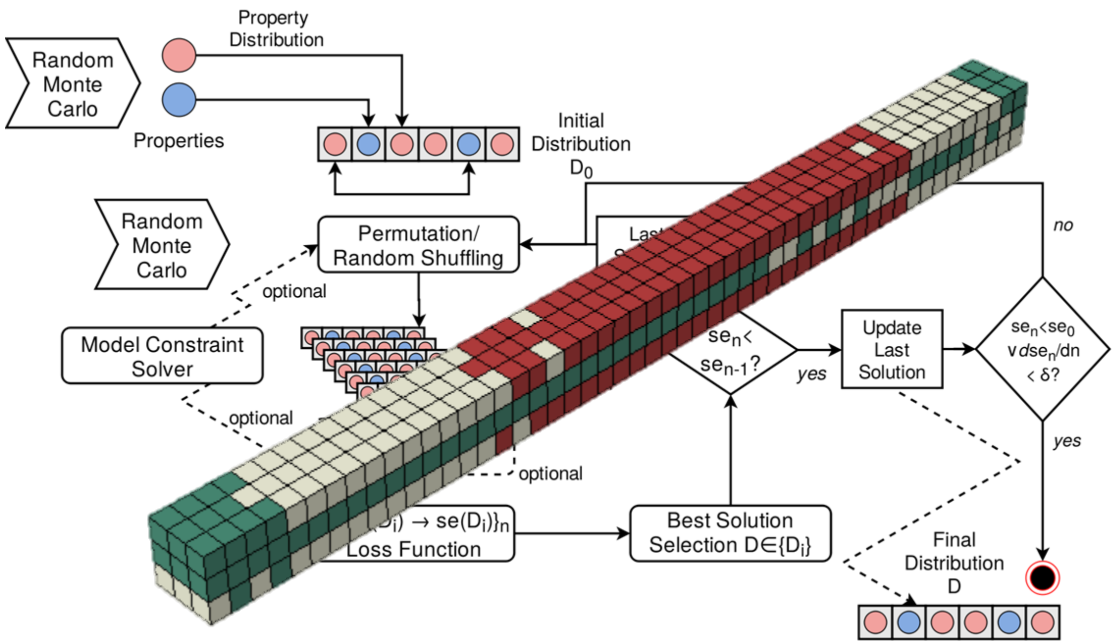
Putting Stiffness where it's needed: Optimizing The Mechanical Response of Multi-Material Structures

Arouna Patouossa Mounchili[1,2], Stefan Bosse[2], Dirk Lehmhus[1] (speaker), Adrian Struß[1]



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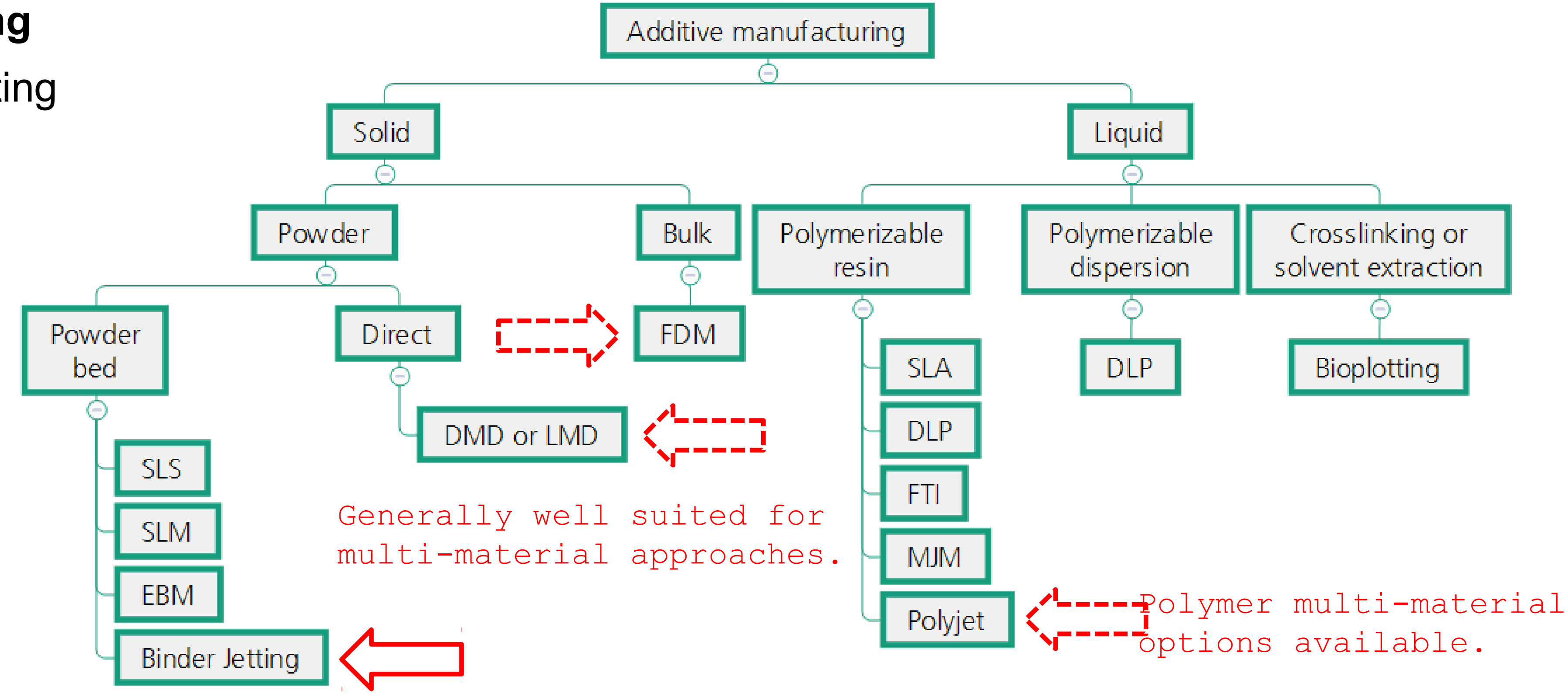
Introduction
Overview

- 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.



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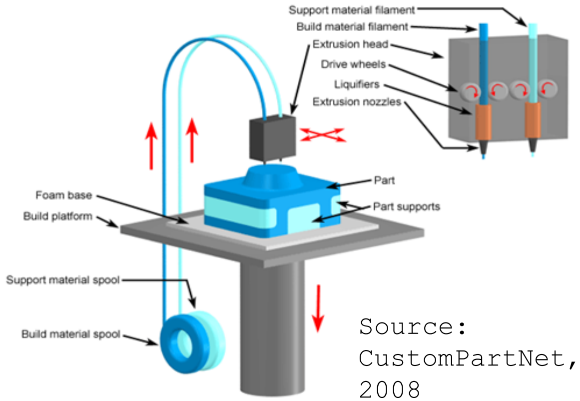
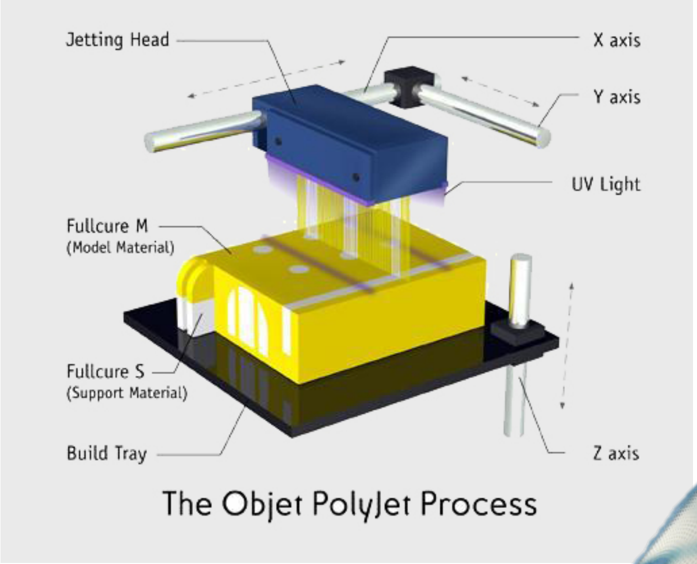
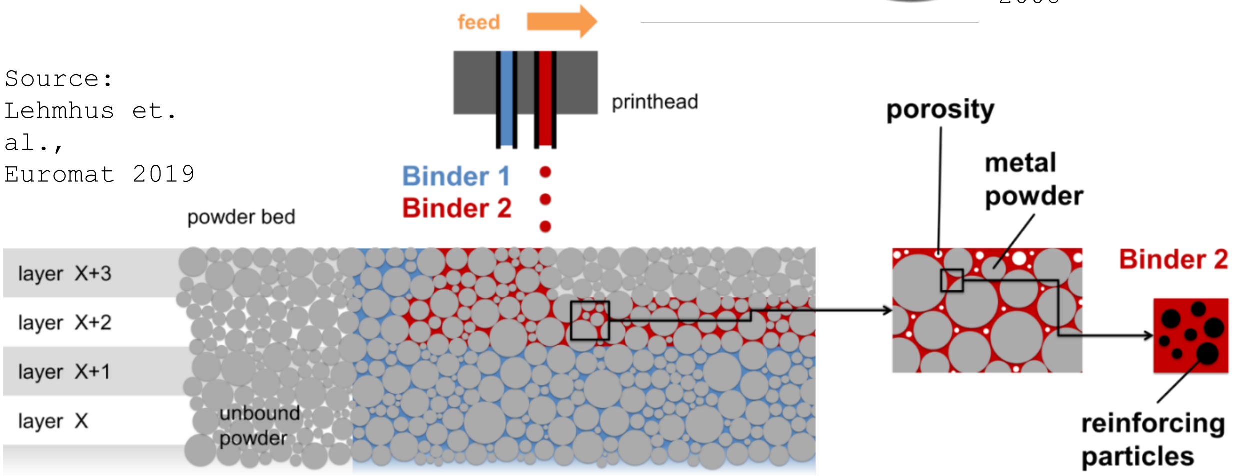


Source: CustomPartNet, 2008

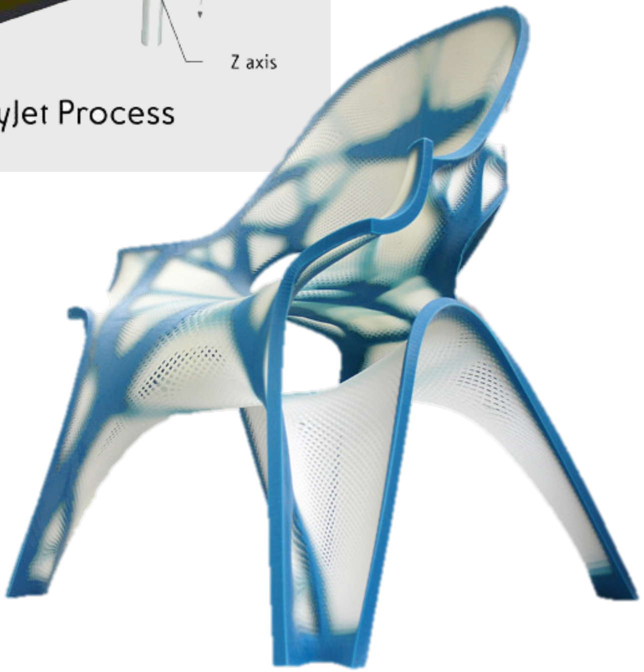


Source: https://proto3000.com/polyjet-matrix-3d-printing-services-process.php

Source: Lehmhus et al., Euromat 2019



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



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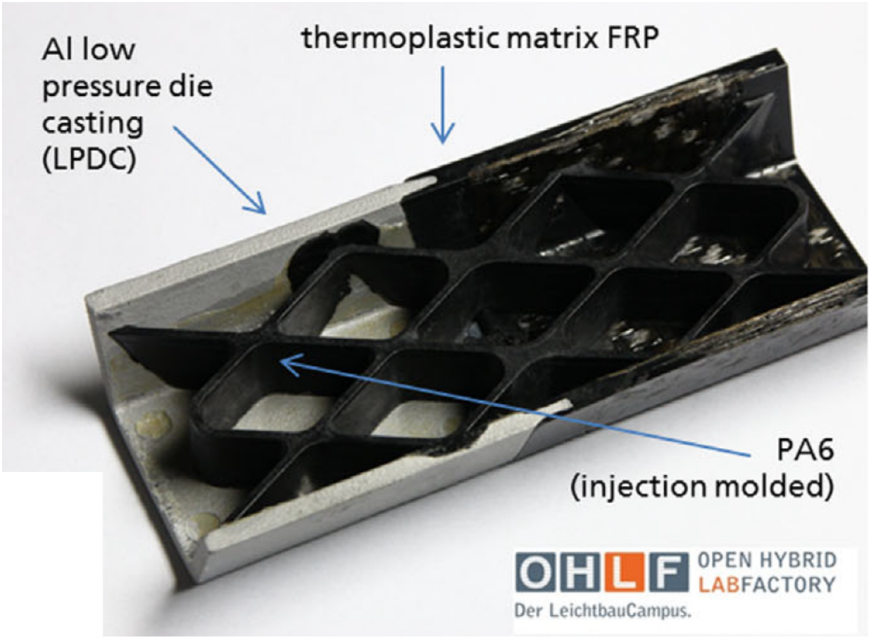

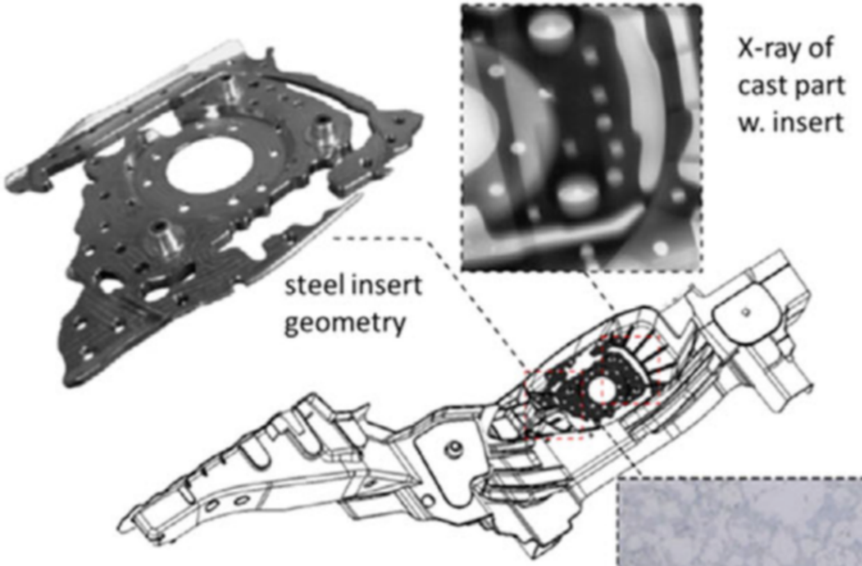

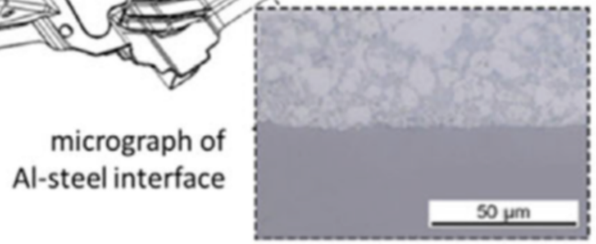

Source:
Lehmhus, D.; von Hehl, A.; Hausmann, J.; Kayvantash, K.; Alderliesten, R.; Hohe, J. New Materials and Processes for Transport Applications: Going Hybrid and Beyond. Advanced Engineering Materials 21 (2019) 1900056.

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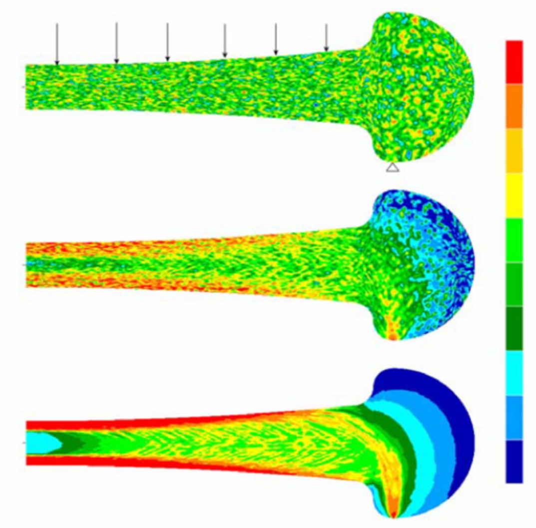
Multi-Phase Topology Optimization
The Basic Principle

- 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.

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



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 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.

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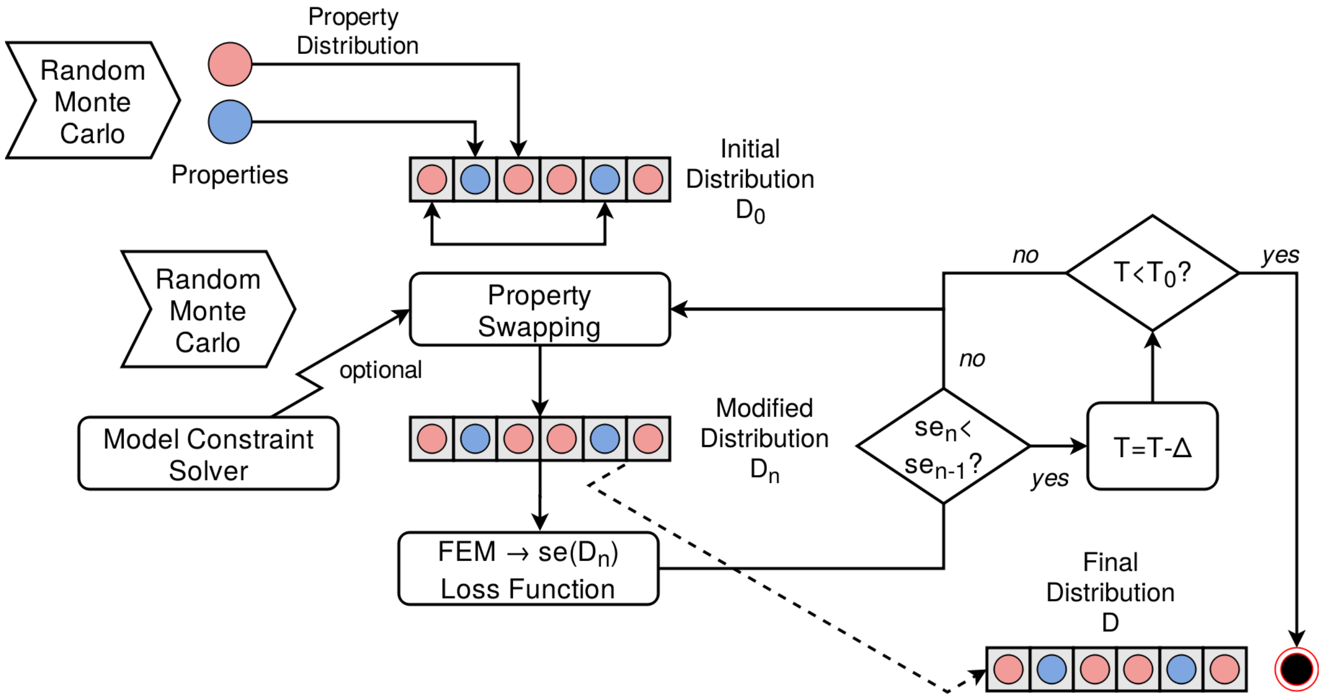
Optimization Strategies
Simulated Annealing

- 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



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Optimization Strategies
Simulated Annealing: Strategic Sorting

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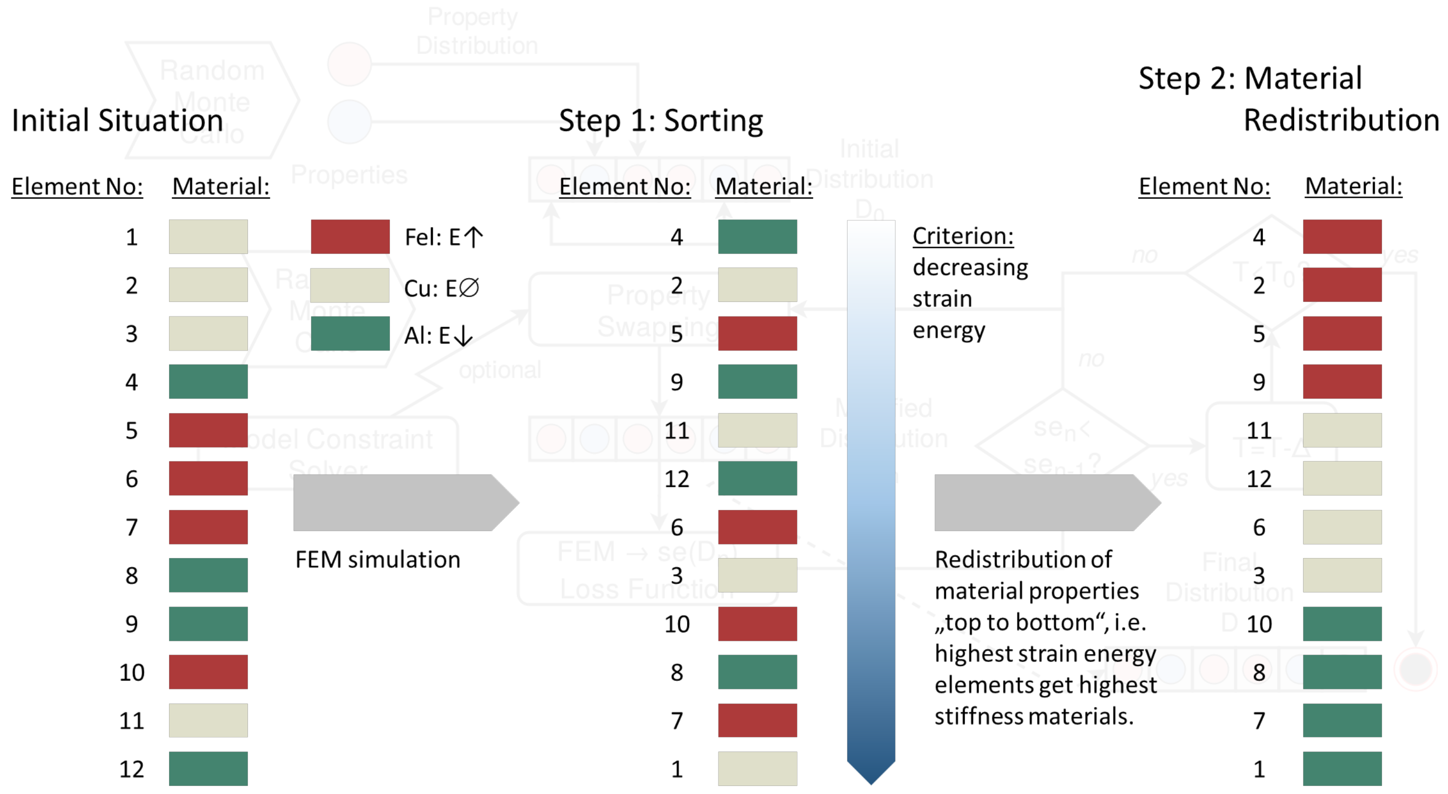
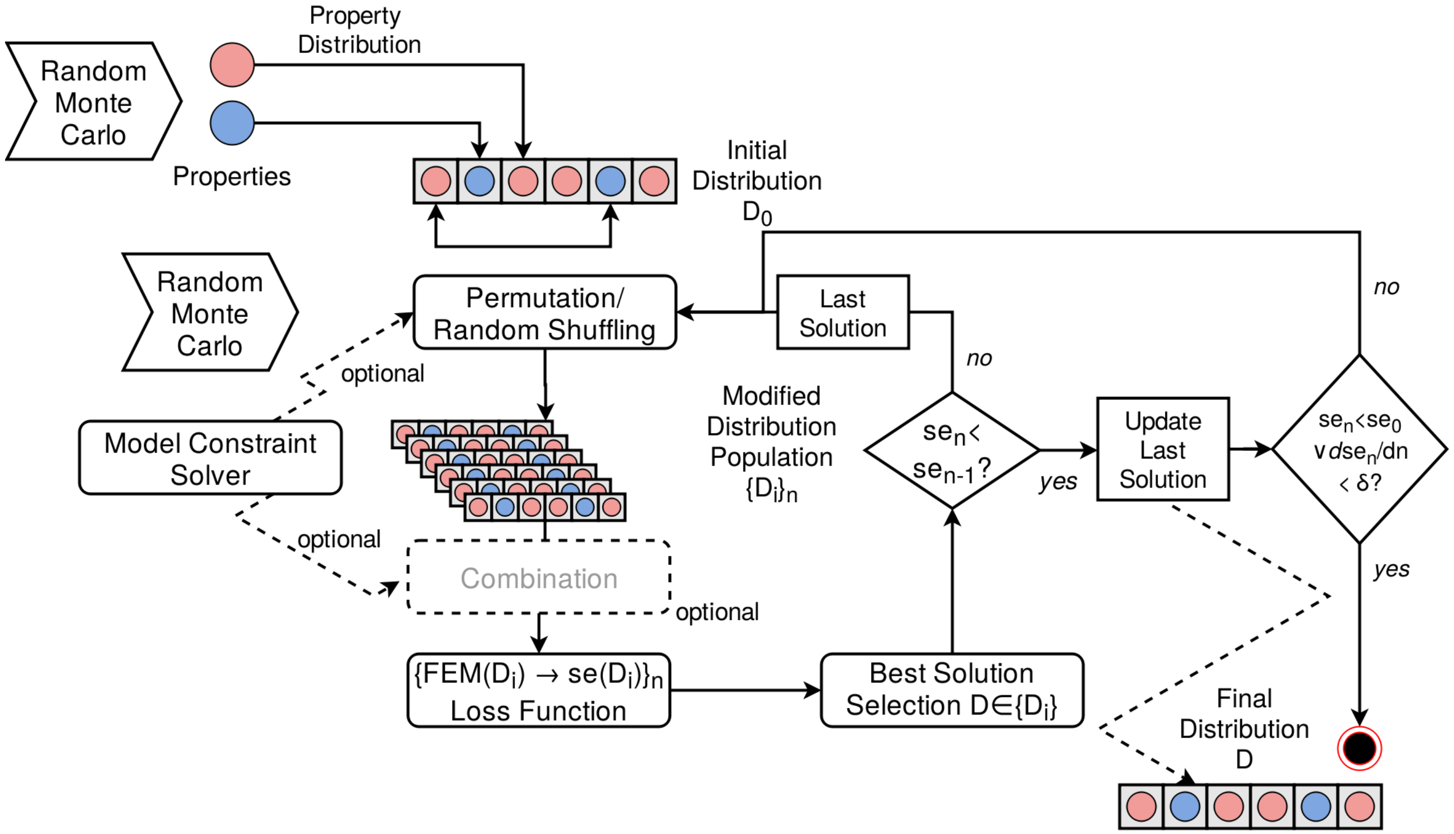
  - constrained and unconstrained



Optimization Strategies
Genetic Algorithms

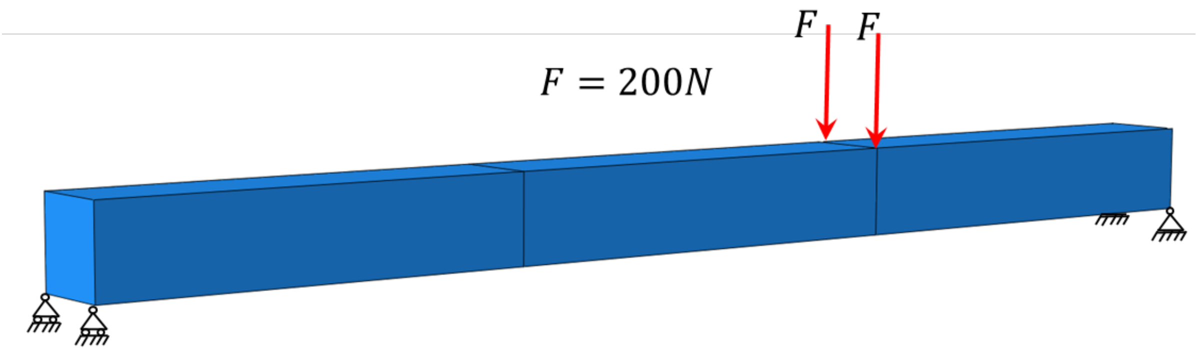
- creation of a population of 20 variants for each (outer) step
- inner steps correspond to the evaluation of the 20 population members, i. e. at this stage, each outer step invariably implies 20 inner steps
- selection of a survivor (best of 20) and crossover with the parent, followed by mutation
-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



Results & Discussion
Load Case

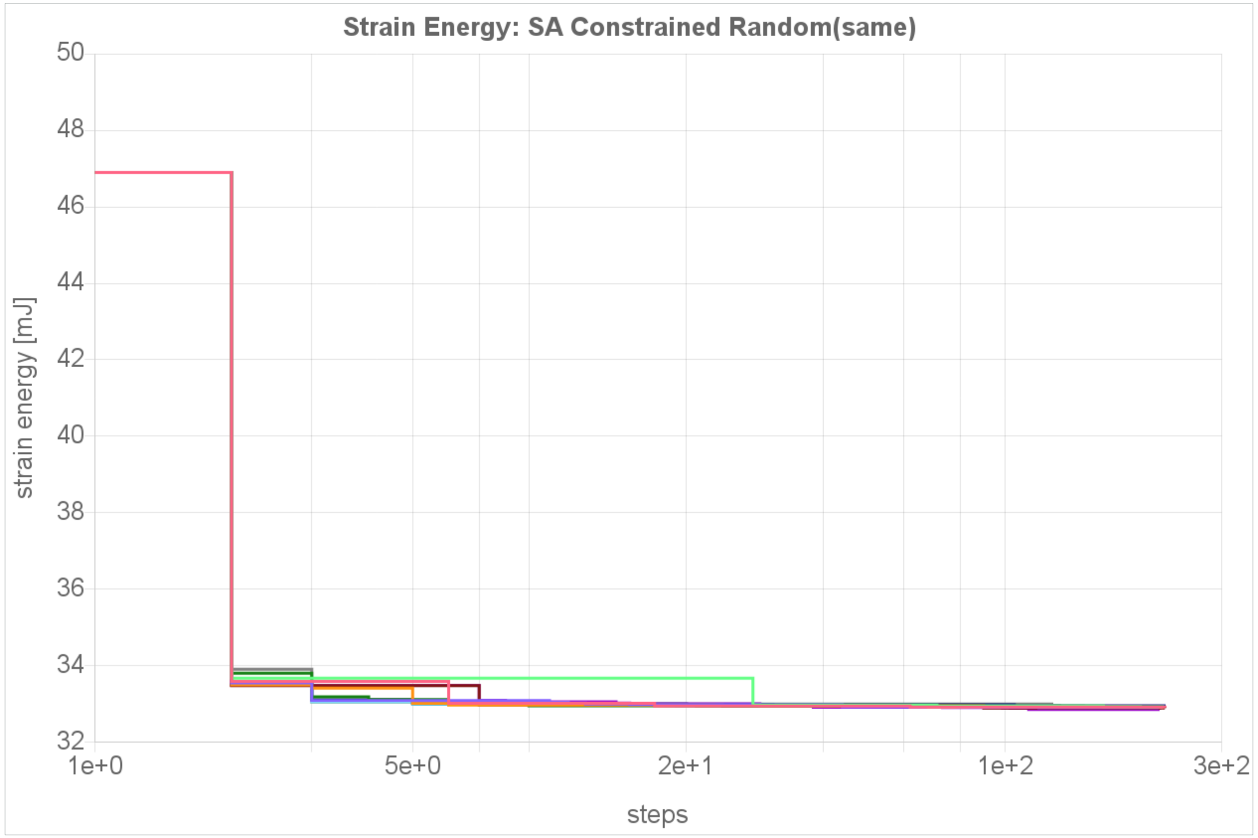
- Selected sample load case: Asymmetric 3-point-bending as depicted below.
- Small initial model for fast calculation and initial comparison of algorithms:
  - 832 elements of type C3D8R.
- Three different materials at equal volume fractions:
  - „aluminum“: E = 70 GPa, Poisson‘s ratio 0,3
  - „copper“: E = 110 GPa, Poisson‘s ratio 0,3
  - „steel“: E = 200 GPa, Poisson‘s ratio 0,3
- Initial configuration left 1/3 of beam Al, centre 1/3 Cu, right 1/3 Fe

sketch of the load case



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.



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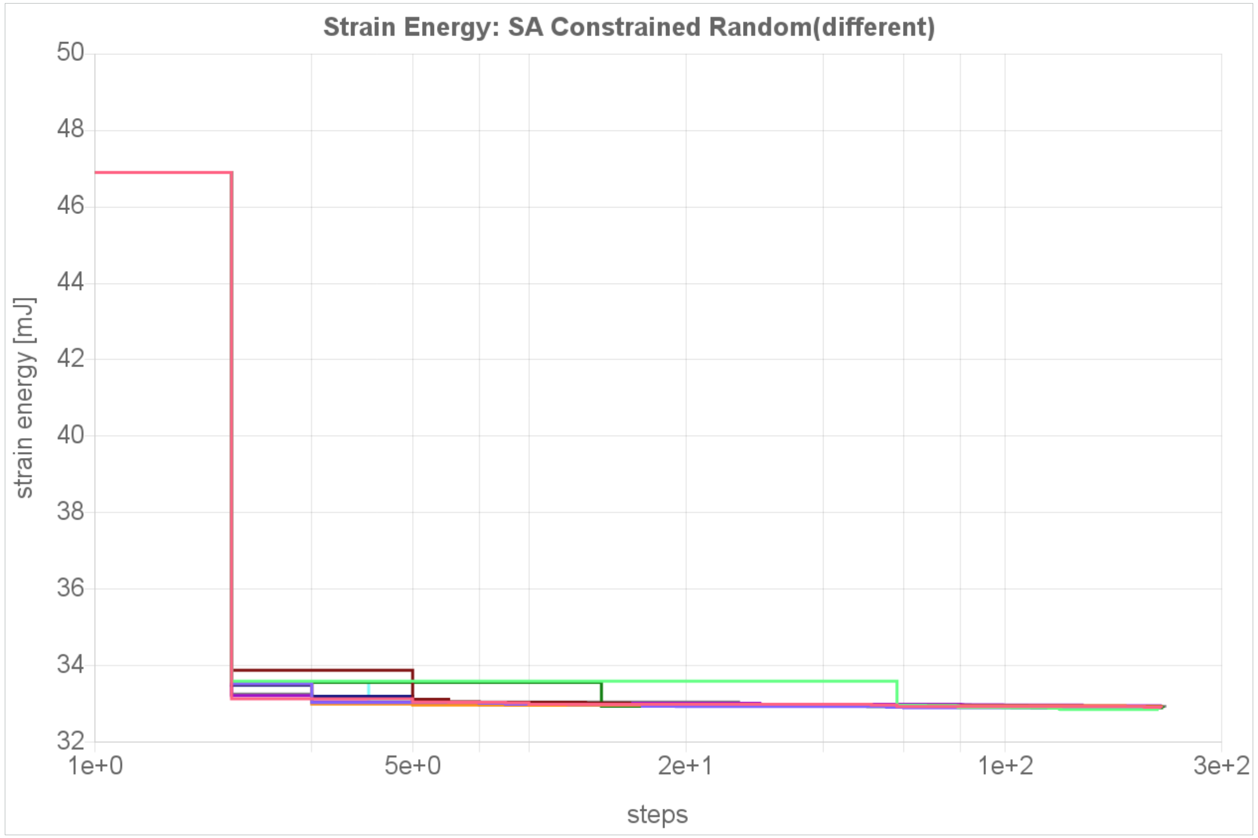
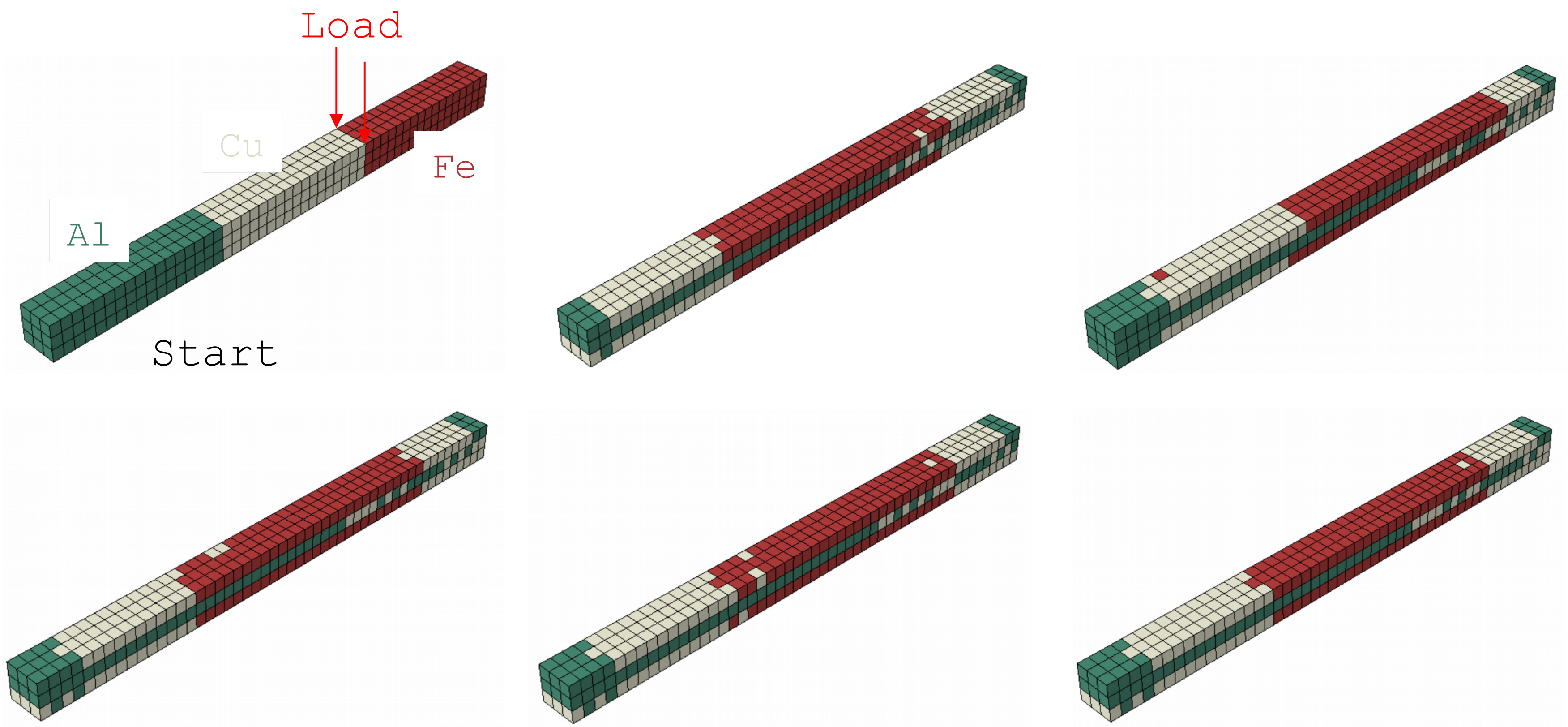
Results & Discussion
Simulated Annealing, Constrained

- 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.



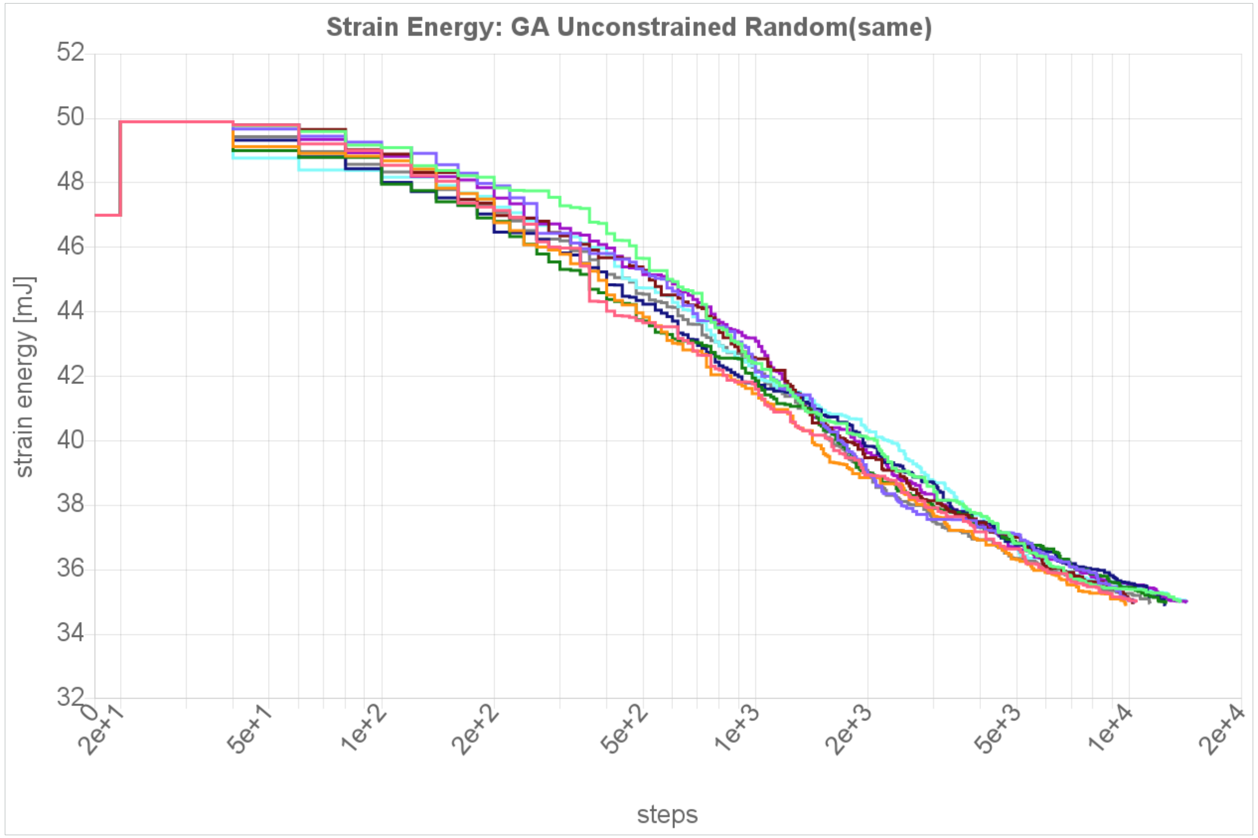
Results & Discussion
Simulated Annealing, Constrained

- 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 strucuture as shown initially.



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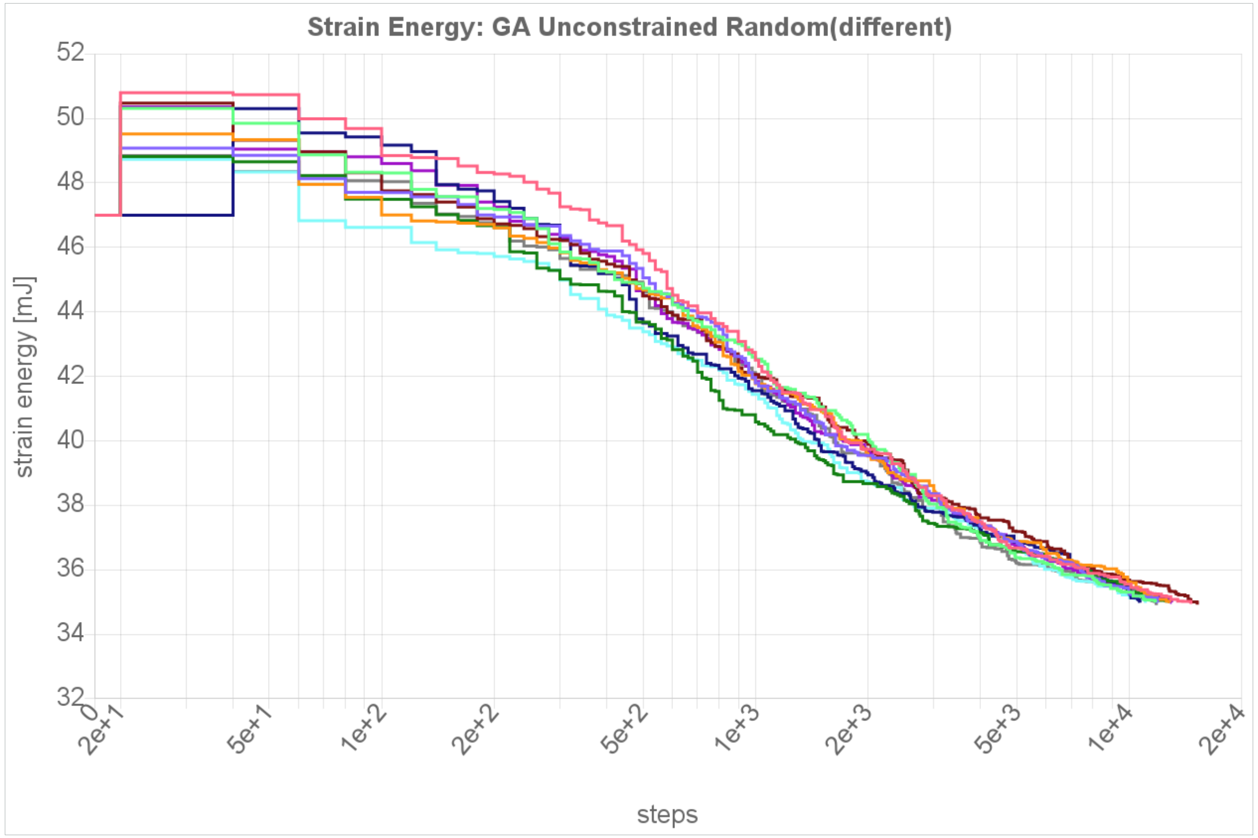
- Monotonic descent of strain energy – GA optimization works.
- Initial rise in strain energy is caused by the fact that the chosen reference at 46.901 mJ is the ordered strucuture as shown initially.
- As expected, more variation in initial strain energies, converging to previous slide‘s results later.



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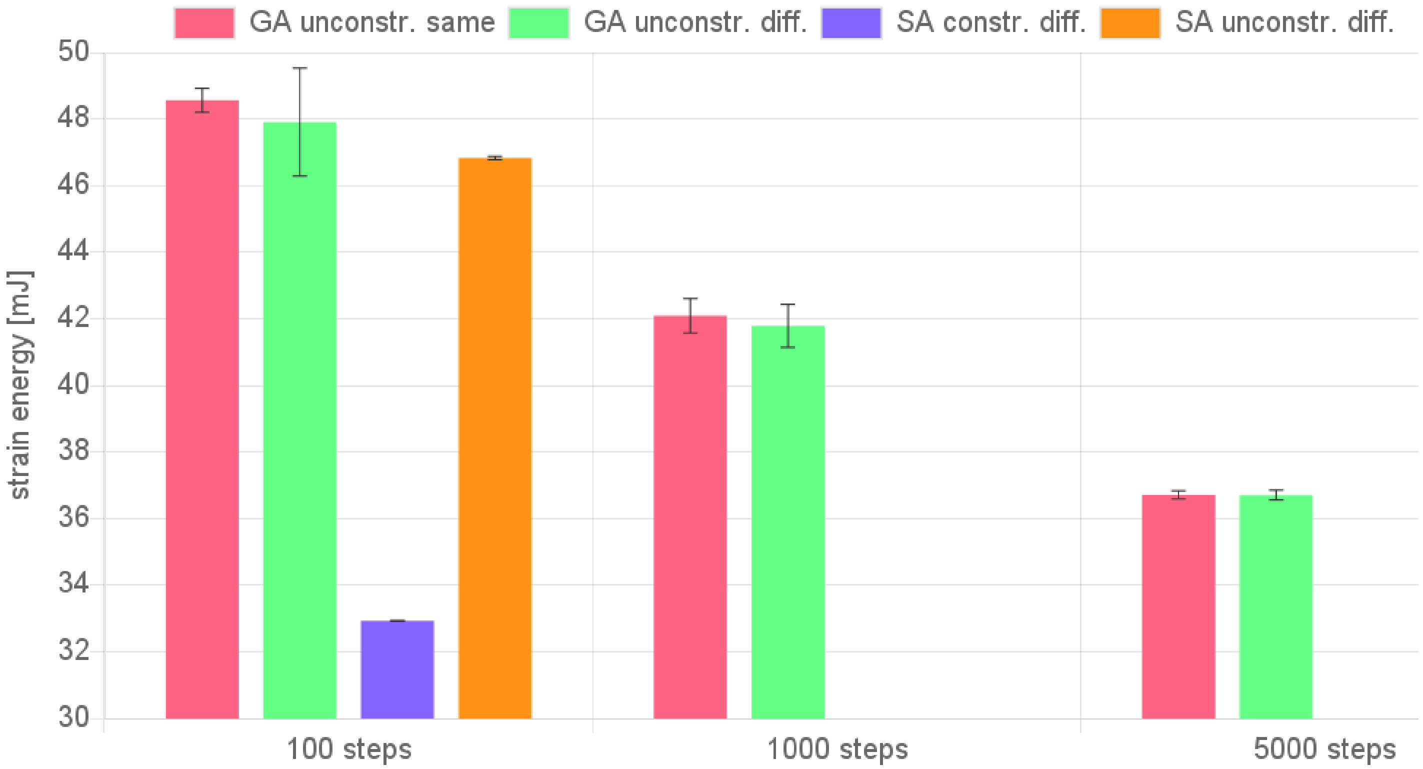
Results & Discussion
Comparison of Optimization Algorithms: Final Strain Energy

- starting point 46.901 mJ
- unconstrained SA achieves next to no improvement
- constraints controlling material redistributionlead 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



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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

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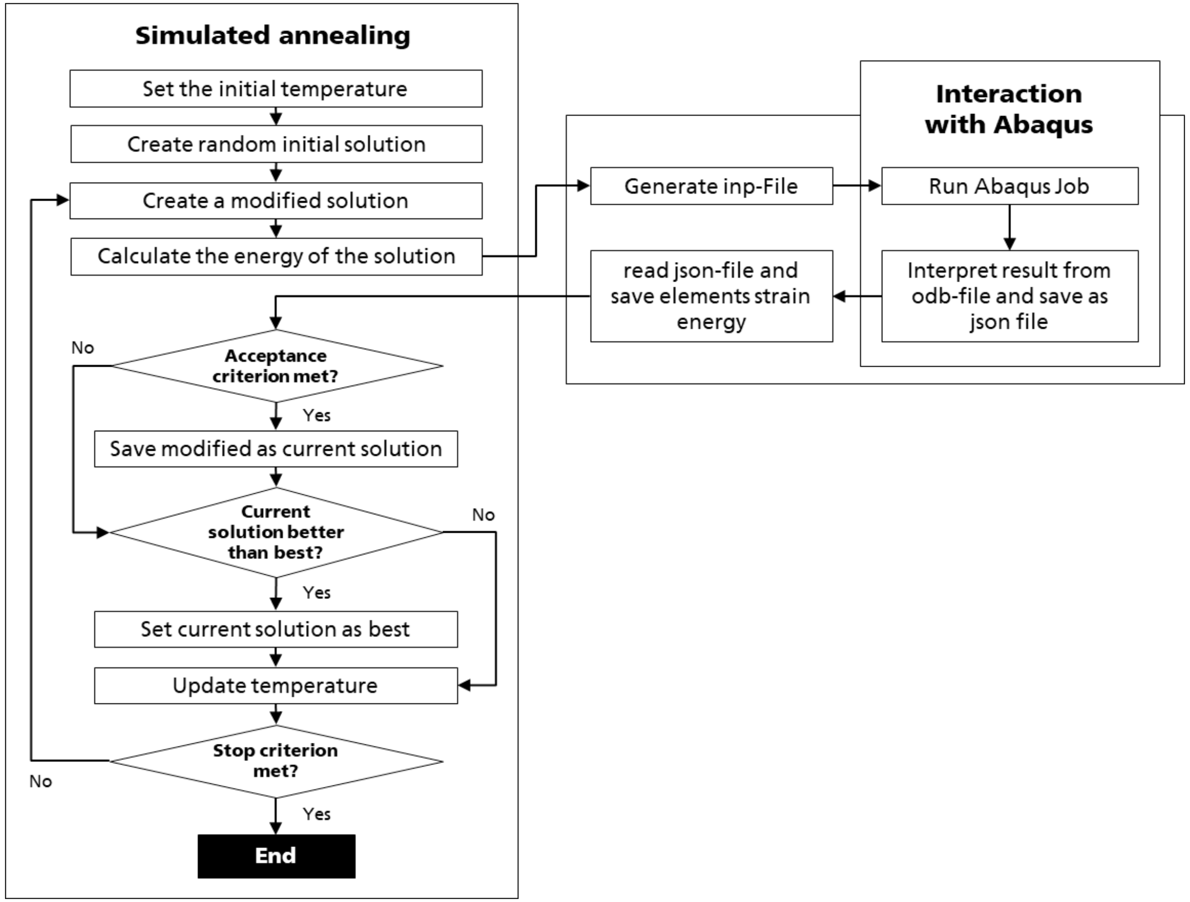

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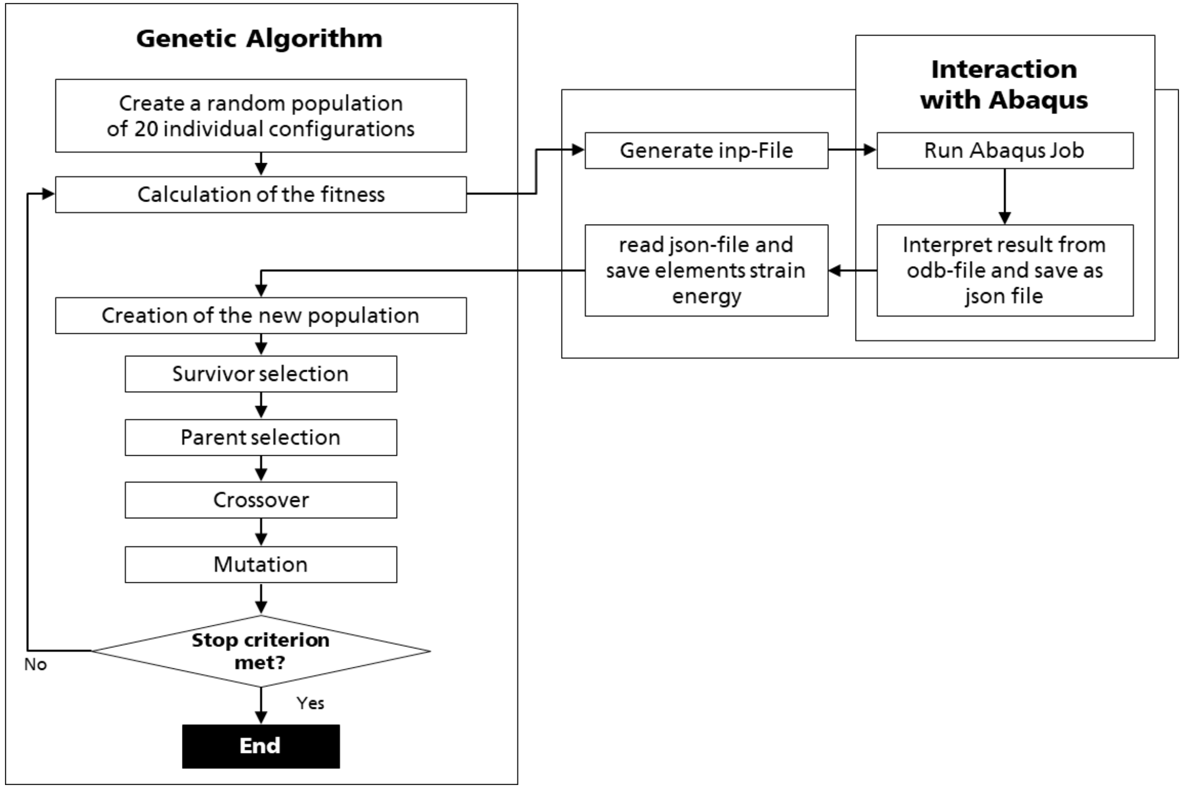

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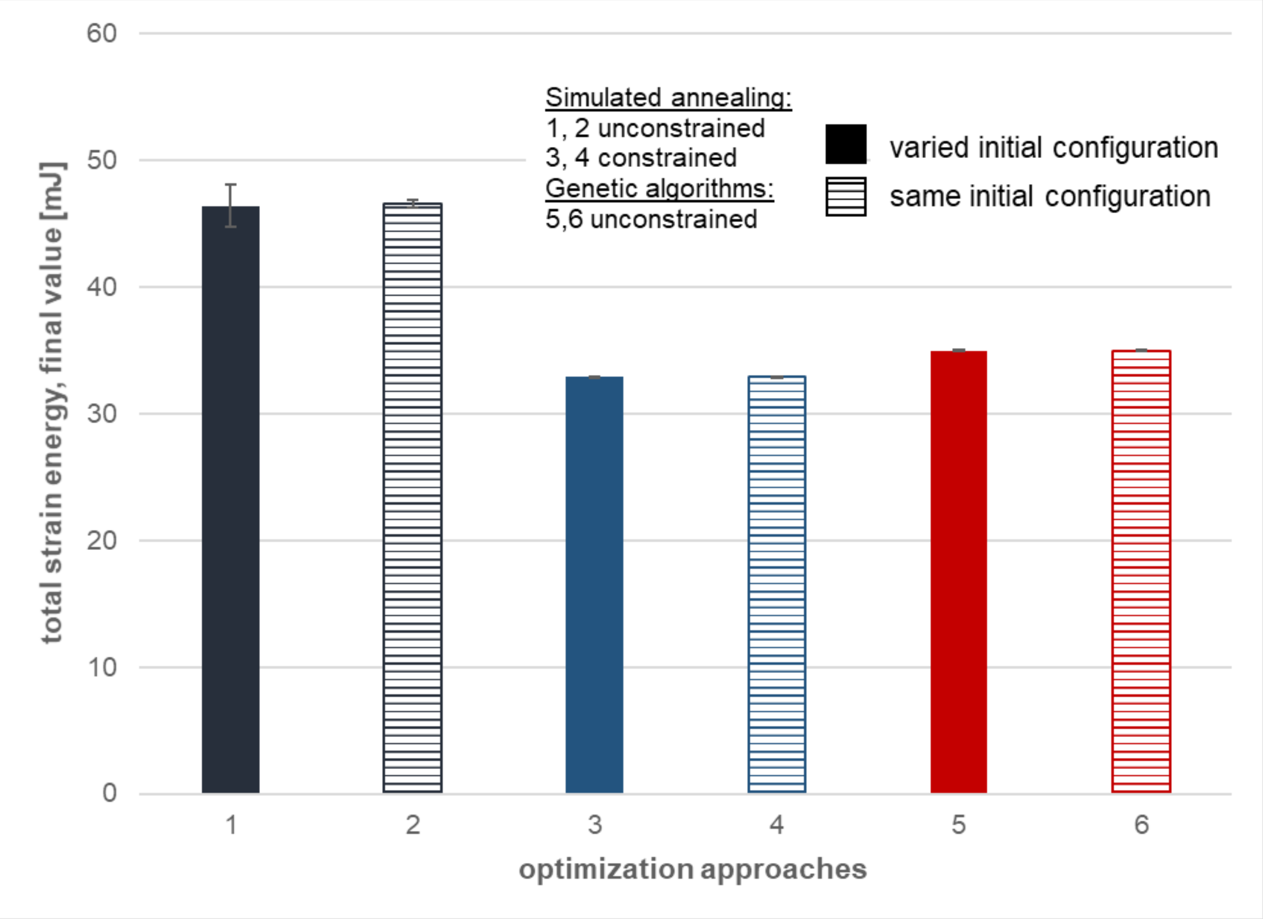

Templates

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- bullet point 1
- bullet point 2
- bullet point 3

Title
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- 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