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Design of Lego-inspired Reconfigurable Modular Blocks for Automated Construction of Engineering Structures

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Smart Infrastructure Lab

- Smart Infrastructure Lab has versatile facility for performing large-scale structural testing, computing, and monitoring.



Background

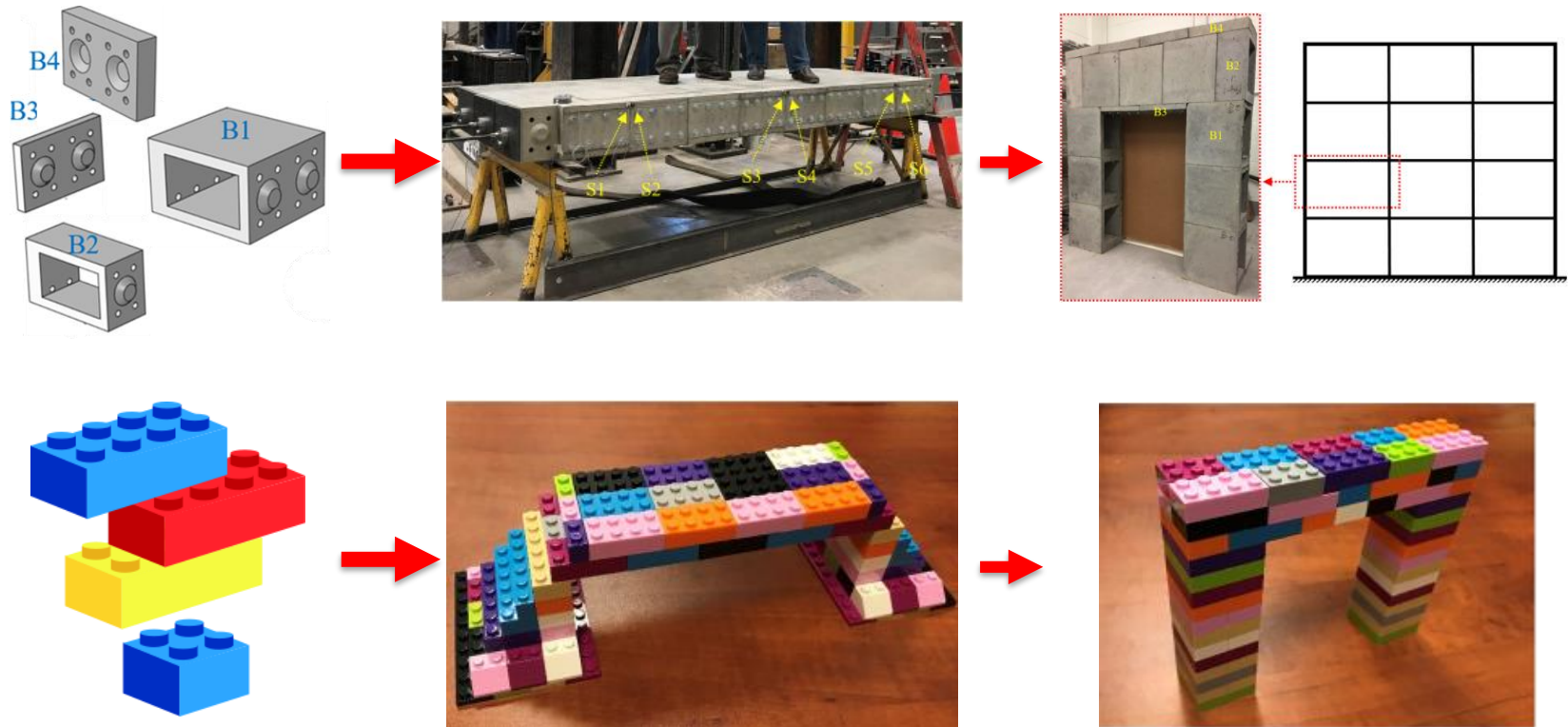
- ❑ Modular structures has many benefits
 - Accelerate construction process
 - Reduce Labor expenses
 - Increase quality and safety



References: <https://cnim-groupe.com/en/businesses/defense-security-and-digital-intelligence/modular-assault-bridge>.
<https://www.bimcommunity.com/files/images/userlib/ChapmanTaylor.jpg>

N. Bertram, S. Fuchs, J. Mischke, R. Palter, G. Strube, J. Woetzel, Modular construction: from projects to products
McKinsey & Company: Capital Projects & Infrastructure (2019), pp. 1-34

- ❑ **Lego-inspired structures** are the reconfigurable modular structures that can be assembled, disassembled, and reassembled for different structures.



Reference: Y. Bao, V.C. Li, Feasibility study of Lego-inspired construction with bendable concrete, *Automation in Construction*, 113 (2020), 103161, doi: 10.1016/j.autcon.2020.103161

Advantages of using Lego-inspired structures

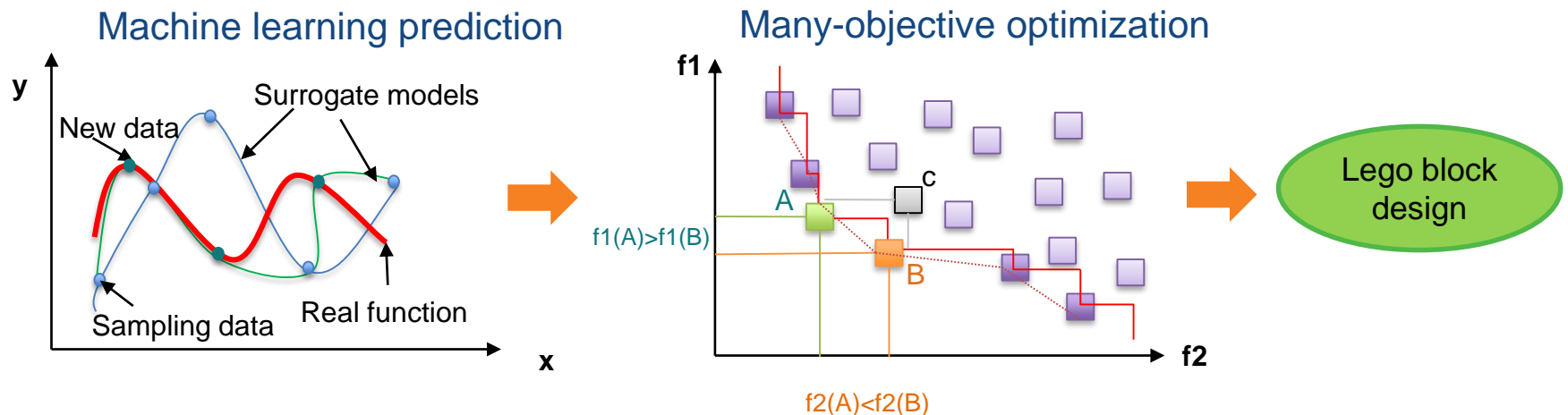
- Improve sustainability and resilience
- Improve construction efficiency and productivity
- Reduce the adverse impact of construction on the environment

Current challenges on design of Lego structures

- There is lack of a knowledge about the computer-aided design and modeling of modular blocks.
- It is unclear how the modular blocks should be designed to improve the mechanical performance of modular structures while minimizing the mass.

Research goal and objectives

- ❑ This study aims to develop a many-objective optimization method to optimize the design of Lego-inspired modular blocks for achieving high mechanical performance of reconfigurable structures.
- ❑ Objectives:
 - To develop high-fidelity surrogate models to predict the load-carrying capacity, stiffness, and ultimate deflection
 - To develop a new many-objective optimization method to obtain optimal design



Methodology

Experiment and simulation

Experimental testing

Simulation on ABAQUS

Dataset development

Machine learning

Machine-learning model

Model evaluation

Prediction of mechanical properties

Optimization

Design variables and objective function

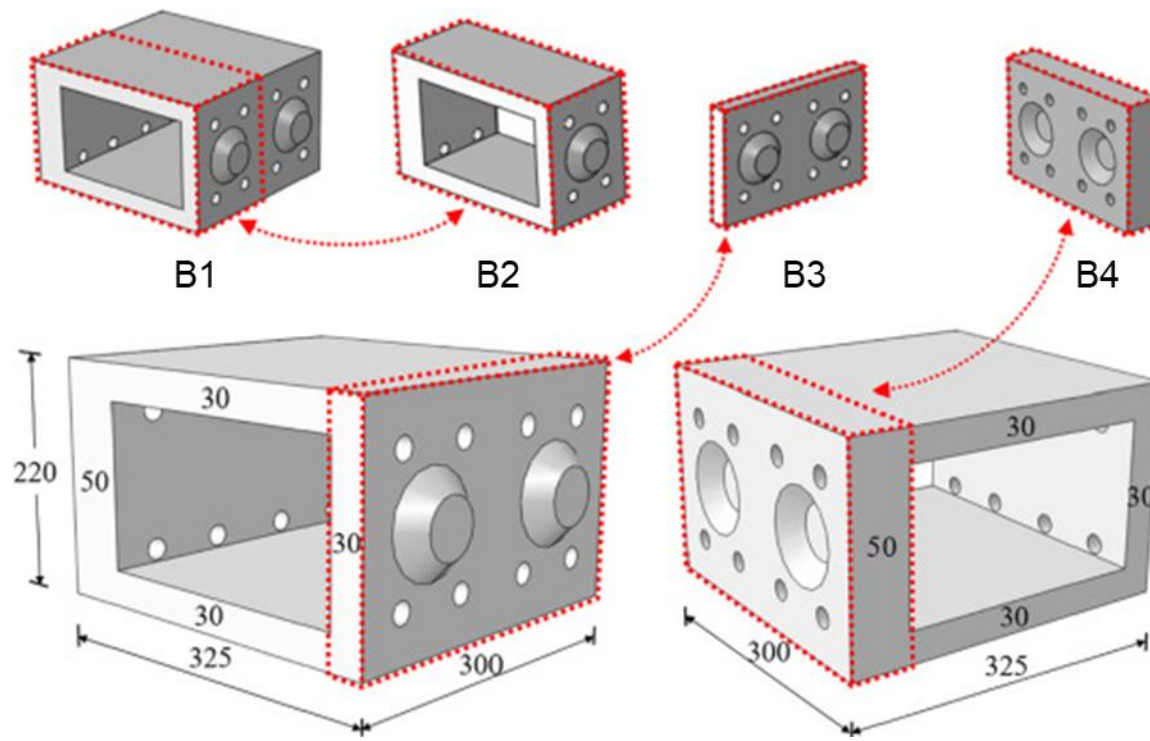
Many-objective optimization

Optimal design

Experimental test

❑ Initial design

A set of four types of Lego-blocks was selected as the initial design for the experiment and optimization process.



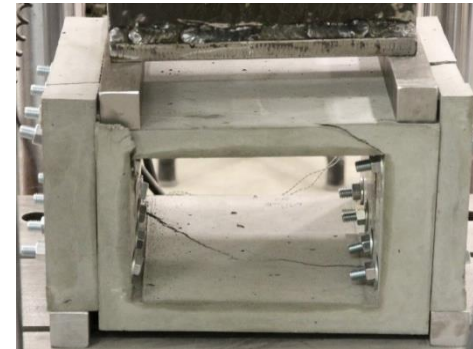
❑ Specimens, test set-up

- Engineered cementitious composite (ECC) is used.
- Three-point bending test was conducted.

Specimen 1



Specimen 2



Finite element model

❑ Simulation details

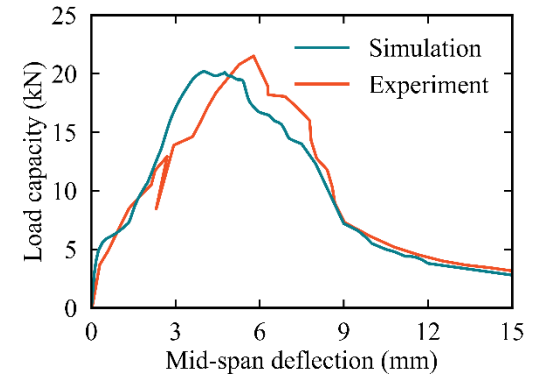
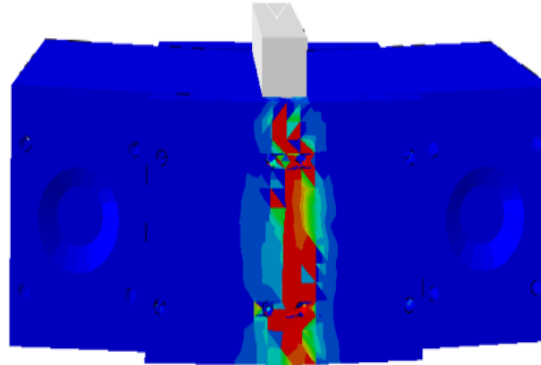
- Assemblages were modeled using eight-node solid elements (C3D8R).
- Contact between blocks were modeled by surface-to-surface hard contact.
- The behavior of concrete was modeled using concrete damage plasticity (CDP), as shown in Table 1 below.

Parameters of the CDP model

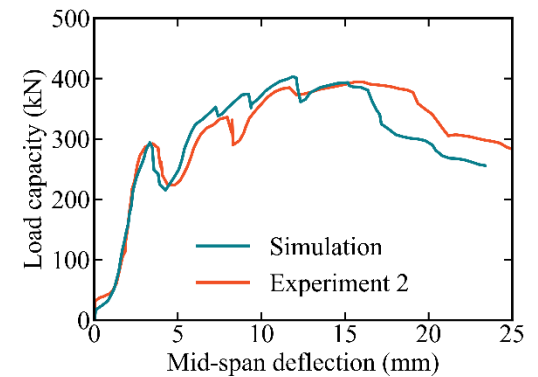
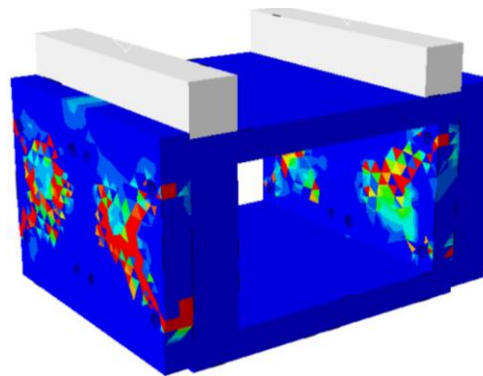
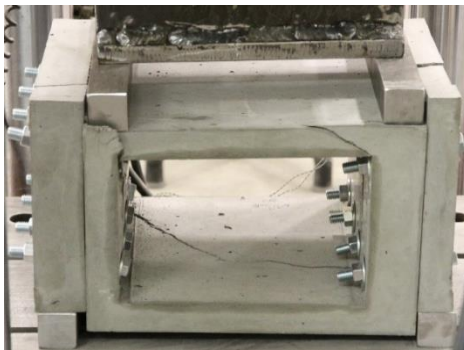
Density (kg/mm ³)	Poisson's ratio	Young's modulus (GPa)	Dilation angle	Eccentricity	f_{b_0}/f_{c_0}	K	Viscosity parameter
2200	0.2	30	36	0.1	1.16	0.67	0

Finite element analysis

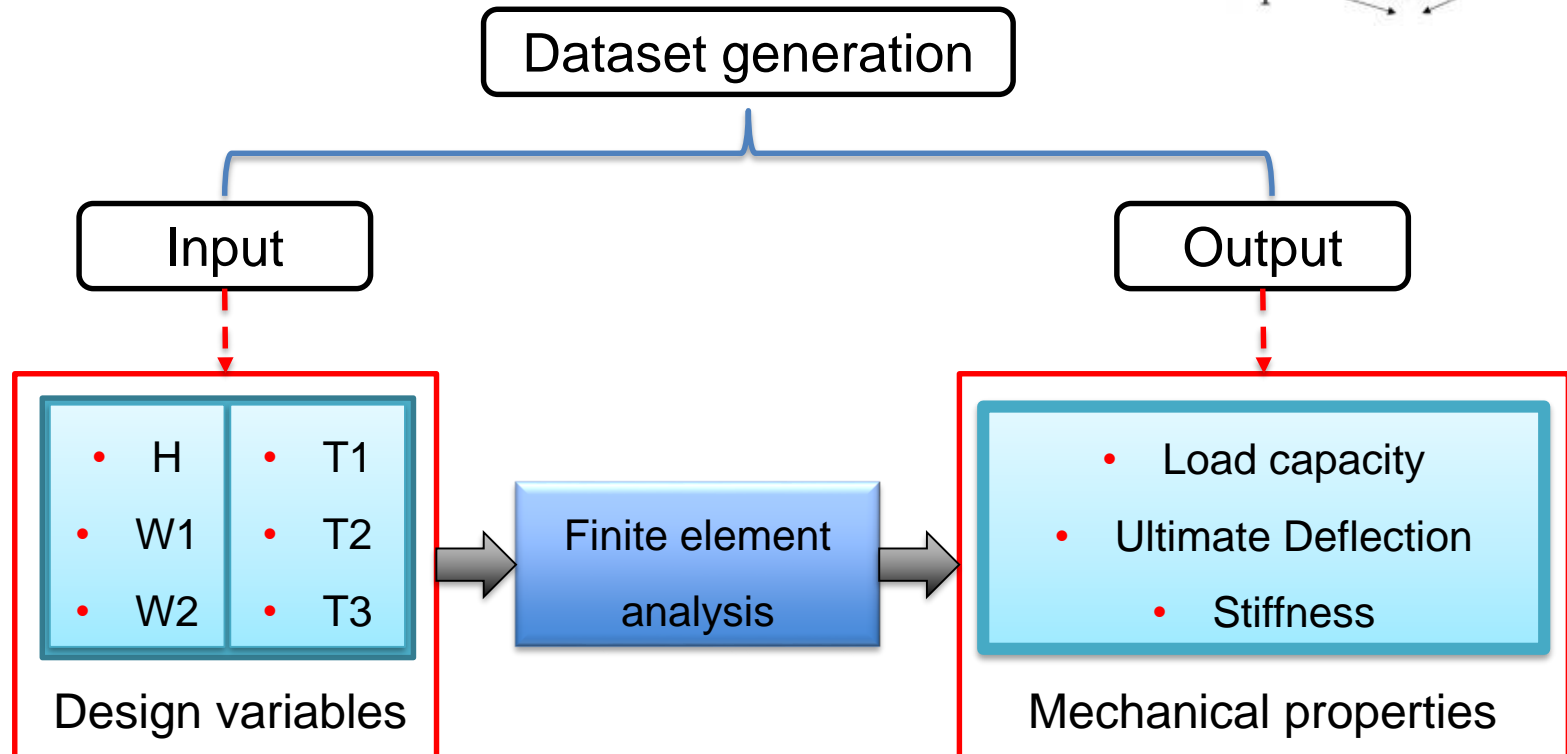
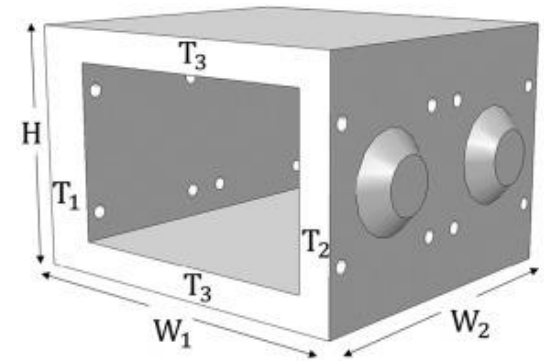
Specimen 1



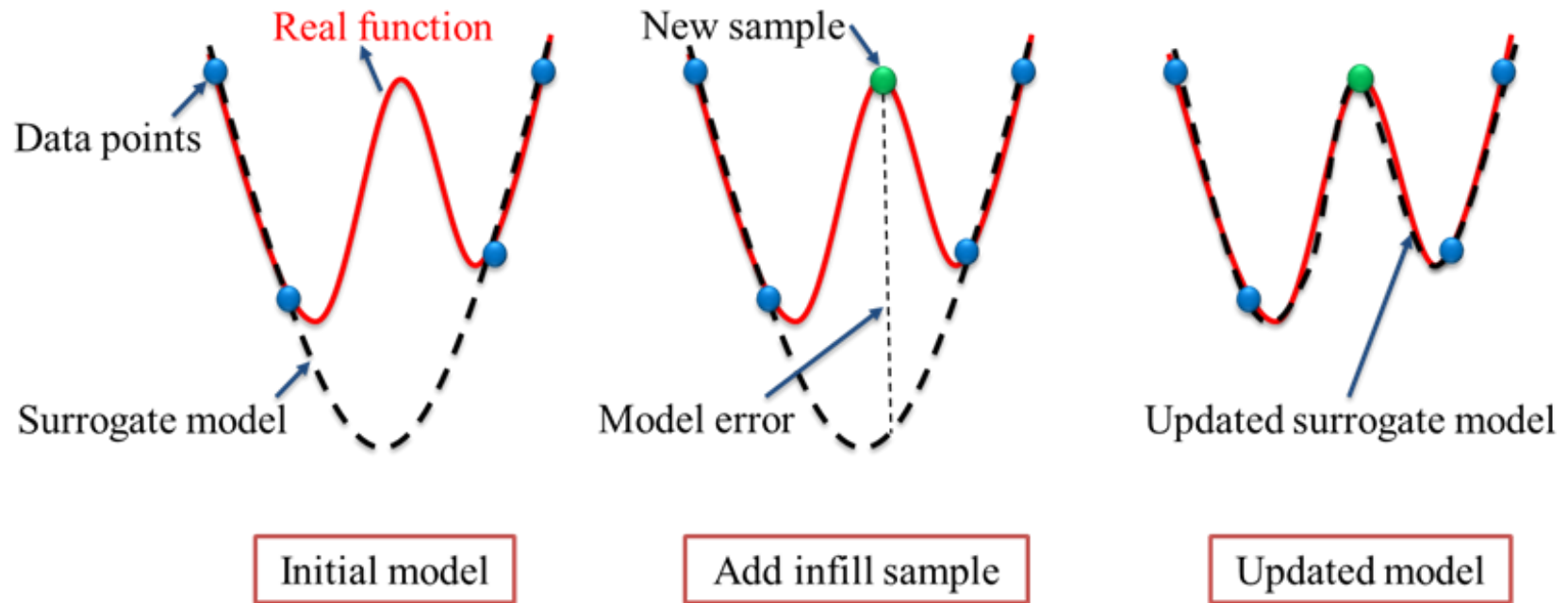
Specimen 2



Dataset development



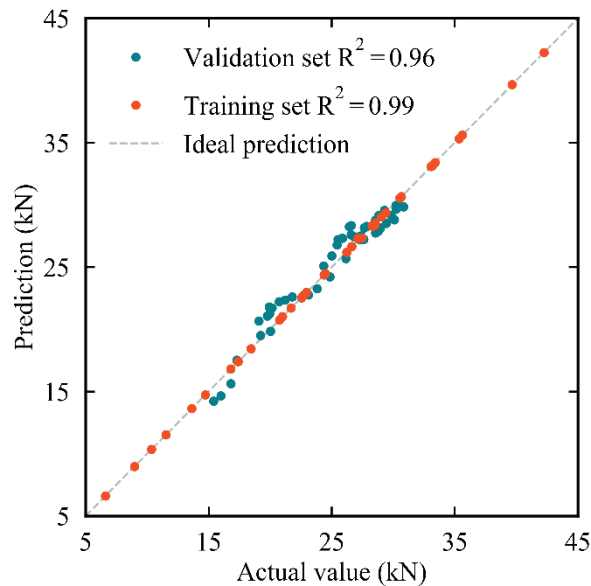
Machine learning (sequential surrogate modeling)



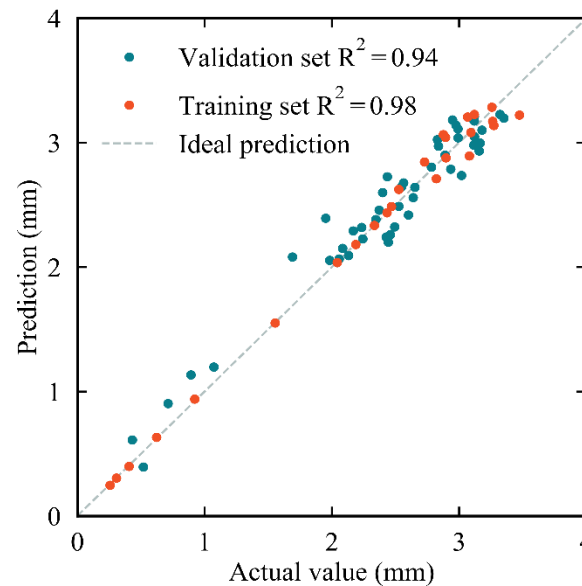
Reference: S.-S. Jin, H.-J. Jung, Sequential surrogate modeling for efficient finite element model updating, Comput. Struct., 168 (2016), pp. 30-45, [10.1016/j.compstruc.2016.02.005](https://doi.org/10.1016/j.compstruc.2016.02.005)

Machine learning models

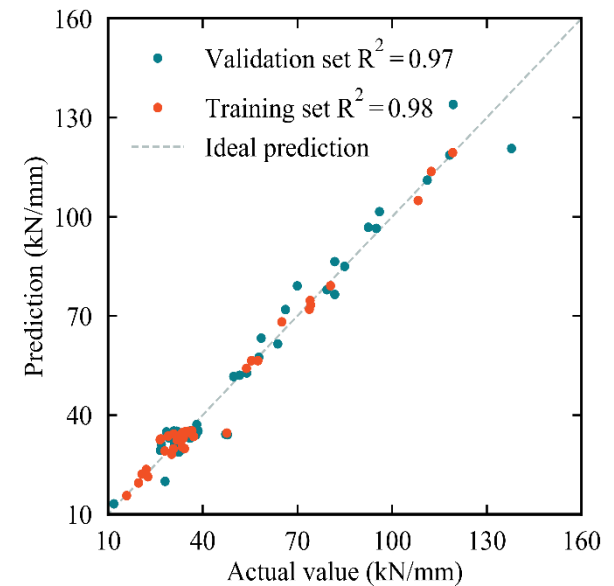
- Three machine learning models were developed for the load-carrying capacity, ultimate deflection, and stiffness



Load-capacity



Deflection



Stiffness

Prediction accuracy

- The typical performance metrics indicate that the models have high accuracy and generalization performance

Set	Metric	Mechanical properties		
		Load capacity	Deflection	Stiffness
Training	R ²	0.99	0.98	0.98
	RMSE	0.04	0.10	0.18
Validation	R ²	0.96	0.94	0.97
	RMSE	0.09	0.16	0.93

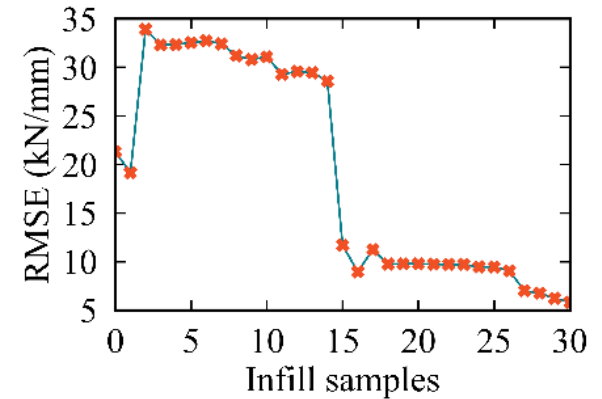
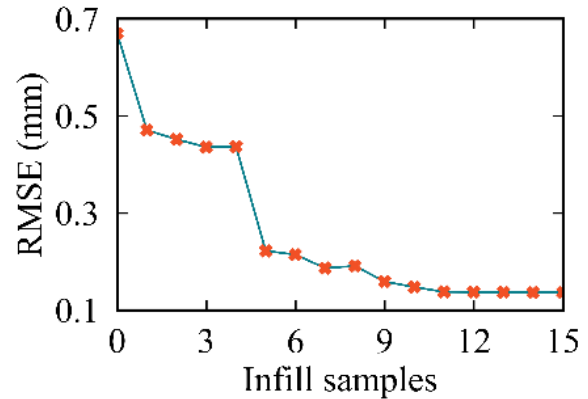
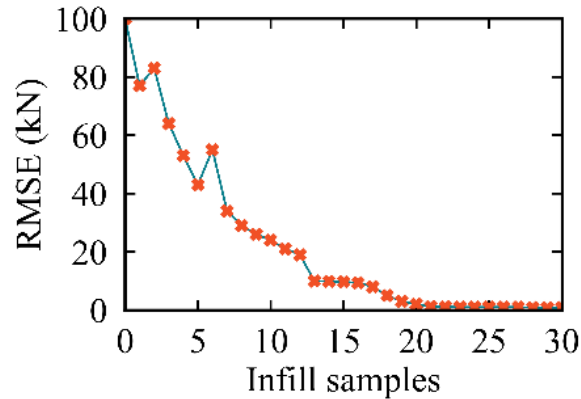
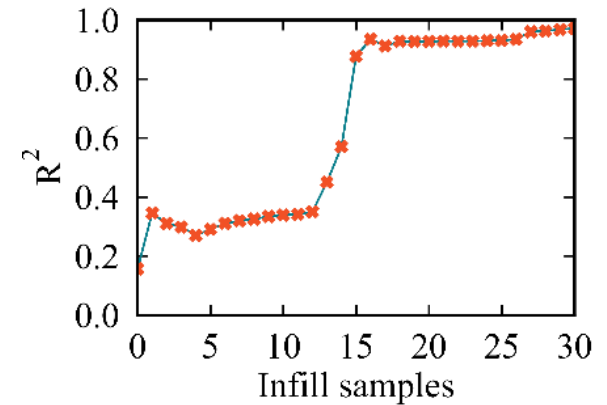
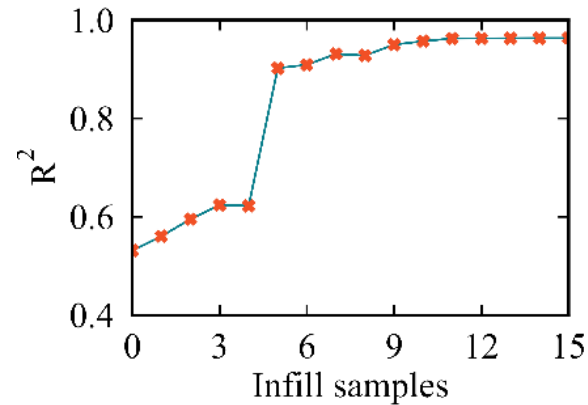
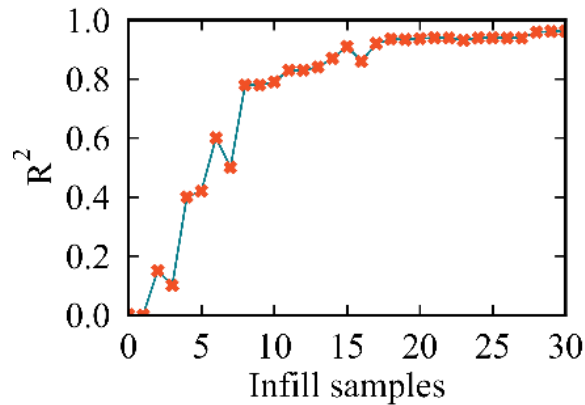
Coefficient of determination $R^2(P) = 1 - \frac{\sum_{i=1}^n (p_i - a_i)^2}{\sum_{i=1}^n [a_i - \text{mean}(a_i)]^2}$

Root mean square error $RMSE(P) = \sqrt{\frac{\sum_{i=1}^n (p_i - a_i)^2}{n}}$

Predictions $P = \{p_1, p_1, \dots, p_n\}$

Actual values $A = \{a_1, a_1, \dots, a_n\}$

Model evaluation



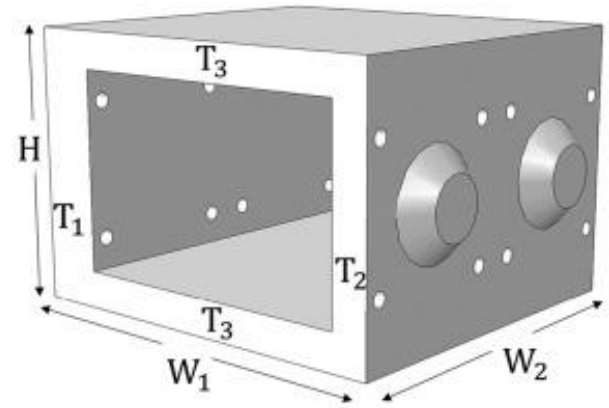
Load-capacity

Deflection

Stiffness

Many-objective optimization

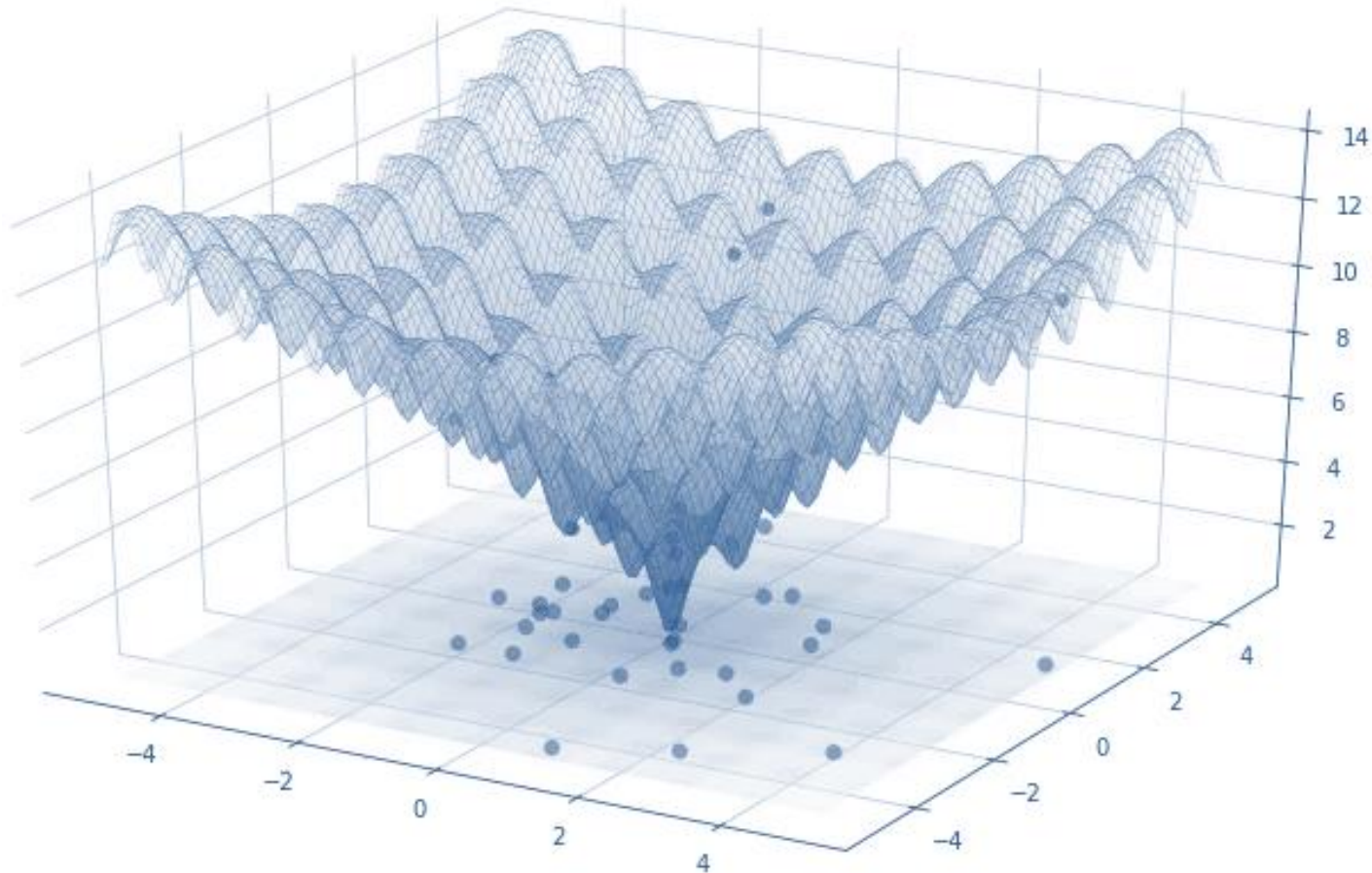
- ❑ A many-objective optimization problem is formulated to optimize the design of Lego-inspired block
- ❑ Six design variables were considered: H , W_1 , W_2 , W_3 , T_1 , T_2 , T_3
- ❑ Four objective functions were considered
 - Load-capacity (maximize)
 - Deflection (maximize)
 - Stiffness (maximize)
 - Volume (minimize)
- ❑ one design constraints are applied:
 - The maximum mass of blocks is limited to 61 kg



Reference: Josyula, S. P., Krasemann, J. T., & Lundberg, L. (2020). Parallel computing for multi-objective train rescheduling. IEEE Transactions on Emerging Topics in Computing.

Optimization process

- ❑ A genetic algorithm is used to solve the optimization problem.



The iterative process for optimization

Optimization results

- ❑ A set of solutions are obtained from the optimization
- ❑ A decision-making algorithm TOPSIS is used to select the optimal design
- ❑ The optimal design of the Lego blocks has highest mechanical properties and minimum volume.

	Optimal design	Initial design	Discrepancy
H (mm)	231	220	5%
W_1 (mm)	216	325	-33.5%
W_2 (mm)	275	300	-8.3%
T_1 (mm)	30	50	-40.0%
T_2 (mm)	18	30	-40.0%
T_3 (mm)	18	30	-40.0%
Load capacity (kN)	24.8	20.2	22.8%
Stiffness (kN/mm)	25.9	11.3	129.2%
Deflection (mm)	2.9	2.6	11.5%
Volume (L)	4.7	9.7	-51.6%

Conclusions

- ❑ The developed machine learning models can predict the mechanical performance of modular blocks with high accuracy and generalization performance.
- ❑ The framework provides an effective solution for design optimization of Lego-inspired modular blocks.
- ❑ The optimal design increased the load-carrying capacity, deformability, and stiffness by 22.8%, 11.5%, and 129.2%, respectively, and reduced the volume by 51.6%.

Thank you!

Questions & Answers

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