Tolerance Optimization Using LS-OPT

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Outline

- Motivation

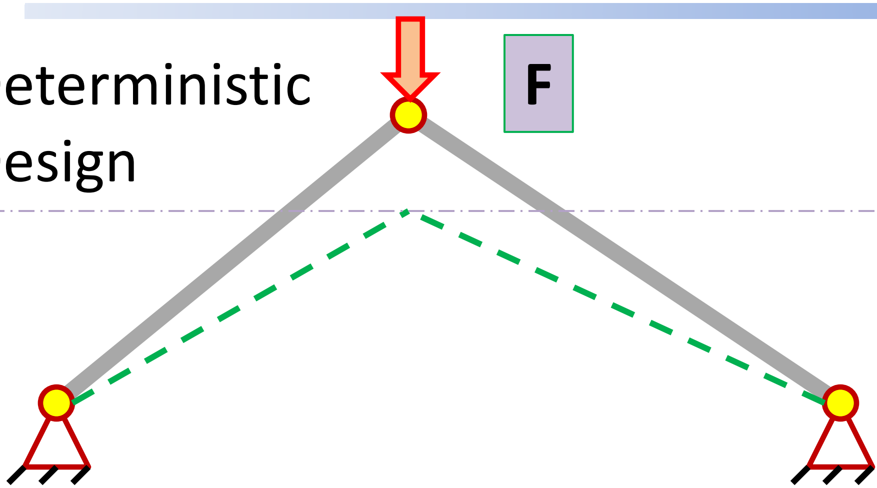
  Deterministic vs tolerance-based design optimization

- Tolerance Optimization Methodology
  - Multilevel LS-OPT setup
  - Parameterization of LS-OPT attributes
  - Extraction of failure probability as respone

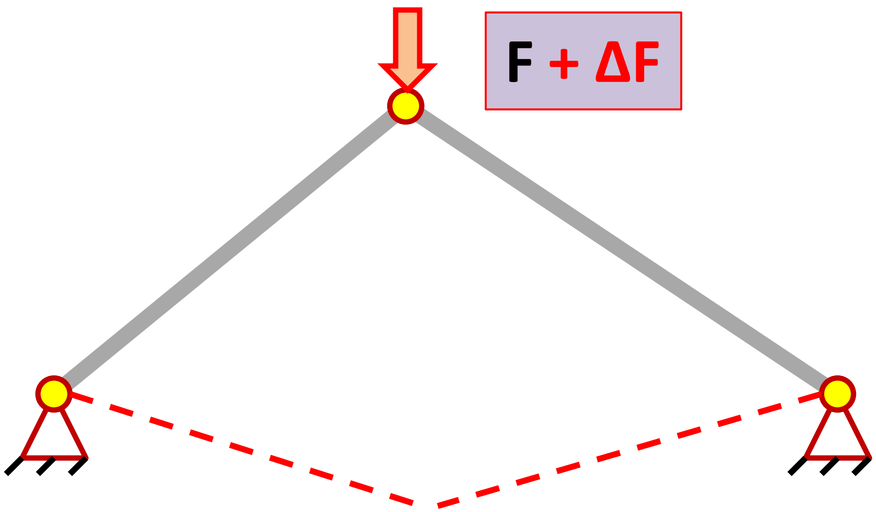
- Example
  - Chevrolet Truck Impact

Deterministic vs Robust Design

Deterministic Design

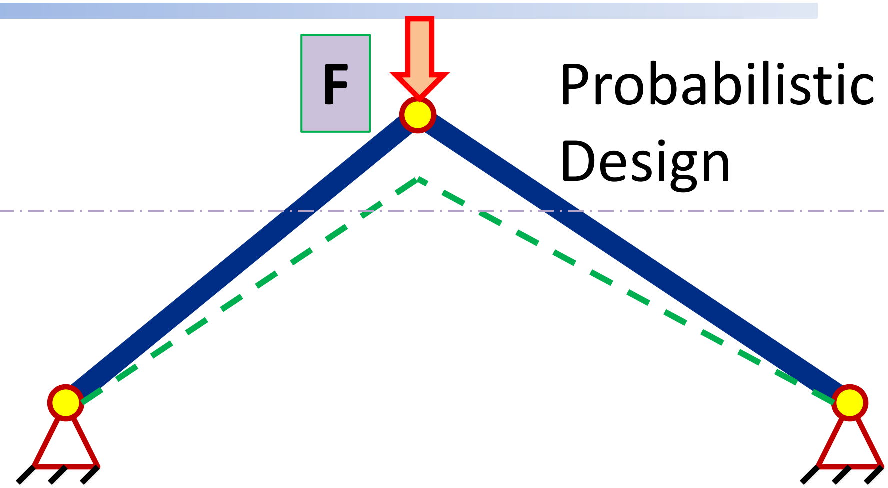


No uncertainty consideration
- **Feasible** mean (deterministic) behavior

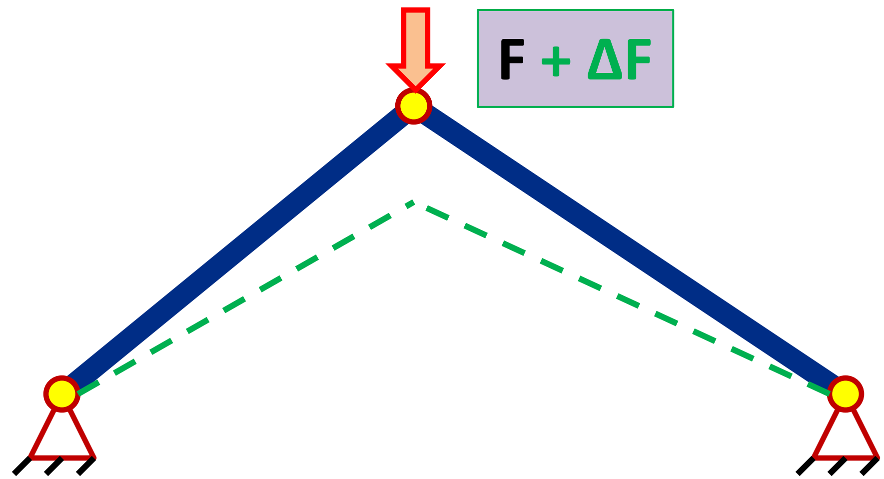


Infeasible perturbed behavior

Probabilistic Design



Feasible nominal behavior



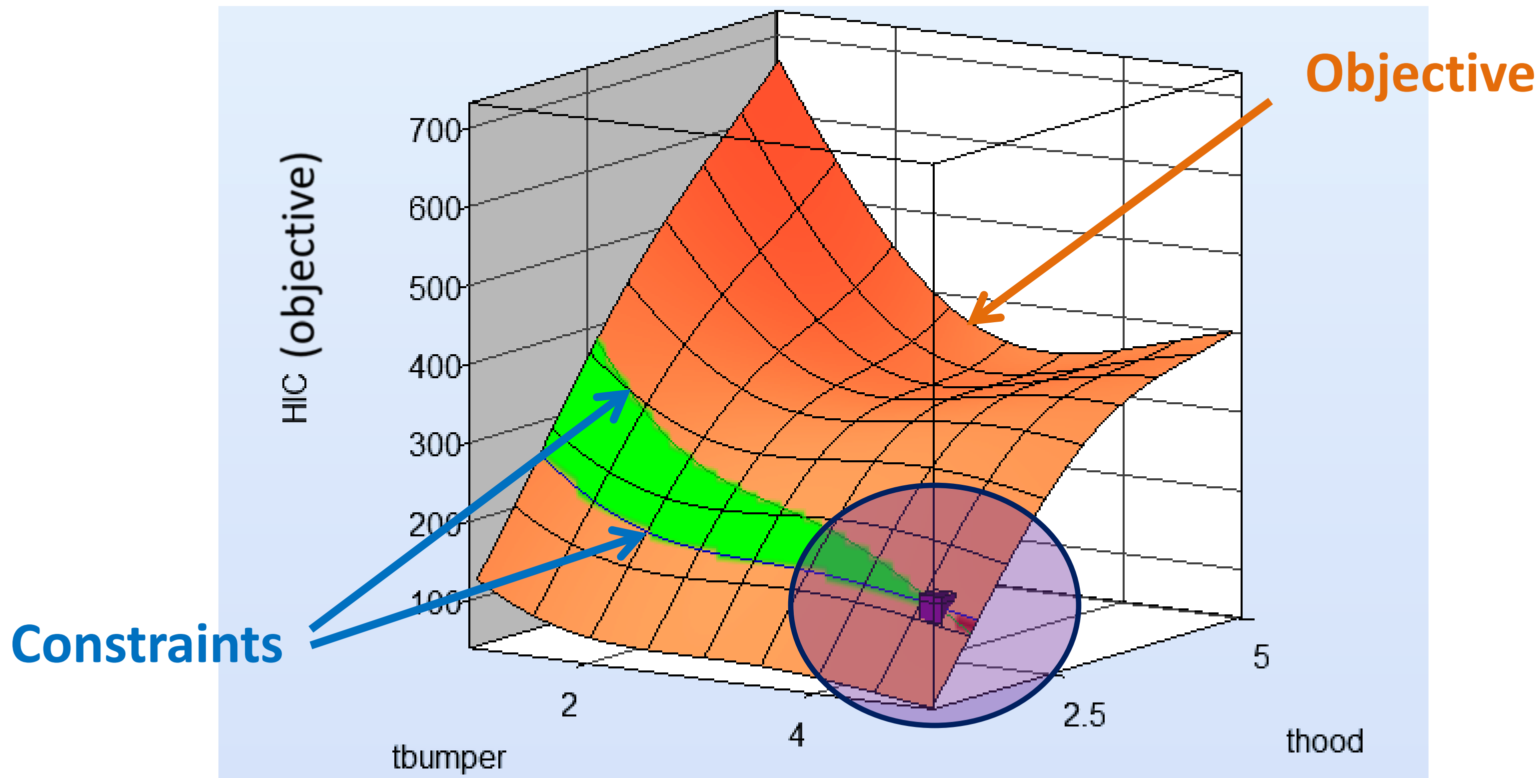
Feasible perturbed behavior

Optimization vs Robustness/Reliability

Deterministic Optimization:

Minimize Objective Function subject to Constraints

Optimum very often lies on the constraint boundary



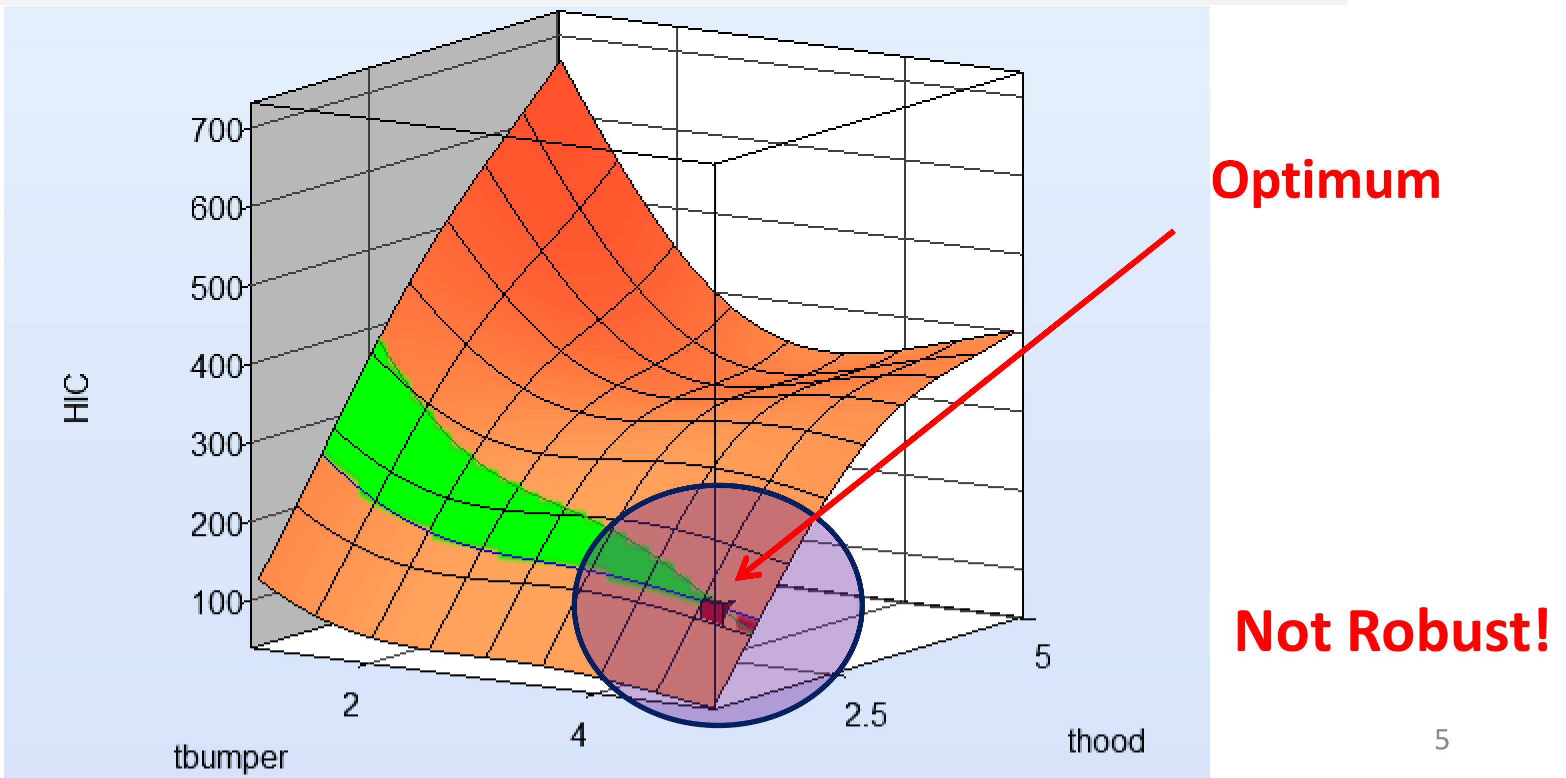
Optimization vs Robustness/Reliability

Is the Optimum Robust??

Sources of uncertainty:

Manufacturing imperfections, Load variations, Environment variations

Approximation/Metamodeling Error, Optimization Error, Analysis Error



LSTC Livermore Software Technology Corp.

Improving Robustness of Optimum

- Reliability-based design optimization (RBDO)
  - Optimize objective function at nominal design
  - Low failure probability target
- Robust design
  - Minimize variance of the objective
- Tolerance-based design
  - Optimize nominal design variables **and tolerances**
  - Maximize tolerance
  - No failure within tolerance

Available as LS-OPT Tasks

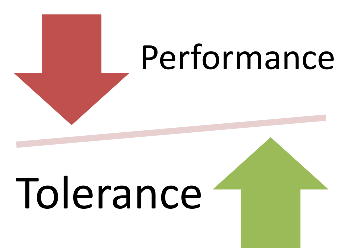
Tolerance Optimization vs RBDO

RBDO:

- Variables associated with distribution
- Mean variable values (distribution means) are optimized

Tolerance Optimization:

- Variables associated with tolerance values - fixing the tolerance value similar to RBDO with truncated PDF
- *Tolerances (i.e. distribution shape) also optimized*
- Set up as a *multilevel problem with parameterized inner level distribution*



Setup for Tolerance Optimization

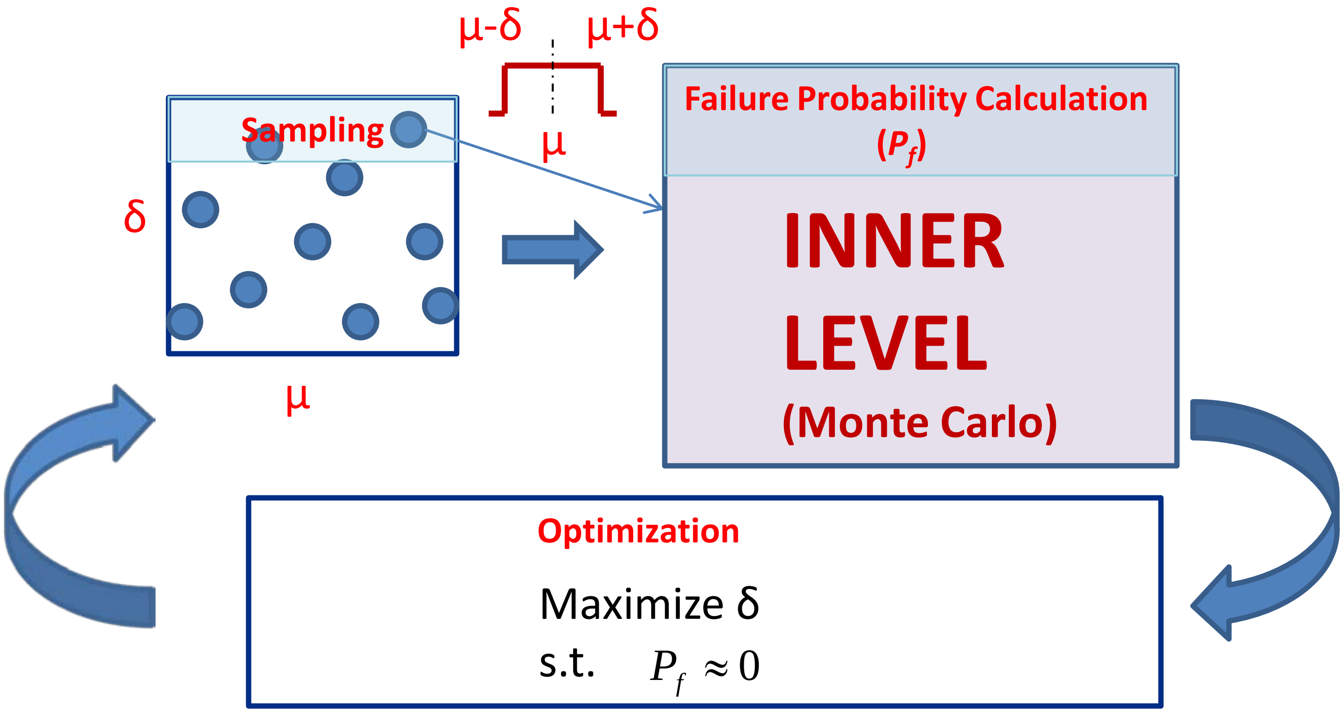
Multilevel (Two level) Setup:

OUTER LEVEL (Direct Optimization):

Variables: Nominal design variables, Tolerance (μ,δ)

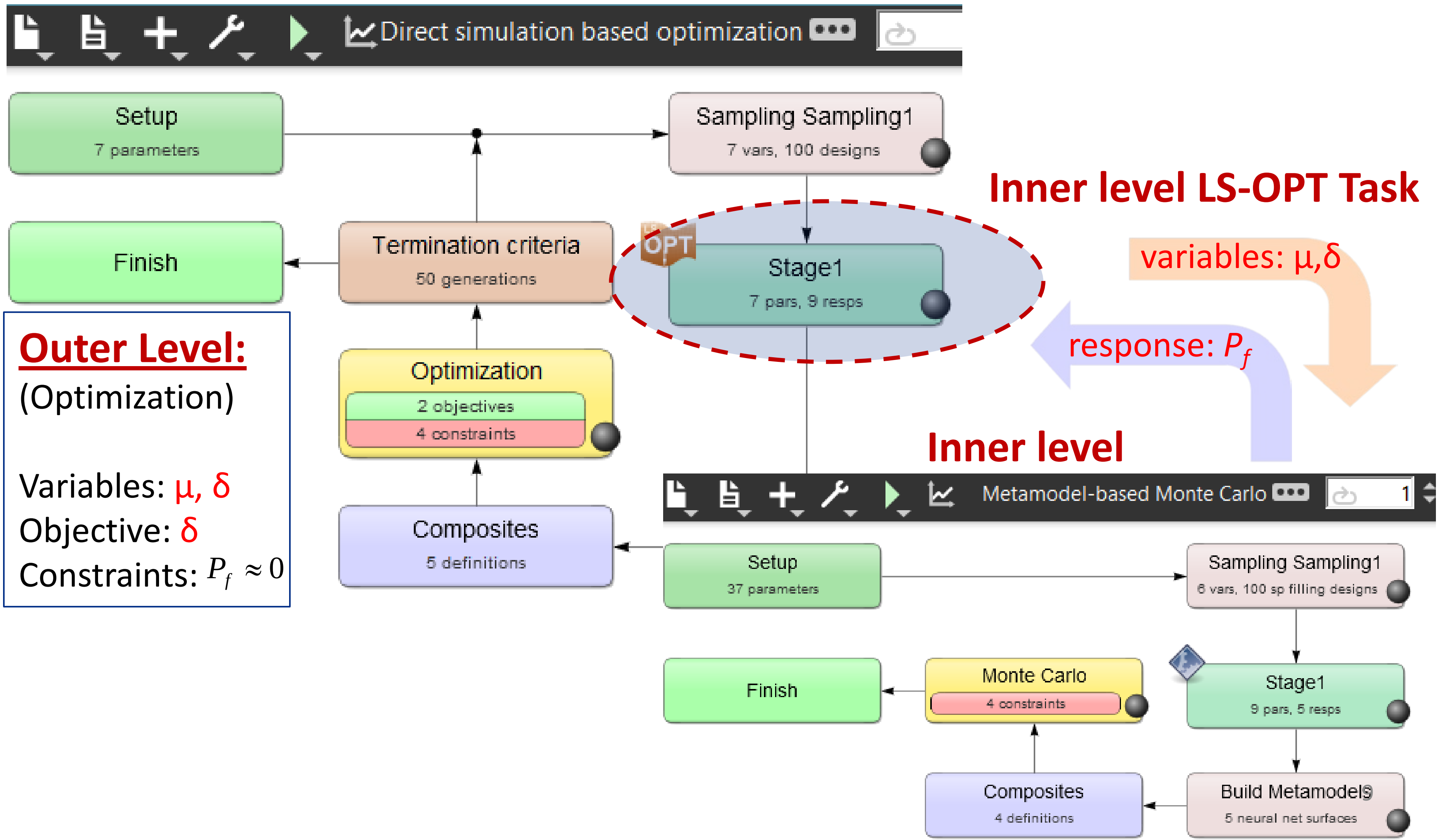
Maximize Tolerance

s.t. Zero failure within tolerance interval, i.e. Failure Probability = 0



Setup for Tolerance Optimization

Multilevel (Two level) Setup:



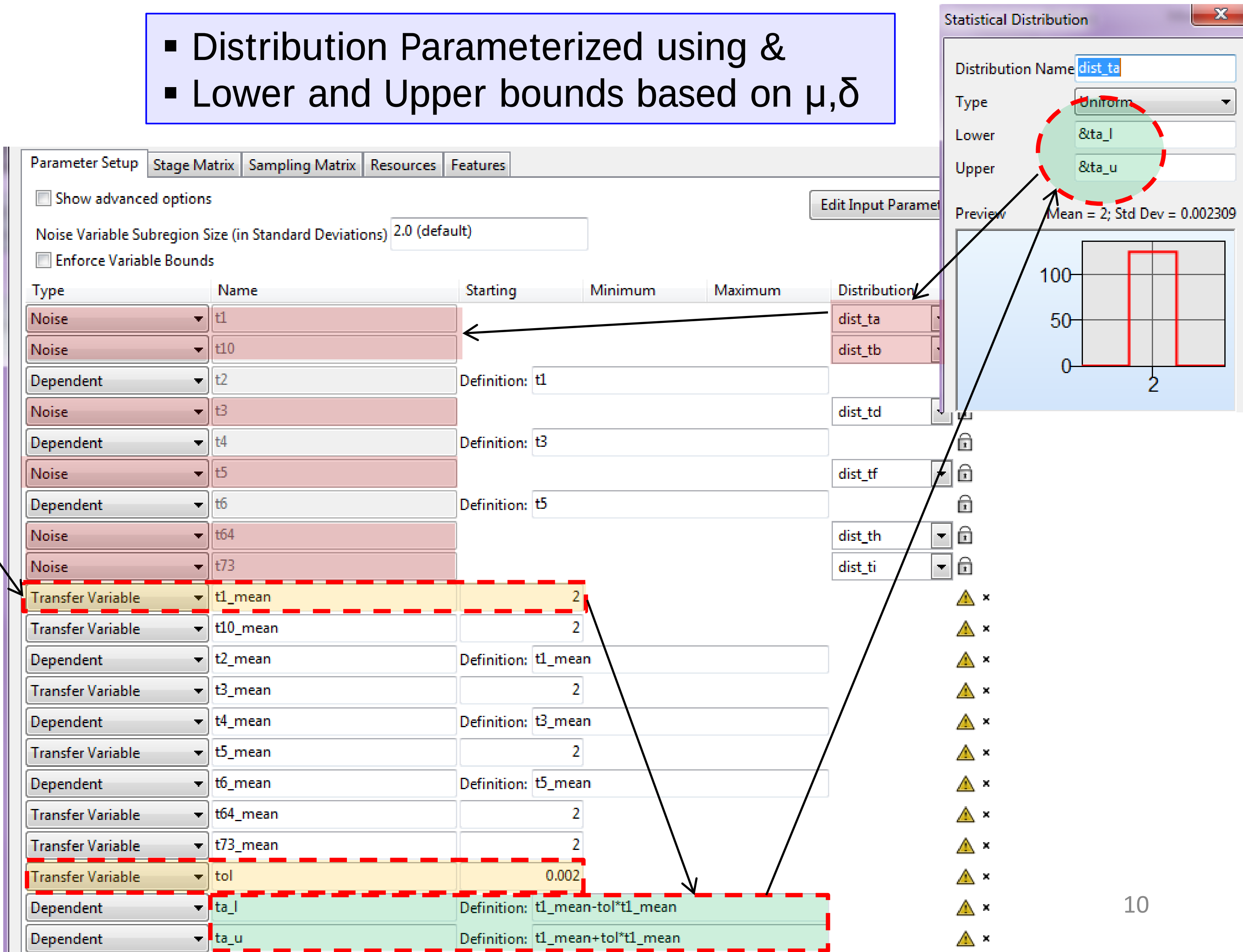
Inner Level – distribution parameterization

Inner Level:
(Monte Carlo)

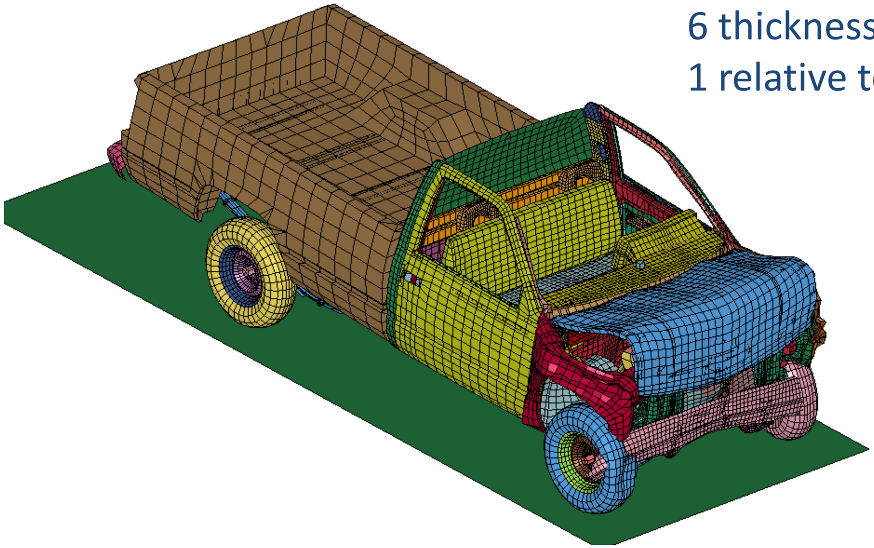
NoiseVariables:
X(μ, δ)

- Distribution Parameterized using &
- Lower and Upper bounds based on μ,δ

From Outer level



Tolerance Optimization: Example



6 thickness design parameters
1 relative tolerance (%) parameter

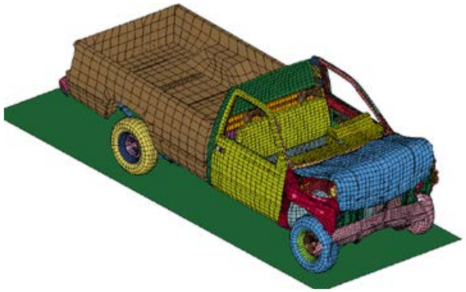
Objectives:
1. Minimize Mass
2. Maximize Tolerance (robust)

Expensive Analysis – Tolerance Optimization requires repeated calls!!

Two Step Solution:
Step 1: LS-DYNA Analysis + Metamodel Construction
Step 2: Only Metamodel Evaluation

Example

Step 1 (Deterministic)



6 thickness design parameters

Objective: Minimize Mass

$$\min_{\bar{t}_1,\bar{t}_2,\bar{t}_3,\bar{t}_4,\bar{t}_5,\bar{t}_6} \quad \text{scaled\_mass}$$

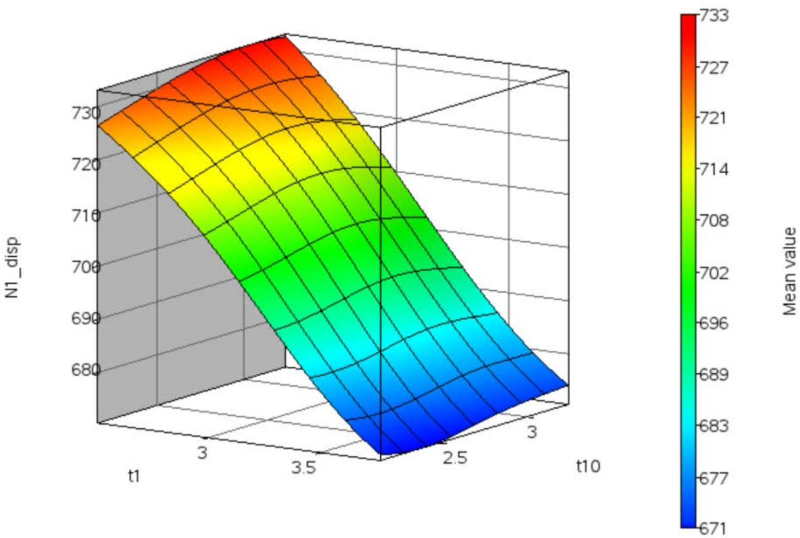
$$s.t. \quad \text{scaled\_stage1\_pulse}(\bar{t}_1,\bar{t}_2,\bar{t}_3,\bar{t}_4,\bar{t}_5,\bar{t}_6) \le 1$$

$$\text{scaled\_stage1\_pulse}(\bar{t}_1,\bar{t}_2,\bar{t}_3,\bar{t}_4,\bar{t}_5,\bar{t}_6) \le 1$$

$$\text{scaled\_disp}(\bar{t}_1,\bar{t}_2,\bar{t}_3,\bar{t}_4,\bar{t}_5,\bar{t}_6) \le 1$$

Baseline Scaled Mass: 1

Optimum Scaled Mass: 0.832

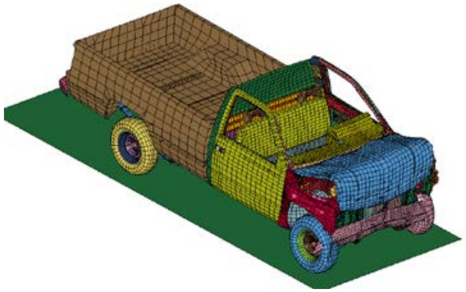


Metamodels with 1000 samples (LS-DYNA)

Analytical formula saved to file

Example

Step 2 (Non-Deterministic)



6 thickness design parameters

1 relative tolerance (%) parameter

Objective Functions:

1. Nominal Scaled Mass (minimize)
2. *Tolerance (maximize)*

$$\max_{\bar{t},\delta_t} \{\delta_t, -scaled\_mass(\bar{t})\}$$

Ensure min performance

$$\text{s.t.} \quad P(scaled\_mass(\mathbf{t}) > 0.9) \le P_{target}$$

$$P(scaled\_stage1\_pulse(\mathbf{t}) > 1) \le P_{target}$$

$$P(scaled\_stage2\_pulse(\mathbf{t}) > 1) \le P_{target}$$

$$P(scaled\_disp(\mathbf{t}) > 1) \le P_{target}$$

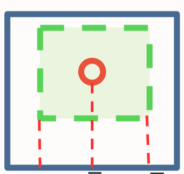
$$P_{target} \approx 0$$

Direct Optimization (50 generation x 100 samples)
7 variables

50 times

100 Samples ($\bar{t}_1, \bar{t}_2, \bar{t}_3, \bar{t}_4, \bar{t}_5, \bar{t}_6, \delta_t$)

Failure Probability Calculation



6 noise variables (t)

$\bar{t}_1 - \delta_t$ $\quad \bar{t}_1 \quad$ $\bar{t}_1 + \delta_t$

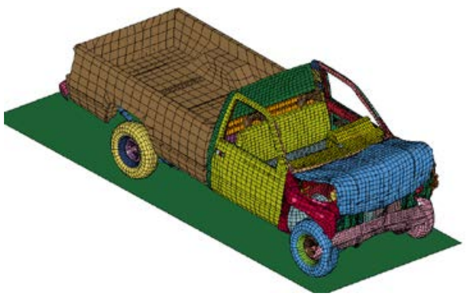
Optimization (Non-dominated points)

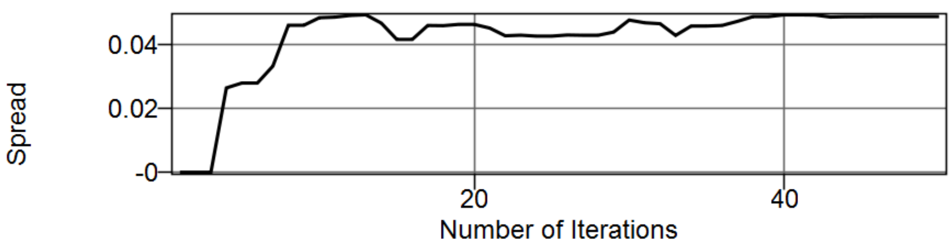
Inner Level
Metamodel-based Monte Carlo
100 samples

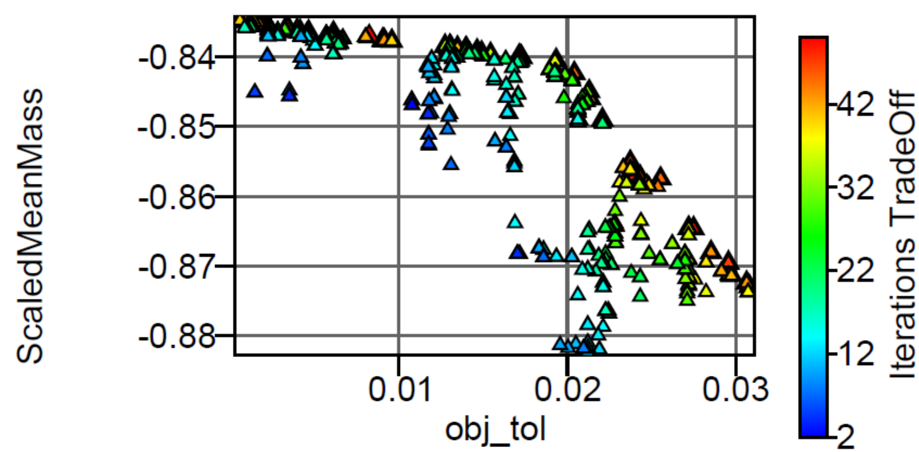
Pareto Front

7 variables:
6 thickness design parameters
1 relative tolerance (%) parameter

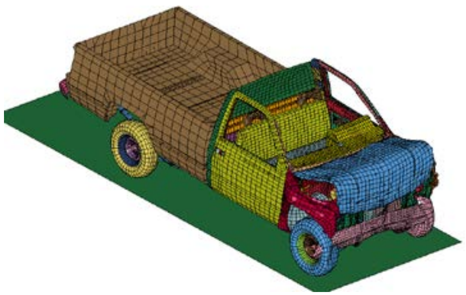
2 objectives:
Minimize nominal mass
Maximize tolerance







Pareto Front



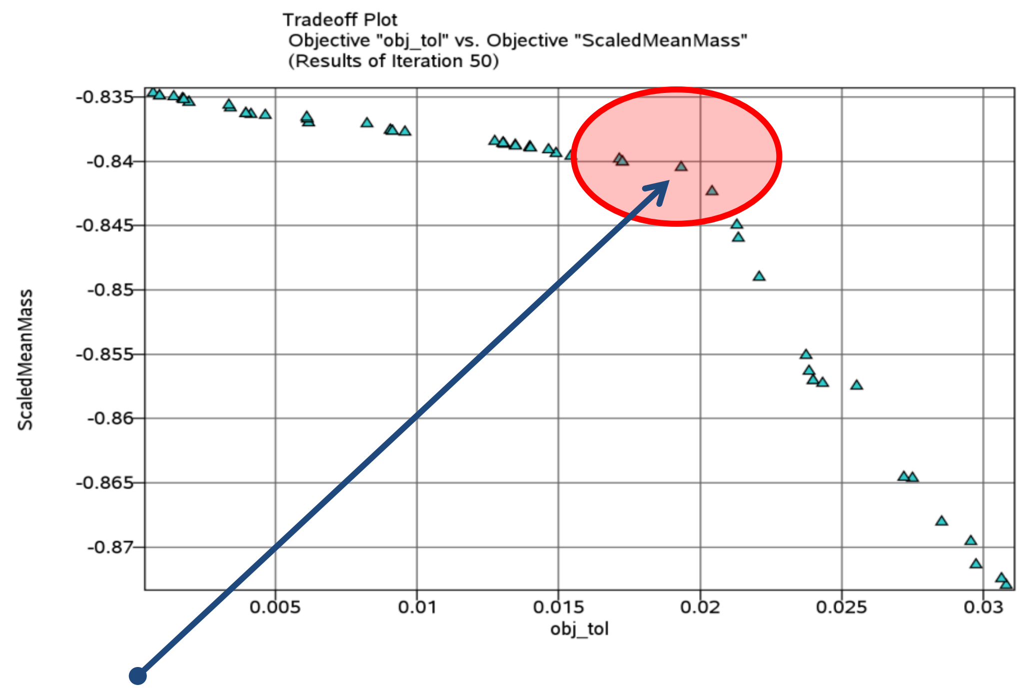
7 variables:
6 thickness design parameters
1 relative tolerance (%) parameter

2 objectives:
Minimize nominal mass
Maximize tolerance

Total vehicle mass: 1800 kg
Mass of optimized parts: 138.14 kg

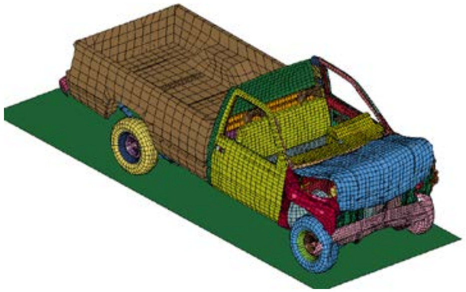
Maximum Mass Reduction: 22.8 kg

Maximum Tolerance: 0.031 or 3.1%
with 17.54 kg mass reduction



2% tolerance with 22 kg mass reduction

Accuracy check



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6 thickness design parameters
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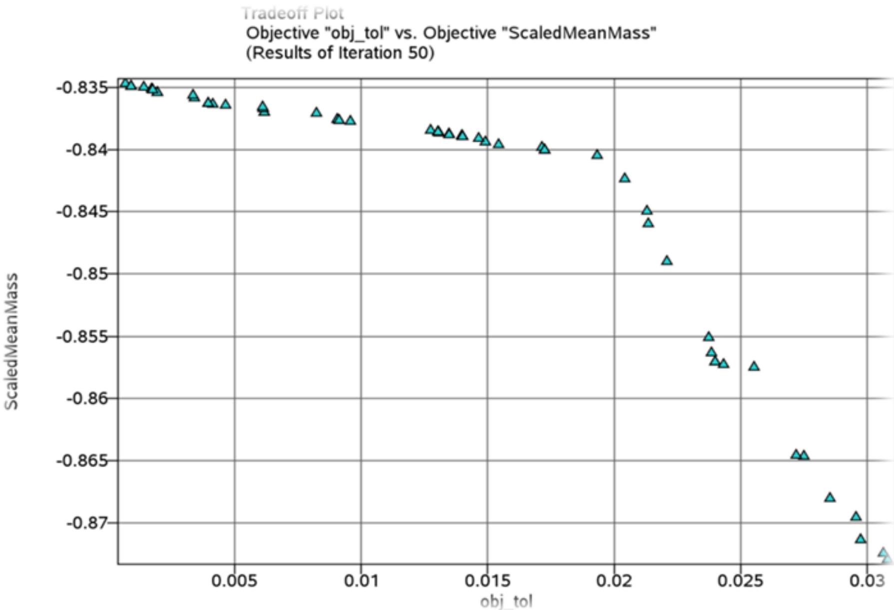
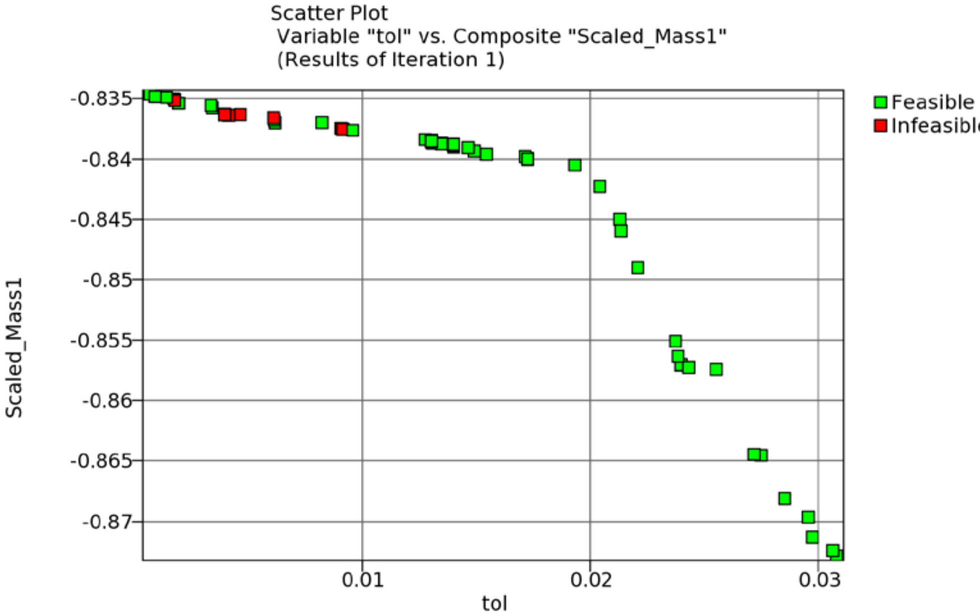


Metamodel



LS-DYNA

Summary

- Tolerance optimization using LS-OPT
- Multi-level optimization, multi-objective setup
- Facilitates the search for a robust optimum
- Two different distinct categories of Pareto Optimal designs obtained for Chevrolet truck
- Future work entails simplification of the interface, allowing a single level setup that handles the multi-level nature of the problem internally