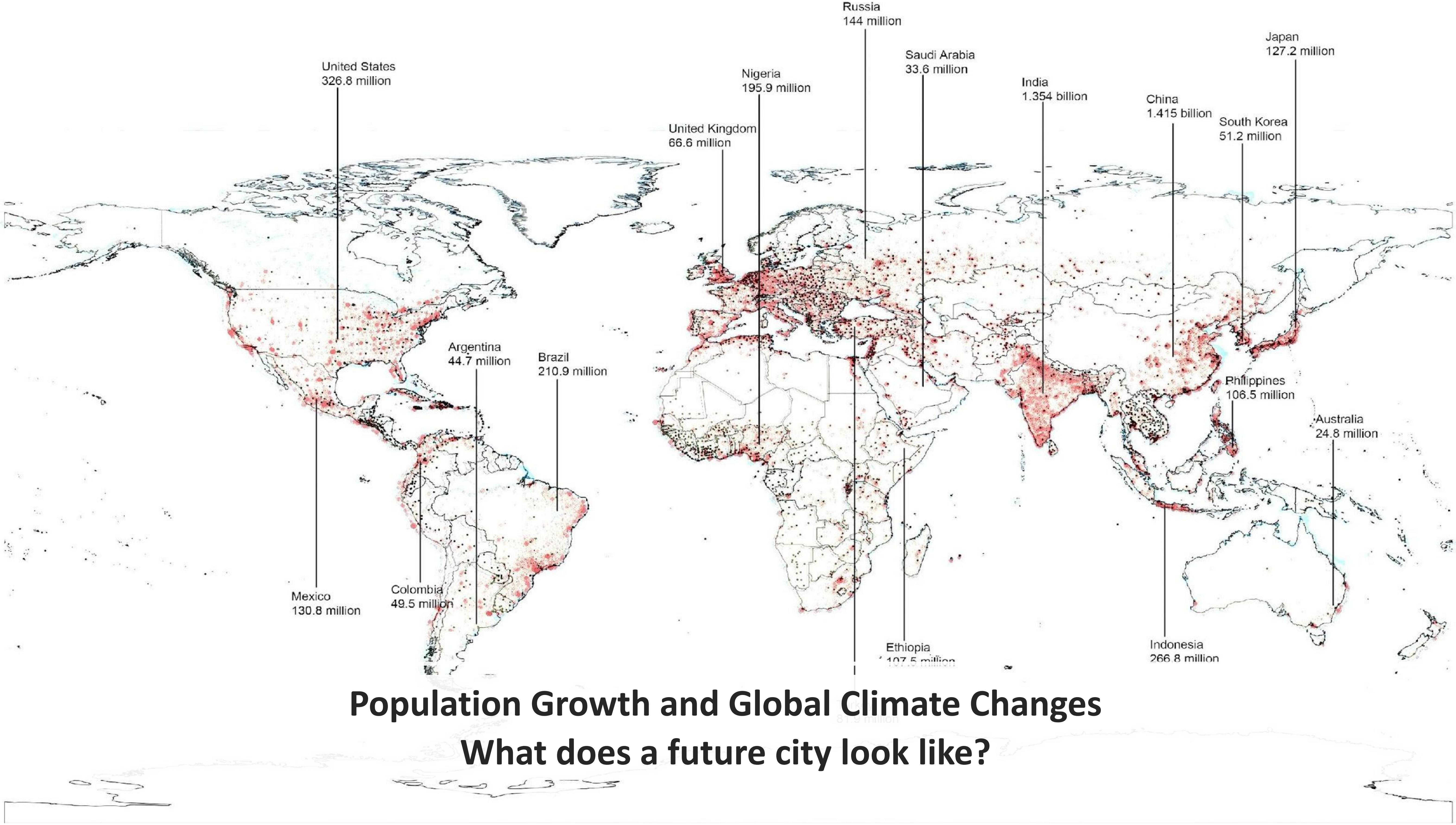
BS 2023
4-6 SEPT
SHANGHAI

The 18th IBPSA International Conference and Exhibition
Building Simulation 2023
September 4-6, 2023
Shanghai, China

Evaluating an Auto Decoder-based Generative Model for the Infomorphism Urban Planning Framework

Fengqi (Frank) Li [1] and Xinwei Zhuang（庄新伟）[2]

1 Rensselaer Polytechnic Institute, United States of America
2 University of California, Berkeley, United States of America



Population Growth and Global Climate Changes

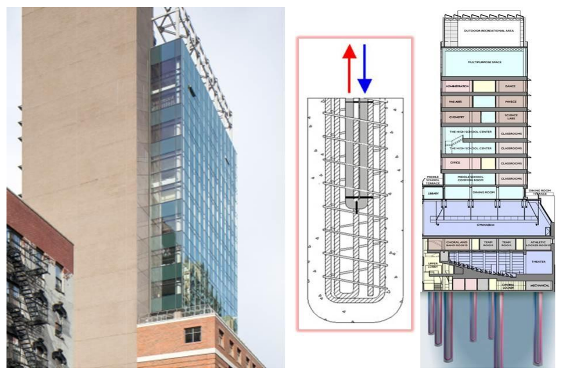
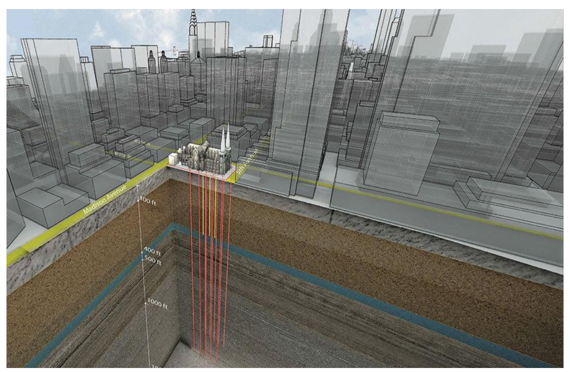
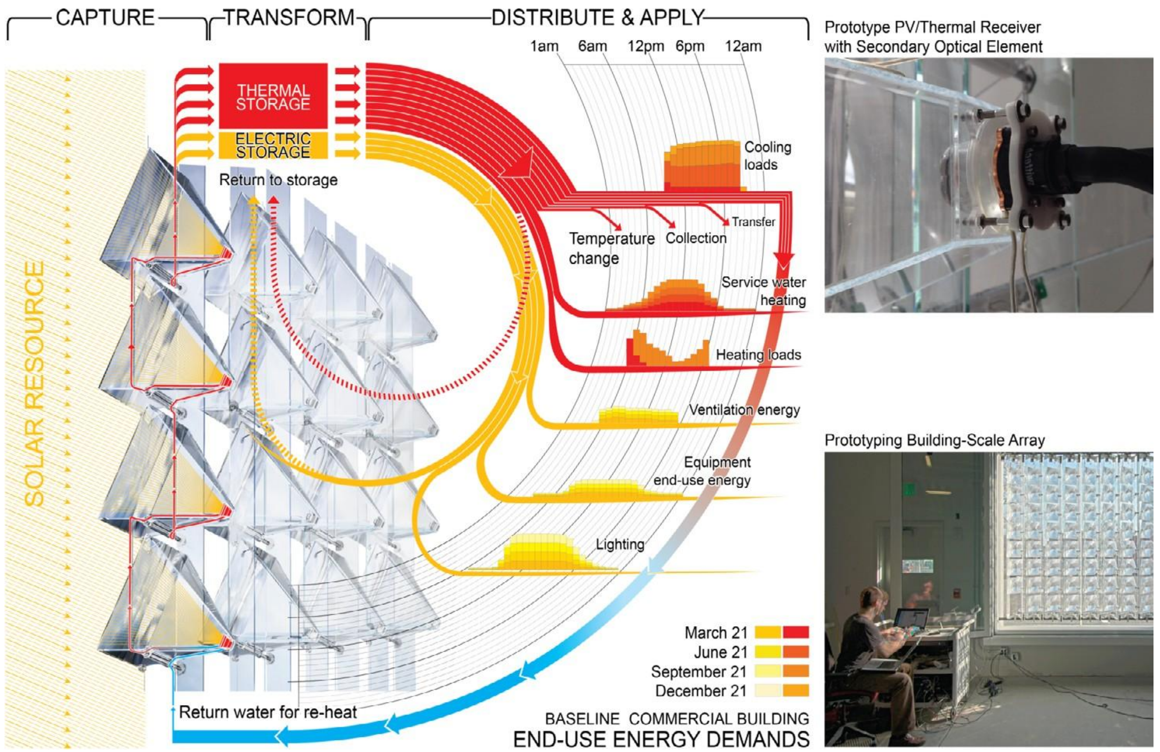
What does a future city look like?

Zero Energy Buildings (ZEBs):

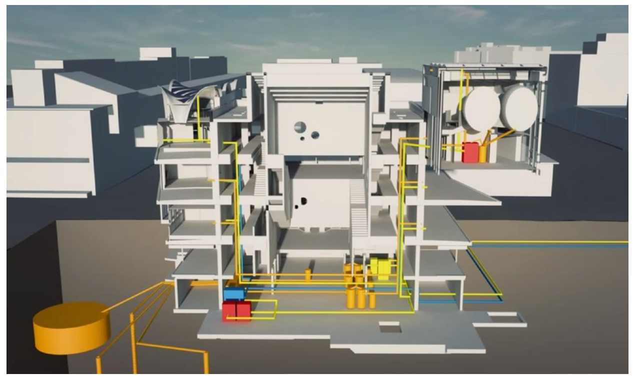
First, buildings can capture local Renewable Energy Resources (RESs);
Second, buildings can store energy locally, and therefore can become independent of the central grid;
Third, buildings can become nodes of a local energy network and share energy through exchange networks;

How can these changes affect architecture and cities?

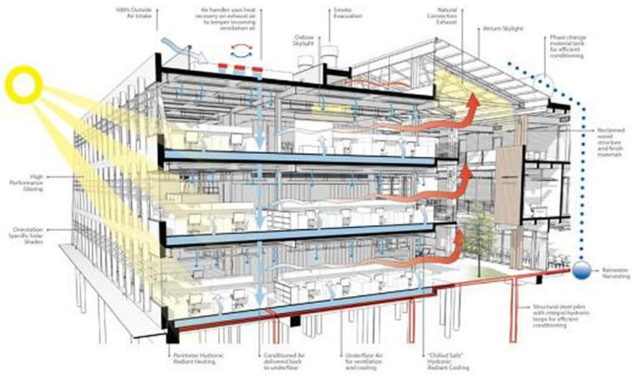
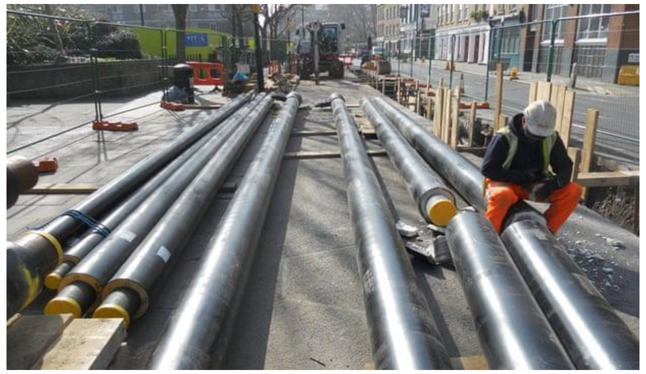


Harvest



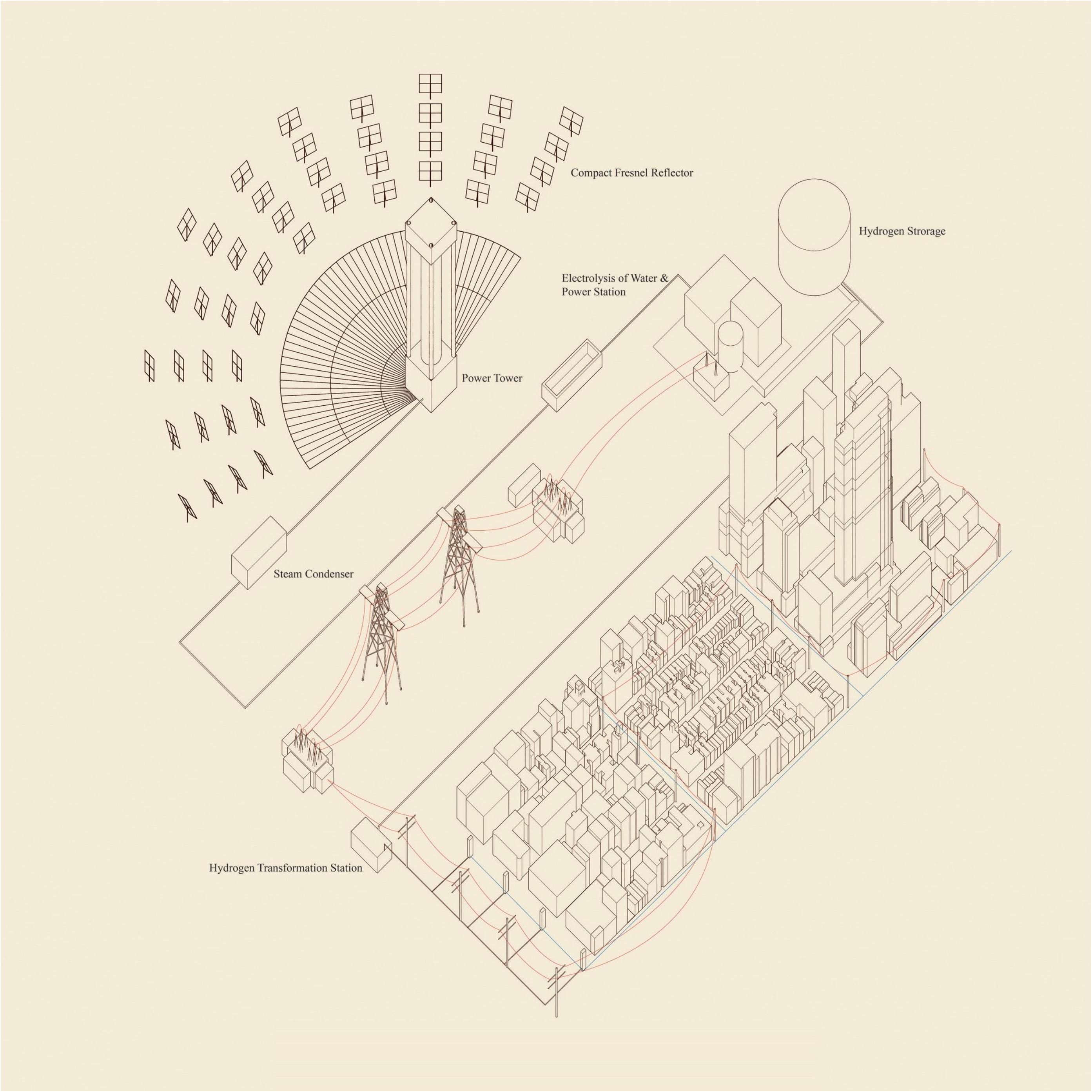
Storage

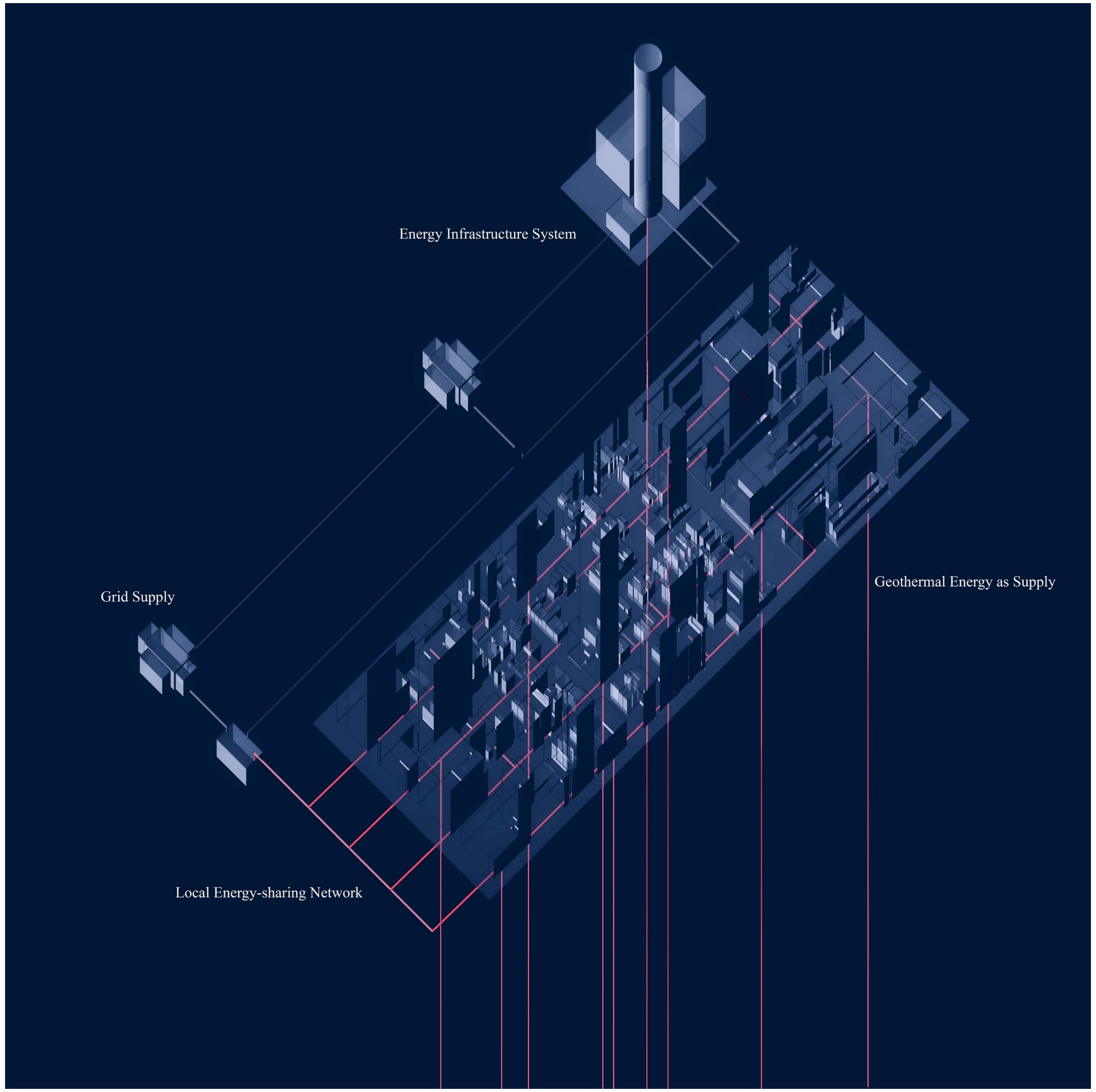

Exchange

Paradigm Shift of Infrastructure System

Centralized Energy System

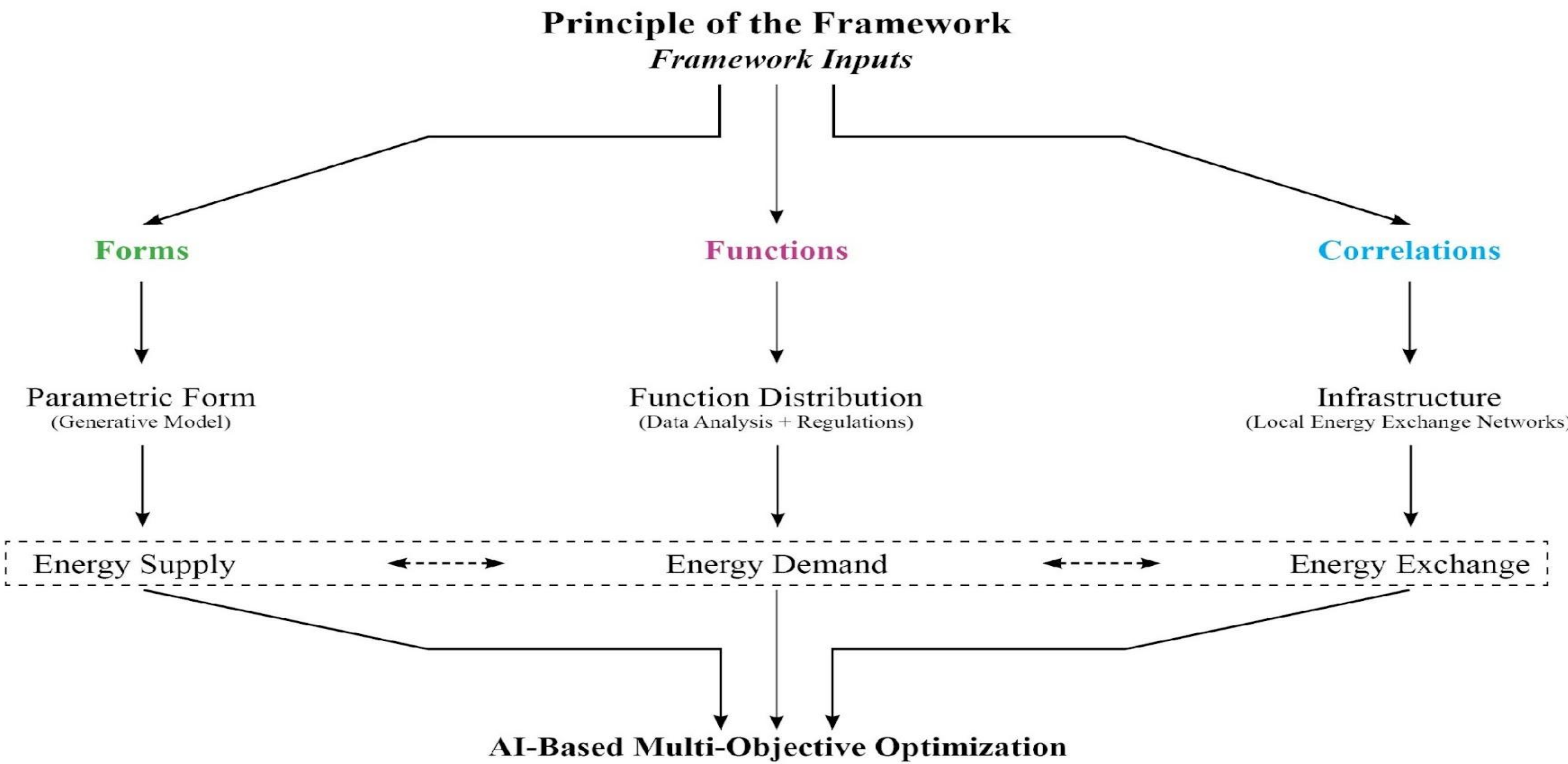


Decentralized Energy System



Data-Driven System Modeling - Principle

How to create an Artificial Intelligence-based computational workflow to fill the gap between Computational Multi-objective Optimization and Joint-simulation-based Data-driven System Modeling?

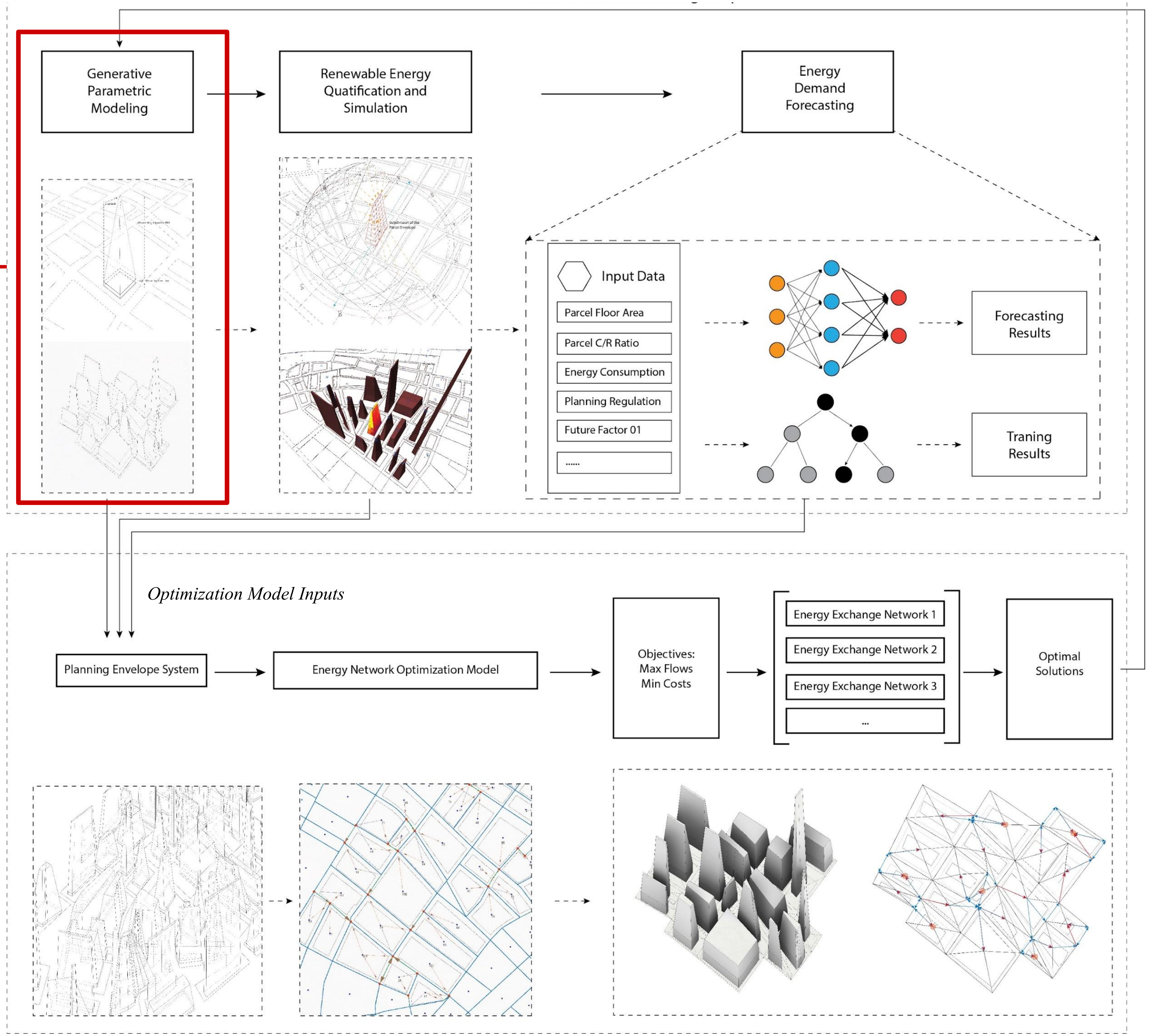


Fengqi Li, Kristen R. Schell, Haolin Yang and Alexandros Tsamis. Infomorphism: An Urban Planning Framework for Local Renewable Energy Integration. In Building Performance Analysis Conference and SimBuild co-organized by ASHRAE and IBPSA-USA. Chicago, IL, September 14-16, 2022

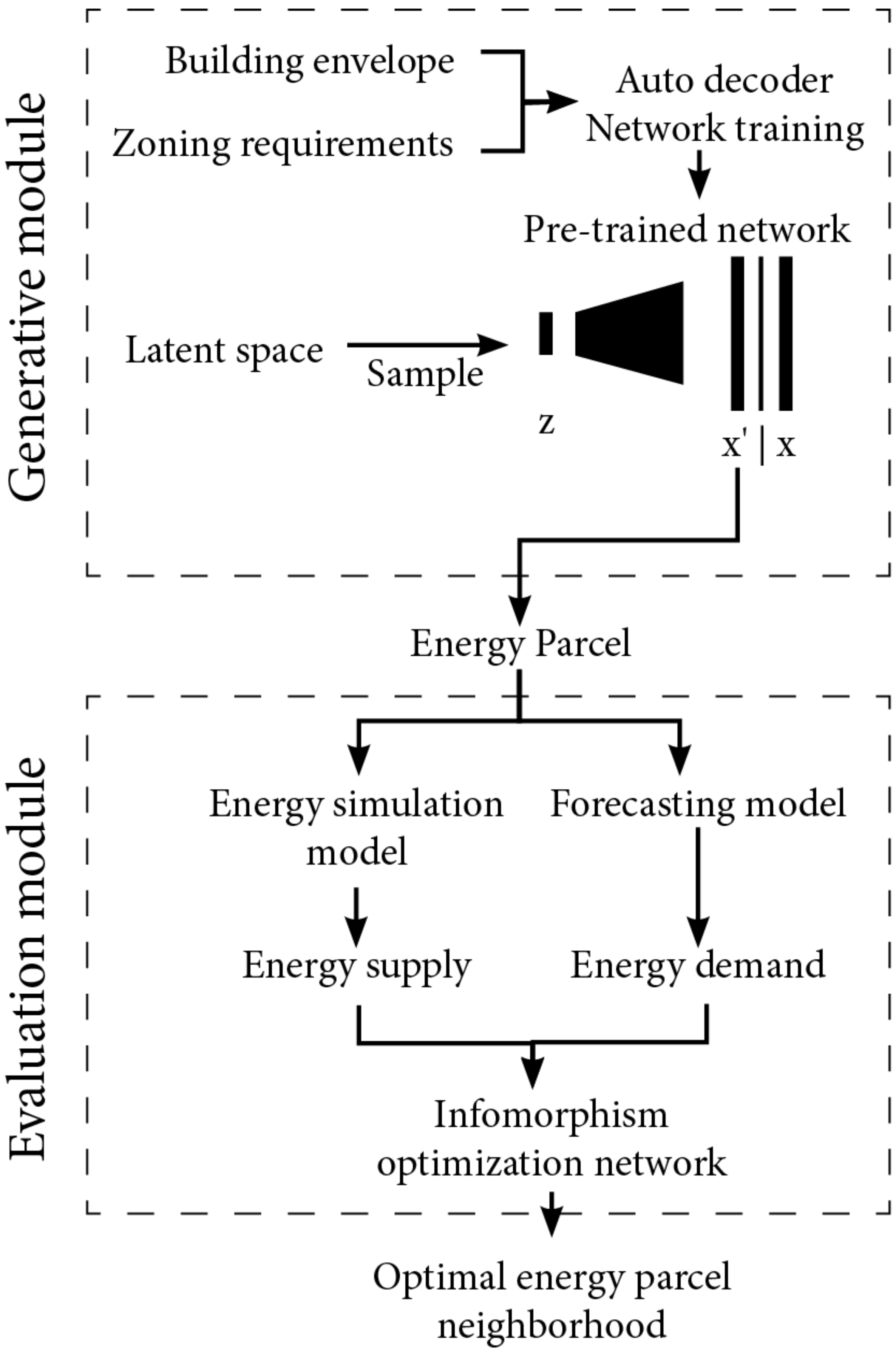
Infomorphism:
A Computational Framework for Local Renewable Energy Integration

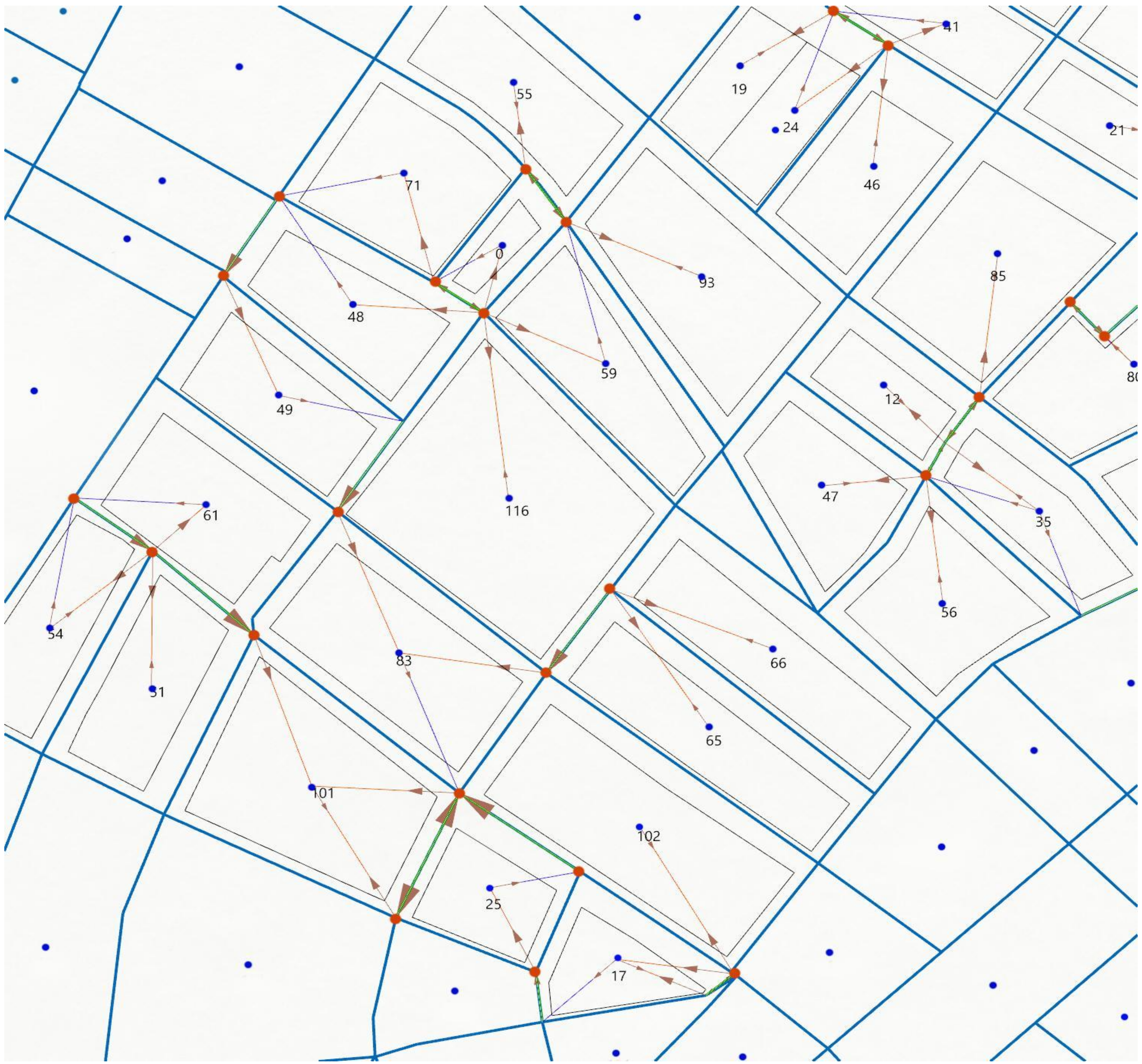
AI-based Generative Model

Design and Network Optimization



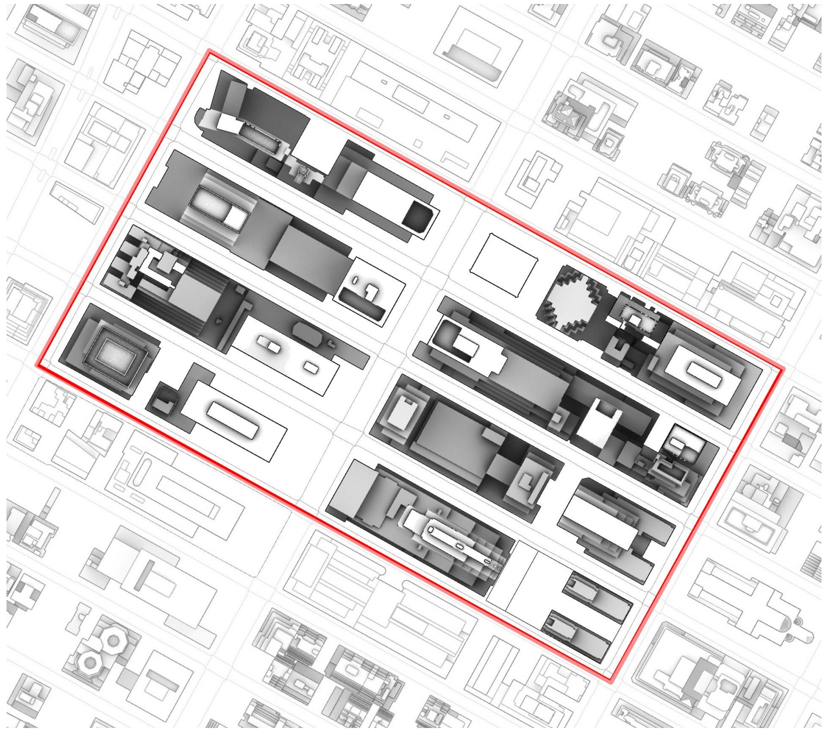
Fengqi Li, Kristen R. Schell, Haolin Yang and Alexandros Tsamis. Infomorphism: An Urban Planning Framework for Local Renewable Energy Integration. In Building Performance Analysis Conference and SimBuild co-organized by ASHRAE and IBPSA-USA. Chicago, IL, September 14-16, 2022



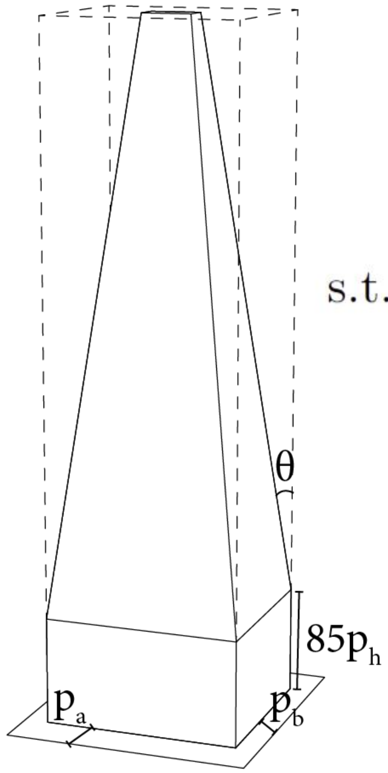


Example of exchange Network

Define base case: Energy Parcel Neighborhood (EPN)



Masterplan



$$\max_{p_a, p_b, p_h, n} (2 * ap_a - n \cdot 15 \tan\theta) * \frac{15n}{\cos\theta} + (2 * bp_b - n \cdot 15 \tan\theta)) * \frac{15n}{\cos\theta} + ap_a \cdot \left\lfloor \frac{85p_h}{15} \right\rfloor + bp_b \cdot \left\lfloor \frac{85p_h}{15} \right\rfloor)$$

— Maximize solar radiance

s.t.

$$\frac{\sum_{i=0}^{n} (ap_a - i \cdot 15 \tan\theta)(bp_b - i \cdot 15 \tan\theta)}{a \cdot b} + \frac{ap_a \cdot bp_b \left\lfloor \frac{85p_h}{15} \right\rfloor}{a \cdot b} \leq FAR$$

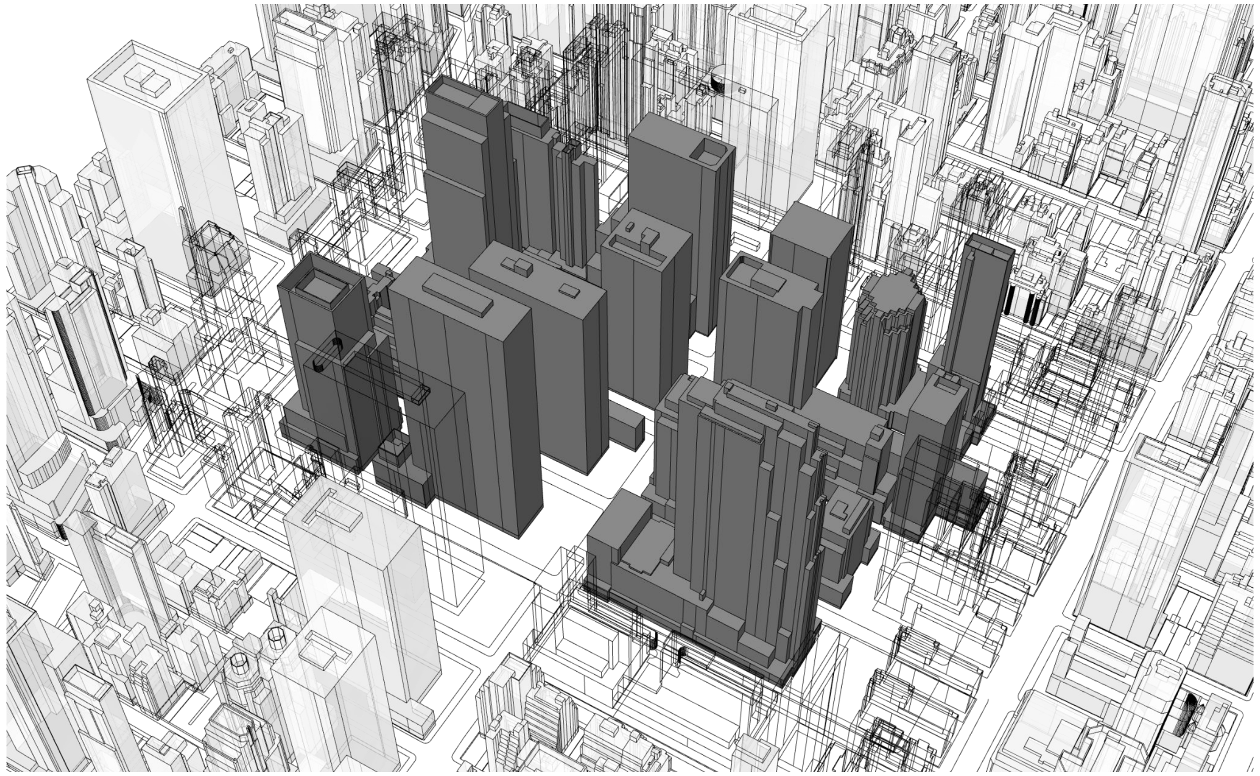
— FAR & height limit

$$0 \leq p_a, p_b, p_h \leq 1$$

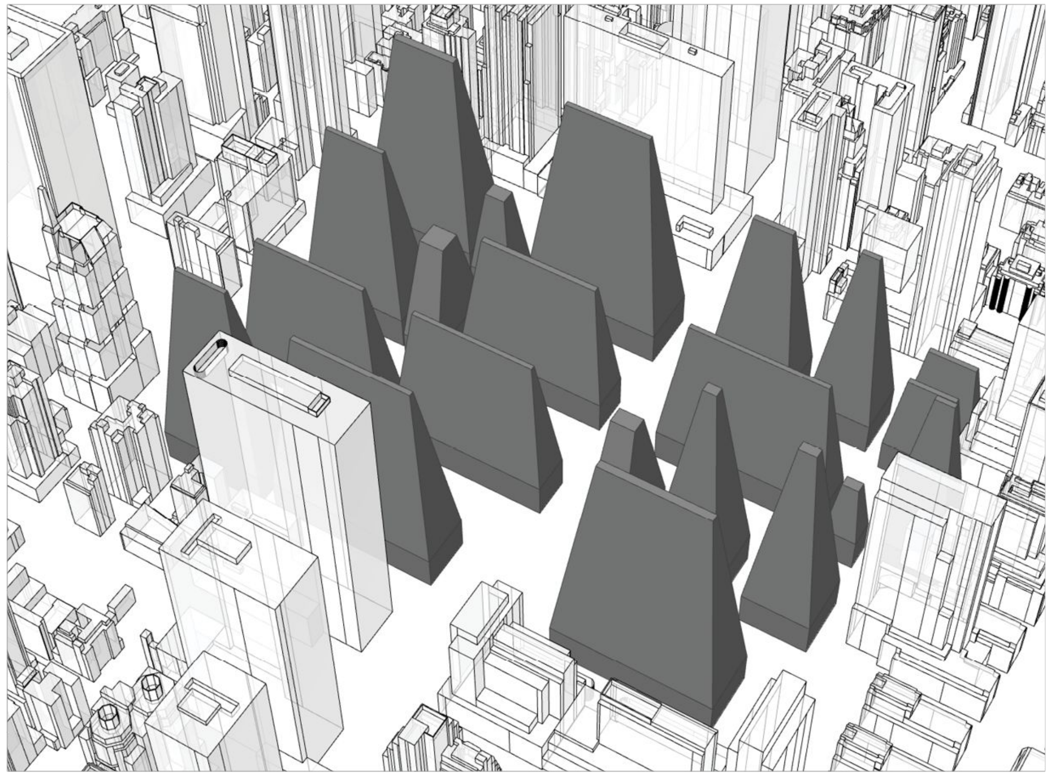
— Setback

$$n \leq \min\left(\frac{ap_a - 10}{15 \tan\theta}, \frac{bp_b - 10}{15 \tan\theta}\right)$$

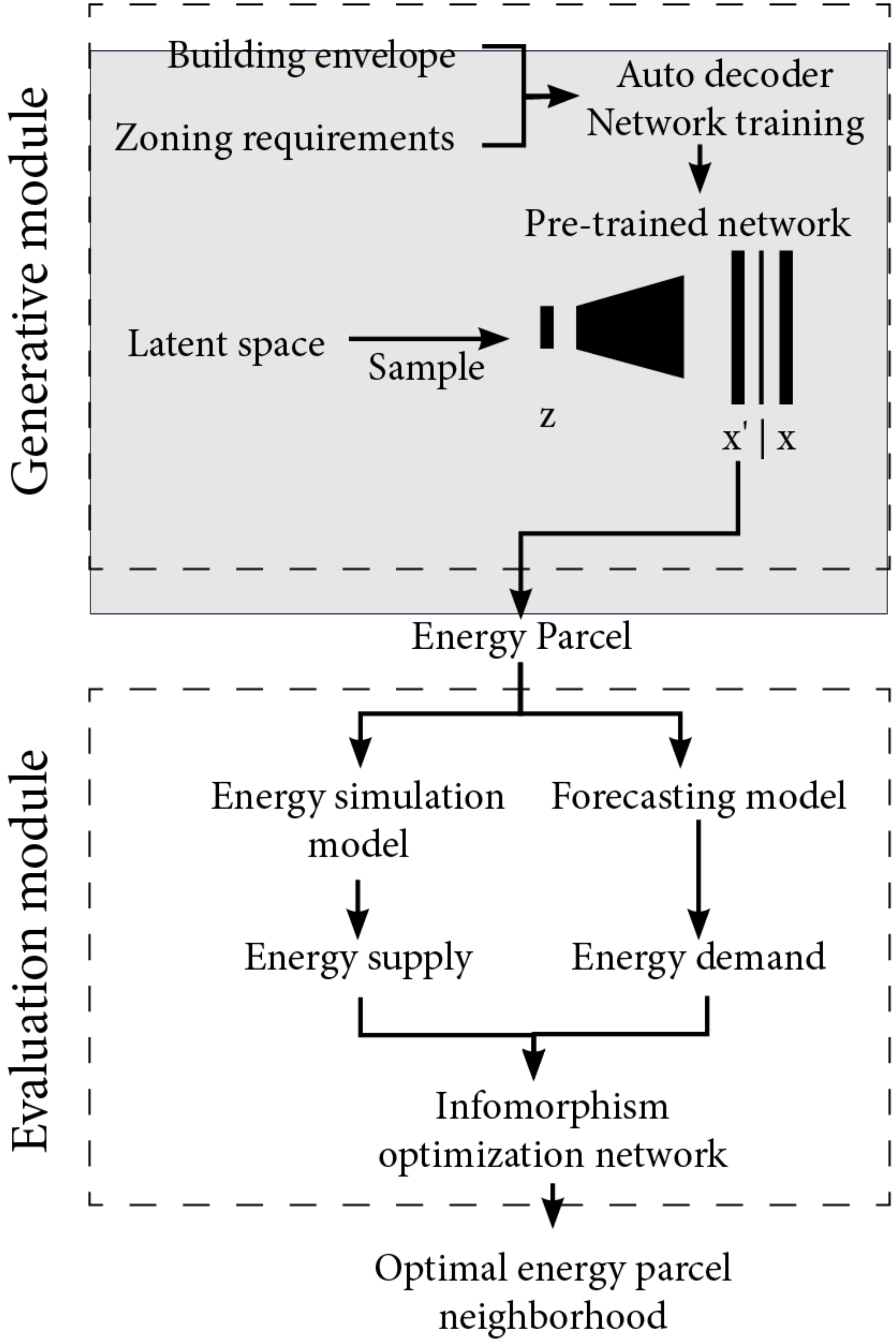
— Solar accessibility plane

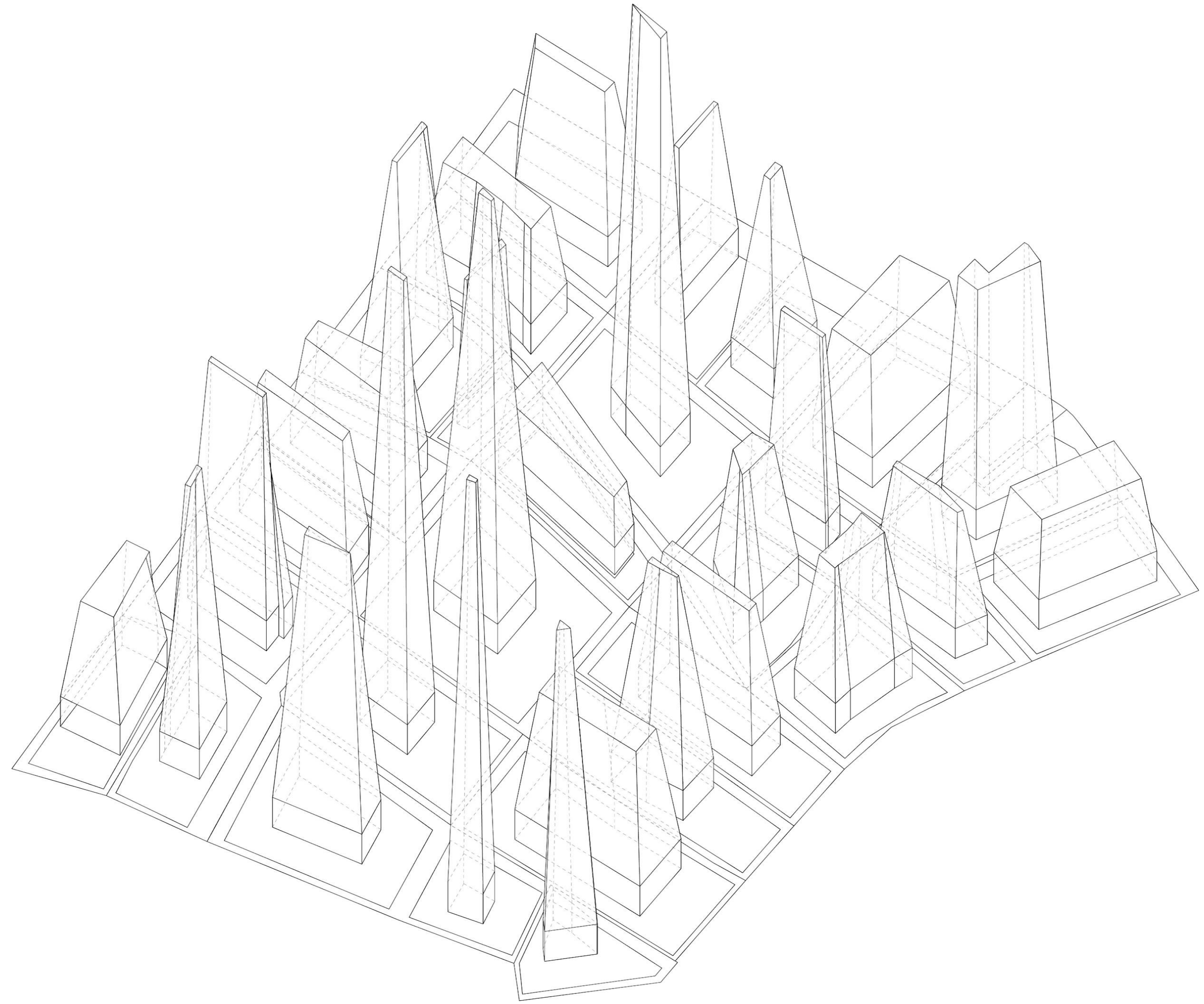


Current condition



Base case - max envelope with zoning regulation

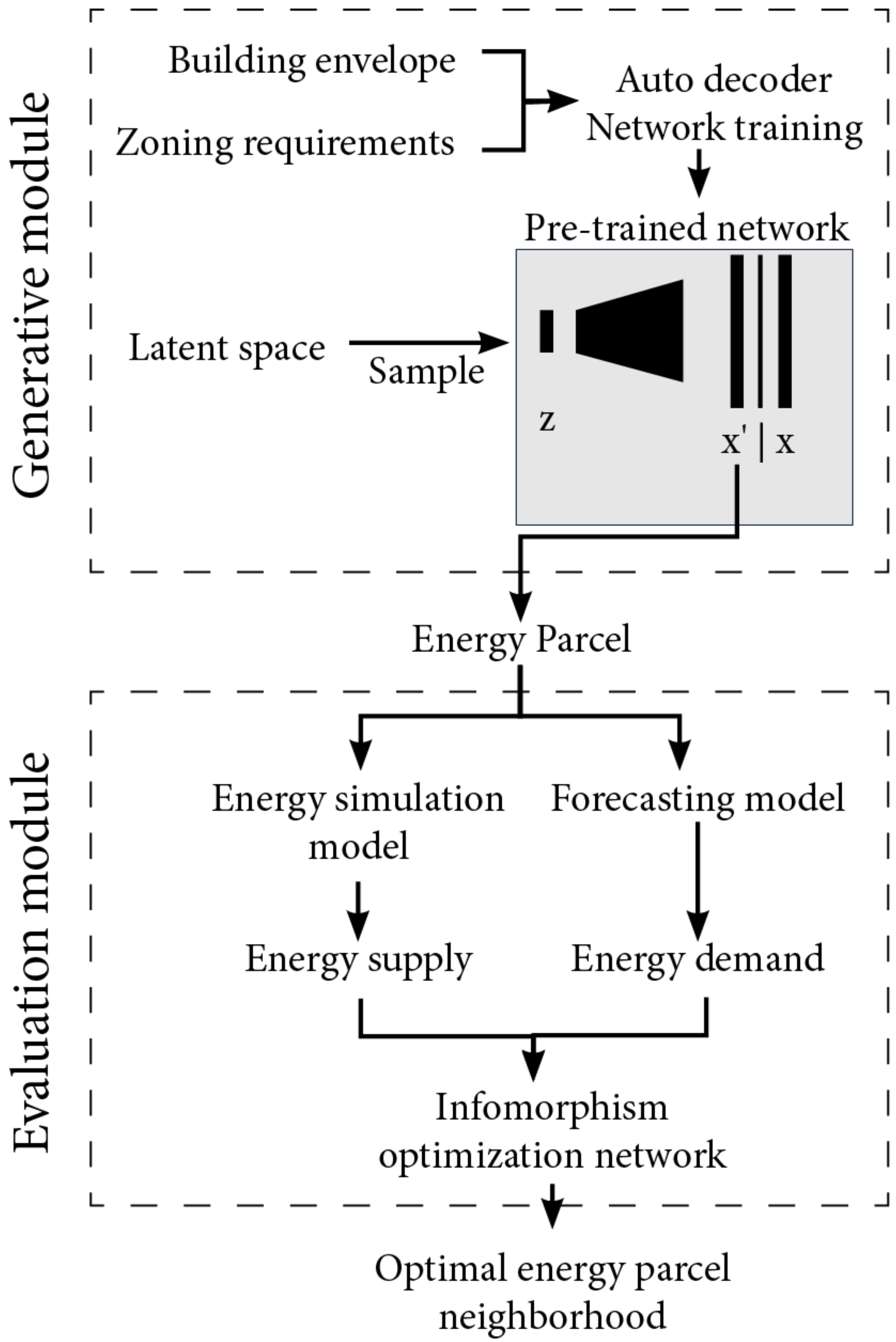


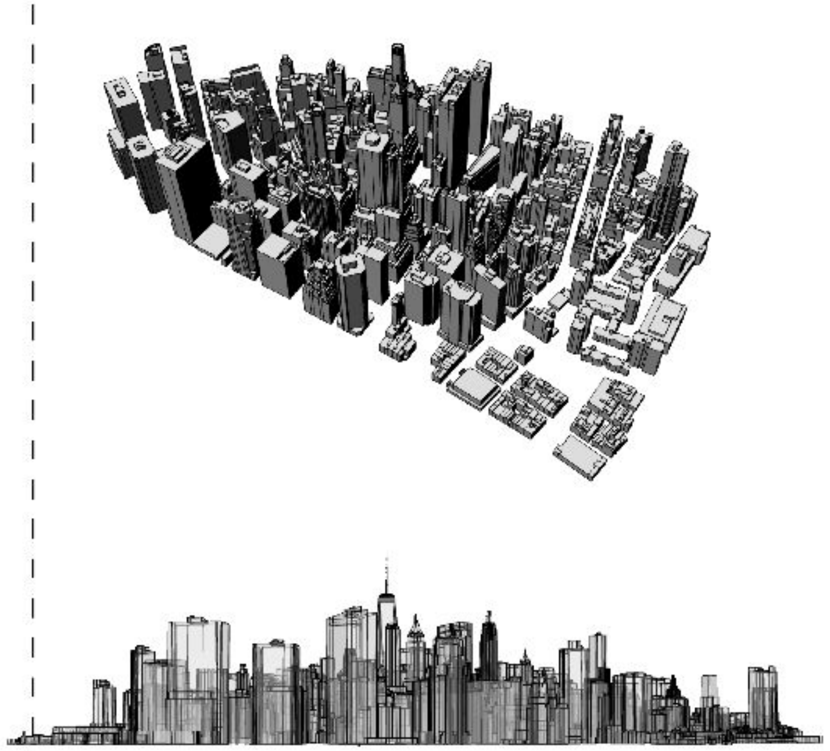


Morphology Optimization by Auto-decoder aided generative design

Objectives:

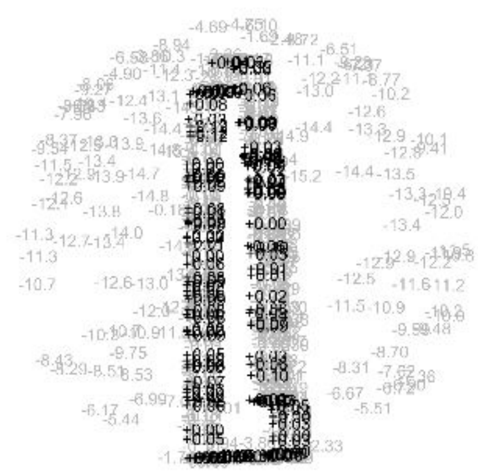
- ***Max Renewables***
- ***Learn the locale-specific morphological features***


Generative module
Building envelope
Zoning requirements
Auto decoder
Network training
Pre-trained network
Latent space
Sample
z
x' | x
Energy Parcel
Evaluation module
Energy simulation model
Forecasting model
Energy supply
Energy demand
Infomorphism optimization network
Optimal energy parcel neighborhood

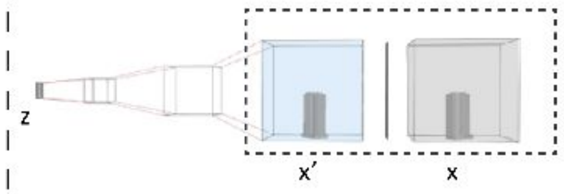


.obj (geometry, no texture)
https://www1.nyc.gov/

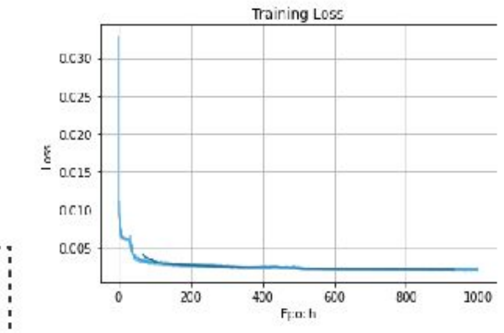
normalization

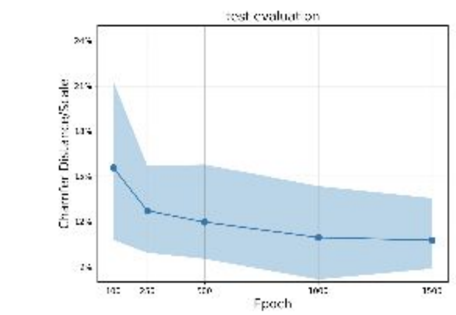


SDF representation



Auto-decoder

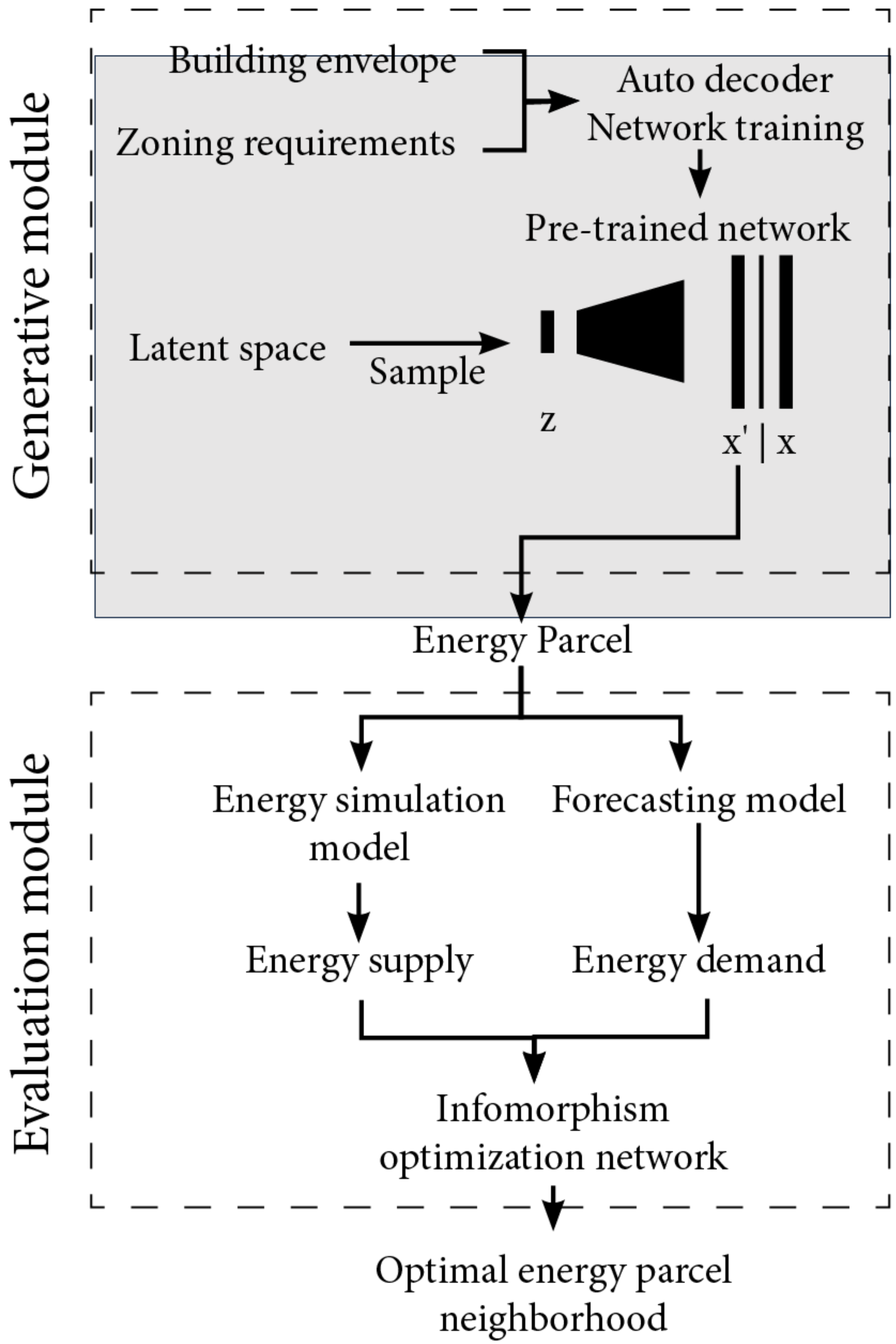


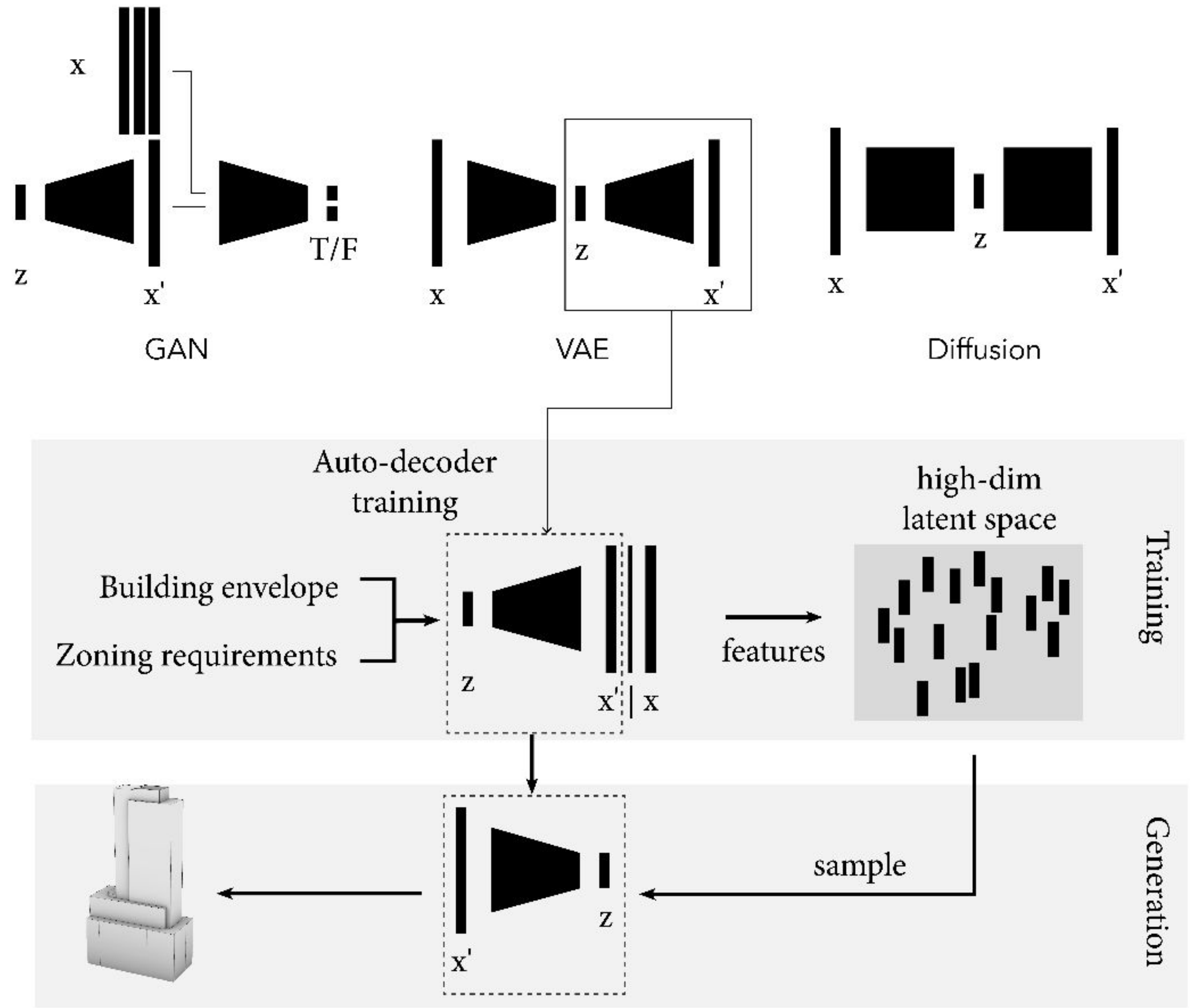


Data preprocessing

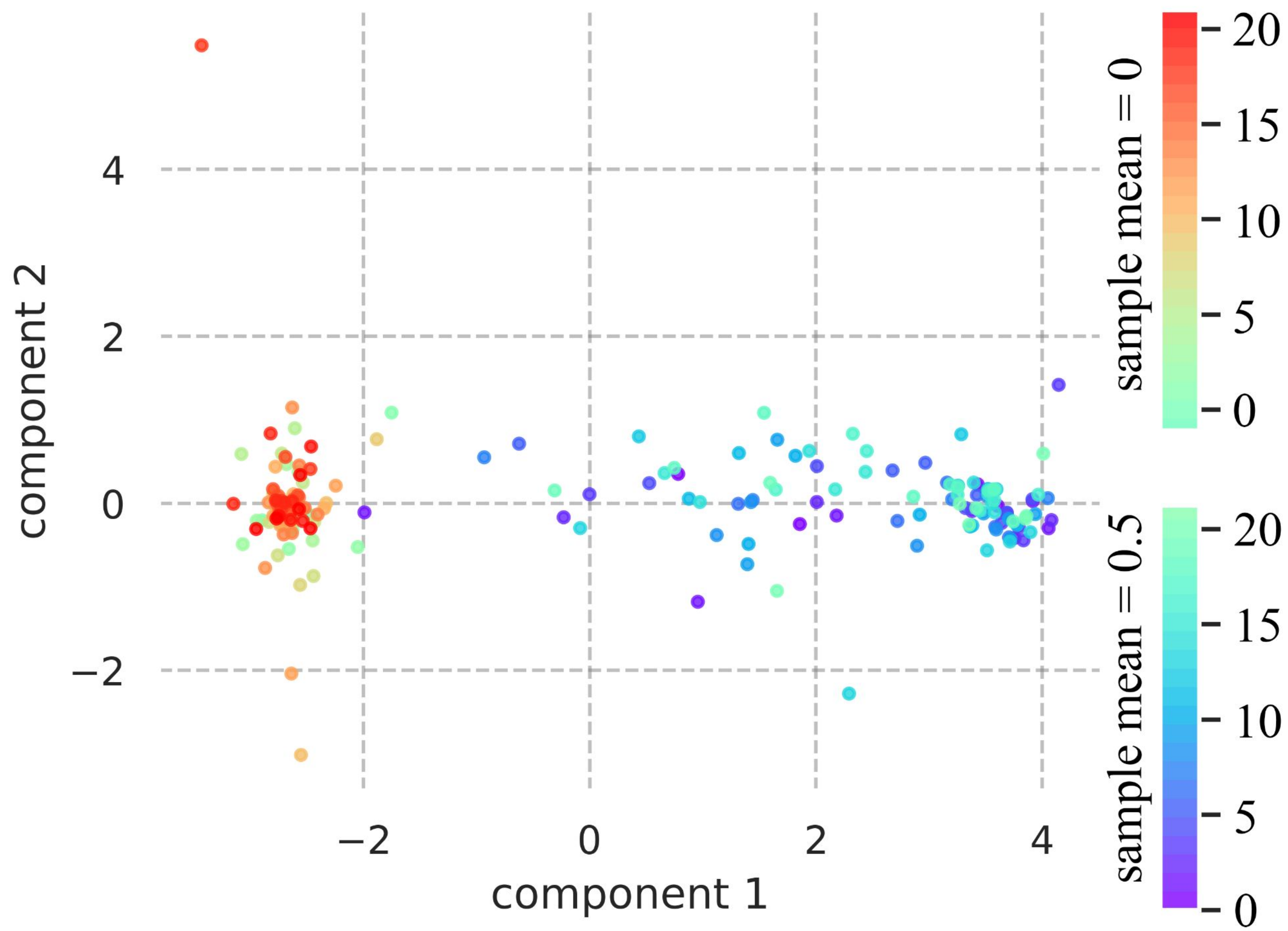
Training

Zhuang X., Ju Y., Yang, A. and Caldas L. (2023) Synthesis and Generation for 3D Architecture Volume with Generative Modeling, in International Journal of Architecture Computing , AI, Architecture, Accessibility, & Data Justice

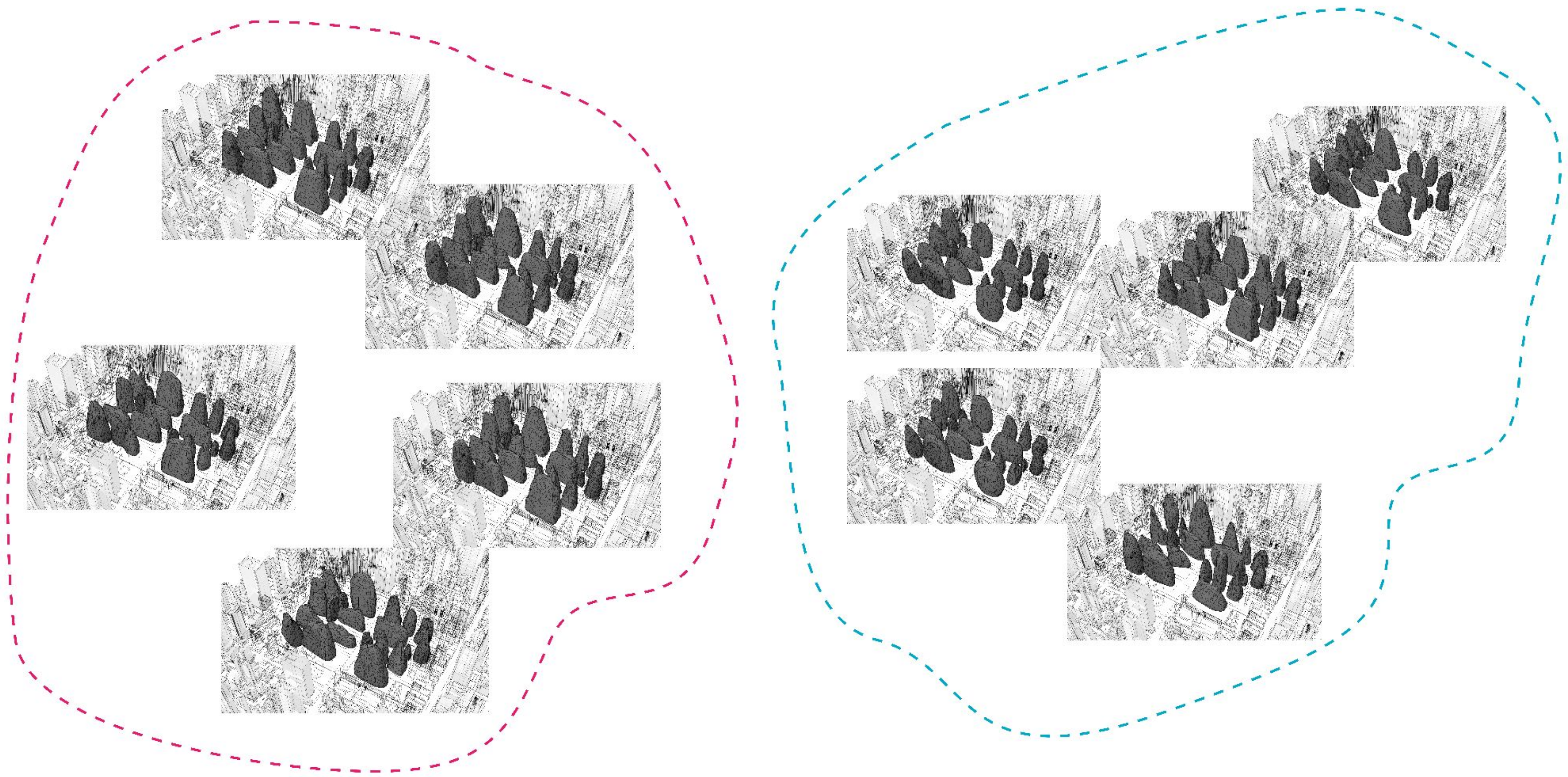

Generative module
Building envelope
Zoning requirements
Auto decoder
Network training
Pre-trained network
Latent space
Sample
z
x' | x
Energy Parcel
Evaluation module
Energy simulation model
Forecasting model
Energy supply
Energy demand
Infomorphism optimization network
Optimal energy parcel neighborhood


x
z
x'
T/F
GAN
x
z
x'
VAE
x
z
x'
Diffusion
Auto-decoder
training
high-dim
latent space
Building envelope
Zoning requirements
z
x' | x
features
Training
sample
x'
z
Generation

Latent space sampling approach - performance-driven sampling

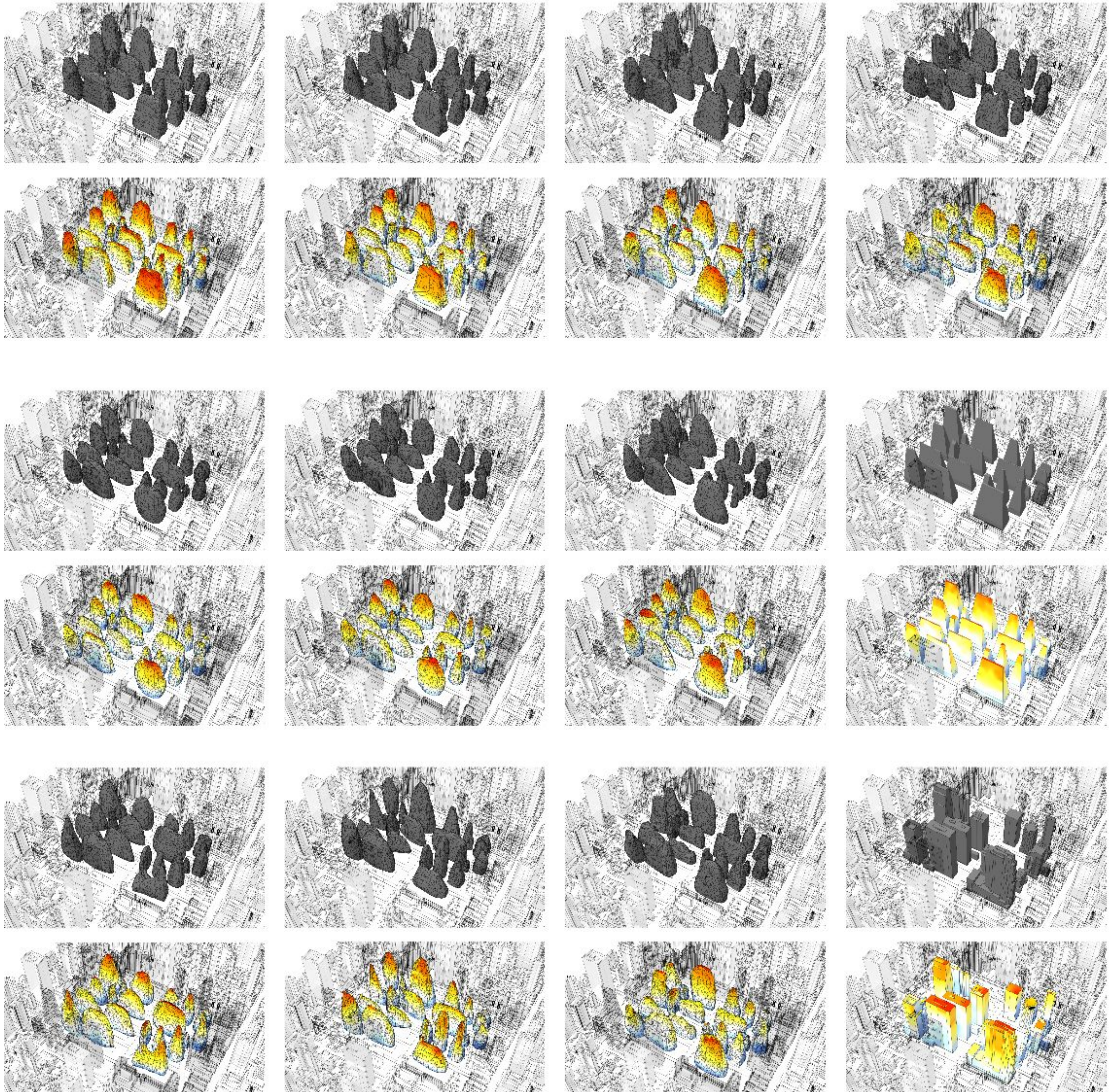


Latent space

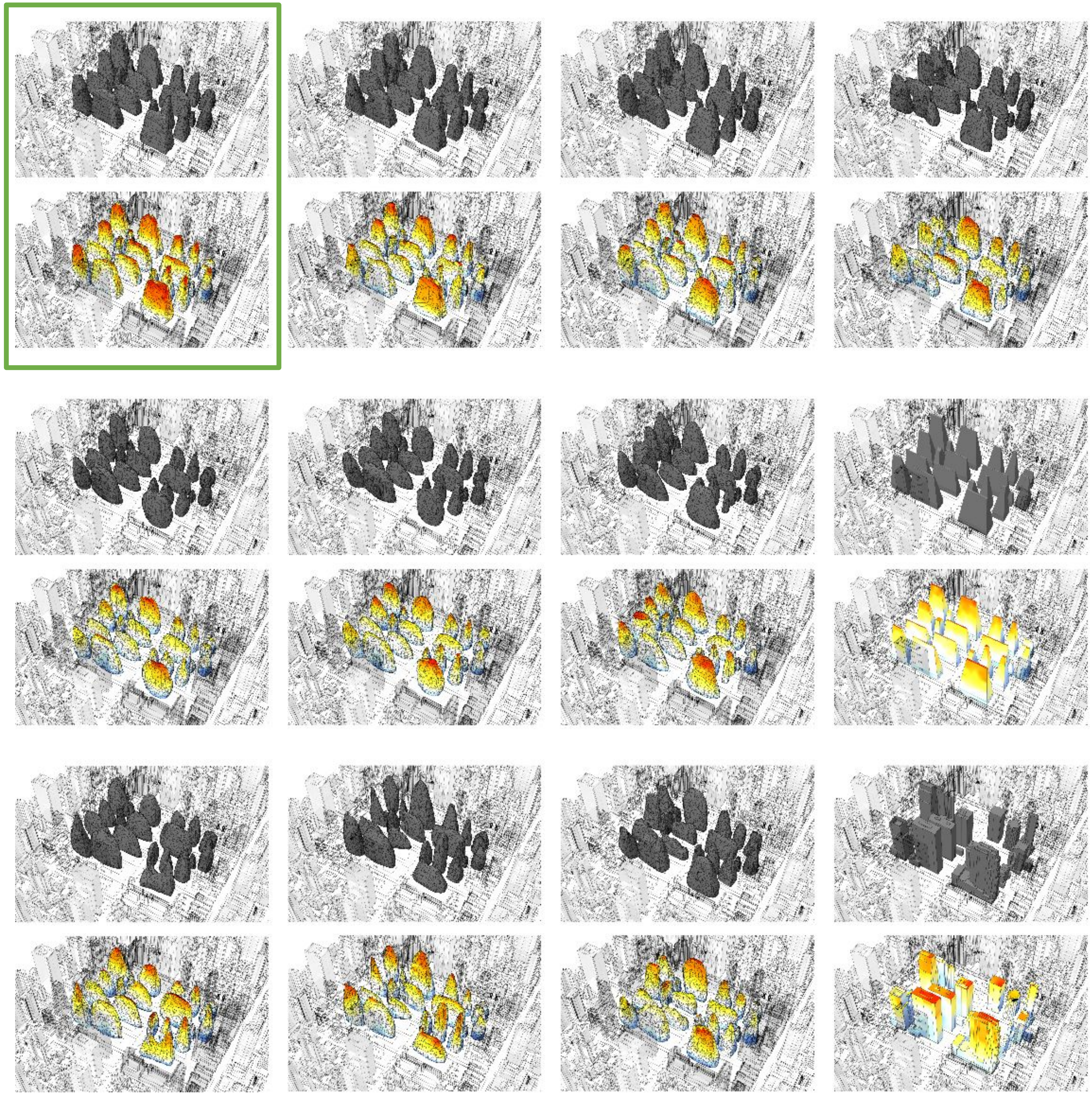


Design solutions

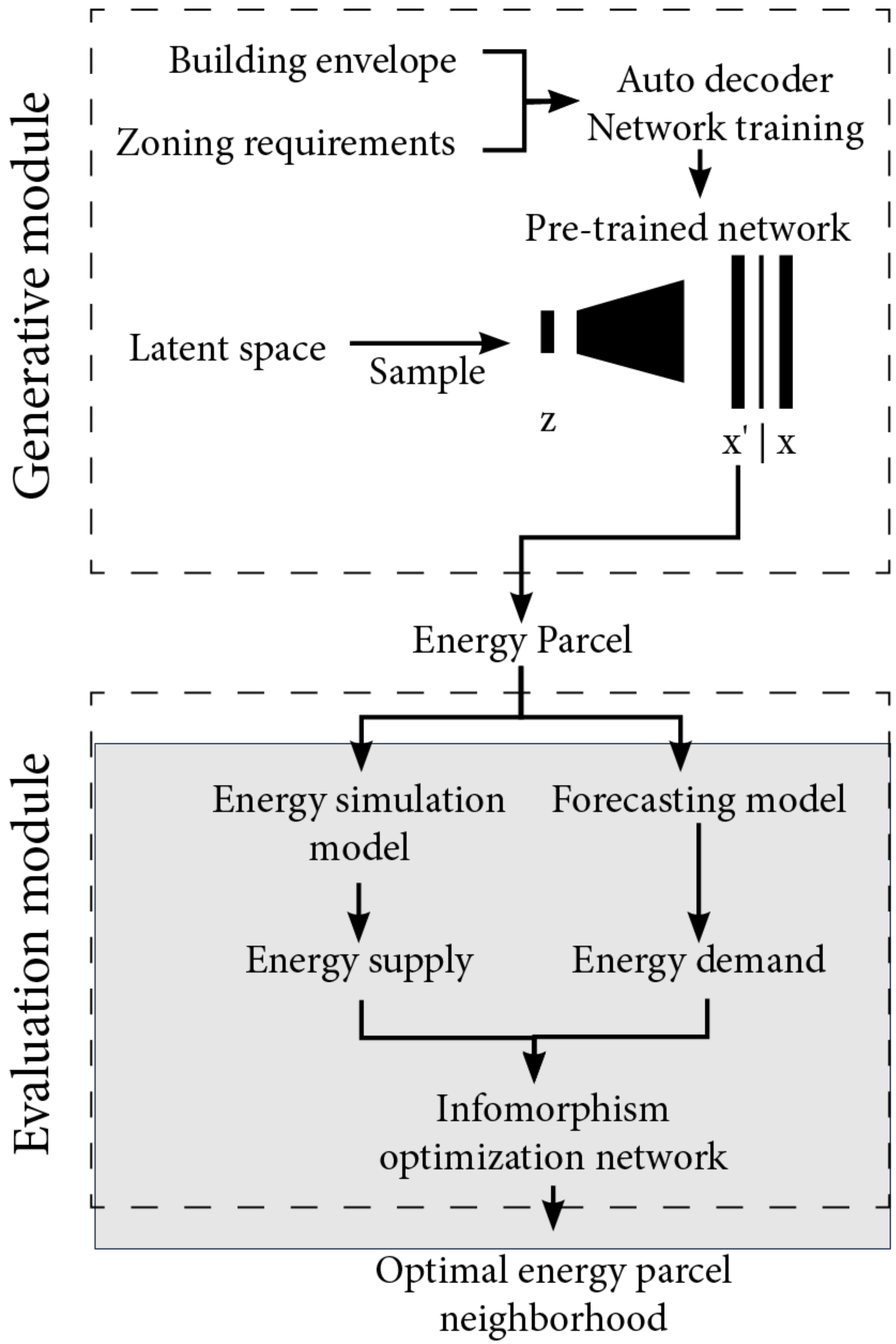
Solar potential evaluation

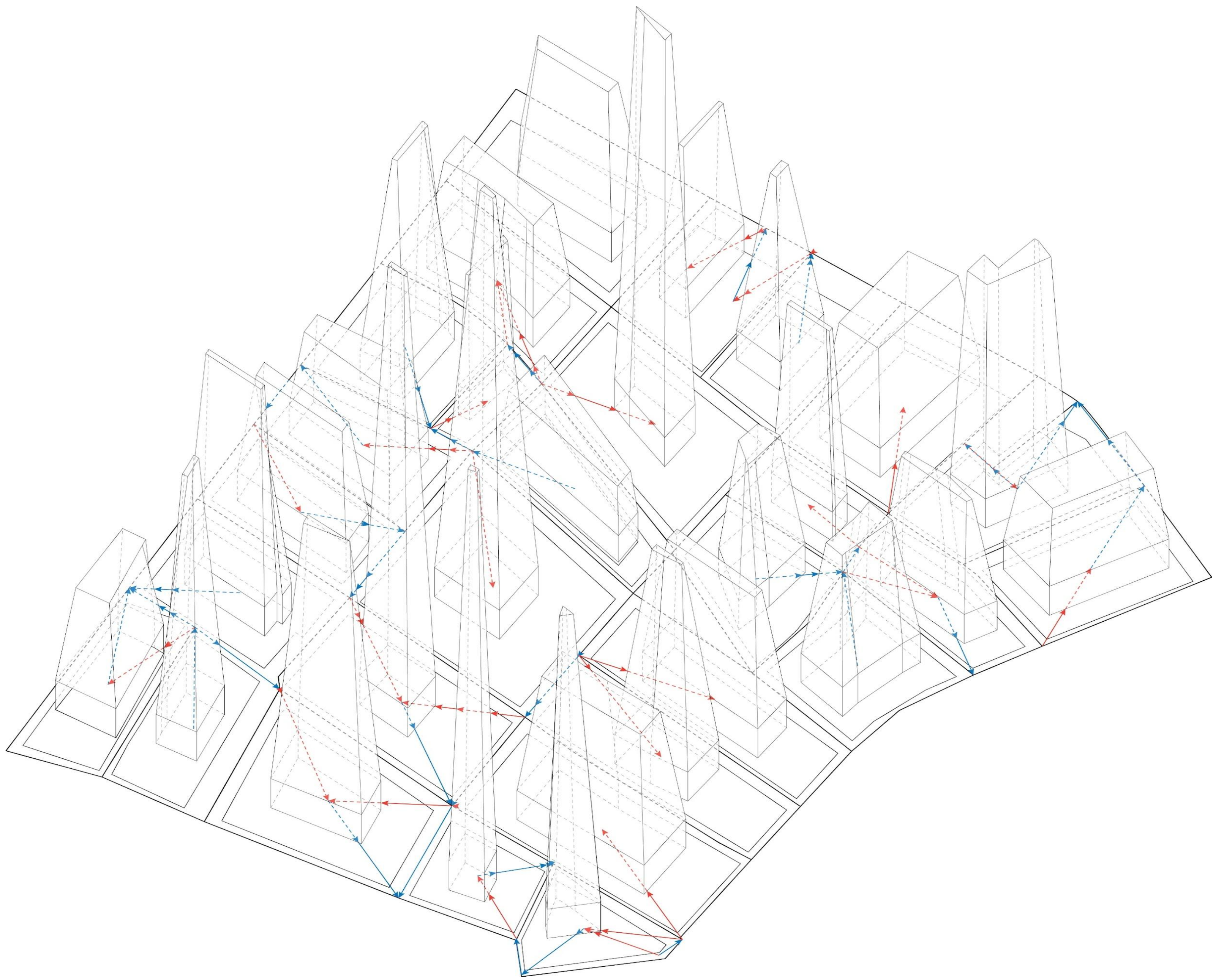


Solar potential evaluation



Ranking	Design option No.	Solar potential (M kBtu)
1	(0,0)	60.69
2	(0,0.1)	50.35
3	baseline	49.48
4	(0,0.5)	48.79
5	(0,0.3)	46.74
6	(0.5,0.5)	41.75
7	(0.5,0.3)	41.22
8	(0.5,0.1)	41.22
9	(0.5,0.05)	41.06
10	(0,0.05)	41.03
11	(0.5,0)	40.56



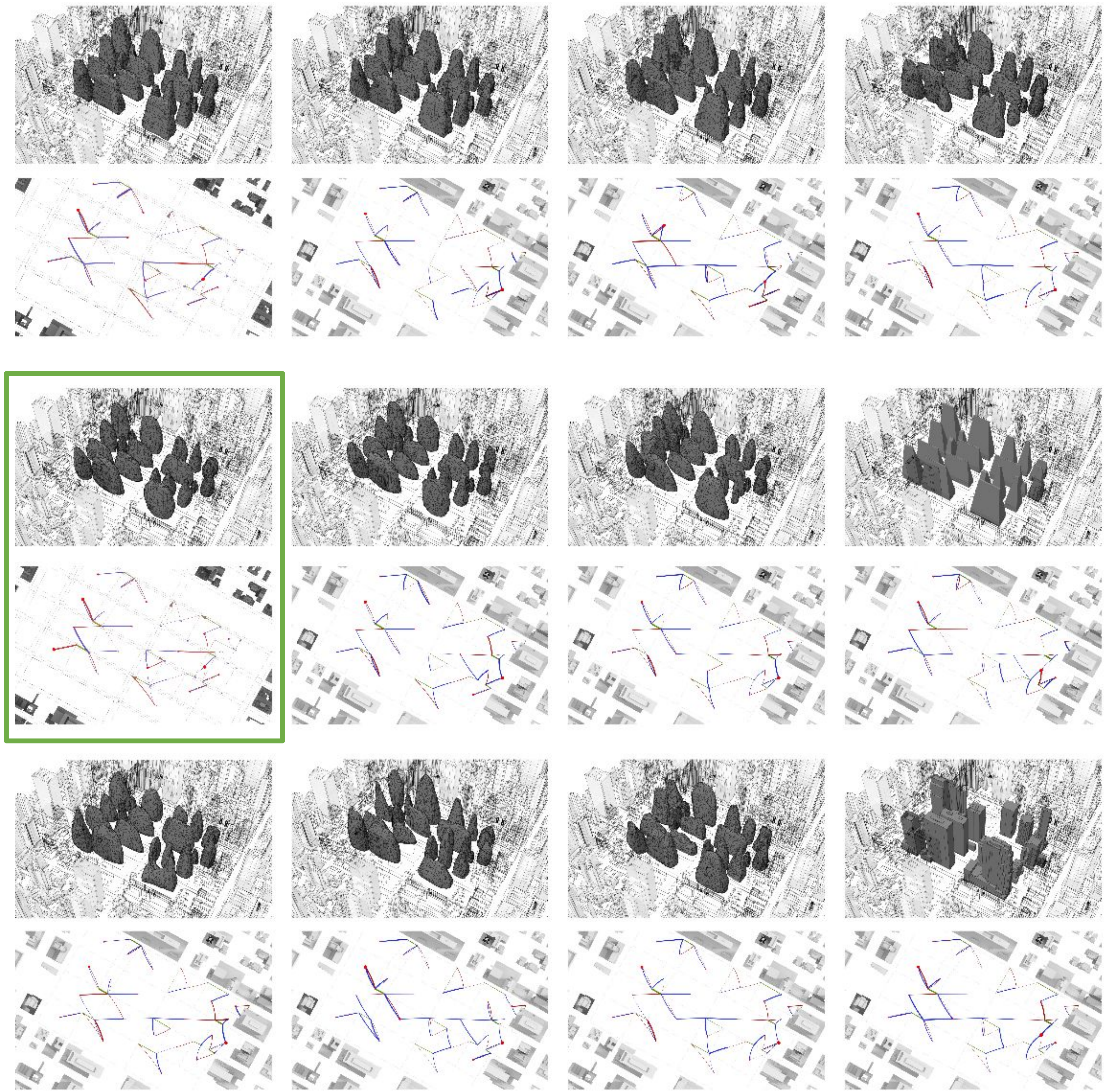


Network Optimization

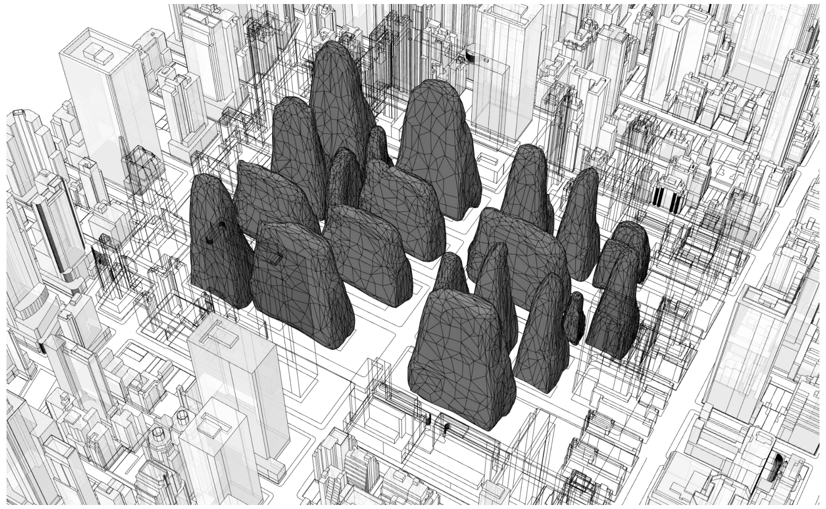
Objectives:

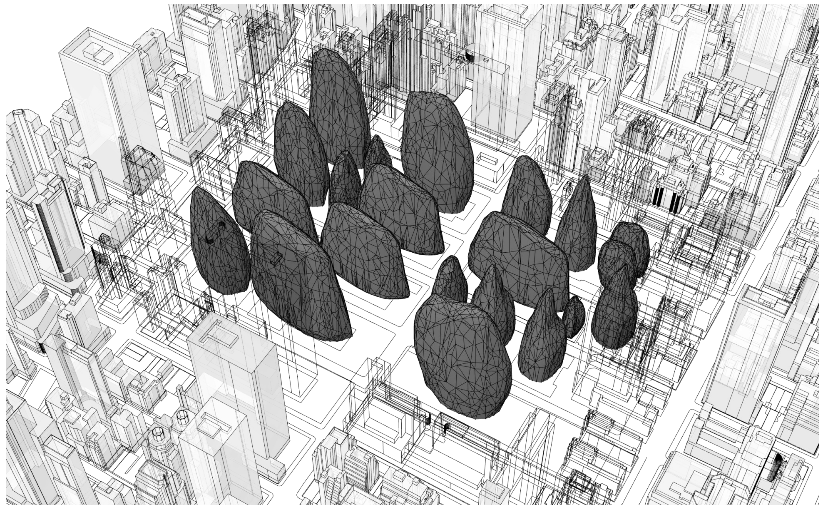
- ***Max Renewables***
- ***Satisfy Demand with Minimum Costs***

Solar potential evaluation



Ranking	Design opt No.	Levelized cost (M $)	Supply (M kBtu)	Demand (M kBtu)
1	(0.5, 0)	26.13	40.56	992.60
2	(0.5, 0.5)	26.15	41.75	99.05
3	(0.5, 0.05)	26.22	41.06	1007.85
4	(0.5, 0.3)	27.59	41.22	1047.95
5	(0, 0.3)	28.79	46.74	1105.02
6	baseline	28.99	49.48	1096.98
7	(0.5, 0.1)	29.11	41.22	1115.13
8	(0, 0.1)	29.85	50.35	1134.80
9	(0, 0.5)	30.12	48.79	1149.66
10	(0, 0.05)	30.17	41.03	1137.11
11	(0, 0)	31.58	60.69	1193.96





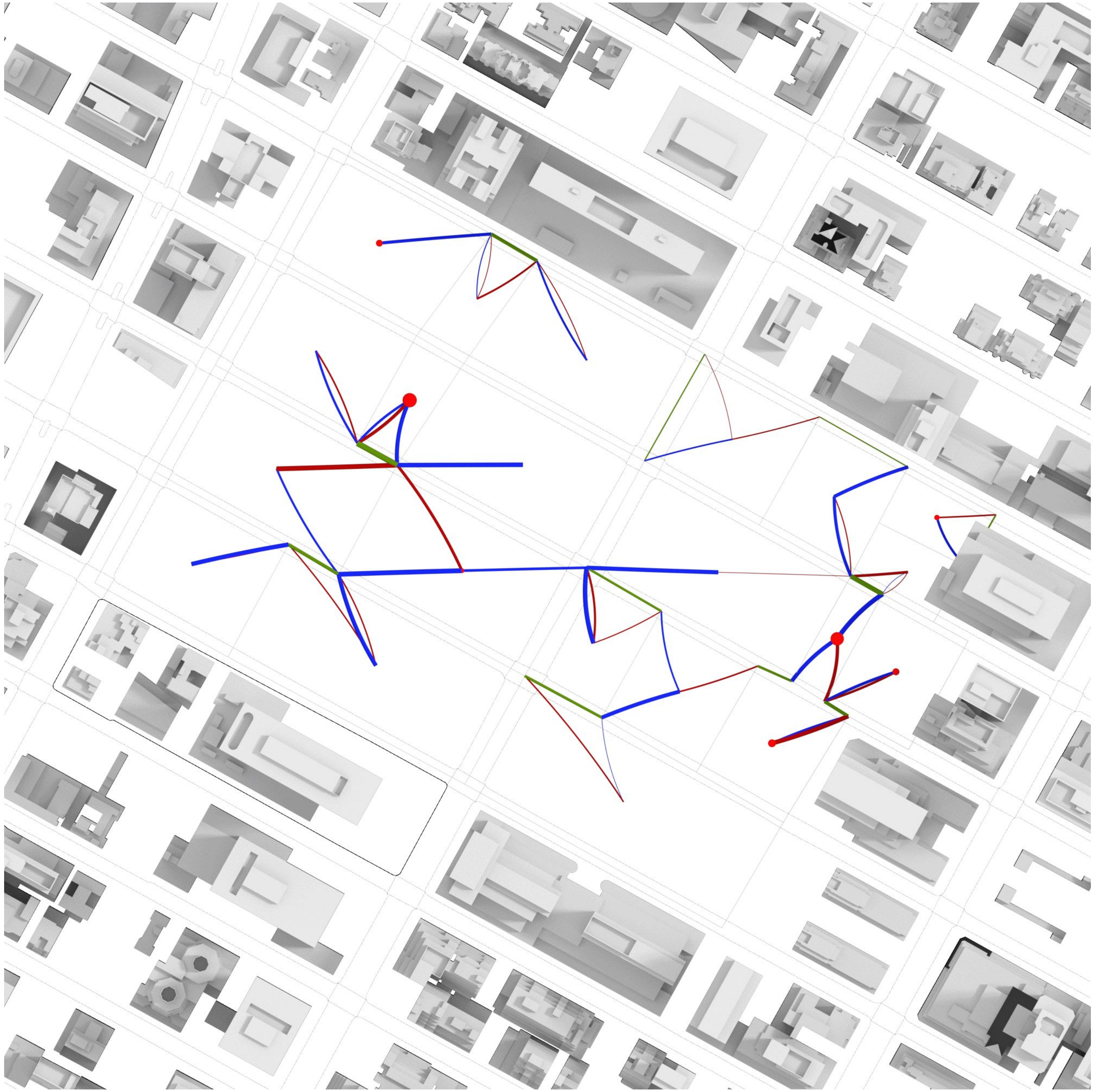
Ranking	Design option No.	Solar potential (M kBtu)
1	(0,0)	60.69
2	(0,0.1)	50.35
3	baseline	49.48
4	(0,0.5)	48.79
5	(0,0.3)	46.74
6	(0.5,0.5)	41.75
7	(0.5,0.3)	41.22
8	(0.5,0.1)	41.22
9	(0.5,0.05)	41.06
10	(0,0.05)	41.03
11	(0.5,0)	40.56

Evaluation of the design solution with solar potential. Values presented in millions. The name of the design option indicates its sample parameters, in the format of (mean, variance)

Ranking	Design opt No.	Levelized cost (M $)	Supply (M kBtu)	Demand (M kBtu)
1	(0.5, 0)	26.13	40.56	992.60
2	(0.5, 0.5)	26.15	41.75	99.05
3	(0.5, 0.05)	26.22	41.06	1007.85
4	(0.5, 0.3)	27.59	41.22	1047.95
5	(0, 0.3)	28.79	46.74	1105.02
6	baseline	28.99	49.48	1096.98
7	(0.5, 0.1)	29.11	41.22	1115.13
8	(0, 0.1)	29.85	50.35	1134.80
9	(0, 0.5)	30.12	48.79	1149.66
10	(0, 0.05)	30.17	41.03	1137.11
11	(0, 0)	31.58	60.69	1193.96

Evaluation of the design solution with energy exchange network and levelized cost. Values presented in millions.

- An **auto-decoder neural network** has been introduced into a building energy modeling framework evaluating both design and energy performance.
- Increased input **flexibility and applicability** of Infomorphism planning framework
- Introduce energy levelized cost to **evaluate** AI-aided generative model



Generating Networks based on Changing Energy Distribution

Questions?

Fengqi (Frank) Li frankdesignx@gmail.com
Xinwei Zhuang xinwei_zhuang@berkeley.edu

Rensselaer
case Center for Architecture Science and Ecology
Berkeley College of Environmental Design