Two-Stage Stochastic and Deterministic Optimization[1]

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Outline

Motivation and Introduction

Stage I: Stochastic Optimization

- Generic Monte Carlo
- Latin Hypercube in LS-OPT

Stage II: Analytic (Deterministic) Optimization

- Identifying Relevant Variables for Analytic Optimization
  - ▷ Variable Screening in LS-OPT (ANOVA)

Example: Van Component Model for Crash

- Problem Description
- Stage I
- Stage II

Conclusions and Outlook

Why Optimization?

Modern Commercial vans have to meet high demands with respect to active and passive safety.

Passive safety considerations play an important role in the design of the Vaneo, Vito, and Sprinter van models at DaimlerChrysler Commercial Vehicles.

Also extremely important for customer value:

- low purchase and maintenance cost,
- good fuel economy,
- high payload.

Passive safety requirements can lead to design requirements at odds with economy and payload! It is essential to analyze many different designs and find the best solution possible.

We need optimization procedures capable of finding an optimal solution for full vehicle crash simulations

Why Two Stages?

Stochastic Optimization

- Advantages/Disadvantages:
  - \+ Very robust for highly nonlinear problems; works surprisingly well
  - \+ number of simulations is independent of total number of design variables (it does depend on number of *relevant* design variables!)
  - – brute-force approach, not very efficient
- Suitable when initial design is far from optimal design, and relevance of design variables is unknown.

Analytic Optimization

- Advantages/Disadvantages:
  - \+ Fast convergence, small number of simulations
  - – May be misled by local optimum
  - – Number of simulations depends on total number of design variables, whether relevant or not
- Suitable when initial design is close to optimal solution, and relevance of design variables is known.

Introduction

Purpose of this presentation:

- propose a two-stage optimization process for highly nonlinear automotive crash problems

Stage I: preliminary stochastic optimization with large number of design variables.

- Obtain a (nearly) optimal solution,
- Use results to identify a small set of design variables relevant to the optimization problem.

Stage II, analytic optimization

- Use only *relevant* design variables of stage I
- Use optimum result of the preceding stochastic optimization as starting point

Procedure is demonstrated using a van-component model used for crash calculations.

LS-OPT is used due to its ability to perform both stochastic (Latin Hypercube) and analytic optimization.

Monte Carlo

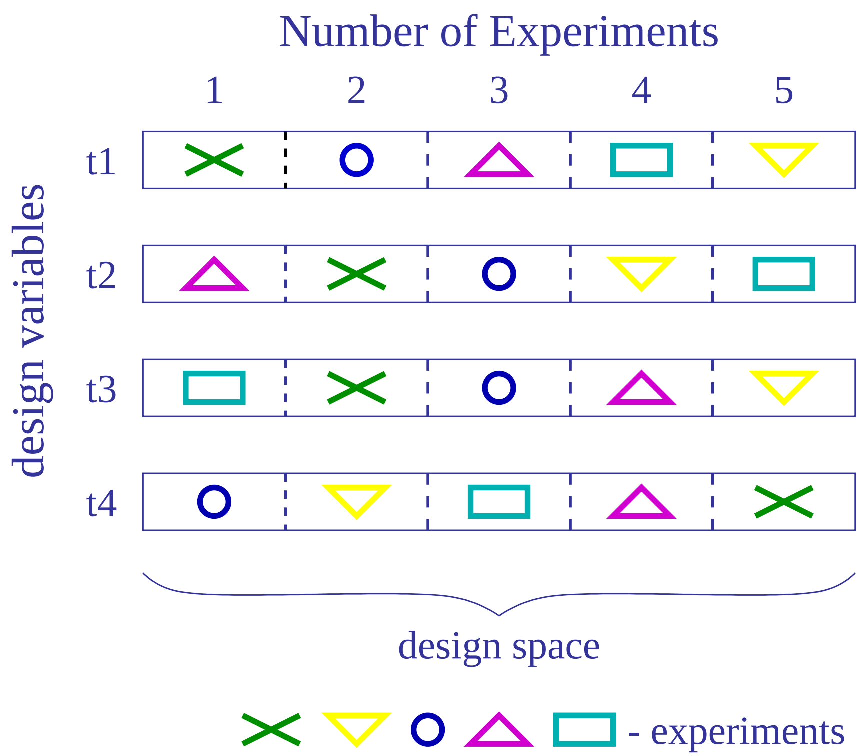
Stochastic optimization can be performed using a generic Monte Carlo method

- Each design variable is confined within its individual, user-defined range
- Vector of input values is determined randomly within bounds for each variable

For the construction of a Monte Carlo design, experiments that violate a constraint are discarded when the set of design points is created. The generation of random values for a single experiment is repeated until a design is found that satisfies the constraint.

Latin Hypercube

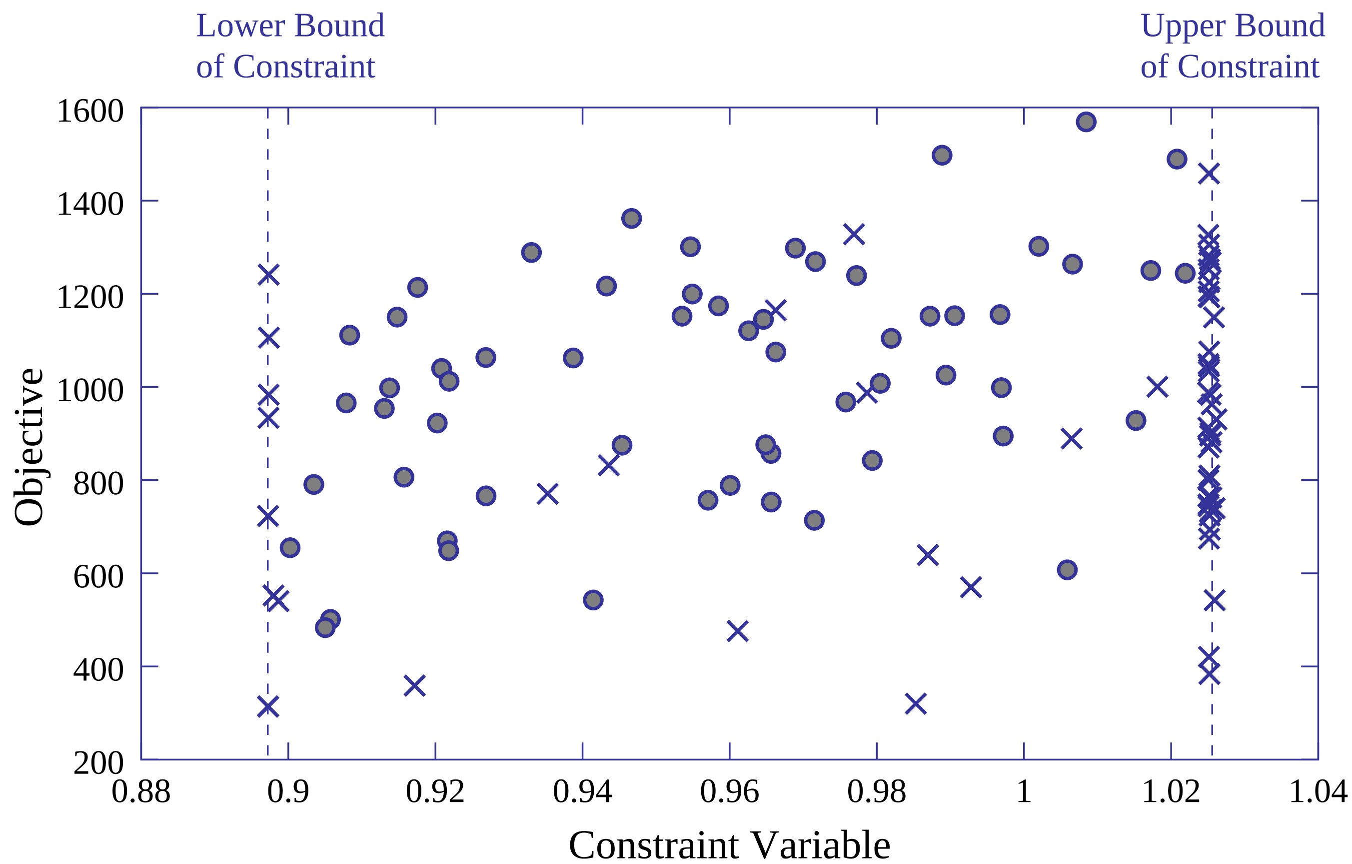
The Latin Hypercube method provided by LS-OPT is a random experimental design process.



- The range of each design variable is subdivided into n equal intervals, where n is the number of experiments (in this example, 5).
- A set of input variables is then determined for each experiment by randomly selecting a value in one of the n sub-ranges for each variable.
- Each sub-range may only be used in a single experiment, thus ensuring that the entire design space is covered.

In LS-OPT, points that violate a constraint are moved to the boundary of the admissible space. Thus, a large number of designs may lie on the boundary of the admissible region.

Monte Carlo and Latin Hypercube



The designs generated by LS-OPT often lie on the bounds of the admissible region, which results in an uneven distribution of the set of design points.

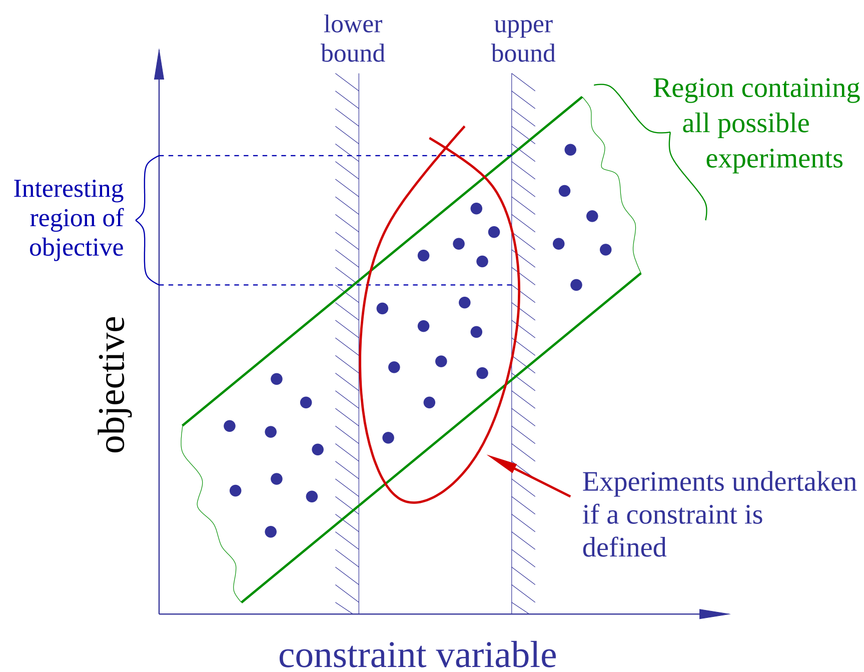
The design points created by the Monte Carlo algorithm are distributed more evenly for each variable.

Advance Evaluation of Constraints

Advantages of advance evaluation of constraints in a Monte Carlo optimization:

- Without constraints, a simulation would be carried out for each of the design points plotted in the diagram.
- By defining a constraint that can be evaluated in advance, experiments that are uninteresting or irrelevant can be rejected in advance.
- Thus, the number of simulations can be reduced.

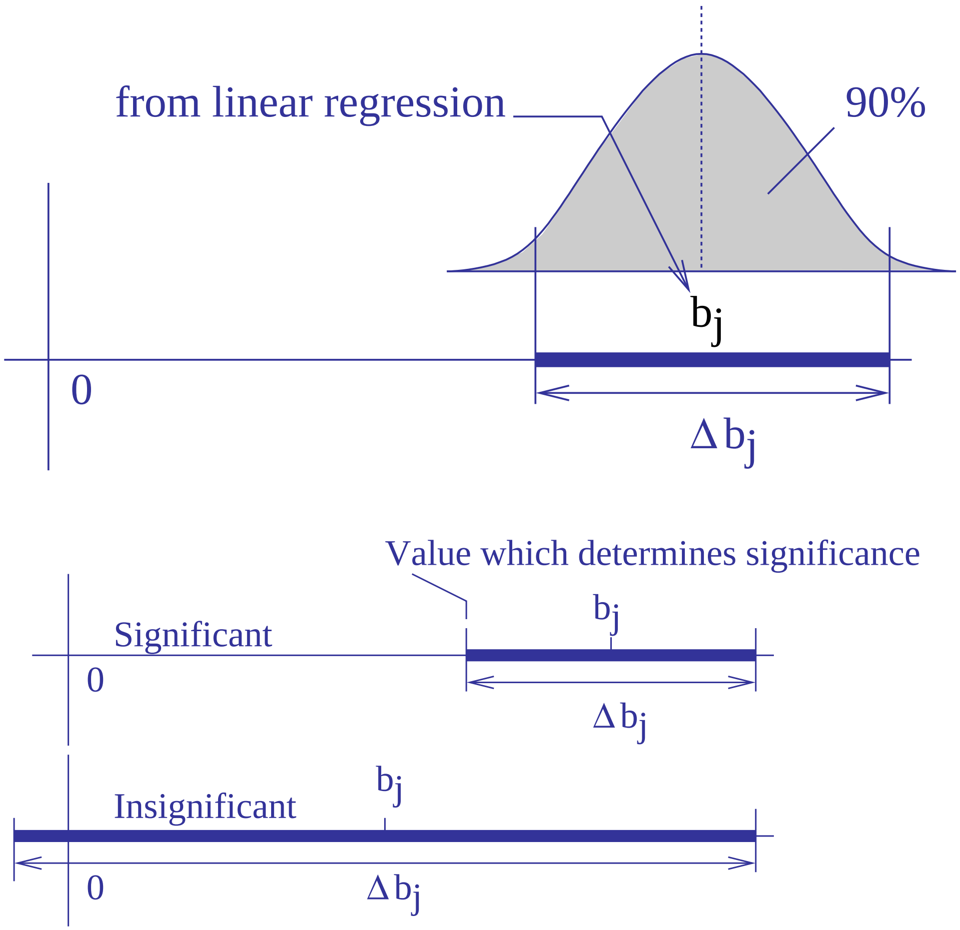
Example: mass constraints



- Frequently, an objective function can be computed in advance, but there are non-trivial constraints. Again, irrelevant experiments can be eliminated.

- E.g. mass as objective function, measure for structural integrity as constraint.

Variable Screening in LS-OPT (ANOVA)

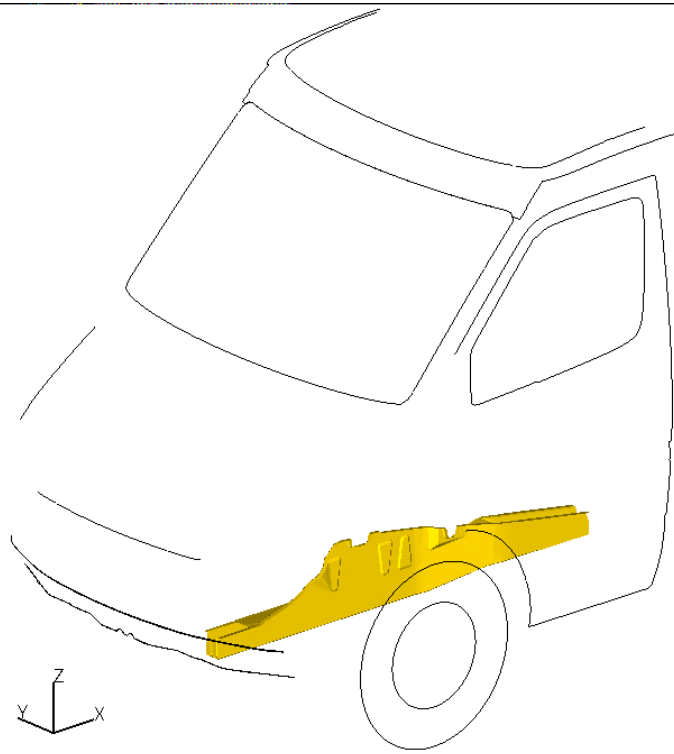


LS-OPT provides the capability of performing a ***significance test*** for each variable in order to remove those coefficients or variables which have a small contribution to the design model.

For each response, the variance of each variable with respect to that response is tracked and tested for significance using the *partial F-test*.

A *90% confidence level* is used to quantify the uncertainty and the variables are ranked based on this level.

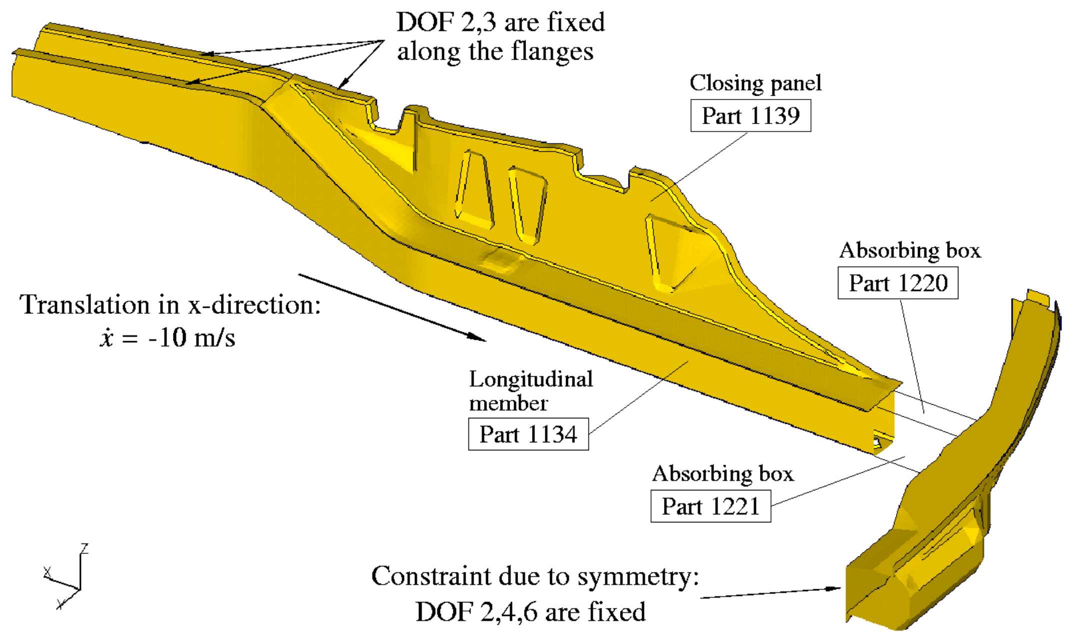
Van Component Model



Components of assembly:

- first cross rail
- front part of one longitudinal frame rail.
- energy absorbing box between first cross rail and longitudinal frame rail
- parts of the wheelhouse; closing panel of frame rail

Van Component Model



The assembly is connected to the floor panel of the body in white at the back part closing panel. In the simulations, the assembly is fixed in y and z at that location. The assembly is displaced in x at a constant velocity and impacts a rigid wall.

For simulation purposes, only half of the frame is represented (since geometry and loads are symmetric to the y-z plane) and the first cross member is cut off in the y-z plane. Therefore, translation in y and rotation about the x and z axis have to be fixed in that plane.

Optimization Problem

Design variables:

- Sheet thicknesses of 15 parts
- geometry of a rib in the frame rail
  - ▷ design variables depth t, x-location x_{min}, x_{max}, z-location z_min, z_{max}
  - ▷ Perl program preprocesses LS-DYNA input file to generate rib
- Total of 20 design variables

Objective: Maximize the ratio of the internal energy $E_{\max}$ and the mass M of the components:

$$E_M = \frac{E_{\max}}{1000\,M} \quad \longrightarrow \quad \max E_M.$$

Constraints:

- Mass constraint: $0.895 < M < 1.022$
- peak of frame rail force: maxRWFORC = 1.25
  - ▷ time history (ASCII-file RWFORC) is filtered using SAE 180

Example Model: Monte Carlo Distribution

First iteration:

- 60 different designs are evaluated
- Variable sets are generated by a Perl program using a module for generating random values
- Total mass of component model is checked directly, designs that violate constraints are rejected a priori
- Repeat this until 60 feasible designs are available

Second iteration:

- Choose three runs with maximum objectives E_M and with a frame rail force less than 1.5 as starting values for 15 additional runs each
- Thus, three sets of 15 variables are randomized with these starting values as centerpoints
- Repeat this for the three best designs of the previous 45 runs with $3 \times 15 = 45$ more runs

Total number of simulations: $1 \times 60 + 3 \times 45 + 3 \times 45 = 150$.

Example Model: Latin Hypercube Distribution

Latin Hypercube designs provided by LS-OPT.

LS-OPT generates an initial 1000 *Latin Hypercube* points (sets of variables). Points that violate the mass constraint are moved automatically into the feasible mass region.

Out of these 1000 feasible points, a sub-set of 60 points is selected by applying the D-Optimality criterion in LS-OPT.

Points chosen by the D-Optimality criterion generally display good capabilities with respect to linear regression.

In the same manner, 30 more points are generated around the best design out of the first 60 runs.

Total number of simulations: $1 \times 60 + 1 \times 30 = 90$.

Example Model: ANOVA Analysis

ANOVA analysis:

- Use first 60 runs of the *Latin Hypercube* Distribution
- LS-OPT ranks variables by using the bound of the 90% confidence interval that is closest to zero as the ranking criterion

Analytic Optimization, Response Surface Method in LS-OPT:

- Choose four most significant variables $t1134$, $t1139$, $t1210$ and $t1221$
- Initial design: Best run of the 150 *Monte Carlo* simulations.
- Values of the remaining 16 variables are also taken from the optimal *Monte Carlo* run and are kept constant.

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Approximating Response 'E_M' using 60 points
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Linear Function Approximation:
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Mean response value          =     0.8890
RMS error                    =     0.2238 (12.33%)
Maximum Residual             =     0.4611 (25.40%)
Average Error                =     0.1824 (10.05%)
Square Root PRESS Residual   =     0.3687 (20.31%)
Variance                     =     0.0751
R^2                          =     0.8524
R^2 (adjusted)               =     0.8524
R^2 (prediction)             =     0.5995
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Individual regression coefficients: confidence intervals

Coeff	Coeff. Value	Confidence Int.(90%) Lower	Confidence Int.(90%) Upper	Confidence Int.(95%) Lower	Confidence Int.(95%) Upper	% Confidence not zero
t1134	1.58	1.255	1.906	1.19	1.971	100
t1139	1.015	0.7089	1.321	0.6476	1.382	100
t1140	−0.6216	−0.9263	−0.3169	−0.9874	−0.2559	100
t1144	−0.2674	−0.6063	0.07145	−0.6743	0.1394	80
t1210	−1.055	−1.416	−0.6931	−1.489	−0.6206	100
t1211	−0.4619	−0.8002	−0.1236	−0.868	−0.05573	97
t1220	−0.5574	−0.8209	−0.294	−0.8737	−0.2411	100
t1221	−0.9985	−1.337	−0.6604	−1.404	−0.5926	100
t1222	0.3766	0.01415	0.739	−0.05852	0.8117	91
t1223	−0.2613	−0.6392	0.1165	−0.7149	0.1923	74
t1224	−0.1445	−0.4433	0.1543	−0.5032	0.2142	57
t1410	−0.0268	−0.3932	0.3396	−0.4666	0.413	10
t1411	−0.05109	−0.3883	0.2861	−0.4559	0.3537	20
t1412	−0.544	−0.8206	−0.2674	−0.876	−0.212	100
t1413	−0.3308	−0.7064	0.04484	−0.7818	0.1202	85
xmin	0.3381	−0.06837	0.7446	−0.1499	0.8261	83
xmax	−0.3318	−0.5868	−0.07684	−0.638	−0.02572	96
zmin	0.2477	−0.02525	0.5206	−0.07996	0.5753	86
zmax	−0.1905	−0.5596	0.1786	−0.6336	0.2526	60
t	0.1564	−0.1283	0.4412	−0.1854	0.4983	63

Ranking of terms based on bound of confidence interval

Coeff	Absolute Value (90%)	10-Scale
t1134	1.255	10.0
t1139	0.7089	5.6
t1210	0.6931	5.5
t1221	0.6604	5.3
t1140	0.3169	2.5
t1220	0.294	2.3
t1412	0.2674	2.1
t1211	0.1236	1.0
xmax	0.07684	0.6
t1222	0.01415	0.1
zmin	Insignificant	0.0
t1413	Insignificant	0.0
xmin	Insignificant	0.0
t1144	Insignificant	0.0
t1223	Insignificant	0.0
t	Insignificant	0.0
t1224	Insignificant	0.0
zmax	Insignificant	0.0
t1411	Insignificant	0.0
t1410	Insignificant	0.0

Selected Variables for Stage II (t1134, t1139, t1210, t1221)

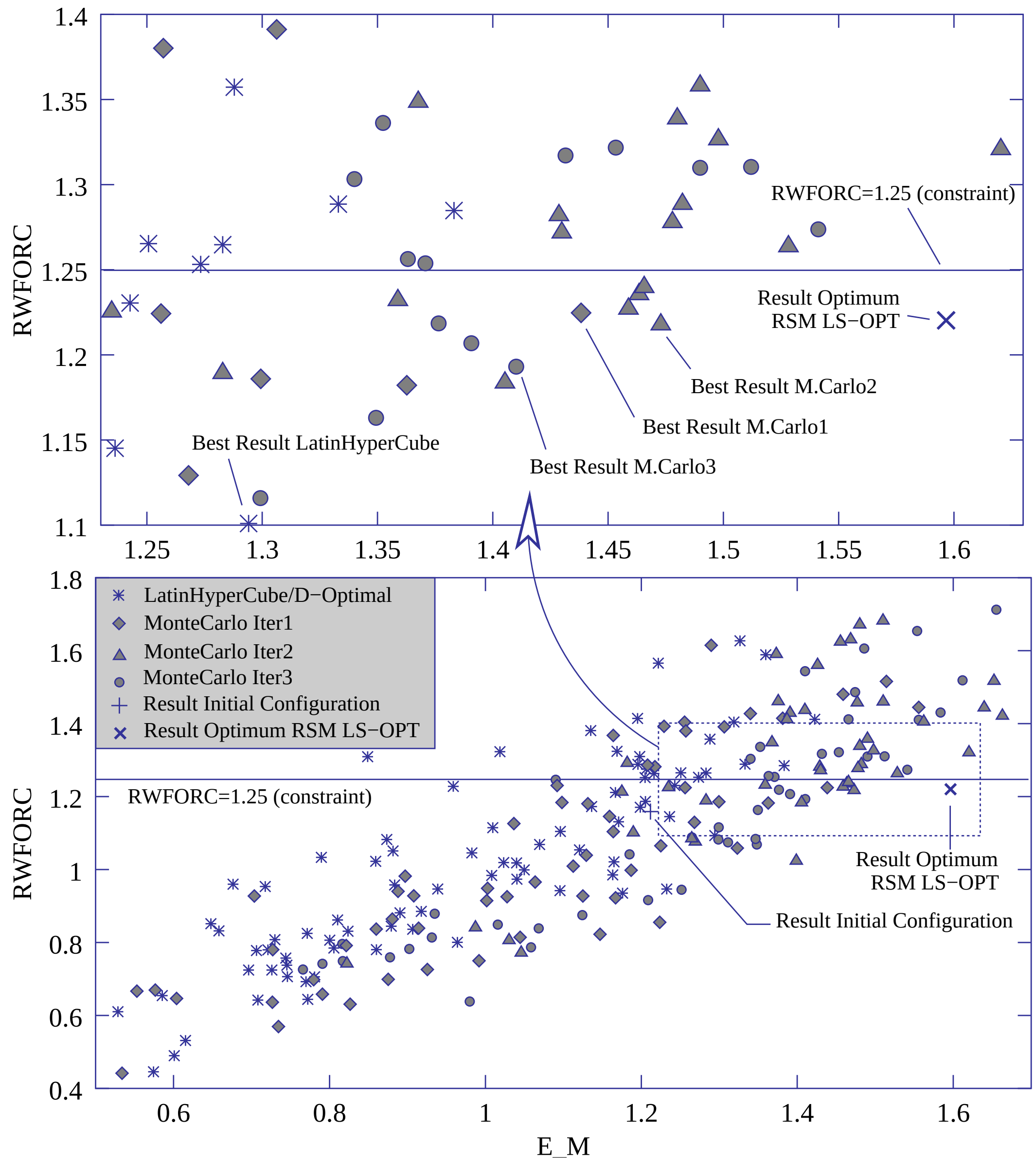
Variables kept constant in Stage II (t1140 through t1410)

Example Model: Results

Results of the *Monte Carlo* and the *Latin Hypercube* simulations of Stage I

Optimum design found by LS-OPT using the response surface method in Stage II

We see significant improvement of the response E_M in Stage II



Conclusions

We have shown a two-stage optimization process:

- Stage I
  - ▷ stochastic optimization, large number of design variables
- Stage II
  - ▷ Small number of relevant design variables
  - ▷ Linear response surface in LS-OPT
  - ▷ Start from optimal design of stochastic optimization

Mass constraint is enforced a priori to avoid unnecessary simulations.

Variable screening using the ANOVA (ANalysis Of VAriance) feature in LS-OPT: insignificant variables are frozen in Stage II

Initial design of the analytic optimization (Stage II): Best design of Monte Carlo simulations.

A significant additional improvement of the Energy/Mass ratio by analytic optimization is observed. In total, an improvement of 32% from the initial configuration (1.205) to the optimum result of LS-OPT (1.60) is achieved.

Our experiments show Two-Stage Optimization to be a viable method for combining the flexibility of stochastic optimization with the efficiency of analytic optimization. Based on the results presented here, Two-Stage Optimization seems a promising method for full vehicle crash problems.