

ICML 2020

# Learning to Simulate and Design for Structural Engineering

Kai-Hung Chang

Research Scientist  
AEC Industry Future, Autodesk Research

Chin-Yi Cheng

Principal Research Scientist  
AI Lab, Autodesk Research



# Problem: Structural Design for Buildings

Why is this important?

# Problem: Structural Design for Buildings

According to the International Energy Agency (IEA 2017),

**Buildings and construction caused ~ 40% of global energy-related CO<sub>2</sub> emissions.**

\*Buildings: 28%; Construction 11%

# Problem: Structural Design for Buildings

Optimized structural  
design for buildings



Less construction  
materials used



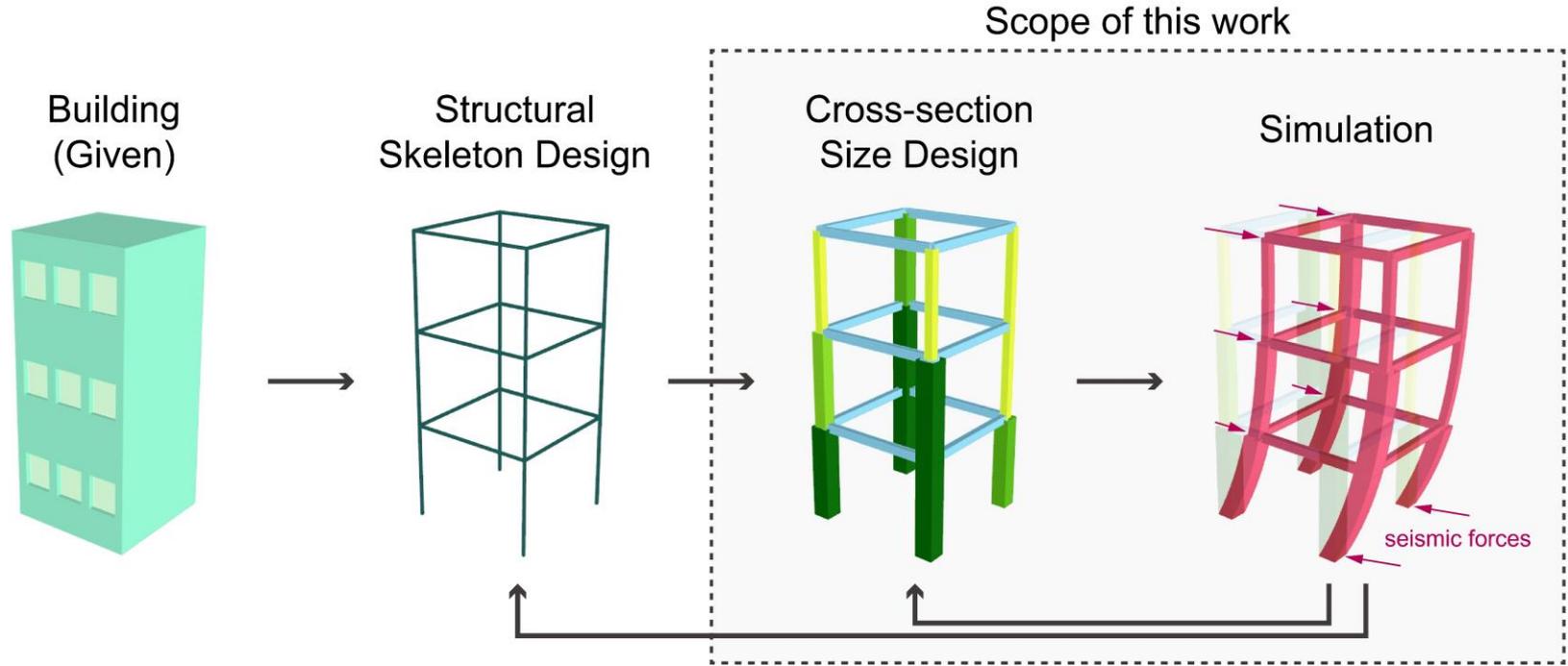
Reduced cost



Decreased  
corresponding  
CO2 emissions

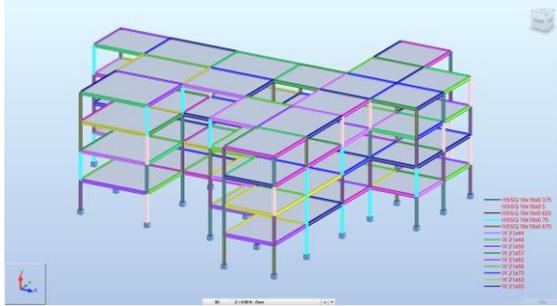
# What Is Structural Design?

A common structural design workflow:



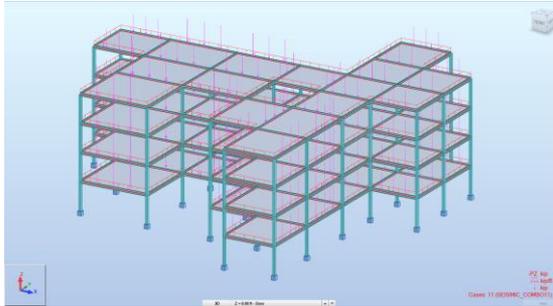
The design iterations in practice are laborious and mostly manual!

# Components and Constraints



Cross Section Library

Column	Beam
HSSQ 16x16x0.375	W21x44
HSSQ 16x16x0.5	W21x48
HSSQ 16x16x0.625	W21x50
HSSQ 16x16x0.75	W21x57
HSSQ 16x16x0.875	W21x62
	W21x68
	W21x73
	W21x83
	W21x93



Load Cases

## Dead Load (L)

- Self Weight
- Super-imposed
- Roof
- Cladding Load

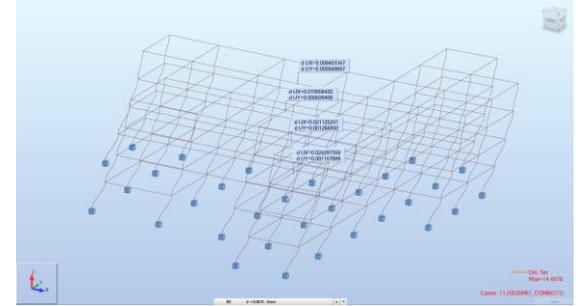
## Live Load (Lr)

- Floor
- Roof

## Seismic (E)

## Combination

- $1.2D + 1.6L + 0.5Lr$
- $0.9D + 1.0E$  (X and Y)

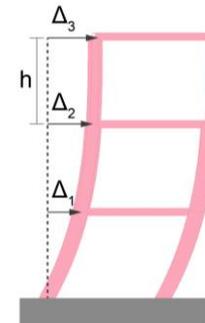


Simulation Results

## Drift Ratio in Ex and Ey

For each story

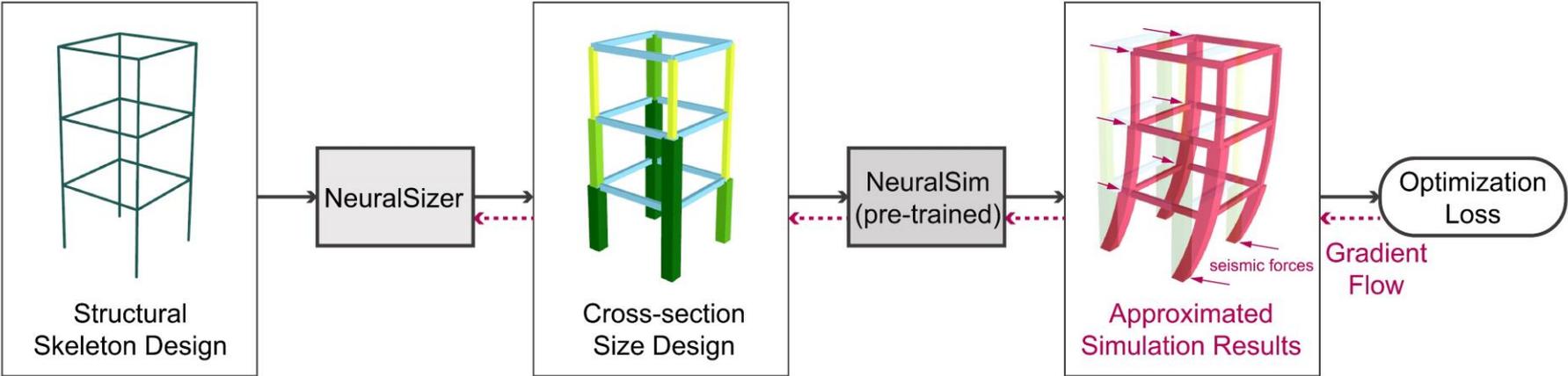
$$dr_x, dr_y$$



$$\langle \text{def} \rangle dr_i = \frac{\Delta_i - \Delta_{i-1}}{h}$$

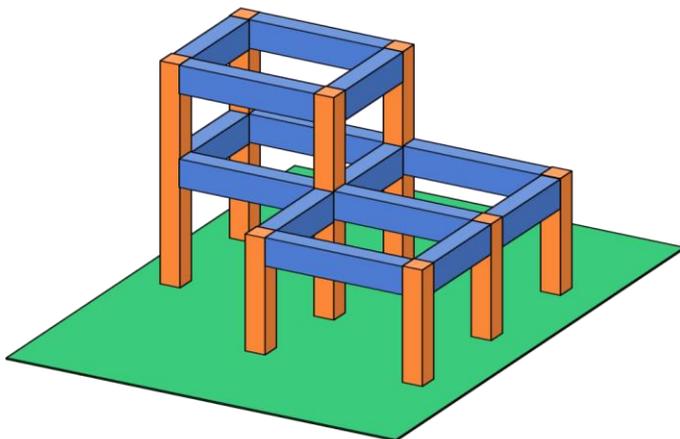
# Pipeline

Using OpenAI's GPT-4 for optimization



Slow, and completely relying on the engineer's knowledge, experience, and intuition

# What is the proper representation?



Building Structure

Voxel?

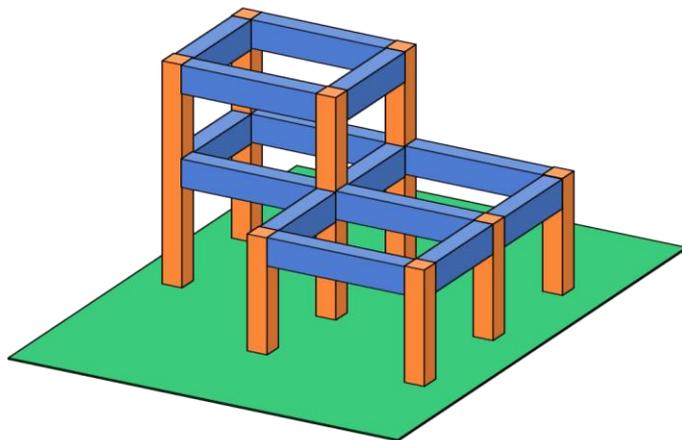
Point clouds?

Meshes?

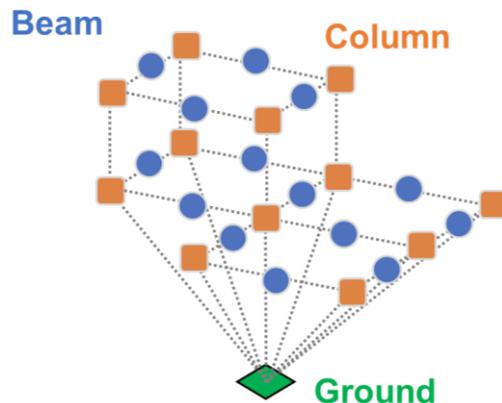
Images with multi-views?

It contains discrete components, is usually large at scale, and has strong connectivity relations.

# Intuition: Representing Structures as Graphs



Building Structure

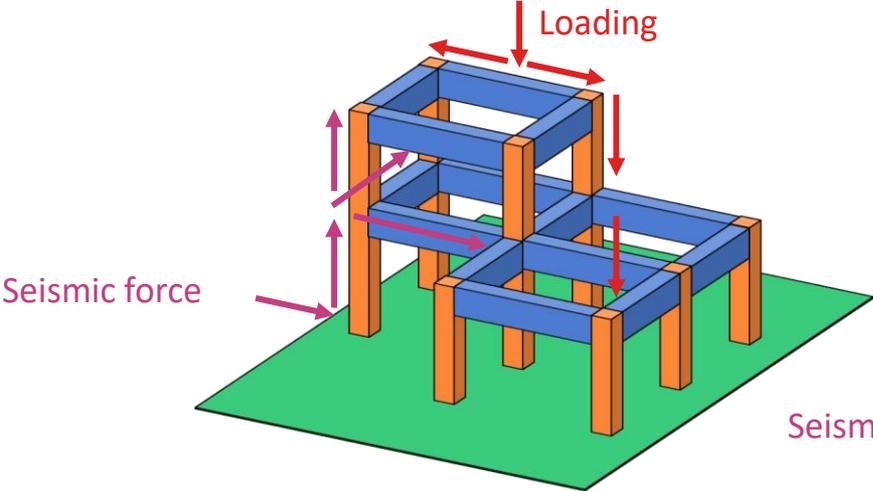


Structural Graph

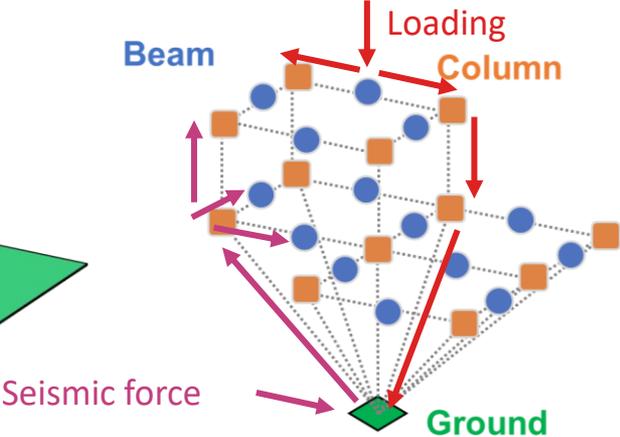
Node feature

Positions		0: column 1: beam	One hot vector of cross section type	if roof	Metal deck area	if boundary
$x_1, y_1, z_1$	$x_2, y_2, z_2$					

# Force Transmissions vs. Message Passing

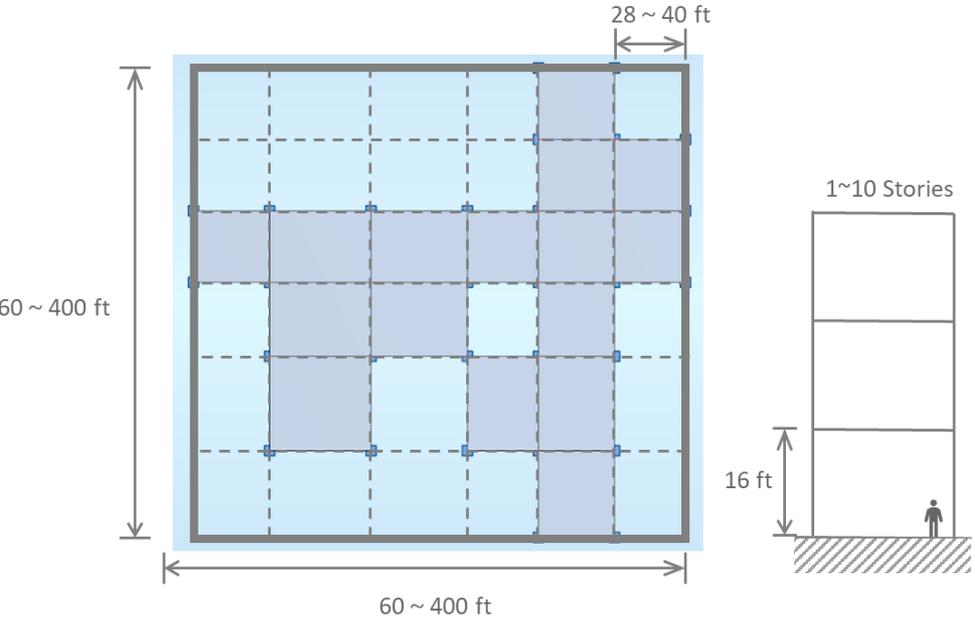


Building Structure

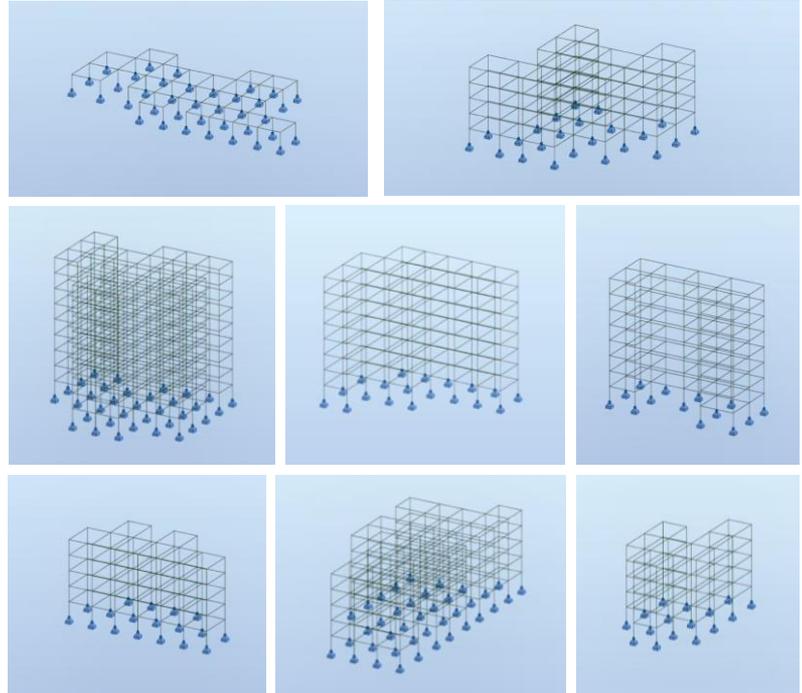


Structural Graph

# Data Generation

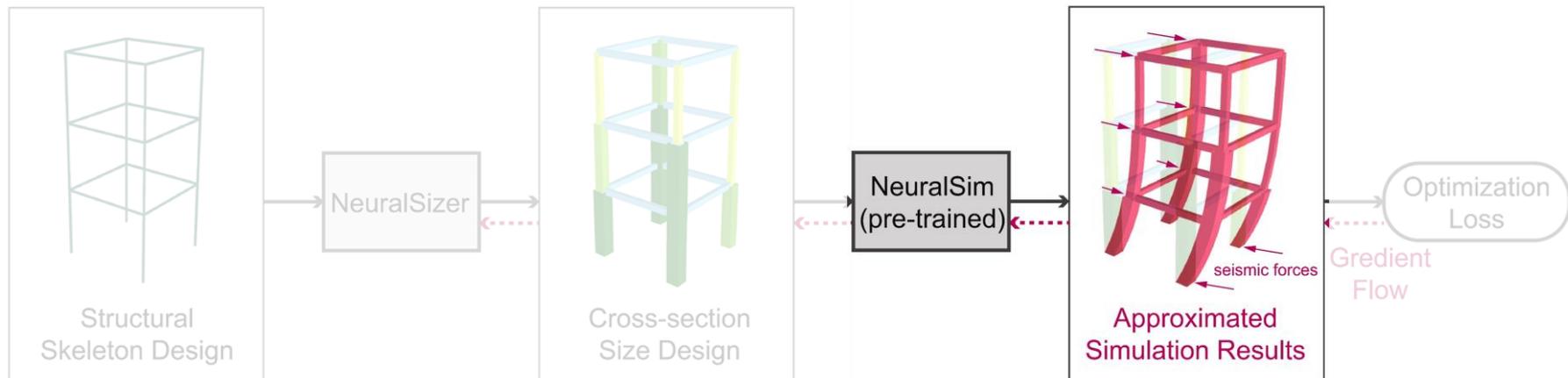


Using Autodesk® Robot™ Structural Analysis  
(free for educational use)



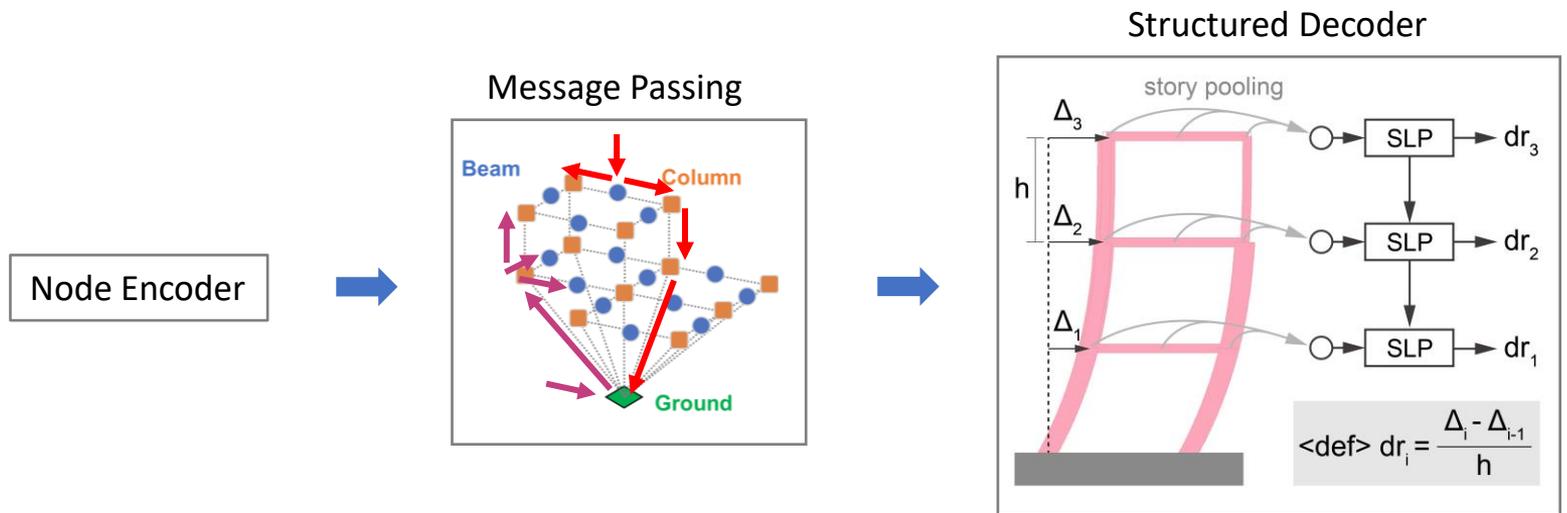
# NeuralSim

## A Graph-Based Neural Approximator for Structural Simulation



# NeuralSim

## A Graph-Based Neural Approximator for Structural Simulation



Drift Ratio Output

Classifier Output

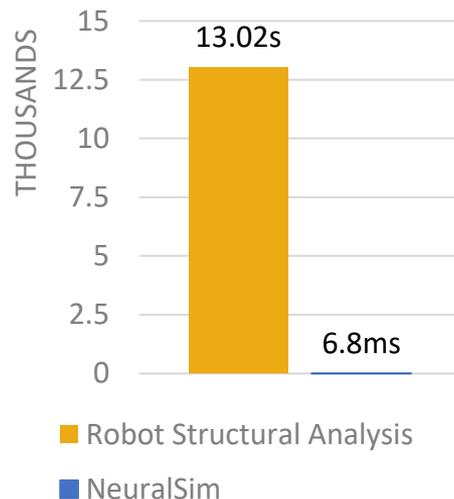
$$Loss = L1Loss(\text{groundtruth}, \underline{\text{output}}) + BCE(\underline{\text{if output}} > \underline{lim}, \text{if groundtruth} > lim)$$

# NeuralSim: Performance

Table 1. NeuralSim Performance Compared To Other Models

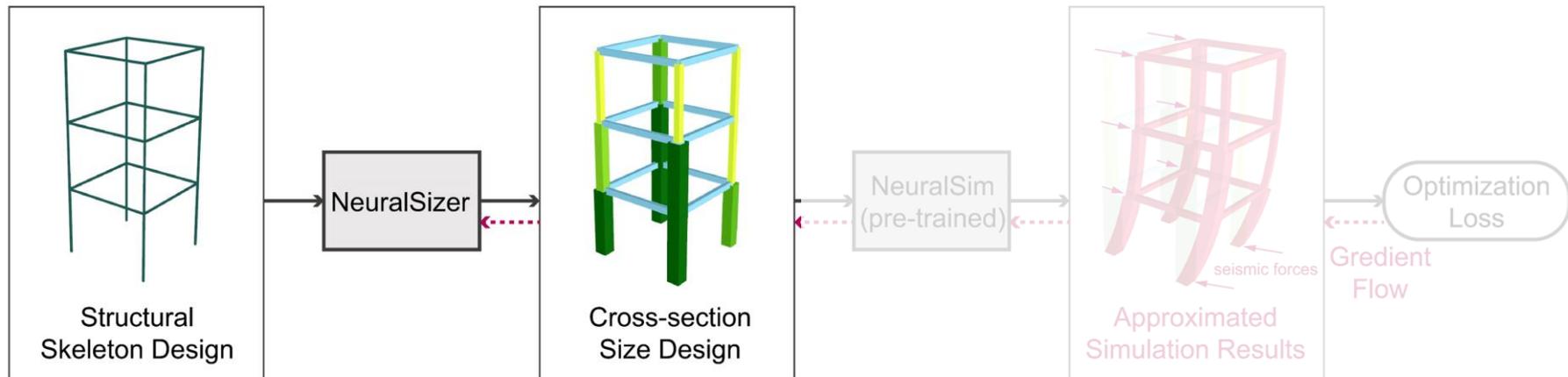
Model	L1 Loss $\times 1e-4$	Relative Accuracy	Classification Accuracy
GCN	16.01	94.86	89.22
GIN	33.85	89.62	84.27
GAT	10.87	96.41	93.35
PGNN	9.39	96.72	94.83
NeuralSim	<b>7.57</b>	<b>97.36</b>	<b>95.64</b>
NeuralSim + PGNN	<b>5.01</b>	<b>98.22</b>	<b>96.43</b>
NeuralSim(no SD)	10.24	96.65	92.71
NeuralSim(only L1 loss)	16.47	95.24	n/a

Speed: ~ 1900x faster



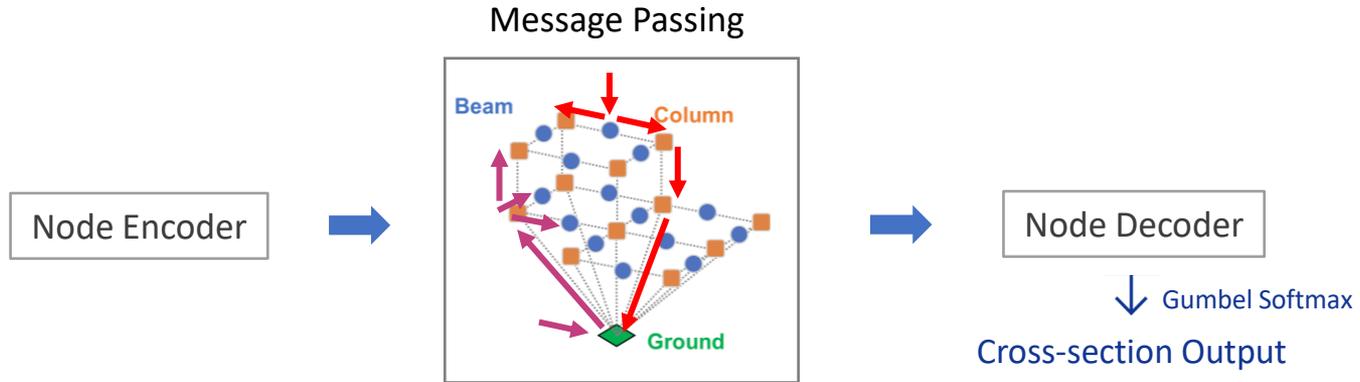
# NeuralSizer

A Graph Neural Network for Proposing Optimal Size Design



# NeuralSizer

A Graph Neural Network for Proposing Optimal Size Design



# NeuralSizer + NeuralSim:

## Optimization Setup

min objective      s.t. constraints

- Mass Objective

$$obj = \sum_{bar} length \times area \times density$$

- Drift Ratio Constraints

$$l_{dr} = Mean\{LeakyReLU(|dr_k| - lim)\} \leq 0$$

- Variety Constraints

$$l_{var} = 1 - SumTop6(usage_{percentage}) = 0$$

- Entropy Constraints

$$l_H = Mean\{H_i\}/H_{max} - \alpha = 0$$

### Column Types

	HSSQ 16x16x0.875
	HSSQ 16x16x0.75
	HSSQ 16x16x0.625
	HSSQ 16x16x0.5
	HSSQ 16x16x0.375

### Beam Types

	W 21x93
	W 21x83
	W 21x73
	W 21x68
	W 21x62
	W 21x57
	W 21x50
	W 21x48
	W 21x44

# NeuralSizer + NeuralSim:

Table 3. NeuralSizer Results Under Different Scenarios

Scenario	Objective Weight	Objective	Constraints	
		Mass Objective	Drift Ratio Constraint	Variety Constraint
High Safety Factor	1	0.870	$6.00 \times 1e-7$	$0.01 \times 1e-8$
	10	0.735	$1.34 \times 1e-7$	$1.04 \times 1e-8$
Low Safety Factor	1	0.592	$6.42 \times 1e-5$	$1.67 \times 1e-8$
	10	0.596	$3.32 \times 1e-5$	$1.78 \times 1e-8$

High / Low Safety Factor : Drift Ratio Limit 0.015 / 0.025

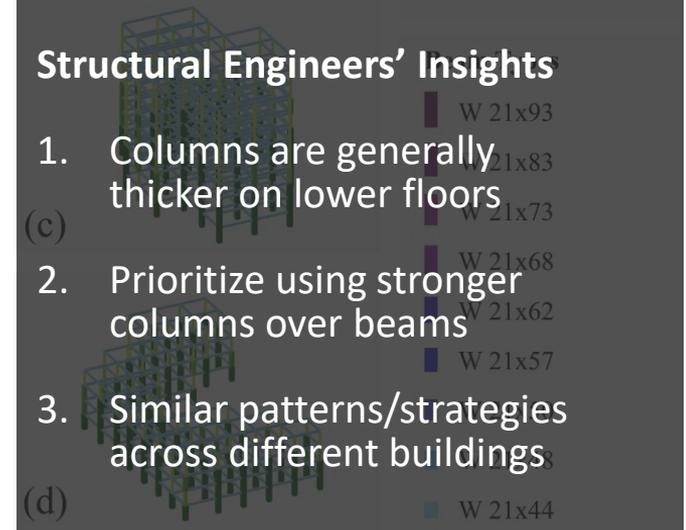
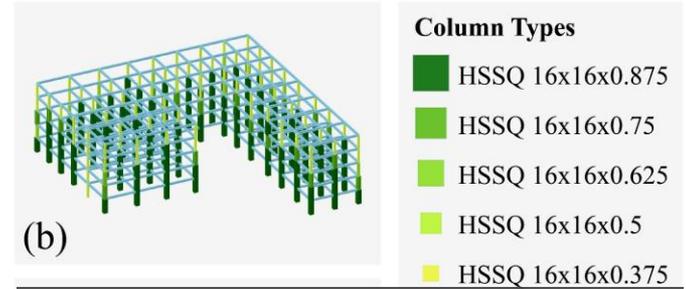
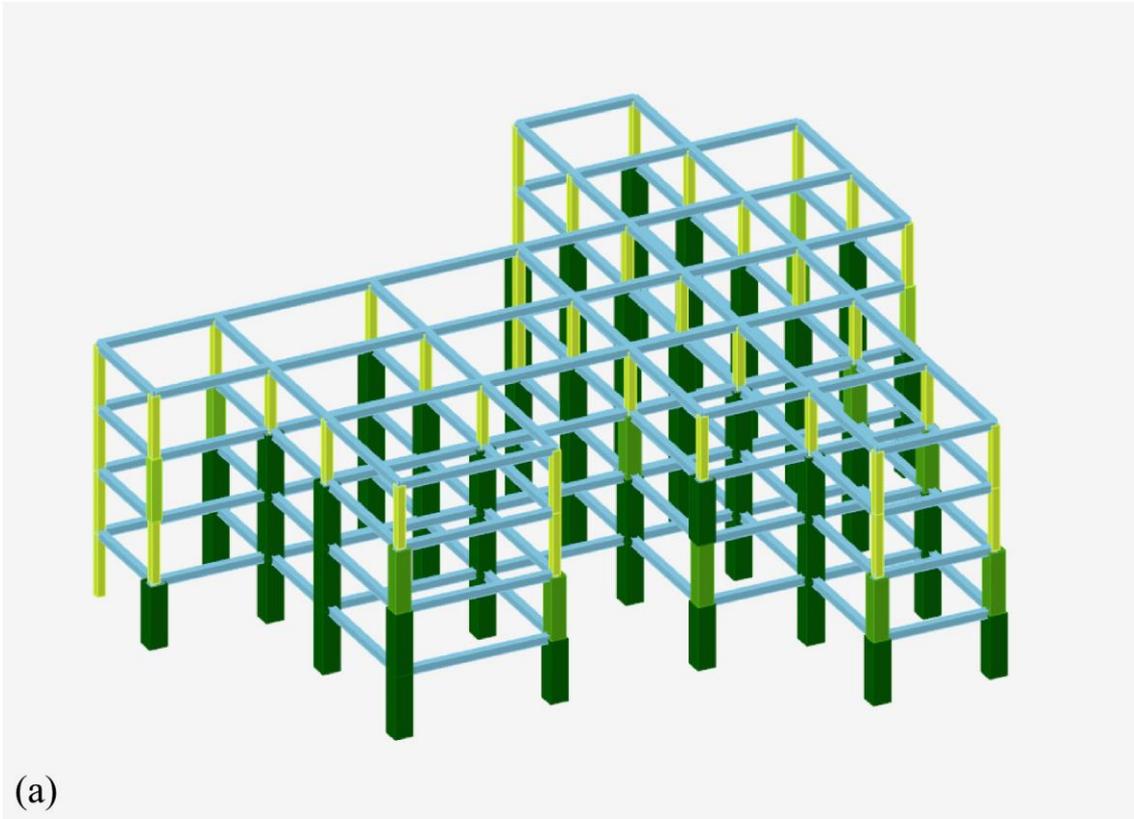
Table 4. NeuralSizer Generalizability (High Safety Factor, Objective Weight = 10)

Train Data	Test Data	Objective	Constraints	
		Mass Objective	Drift Ratio Constraint	Variety Constraint
1~10 story (Baseline)	1~3 story	0.738	$1.62 \times 1e-7$	$0.80 \times 1e-8$
	4~7 story	0.725	$1.28 \times 1e-7$	$0.97 \times 1e-8$
	8~10 story	0.711	$1.69 \times 1e-7$	$1.06 \times 1e-8$
4~7 story	1~3 story	0.773	$2.96 \times 1e-7$	$1.30 \times 1e-8$
	4~7 story	0.746	$3.50 \times 1e-7$	$1.25 \times 1e-8$
	8~10 story	0.728	$3.68 \times 1e-7$	$1.01 \times 1e-8$

- Inference Time: 5.41ms

# NeuralSizer + NeuralSim:

## Result Visualization

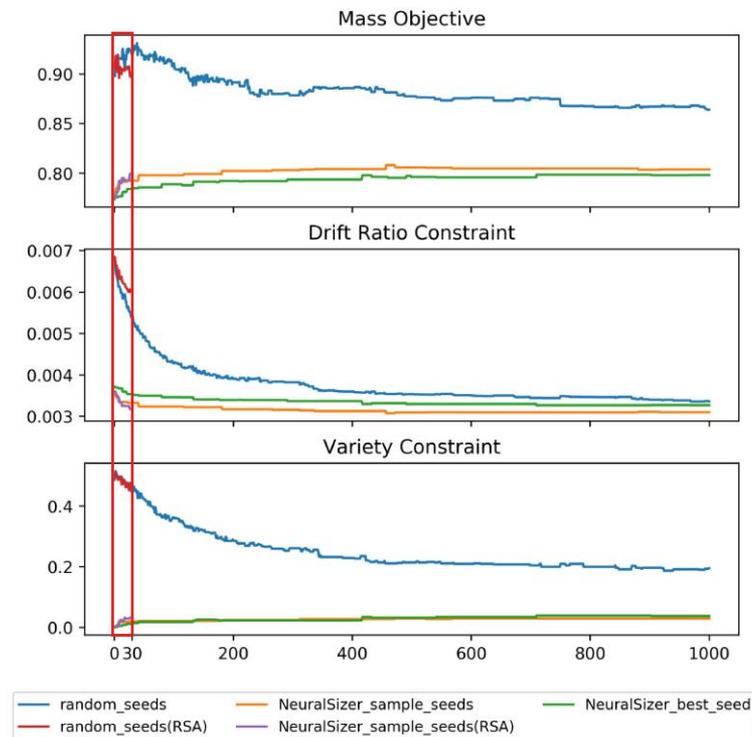


# Speed Comparison with Genetic Algorithm (G.A.)

Table 5. Time Comparison of GA under Different Setups

Setup	Time	Total Iterations	Time / Iteration
NeuroSizer	10.07 ms	-	-
GA + RSA	24 hr	30	-
→ ( <i>estimated</i> )	2 weeks	1000	20.16 mins
GA + NeuralSim	30 mins	1000	0.03 mins

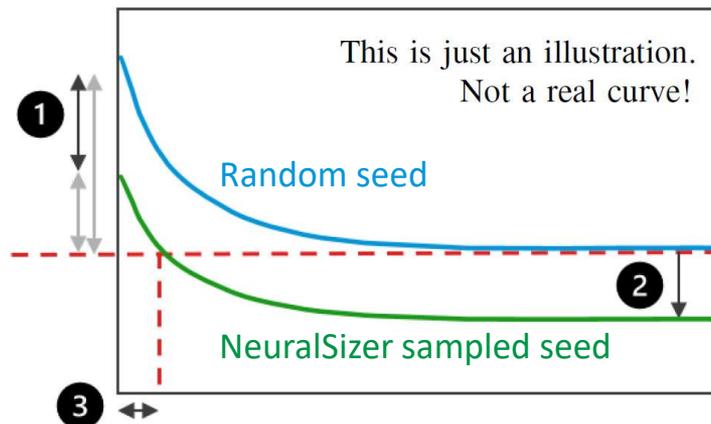
Figure 3. Performance Curves of GA Using Different Seeding Approaches.



# G.A. with Random vs. NeuralSizer Seed

Table 6. NeuralSizer Seeding Performance

Metric	Mass Objective	Drift Ratio Constraint	Variety Constraint
High Safety Factor			
1	232.60%	115.30%	186.20%
2	7.43%	25.70%	95.82%
3	0	25.6	0
Low Safety Factor			
1	83.15%	95.35%	156.22%
2	4.16%	49.22%	32.53%
3	128	0	0



# Conclusion

- We propose an end-to-end pipeline for cross-section size design optimization problem in structural engineering
  - NeuralSim – Fast, accurate
  - NeuralSizer – Qualified design comparable GA results
- Research on improving building and construction performance can bring **positive impact, especially on energy consumptions and CO<sub>2</sub> emissions**
- Open-source data is public at <https://github.com/AutodeskAILab/LSDSE-Dataset>