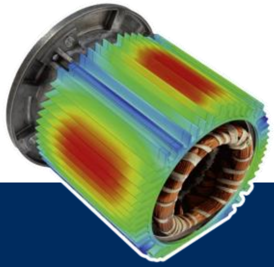
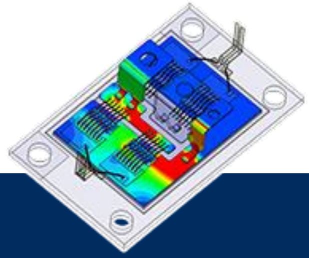
CADFEM®

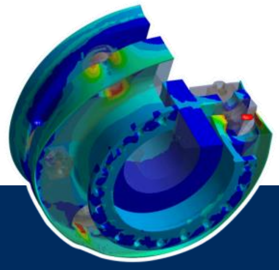
ANSYS®

Competence Center FEM

Simulation ist mehr als Software®







Optimization characteristics of continuous fiber-reinforced plastics

Dipl.-Ing. Markus Kellermeyer, CADFEM GmbH
Prof. Dr.-Ing. Sandro Wartzack, Universität Erlangen-Nürnberg

Lehrstuhl für
Konstruktionstechnik
Prof. Dr.-Ing. Sandro Wartzack

KT mfk

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:

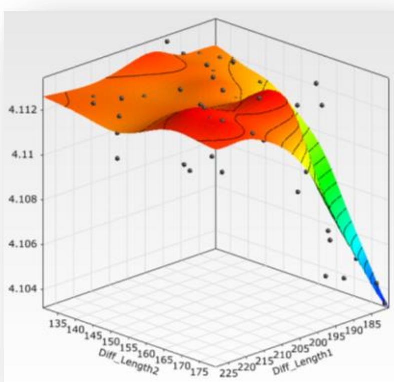
Decision support for a composite optimization

- 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

© CADFEM 2014

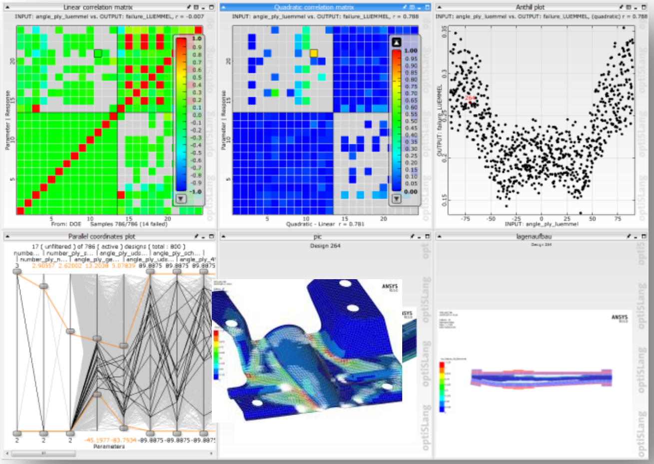
Optimization characteristics of continuous fiber-reinforced plastics

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

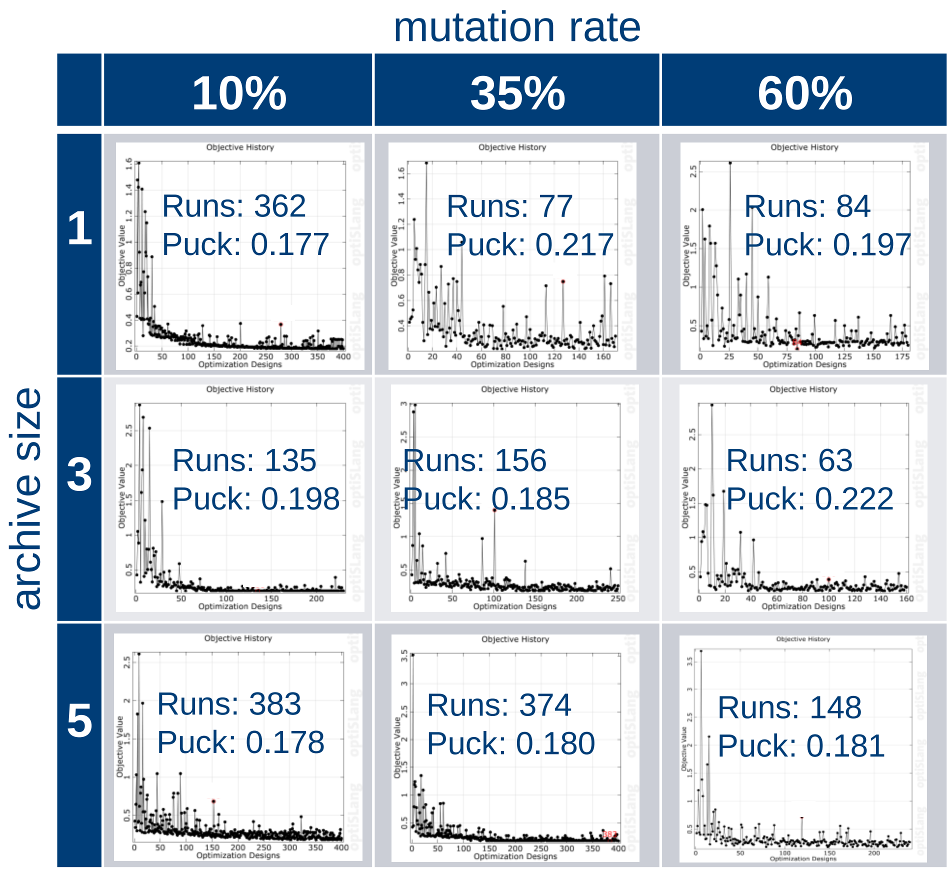
Detecting good optimization settings

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

© CADFEM 2014

Detecting good optimization settings

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



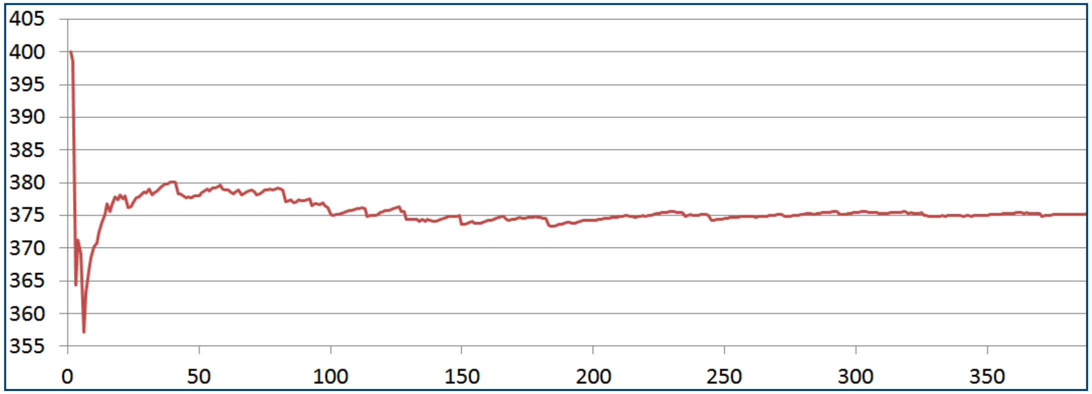
But is this a fair comparision of the optimization settings?

© CADFEM 2014

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 it‘s standard deviation (get a quick result to safe time; and preferably always for a good caculability)

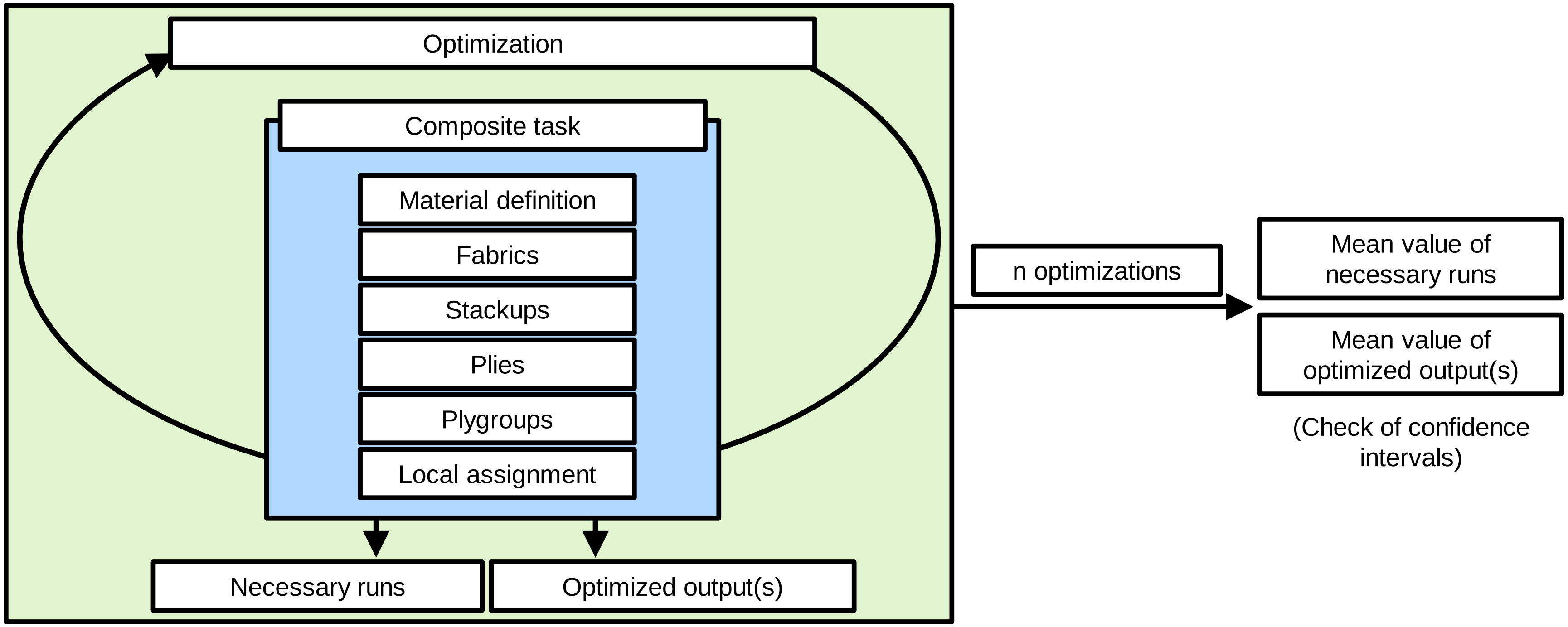
Mean value of the necessary runs



Number of optimizations

Detecting good optimization settings

- Flow chart of the evaluation



Benchmark to detect the appropriate optimization settings

Benchmark to detect the appropriate optimization settings

- The choosen 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

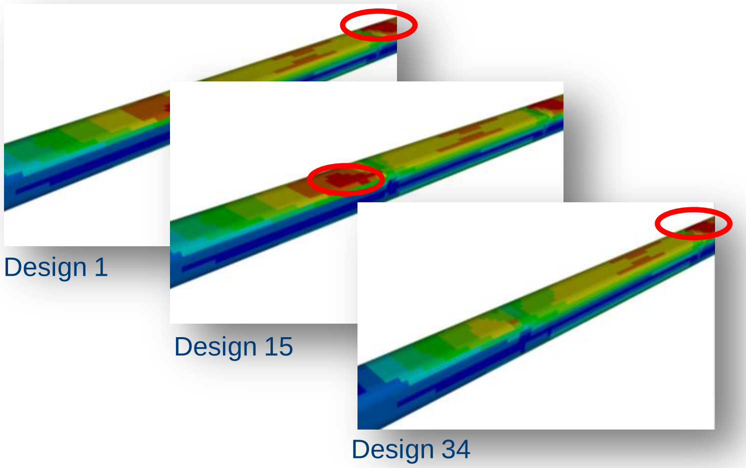
Examples: Identifying the characteristics by using a sensitivity study

- 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 reasonalbe interpretation of the results is not possible anymore. The CoP is small.

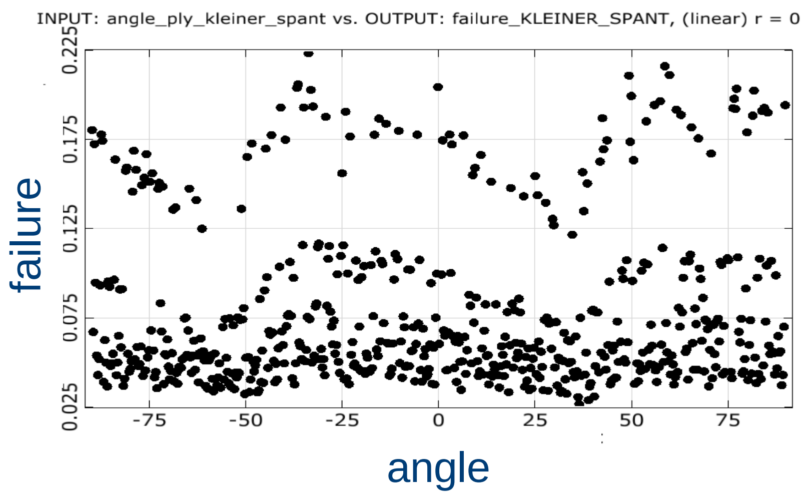
‚failure modes' must be evaluated seperately

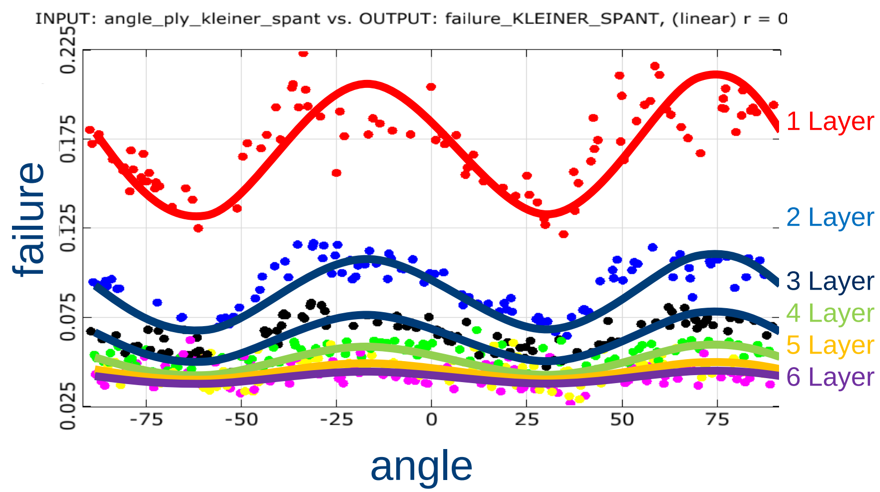
→ Change of the parametrization increases the CoP for the failure criterias and therefore a goal-oriented optimization

© CADFEM 2014

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.

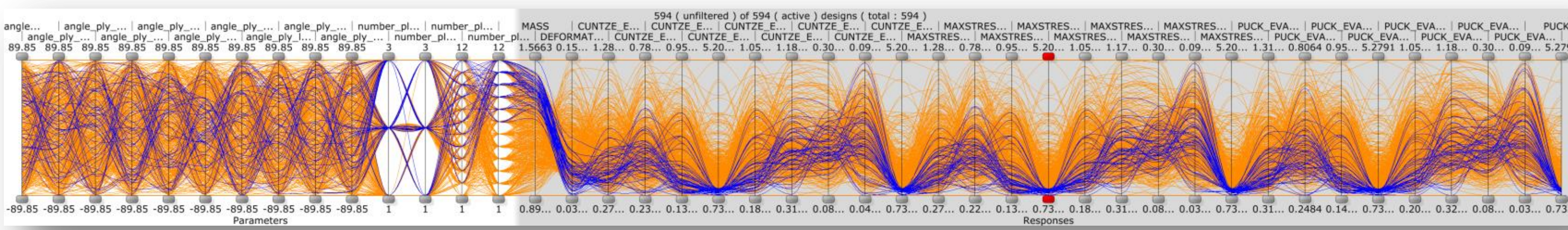




Examples: Identifying the characteristics by using a sensitivity study

- Sensitivity study shows:
  - Failure criterias are violated very often:

    ~ 90% of all designs violate max. stress, puck, cuntze or a an acceptable deformation



blue: valid designs

orange: invalid designs

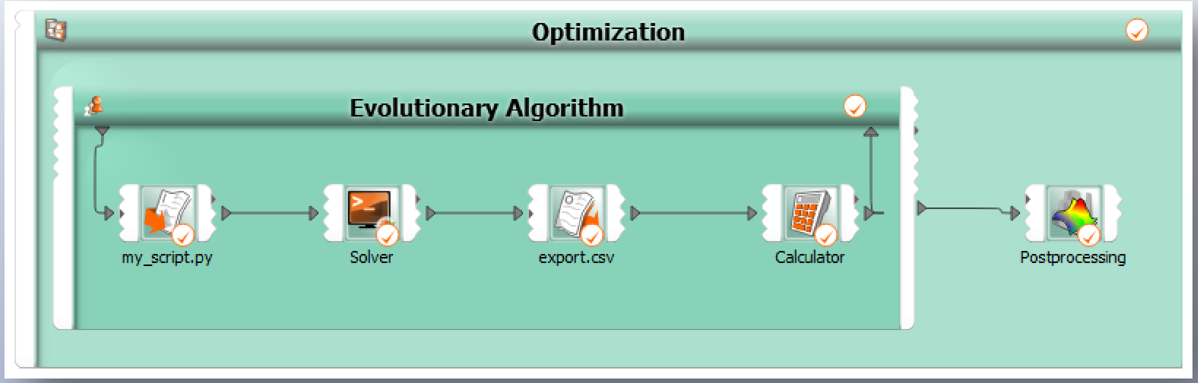
Example: Detecting good optimization settings

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?

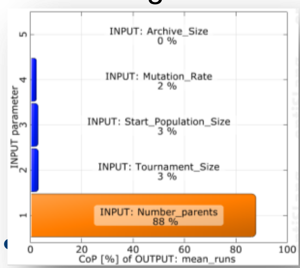
my_script.py →



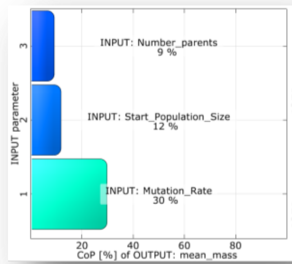
Example: Detecting good optimization settings

- Sensitivity study for the settings of an evolutionary algorithm:

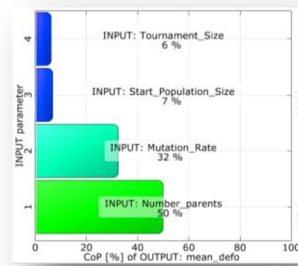
Ø design runs



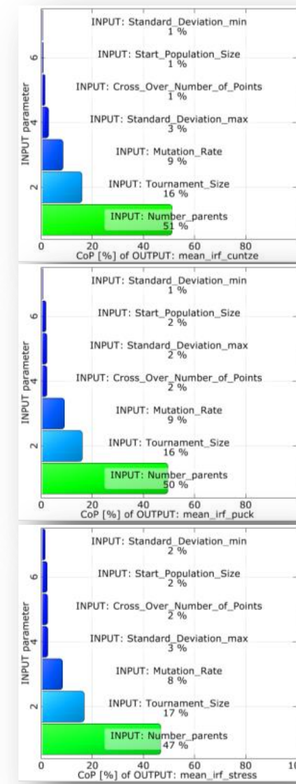
Ø mass



Ø deformation



Ø failure



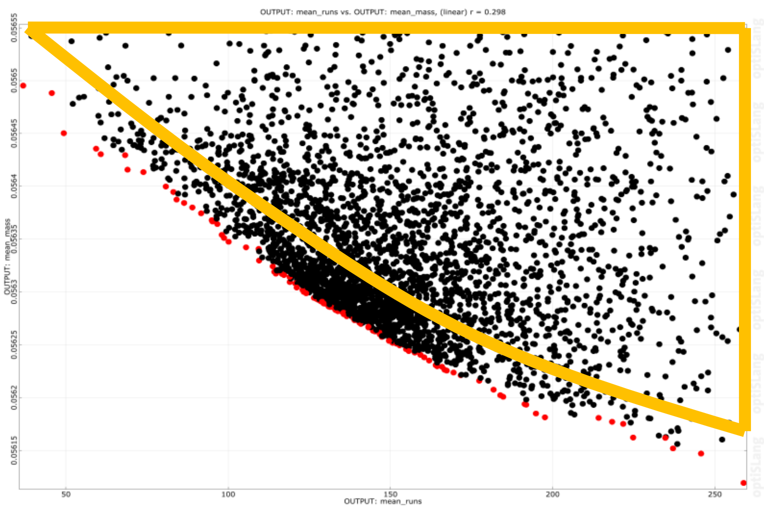
- All mean values have a high CoP
- Ø number of runs mainly depends on the number of parents
- Ø mass on mutation rate, start population and number of parents
- Ø deformation on number of parents and mutation rate
- Ø failure criterias show similar sensitivities:
  number of parents, tournament size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

Preferably a small mass

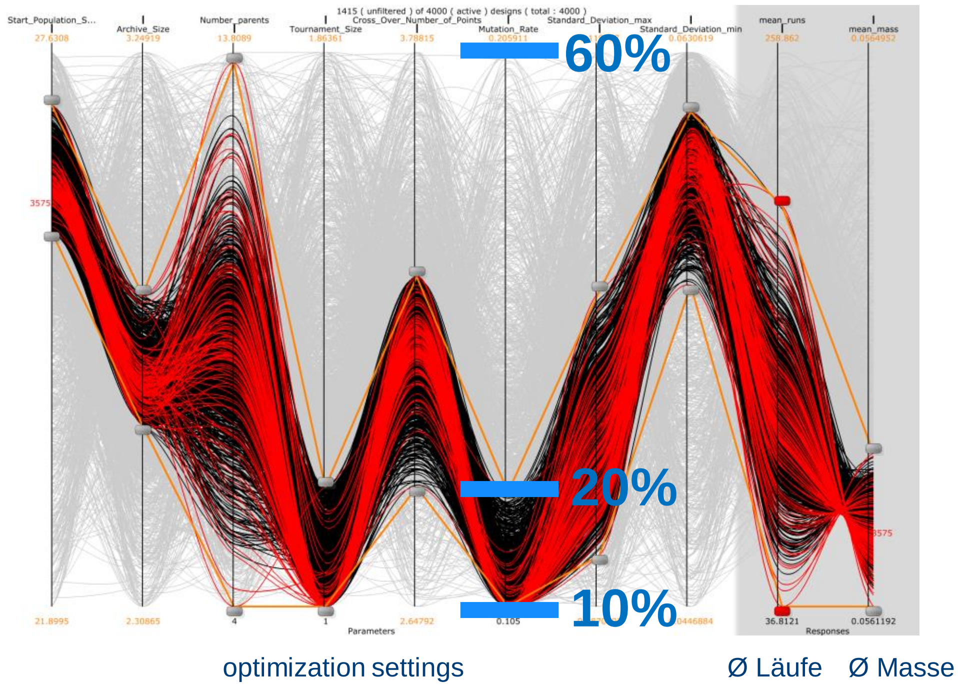


Preferably small number of runs

- 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



mutation rate

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

CADFEM KT mfk

ANSYS Competence Center FEM

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.

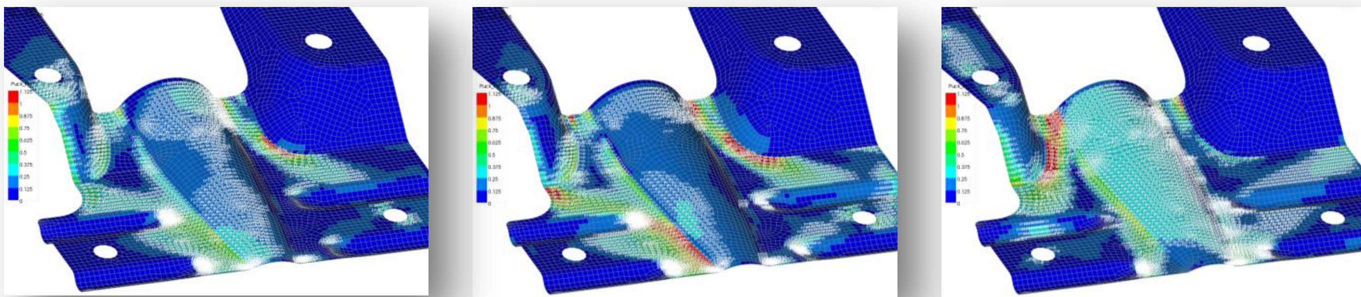
1. Preliminary thoughts
   - There's just one objective
   - There are continuous and discrete parameters
   - The variation range of the fiber angles is large
2. Sensitivity study shows:
   - Failure criterias change locally (pictures)
   - The failure criterias are violated very often (parallel plot)
   - 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:↓

© CADFEM 2014

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

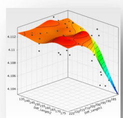
Summary

© CADFEM 2014

Summary

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

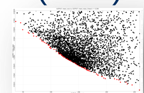
Sensitivity study:
Local change of output
Violation of failure criteria
Change of failure layer
Correlation of failure criterias



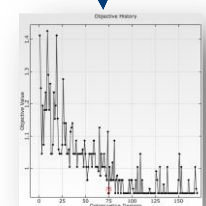
Number of desired runs

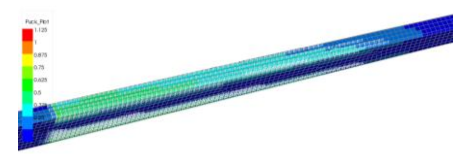
Correct local change of outputs by changing parametrization

database (MoP)



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





Improved design

Thank you for your attention!

Dipl.-Ing. Markus Kellermeyer
CADFEM GmbH
08092 / 7005-942
mkellermeyer@cadfem.de

© CADFEM 2014