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Stiffness-oriented Optimization of Material Distribution in Multi-Material Components

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Optimization of Material Distribution in Multi-Material Components

Presentation Overview

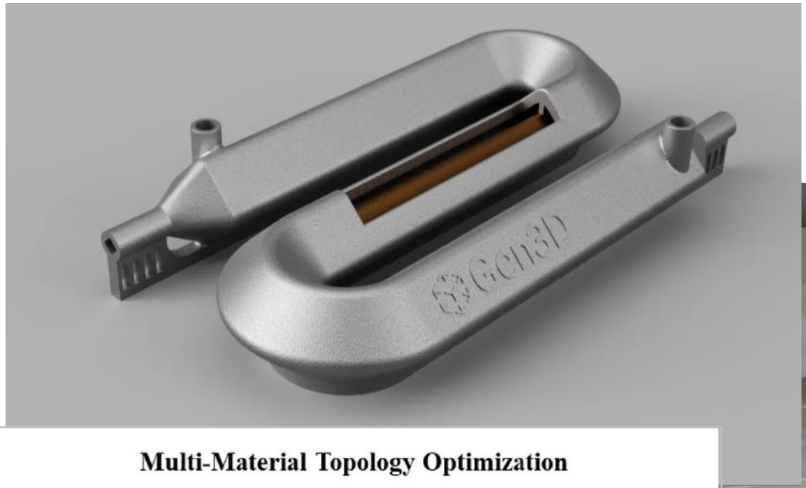
1. **Introduction**
   - Multi-Material Structures for Functional as well as Structural Applications.
   - Multi-Material Production Processes: Achieving free Arrangement of Materials.
2. **Multi-Phase Topology Optimization**
   - Basic Principle.
   - Comparison of Optimization Algorithms.
     - Simple Stochastic Approach, unconstrained.
     - Simple Stochastic Approach, constrained.
     - Genetic Algorithm.
3. **Conclusion and Outlook**
   - Summary of Results.
   - Next Steps.

Introduction

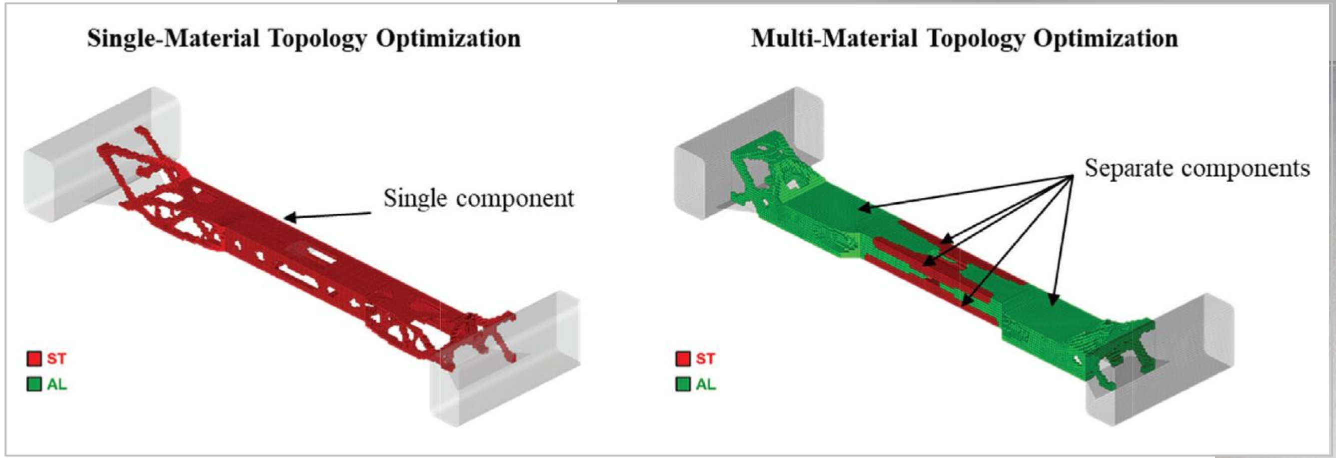
Multi-Material Structures for Functional as well as Structural Applications.

Applications mainly in …

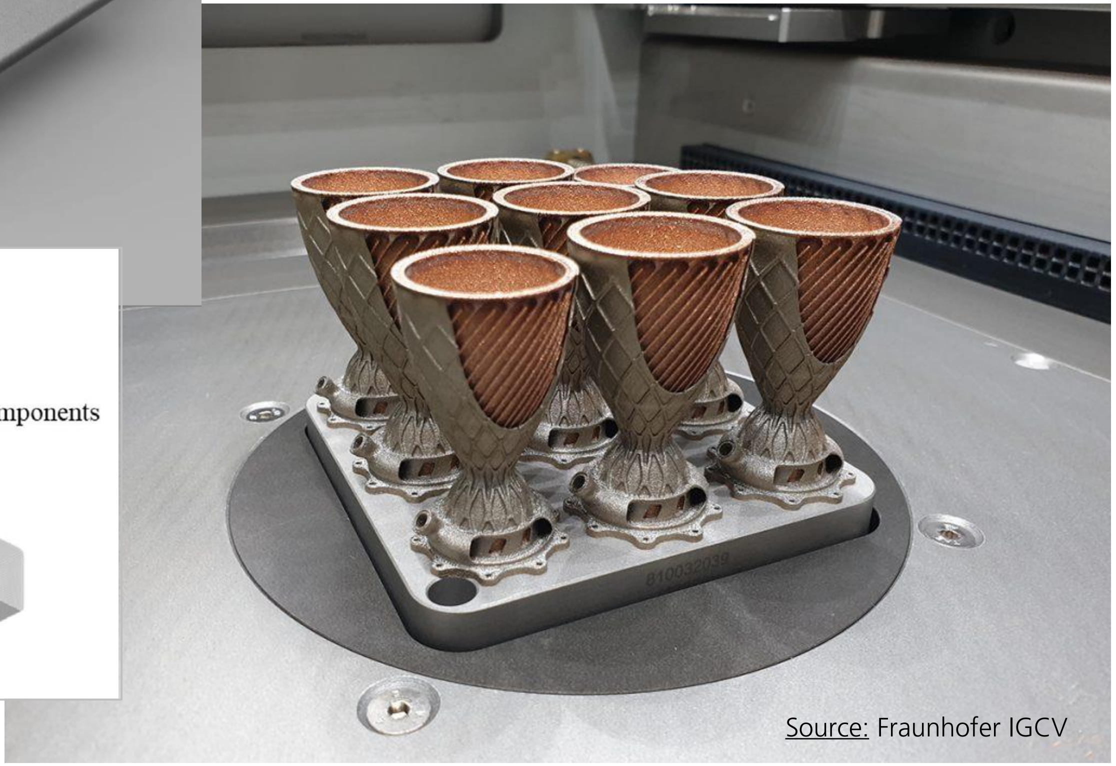
- thermal management and
- structural reinforcement.



Source: https://aerosint.com/multimaterial-heat-exchanger/



Source: Florea et al., Int. J. Numer. Methods Eng. 121 (2020) 1558-1594.



Source: Fraunhofer IGCV

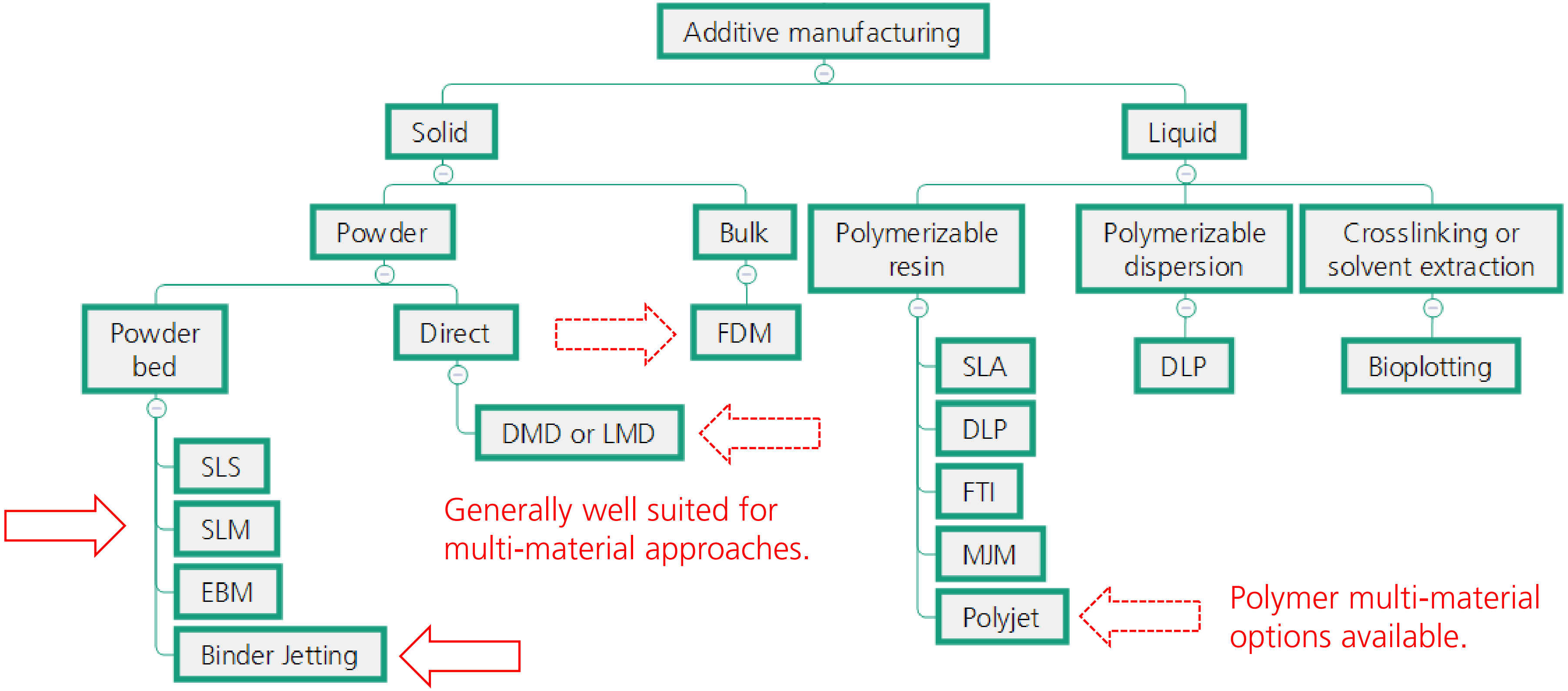
Introduction

Multi-Material Manufacturing Approaches.

Additive Manufacturing

Compound/Hybrid Casting

etc.



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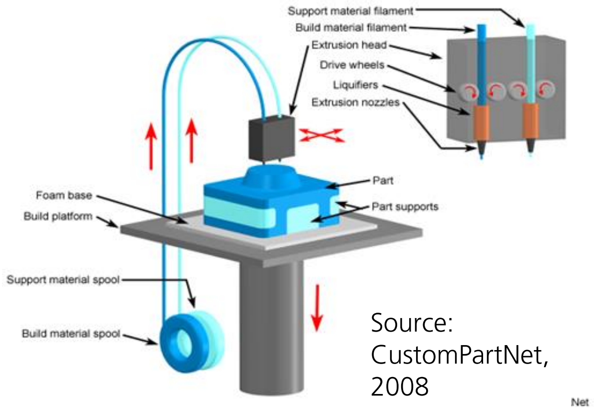
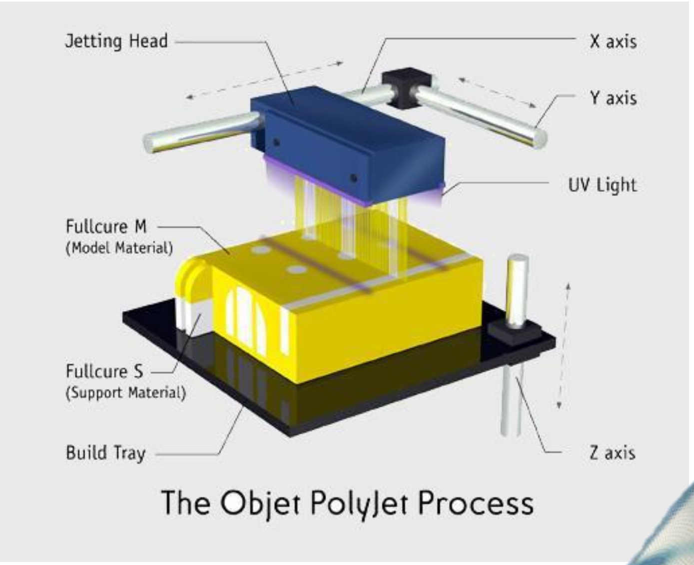


Source:
CustomPartNet,
2008



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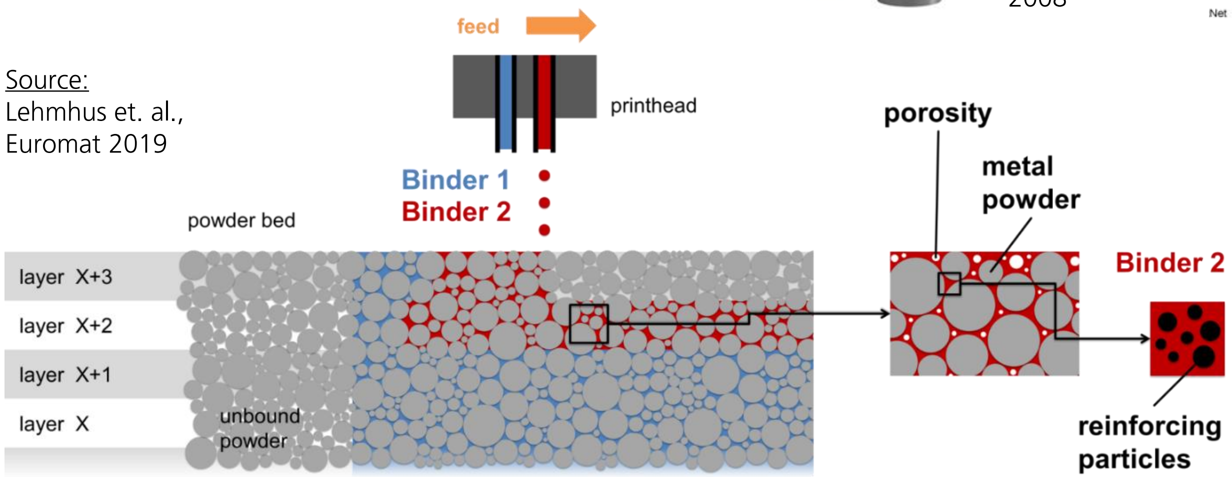
<u>Source:</u>
Lehmhus et. al.,
Euromat 2019



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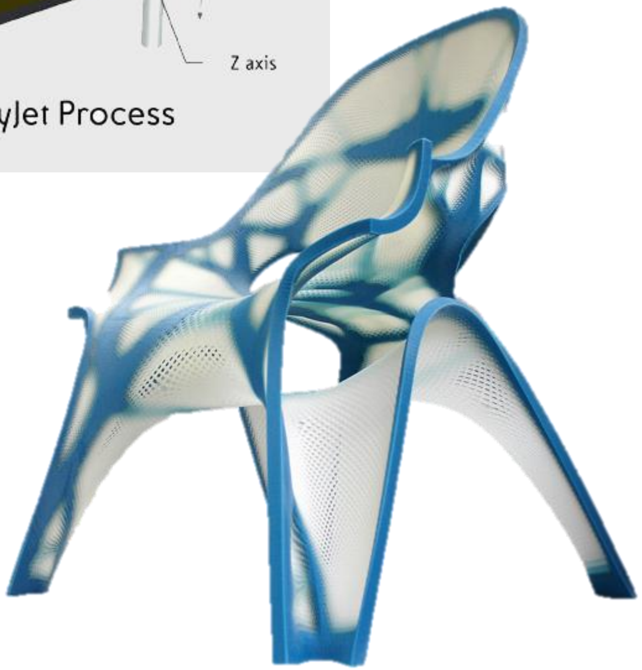

Introduction

Multi-Material Manufacturing Approaches.

Additive Manufacturing: Aerosint Process by Desktop Metal

Special, proprietary Selective Powder Deposition (SPD) recoater design.

aerosint
Desktop Metal Company

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

Source: Lehmhus et. al., Euromat 2019

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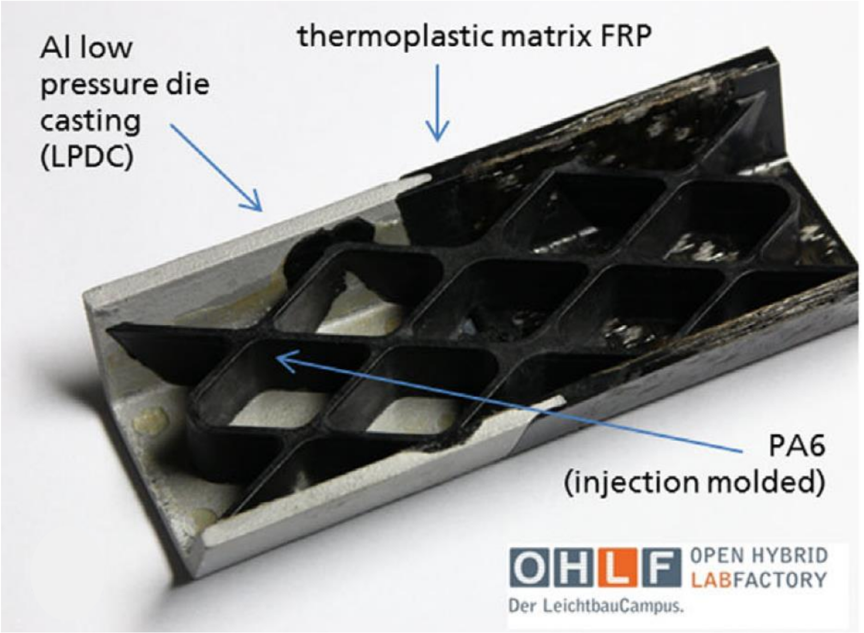
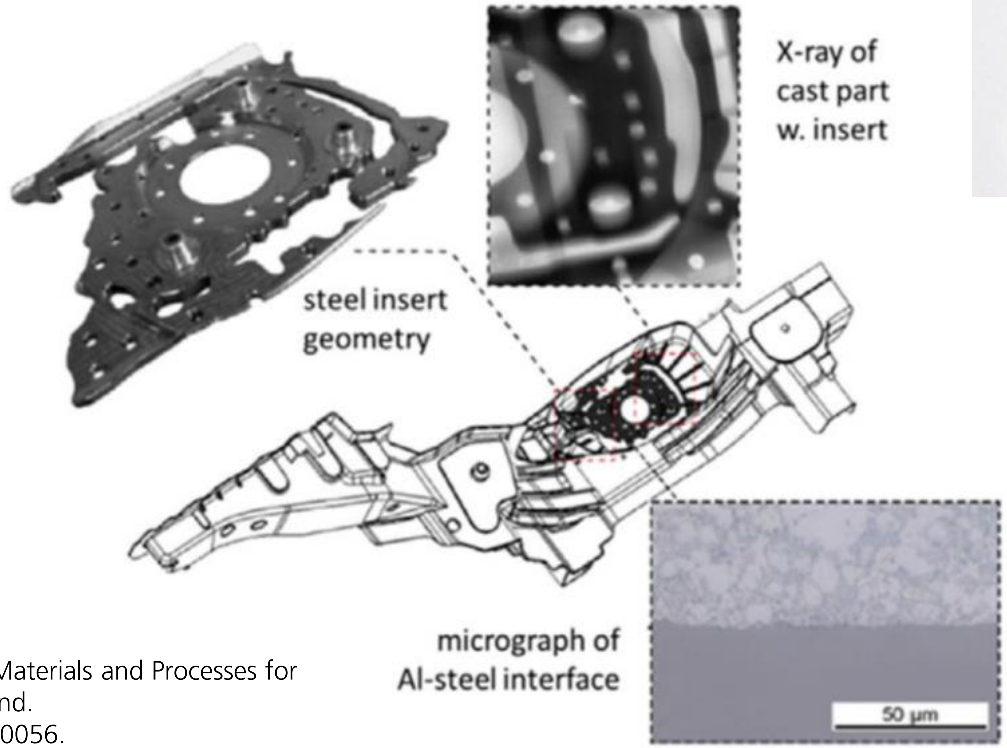




Source:
Lehmhus, D.; von Hehl, A.; Hausmann, J.;
Kayvantash, K.; Alderliesten, R.; Hohe, J. New Materials and Processes for Transport Applications: Going Hybrid and Beyond.
Advanced Engineering Materials 21 (2019) 1900056.

Multi-Phase Topology Optimization

The Basic Principle.

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

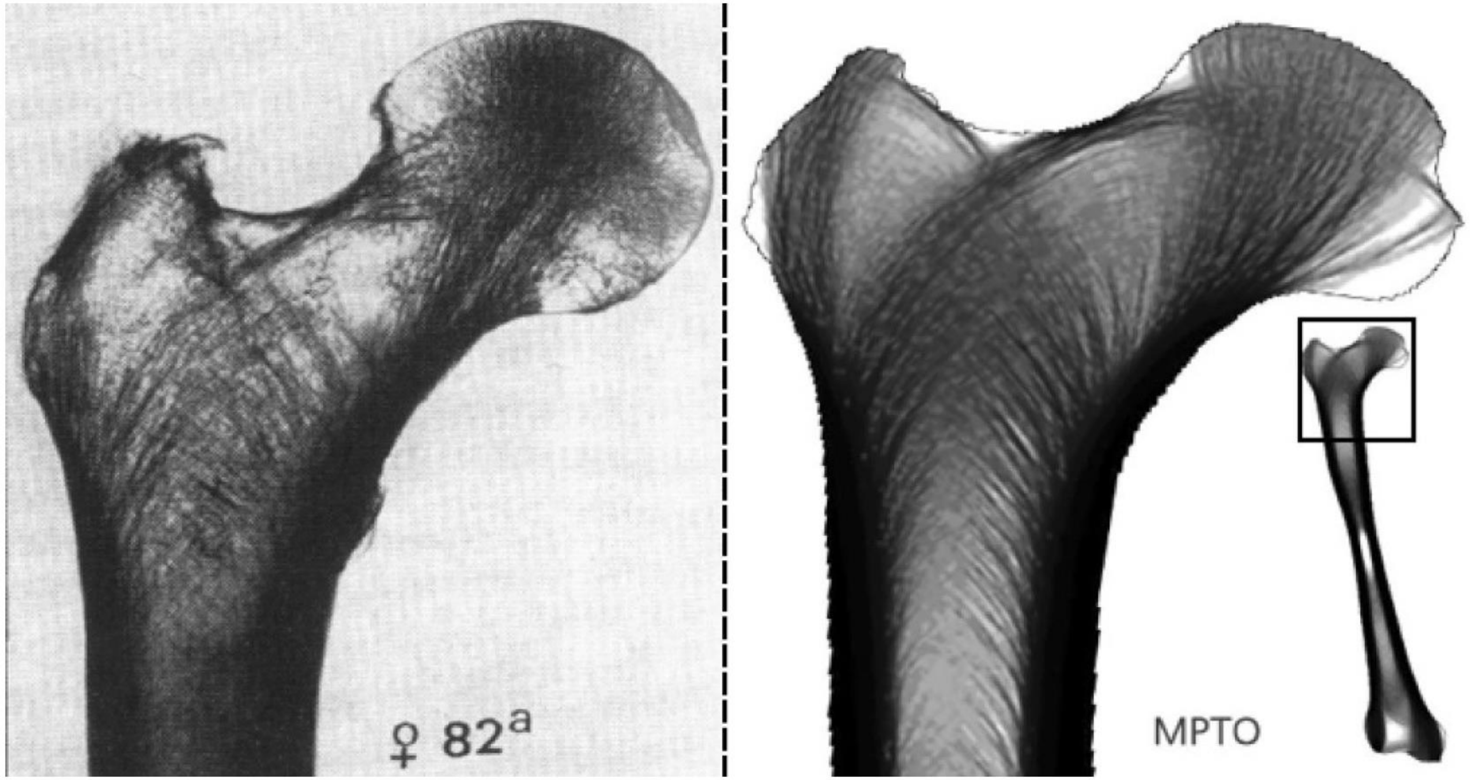
Optimization problem:
Minimization of total strain energy

<u>Basis:</u> 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>Source:</u> Schittenhelm, B.; Burblies, A.; Busse, M. Stahlverstärkter Aluminiumguss – Bauraumoptimierung durch lastfallgerechte Auslegung einen Verbund-Hecklängsträgers mittels Mehrphasen-Topologieoptimierung. Computer Based Porosity Design by Multi Phase Topology Optimization. Forsch. Ingenieurwes. 82 (2018) 131-147.

Multi-Phase Topology Optimization

The Basic Principle.

1. Set up the FE model of the problem under scrutiny.
2. Predefine number, volume fraction and (elastic) properties of materials.
3. Associate material properties to finite element sets, maintaining the predefined volume fractions.
4. Randomly redistribute material properties over the FE model to generate an arbitrary starting point.
5. **Perform FE simulations and record element-level strain energies, as well as total strain energy (model-level).**
6. **Redistribute materials (a) randomly or (b) based on a specific optimization strategy, best including some random element.**
7. Make sure material fractions are maintained – if this is not the case, apply appropriate changes.
8. 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 new candidate models.
9. Continue until further iterations do not yield significant improvements anymore.

Optimization Strategies

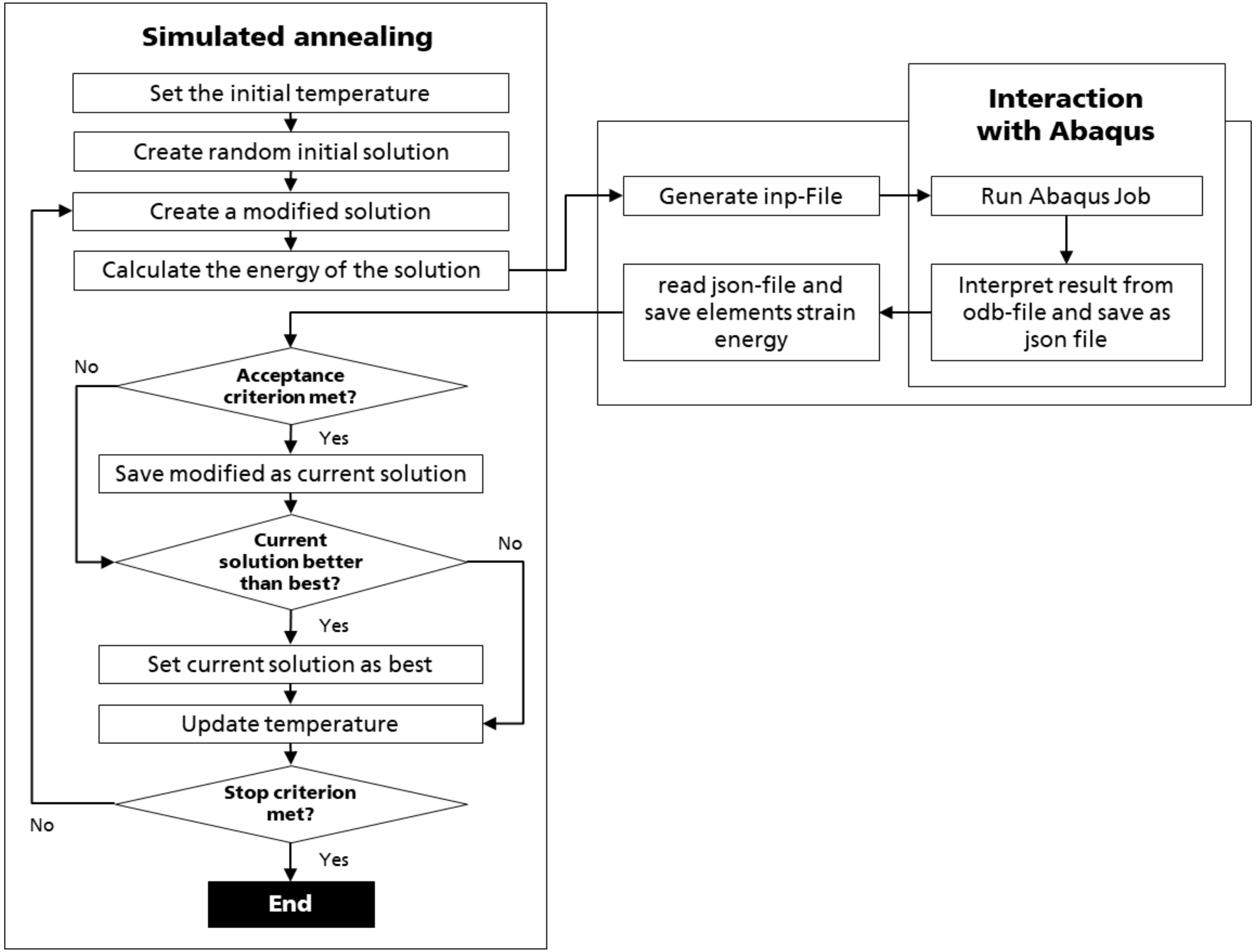
Stochastic Approach.

Randomized exchange of elements to create a new configuration

Repetition (inner steps) until improvement over previous state achieved (outer steps).

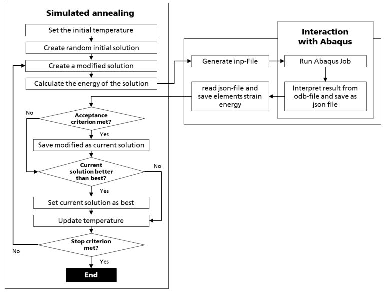
Variants compared:

- fraction of elements subject to random exchange varied
- unconstrained (i. e. random) exchange



Optimization Strategies

Targeted Approach.

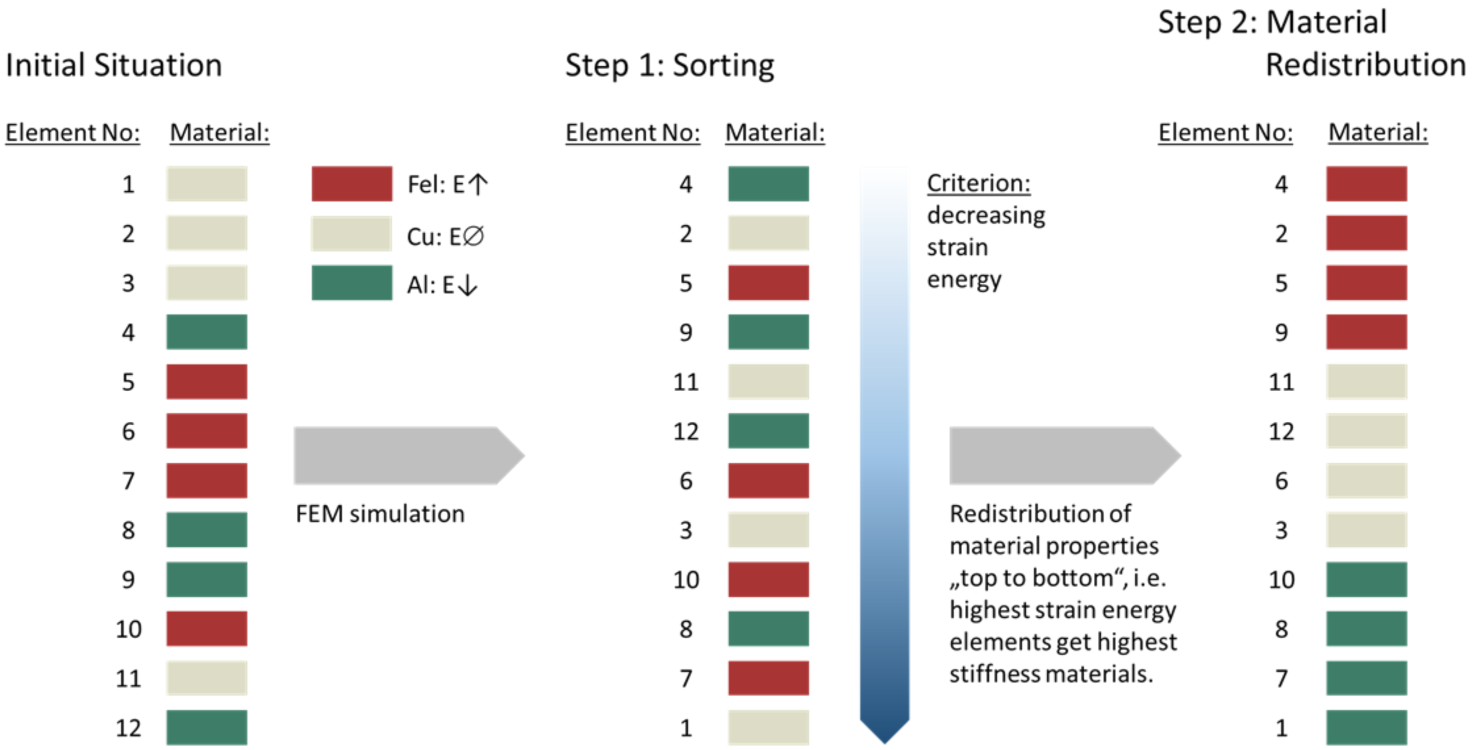


Randomized exchange of elements to create a new configuration

Repetition (inner steps) until improvement over previous state achieved (outer steps).

Variants compared:

- fraction of elements subject to random exchange varied
- unconstrained (i. e. random) exchange vs.
- **constrained exchange following a specific strategy**



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Optimization Strategies

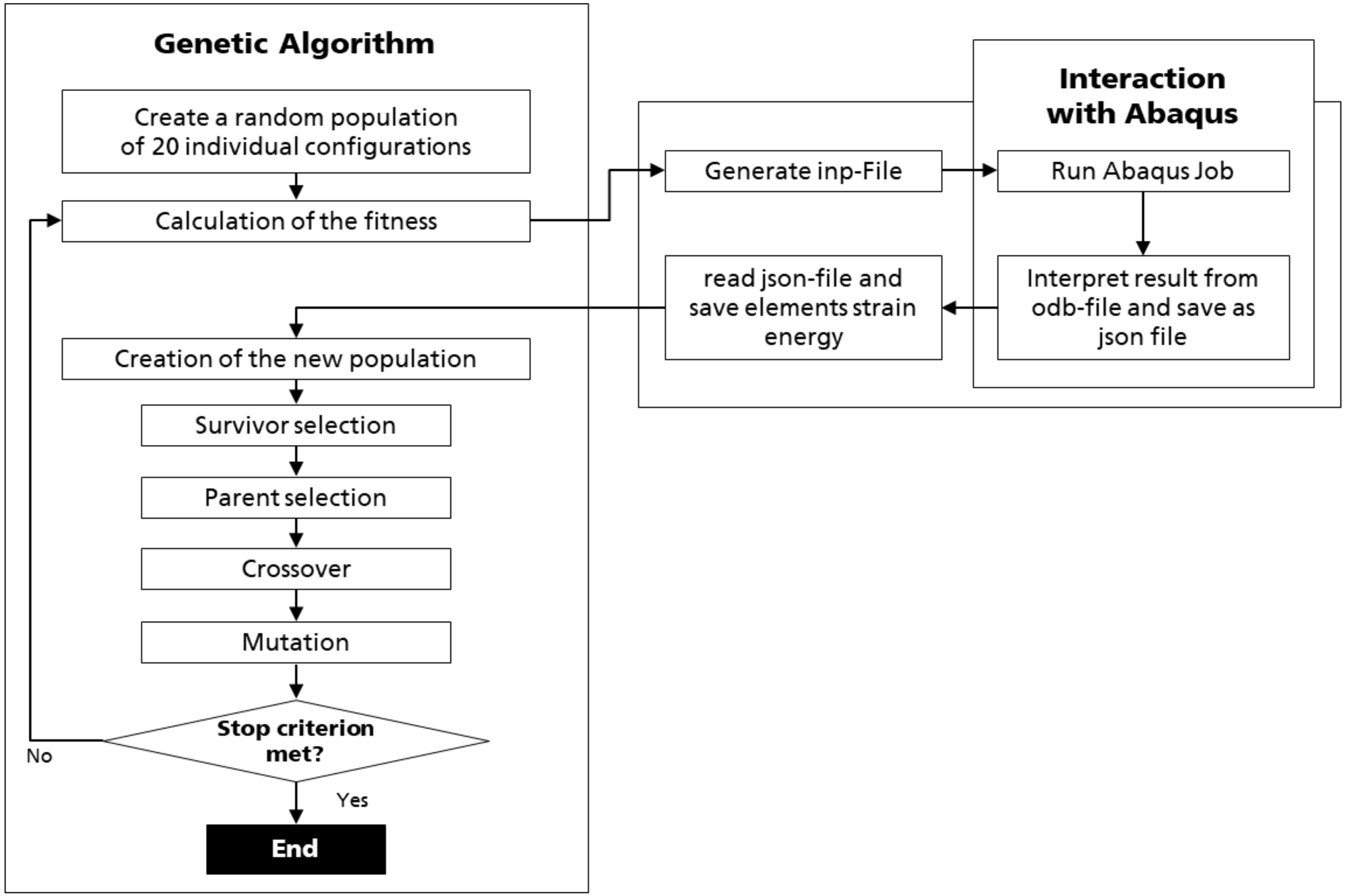
Genetic Algorithm.

Creation of a population of 20 random variants for the initial step, of 20 variants based on previous set of results for each subsequent (outer) step.

Inner steps correspond to evaluation of the 20 population members, i. e. at this stage, each outer step invariably implies 20 inner steps, each of which is an FEM simulation.

Selection of a survivor (best of 20) and crossover with the parent, followed by mutation. Degree of mutation varied.

No further constraint implemented.



Results & Discussion

Simple Test Load Case.

Selected sample load case: Asymmetric 3-point-bending as depicted below.

Small initial model for fast calculation and initial comparison of algorithms:

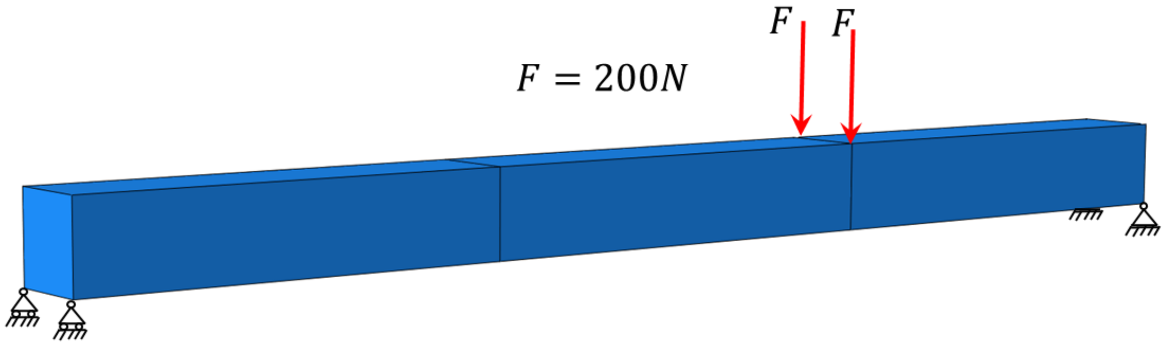
832 elements of type C3D8R.

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

<u>sketch of the load case</u>



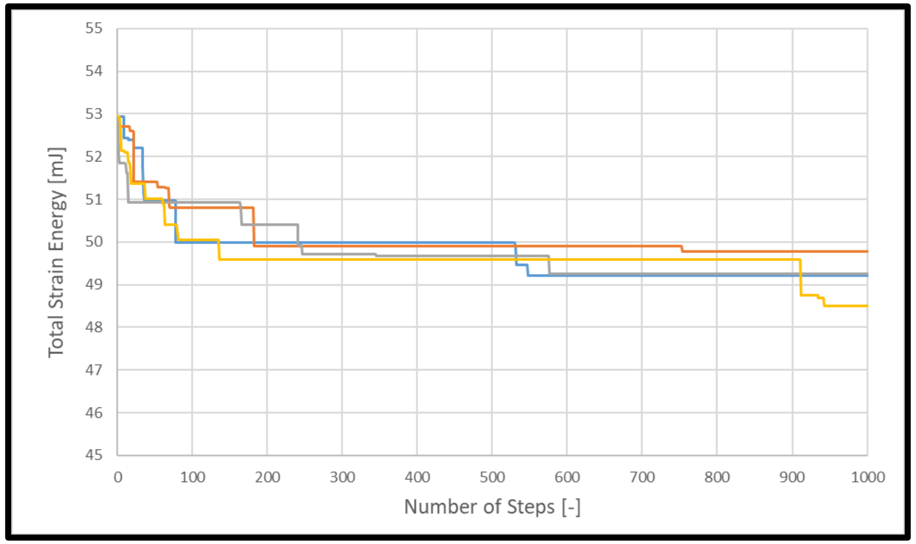
Results & Discussion

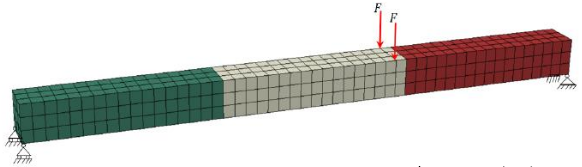
Shifting the Building Blocks: Comparison of the Approaches.

- **Stochastic Approach:**
  Extremely slow convergence, high computational effort with final results falling short of genetic algorithm and targeted approach.

- **Genetic Algorithm:**
  Limited convergence, as each inner step requires 20 instead of 1 FEM calculation. Still showing better results than the stochastic approach.

- **Targeted Approach:**
  Highly efficient on a small model with negelctable likeli-hood of local minima.





SA, TA: 5% random variation
GA: 1% mutation rate

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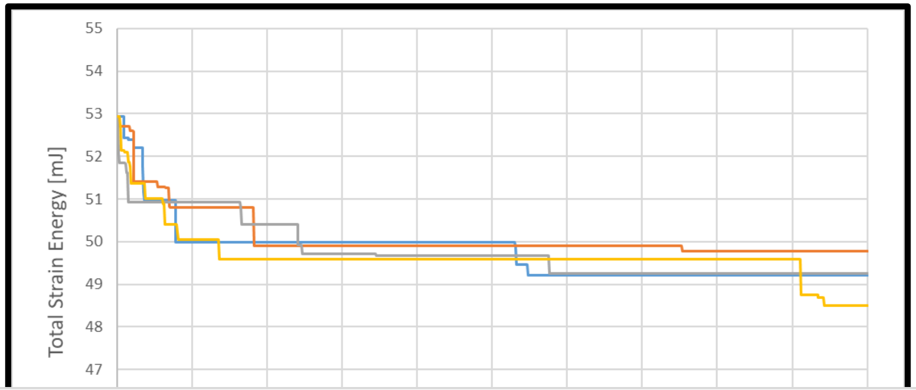

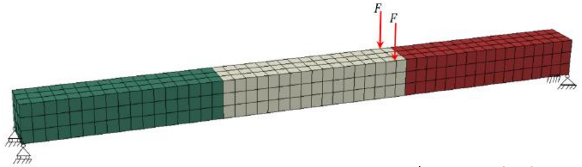

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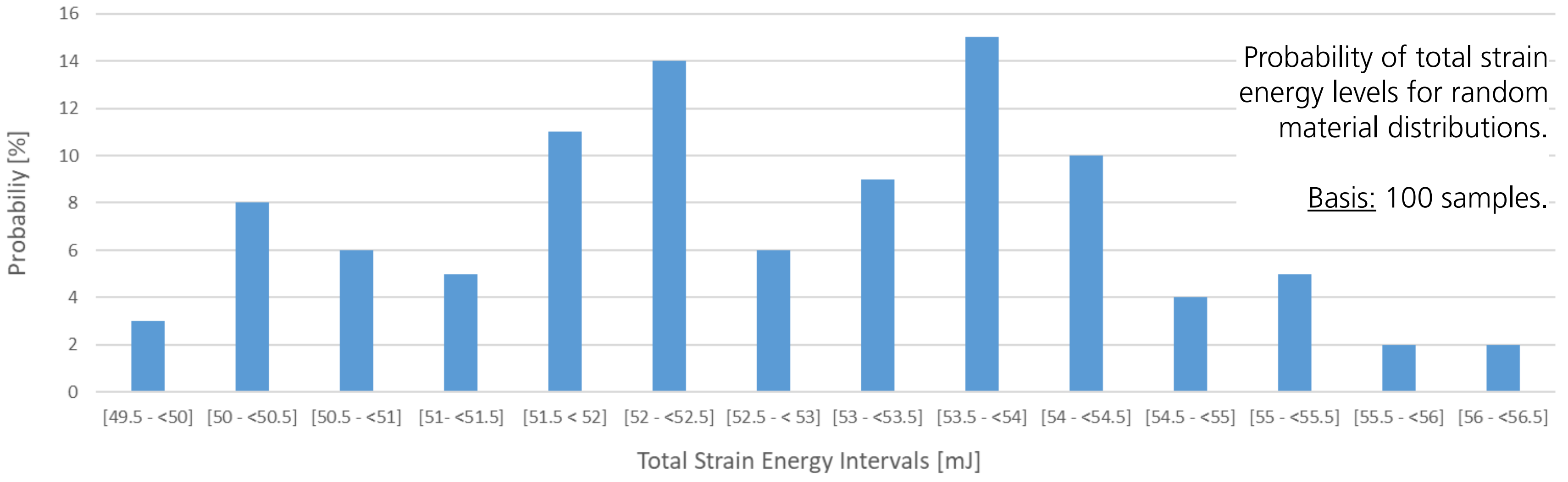

Probability of total strain energy levels for random material distributions.

Basis: 100 samples.

Results & Discussion

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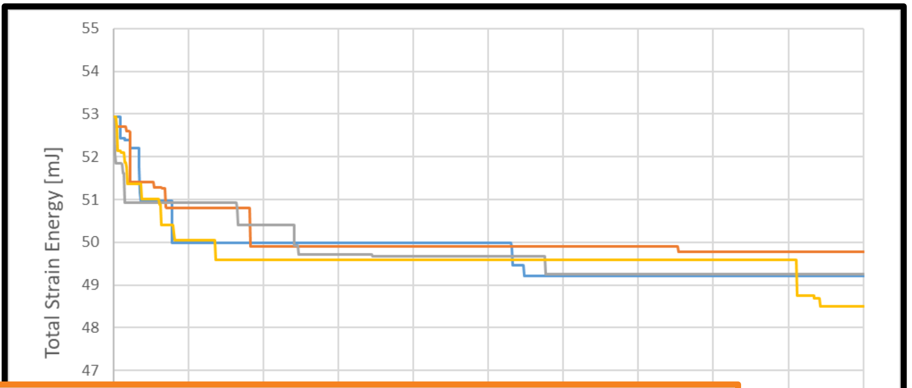
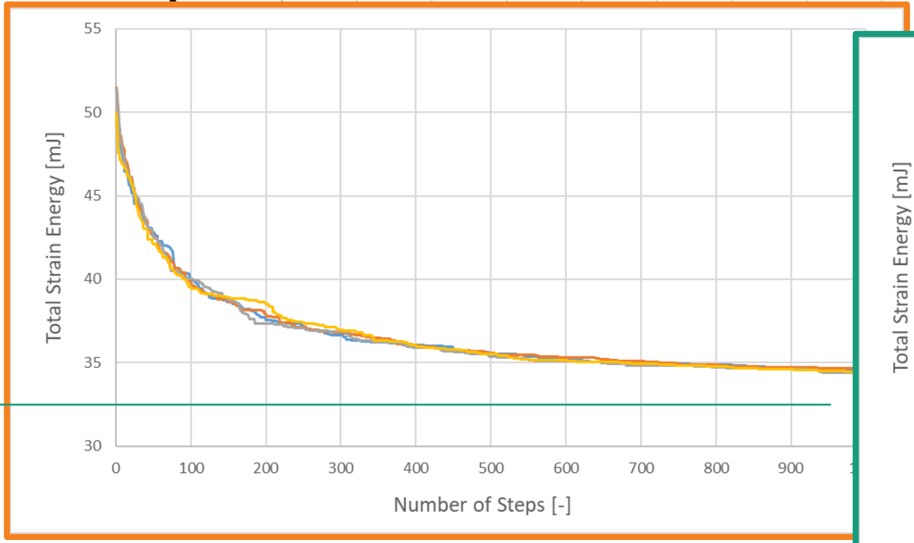
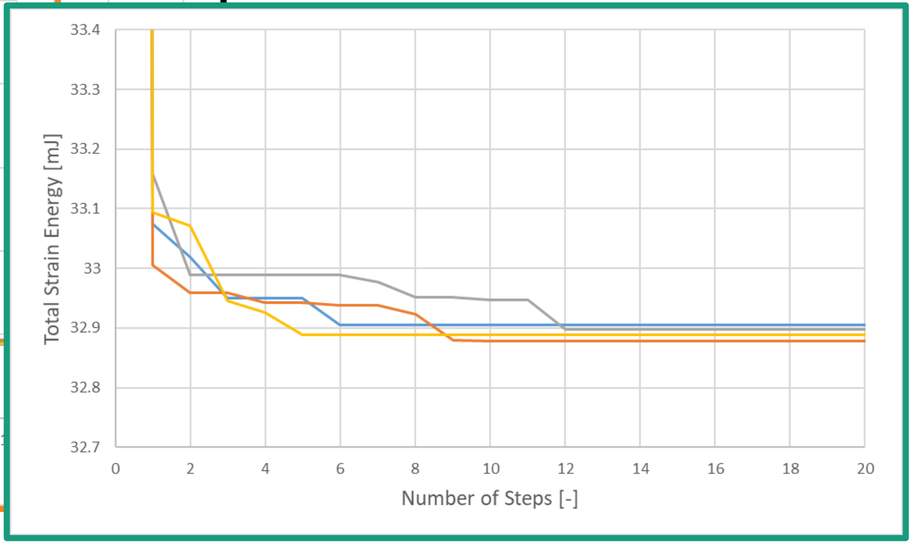
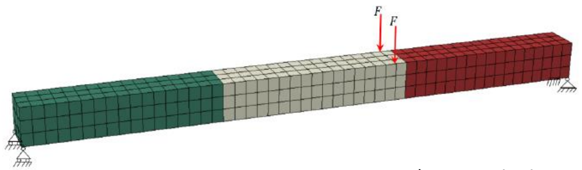




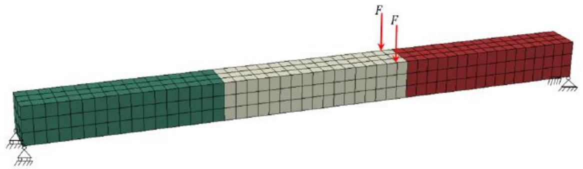




SA, TA:	5% random variation
GA:	1% mutation rate

Results & Discussion

Shifting the Building Blocks: Comparison of the Approaches.



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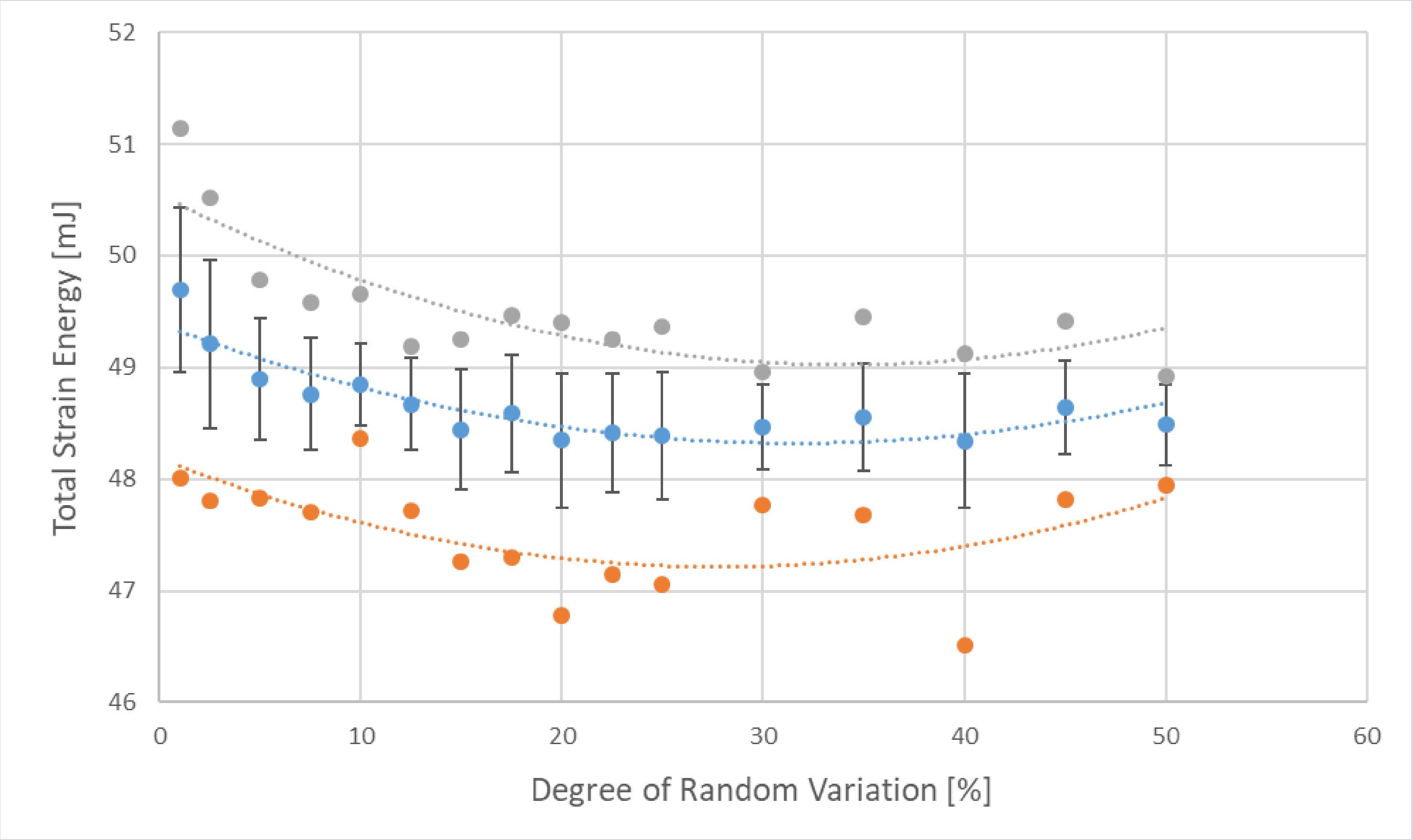
Results & Discussion

Stochastic Approach: Influence of the Degree of Random Variation.

- 20 runs performed per degree of random variation.
- For each of these 20 runs, the same initial distribution was used.
- Initial value of the total strain energy was 52.946 mJ.
- Optimization was stopped after 1000 steps.



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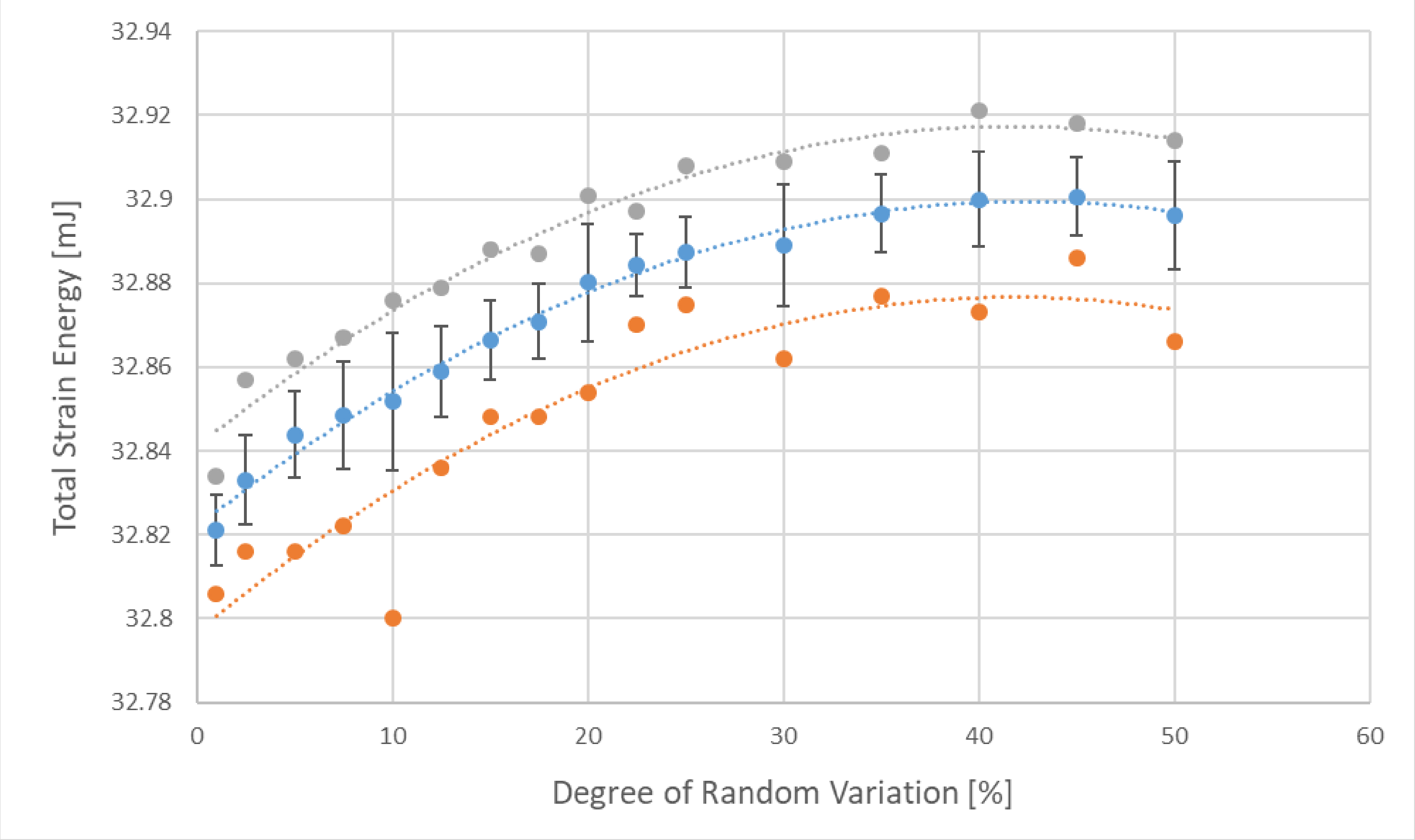

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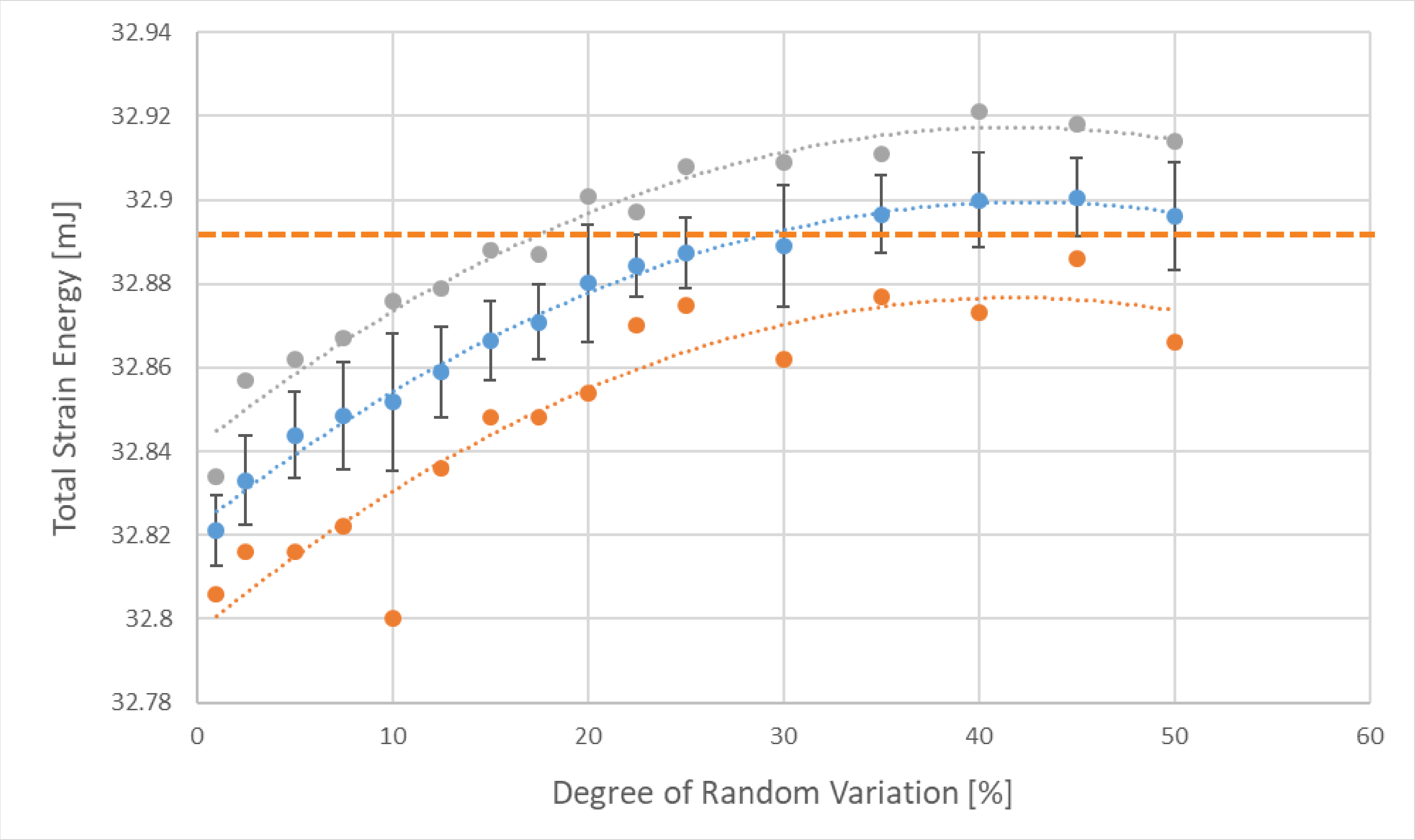
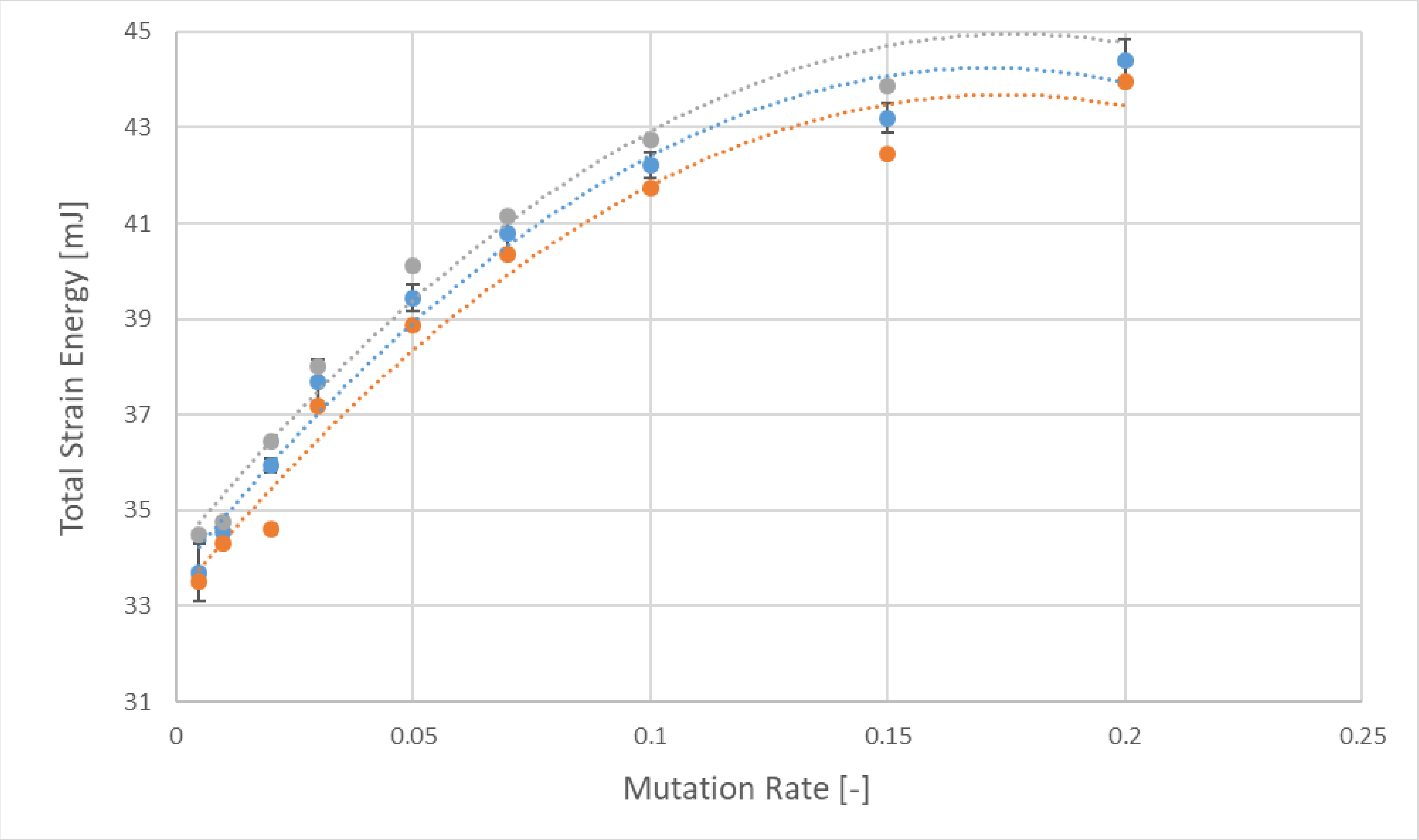
- 20 runs performed per degree of random variation.
- For each of these 20 runs, the same initial distribution was used.
- Initial value of the total strain energy was 52.946 mJ.
- Optimization was stopped after 1000 steps.
- **At 0% random variation, for the chosen initial material/property distribution, the algorithm unanimously leads to a total strain energy value of 32.893 mJ.**



Results & Discussion

Genetic Algorithm: Influence of the Degree of Random Variation.

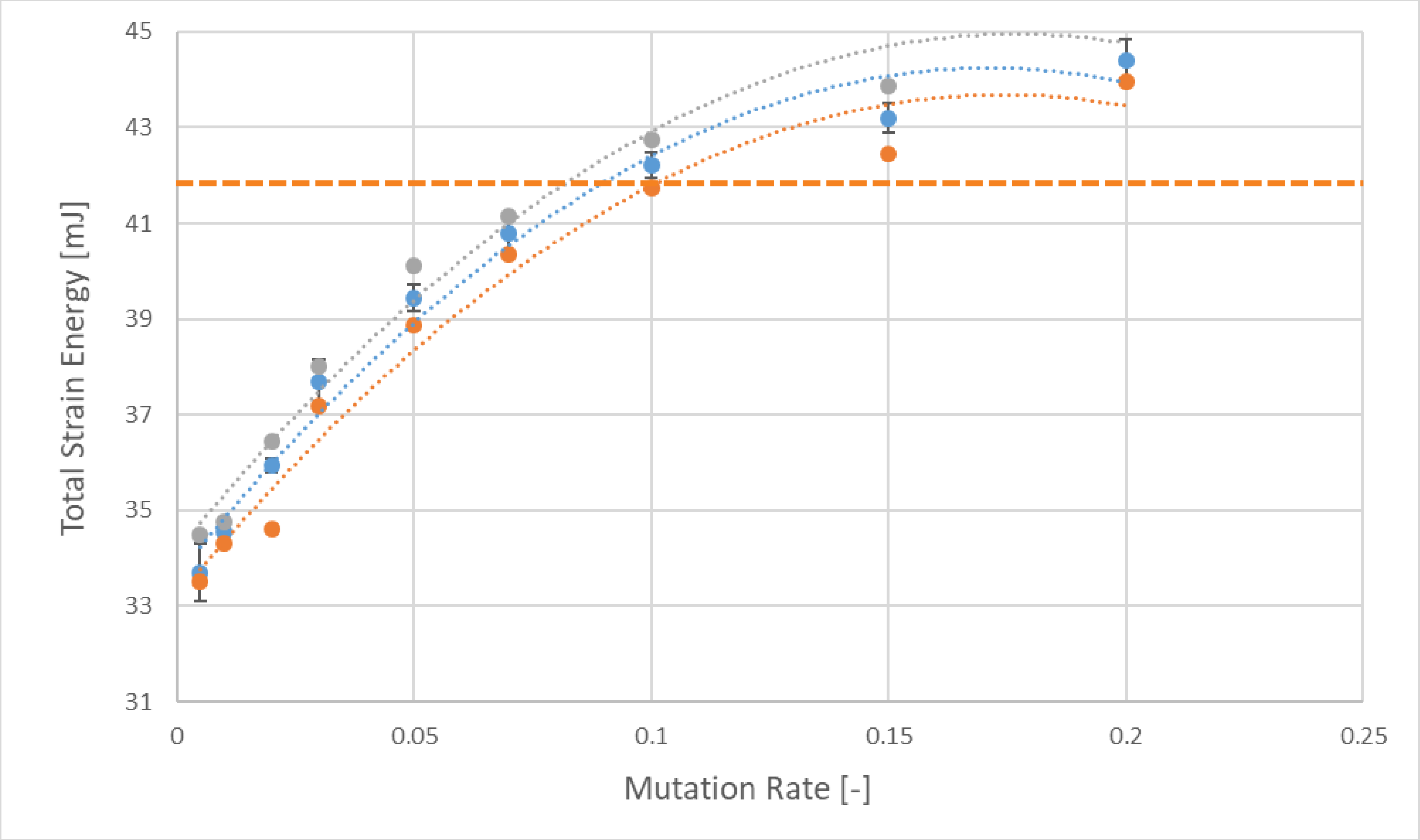
- 10 runs performed per degree of random variation.
- Optimization was stopped after 1000 steps.



Results & Discussion

Genetic Algorithm: Influence of the Degree of Random Variation.

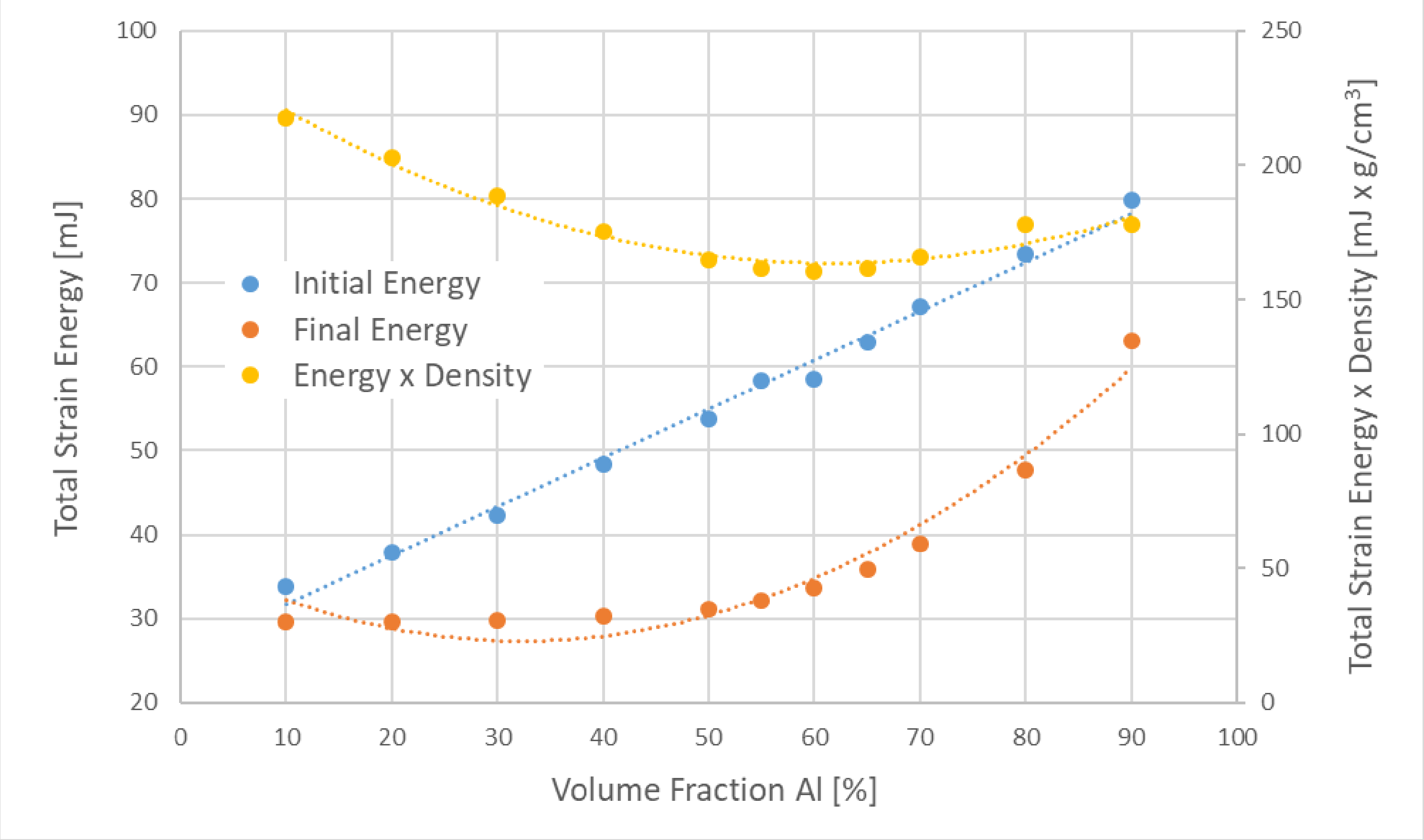
- 10 runs performed per degree of random variation.
- Optimization was stopped after 1000 steps.
- **At 0% mutation rate, the algorithm leads to total strain energy values in a range from 41.039 to 43.019 mJ, with an average of 41.886 mJ.**



Results & Discussion

Targeted Approach: Lightweighting of a Two-Material Structure.

- Targeted approach used on configurations with varied fractions of aluminum and steel.
- Optimization was stopped after 1000 steps.
- 6 runs were performed for each variant, starting with varied initial configurations.
- Degree of variation was set to 1%.
- Product of density and final strain energy as measure of performance – lowest value assumed to signify optimum lightweighting, achieved here at approx. 60 vol.-% Al.



Conclusion & Outlook

Main Findings.

Summary of current results.

- The unconstrained **stochastic approach** require far too many iterations.
- Suitable constraints can lead to really significant improvements, as shown by the **targeted approach**.
- The targeted approach also outperforms the indiscriminative **genetic algorithm**.
- However, the genetic algorithm does outperform the stochastic approach.
- For all approaches compared, variation of results when using identical as opposed to different random distributions as starting point is slightly reduced, but remains in a similar range. Also, the final levels of total strain energy are similar irrespective of identical or varied starting points.

Conclusion & Outlook

Next Steps.

Summary of current results.

- Further optimization of algorithms, including pre-check of new configurations prior to FE simulation runs to further computational effort, and thus reduce runtime.
- Adding the concept of constraints to the genetic 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.

Many thanks for your kind attention.

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In case of further questions …

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