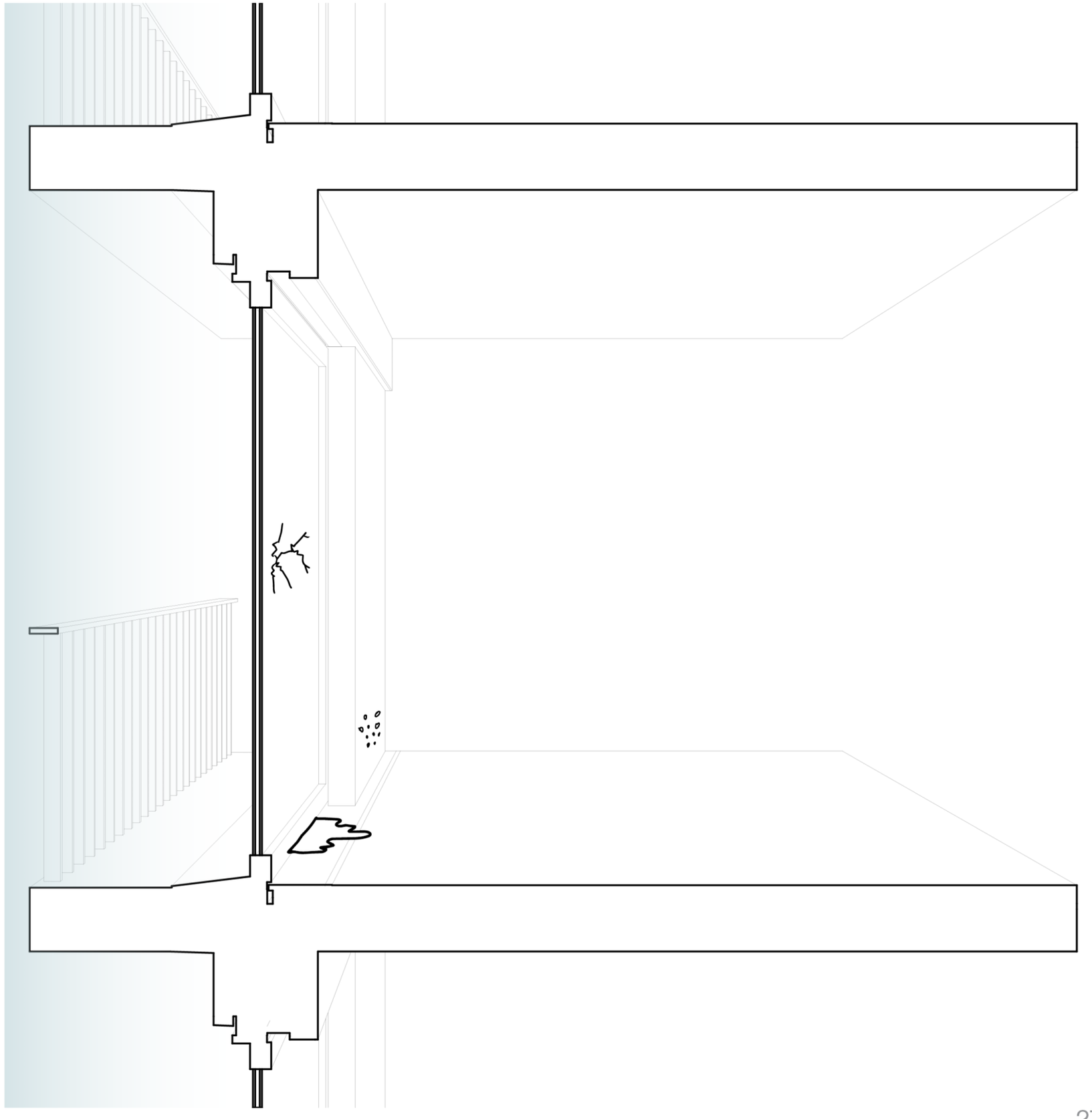
Facade Failure

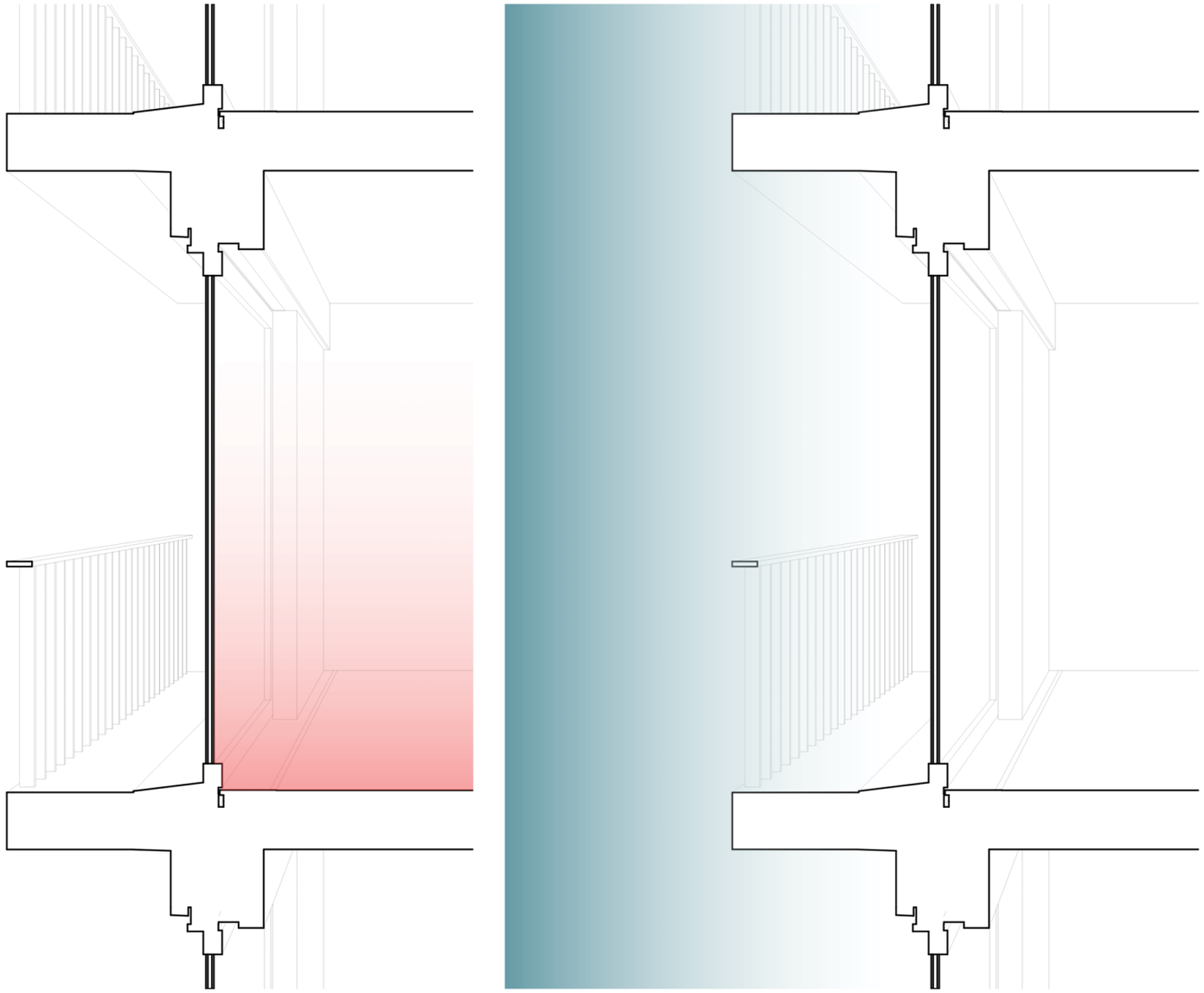


Moisture Accumulation



Rainwater Ingress





Why Multi-Hazard?

It can happen sequentially

Why Multi-Hazard?



Understanding multi-hazard risk is crucial for disaster preparedness, as different hazards can interact, amplifying their impacts and requiring integrated mitigation strategies.

Gacu et al., "Integrated Multi-Hazard Risk Assessment under Compound Disasters Using Analytical Hierarchy Process (AHP)."



Many areas of the world are prone to several natural hazards, and effective risk reduction is only possible if all relevant threats are considered and analyzed

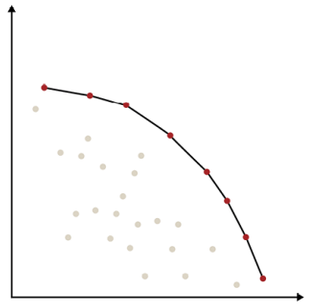
Kappes et al., "Challenges of Analyzing Multi-Hazard Risk."

Problem Statement

Current façade design workflows lack the **computational efficiency** and **multi-hazard** framework necessary to systematically **balance** the non-linear **trade-offs** between thermal and wind resilience.

Research Question

How can **multi-objective optimization** approach be used to relate **façade design parameters** to **wind and thermal resilience metrics** and to **generate design options** that support designers in balancing trade-offs between multiple hazards?



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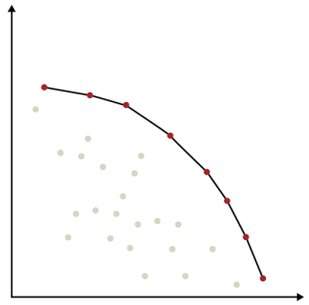

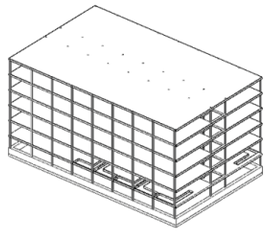

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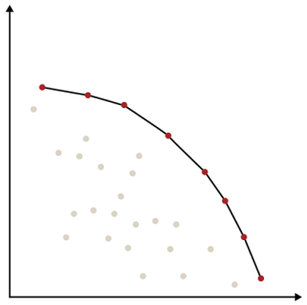

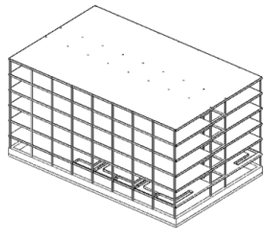

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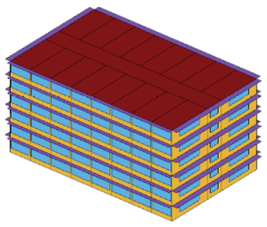

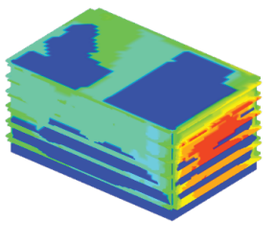

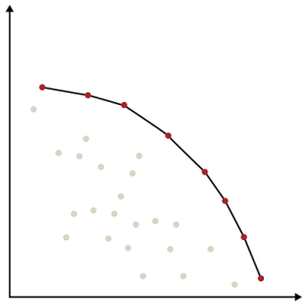

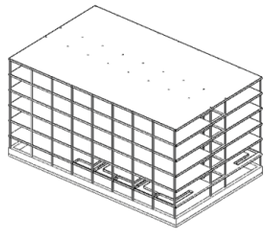

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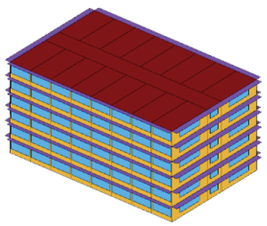
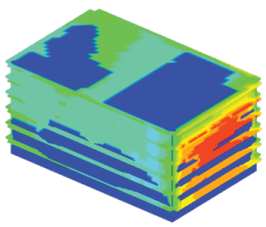
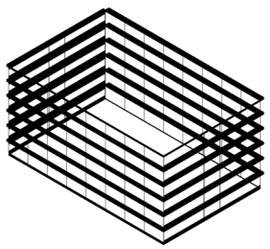




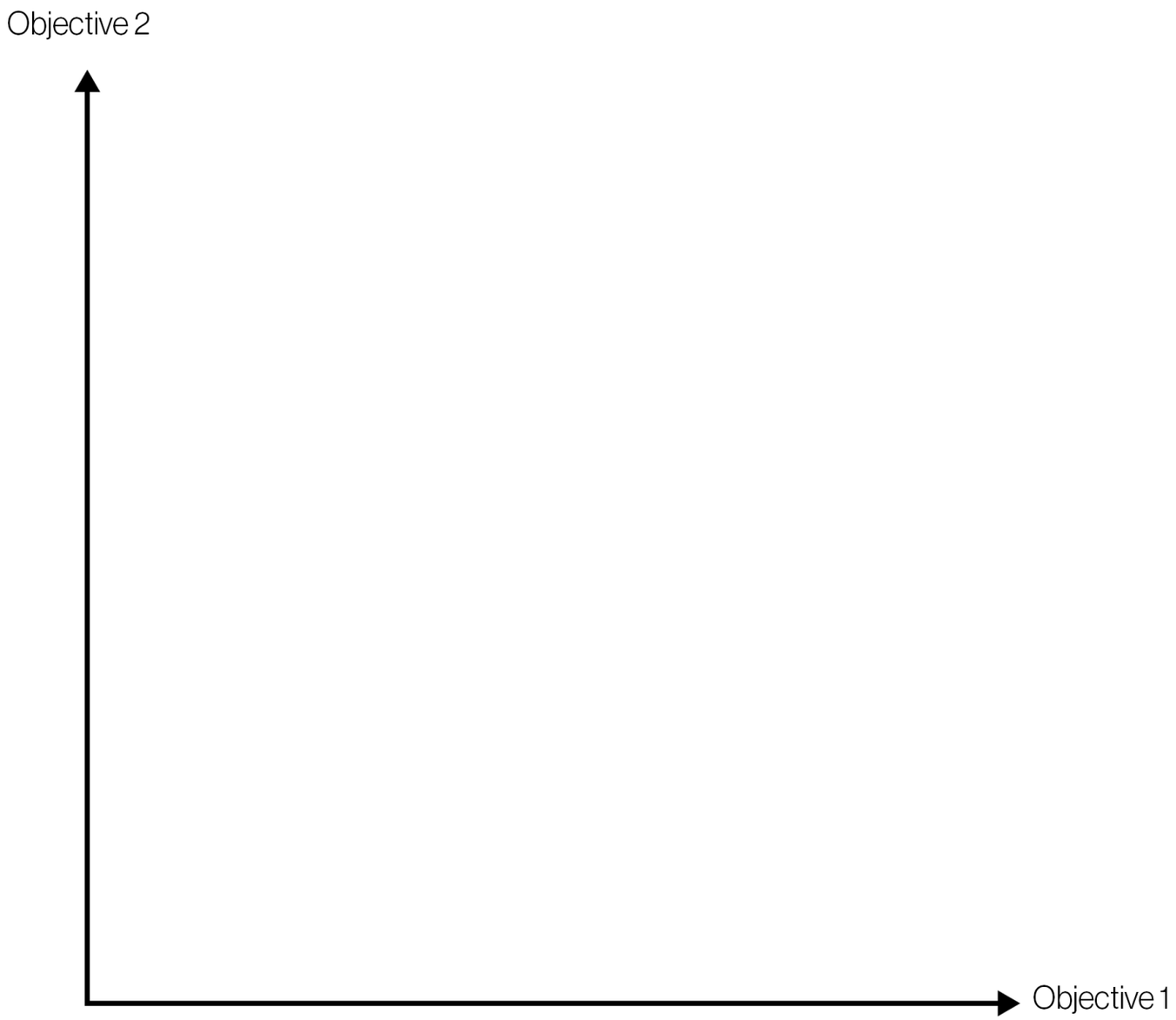


What is Multi-Objective Optimization?

Optimization with several objectives at the same time (often conflicting)

Why is it useful?

Real design problems rarely have a single objective; it reveals the trade-off surface, offers multiple high-quality alternatives instead of one “best” point, and supports informed decision-making when objectives conflict.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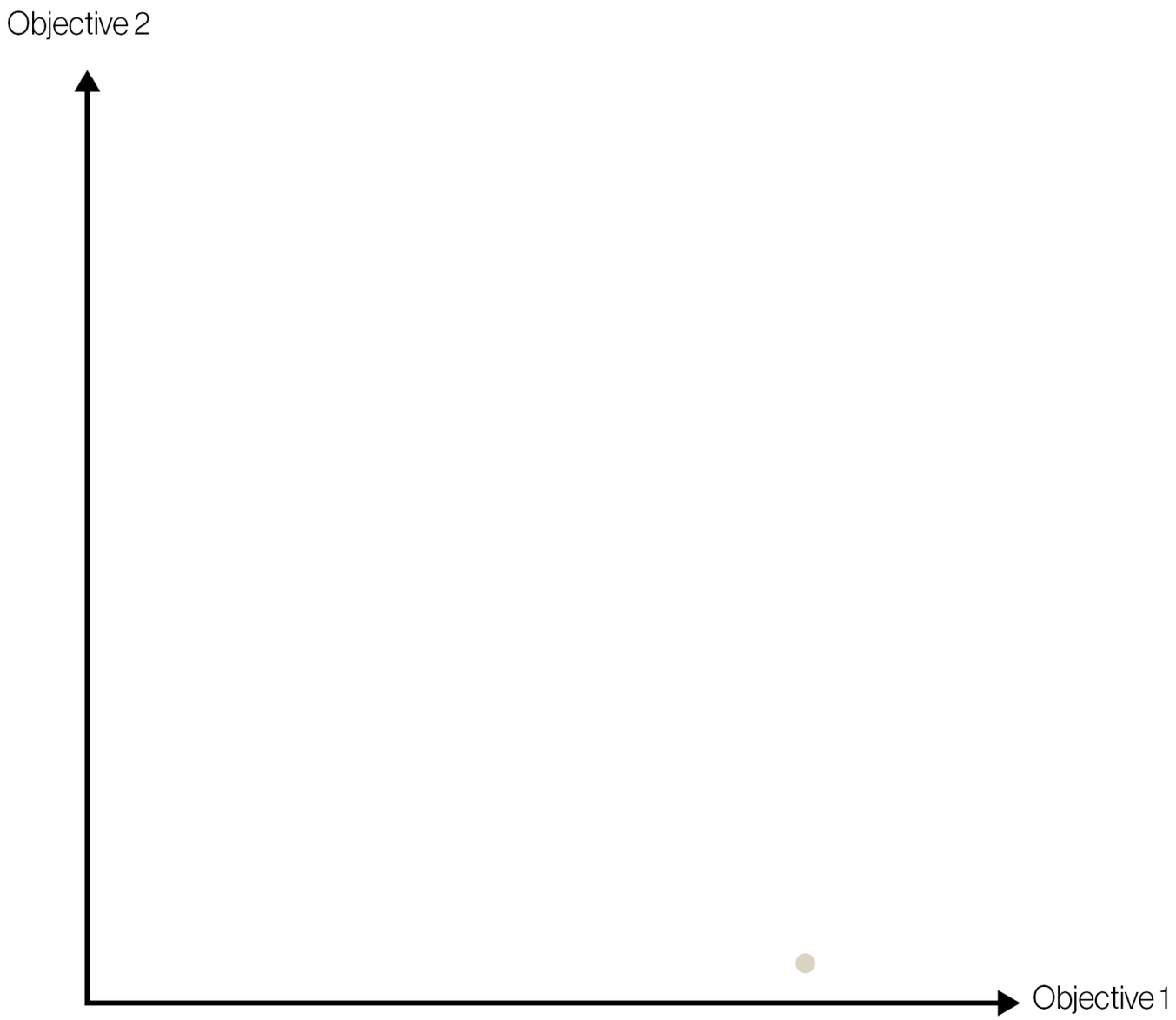
Objective 1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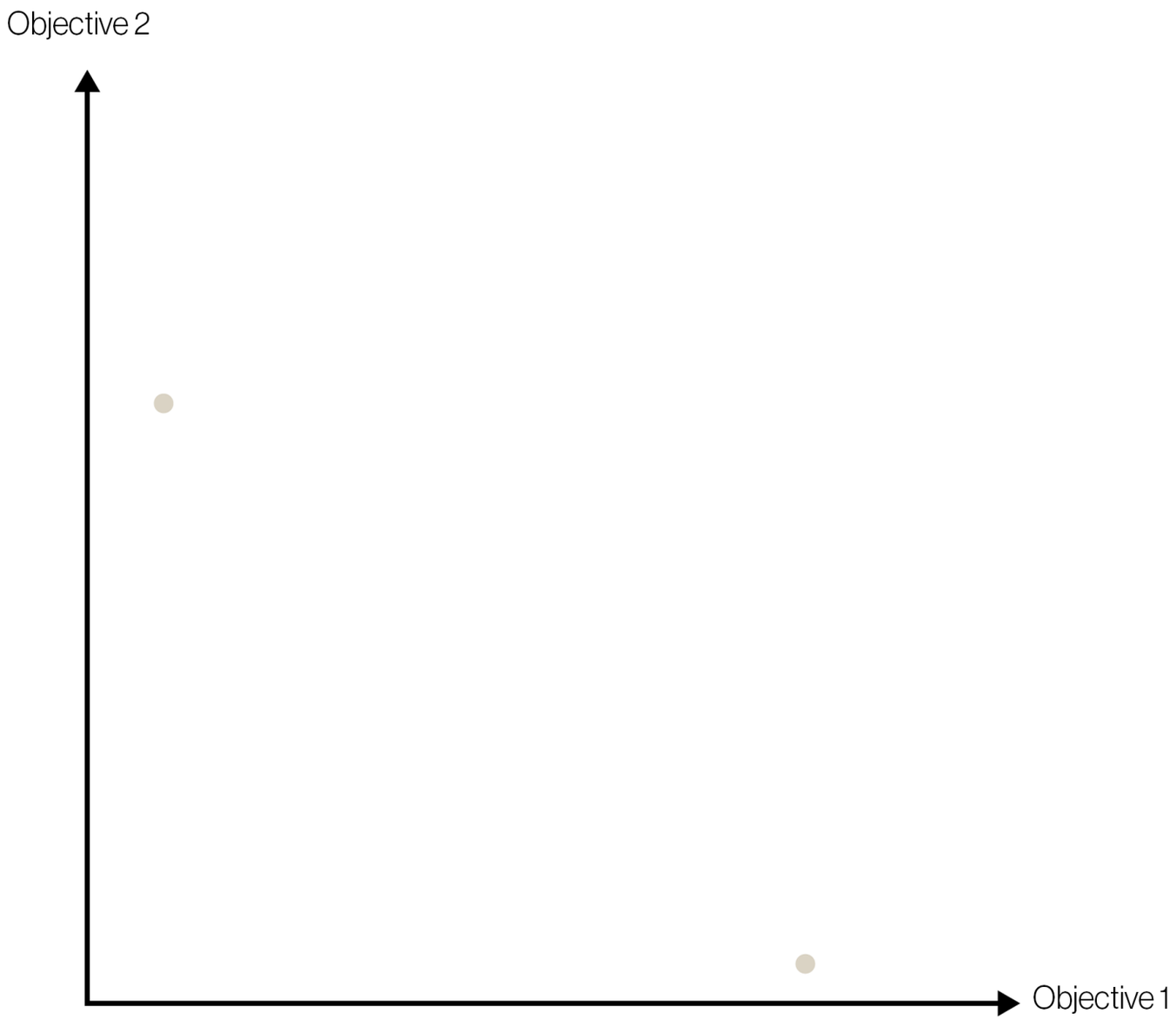
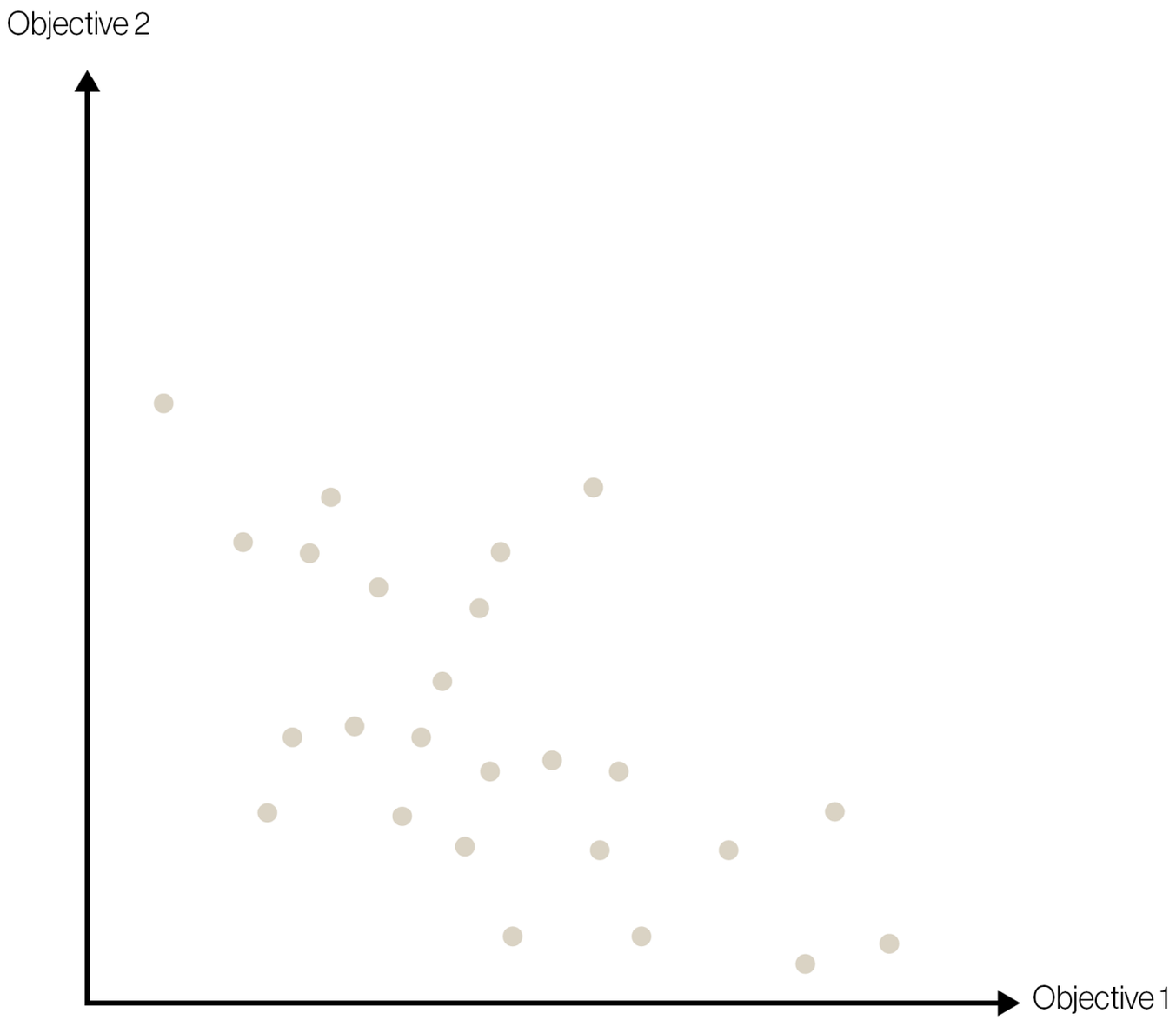

Objective 2
Objective 1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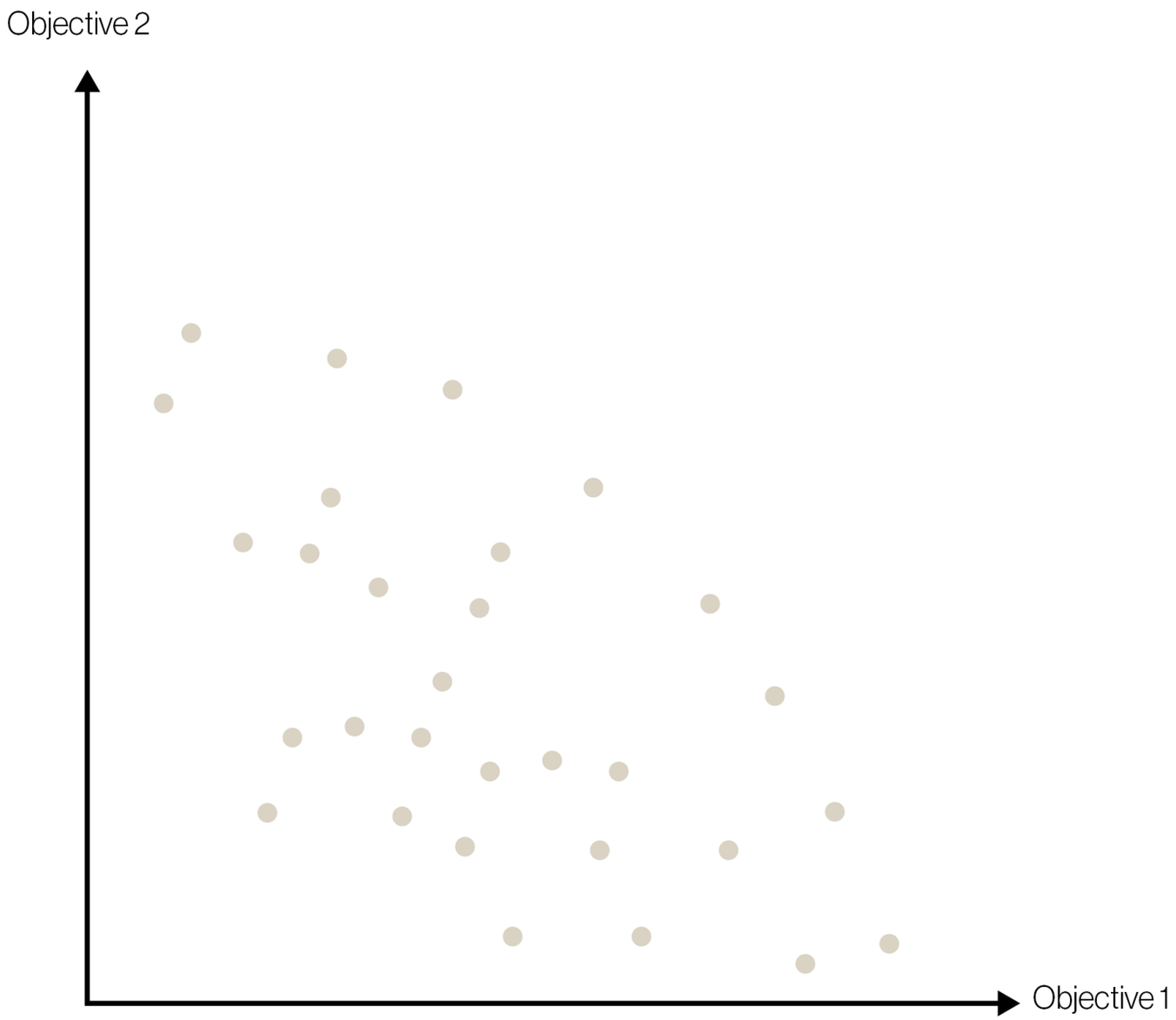
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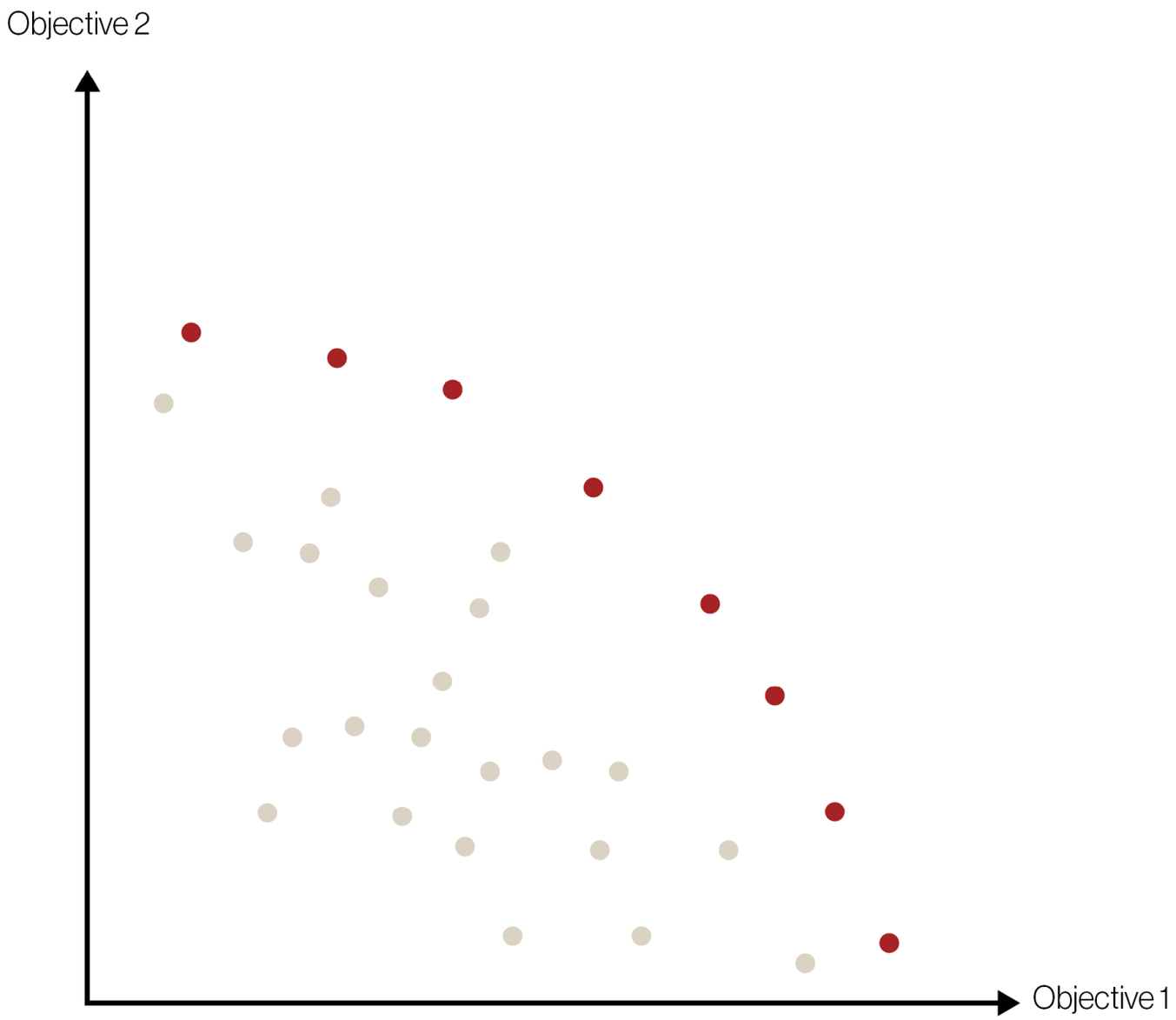
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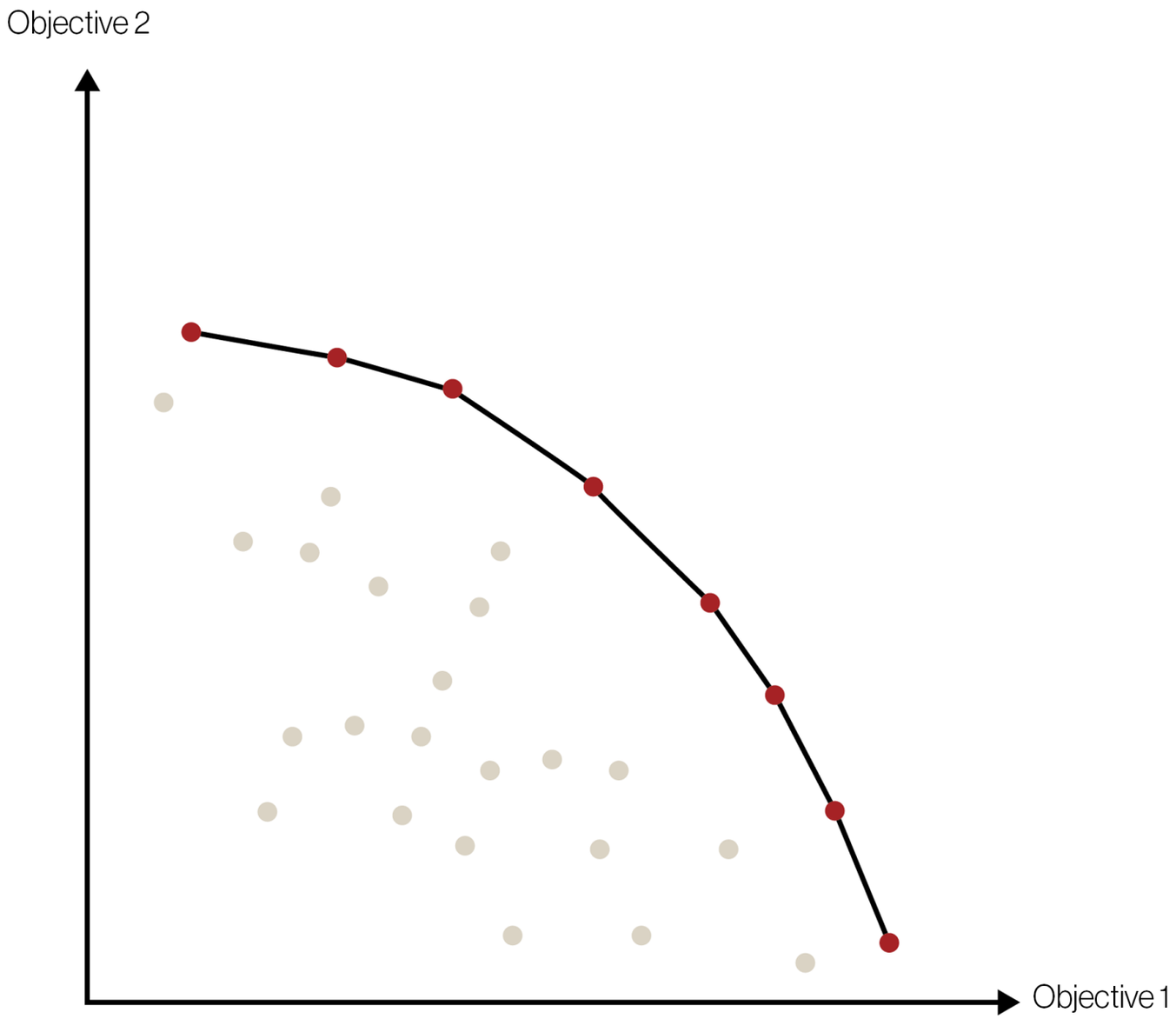
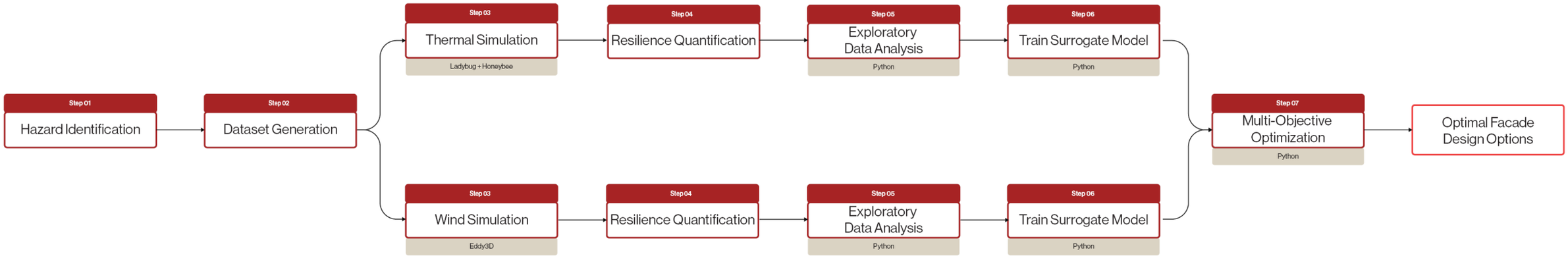

Objective 2
Objective 1

Resilence-Based + Multi-Objective Optimization

Facade Design Framework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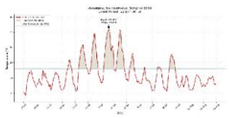

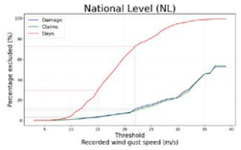

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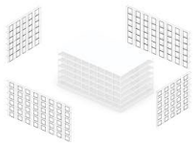

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Step 04

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Step 05

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Step 06

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Step 07

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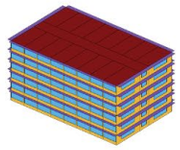

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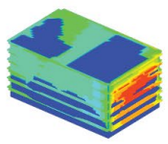



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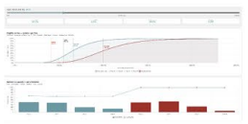



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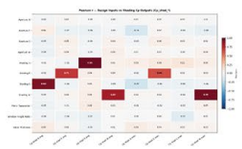

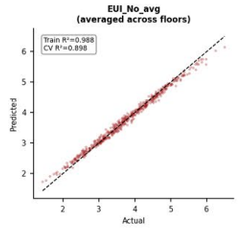

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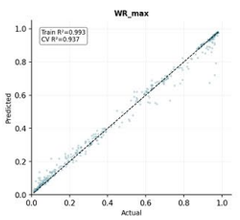

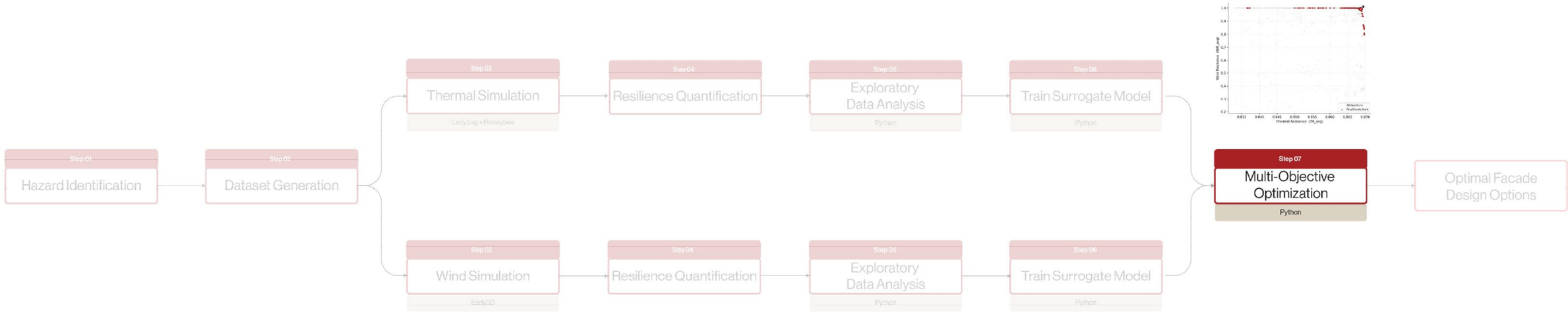
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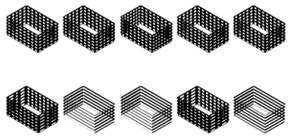

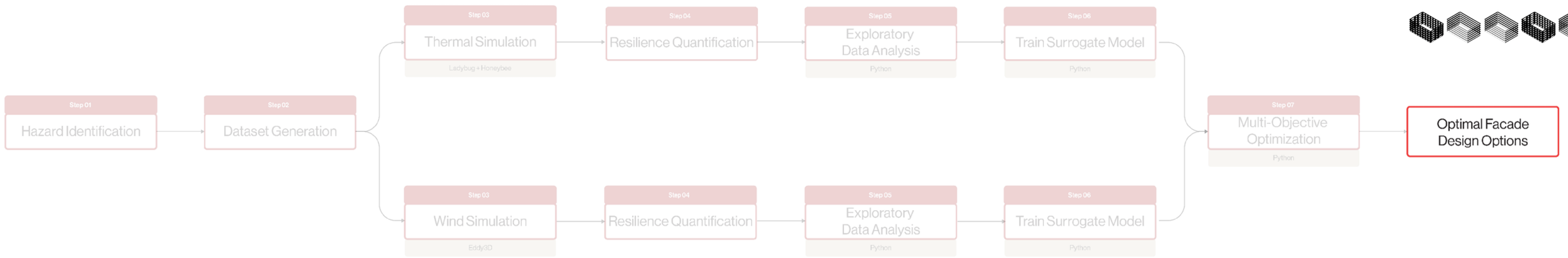
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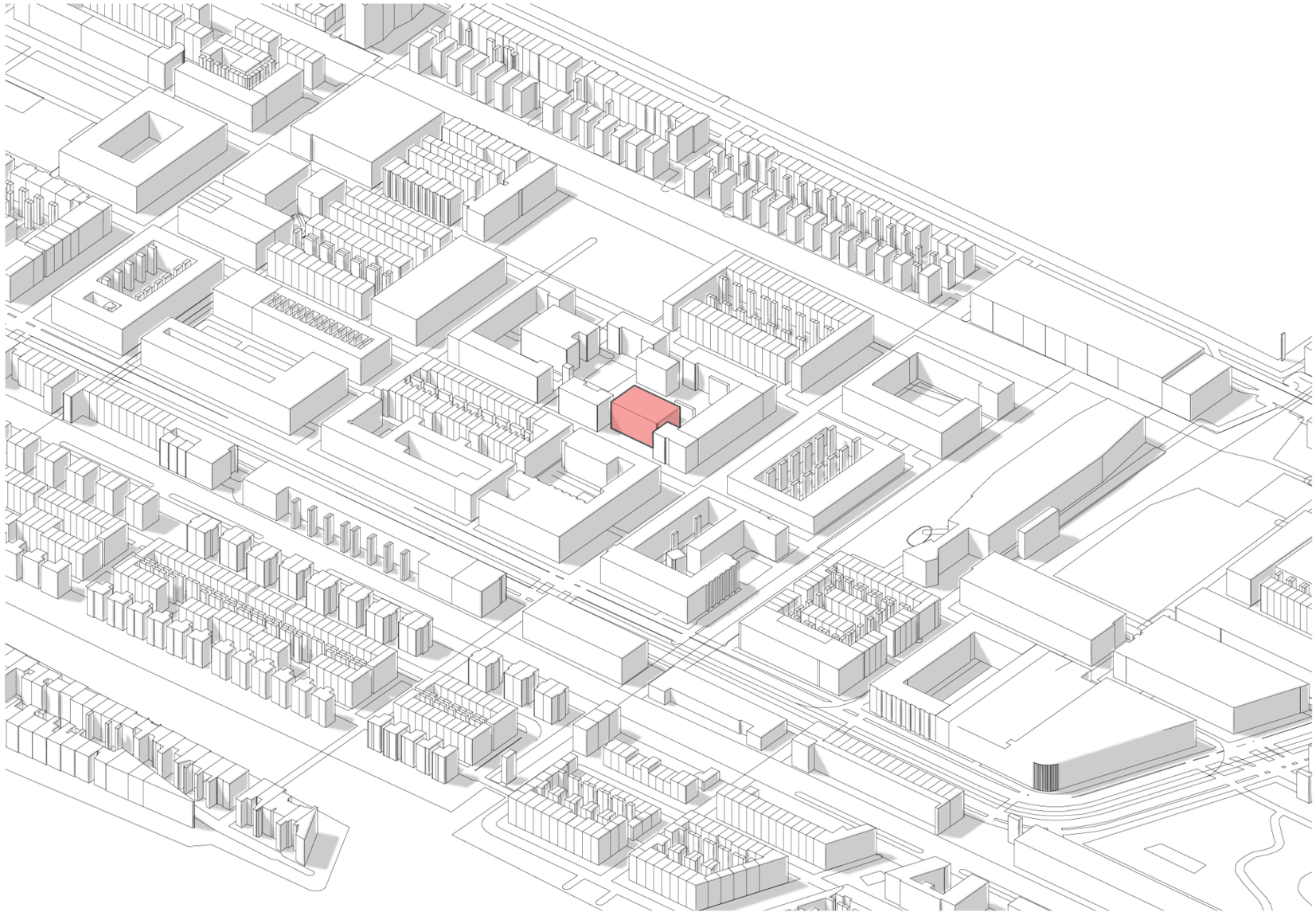
Case Study

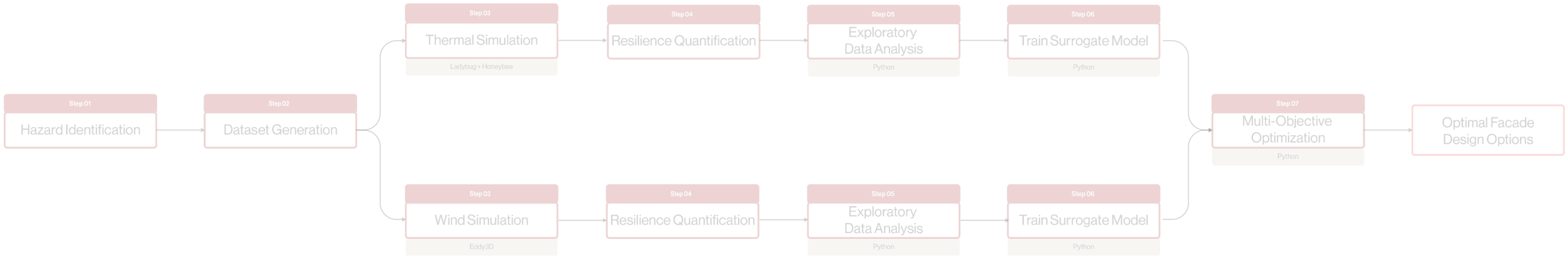
Residential Building

Location





Maria Austriastraat 9611087JB Amsterdam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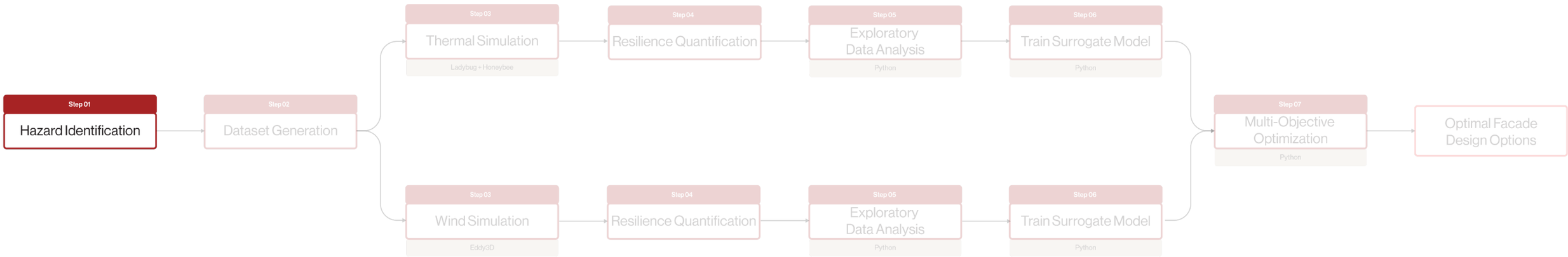
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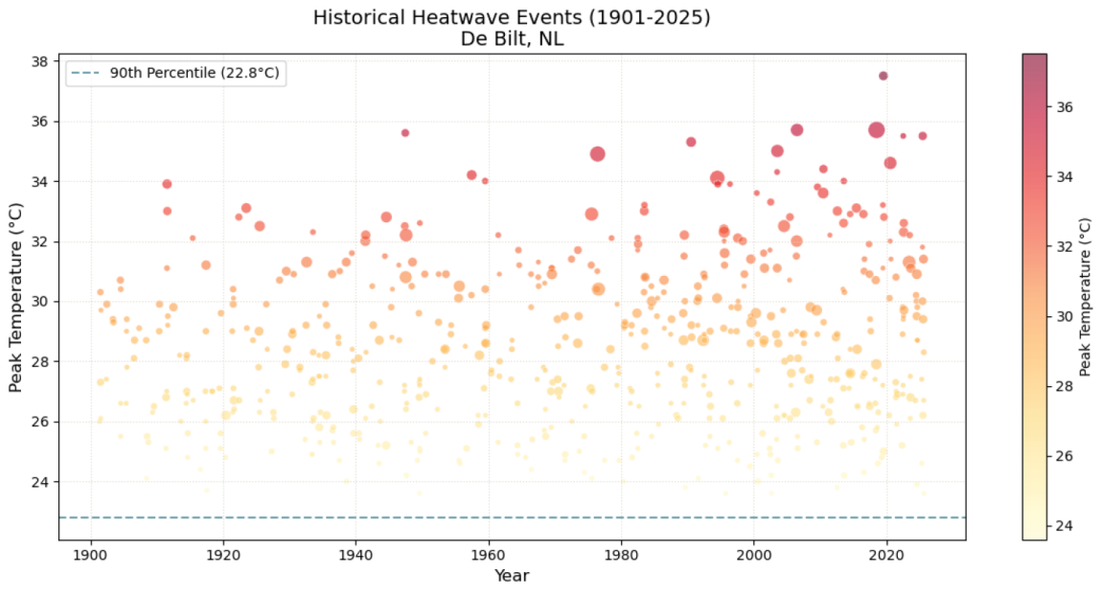
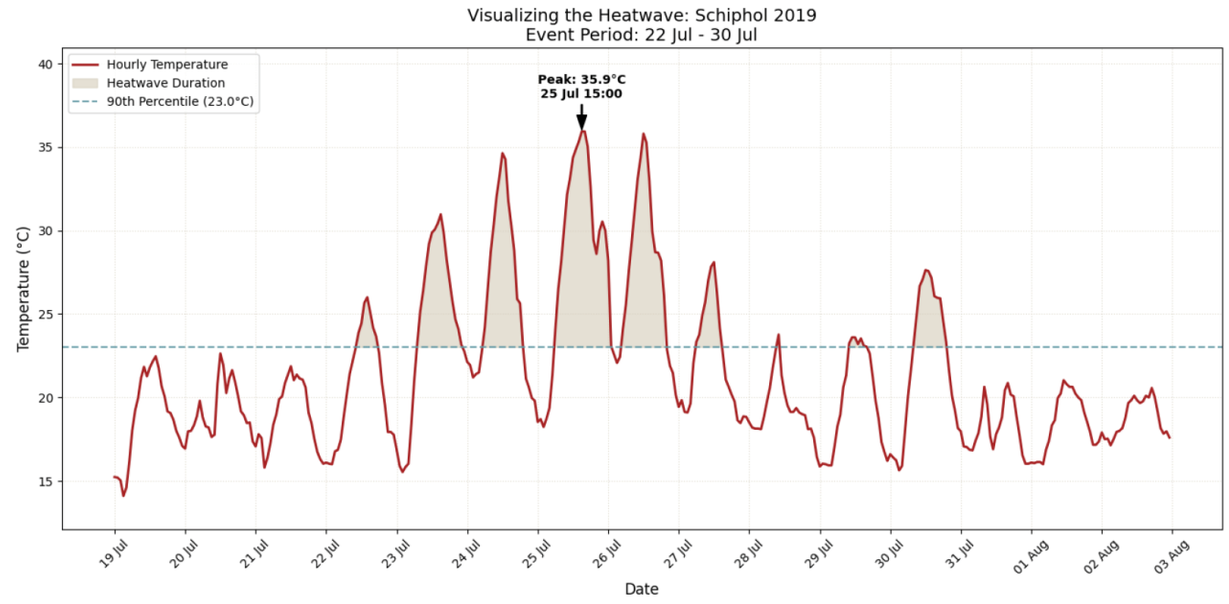
Hazard Identification

Heatwave





Period when the maximum daily temperature exceeds the 90th percentile for at least three consecutive days. (CTX90pct)

The most exreme heatwave was found during 22 Jul - 30 Jul 2019

Hazard Identification

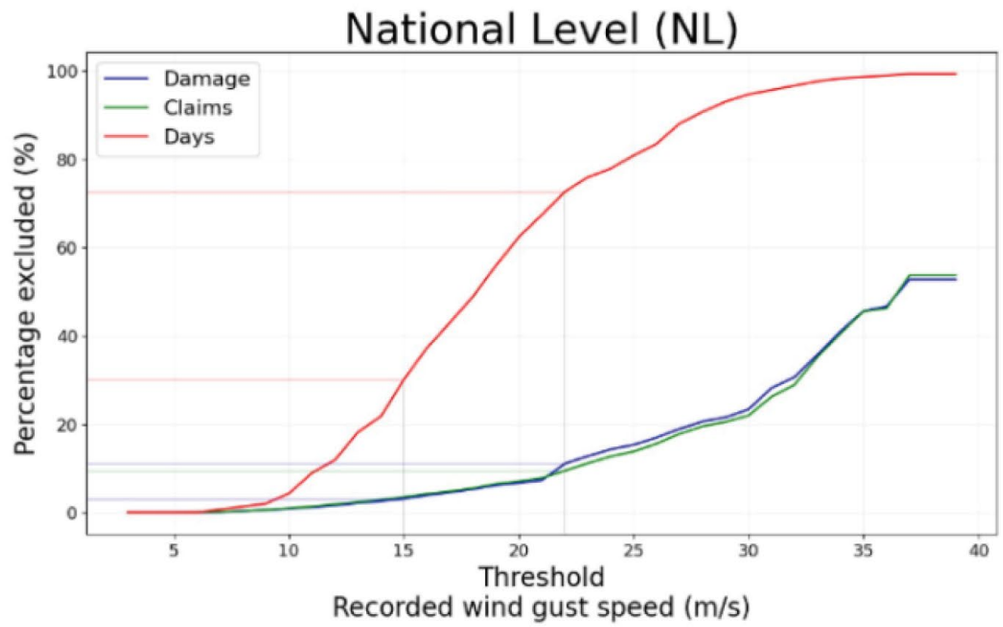
Extreme Wind Event Identification

Wind Direction

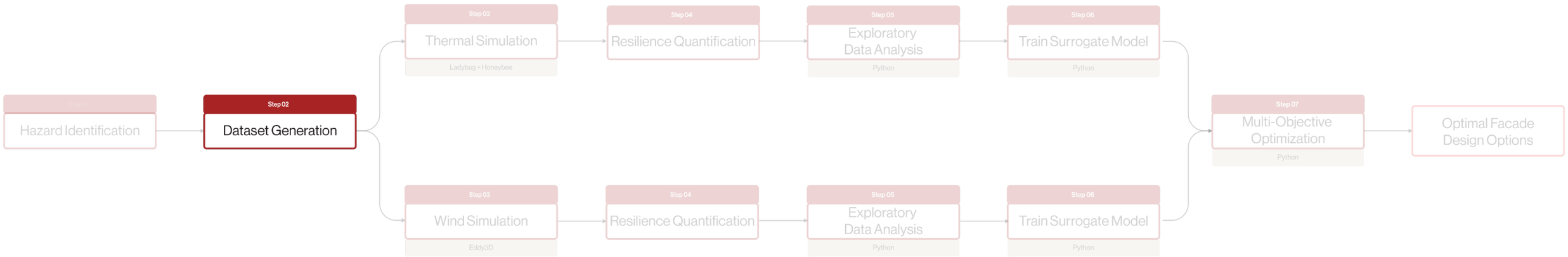


(Pérez-Bella et al., 2025)

Wind Velocity



(Fonseca Cerda et al., 2025)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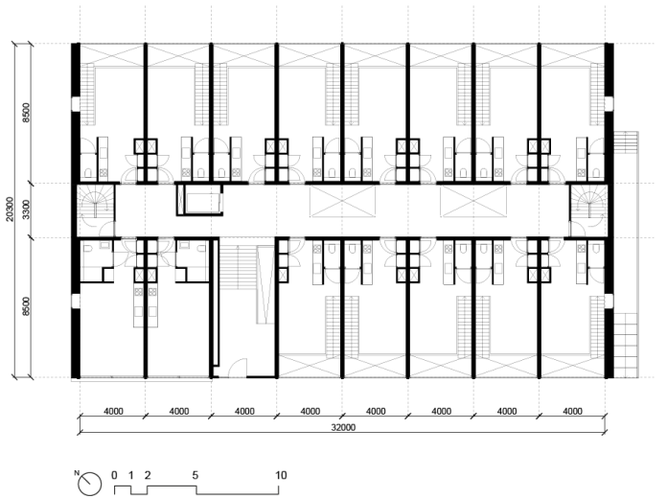
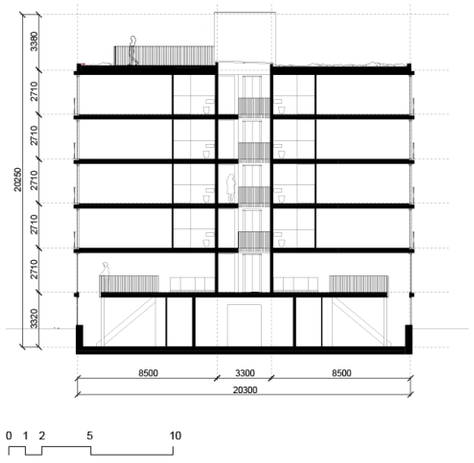
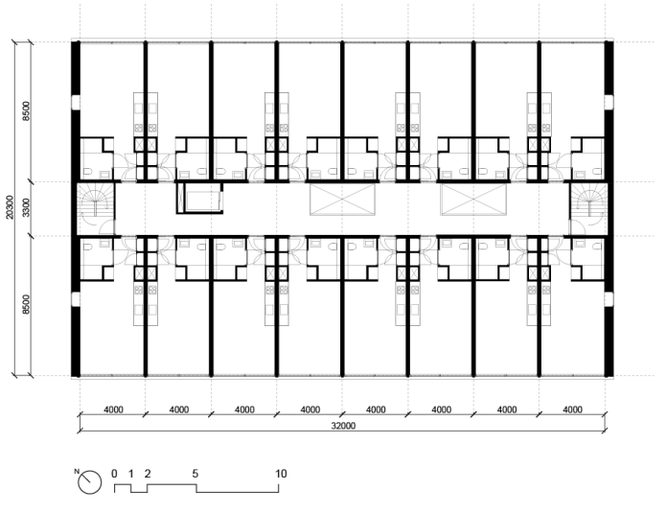
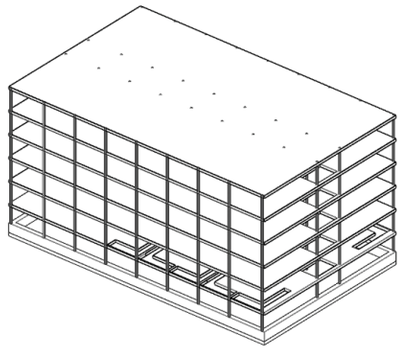
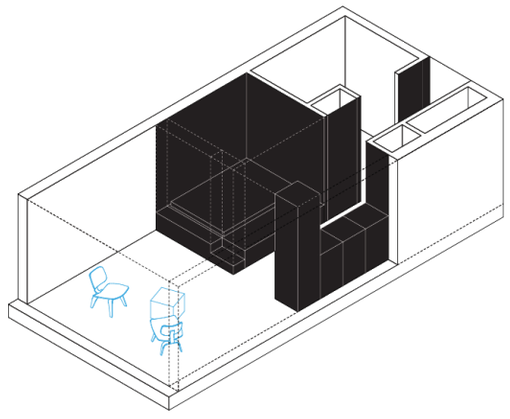


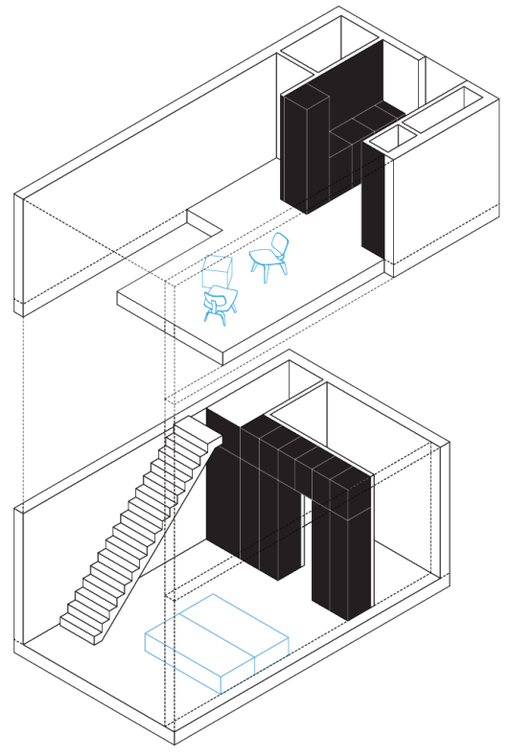








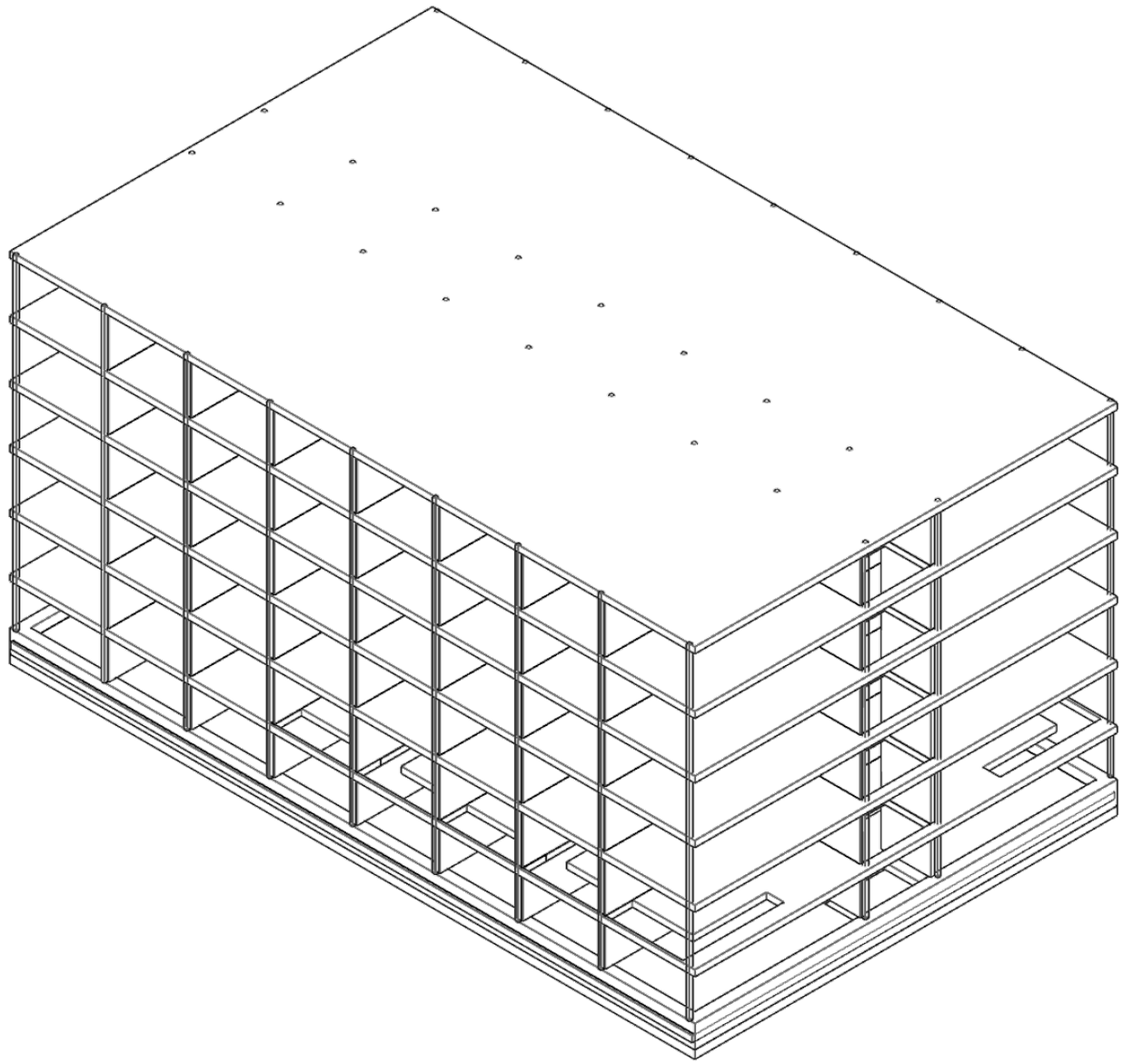
MICROAPPARTEMENT | 66 STUKS | CA. 30 M2



MAISONETTE | 13 STUKS | CA. 50M2

Dataset Generation

Case Study Set up



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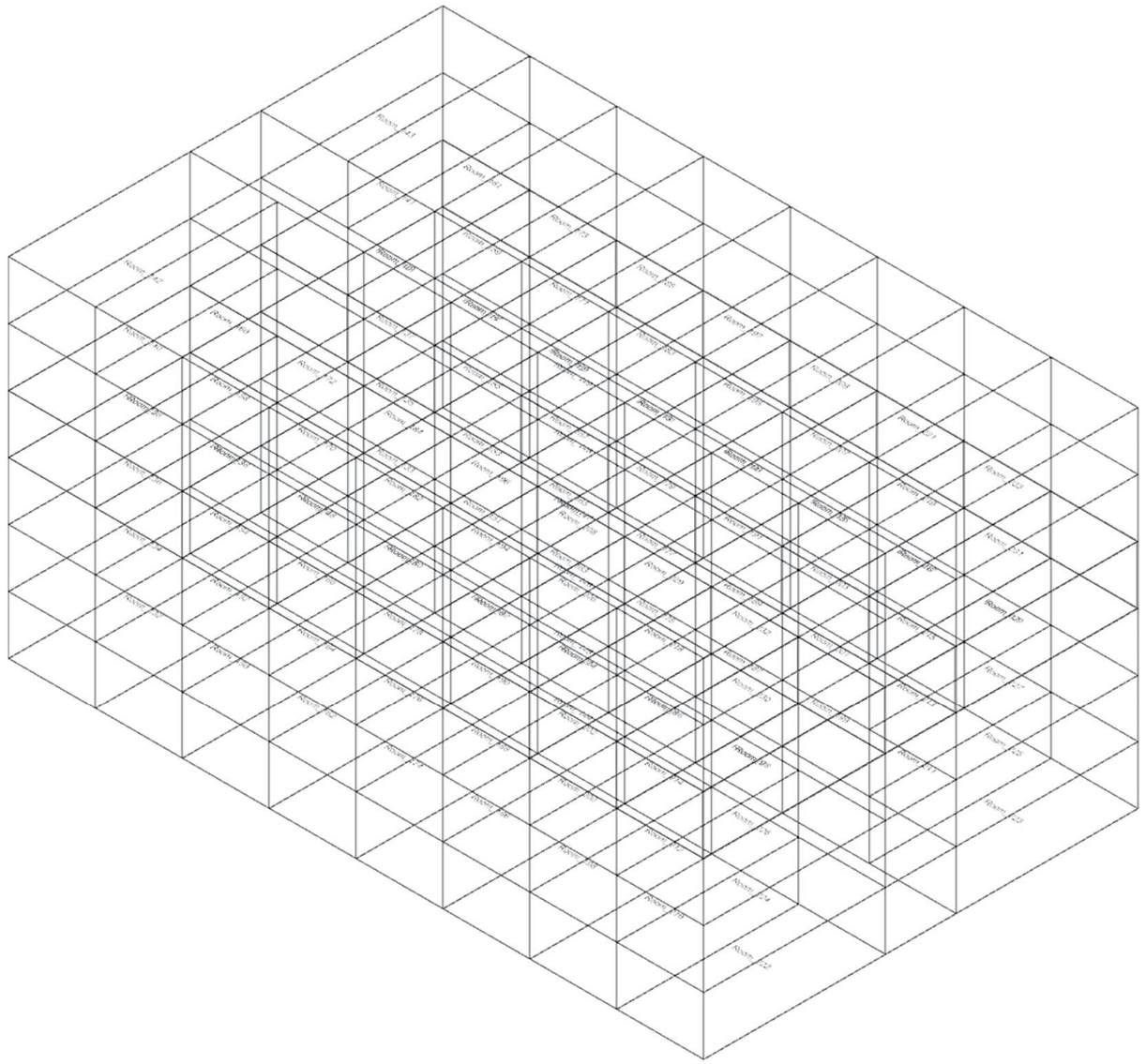
Case Study Set up



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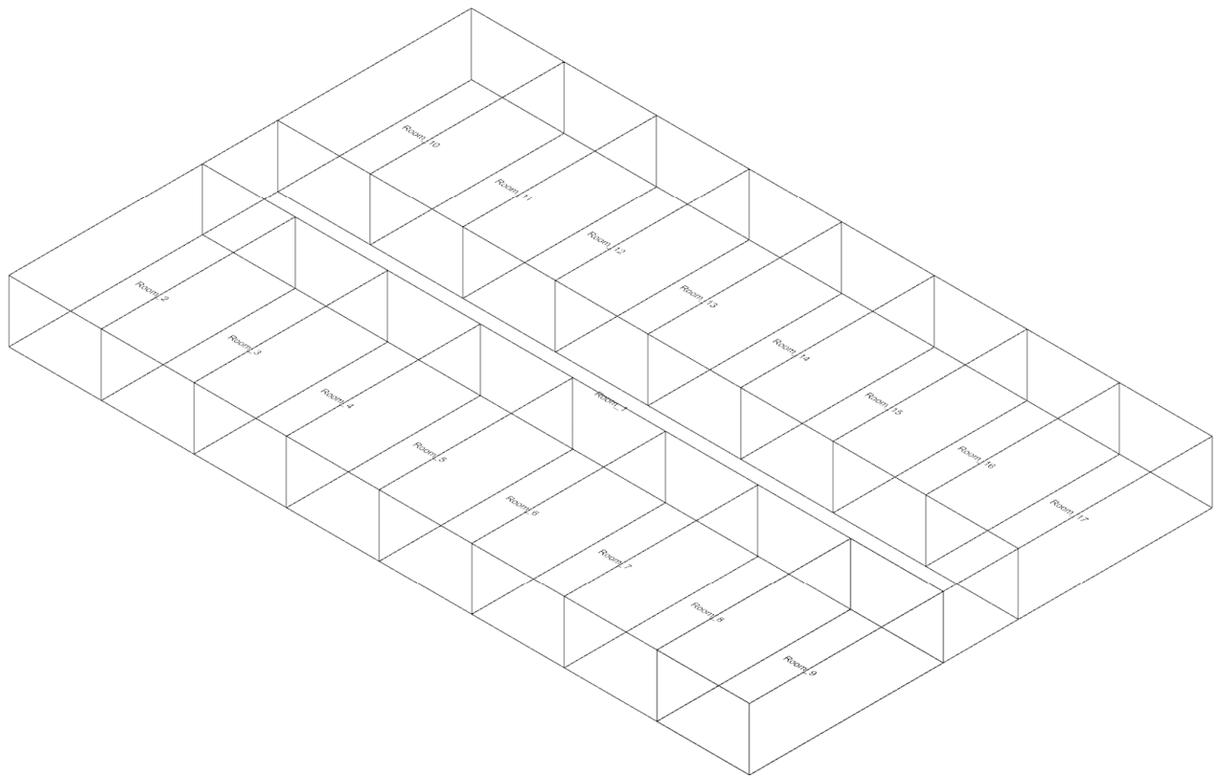

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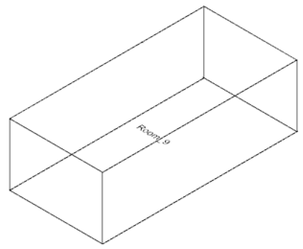

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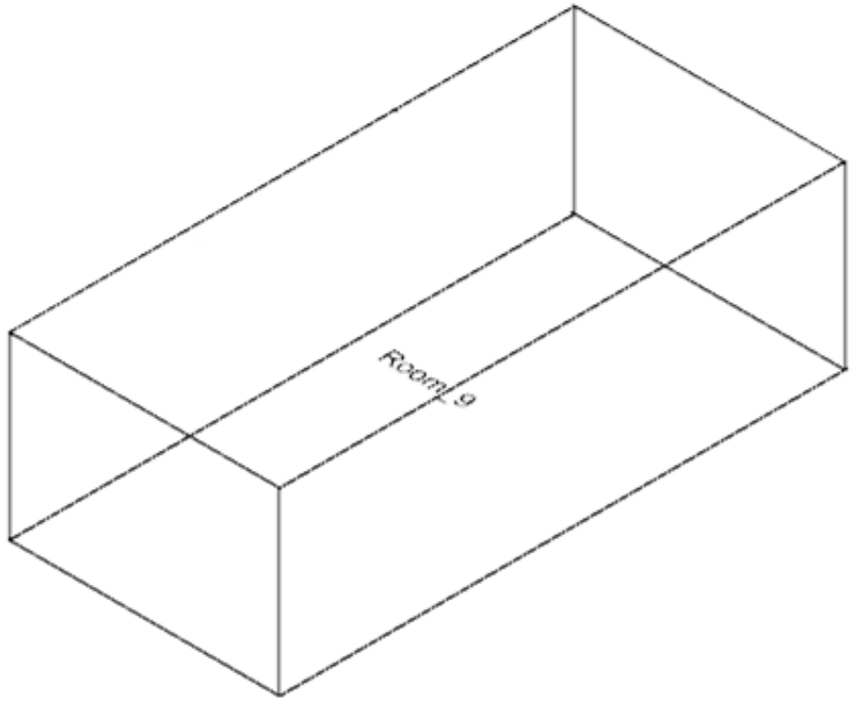
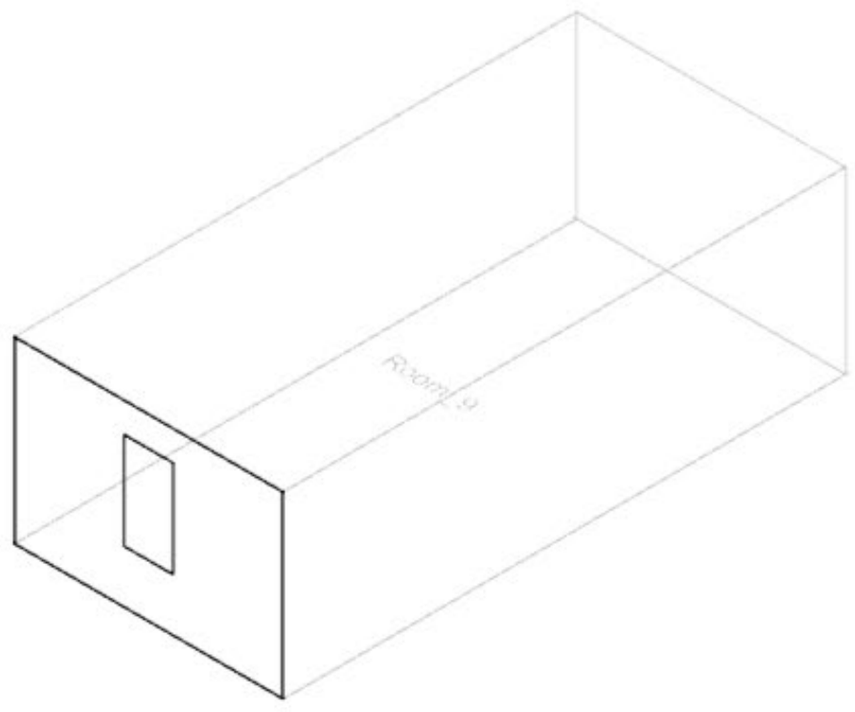


Dataset Generation

Facade Configuration





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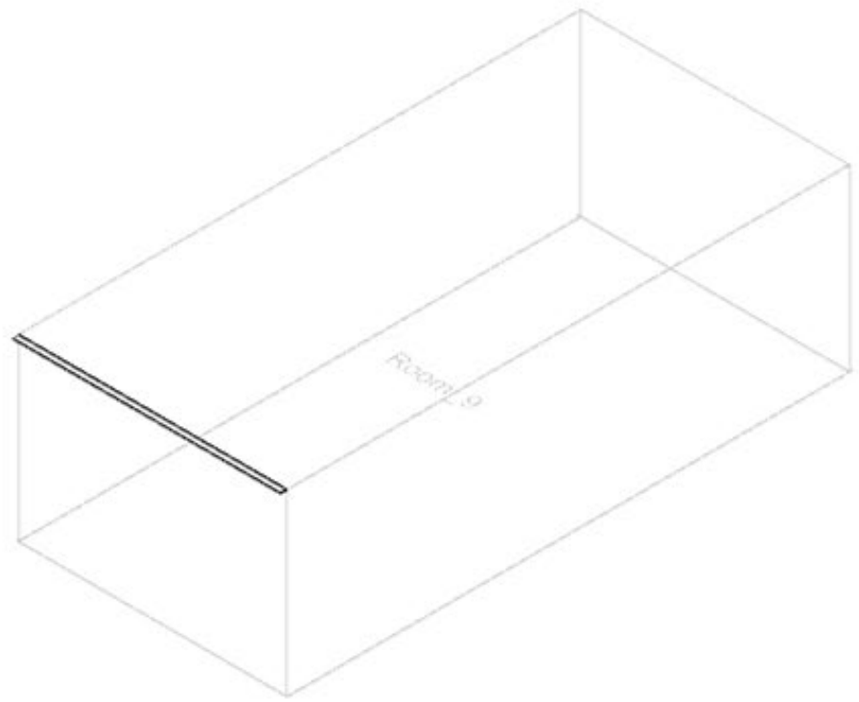

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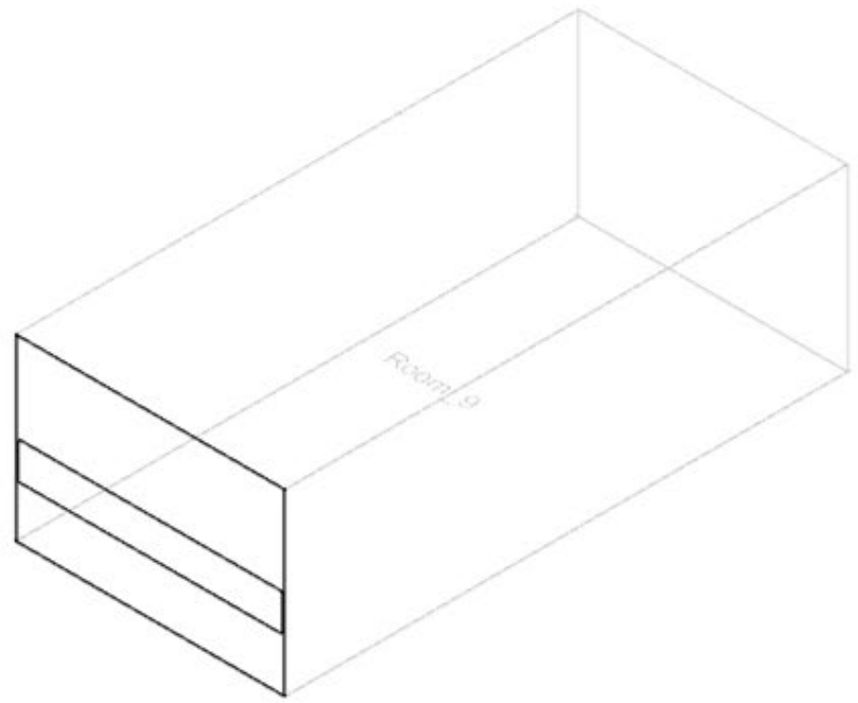

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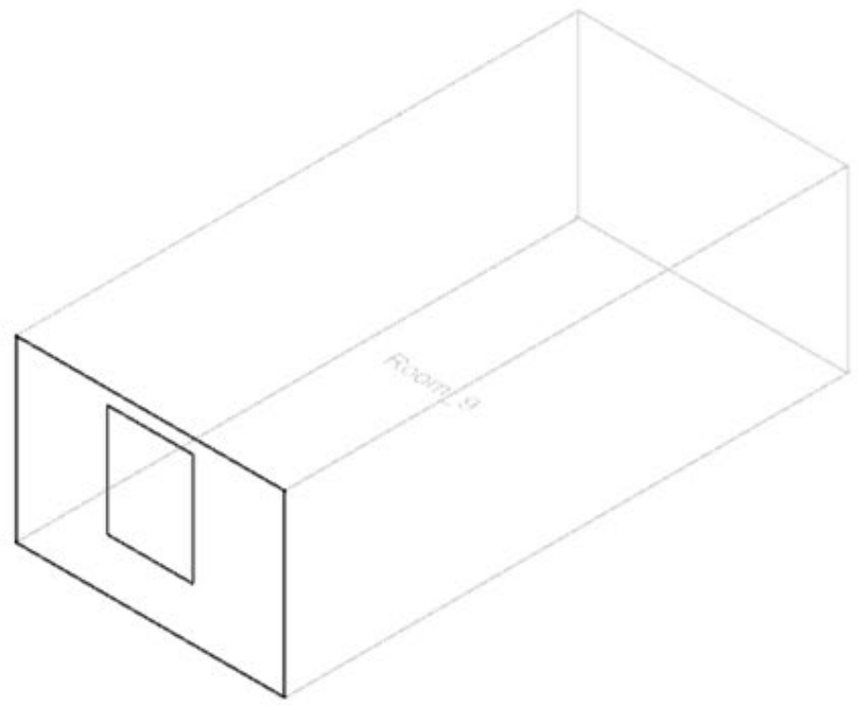

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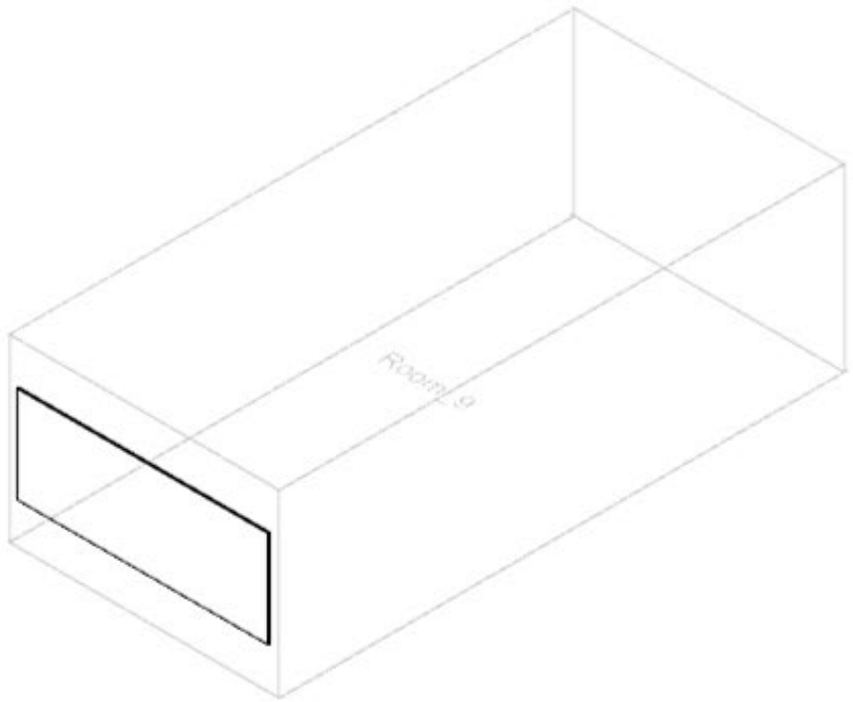


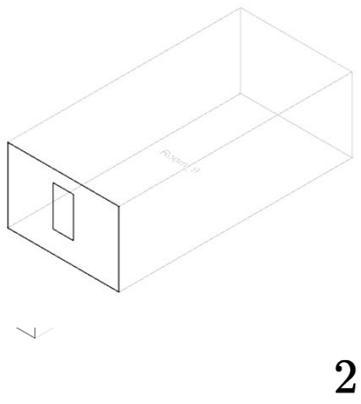


Dataset Generation

Facade Configuration

9^4





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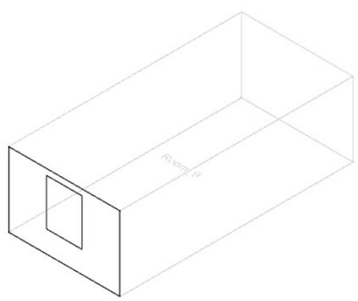

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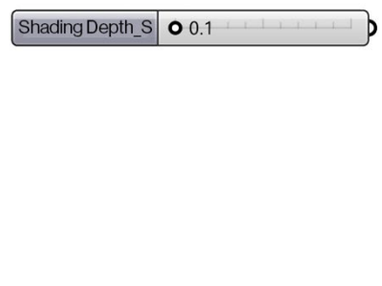

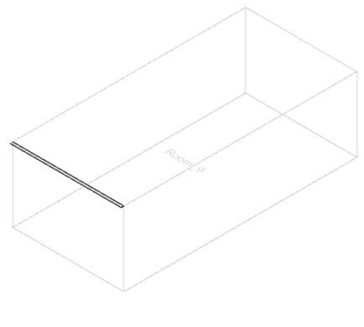

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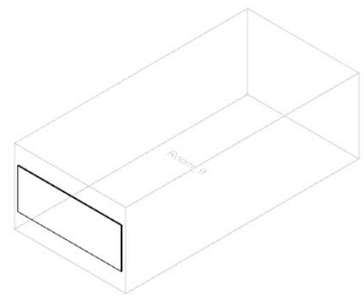

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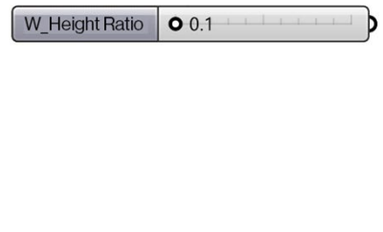
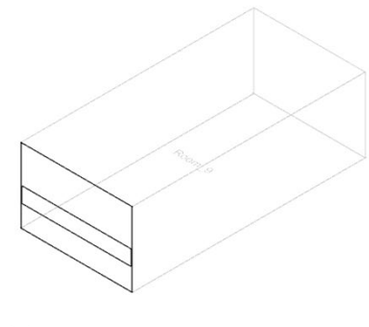




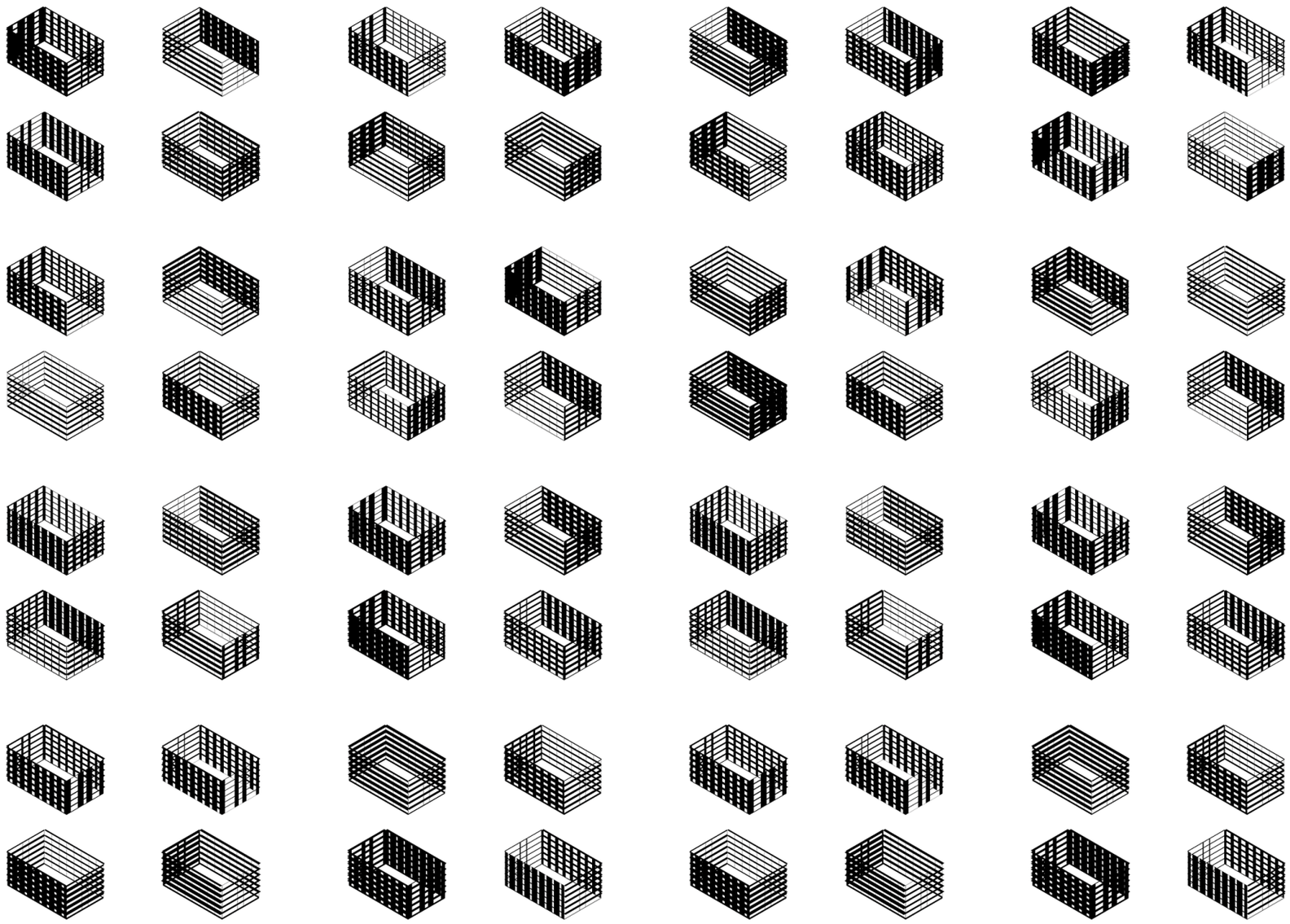
$$9^4 \times 10^4 \times 9 \times 2 \times 2 \; =$$

2.624.400.000

Over 2.6 billion configurations

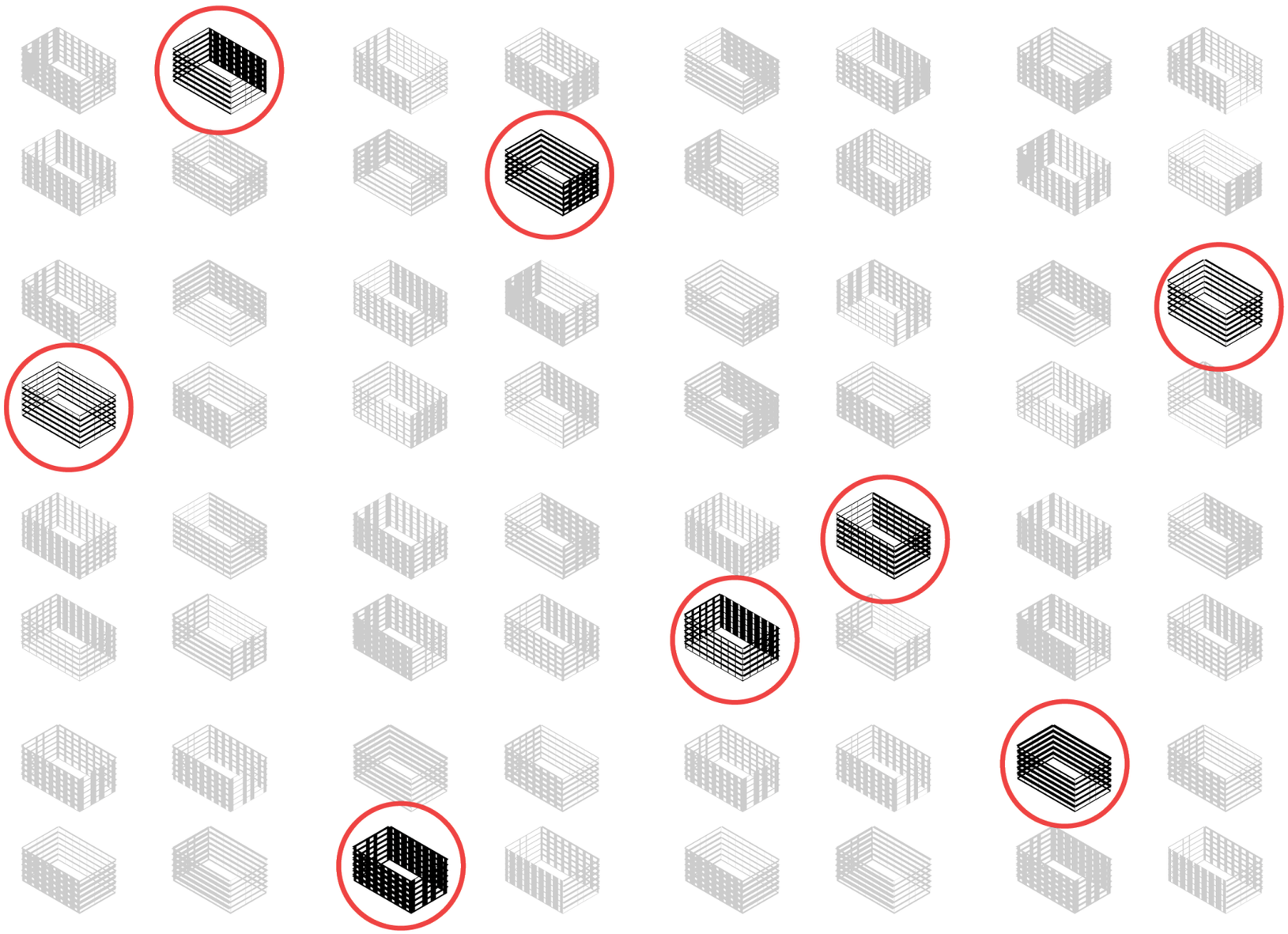
Dataset Generation

Latin Hypercube Sampling



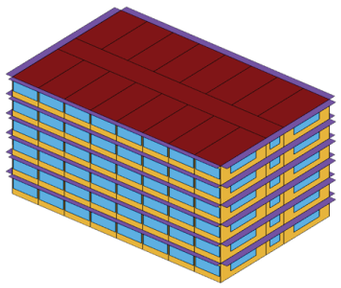
Dataset Generation

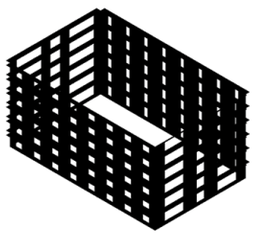
Latin Hypercube Sampling



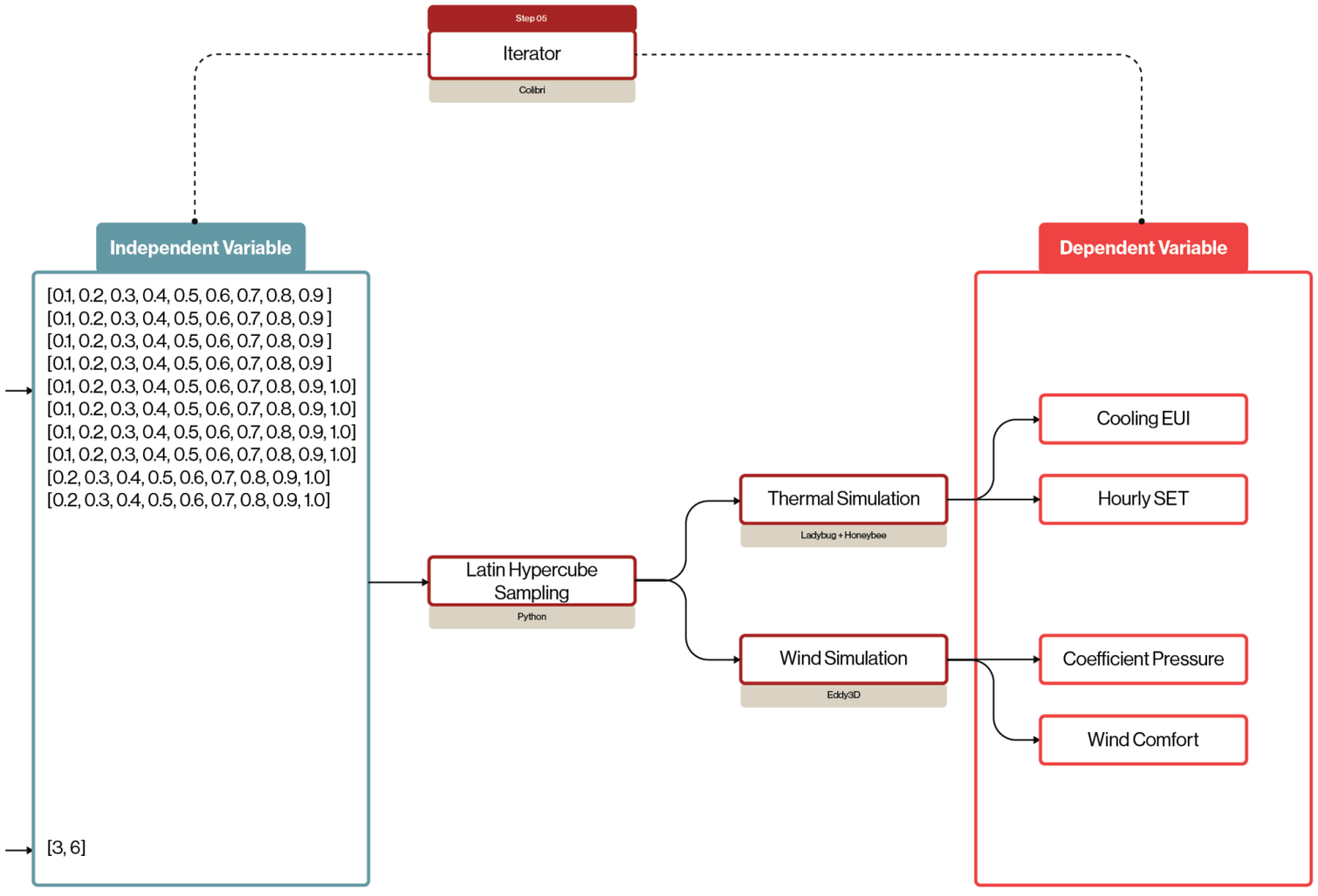
Dataset Generation

For Training Dataset

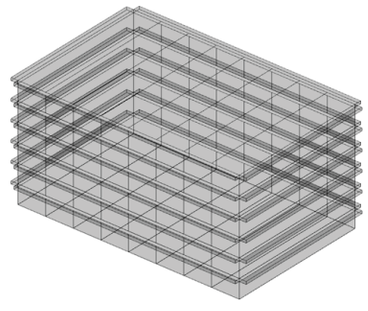




500 configurations



500 configurations

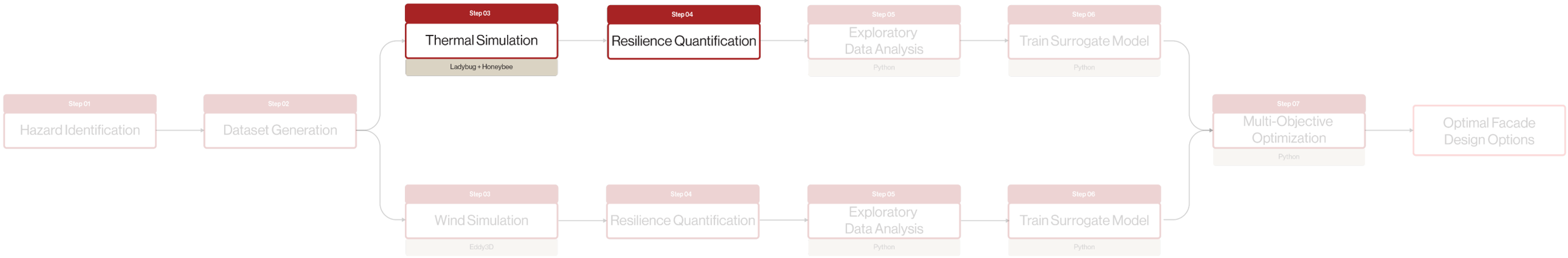


500 configurations

Input | Task | Output | Tool

Case Study

Thermal Resilience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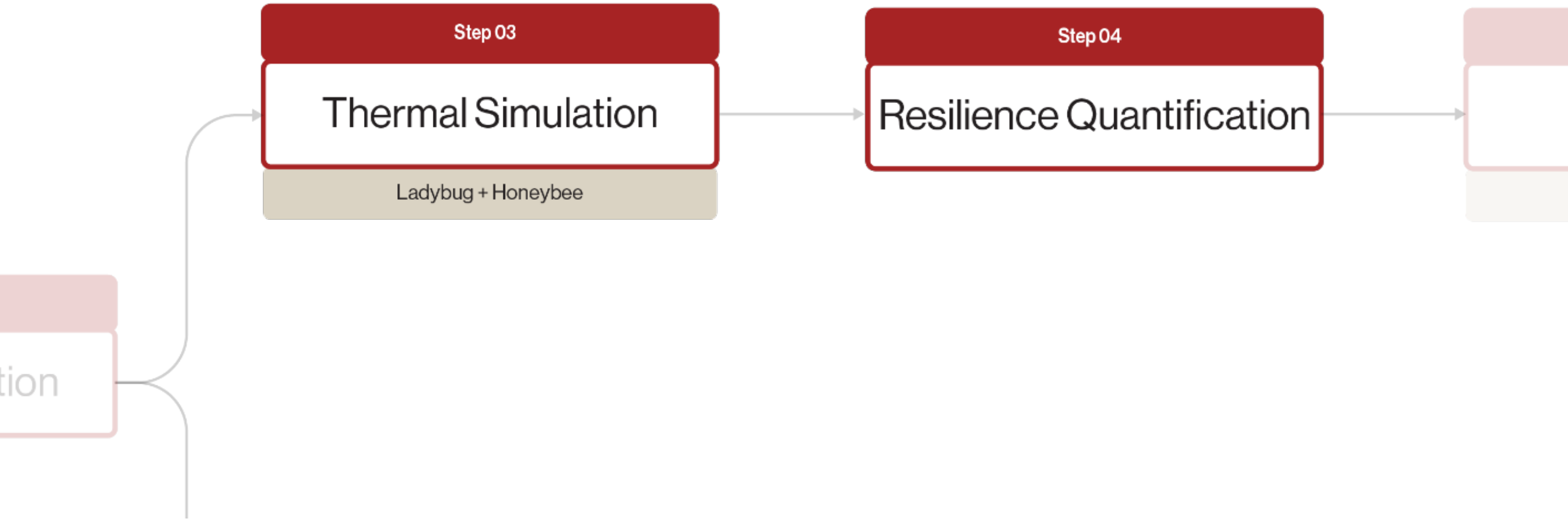
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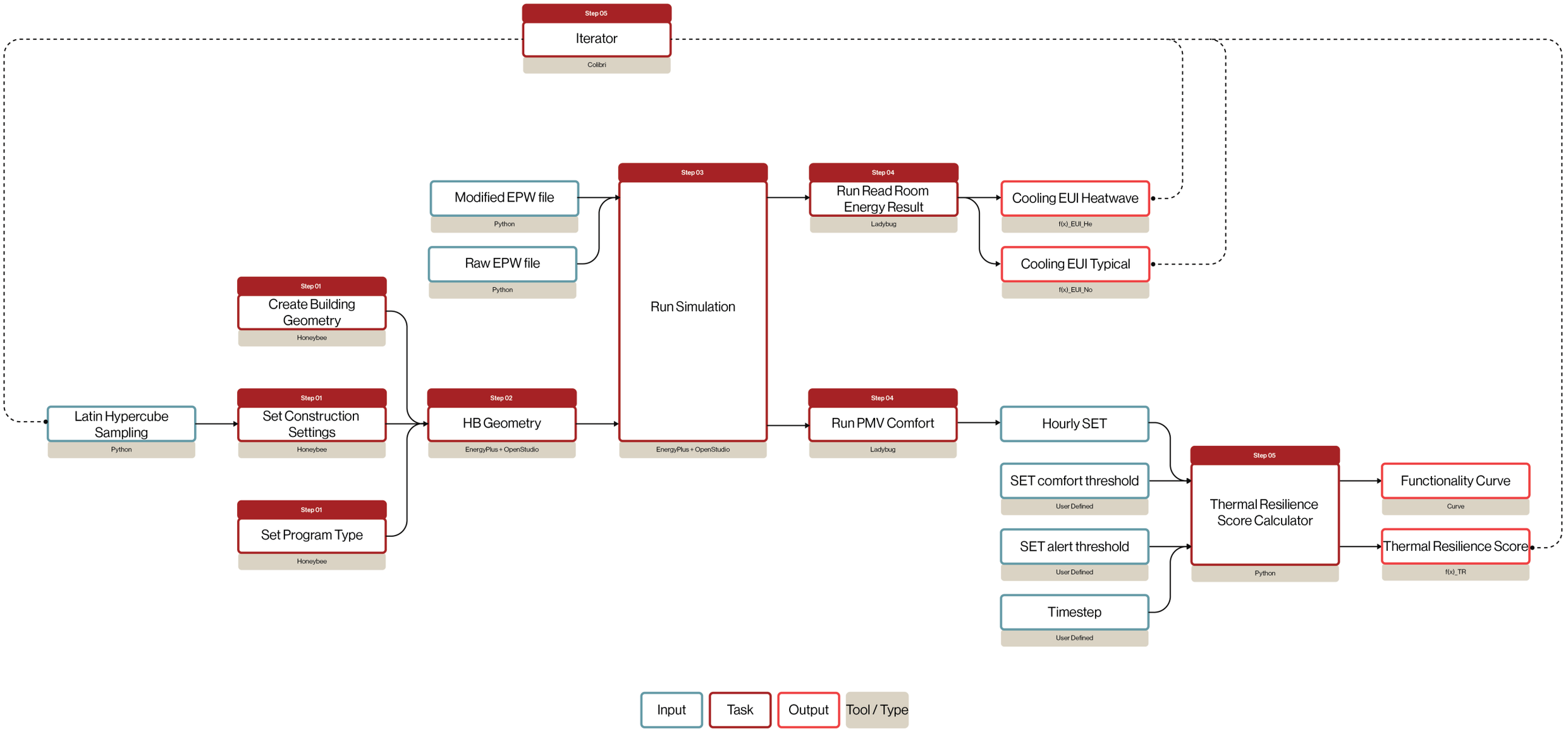
Ladybug + Honeybee
Step 04
Resilience Quantification
tion

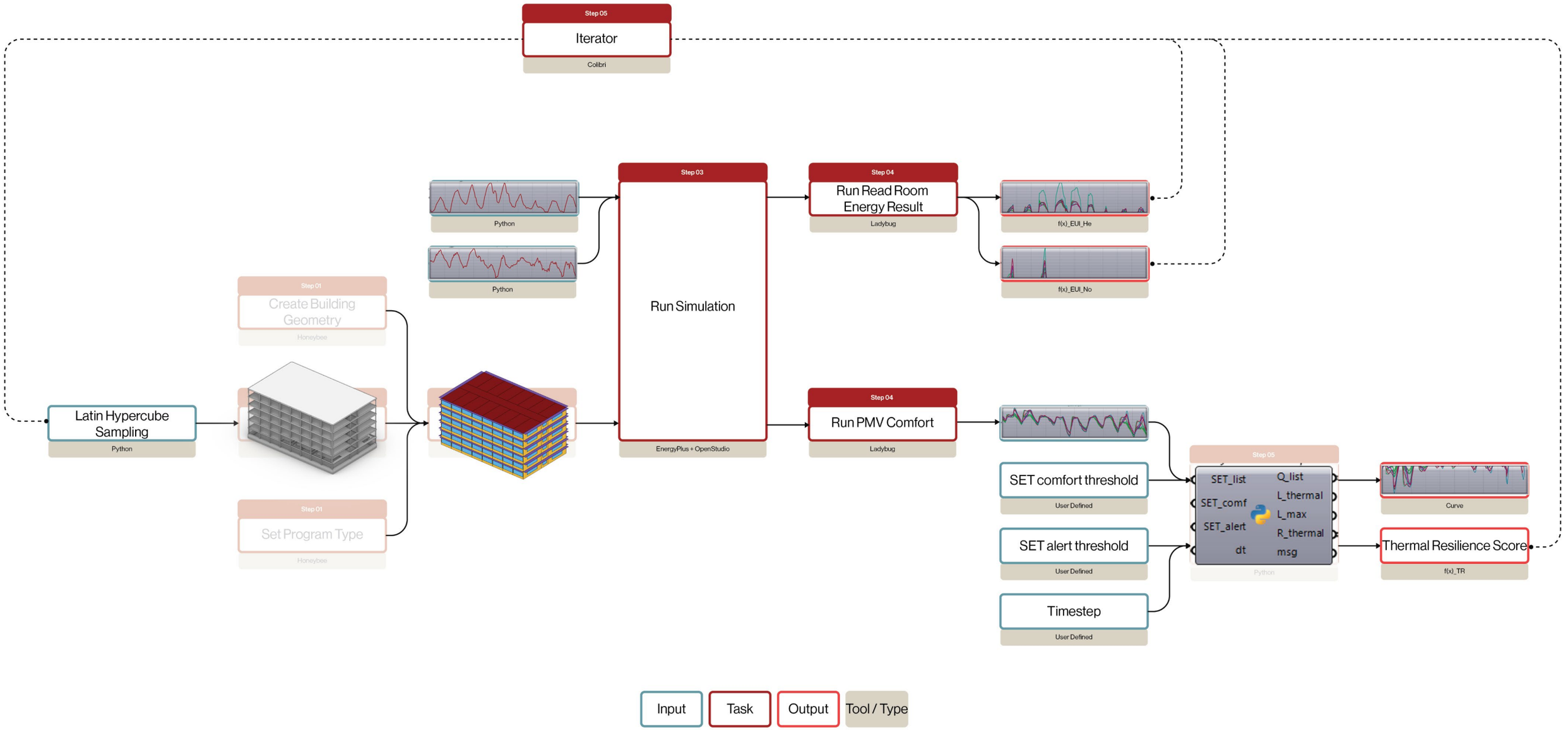
Thermal Simulation

Workflow



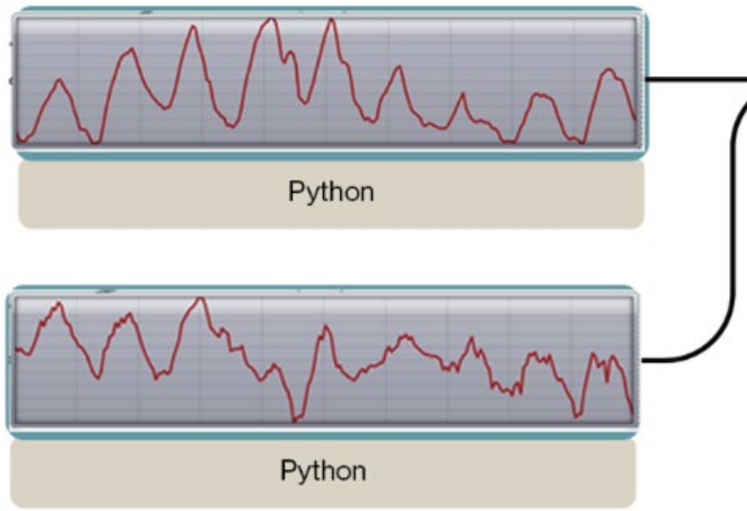
Thermal Simulation

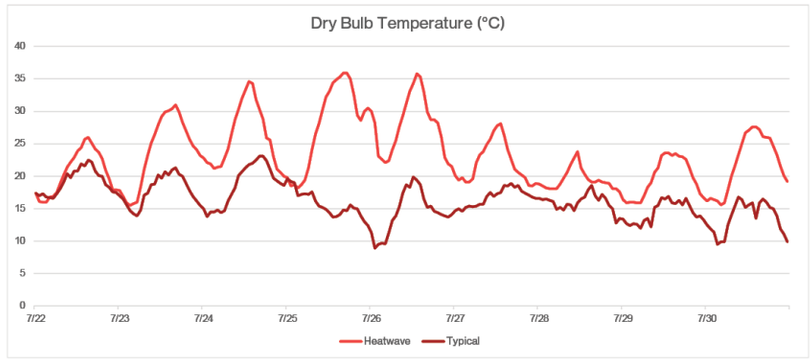
Applied to Case Study



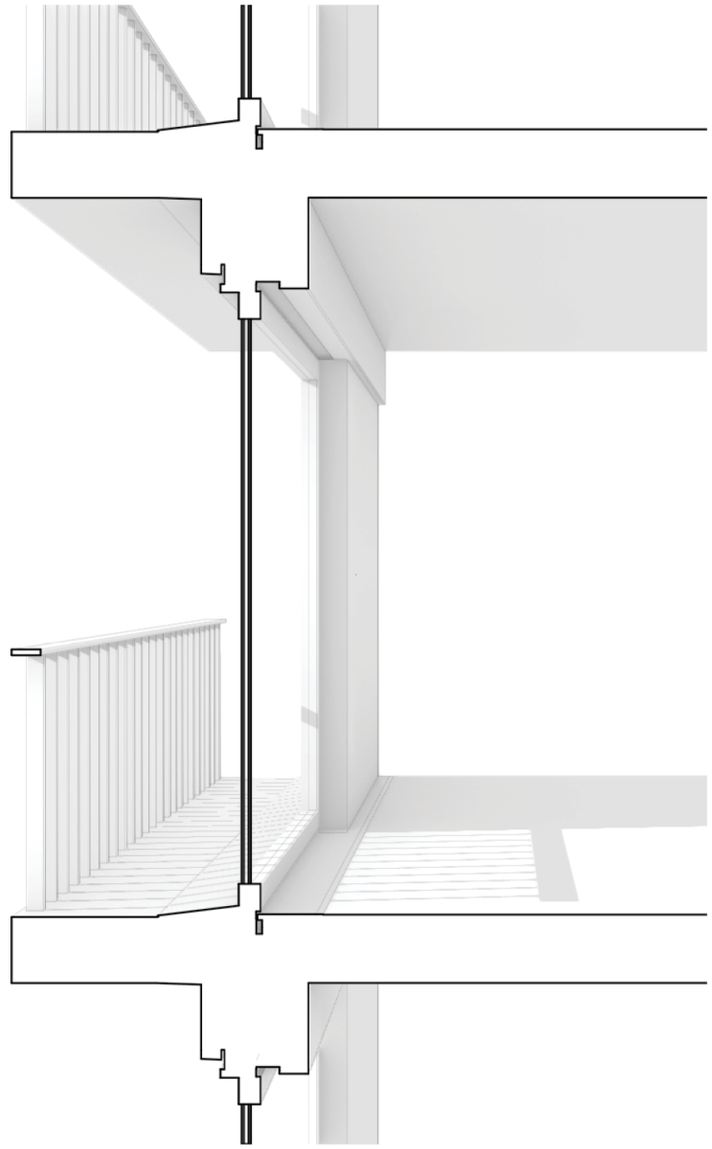
Thermal Simulation

Applied to Case Study



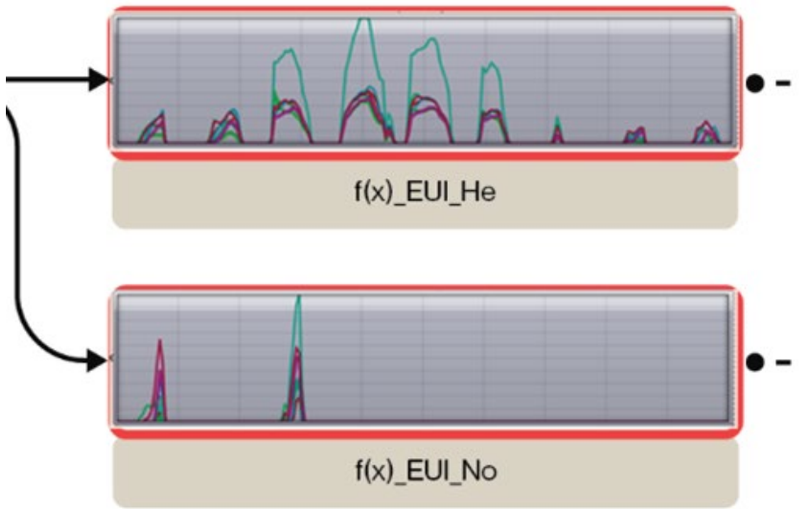


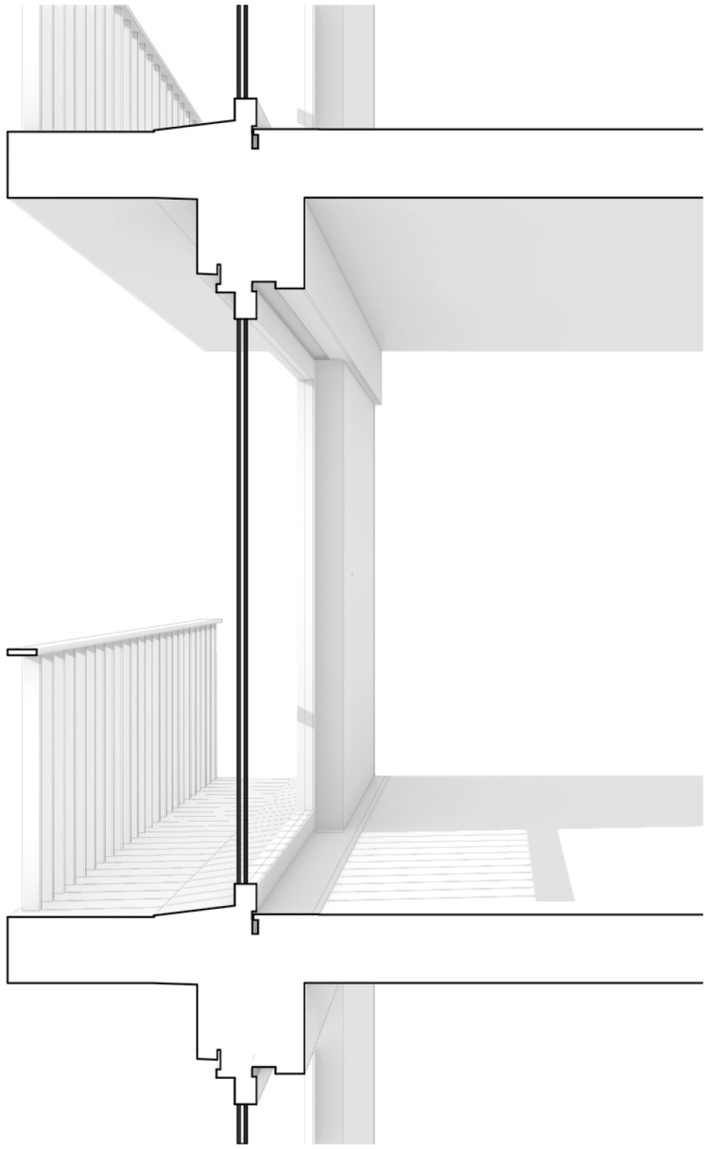
Period when the maximum daily temperature exceeds the 90th percentile for at least three consecutive days. (CTX90pct)

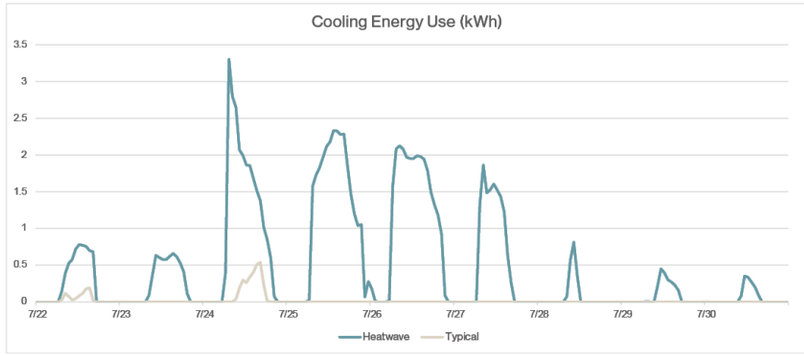


Thermal Simulation

Applied to Case Study



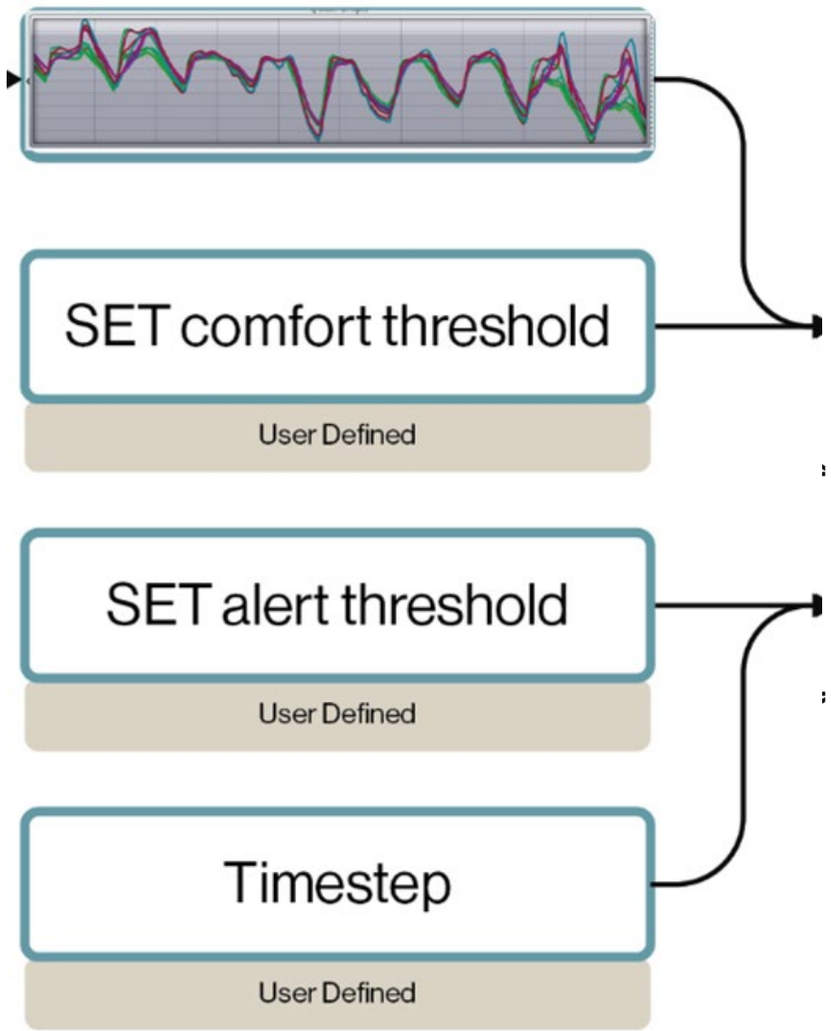


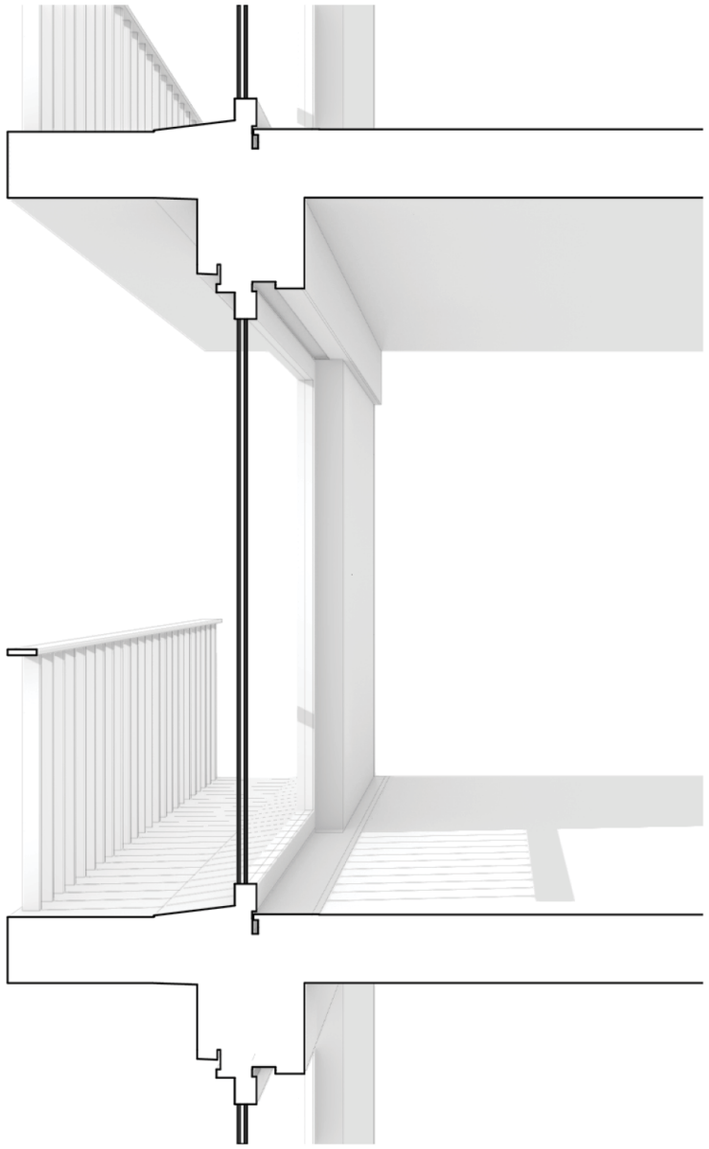


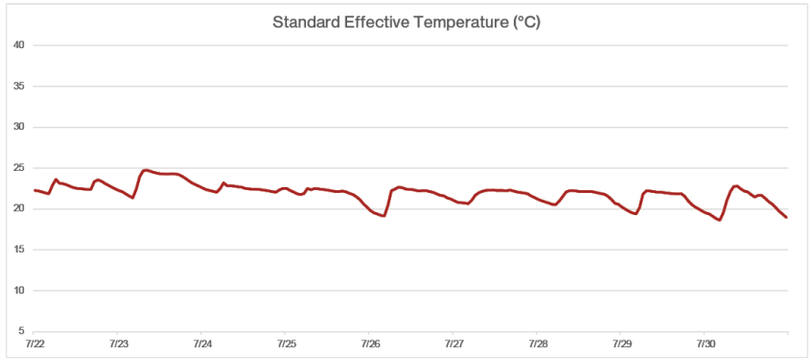
Cooling Energy Used During Heatwave (kWh)
Cooling Energy Used During Typical Condition (kWh)

Thermal Resilience

Applied to Case Study



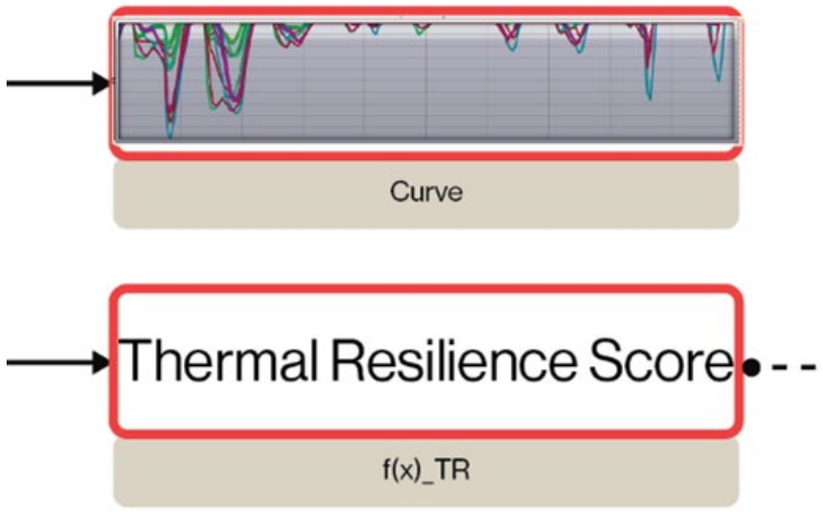


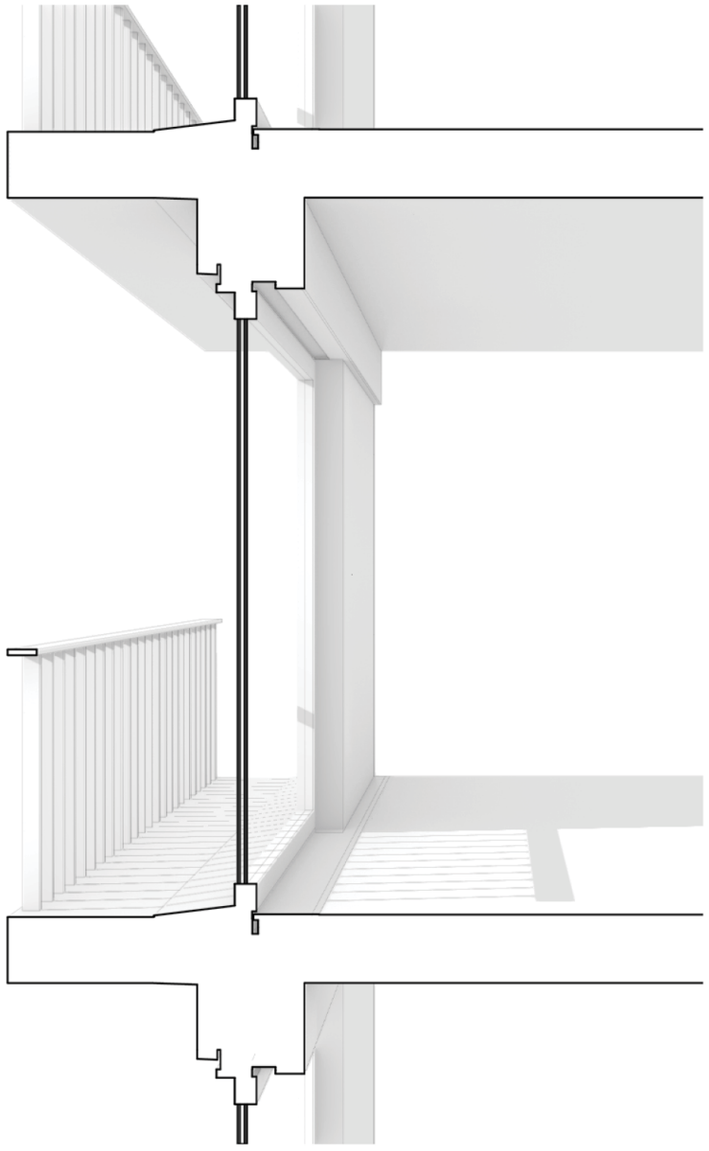


Thermal Comfort Index (ASHRAE 55)
at 50% Relative Humidity
Air Speed < 0.1 m/s
Occupant 1.0 met
Clothing 0.6

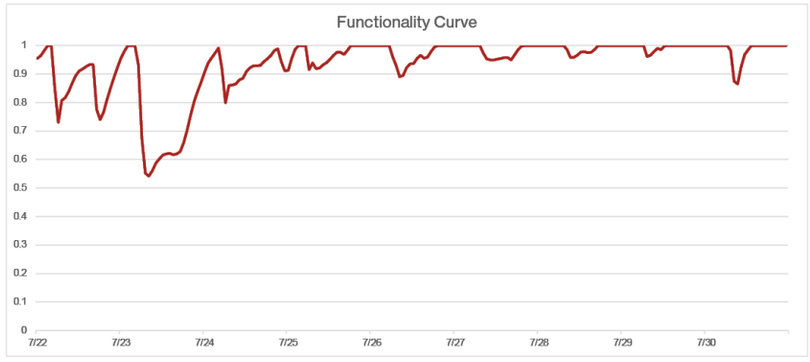
Thermal Resilience

Applied to Case Study





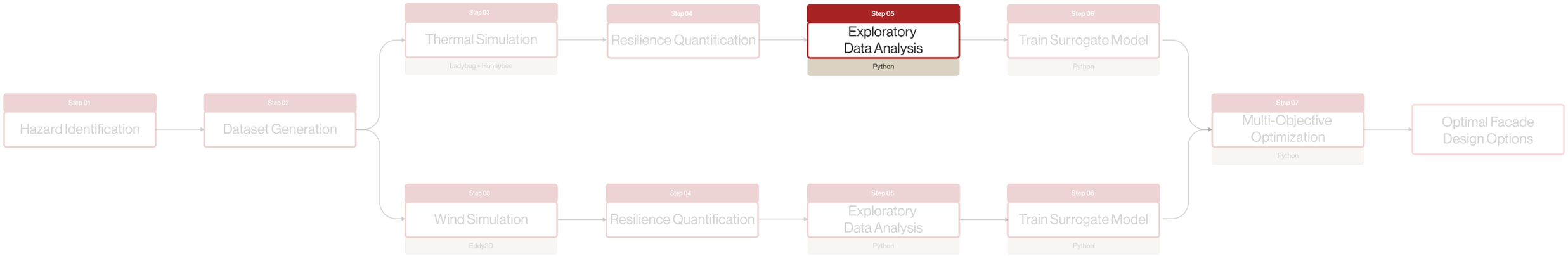
Quality Function



$$Q\left(t\right) = \begin{cases} 1 & \text{if } SET_{(t)} \leq SET_{comf} \\ 0 & \text{if } SET_{(t)} \geq SET_{alert} \\ \frac{SET_{alert} - SET_{(t)}}{SET_{alert} - SET_{comf}} & \text{otherwise} \end{cases}$$

$$L_{thermal} = \int_{t_0}^{t_1} [1 - Q(t)]dt$$

$$R_{thermal} = 1 - \frac{L_{thermal}}{L_{thermal,max}} \quad [0,1]$$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Step 04

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Step 05

Exploratory
Data Analysis

Python

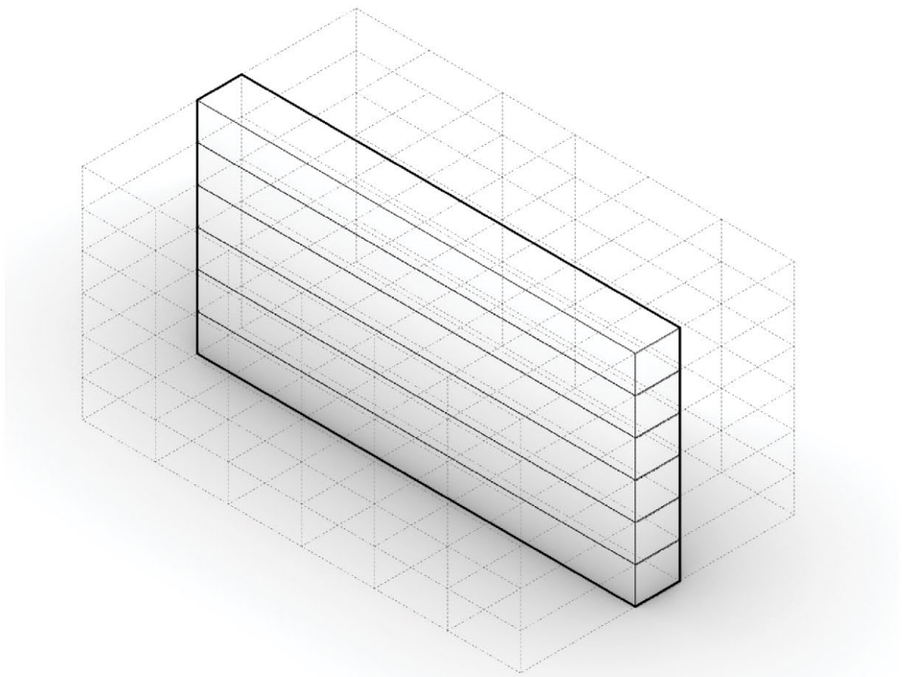
Step 06

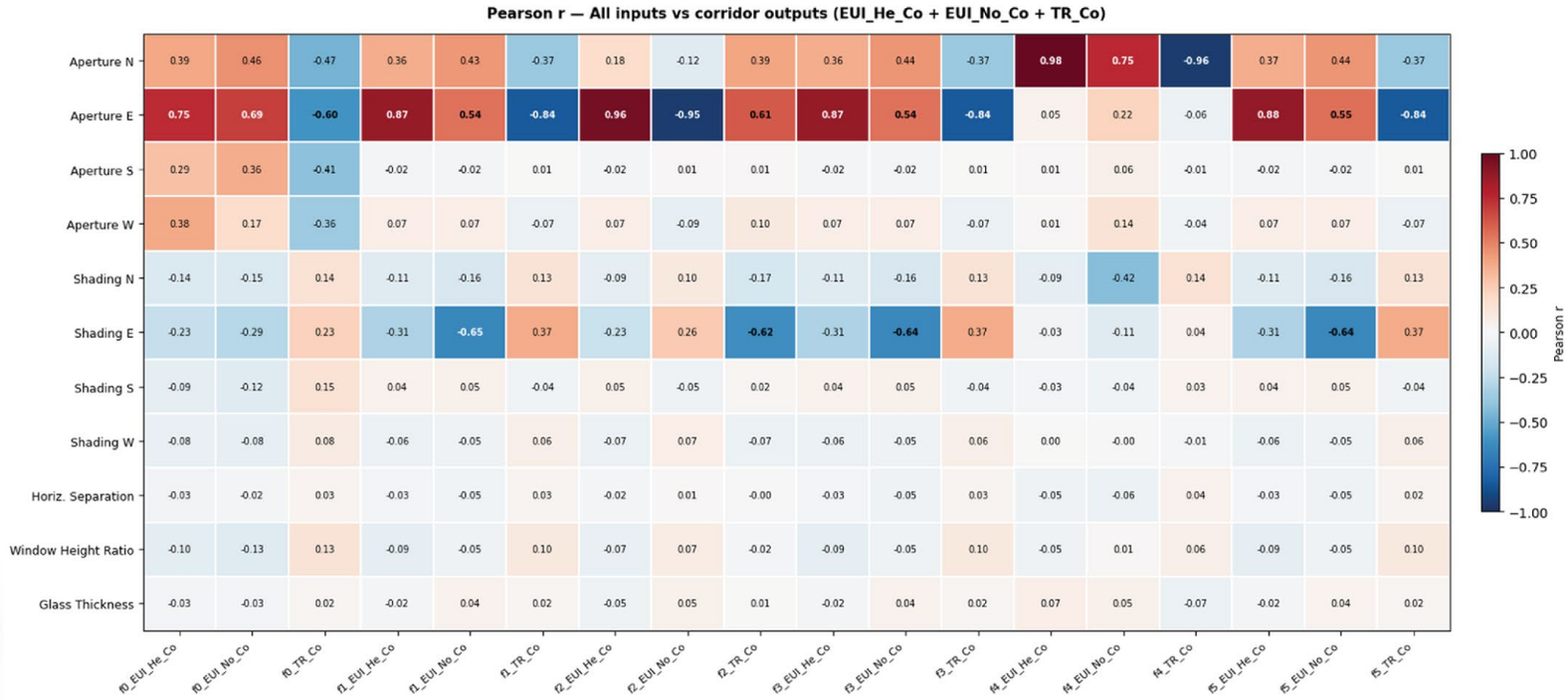
Train Surrogate Model

Python

Correlation Analysis

Corridor Area





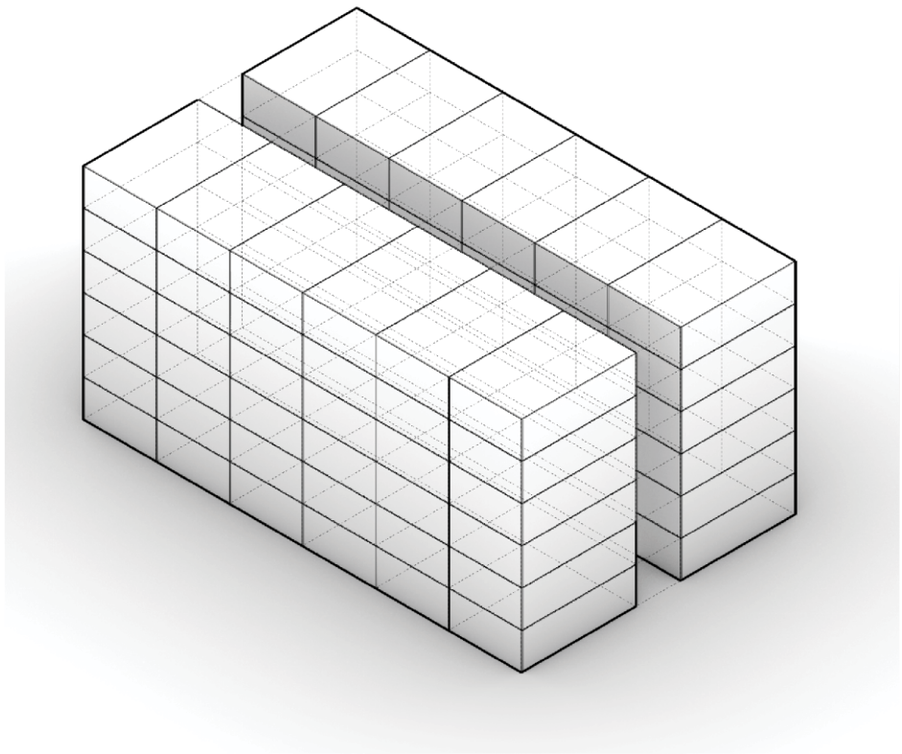
Findings

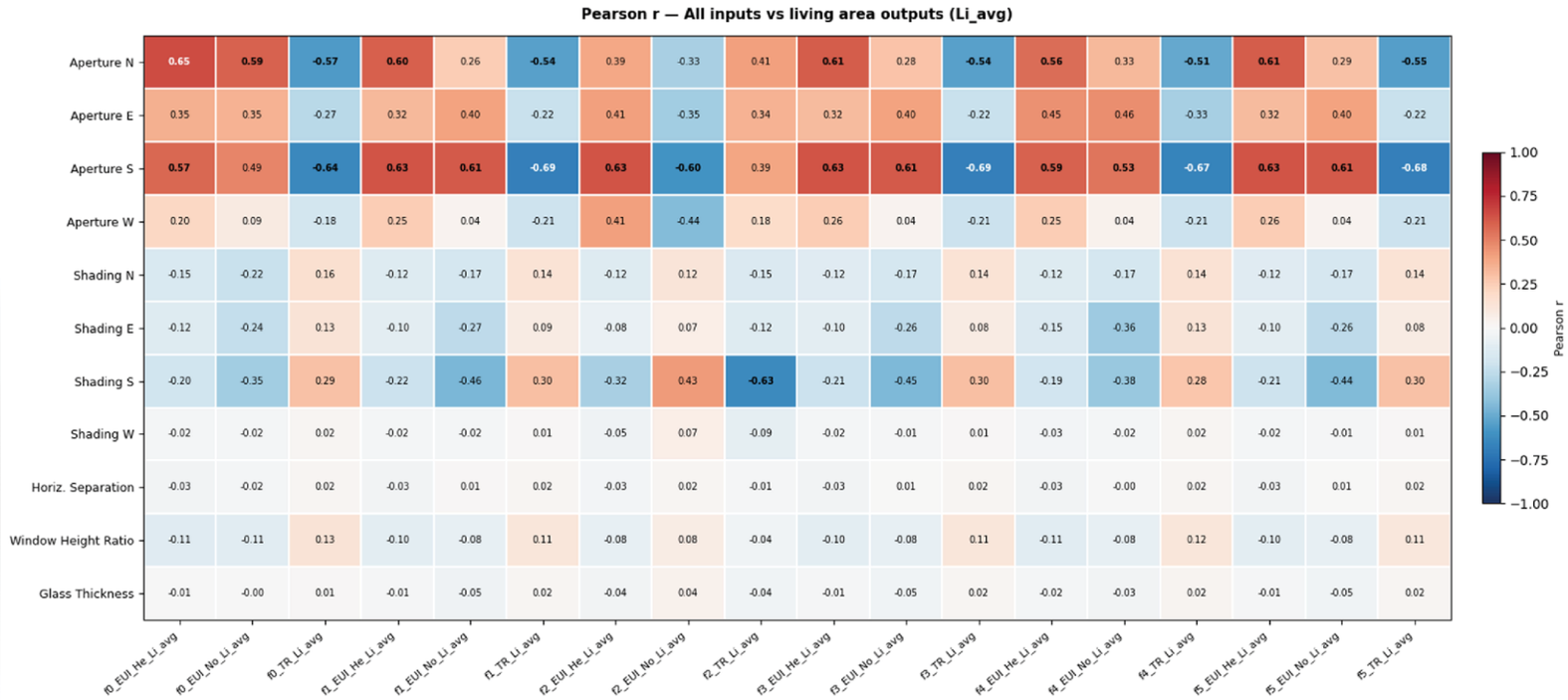
Aperture East = consistently strong accross most outputs

on Energy Use	r = +0.96
on Thermal Resilience	r = -0.95

Correlation Analysis

Living Area





Findings

Aperture South = most consistently influential variable, moderate to strong

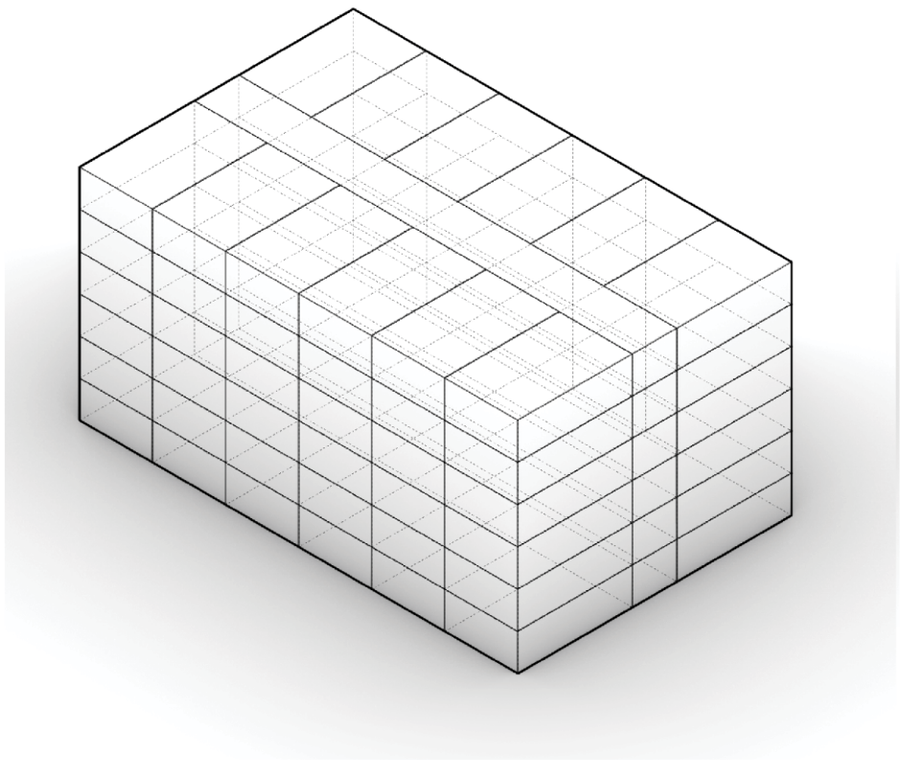
on Energy Use	r = +0.49 to +0.63
on Thermal Resilience	r = -0.55 to -0.69

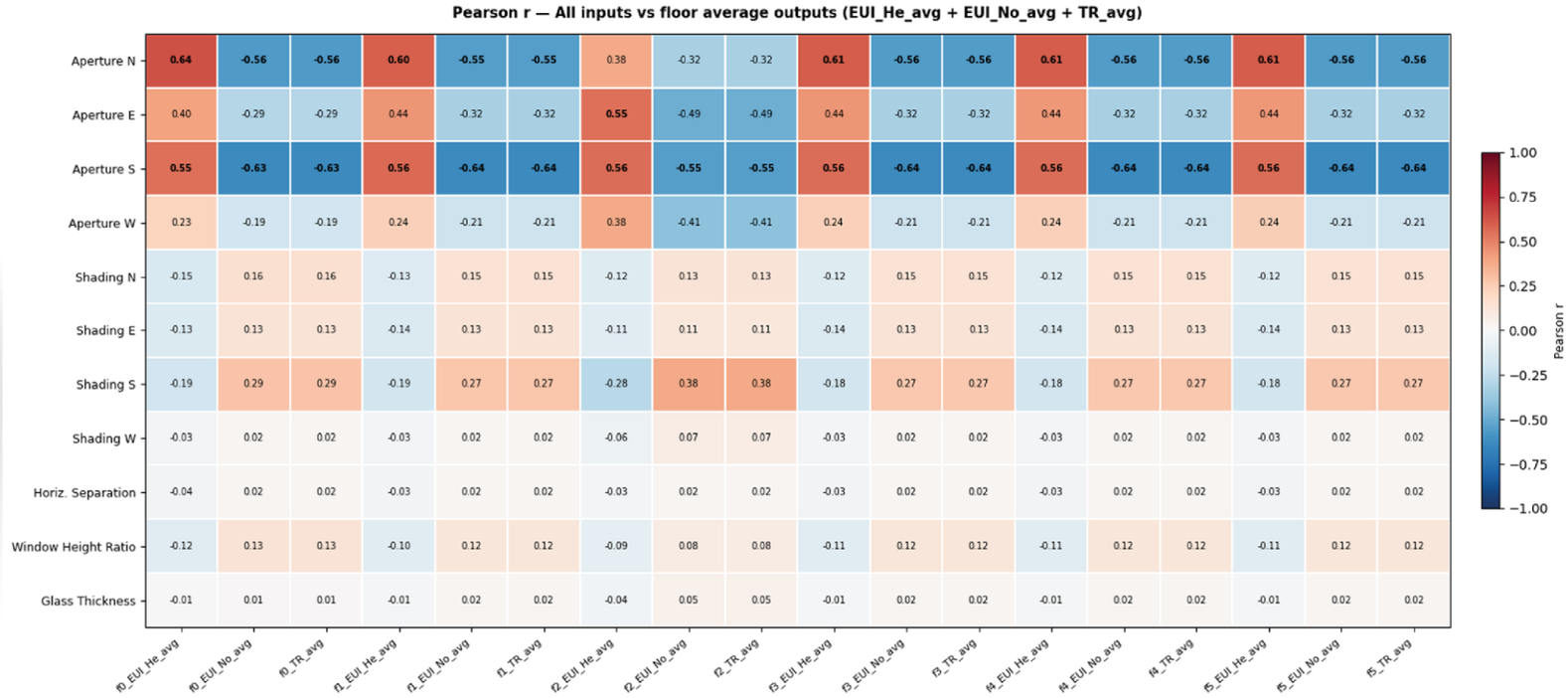
Aperture North = second most meaningful,

on Energy Use	r = +0.56 to +0.65
on Thermal Resilience	r = -0.51 to -0.57

Correlation Analysis

All Area





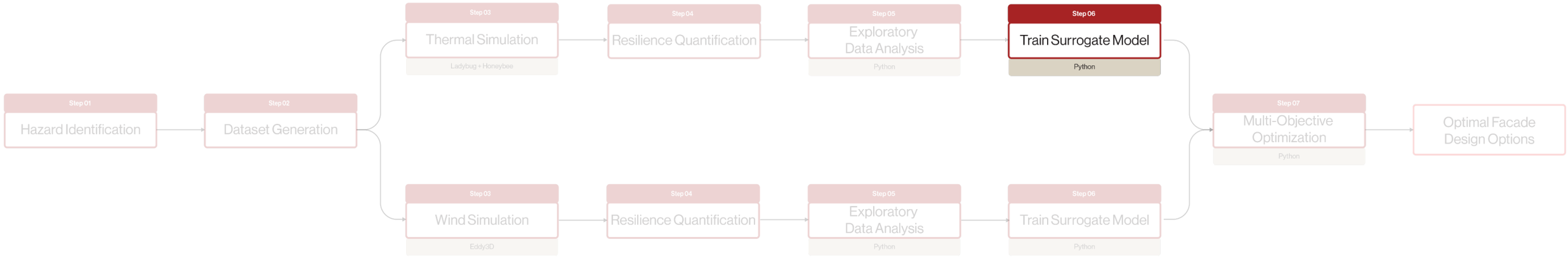
Findings

Aperture South = stable and strong influence across all floors and metrics

on Energy Use	r = +0.55 to +0.64
on Thermal Resilience	r = -0.55 to -0.64

Aperture North = behave similarly

on Energy Use	r = +0.60 to +0.64
on Thermal Resilience	r = -0.55 to -0.56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Exploratory Data Analysis

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Train Surrogate Model

Python

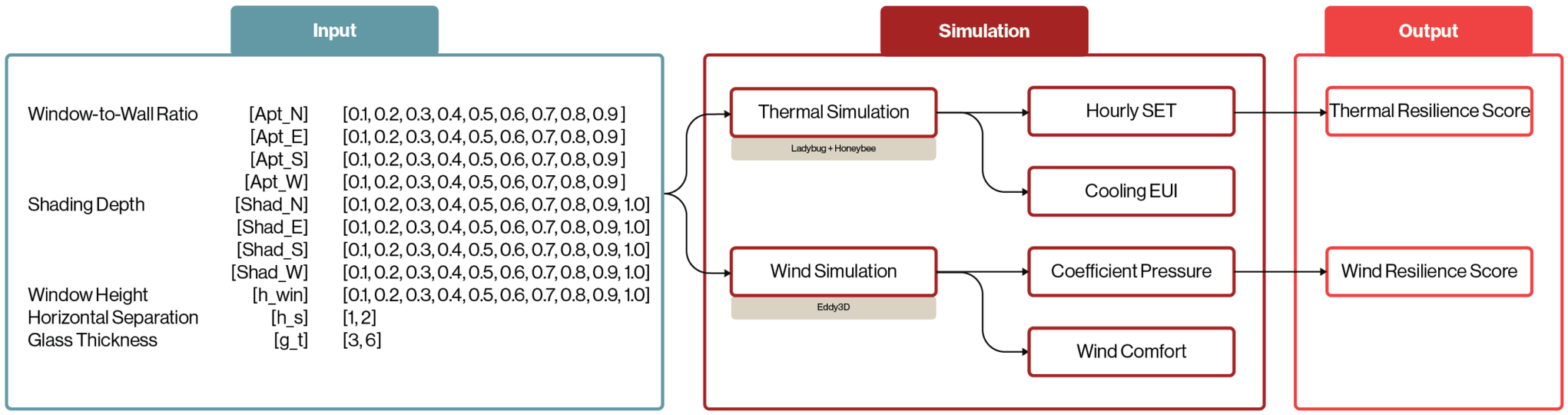
Step 07

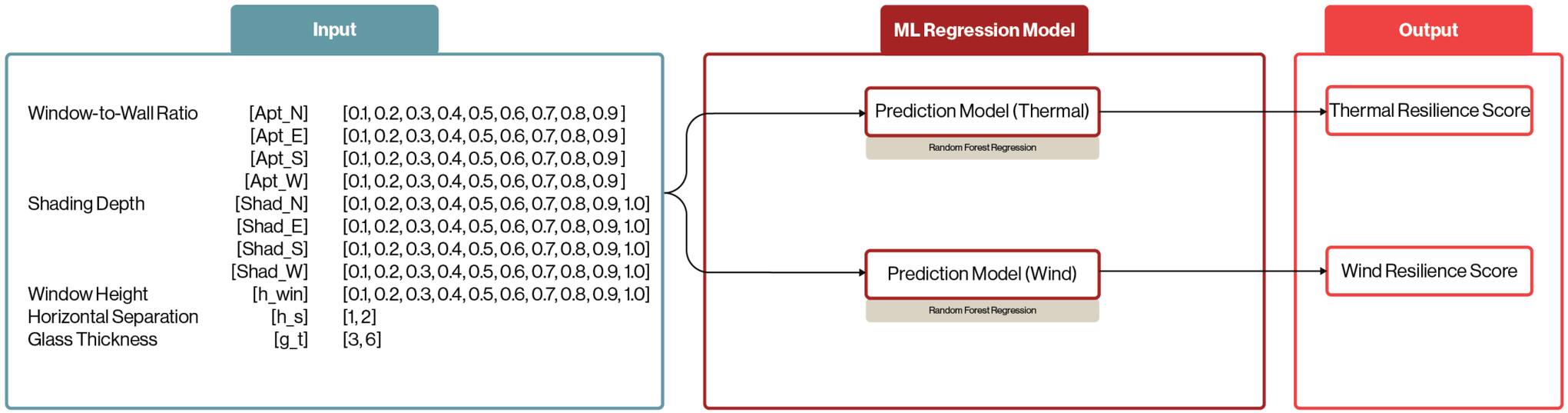
Multi-Objective Optimization

Python

Random Forest Regression

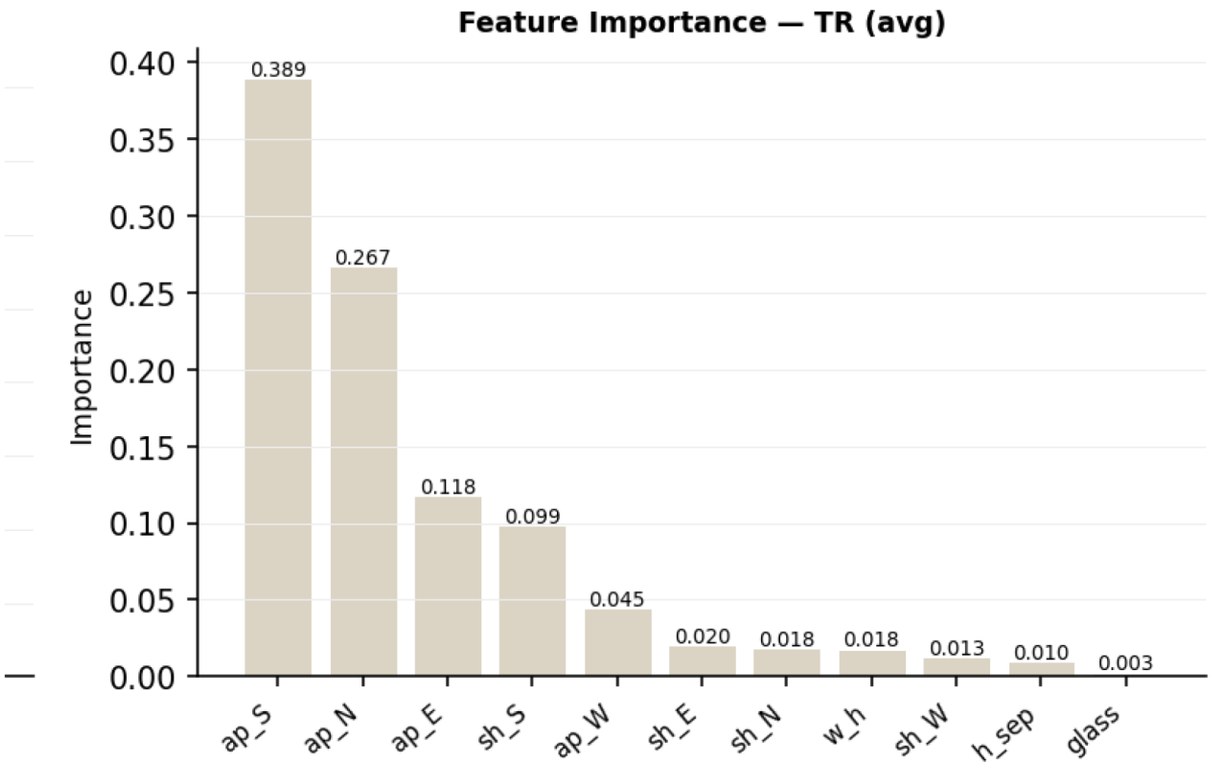
Supervised Machine Learning



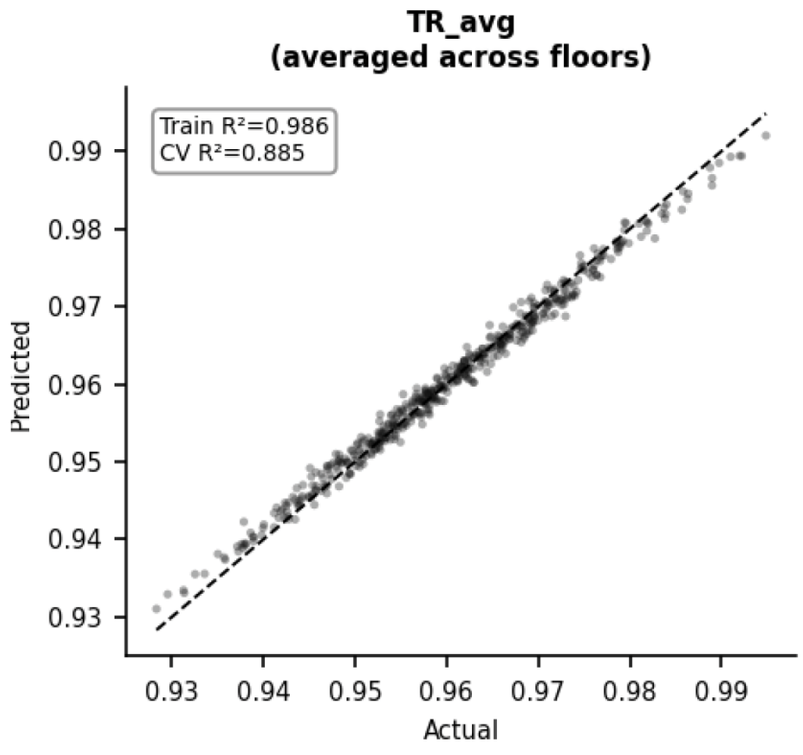


Random Forest Regression

Feature Importance



Parity Plots



Findings

For Thermal Resilience the dominant drivers are:

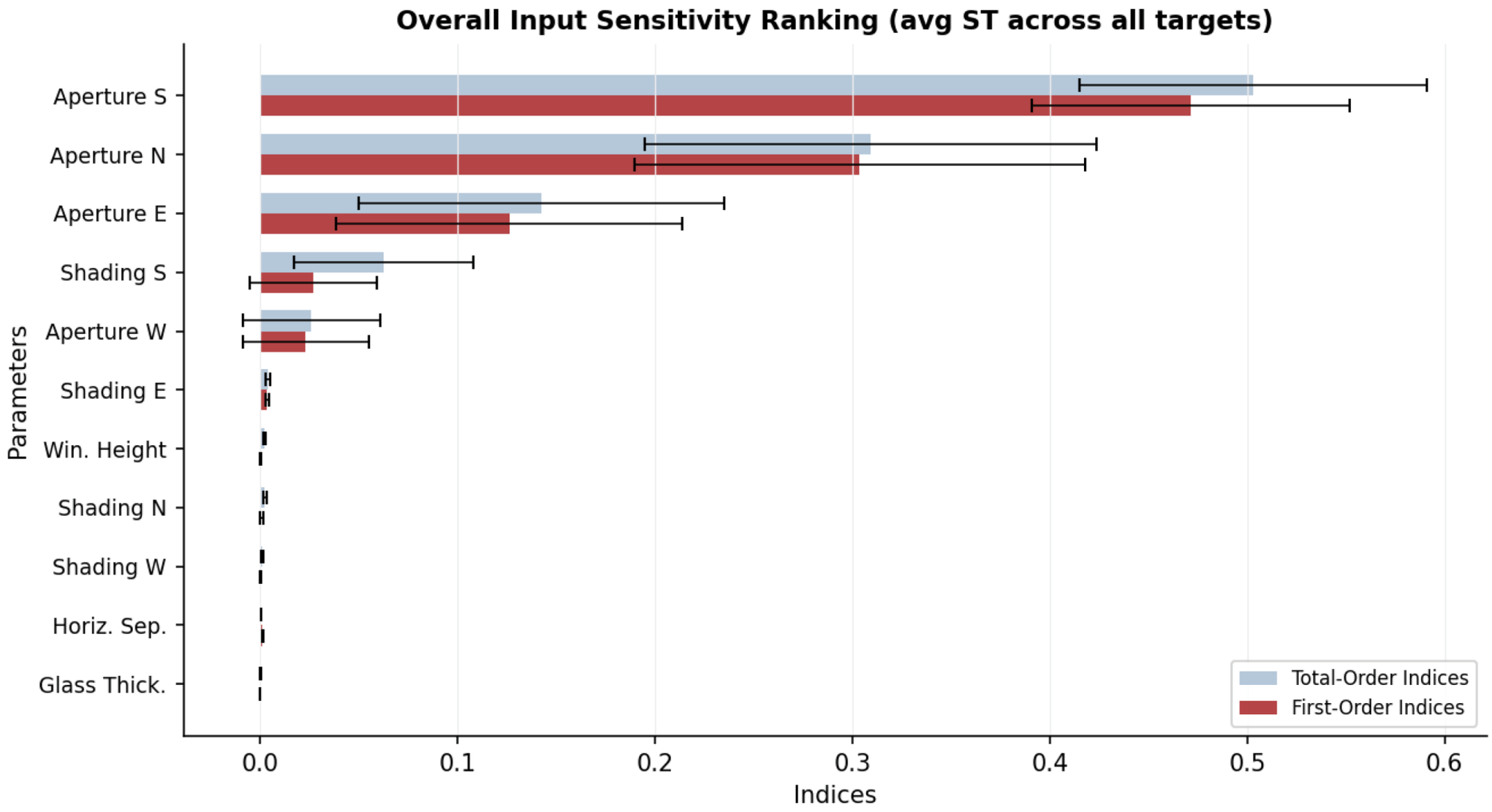
Aperture South (0.389)
Aperture North (0.267)

For Thermal Resilience the dominant drivers are:

Aperture South (0.389)
Aperture North (0.267)

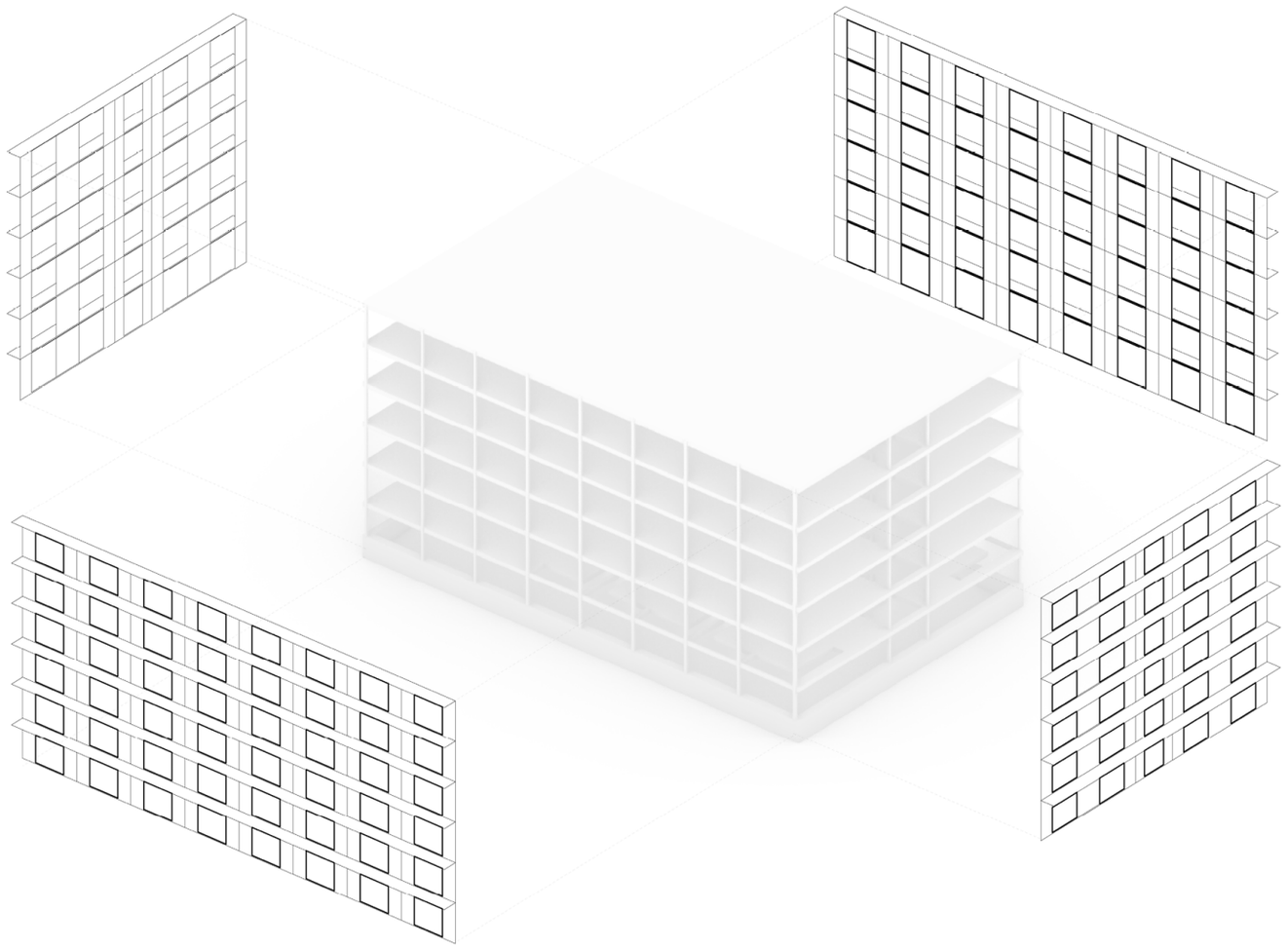
Sobol's Method

Sensitivity Analysis



Thermal resilience is dominated by **Aperture South**, **North**, and **East**, with **Shading South** as an interaction-driven secondary contributor and the remaining six variables effectively negligible.

Key Findings
Strongest Drivers



Aperture North

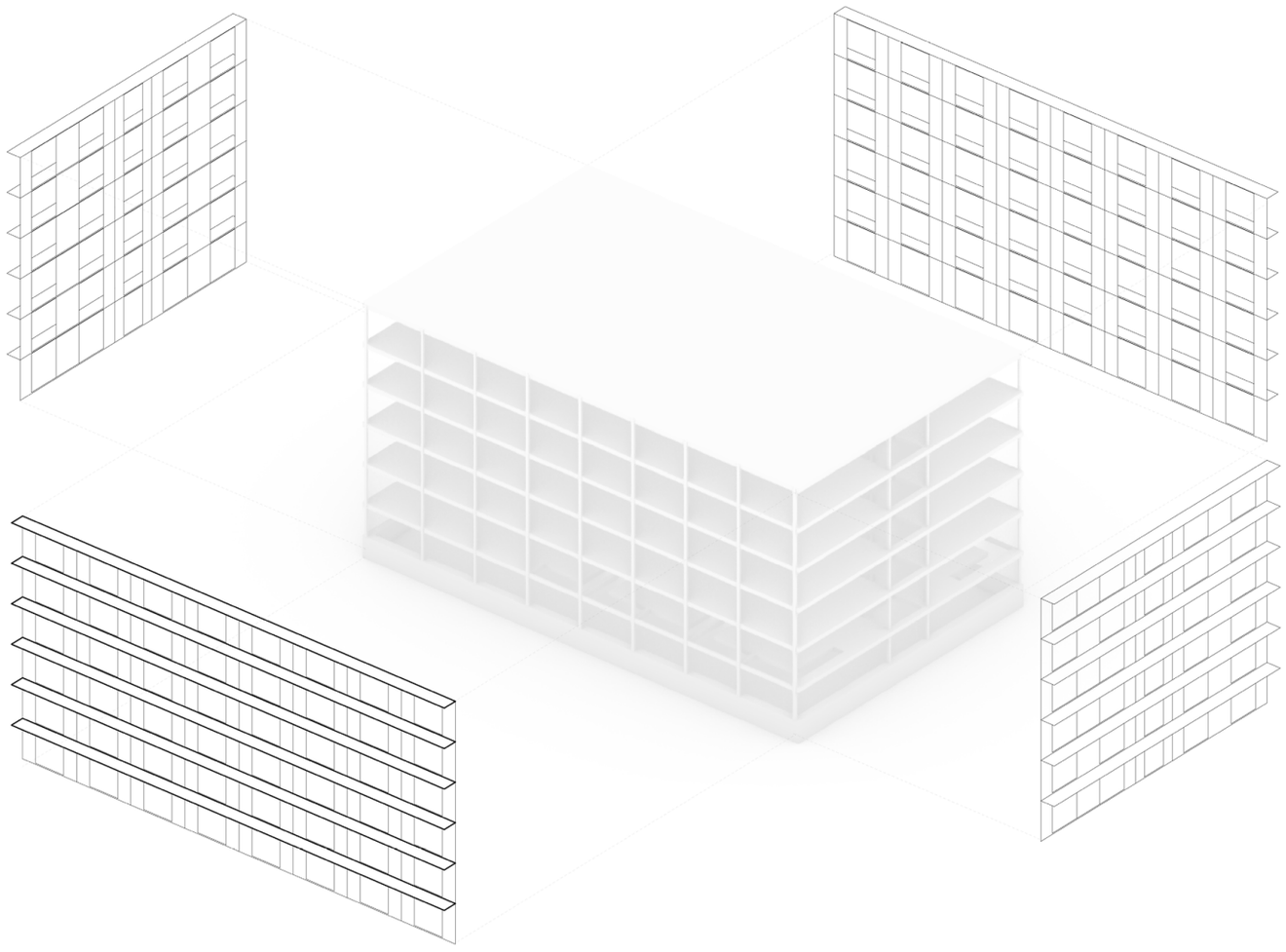
Aperture South

Aperture East

Aperture S, Aperture N, and Aperture E consistently appear as the three strongest drivers across all three analyses, jointly accounting for the majority of the variance in cooling energy and thermal resilience. Aperture S alone accounts for approximately half of the variance attributed to the eleven design variables.

Key Findings

Moderate, interaction driven secondary effect



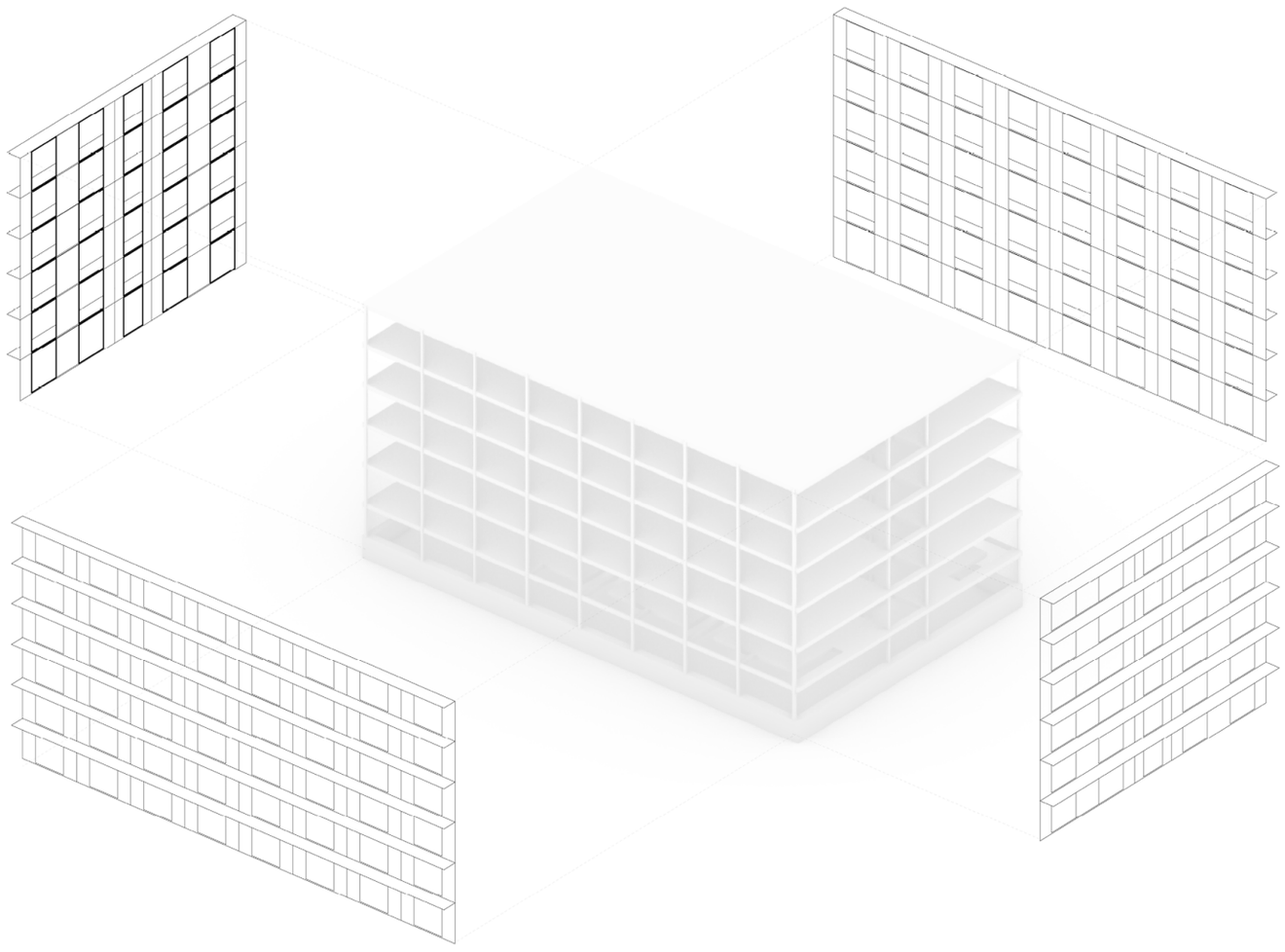
Shading South

Shading S contributes a moderate, interaction-driven secondary effect. Its influence is more visible in the random forest and Sobol analyses than in the Pearson correlation, indicating that part of its effect emerges through interactions with other design variables rather than through a direct linear association.

Key Findings

Small but discernible influence

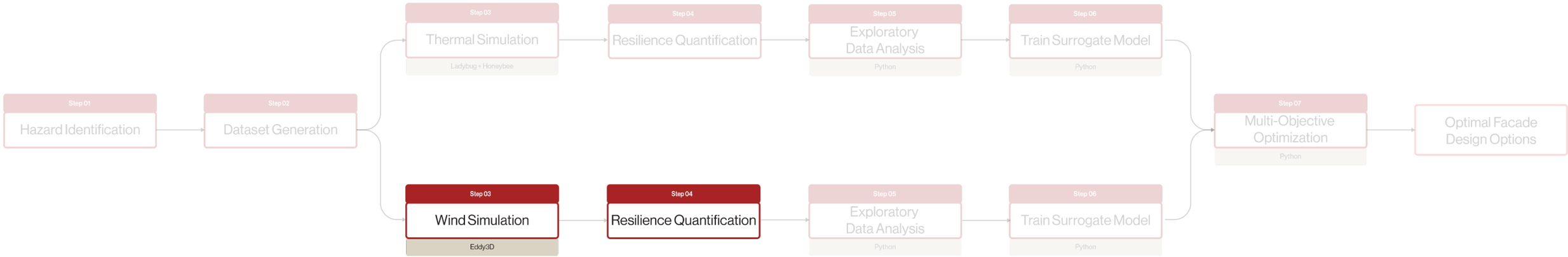
Aperture West



•Aperture W exerts a small but discernible influence, ranking just below the three dominant apertures and Shading S in both feature importance and total-order Sobol indices.

Case Study

Wind Resilience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Step 03

Wind Simulation

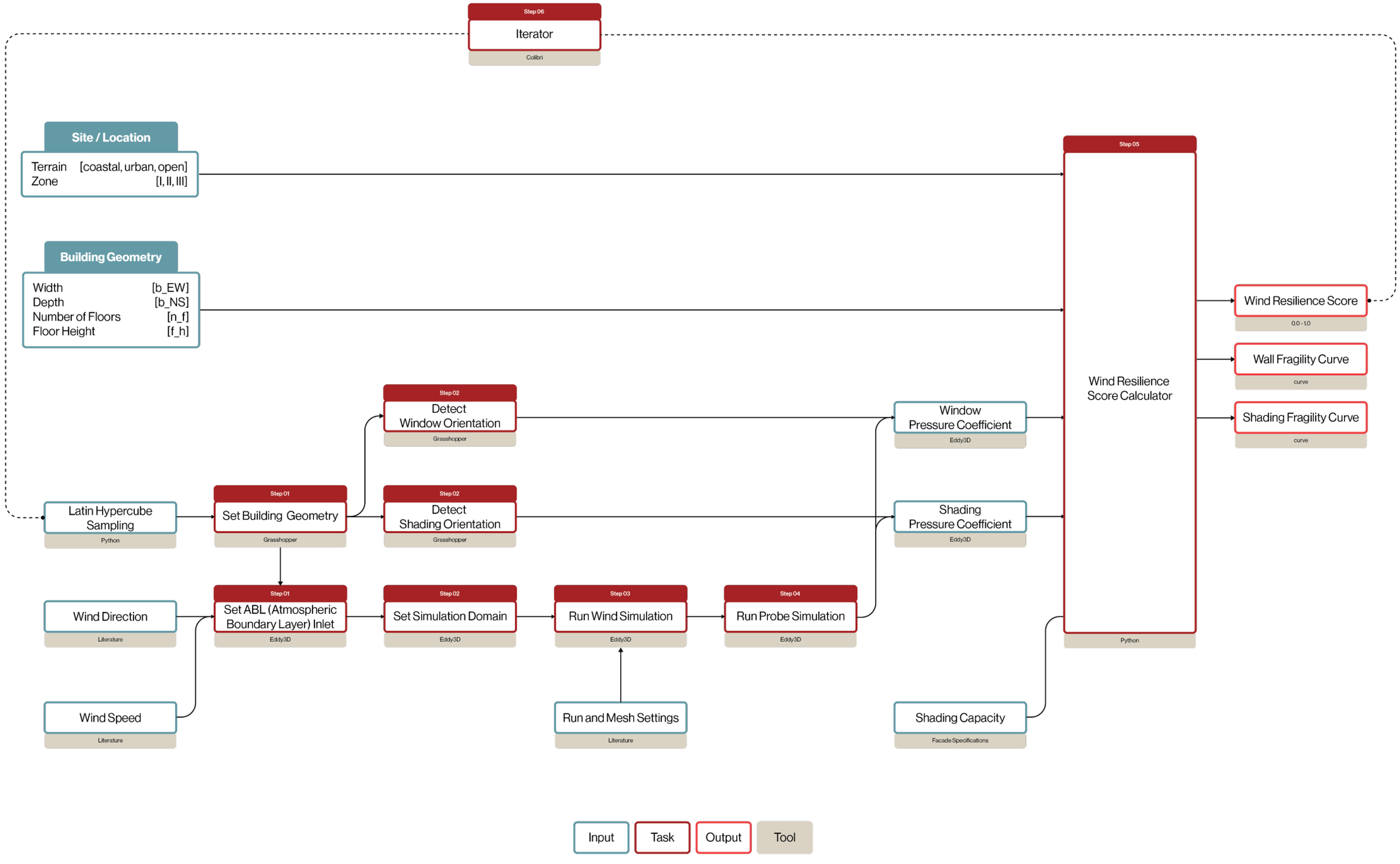
Eddy3D

Step 04

Resilience Quantification

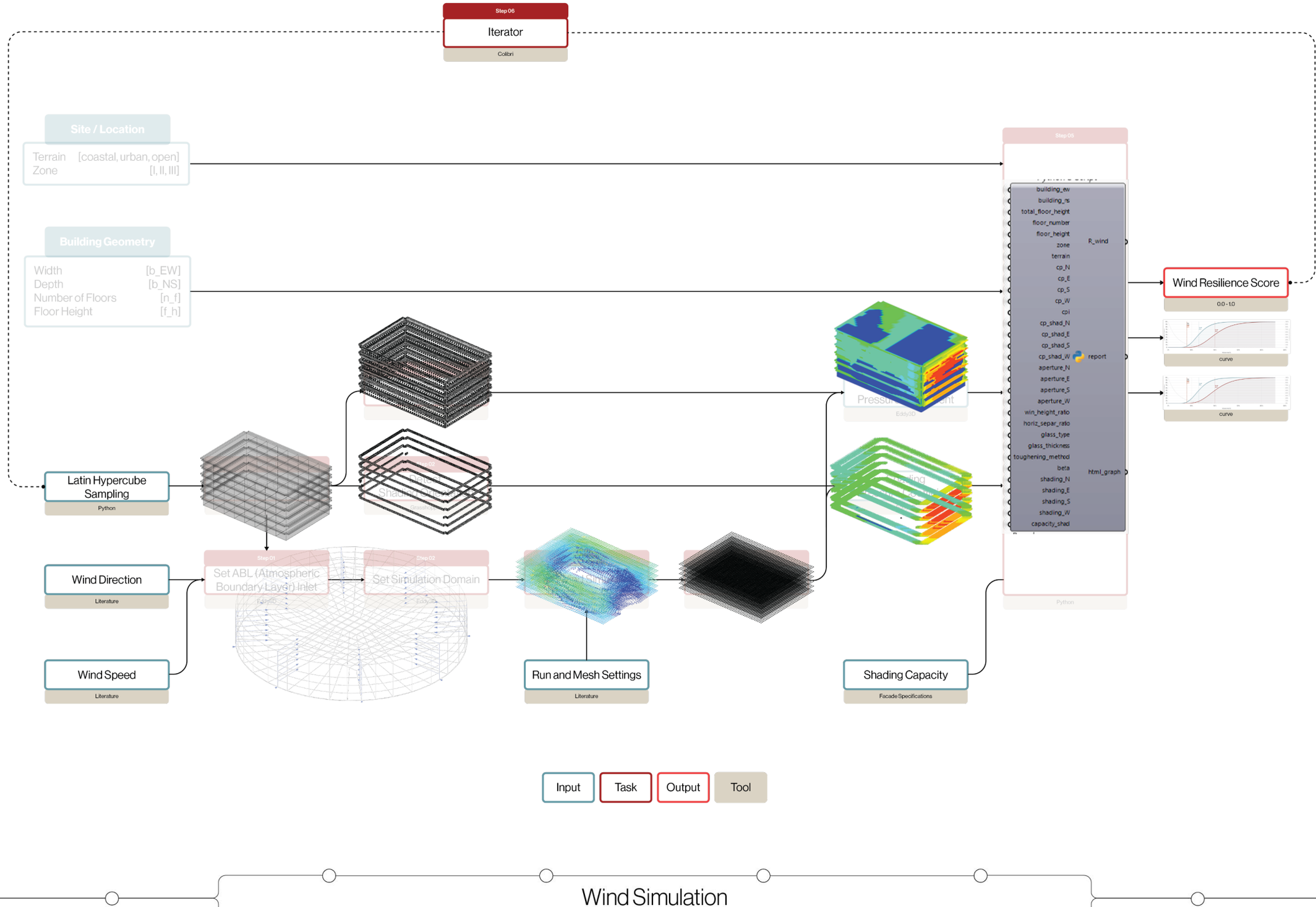
Wind Simulation

Workflow



Wind Simulation

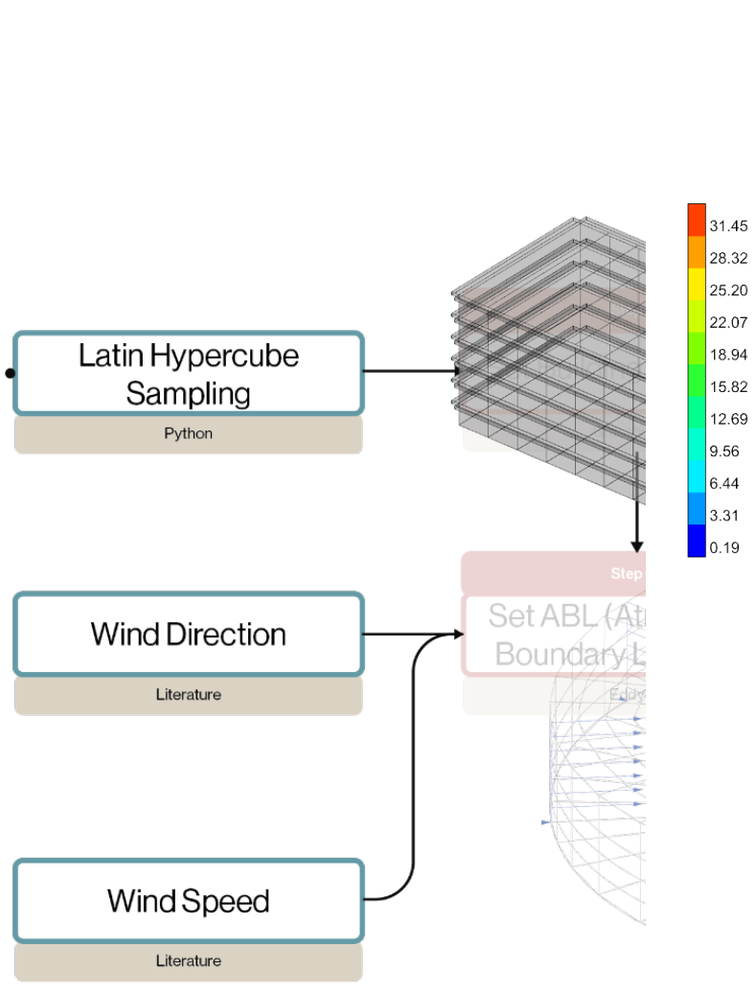
Applied to Case Study

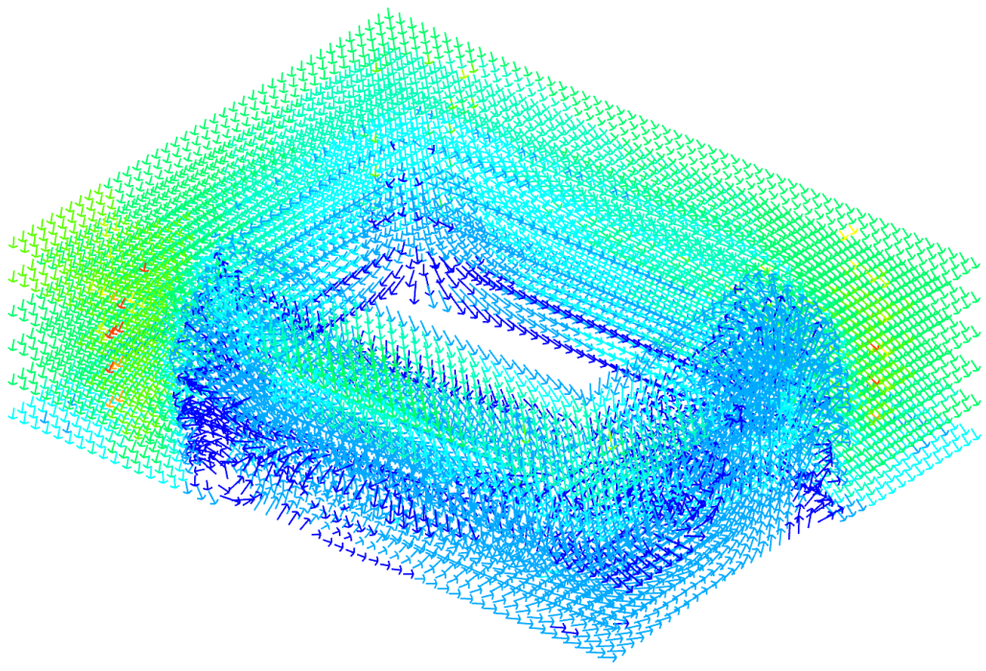


Input | Task | Output | Tool

Wind Simulation

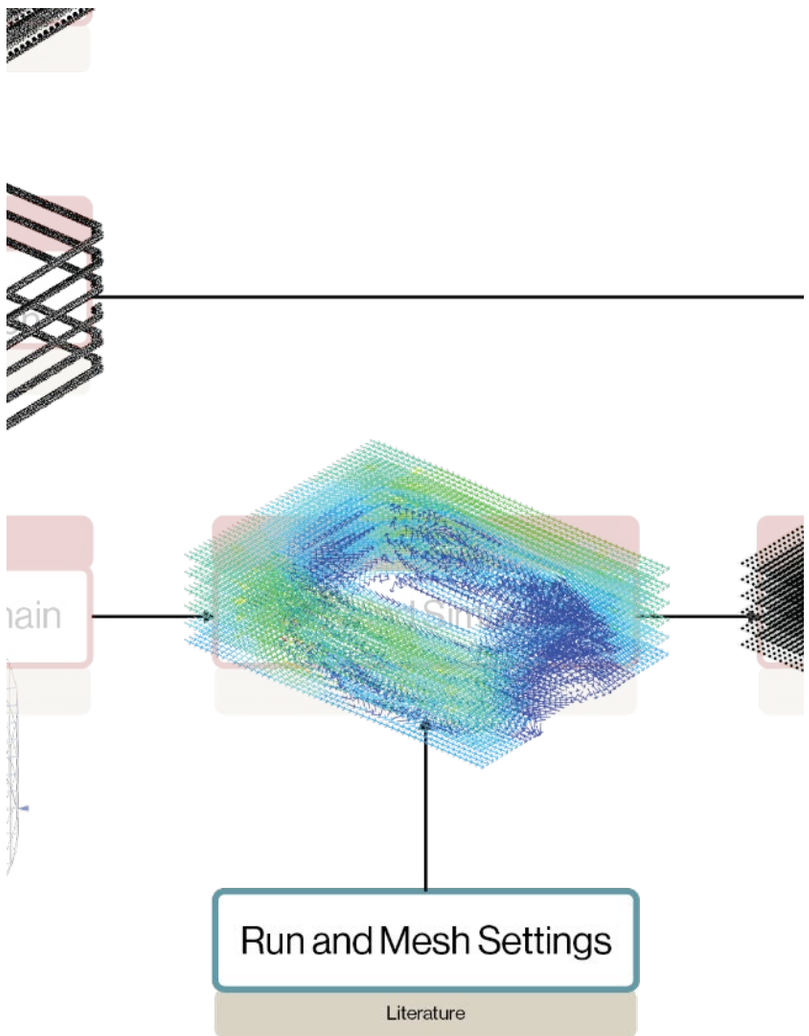
Applied to Case Study

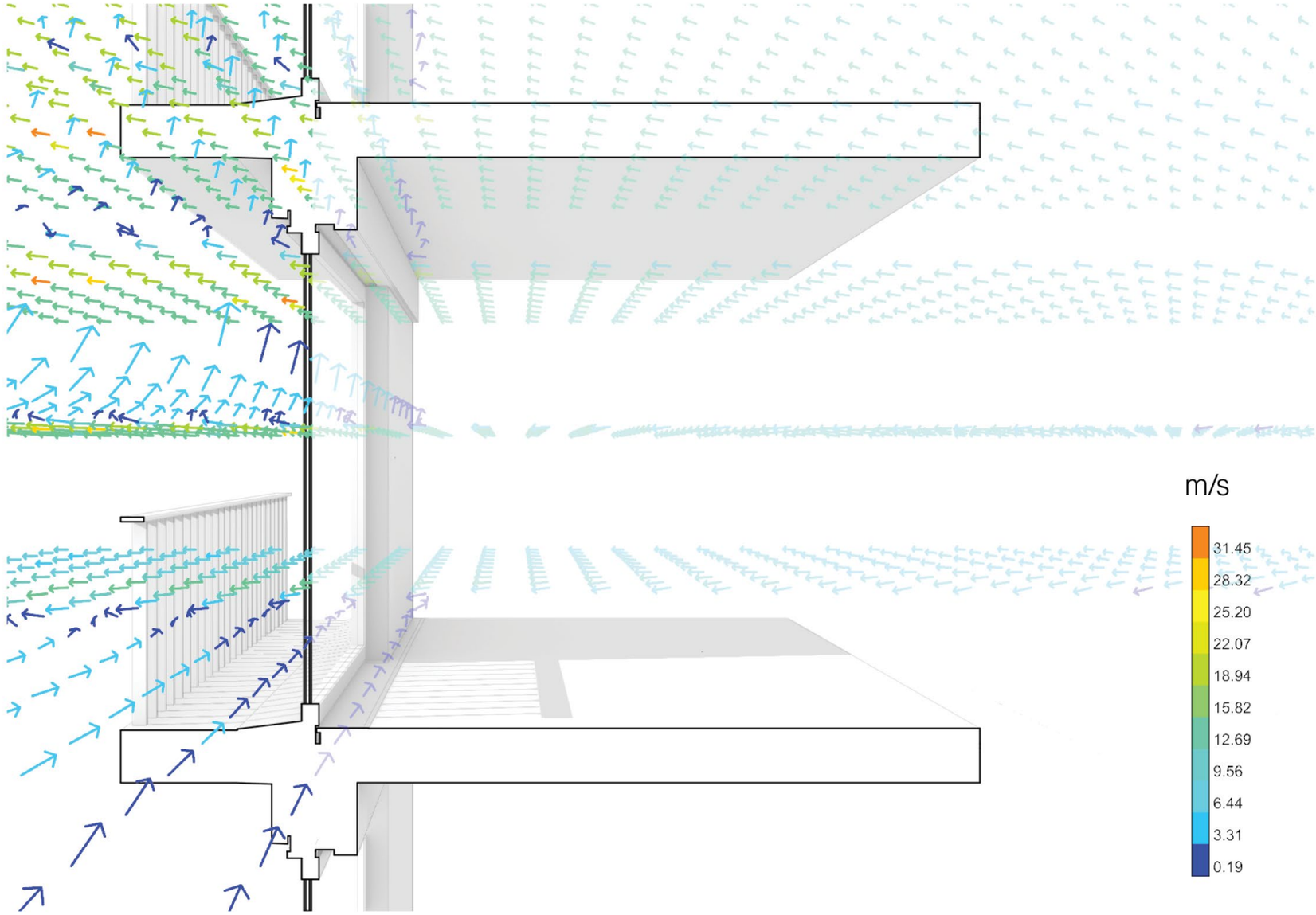




Wind Simulation

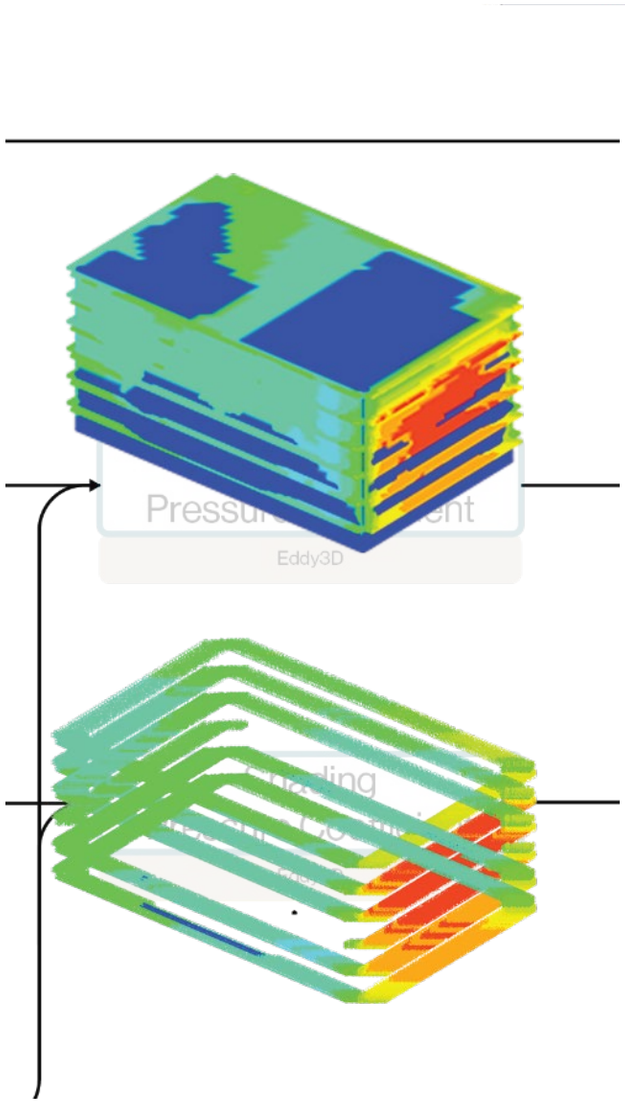
Applied to Case Study

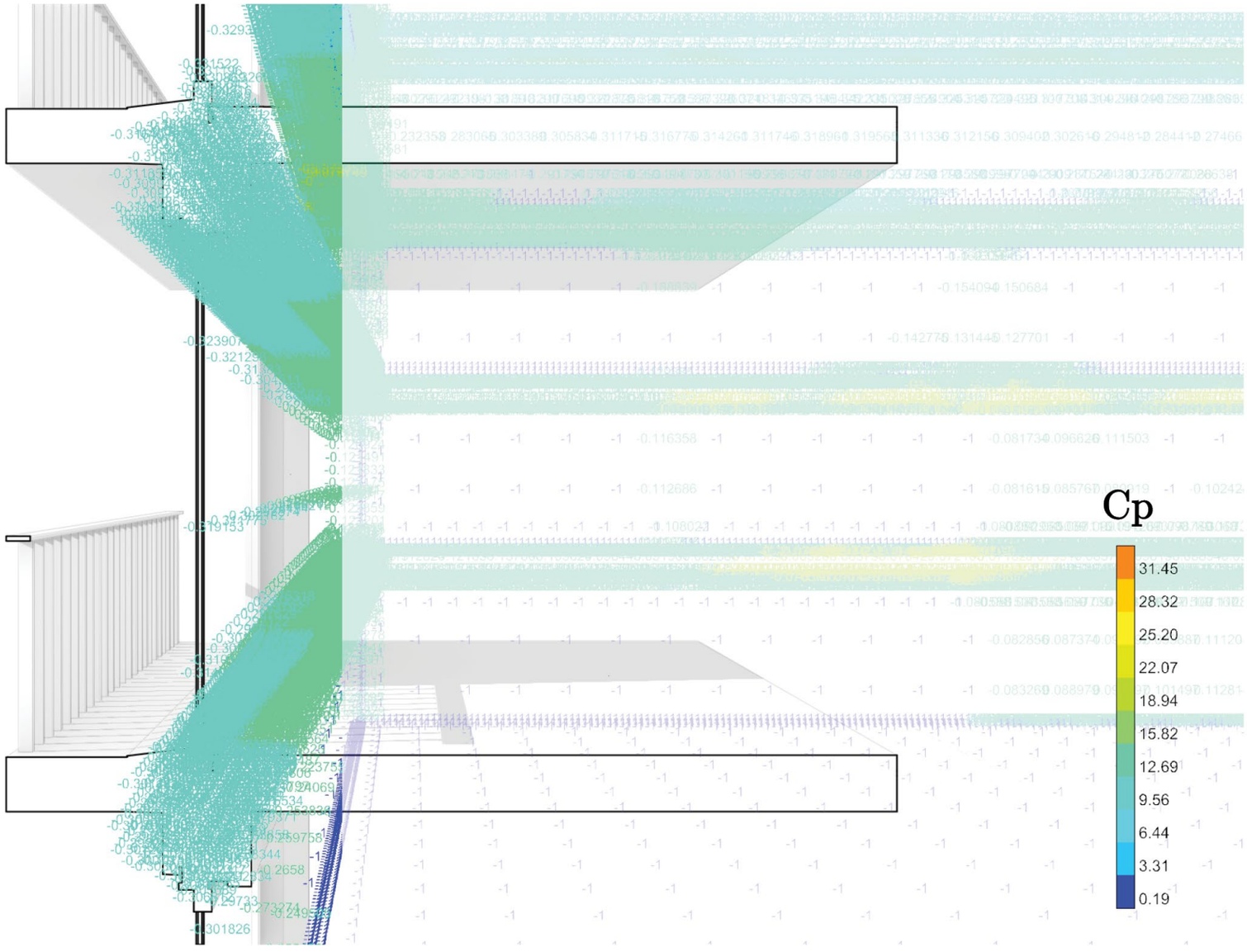




Wind Simulation

Applied to Case Study





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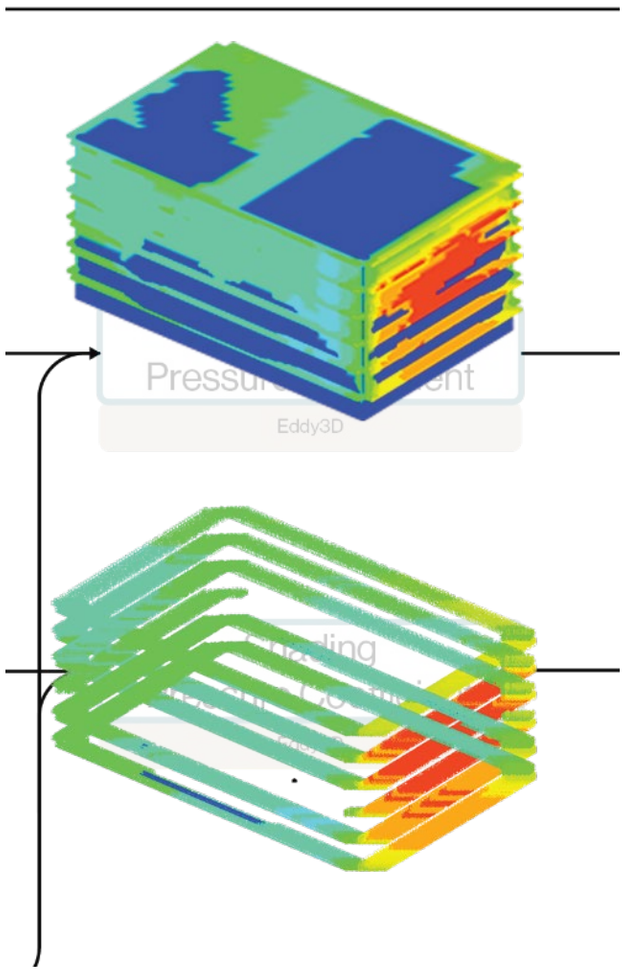
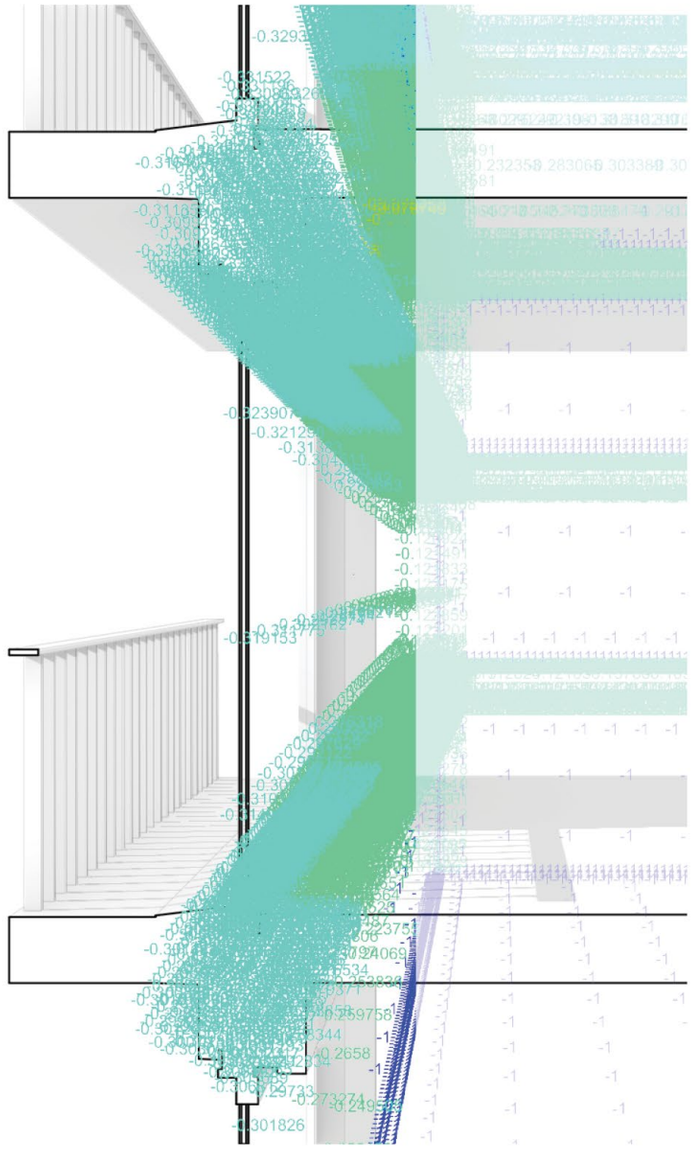
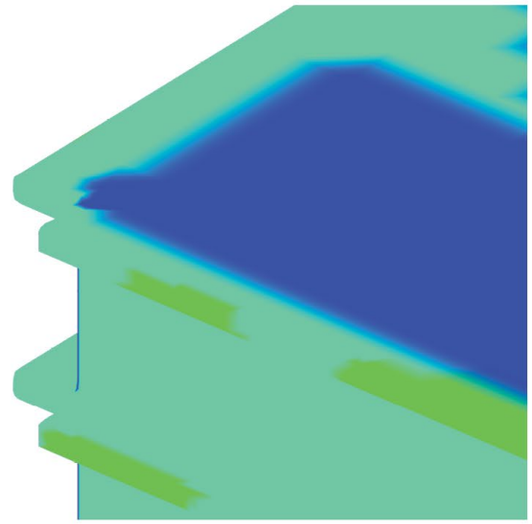
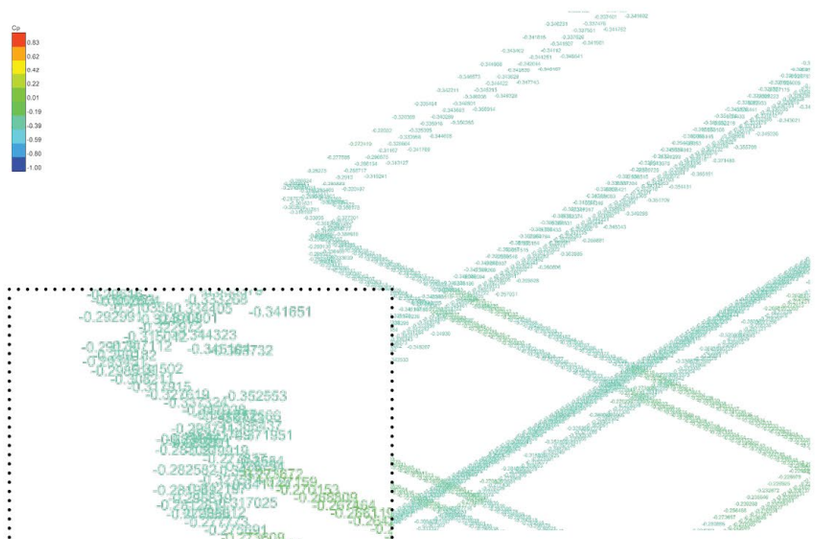
Applied to Case Study







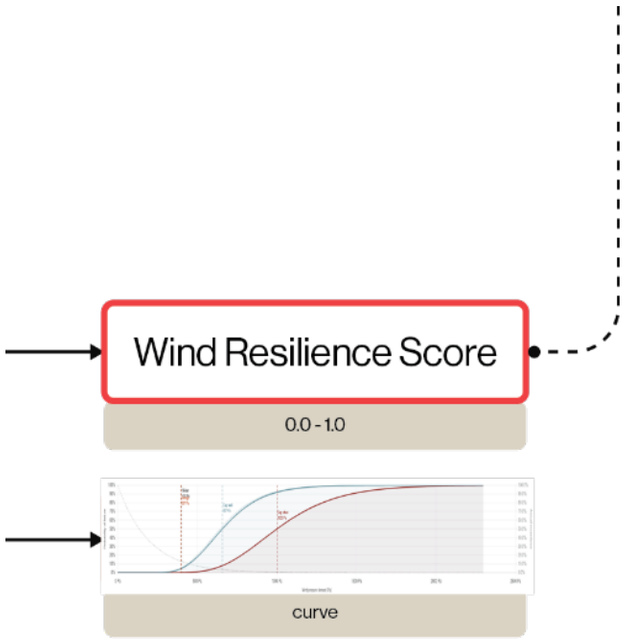
Pressure Coefficient on Wall (Close Up)



Pressure Coefficient on Shading Element (Close Up)

Wind Resilience

Applied to Case Study



Resilience Quantification

Wall Demand

$$D_{wall} = q_p \cdot |Cp| \quad [Pa]$$

Wall Capacity

$$C_{wall} = \frac{f_{g,d} \cdot h^2}{k_1 \cdot a^2} \quad [Pa]$$

NEN-EN 16612:2019

Wall Probablity of Failure

$$P_{wall} = \Phi\left(\frac{\ln(D_{wall}/C_{wall}}{\beta}\right)$$

FEMA P-58

Shading Demand

$$D_{shad} = q_p \cdot |Cp| \quad [Pa]$$

Shading Capacity (user input)

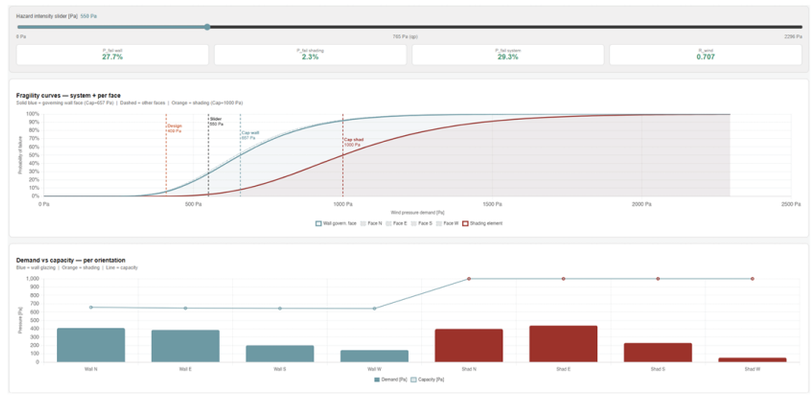
$$C_{shad} \quad [Pa]$$

Shading Probablity of Failure

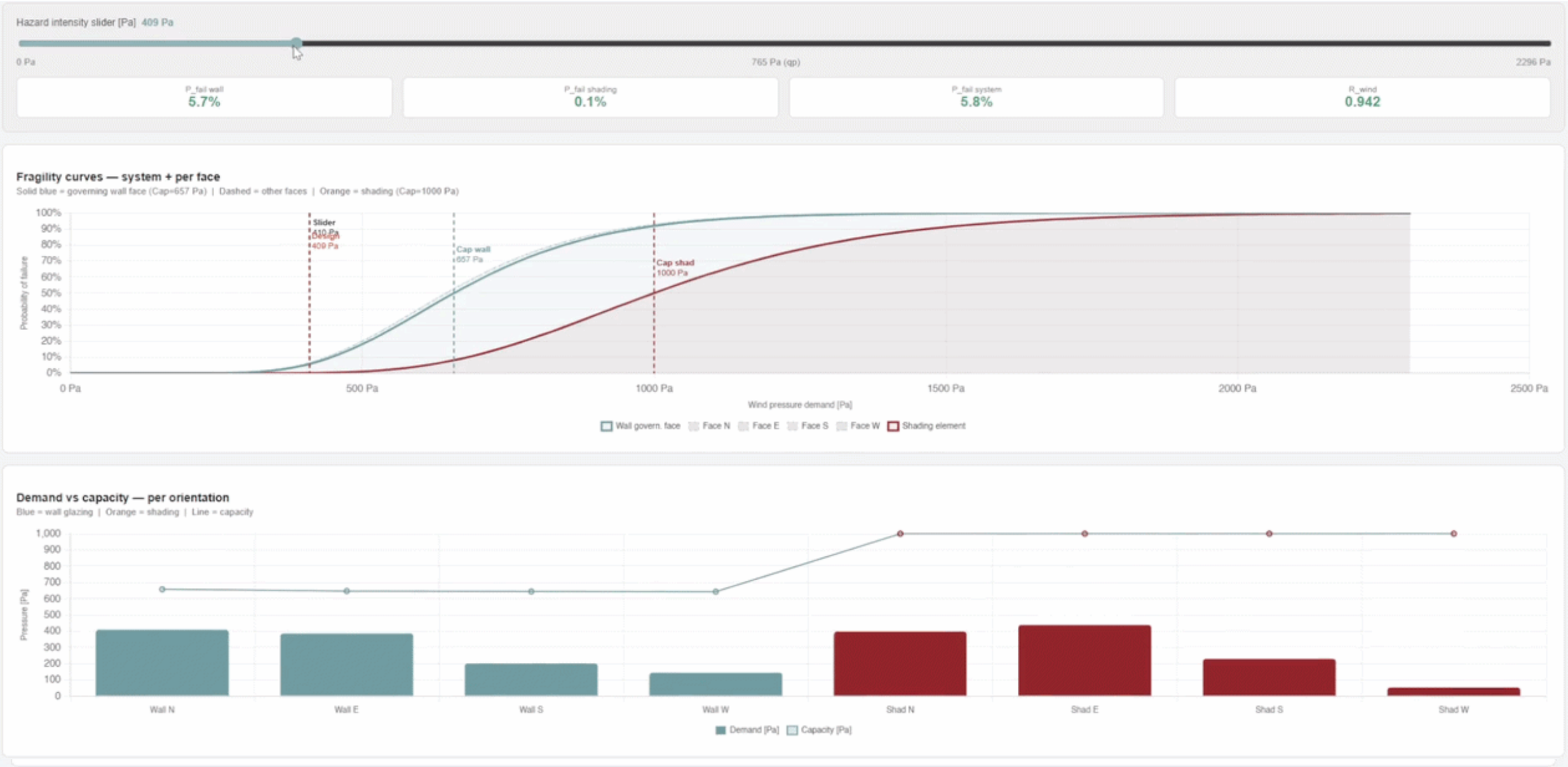
$$P_{shad} = \Phi\left(\frac{\ln(D_{shad}/C_{shad}}{\beta}\right)$$

FEMA P-58

Fragility Curve



Fragility Curve
Viewer



Fragility Curve
Viewer

Hazard intensity slider [Pa] 550 Pa

0 Pa — 765 Pa (qp) — 2296 Pa

P_fail wall	P_fail shading	P_fail system	R_wind
27.7%	2.3%	29.3%	0.707

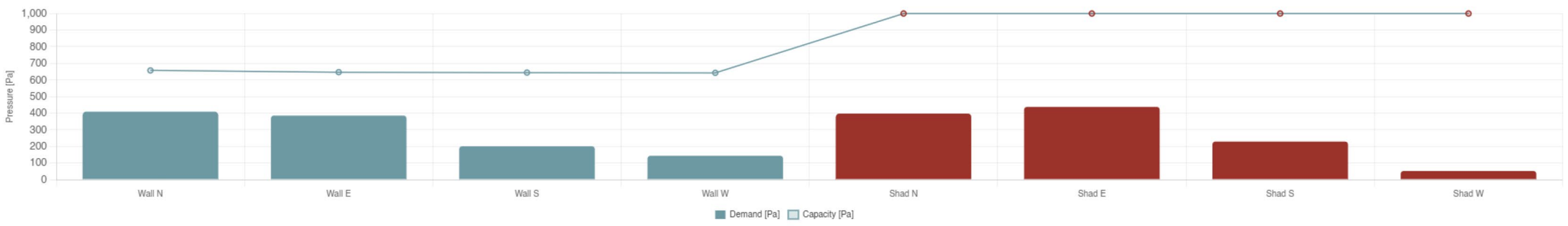
Fragility curves — system + per face

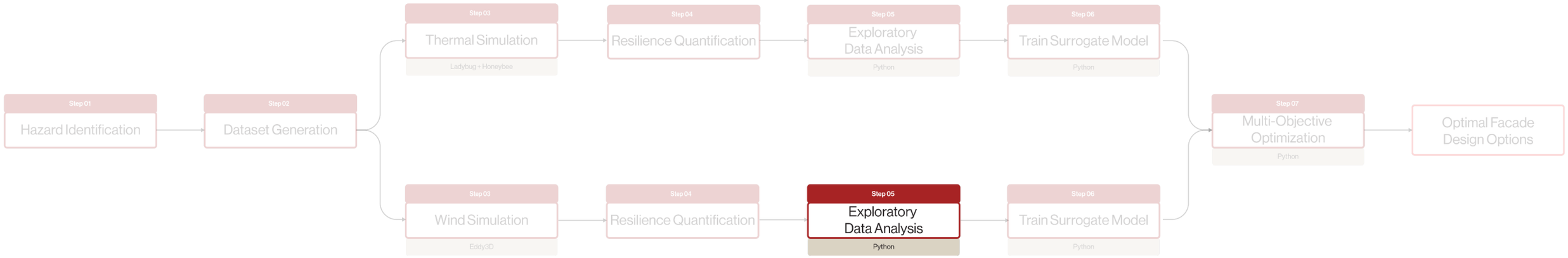
Solid blue = governing wall face (Cap=657 Pa) | Dashed = other faces | Orange = shading (Cap=1000 Pa)



Demand vs capacity — per orientation

Blue = wall glazing | Orange = shading | Line = capacity

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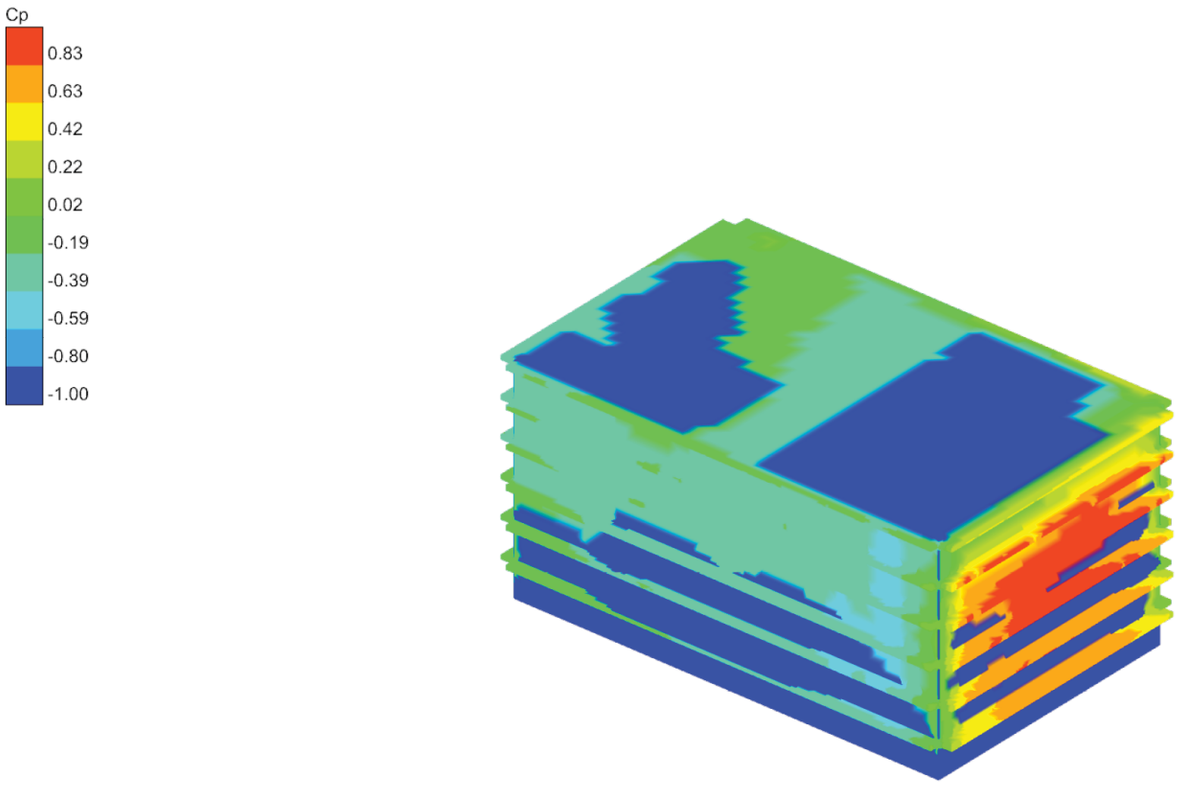
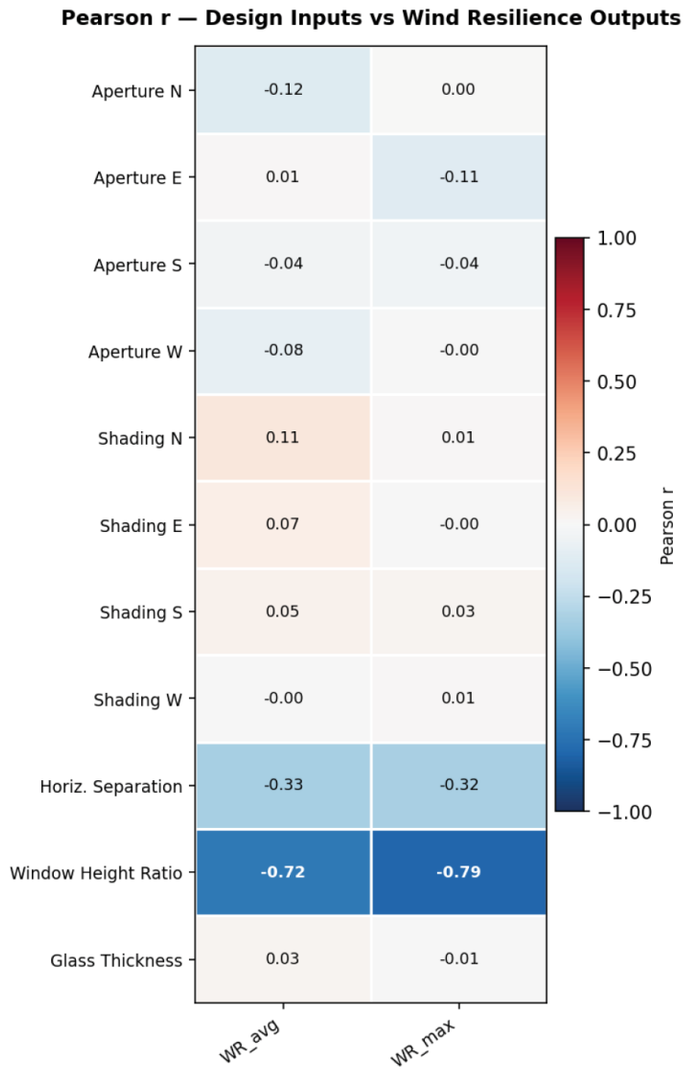
Correlation Analysis

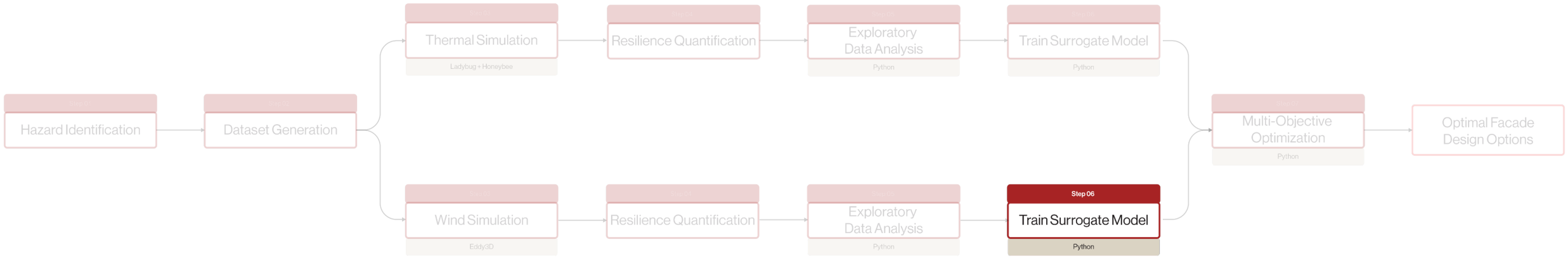
Wind Resilience





Findings

Window Height Ratio	on Wind Resilience Average	r = +0.72
Window Height Ratio	on Wind Resilience Max	r = +0.79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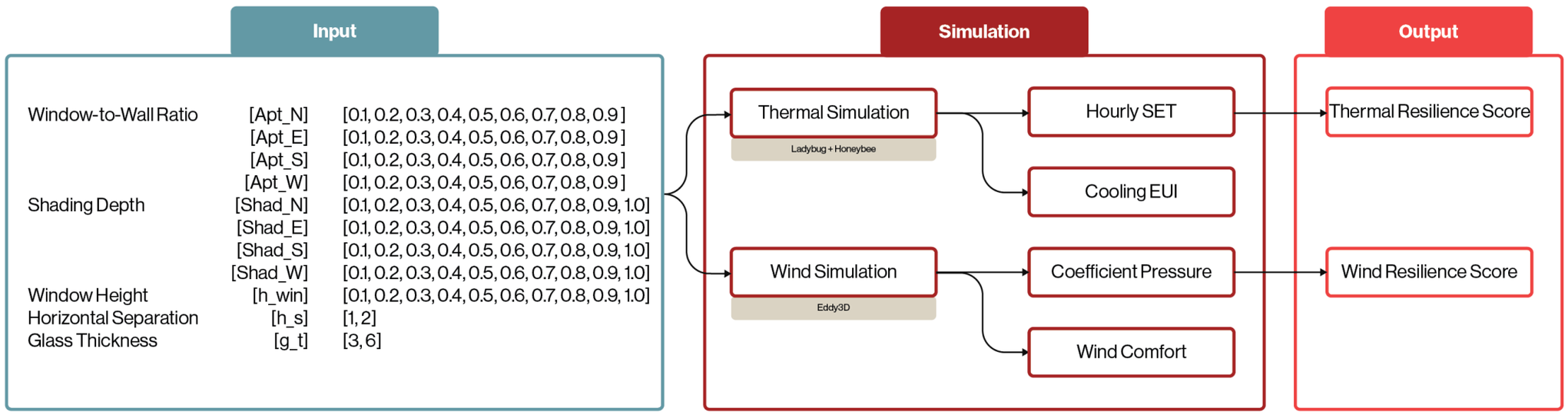
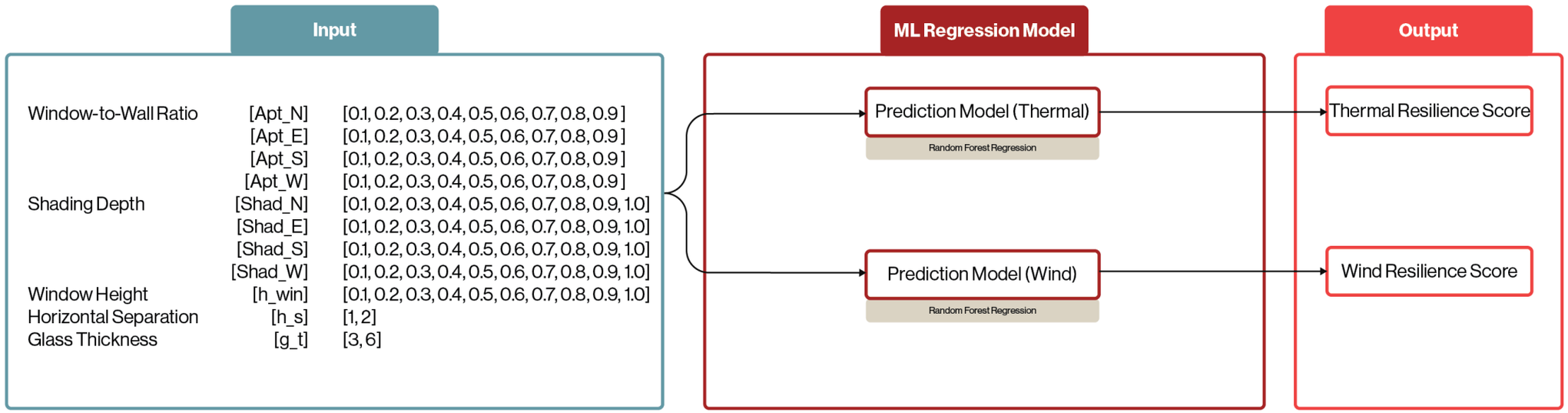
Random Forest Regression

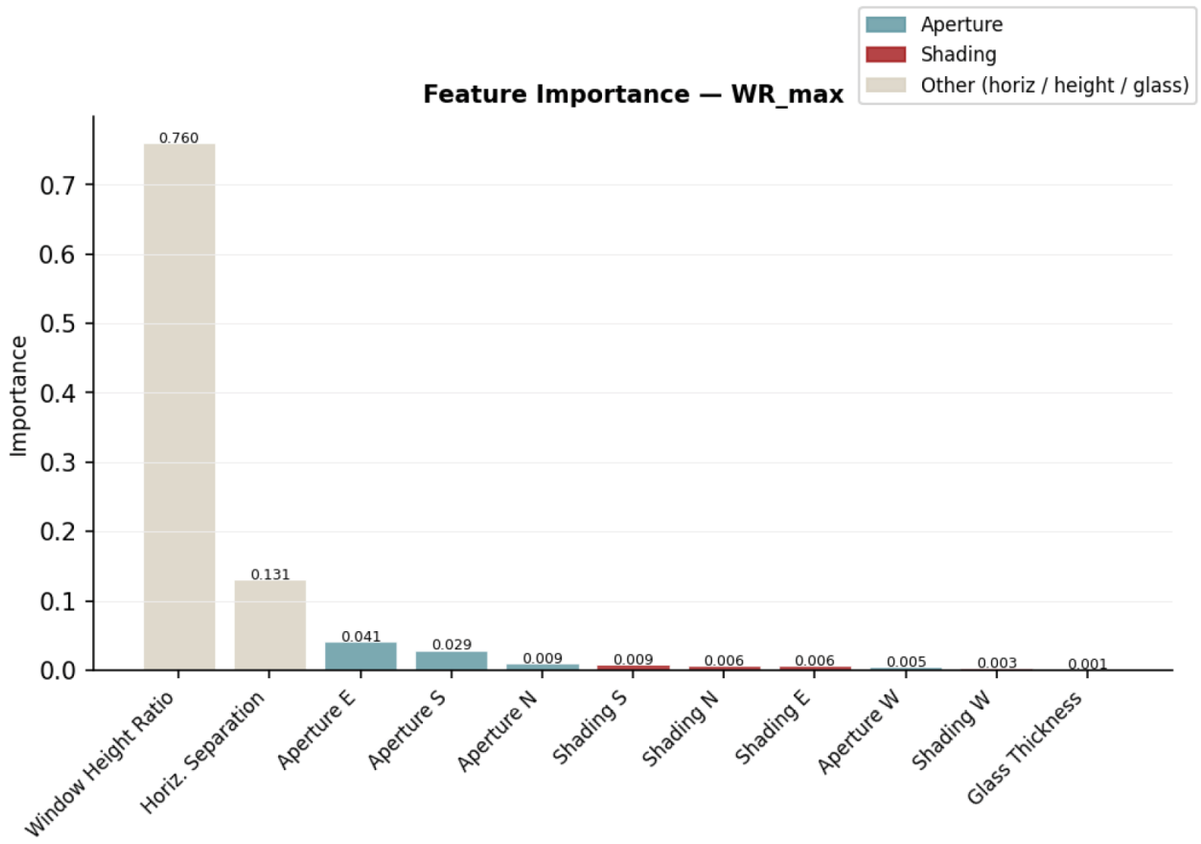
Dataset Distribution



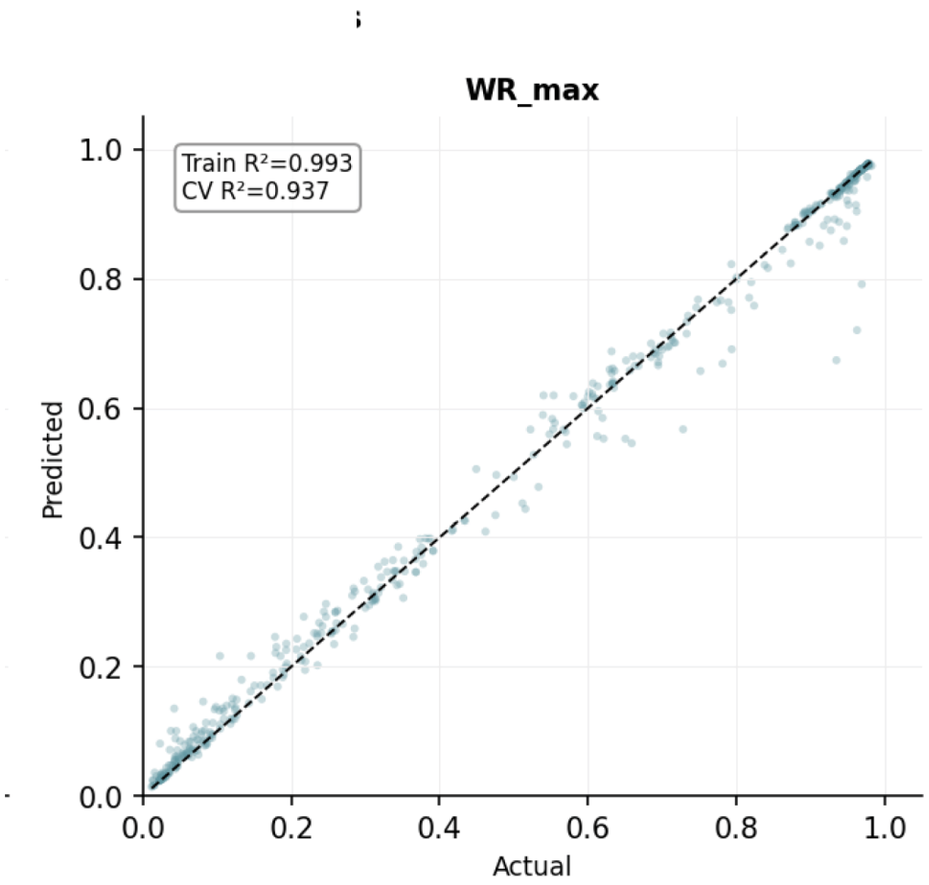


Random Forest Regression

Feature Importance



Parity Plots



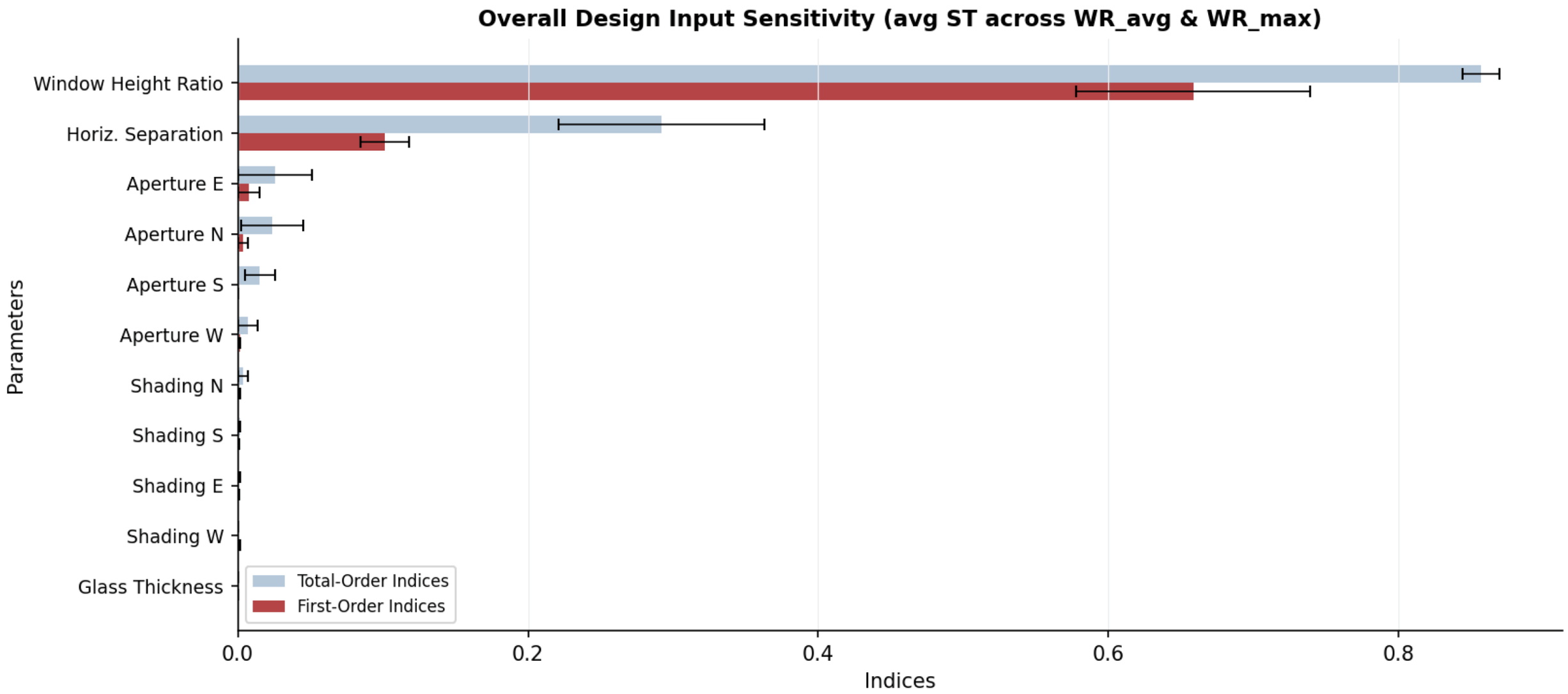
Findings

For both Wind Resilience Average and Wind Resilience Maximum, the strongest drivers are:

Window Height Ratio (0.614)
Horizontal Separation (0.233)

Sobol's Method

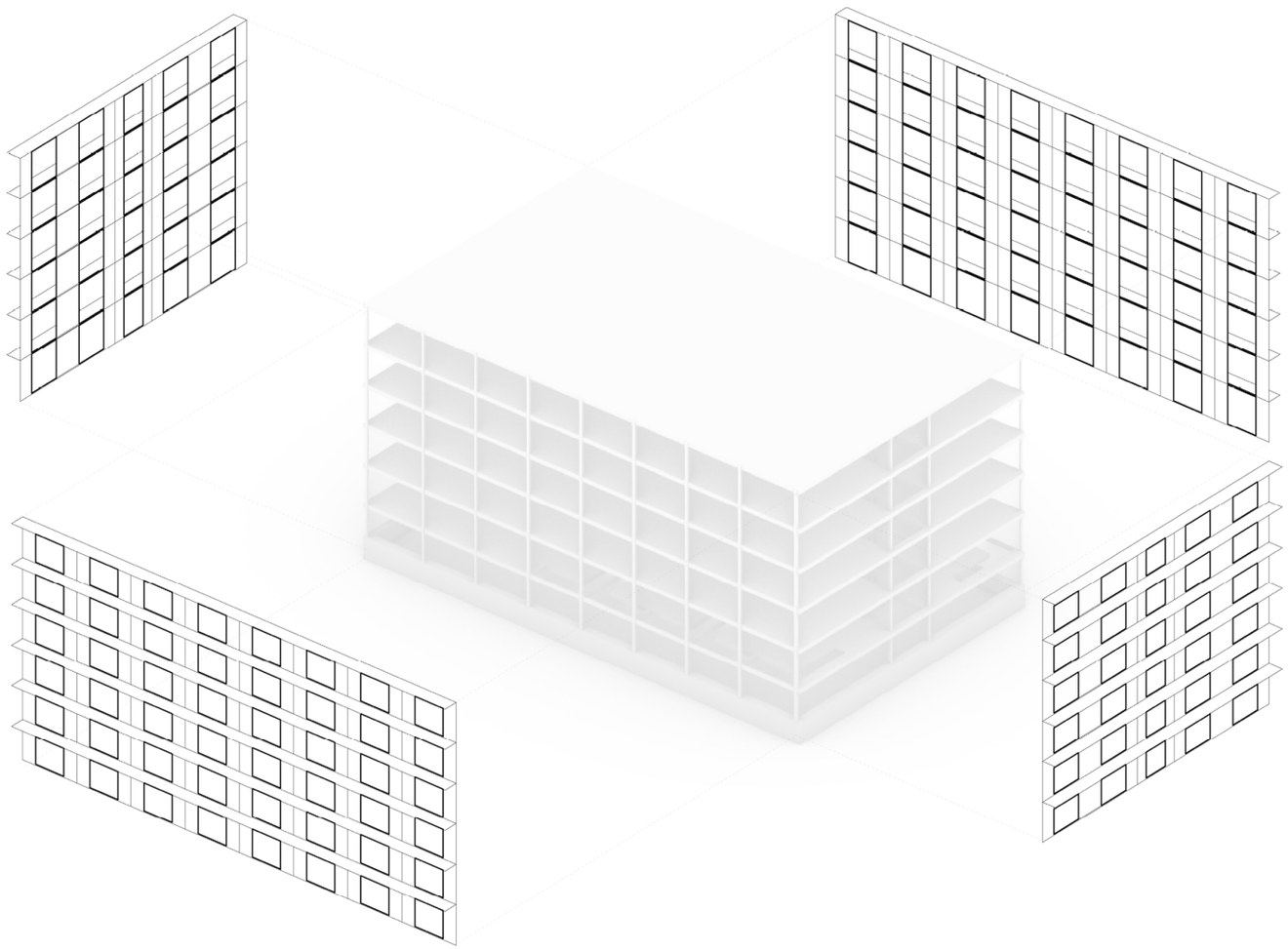
Sensitivity Analysis



Wind resilience is governed almost entirely by the two window subdivision parameters acting jointly:
Window Height Ratio and **Horizontal Separation**. with the apertures, shading depths, and glass thickness all contributing negligibly within the explored design space.

Key Findings

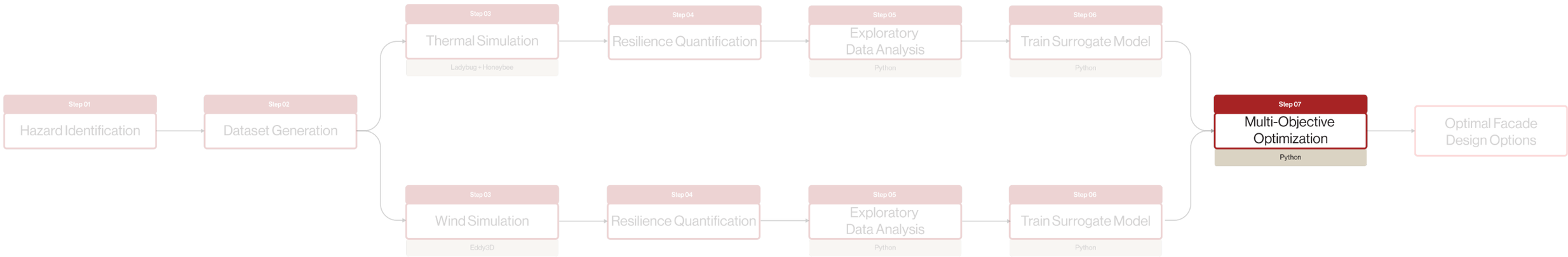
Window Height



The window subdivision parameters dominate the wind resilience response. The window height ratio alone accounts for approximately 85 % of the total-order Sobol variance across both WR_avg and WR_max, and the horizontal separation ratio adds a further 29 %. Together, the two parameters explain the overwhelming majority of the variability in the wind resilience score across the design space.

Case Study

Multi-Objective Optimization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Step 07

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Step 06

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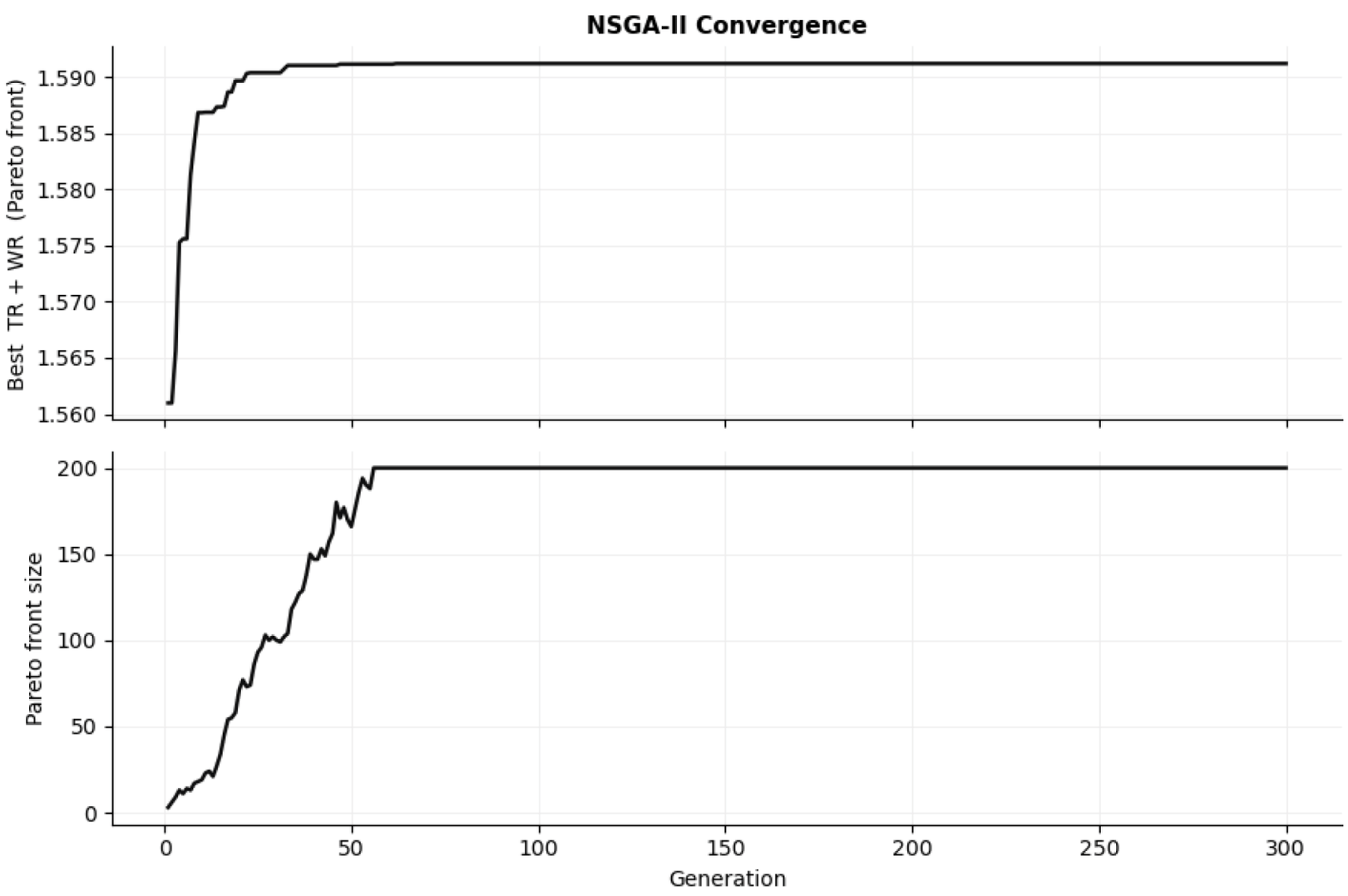
Multi-Objective Optimization

Setting



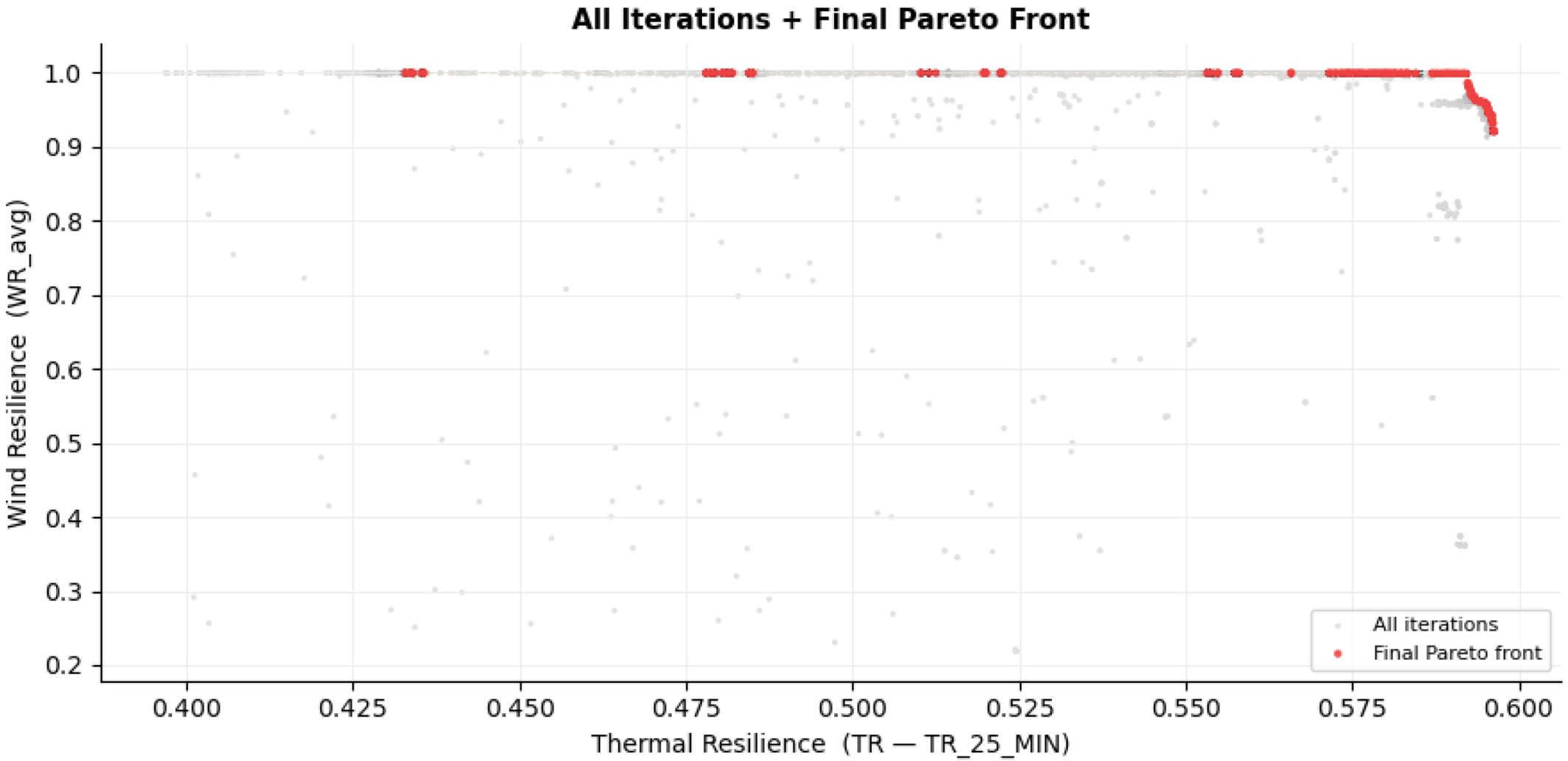
NSGA-II Algorithm

Population Size : 200

Termination Criterion : 300

Multi-Objective Optimization

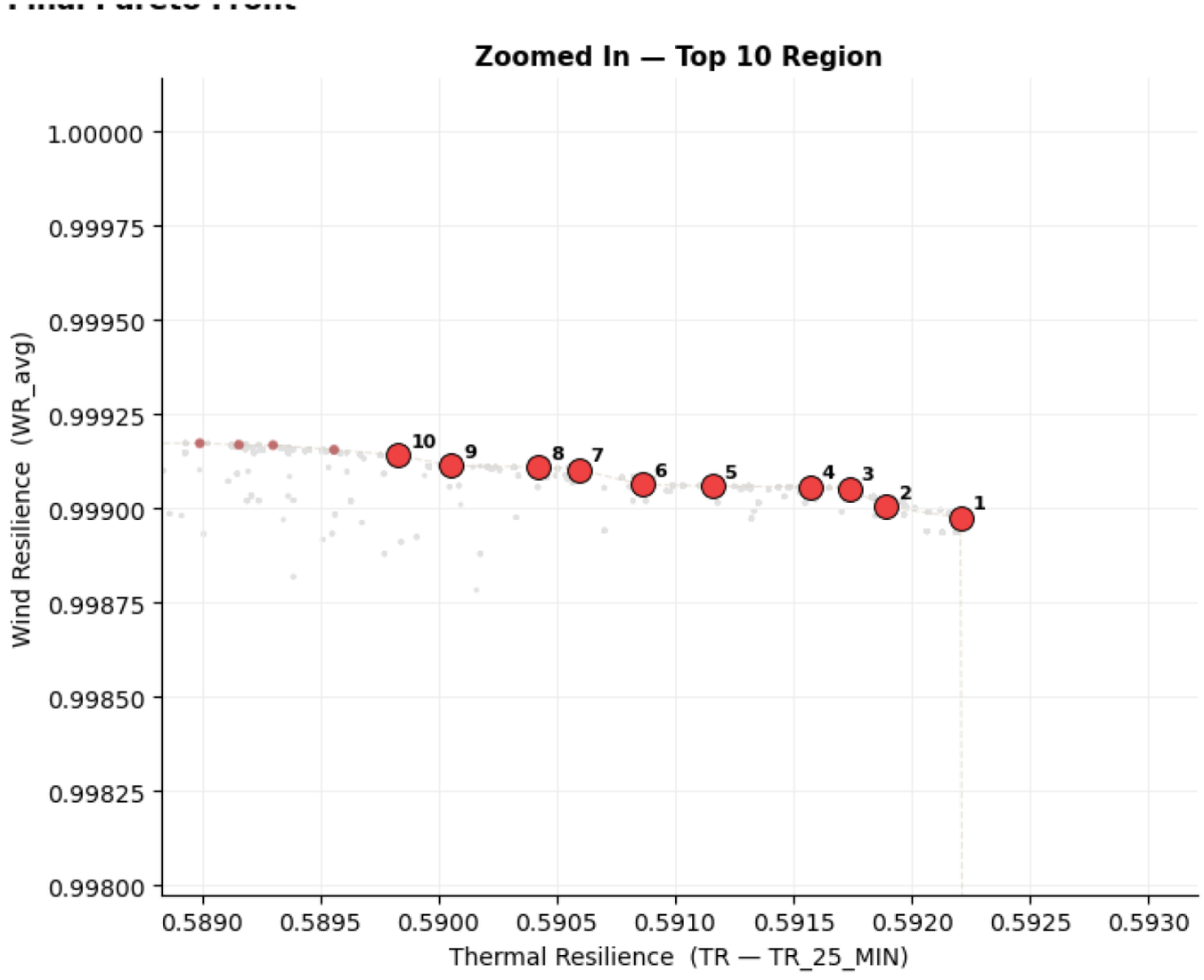
Result



The optimisation produces an L-shaped Pareto front with a sharp knee at approximately (TR_avg, WR_avg) = (0.969, 0.99), inside which the top-five solutions cluster tightly within sub-percent differences, defining a clear best-compromise region beyond which further gain in one objective comes at sharp expense to the other.

Multi-Objective Optimization

Result



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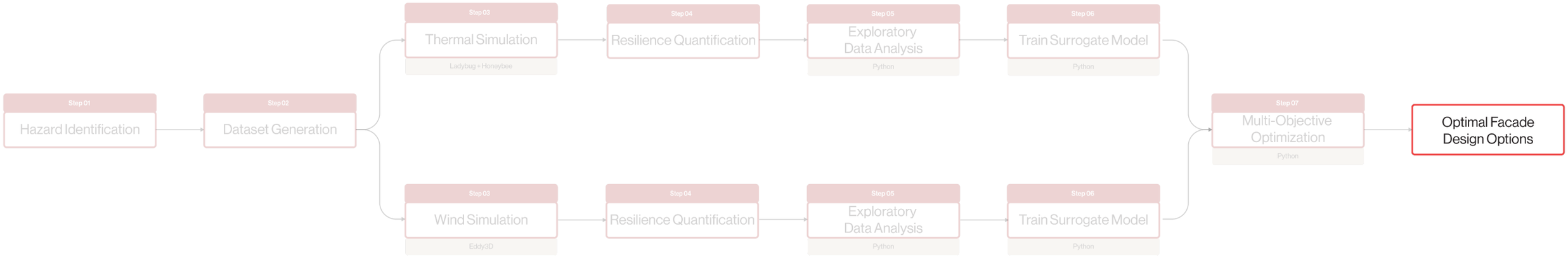
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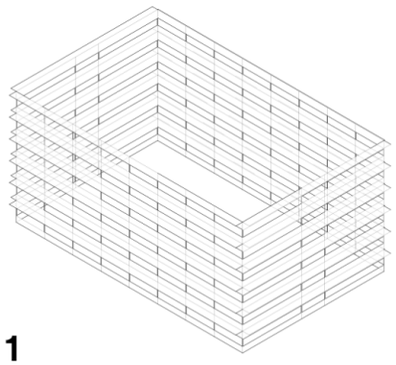
Optimal Facade Design Options

Multi-Objective Optimization Result

Top 5 Options



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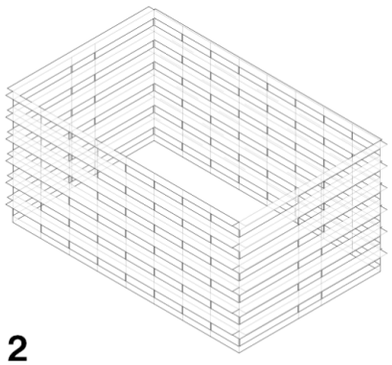

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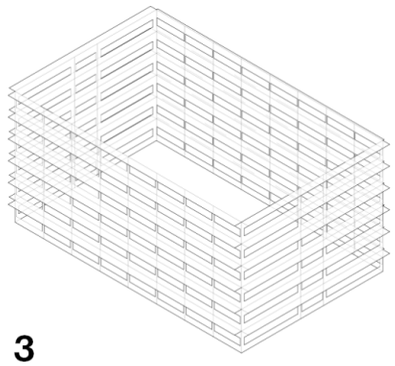

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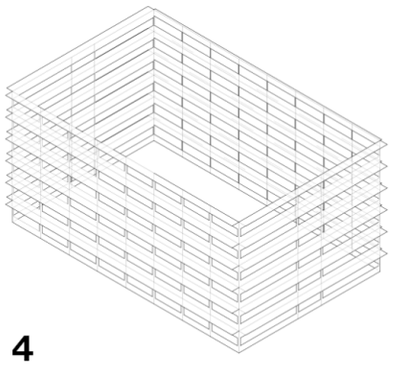

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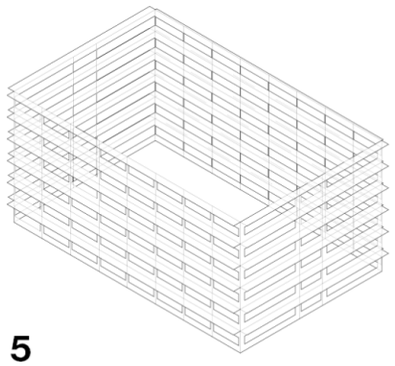
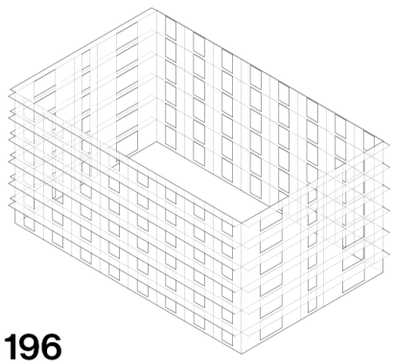


5

Rank	TR	WR	Apt_N	Apt_E	Apt_S	Apt_W	Shad_N	Shad_E	Shad_S	Shad_W	H_s_r	W_h	G_t
1	0.5922	0.999	0.327	0.312	0.347	0.302	0.087	0.964	0.984	0.756	0.326	0.059	6
2	0.5919	0.999	0.327	0.312	0.347	0.302	0.210	0.964	0.984	0.757	0.326	0.074	6
3	0.5917	0.998	0.332	0.313	0.316	0.304	0.192	0.978	0.984	0.846	0.336	0.277	6
4	0.5916	0.998	0.416	0.334	0.317	0.348	0.207	0.998	0.984	0.832	0.306	0.284	6
5	0.5912	0.998	0.372	0.307	0.321	0.422	0.208	0.972	0.975	0.817	0.341	0.294	6

Multi-Objective Optimization Result

Last 200 Options



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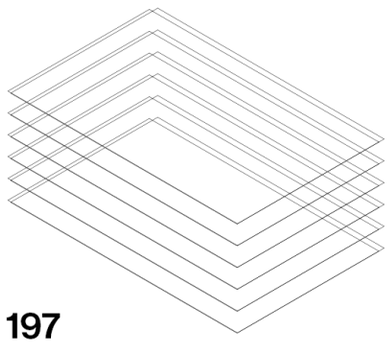

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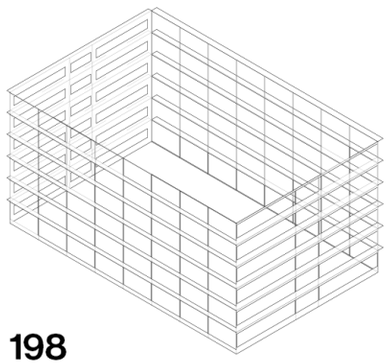

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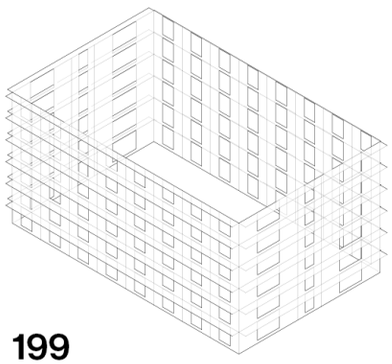

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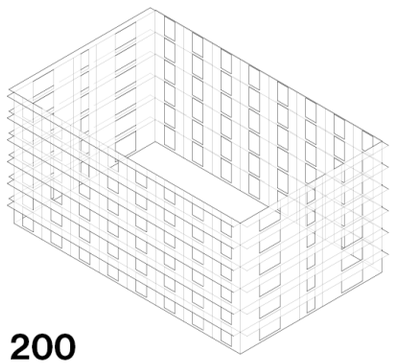
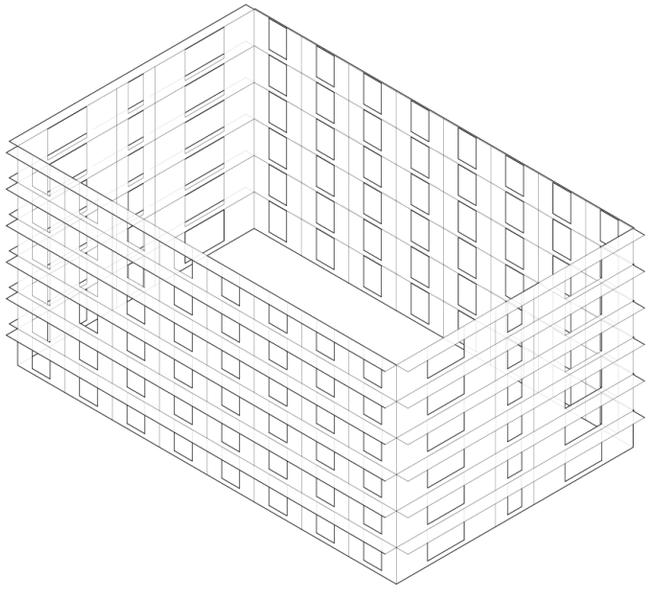


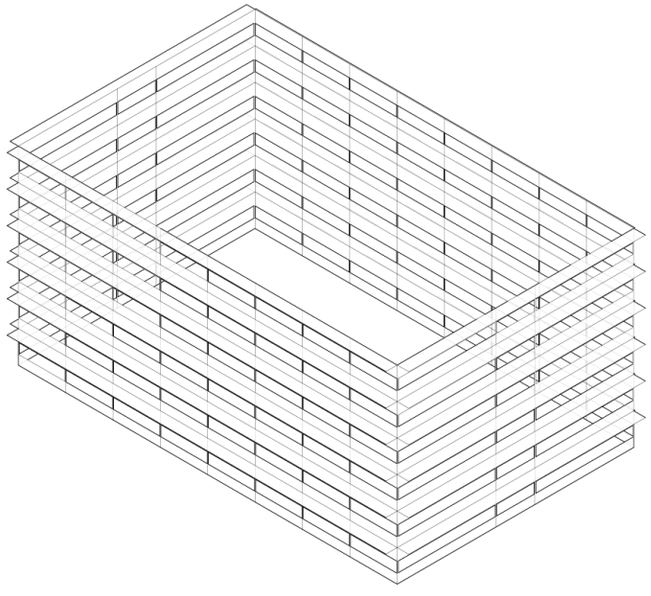
200

Rank	TR	WR	Apt_N	Apt_E	Apt_S	Apt_W	Shad_N	Shad_E	Shad_S	Shad_W	H_s_r	W_h	G_t
196	0.5963	0.921	0.319	0.314	0.312	0.307	0.075	0.997	0.967	0.724	0.304	0.870	6
197	0.4329	0.921	0.959	0.601	0.777	0.349	0.757	0.004	0.059	0.449	0.41	0.343	3
198	0.4329	0.921	0.936	0.602	0.777	0.349	0.757	0.004	0.059	0.449	0.41	0.343	3
199	0.5963	0.920	0.319	0.314	0.322	0.334	0.083	0.997	0.966	0.710	0.304	0.869	6
200	0.5963	0.919	0.321	0.306	0.329	0.307	0.083	0.979	0.959	0.719	0.346	0.898	6

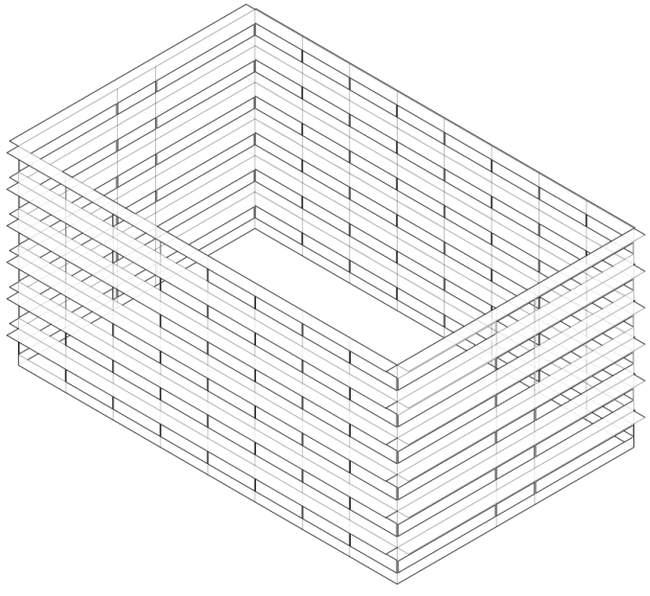
Multi-Objective Optimization Result



Best for Thermal Resilience



Best for Wind Resilience



Balanced

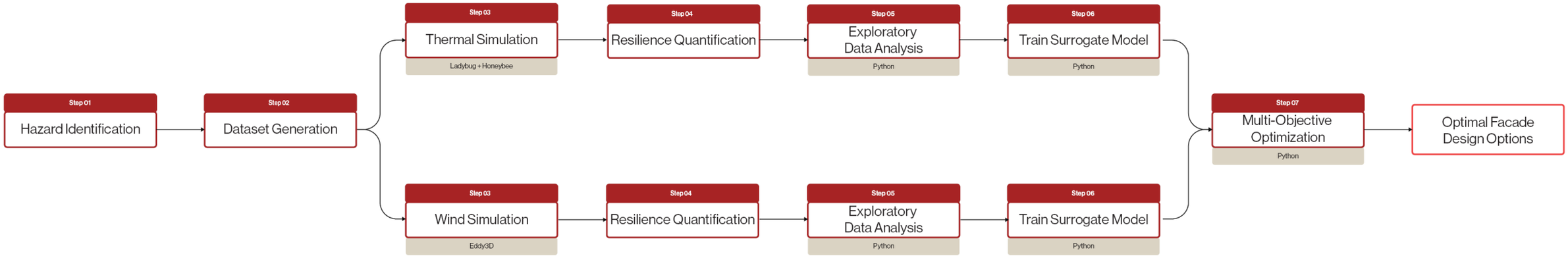
Rank	TR	WR	Apt_N	Apt_E	Apt_S	Apt_W	Shad_N	Shad_E	Shad_S	Shad_W	H_s_r	W_h	G_t
Best TR	0.5963	0.921	0.319	0.314	0.322	0.334	0.083	0.997	0.966	0.710	0.304	0.869	6
Best WR	0.4329	0.999	0.936	0.602	0.777	0.349	0.757	0.004	0.059	0.449	0.410	0.343	3
Balanced	0.5922	0.998	0.327	0.312	0.347	0.302	0.087	0.964	0.984	0.756	0.326	0.059	6

Evaluation

Research Question

How can **multi-objective optimization** approach be used to relate **façade design parameters** to **wind and thermal resilience metrics** and to **generate design options** that support designers in balancing **trade-offs** between **multiple hazards**?

Key Takeaways



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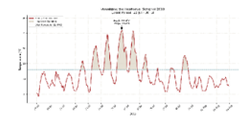
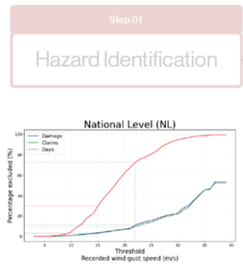
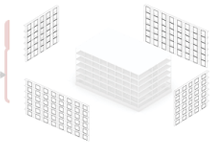
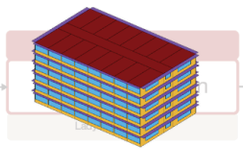


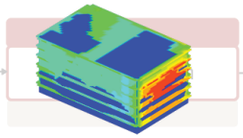
Step 01

Hazard Identification







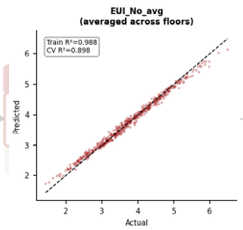


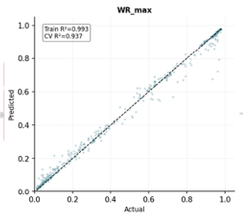


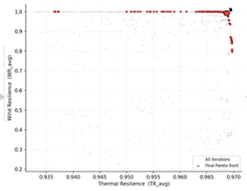


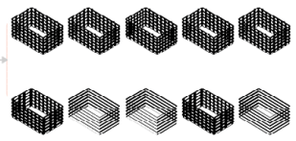






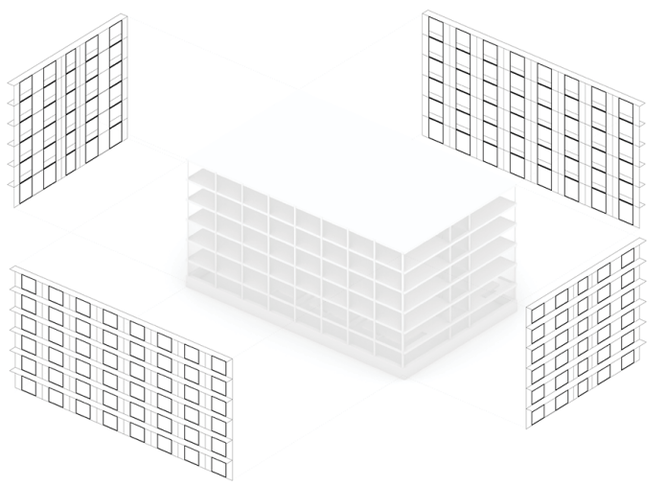






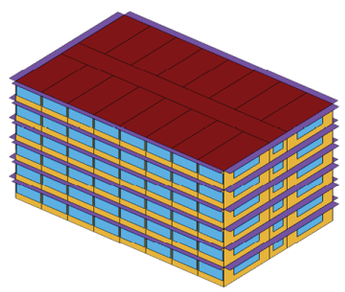
Discussion

Facade Design Parameter

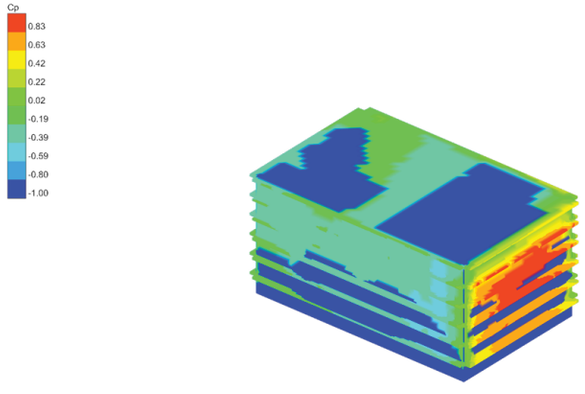


Relevance of the chosen design parameter

Multi Hazard Resilience Quantification



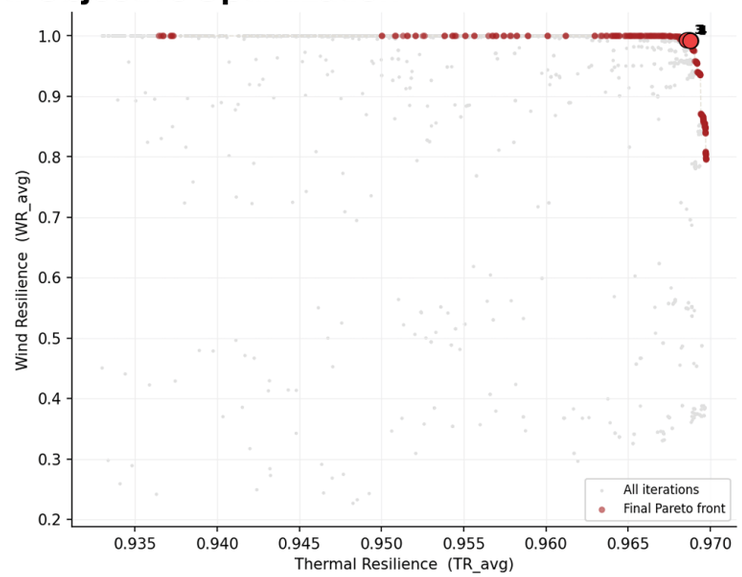
Validity of SET threshold

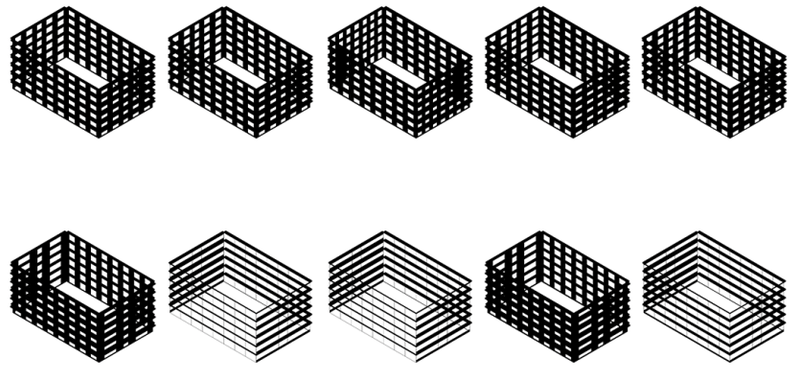


Validity of Hazard Intensity

Validity of Fragility Curve

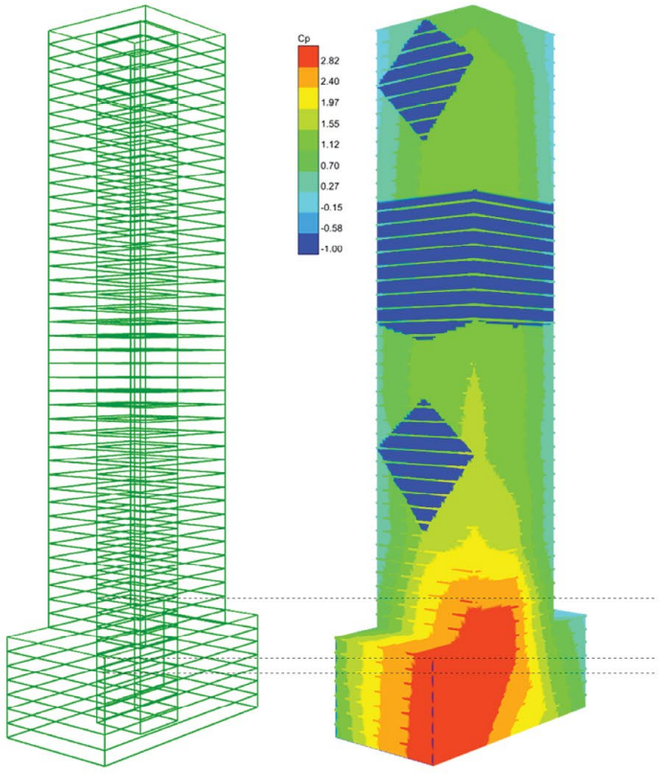
Multi-Objective Optimization





Applicability

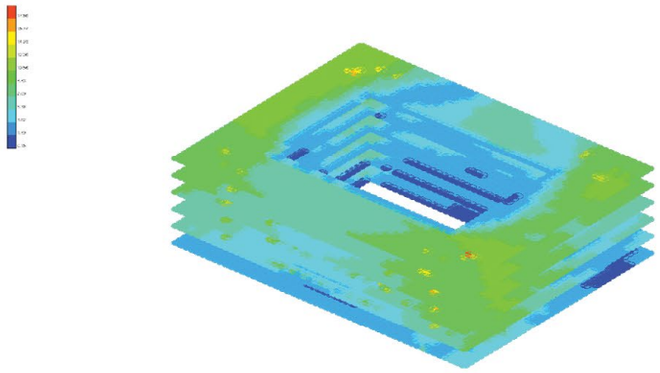
Future Research

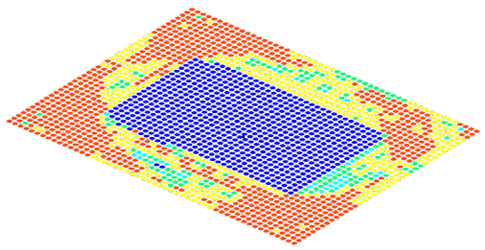


Base Model

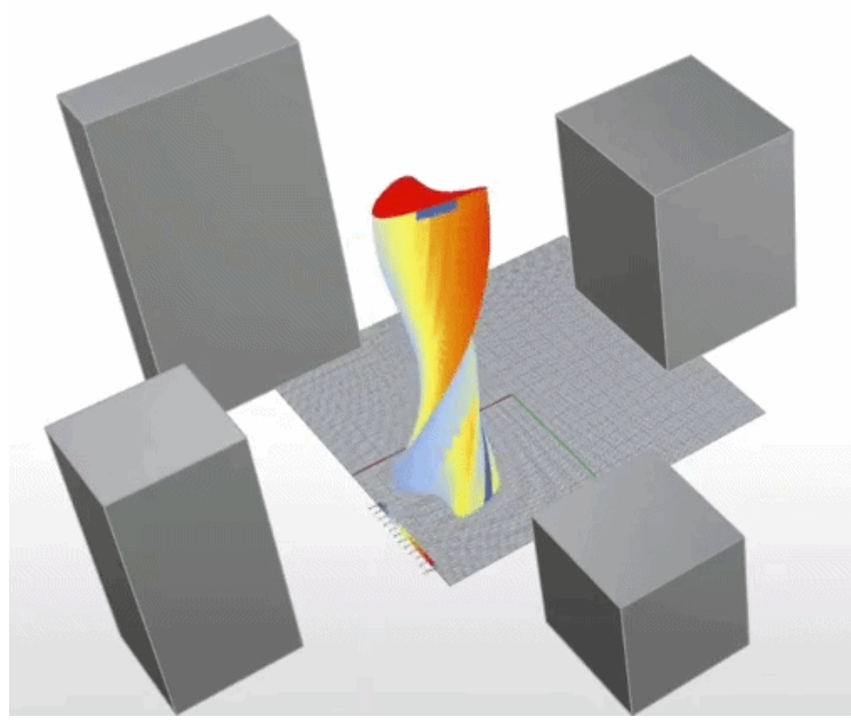
CFD Simulation

Upscaling





Objective Addition



Broaden Parametric Scope

Thank you