



SANTA CLARA UNIVERSITY
SCHOOL OF ENGINEERING

Surrogate-Assisted Optimization of a 1D Heterogeneous Bar

MECH 293 Final Project

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Motivation

Why this project?

- Structural optimization is expensive
- Each design evaluation needs FEA
- Surrogate models (NN, GP, etc.) can approximate FEA

Goal

- Use a simple 1D bar problem
- Build a neural-network surrogate for compliance and mass
- Compare direct FEA search vs surrogate-assisted search



Problem Setup

1D Heterogeneous Bar

- Length $L = 1$, area $A = 1$, load $F = 1$
- Fixed at left end, traction at right end
- 10 elements, element-wise Young's modulus E_i

Optimization problem

- Minimize compliance $C = F u(L)$
- Subject to $M(z) \leq 0.7 M$ (fully stiff)

Design variables

- $E_i \in [1, 10]$ for each element
- Density–modulus tradeoff:

$$\rho_i = 1 + \left(\frac{E_i - 1}{10 - 1} \right)^2 \cdot 2$$

- High E_i becomes disproportionately heavy
- Mass limit: $M \leq 0.7 M_{\text{full}} = 2.1$



FEA Model

Linear 1D bar elements

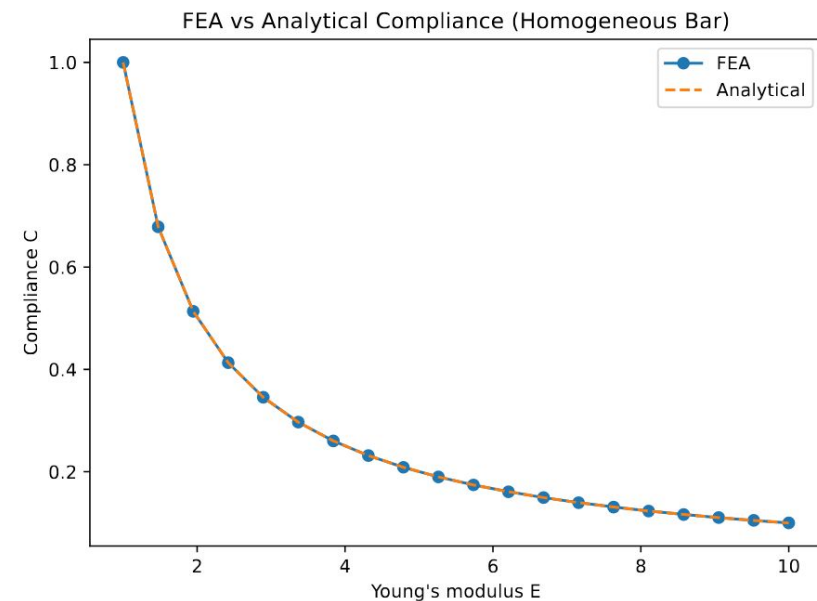
Local stiffness: $k^{(i)} = \frac{AE_i}{\Delta L} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$

Assemble global K, apply $u(0) = 0$, solve for u

Verification:

Compare FEA with analytical solution:

$u(L) = FL/(AE)$, $C = F^2L/(AE)$, Max relative error $\approx 2 \times 10^{-15}$





Neural Network Surrogate

Dataset:

Random sample $E_i \sim U(1,10)$

Compute true (C,M) via FEA
and density model

Train: 4,000 samples

Test: 1,000 samples

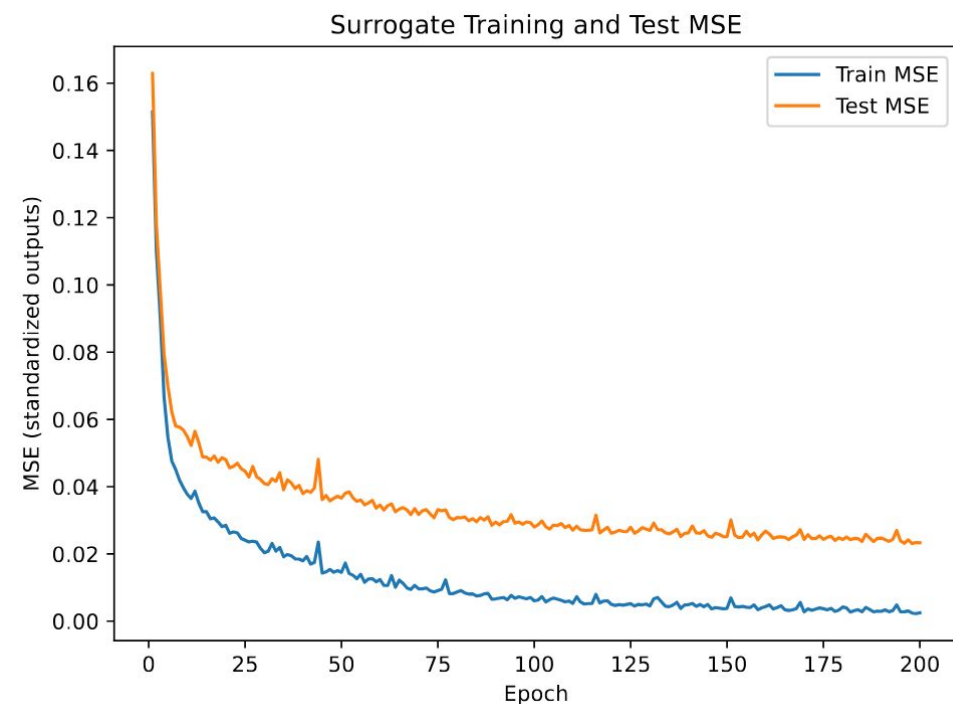
Network:

Fully connected MLP with
10 element input

Hidden: 3 layers $\times$ 64 ReLU

Output:

2 (Compliance, mass)





Surrogate Accuracy

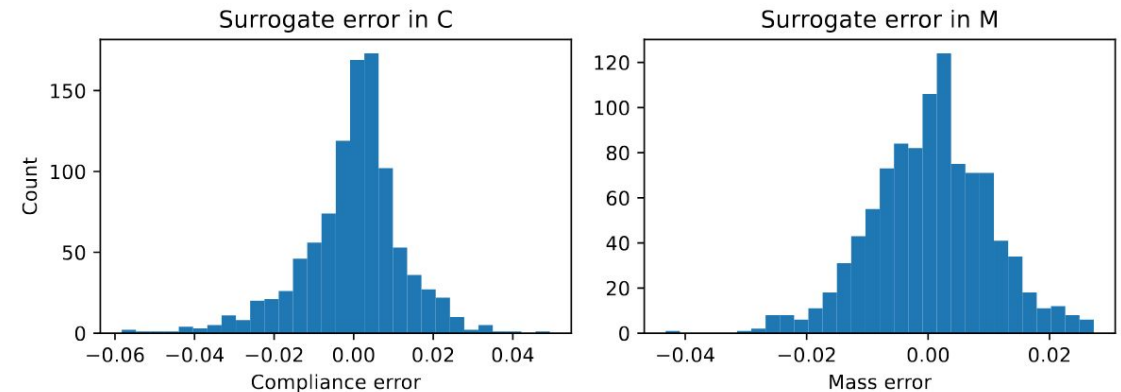
Test set results:

RMSE in compliance $\approx 1.27 \times 10^{-2}$

RMSE in mass $\approx 9.77 \times 10^{-3}$

Errors roughly zero mean, light tails

**Good regression accuracy overall,
but small errors in C can still change design ranking.**





Optimization Strategies

Direct FEA random search

2,000 random designs

evaluate each with FEA

Keep designs with $M \leq M_{\max}$

Choose lowest compliance design

Surrogate method

20,000 random designs

Evaluate with surrogate

Filter by predicted mass $M^{\wedge} \leq M_{\max}$

Take top 50 by predicted $C^{\wedge}$

Re-evaluate only these 50 with FEA



Baseline Results

Method	C_{best}	M_{best}	FEA calls	Surrogate calls
Direct random search	0.140773	2.086059	2000	0
Surrogate pre-screening	0.135981	2.054015	50	20000

- Surrogate-assisted method: better compliance, similar mass
- FEA calls reduced by $\sim 40\times$



Discussion

- Surrogates can meaningfully reduce FEA calls.
- Two-stage scheme (screen + re-eval) is safer than surrogate-only.

Limitations:

- Very small 1D problem, FEA is cheap here.
- Only random search, no gradient-based or Bayesian optimization.



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Thank you! Questions?