Optimization characteristics of continuous fiber-reinforced plastics

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Overview

• Motivation

• Parametric optimization in optiSLang

• Optimization characteristics of continuous fiber-reinforced plastics

• Strategy for composite optimization

• Summary
Motivation

- Continuous fiber-reinforced plastics
  - Show a more complex material description than conventional metallic materials

- Parametric optimization
  - Can be applied to a simulation that is suited to a manufacturing process

Goal:

**Decision support** for a composite optimization
- Provide information to facilitate decision-making when choosing the appropriate optimization settings
Motivation

• There’s a large amount of parametric optimization methods
• The suitable method depends on the composite task
• This decision is difficult as there are a lot of settings that must be chosen correctly

Understand the optimization characteristic

Choose the appropriate settings
Parametric optimization in optiSLang
Parametric optimization in optiSLang

• Which algorithm is the most efficient one and which settings should be chosen?
  • Gradient-based optimization algorithm
  • Adaptive response surface method
  • Evolutionary algorithm
  • Particle swarm algorithm
  • Stochastic methods
  • ...

[DDS11]: David Schneider, Daniela Ochsenfahrt, Stephan Blum: Benchmark of Nature-inspired Optimization Algorithms in fields of single and multiobjective scopes
Optimization characteristics of continuous fiber-reinforced plastics
Optimization characteristics of continuous fiber-reinforced plastics

• Can be identified immediately:
  • Is there just one or are there more objective functions?
  • Are there just continuous (fiber angles, ..) or also discrete parameters (order/number of fabrics/plies)?
  • How large is the range of the fiber orientations?
Optimization characteristics of continuous fiber-reinforced plastics

• Identification using a sensitivity study:
  • How many (important) input parameters exist?
  • Can the objective(s) be achieved with the current preliminary concept?
  • What’s the probability of failed designs?
  • How often will the failure criterias be violated?
  • How much numerical noise?
  • Are there local jumps with regard to the evaluation areas?
  • Does the failure layer change?
  • Do the failure criterias change?
  • How long / inhomogeneous is the computational time?
Detecting good optimization settings
Detecting good optimization settings

How can good optimization settings be detected for the corresponding characteristic?
Detecting good optimization settings

Example: In an evolutionary algorithm - mutations rate and - archive size are varied and compared

<table>
<thead>
<tr>
<th></th>
<th>10%</th>
<th>35%</th>
<th>60%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Runs: 362 Puck: 0.177</td>
<td>Runs: 77 Puck: 0.217</td>
<td>Runs: 84 Puck: 0.197</td>
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<tr>
<td>3</td>
<td>Runs: 135 Puck: 0.198</td>
<td>Runs: 156 Puck: 0.185</td>
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<tr>
<td>5</td>
<td>Runs: 383 Puck: 0.178</td>
<td>Runs: 374 Puck: 0.180</td>
<td>Runs: 148 Puck: 0.181</td>
</tr>
</tbody>
</table>

But is this a fair comparision of the optimization settings?
Detecting good optimization settings

- In a stochastic-based method one must expect a different result in each optimization run
- Evaluation by using the mean value and its standard deviation (get a quick result to save time; and preferably always for a good calculability)
Detecting good optimization settings

• Flow chart of the evaluation

![Flow chart of the evaluation](image-url)
Benchmark to detect the appropriate optimization settings
Benchmark to detect the appropriate optimization settings

• The chosen benchmark owns the following characteristics:
  • One or more objectives can be selected
  • Continuous or continuous+discrete parameters
  • Range of the fiber angles can be set
  • Consideration of one or several failure criterias at the same time
  • Frequent / sporadic change of the failure criterias
  • Numerical noise large/small
  • Frequent / sporadic change of the failure location
  • Frequent / sporadic change of the failure layer

• This benchmark is used to test different situations
Example: Identifying the characteristics by using a sensitivity study
Examples: Identifying the characteristics by using a sensitivity study

• Sensitivity study shows:
  • Almost no failed designs

• Range of results:
  • Mass: 892g – 1560g
  • Inverse reserve factor Cuntze: 0.73 – 5.20 (<1)
  • Inverse reserve factor Max. Stress: 0.73 – 5.21 (<1)
  • Inverse reserve factor Puck: 0.73 – 5.28 (<1)
  • Deformation: 3.8cm – 15.2cm (<8cm)
Examples: Identifying the characteristics by using a sensitivity study

• Sensitivity study shows:
  • Local change of the output parameters can be observed:

In a global examination of the max. failure a reasonable interpretation of the results is not possible anymore. The CoP is small. 'failure modes' must be evaluated separately.

→ Change of the parametrization increases the CoP for the failure criterias and therefore a goal-oriented optimization
Examples: Identifying the characteristics by using a sensitivity study

- Sensitivity study shows:
  - Influence of the fiber angle changes if the number of discrete parameters (number of layers) changes. Maybe a response surface based method is not the best choice.

![Graph showing failure vs. angle for different layer counts](image)
Examples: Identifying the characteristics by using a sensitivity study

- Sensitivity study shows:
  - Failure criteria are violated very often:
    ~ 90% of all designs violate max. stress, puck, cuntze or an acceptable deformation

blue: valid designs
orange: invalid designs
Example: Detecting good optimization settings
Example: Detecting good optimization settings

• Now the optimization settings are regarded as input parameters! (number of parents, mutation rate, …)

→ Which settings deliver a good optimum with a minimum number of runs?

my_script.py →
Example: Detecting good optimization settings

• Sensitivity study for the settings of an evolutionary algorithm:

  - Ø design runs
  - Ø mass
  - Ø deformation
  - Ø failure

• All mean values have a high CoP
• Ø number of runs mainly depends on the number of parents
• Ø mass on mutation rate, start population and number of parents
• Ø deformation on number of parents and mutation rate
• Ø failure criterias show similar sensitivities: number of parents, tournament size and mutation rate

• Other settings like e.g. archive size, samples for cross over, max. / min. standard deviation of the mutation, … are less important.
Example: Detecting good optimization settings

• Which setting should be chosen?

- There's no setting to get the smallest mass with a minimum number of runs
- But there are a lot of (combinations of) settings that should be avoided
Example: Detecting good optimization settings

- Excluding non-efficient settings

- Red design constellations in this parallelplot show the pareto front
- Example: The mutation rate should not be chosen with a value higher than 20%
Example for decision support
Example for decision support

• From these benchmarks the answer for the following question can be derived:

I have ~4 hours, so I can afford about ~250 simulation runs. For this number of runs I would like to find a setting to get a good valid candidate.

1. Preliminary thoughts
   • There's just one objective
   • There are continuous and discrete parameters
   • The variation range of the fiber angles is large

2. Sensitivity study shows:
   • Failure criterias change locally (pictures)
   • The failure criterias are violated very often (parallel plot)
   • Numerical noise is acceptable
   • There's a change of the failure layer (pictures)
   • Failure criterias show same correlations (correlation matrix)

3. Correct local change by changing the output parametrization

4. The possibility, to get a good candidate with about 250 runs can most likely be achieved with these EA setting proposals:
   Start population:↑   Number of parents:→   Tournament size:↑   Mutation rate:↓
Strategy applied to a model
Strategy applied to a model

• result*: Mass reduction on average the same (+/-1%)
• effort*: On average 48% less simulation runs necessary

* In comparison to a default optimization setting that is not adjusted to a composite characteristic
Summary
Summary

Number of objectives
Cont./dis. parameters
Range of variation

Sensitivity study:
Local change of output
Violation of failure criteria
Change of failure layer
Correlation of failure criterias

Correct local change of outputs by changing parametrization

Startpopulation: ↑
Number of parents: ↑
Tournament Size: ↓
Mutation rate: ↓

Improved design
Thank you for your attention!

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