Putting Stiffness where it’s needed: Optimizing The Mechanical Response of Multi-Material Structures

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Introduction
Overview

- Motivation: Multi-Material Manufacturing
- Multi-Phase Topology Optimization (MPTO)
  - Basic Principle
  - Implementation
- Optimization Strategies: Simulated Annealing vs. Genetic Algorithms
- Results and Discussion
  - Simple Problem: Asymmetric 3-Point Bending
- Conclusion and Outlook
Motivation
Multi-Material Manufacturing

- Additive Manufacturing
- Compound/Hybrid Casting
- etc.

Generally well suited for multi-material approaches.

Polymer multi-material options available.
Motivation
Multi-Material Manufacturing

- Additive Manufacturing
- Compound/Hybrid Casting
- etc.

Source: Lehmhus et. al., Euromat 2019

Source: CustomPartNet, 2008

Source: https://www.dezeen.com/2014/10/28/acadia-annual-conference-3d-printed-designs-zaha-hadid-francis-bitonti/

Source: https://proto300.com/polyjet-matrix-3d-printing-services-process.php
Motivation
Multi-Material Manufacturing

- Additive Manufacturing
- Compound/Hybrid Casting
- etc.

Source:
Lehmhus, D.; von Hehl, A.; Hausmann, J.; Kayvantash, K.; Alderliesten, R.; Hohe, J. New Materials and Processes for Transport Applications: Going Hybrid and Beyond. Advanced Engineering Materials 21 (2019) 1900056.
Multi-Phase Topology Optimization
The Basic Principle

- **Optimization problem:** Minimization of total strain energy
- **Basis:** Finite Element (FE) model including loads and boundary conditions.
- **Representation of material via finite element properties.**
- **Linear elastic FE simulation yields element-based strain energy data.**
- **Element-wise redistribution of material properties leads to improved variants.**

\[ U = \frac{1}{2} \int_V \varepsilon^T \cdot \sigma \cdot dV = \frac{1}{2} \int_V \varepsilon^T \cdot D \cdot \varepsilon \cdot dV \]

Burblies, A.; Busse, M. Computer Based Porosity Design by Multi Phase Topology Optimization. Multiscale & Functionally Graded Materials Conference (FGM2006), Honolulu (USA), Oct. 15th -18th 2006.
Multi-Phase Topology Optimization
The Basic Principle

- Set up the FE model of the problem under scrutiny.
- Predefine number, volume fraction and (elastic) properties of materials.
- Associate material properties to finite element sets, maintaining the predefined volume fractions.
- Randomly re-distribute material properties over the FE model.
- Perform FE simulations and record element-level strain energies and volume, as well as total strain energy (model-level).
- Redistribute material properties (a) randomly, (b) based on a specific optimization strategy, or (c) strategically, but including some random element.
- Make sure material fractions are maintained – if this is not the case, apply appropriate changes.
- Perform an FE simulation, and check whether total strain energy has been reduced – if yes, continue with the present configuration above (iteration), if not, create and evaluate a new candidates.
- Continue until further iterations do not yield significant improvements anymore.
Multi-Phase Topology Optimization
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- Continue until further iterations do not yield significant improvements anymore.
Optimization Strategies
Simulated Annealing

- randomized exchange of elements to create a new configuration
- repetition (inner steps) until improvement over previous state achieved (outer steps)
- variations initially tested
  - fraction of elements subject to random exchange
  - constrained and unconstrained
Optimization Strategies
Simulated Annealing: Strategic Sorting

- randomized exchange of elements to create a new configuration
- repetition (inner steps) until improvement over previous state achieved (outer steps)
- variations initially tested
  - fraction of elements subject to random exchange
  - constrained and unconstrained
Optimization Strategies
Genetic Algorithms

- creation of a population of 20 variants for each (outer) step
- inner steps correspond to the evaluation of the 20 population members, i.e., at this stage, each outer step invariably implies 20 inner steps
- selection of a survivor (best of 20) and crossover with the parent, followed by mutation
- So far, no constraint implemented
Results & Discussion
Load Case

- Selected sample load case: Asymmetric 3-point-bending as depicted below.
- Small initial model for fast calculation and initial comparison of algorithms:
  - 832 elements of type C3D8R.
- Three different materials at equal volume fractions:
  - „aluminum“: $E = 70 \text{ GPa}$, Poisson's ratio 0.3
  - „copper“: $E = 110 \text{ GPa}$, Poisson's ratio 0.3
  - „steel“: $E = 200 \text{ GPa}$, Poisson's ratio 0.3
- Initial configuration left 1/3 of beam Al, centre 1/3 Cu, right 1/3 Fe
Results & Discussion
Simulated Annealing, Constrained

- Comparison of 10 runs with identical initial configuration, i.e. distribution of materials.
- First constraint solving leads to a major drop in strain energy.
- Afterwards, fine-grained minimization based on the Monte Carlo simulation approach.
Results & Discussion
Simulated Annealing, Constrained

- Comparison of 10 runs with varied initial configuration, i.e. distribution of materials.
- First constraint solving leads to a major drop in strain energy.
- Afterwards, fine-grained minimization based on the Monte Carlo simulation approach.
- No major difference caused by variation of starting configurations.
Results & Discussion
Simulated Annealing, Constrained

- Moving elements: Simulated annealing, with constraints.
Results & Discussion
Genetic Algorithm, Unconstrained

- Comparison of 10 runs with identical initial configuration, i.e. distribution of materials.
- Monotonic descent of strain energy – GA optimization works.
- Initial rise in strain energy is caused by the fact that the chosen reference at 46.901 mJ is the ordered structure as shown initially.
Comparison of 10 runs with varied initial configuration, i.e. distribution of materials.

Monotonic descent of strain energy – GA optimization works.

Initial rise in strain energy is caused by the fact that the chosen reference at 46.901 mJ is the ordered structure as shown initially.

As expected, more variation in initial strain energies, converging to previous slide’s results later.
Results & Discussion

Comparison of Optimization Algorithms: Final Strain Energy

- starting point 46.901 mJ
- unconstrained SA achieves next to no improvement
- constraints controlling material redistribution lead to approx. 30% reduction in total strain energy
- GA achieve notable strain energy reduction (approx. 25%) even when unconstrained
- scatter (10 runs each) is only slightly lower when starting from identical random distributions rather than different ones
Conclusion
Main Findings

- Unconstrained simulated annealing algorithms require far too many iterations steps.
- Suitable constraints can lead to really significant improvements.
- Constrained simulated annealing approaches outperform unconstrained genetic algorithms.
- However, while unconstrained simulated annealing does not succeed in reducing strain energy, unconstrained GA does (10% margin after approx. 1000 steps).
- For both simulated annealing and genetic algorithms, variation of results when using identical as opposed to different random distributions as starting point is slightly reduced, but remains in a similar range.
Outlook
What else to ask for?

- Further optimization of algorithms, including pre-check of new configurations prior to FE simulation runs to further reduce runtime.
- Adding the concept of constraints to the GA algorithm.
- Evaluation of higher complexity problems (more elements, materials, loads, …).
- Extension towards plasticity: Check for local transgression of material-dependent yield stress and correct where needed.
Thank you
for your kind attention!

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Backup Slides
Optimization Strategies

Simulated Annealing

- randomized exchange of elements to create a new configuration
- repetition (inner steps) until improvement achieved (outer steps)
- variations
  - fraction of elements subject to random exchange
  - constrained and unconstrained
Optimization Strategies
Genetic Algorithms

- creation of a population of 20 variants for each (outer) step
- inner steps correspond to the evaluation of the 20 population members, i.e. at this stage, each outer step implies 20 inner steps
- selection of a survivor and crossover with the parent, followed by mutation
- no constraint implemented
Results & Discussion
Comparison of Optimization Algorithms: Final Strain Energy

- starting point 46.901 MJ strain energy
- unconstrained simulated annealing achieves next to no improvement
- constraints controlling redistribution of materials lead to approximately 30% reduction in total strain energy
- genetic algorithms result in significant strain energy reduction (approx. 25%) even when unconstrained
- scatter (10 runs each) is slightly lower when starting from identical random distributions compared to different ones

![Comparison of Optimization Algorithms](chart.png)

- Simulated annealing: 1, 2 unconstrained
- 3, 4 constrained
- Genetic algorithms: 5, 6 unconstrained
- varied initial configuration
- same initial configuration
Templates
Title
Subtitle

- bullet point 1
- bullet point 2
- bullet point 3
Title
Subtitle

- bullet point 1, level 1
- bullet point 2, level 1
  - bullet point 1, level 2
  - bullet point 2, level 2
  - bullet point 3, level 2
- bullet point 3, level 1
- bullet point 4, level 1