Successive robust design optimization of an electronic connector

Dirk Roos[1*] & Ralf Hoffmann[2]

[1] DYNARDO – Dynamic Software and Engineering GmbH, Weimar, Germany

[2] Tyco Electronics AMP GmbH, Berlin, Germany

Abstract

Within the design development phases the Design for Six Sigma concept optimizes a design such that the products conform to Six Sigma quality. Which means that robustness and reliability are explicit optimization goals even with variations e.g. in manufacturing, design configuration and environment. The application of the reliability- and variance-based robust design optimization results in optimized designs such that they are insensitive to uncertainties up to a six sigma safety level. The paper shows an efficient iterative decoupled loop approach for reducing the necessary number of design evaluations. This is exemplary applied to a CAD parameter-based robust design optimization of an electronic connector element. Whereby, the CAE integration is realized by the optiSLang and ANSYS Workbench environment.

Keywords: robust design optimization, design for six sigma, robustness evaluation, reliability analysis, electronic connector.

[*] Contact: Dr.-Ing. Dirk Roos, DYNARDO – Dynamic Software and Engineering GmbH, Luthergasse 1d, D-99423 Weimar, E-Mail: dirk.roos [@] dynardo.de

1 Introduction

A large number of problems in manufacturing processes, production planning, finance and engineering design require an understanding of potential sources of variations and quantification of the effect of variations on product behaviour and performance. Traditionally, in engineering problems uncertainties have been formulated only through coarse safety factors. Such methods often lead to over-designed products. Otherwise, the application of the deterministic optimization often results in designs with high imperfection sensitivities (oversensitivity designs) and non-robust and unsafe (under designed products) behaviour because the deterministic optimal design is frequently pushed to the design space boundary. The design properties have no room for tolerances or uncertainties. Because of that, an integration of the assessment of robustness, reliability and safety into the optimization is necessary. Within the robust design optimization the design parameters can be random variables themselves and in addition the objective and the constraint functions can be random types. Using the robust design optimization we obtain robust optimized designs such that they are insensitive to uncertainties within a safety level of 2 sigma. The reliability-based optimization includes the failure probability as constraint condition or as a term of the objective function itself. So we obtain designs with minimal failure probability applicable for all safety levels up to 6 sigma.

Usually, the robust design optimization problem is solved as a combination of a deterministic optimization in the design space and a stochastic analysis in the space of the random influences for every deterministic design. This procedure leads in general to an inefficient double loop with a large number of design evaluations, e.g. finite element analysis. Furthermore, in real case applications of the virtual prototyping process, it is not always possible to reduce the complexity of the physical models and to obtain numerical models which can be solved quickly. Usually, every single numerical simulation takes hours or even days. Although the progresses in numerical methods and high performance computing, in such cases, it is not possible to explore various model configurations. An overview about advanced methods to solve robust design optimization problems can be found e.g. in Roos (2008). However, their use is restricted to problems with few random and optimization variables.

2 Successive robust design optimization

The most general way for reducing the required number of design evaluations is the application of an iterative decoupled loop approach (see e.g. Chen et al. (2003)) in combination with identification of the most significant random and design variables using the multivariate statistic within the robustness evaluation. According the flow diagram in figure 1, in a first step the robustness evaluation can be used to prove the predictive capability of the simulation model and to identify the most important design parameters to solve the deterministic optimization problem, efficiently. After that, it is necessary to evaluate robustness and safety of the design at the current deterministic optimum.

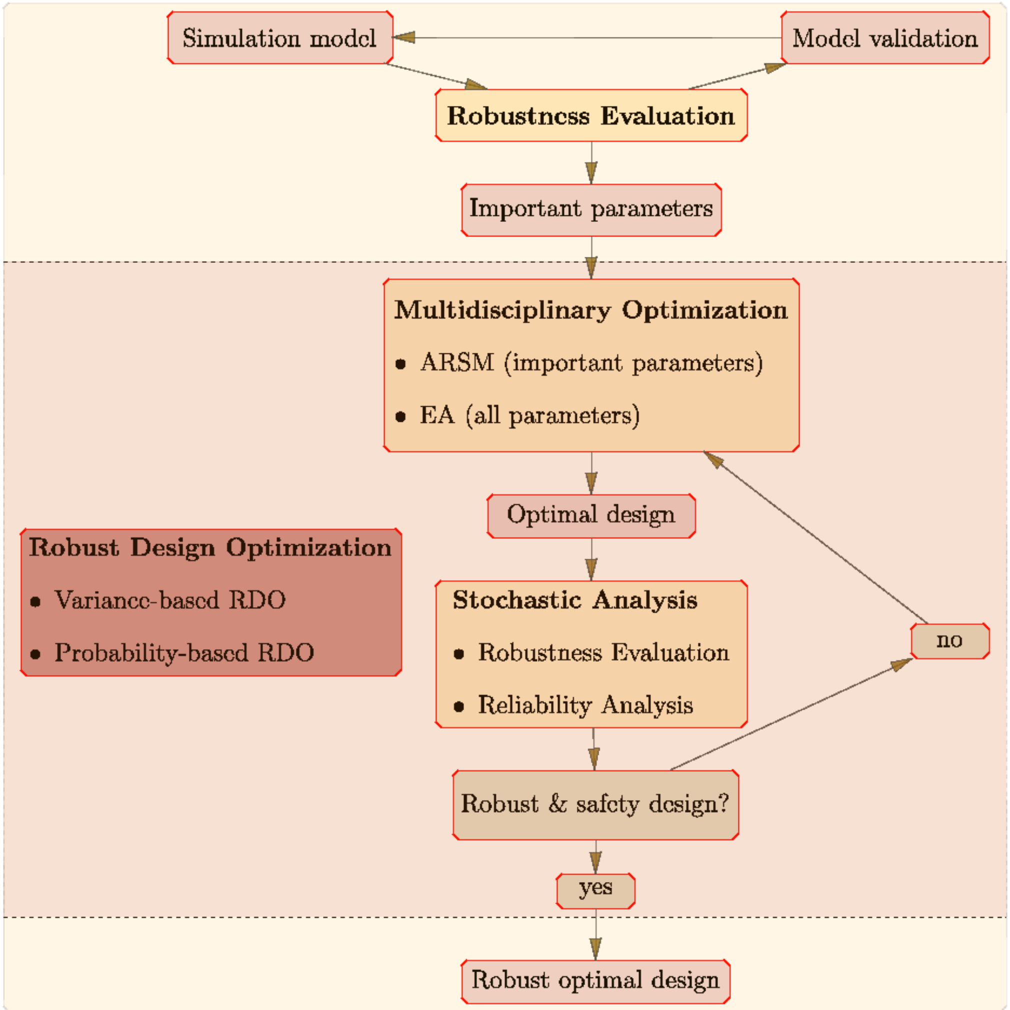


Figure 1: Basic concept of a successive robust design optimization.

Afterwards the deterministic formulation of the constraints and the objectives is to modify according to the achieved robustness, reliability or sigma level and the deterministic optimization have to be repeated until the requirements in terms of robustness and safety are fulfilled. Although, the optimization and reliability analysis runs mostly efficient in the space of the current significant parameters. So every size of problem definition (number of design and random parameters) is solvable for all kind of robustness values in combination with the consideration of the failure probability within all sigma levels. Furthermore, this proceeding allows highly flexible user interactions at every iteration step. At any time, the user can adapt the optimization problem with respect to the optimization goals, constraints and model configurations and can add additional requirements as a result of the advanced virtual design processes.

However, for a global variance-based robustness analysis (see e.g. Bucher (2007)) it is recommended to scan the design space using stochastic sampling methods and to estimate the sensitivity using the multivariate statistic based on surrogate models (for detailed reading see optiSLang (2009)).

In contrast to a standard Latin Hypercube sampling with Cholesky decomposition of the correlation matrix the advanced method minimizes the sampling error of the linear correlations by an internal optimization procedure using a column-pairwise-switch algorithm. This approach works independently of the sample size, thus it is also applied for a number of design evaluations which are smaller than the number of parameters. Additional to the generation of an initial design this advanced Latin Hypercube sampling method can be used to generate additional samples to an existing sample set. Any sampling type of the existing set can be considered, the final set is obtained by minimizing the correlation errors of the merged set of initial and additional samples. If the existing set is also generated by Latin Hypercube sampling, the optimal number of additional samples is the double amount of the initial number.

Results of a global variance-based sensitivity study are the most significant parameters of the optimization or random variables due to important model responses. So, it is possible to identify the sub domains and very efficient adaptive approximation methods can be used for optimization and reliability analysis (Roos et al. (2006)).

3 Process integration

3.1 Introduction

Typically, there are two ways for integration of arbitrary external CAD and CAE programs, as shown in figure 2. First, reading and writing of parametric data to and from ASCII input and output files, is the most general way to doing integration of any engineering processes. The second way provides CAD-based parameterization using bidirectional interfaces to binary input and output parameters. Therefore exit several optiSLang interfaces, e.g. for ANSYS, ABAQUS, CATIA and EXCEL. Within the application example we used the optiPlug interface to ANSYS Workbench.

3.2 Binary-based parameter process integration

For a most user-friendly integration of the CAD model and FEM analysis we used the ANSYS Workbench environment, as shown in figure 3. ANSYS Workbench reads and writes binary data to and from many CAD software in order to explore a wide range of responses. Within Workbench all input and output parameters are created. The optiPlug interface creates an optiSLang project with predefined parameter descriptions and writes and reads the current parameters and responses. Furthermore, optiSLang starts Workbench as a batch process, if necessary using parallel distribution of several Workbench processes.

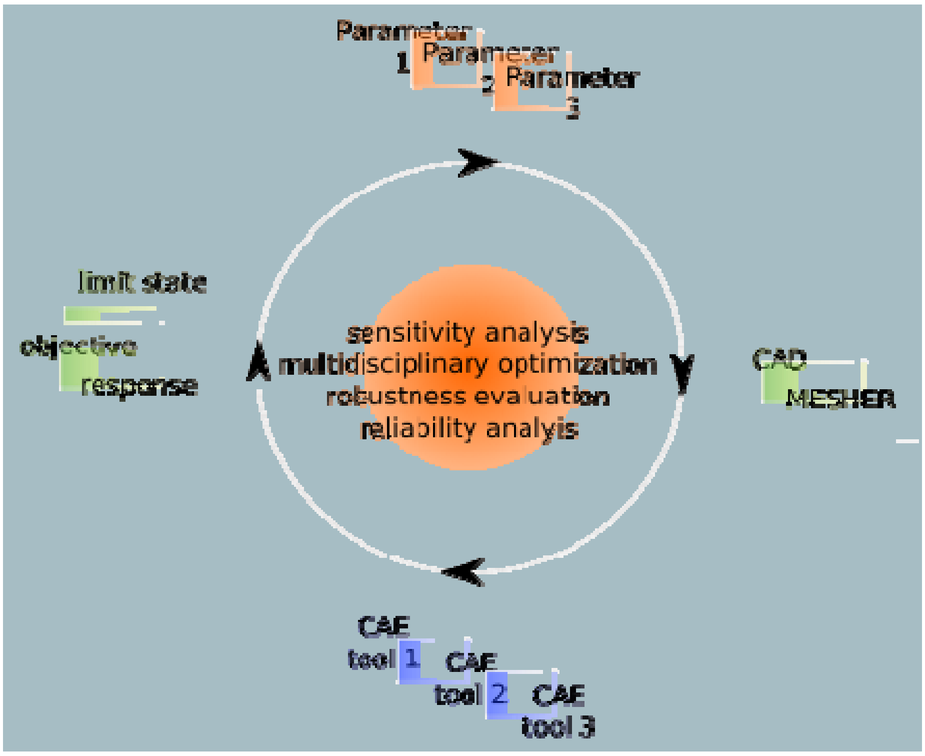


Figure 2: Definition of parameters and optimization task and process integration of arbitrary CAD and CAE tools in the context of optimization and stochastic analysis.

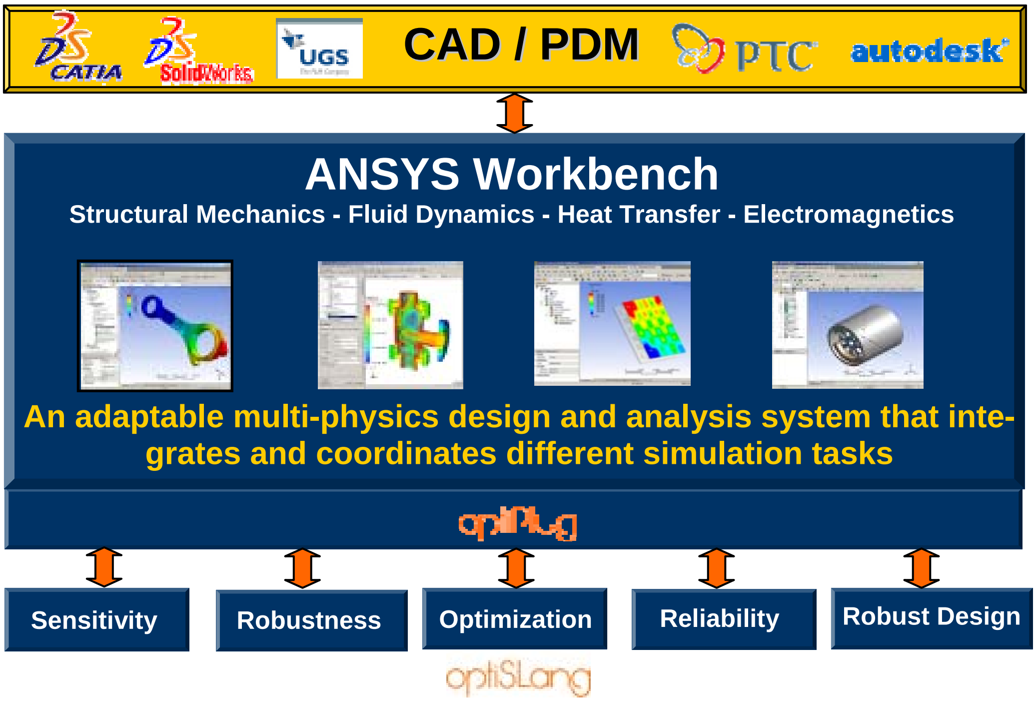


Figure 3: Binary-based CAE parameter definition within the ANSYS Workbench environment and using the optiPlug interface of optiSLang.

4 Application example

4.1 Design for six sigma of the connector element

The figure 4 shows the CAD model of the electronic connector element with two double counted spring rows. To ensure the functionality of the connector 50% of the contact forces should be greater than 1N and the sum of all forces should be lesser than 50N. Due to the influence of the body deformation the contact forces of each spring is influenced by the forces of all other springs. Related design parameters are the geometry parameters of the springs, as shown in figure 5. To solve this kind of design problem the deterministic optimization could be used but the reliability of the connector element is determined by the influence of the uncertainty of the geometry. To prove the reliability of the initial design we used the robustness analysis to estimate the sigma level. And the robust design optimization is used to increase the reliability to achieve six sigma design.

4.2 Model description

The ProE-model of MCon63 with full parametric definition of contact spring is given in Figure 4.

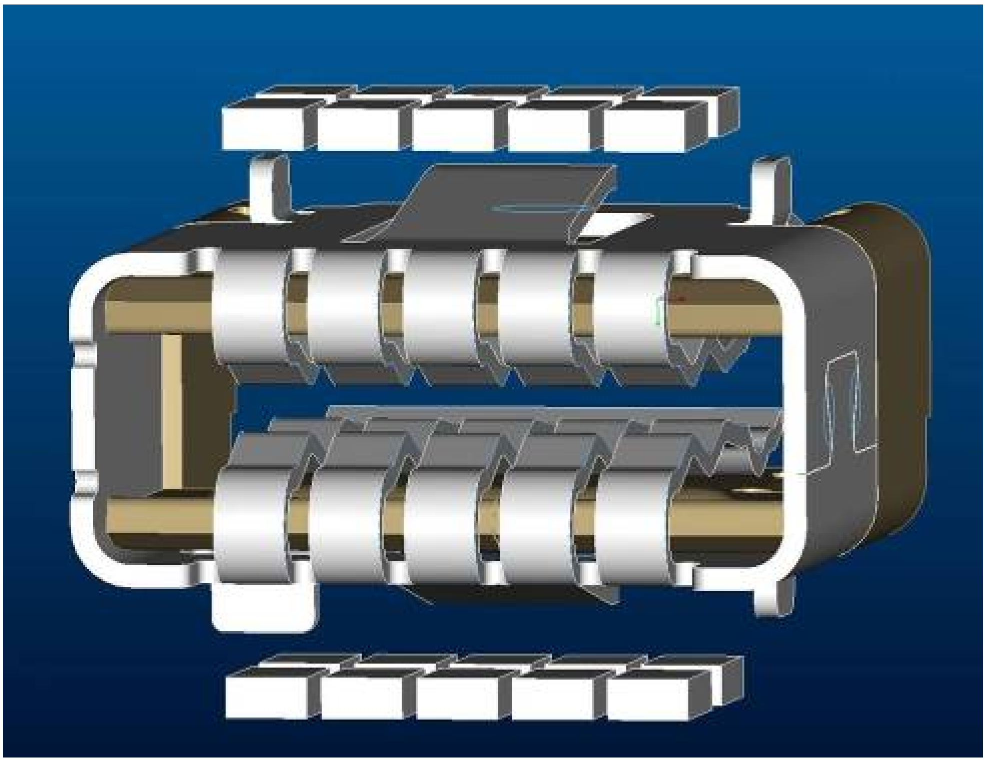


Figure 4: ProE CAD model of MCon63

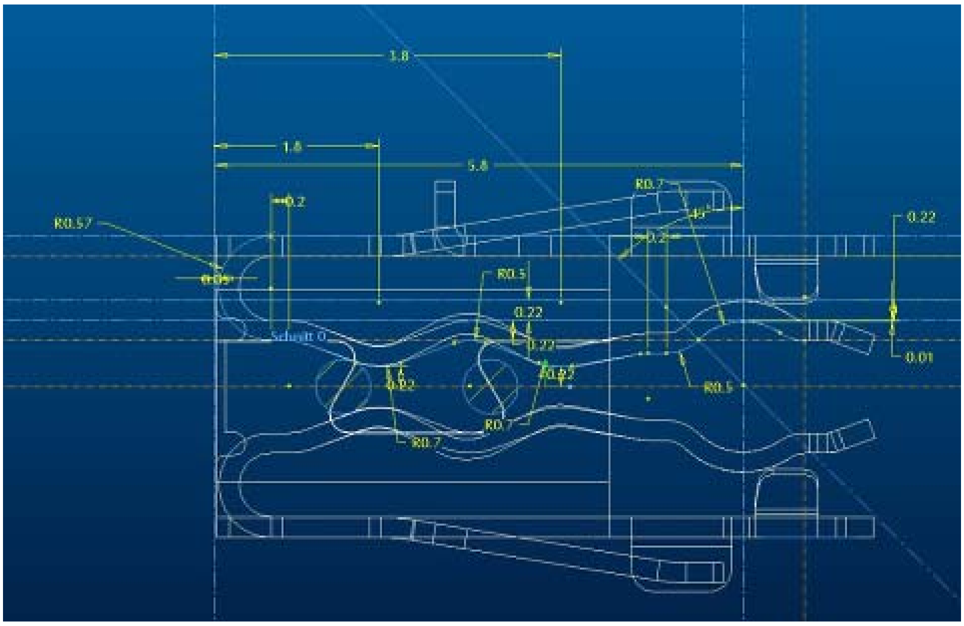


Figure 5: ProE CAD with 36 defined geometric parameters.

In sketch of CAD-model in Figure 5 all parameters of influence on gape size and spring alignment to body are defined.

4.3 Design parameters and uncertainties

The design parameters P1…P36 are used for description of the uncertainties of the input parameter in geometry. All parameters are independent to each other in wide range and therefore also geometry is changeable. Definition of parameters in sketch must obtain that all parameters are changeable in wide range without any errors in CAD-Model.

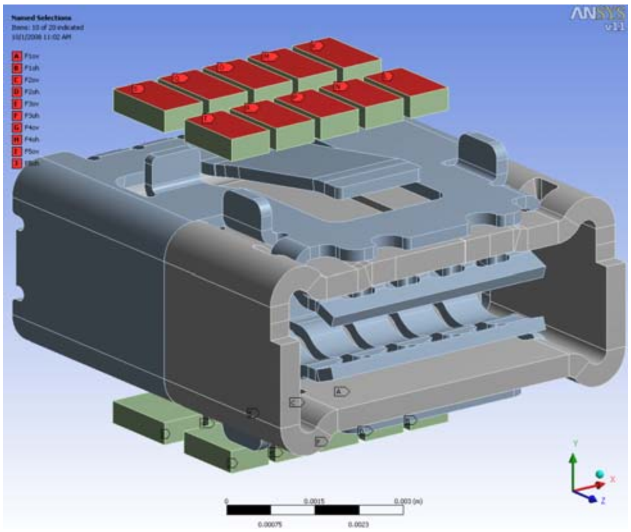


Figure 6: ANSYS Workbench model with 10 response parameters of the contact forces.

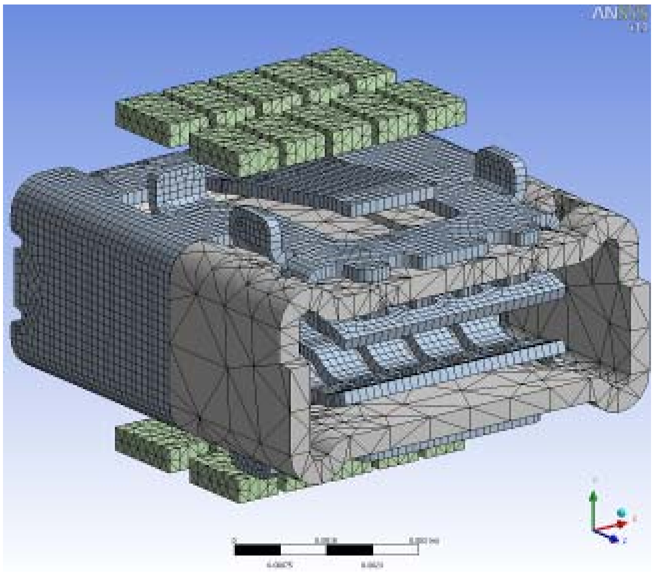
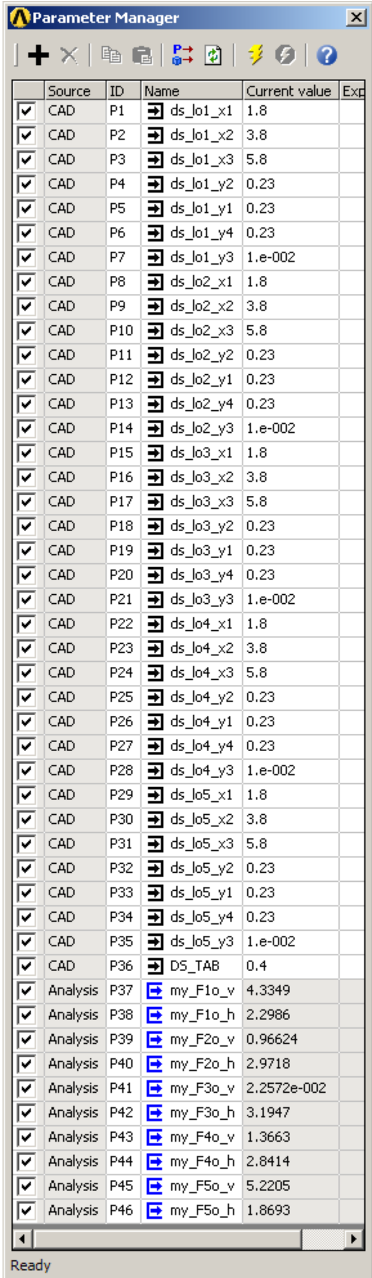


Figure 7: ANSYS Workbench finite element model with 35.000 nodes.



	Source	ID	Name	Current value	Exp
☑	CAD	P1	ds_lo1_x1	1.8	
☑	CAD	P2	ds_lo1_x2	3.8	
☑	CAD	P3	ds_lo1_x3	5.8	
☑	CAD	P4	ds_lo1_y2	0.23	
☑	CAD	P5	ds_lo1_y1	0.23	
☑	CAD	P6	ds_lo1_y4	0.23	
☑	CAD	P7	ds_lo1_y3	1.e-002	
☑	CAD	P8	ds_lo2_x1	1.8	
☑	CAD	P9	ds_lo2_x2	3.8	
☑	CAD	P10	ds_lo2_x3	5.8	
☑	CAD	P11	ds_lo2_y2	0.23	
☑	CAD	P12	ds_lo2_y1	0.23	
☑	CAD	P13	ds_lo2_y4	0.23	
☑	CAD	P14	ds_lo2_y3	1.e-002	
☑	CAD	P15	ds_lo3_x1	1.8	
☑	CAD	P16	ds_lo3_x2	3.8	
☑	CAD	P17	ds_lo3_x3	5.8	
☑	CAD	P18	ds_lo3_y2	0.23	
☑	CAD	P19	ds_lo3_y1	0.23	
☑	CAD	P20	ds_lo3_y4	0.23	
☑	CAD	P21	ds_lo3_y3	1.e-002	
☑	CAD	P22	ds_lo4_x1	1.8	
☑	CAD	P23	ds_lo4_x2	3.8	
☑	CAD	P24	ds_lo4_x3	5.8	
☑	CAD	P25	ds_lo4_y2	0.23	
☑	CAD	P26	ds_lo4_y1	0.23	
☑	CAD	P27	ds_lo4_y4	0.23	
☑	CAD	P28	ds_lo4_y3	1.e-002	
☑	CAD	P29	ds_lo5_x1	1.8	
☑	CAD	P30	ds_lo5_x2	3.8	
☑	CAD	P31	ds_lo5_x3	5.8	
☑	CAD	P32	ds_lo5_y2	0.23	
☑	CAD	P33	ds_lo5_y1	0.23	
☑	CAD	P34	ds_lo5_y4	0.23	
☑	CAD	P35	ds_lo5_y3	1.e-002	
☑	CAD	P36	DS_TAB	0.4	
☑	Analysis	P37	my_F1o_v	4.3349	
☑	Analysis	P38	my_F1o_h	2.2986	
☑	Analysis	P39	my_F2o_v	0.96624	
☑	Analysis	P40	my_F2o_h	2.9718	
☑	Analysis	P41	my_F3o_v	2.2572e-002	
☑	Analysis	P42	my_F3o_h	3.1947	
☑	Analysis	P43	my_F4o_v	1.3663	
☑	Analysis	P44	my_F4o_h	2.8414	
☑	Analysis	P45	my_F5o_v	5.2205	
☑	Analysis	P46	my_F5o_h	1.8693	

Figure 8: Defined input and output parameters.

4.4 Results of the robust design optimization

4.4.1 Evaluate the robustness of the initial design

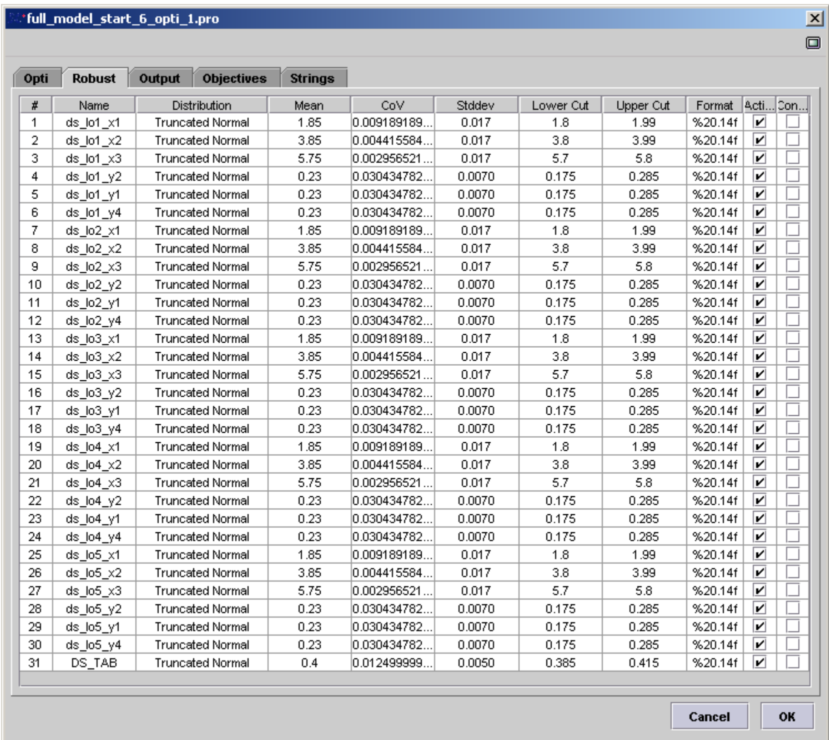
The first most important step for a successful and efficient optimization procedure is to evaluate the robustness of the initial design. Introducing the given uncertainties of the n=31 important random parameters, as shown in figure 8, the Latin

Hypercube sampling with N=90 design evaluations in parallel gives the scatter of all performance relevant response parameters, as shown in figure 9. In this figure a relative large number of design evaluations fail cause the contact force F3o_v is equal to zero. The statistic of the response parameters samples can be explained by the histogram of the response parameters. Figure 11 shows the histogram of the critical contact force F3o_v with the limit state condition for the contact force is 1N, including the numerical outliers.

The estimation of the failure probability using the distribution fit in figure 12 gives an unacceptable value of 89% for violating the limit state condition.

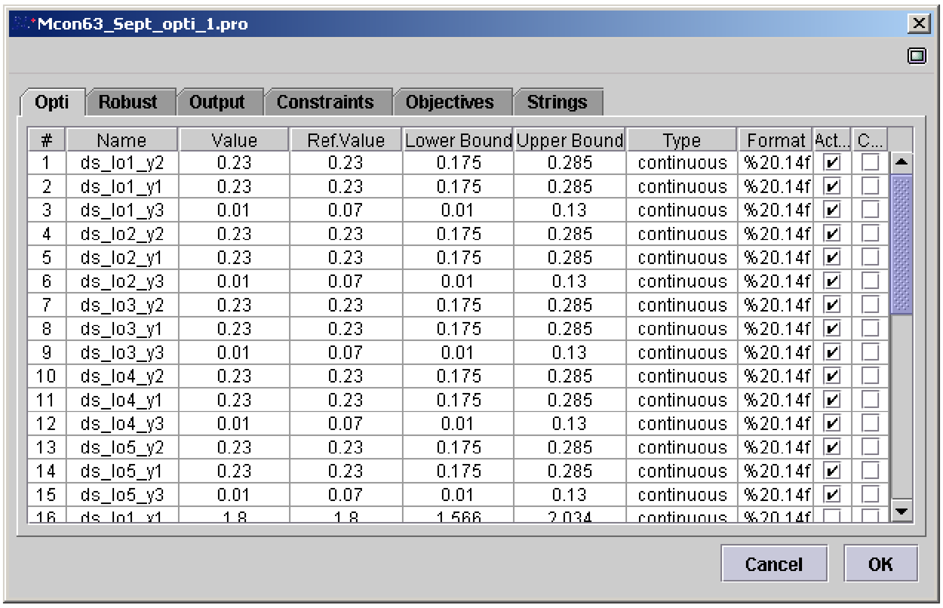
The matrix of the linear coefficients of correlation in figure 14 shows only few input parameters for each contact force which have a strong linear correlation. The matrix shows only the statistical significant correlations which are greater than the statistical error of the simulated correlation of the input parameters. The confidence levels of the coefficients of correlation 0.5 and 0.7 show the possibility to reduce the necessary number of design evaluation for the next robustness evaluations.

The coefficients of importance (COI) can be used to detect multivariate significant input parameters. Figure 13 shows e.g. all COI for the critical output F3o_v. Whereby the most important parameters are lo3_y1 and lo3_y2. The adjusted value of R^2 gives the amount of variance of F3o_v that can explained by a linear regression model including all significant input parameters and gives the optimization potential within the given design parameter boundaries.



#	Name	Distribution	Mean	CoV	Stddev	Lower Cut	Upper Cut	Format	Acti...	Con...
1	ds_lo1_x1	Truncated Normal	1.85	0.009189189...	0.017	1.8	1.99	%20.14f	☑	☐
2	ds_lo1_x2	Truncated Normal	3.85	0.004415584...	0.017	3.8	3.99	%20.14f	☑	☐
3	ds_lo1_x3	Truncated Normal	5.75	0.002956521...	0.017	5.7	5.8	%20.14f	☑	☐
4	ds_lo1_y2	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
5	ds_lo1_y1	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
6	ds_lo1_y4	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
7	ds_lo2_x1	Truncated Normal	1.85	0.009189189...	0.017	1.8	1.99	%20.14f	☑	☐
8	ds_lo2_x2	Truncated Normal	3.85	0.004415584...	0.017	3.8	3.99	%20.14f	☑	☐
9	ds_lo2_x3	Truncated Normal	5.75	0.002956521...	0.017	5.7	5.8	%20.14f	☑	☐
10	ds_lo2_y2	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
11	ds_lo2_y1	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
12	ds_lo2_y4	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
13	ds_lo3_x1	Truncated Normal	1.85	0.009189189...	0.017	1.8	1.99	%20.14f	☑	☐
14	ds_lo3_x2	Truncated Normal	3.85	0.004415584...	0.017	3.8	3.99	%20.14f	☑	☐
15	ds_lo3_x3	Truncated Normal	5.75	0.002956521...	0.017	5.7	5.8	%20.14f	☑	☐
16	ds_lo3_y2	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
17	ds_lo3_y1	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
18	ds_lo3_y4	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
19	ds_lo4_x1	Truncated Normal	1.85	0.009189189...	0.017	1.8	1.99	%20.14f	☑	☐
20	ds_lo4_x2	Truncated Normal	3.85	0.004415584...	0.017	3.8	3.99	%20.14f	☑	☐
21	ds_lo4_x3	Truncated Normal	5.75	0.002956521...	0.017	5.7	5.8	%20.14f	☑	☐
22	ds_lo4_y2	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
23	ds_lo4_y1	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
24	ds_lo4_y4	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
25	ds_lo5_x1	Truncated Normal	1.85	0.009189189...	0.017	1.8	1.99	%20.14f	☑	☐
26	ds_lo5_x2	Truncated Normal	3.85	0.004415584...	0.017	3.8	3.99	%20.14f	☑	☐
27	ds_lo5_x3	Truncated Normal	5.75	0.002956521...	0.017	5.7	5.8	%20.14f	☑	☐
28	ds_lo5_y2	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
29	ds_lo5_y1	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
30	ds_lo5_y4	Truncated Normal	0.23	0.030434782...	0.0070	0.175	0.285	%20.14f	☑	☐
31	DS_TAB	Truncated Normal	0.4	0.012499999...	0.0050	0.385	0.415	%20.14f	☑	☐

Figure 9: User-defined random parameters to evaluate the robustness and to estimate the failure rate of the initial design.



#	Name	Value	Ref.Value	Lower Bound	Upper Bound	Type	Format	Act...	C...
1	ds_lo1_y2	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
2	ds_lo1_y1	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
3	ds_lo1_y3	0.01	0.07	0.01	0.13	continuous	%20.14f	☑	☐
4	ds_lo2_y2	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
5	ds_lo2_y1	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
6	ds_lo2_y3	0.01	0.07	0.01	0.13	continuous	%20.14f	☑	☐
7	ds_lo3_y2	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
8	ds_lo3_y1	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
9	ds_lo3_y3	0.01	0.07	0.01	0.13	continuous	%20.14f	☑	☐
10	ds_lo4_y2	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
11	ds_lo4_y1	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
12	ds_lo4_y3	0.01	0.07	0.01	0.13	continuous	%20.14f	☑	☐
13	ds_lo5_y2	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
14	ds_lo5_y1	0.23	0.23	0.175	0.285	continuous	%20.14f	☑	☐
15	ds_lo5_y3	0.01	0.07	0.01	0.13	continuous	%20.14f	☑	☐
16	ds_lo1_x1	1.8	1.8	1.566	2.034	continuous	%20.14f	☐	☐

Figure 10: Activated n = 15 most important CAD design parameters for the first deterministic optimization using the adaptive response surface method.

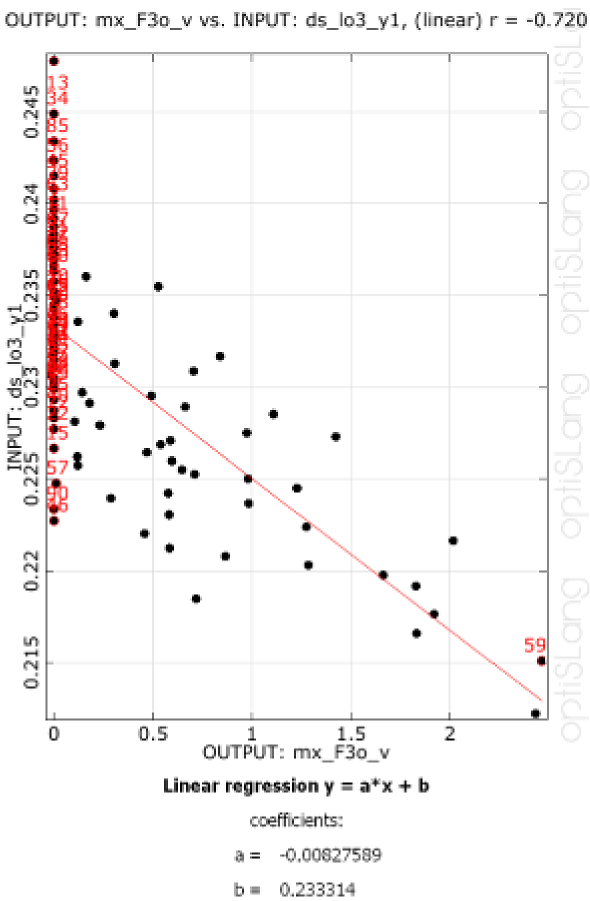
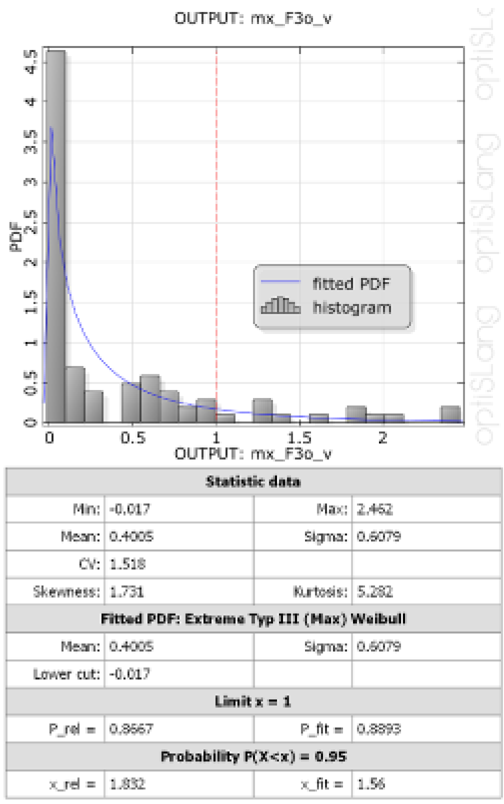


Figure 11: Anthill plot of the contact force scatter of F3o_v with the largest value and numerical outliers.



Statistic data			
Min:	-0.017	Max:	2.462
Mean:	0.4005	Sigma:	0.6079
CV:	1.518		
Skewness:	1.731	Kurtosis:	5.282
Fitted PDF: Extreme Typ III (Max) Weibull			
Mean:	0.4005	Sigma:	0.6079
Lower cut:	-0.017		
Limit x = 1			
P_rel =	0.8667	P_fit =	0.8893
Probability P(X<x) = 0.95			
x_rel =	1.832	x_fit =	1.56

Figure 12: Histogram of the critical contact force F3o_v with fitted distribution function (PDF) of the contact force F3o_v. The estimated failure probability is inside of 89% (based on the PDF) and 87% (based on the histogram).

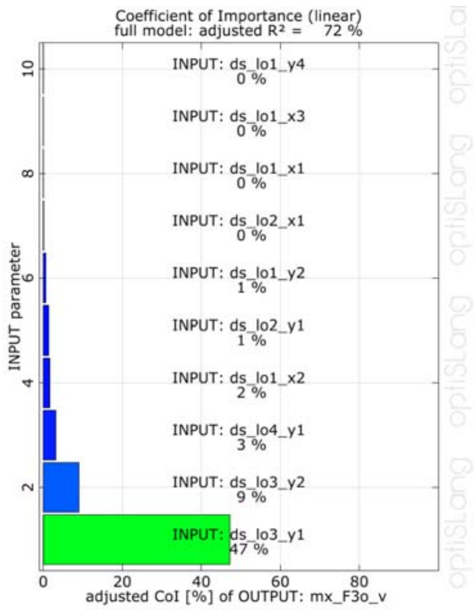


Figure 13: Coefficients of importance to detect multivariate significant input parameters e.g. for the critical output F3o_v. The adjusted value of R^2 gives the amount of variance of F3o_v that can explained by a linear regression model including all significant input parameters.

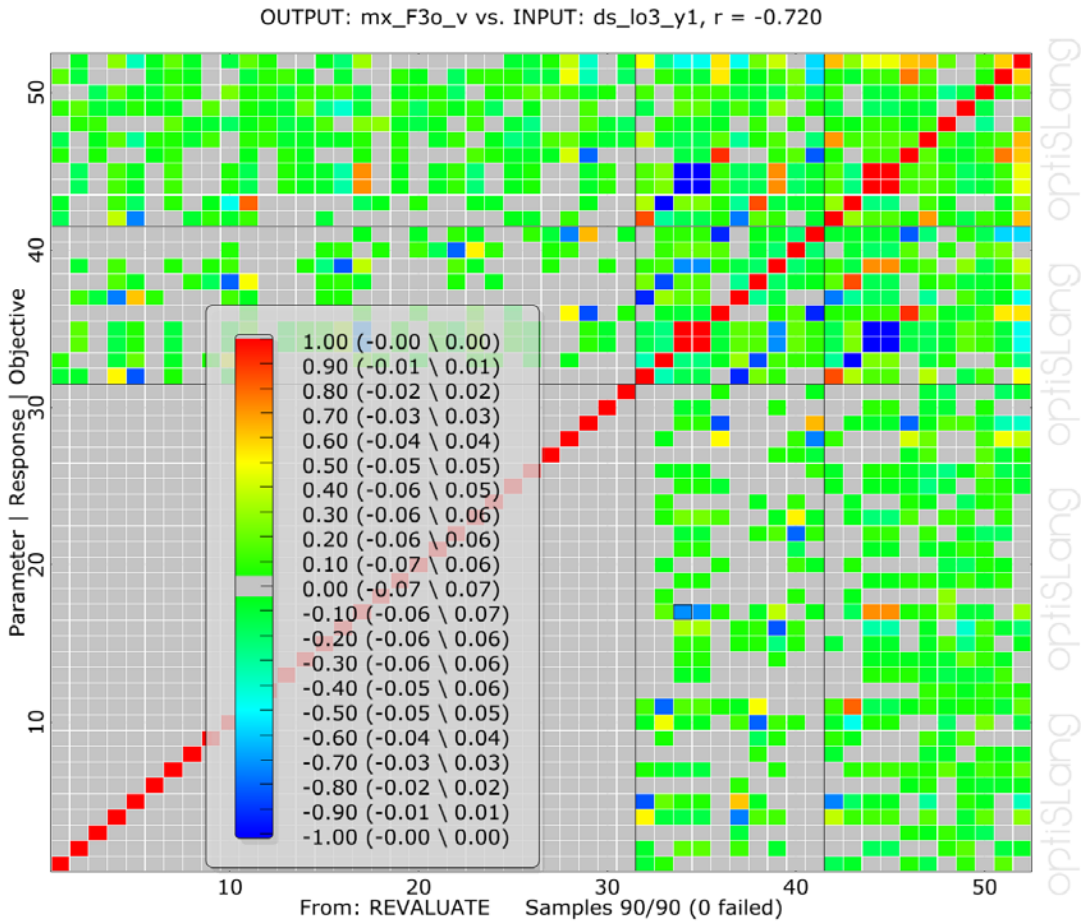
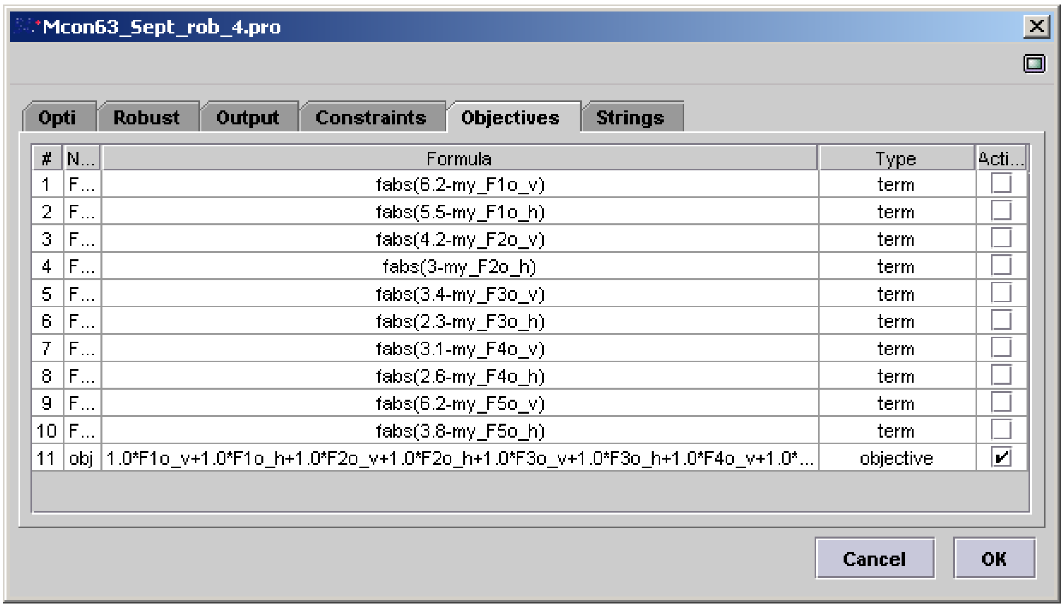


Figure 14: Matrix of the linear coefficients of correlation of the first robustness evaluation. The values in the brackets give the confidence level of the coefficients of correlation. The matrix shows only the statistical significant correlations which are greater than the statistical error of the simulated correlation of the input parameters.

4.4.2 Deterministic optimization of the initial design

Furthermore, the multivariate statistic can be used to get the most sensitive design and random parameters to increase reliability and the sigma level using the robust design optimization within a further step. An overview of all most important input parameters is given in Figure 10. As a result of the multivariate statistic the optimization problem can be reduced to n = 15 design parameters. So it is possible to use highly efficient adaptive response surface methods to maximize the distance between the mean value of the contact forces and the limit state condition of the critical contact force of 1N.

Whereby the target distance has to be greater than 4.5 times the current standard deviation of the contact force to estimate a failure probability of 3.4 out of 1 million with the assumption of normal distributed contact forces and constant standard deviations during the optimization process. Of course, this is only a rough estimation within a six sigma concept and a reliability analysis of the final design is recommended.



#	N...	Formula	Type	Acti...
1	F...	fabs(6.2-my_F1o_v)	term	☐
2	F...	fabs(5.5-my_F1o_h)	term	☐
3	F...	fabs(4.2-my_F2o_v)	term	☐
4	F...	fabs(3-my_F2o_h)	term	☐
5	F...	fabs(3.4-my_F3o_v)	term	☐
6	F...	fabs(2.3-my_F3o_h)	term	☐
7	F...	fabs(3.1-my_F4o_v)	term	☐
8	F...	fabs(2.6-my_F4o_h)	term	☐
9	F...	fabs(6.2-my_F5o_v)	term	☐
10	F...	fabs(3.8-my_F5o_h)	term	☐
11	obj	1.0*F1o_v+1.0*F1o_h+1.0*F2o_v+1.0*F2o_h+1.0*F3o_v+1.0*F3o_h+1.0*F4o_v+1.0*...	objective	☑

Figure 15: Objective function definition as a weighted minimal distance approach with respect to the 10 contact force limits of 1N. The target contact forces are result from six sigma estimation based on the means and standard deviations of the assigned histograms (e.g. the histogram of the critical contact force of the figure 23).

Figure 15 shows the minimal distance function approach to define a weighted objective function to ensure an adequate distance of the mean values with respect to the limit contact force of 1N. The distance depends on the means and standard deviations of the current iteration. First, we used a very efficient adaptive response surface approach to get a pre-optimized design with a very small number of design evaluations of N=126. The adaptive D-optimal design of experiment is shown in figure 16.

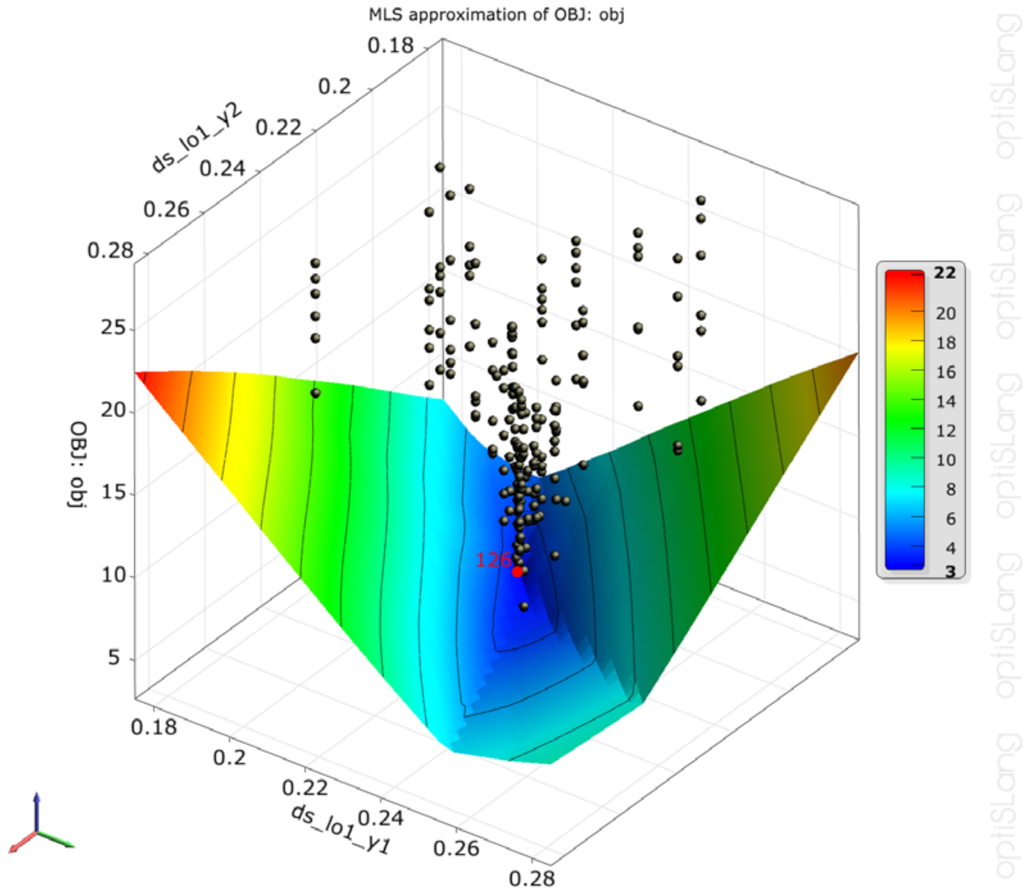
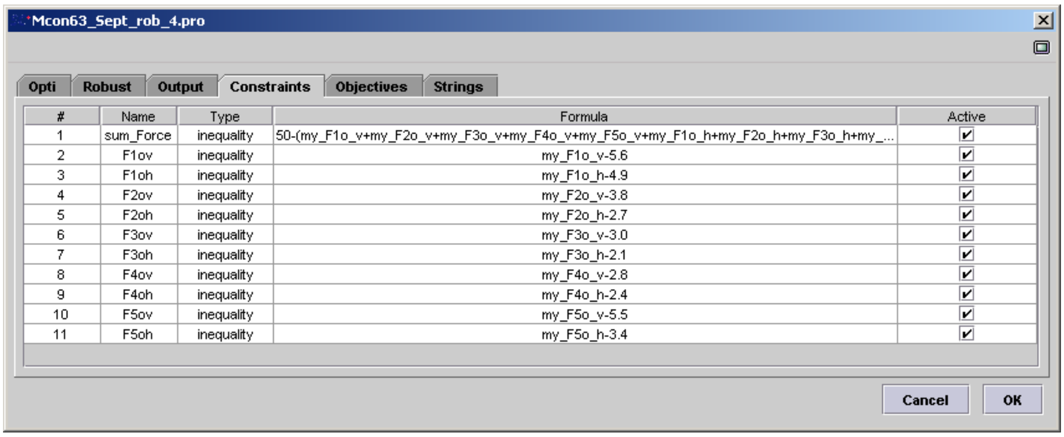


Figure 16: Visualization of the objective function in the two-dimensional subspace. After the 5th adaption of the D-optimal design of experiment the optimization process ends with a stagnation of the objective improvement with the best design 126. The calculation time amounts 25 hours on 8 Xeon 2.66 GHz CPUs.

However, after the 5th adaption of the design of experiment a stagnation of the objective improvement appears (as shown in figure 16) as a result of using the objective terms to shift the mean values instead using of constraints. In particular the performance critical contact force is F3o_v has to be formulated as a restriction. For this kind of problems it is recommended to search for feasible designs introducing restrictions with respect to the contact force limitations in combination with an evolutionary global search strategy.



Mcon63_Sept_rob_4.pro

Opti | Robust | Output | Constraints | Objectives | Strings

#	Name	Type	Formula	Active
1	sum_Force	inequality	50-(my_F1o_v+my_F2o_v+my_F3o_v+my_F4o_v+my_F5o_v+my_F1o_h+my_F2o_h+my_F3o_h+my_...	☑
2	F1ov	inequality	my_F1o_v-5.6	☑
3	F1oh	inequality	my_F1o_h-4.9	☑
4	F2ov	inequality	my_F2o_v-3.8	☑
5	F2oh	inequality	my_F2o_h-2.7	☑
6	F3ov	inequality	my_F3o_v-3.0	☑
7	F3oh	inequality	my_F3o_h-2.1	☑
8	F4ov	inequality	my_F4o_v-2.8	☑
9	F4oh	inequality	my_F4o_h-2.4	☑
10	F5ov	inequality	my_F5o_v-5.5	☑
11	F5oh	inequality	my_F5o_h-3.4	☑

Cancel | OK

Figure 17: Definition of the constraints to obtain a feasible start design for the next optimization step.

Whereby the sum of the contact force is defined as an additional restriction and has to be lesser than 50N, as shown in figure 17.

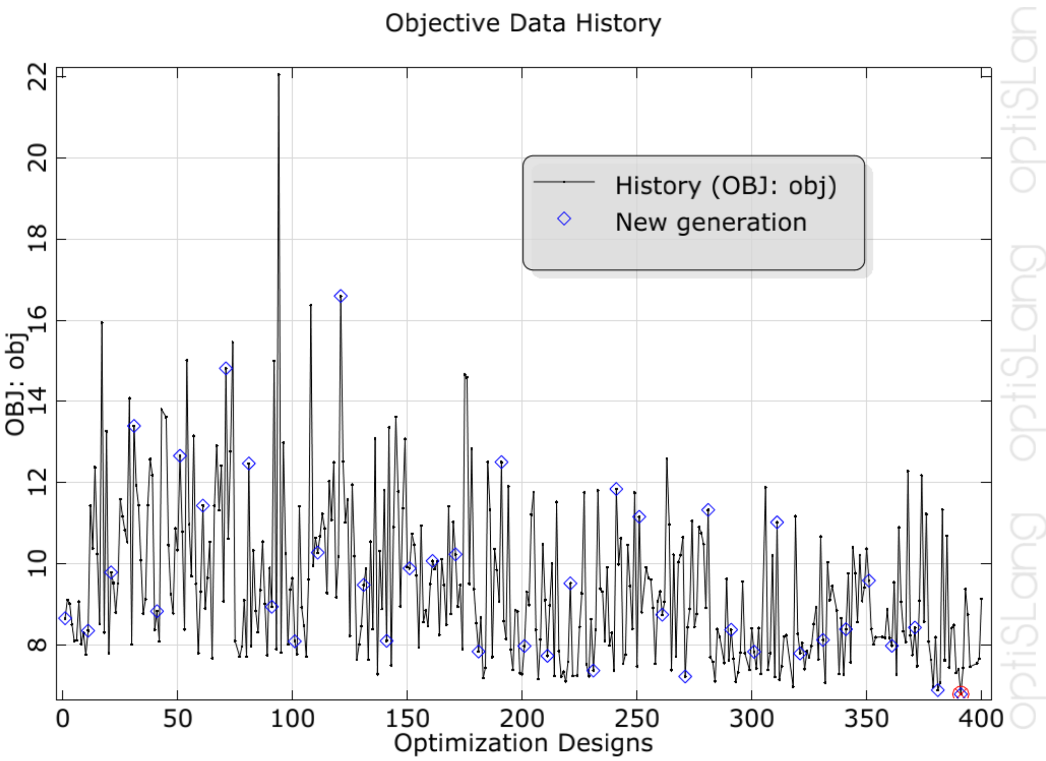


Figure 18: History of the objective convergence of the global evolutionary search strategy with N=391 parallel finite element calculation and a calculation time of 80 hours. The slow convergence is a result of the global feasible search strategy to satisfy the contact force restrictions.

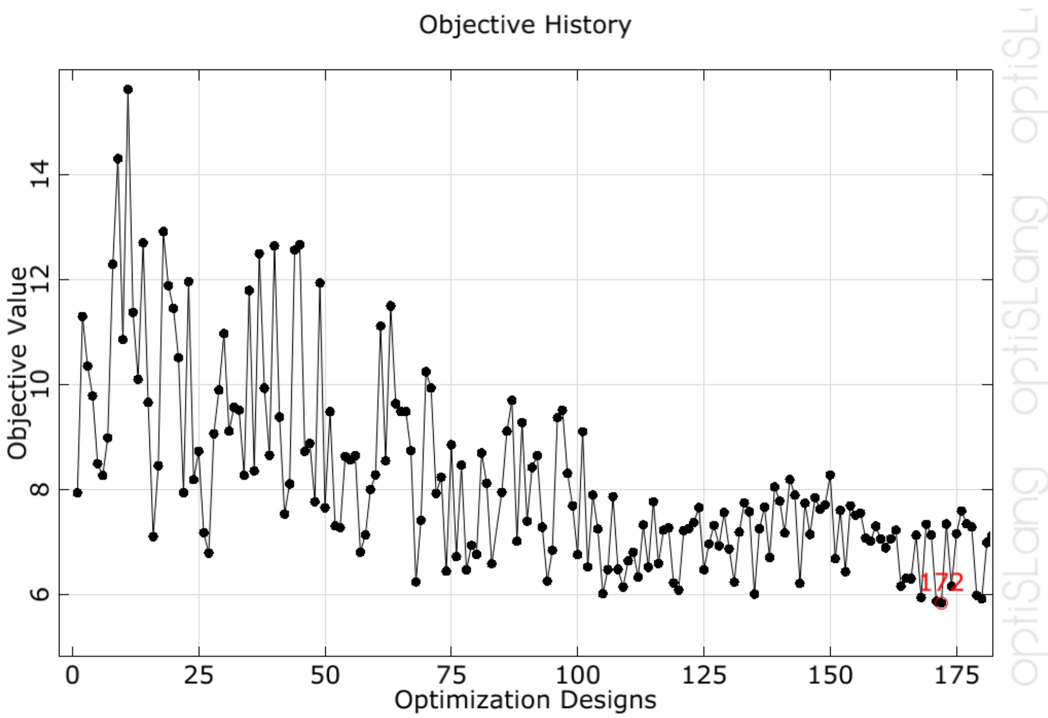


Figure 19: History of the objective convergence of the local design improvement using an adaptive D-optimal design of experiment in combination with ARSM with N=172 parallel finite element calculation and a calculation time of 35 hours.

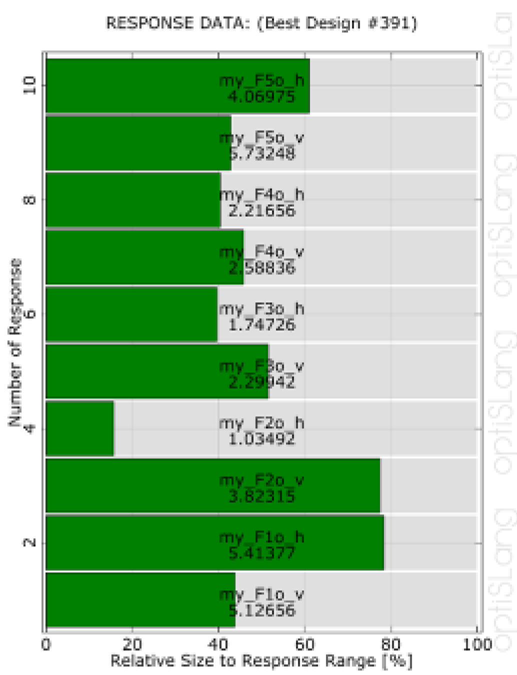


Figure 20: Mean values of the contact forces as a result of the global feasible design search. The mean value of the performance critical contact force F3o_v increases.

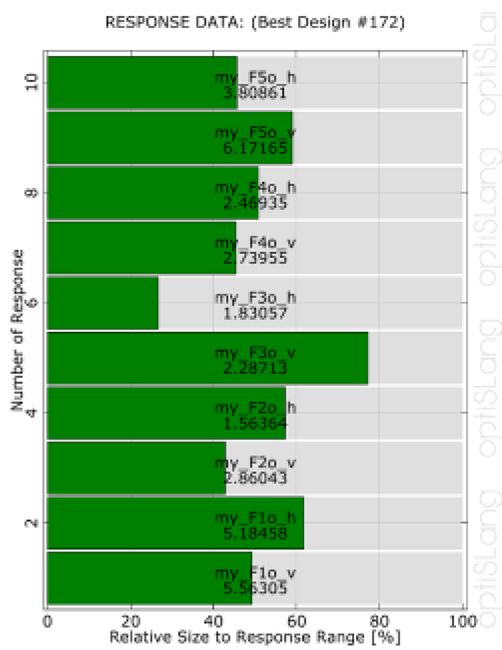
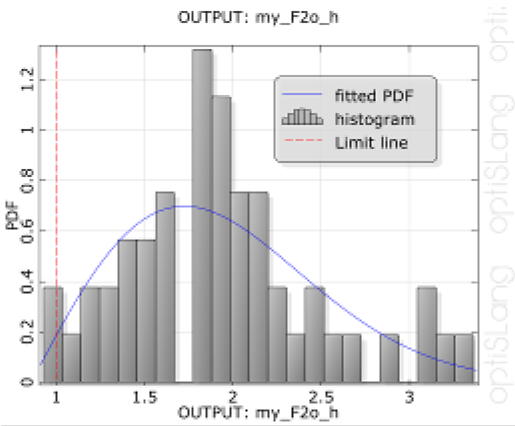


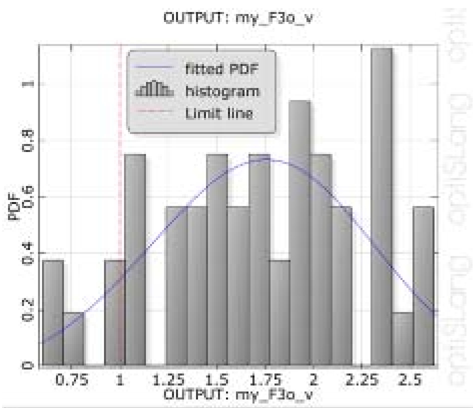
Figure 21: The mean value of the non-critical contact force F2o_h decreases during the local design improvement using ARSM.

The global search evolutionary optimization is based on the best design of the first global ARSM optimization and needs 391 parallel finite element calculations to obtain a feasible start design in the total design space with n=30 design parameters, as shown in figure 18. In figure 20, the resulting mean values of the contact forces show an increasing of the critical contact force F3o_v but a decreasing of the mean value of F2o_h. A local (the start range takes 20% of the total design space) design improvement with the objective convergence a shown in figure 19 using an adaptive D-optimal design of experiment in combination with adaptive response surfaces increases the mean of the force F2o_h to an acceptable compromise result as shown in figure 21. As a result of the three deterministic optimization steps the mean values of all contact forces do not violate the limit state of 1N.



Statistic data			
Min:	0.9273	Max:	3.364
Mean:	1.944	Sigma:	0.5676
CV:	0.2919		
Skewness:	0.5921	Kurtosis:	3.084
Fitted PDF: Rayleigh			
Mean:	1.944	Sigma:	0.5676
Limit x = 1			
P_rel =	0.02	P_fit =	0.0133
Probability P(X<x) = 0.95			
x_rel =	3.078	x_fit =	2.979

Figure 22: Histogram with fitted distribution function (PDF) of the contact force F2o_h. The estimated failure probability is inside of 1% (based on the PDF) and 2% (based on the histogram).

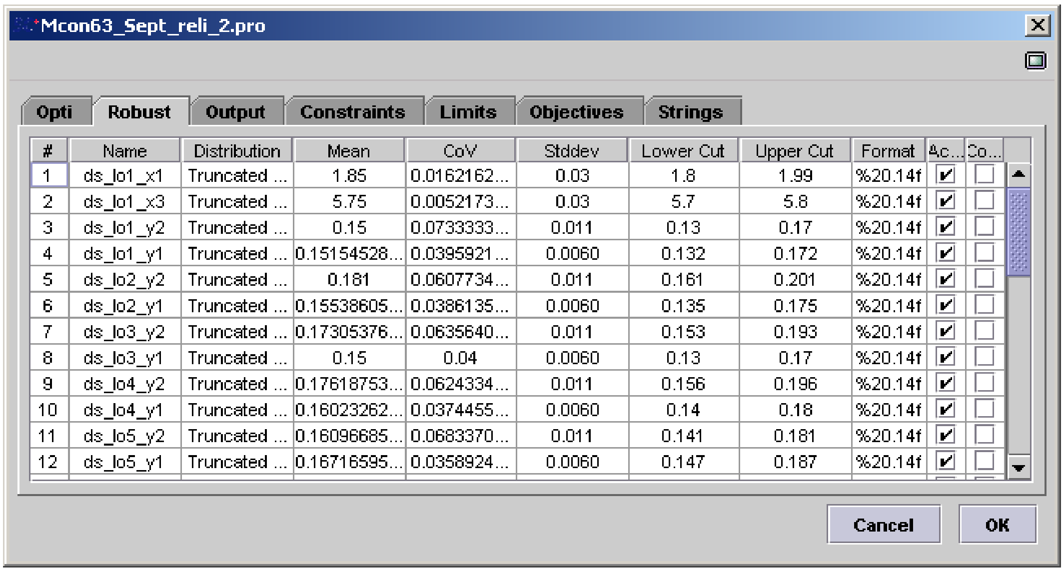


Statistic data			
Min:	0.5997	Max:	2.622
Mean:	1.728	Sigma:	0.525
CV:	0.3038		
Skewness:	-0.2233	Kurtosis:	2.251
Fitted PDF: Weibull (2p)			
Mean:	1.728	Sigma:	0.525
Limit x = 1			
P_rel =	0.08	P_fit =	0.08832
Probability P(X<x) = 0.95			
x_rel =	2.575	x_fit =	2.585

Figure 23: Histogram with fitted distribution function (PDF) of the contact force F3o_v. The estimated failure probability is inside of 9% (based on the PDF) and 8% (based on the histogram).

4.4.3 Evaluate the robustness of the optimized design

The third step within an iterative stepwise robust design optimization is to evaluate the robustness of the current optimal design. Introducing the given uncertainties of the n=36 CAD parameters an advanced Latin Hypercube sampling with N=50 design evaluations is used to prove the robustness of the structural system by means of the target distance of the mean values of the contact forces to the limit state condition of 1N.


*Mcon63_Sept_reli_2.pro

Opti | Robust | Output | Constraints | Limits | Objectives | Strings

#	Name	Distribution	Mean	CoV	Stddev	Lower Cut	Upper Cut	Format	Ac...	Co...
1	ds_lo1_x1	Truncated ...	1.85	0.0162162...	0.03	1.8	1.99	%20.14f	☑	☐
2	ds_lo1_x3	Truncated ...	5.75	0.0052173...	0.03	5.7	5.8	%20.14f	☑	☐
3	ds_lo1_y2	Truncated ...	0.15	0.0733333...	0.011	0.13	0.17	%20.14f	☑	☐
4	ds_lo1_y1	Truncated ...	0.15154528...	0.0395921...	0.0060	0.132	0.172	%20.14f	☑	☐
5	ds_lo2_y2	Truncated ...	0.181	0.0607734...	0.011	0.161	0.201	%20.14f	☑	☐
6	ds_lo2_y1	Truncated ...	0.15538605...	0.0386135...	0.0060	0.135	0.175	%20.14f	☑	☐
7	ds_lo3_y2	Truncated ...	0.17305376...	0.0635640...	0.011	0.153	0.193	%20.14f	☑	☐
8	ds_lo3_y1	Truncated ...	0.15	0.04	0.0060	0.13	0.17	%20.14f	☑	☐
9	ds_lo4_y2	Truncated ...	0.17618753...	0.0624334...	0.011	0.156	0.196	%20.14f	☑	☐
10	ds_lo4_y1	Truncated ...	0.16023262...	0.0374455...	0.0060	0.14	0.18	%20.14f	☑	☐
11	ds_lo5_y2	Truncated ...	0.16096685...	0.0683370...	0.011	0.141	0.181	%20.14f	☑	☐
12	ds_lo5_y1	Truncated ...	0.16716595...	0.0358924...	0.0060	0.147	0.187	%20.14f	☑	☐

Cancel | OK

Figure 24: *n*=12 most sensitive parameters with a large coefficient of importance of the contact forces.

The required distance depends on the current standard deviation of the contact force to estimate a failure probability less than 10%. The figures 22 and 23 show the contact forces with the largest failure probabilities up to 9%, which is less than the failure probability 89% of the initial design (see figure 12). In addition, numerical outliers are not longer available for the optimized design.

An additional result of the global variance-based sensitivity study is the identification of the most significant parameters of the random variables due to important model response contact forces. Figure 24 shows the most important *n*=12 out of 36 CAD parameters which have a large influence of the variance of the contact forces.

4.4.4 Reliability analysis of the optimized design

In the previous section the estimation of the failure probability is based on a fitting of the histogram with a probability density function using *N*=50 samples (design evaluations). Of course, this is only a rough estimation within a six sigma concept and a reliability analysis of the final design is recommended, especially for small probability levels less than 4.5% or a sigma level greater than 2.

With the identification of the random sub domain (see figure 25) a very efficient adaptive approximation methods can be used for reliability analysis (Roos et al. (2006)). Whereby, the failure state is defined by means of a critical number of contacts which have a contact force less than 1N. In our case this is given in case of more than 50% of the contacts of the electronic connector.

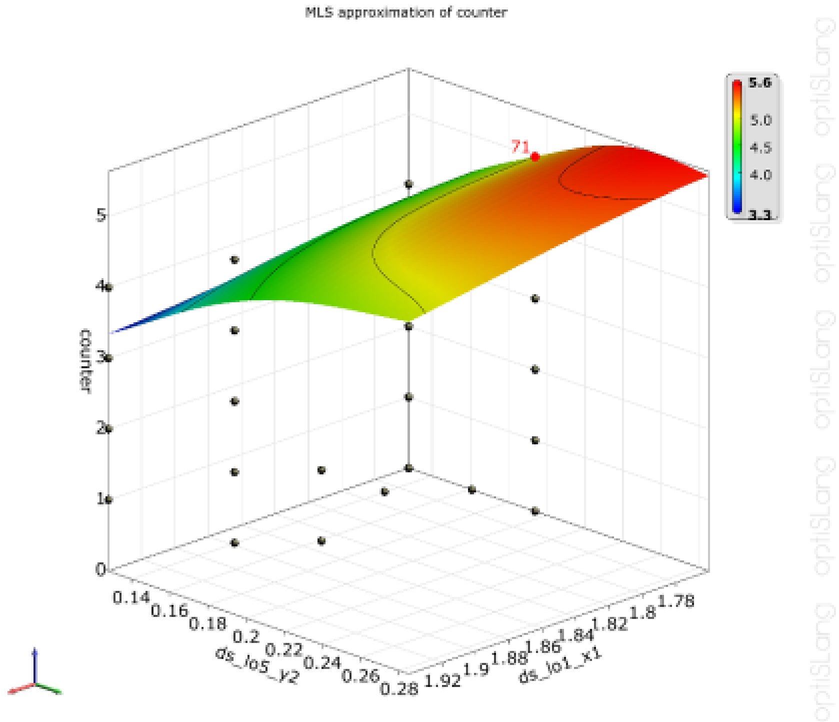


Figure 25: N=137 D-optimal design of experiment support points and a moving least square approximation of the state function $g(\mathbf{X}) > 5$.

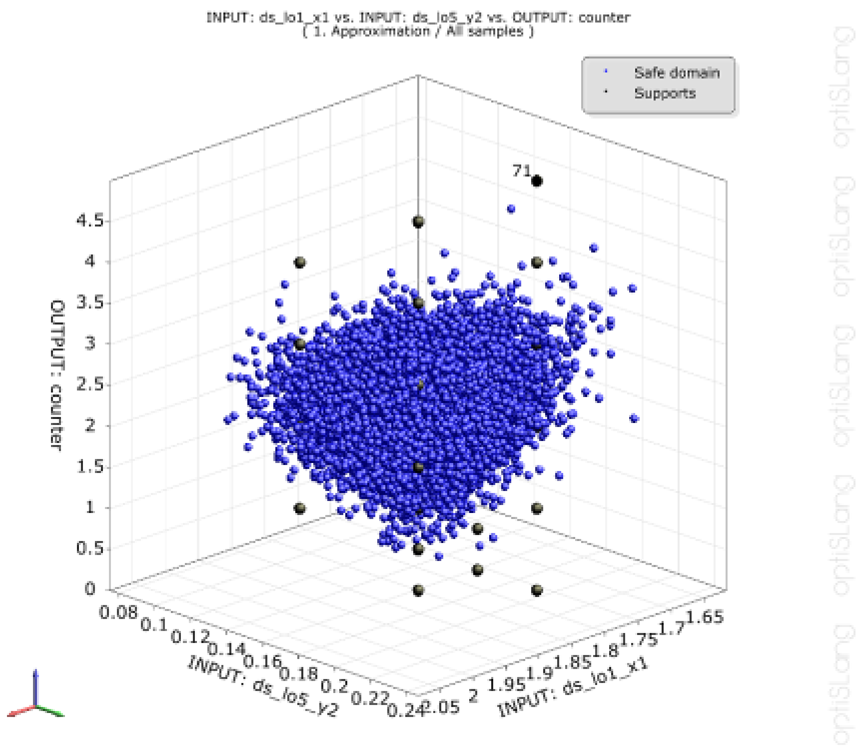


Figure 26: Adaptive sampling on the approximation of the state function without samples in the unsafe domain and a failure probability near zero.

For the optimized design the adaptive response surface method is based on *N*=137 design evaluations of a D-optimal design of experiment, as shown in figure 25. The adaptive sampling procedure in figure 26 on the surrogate model does not detect samples in the unsafe domain. This means that the failure probability is numerically zero. So it is proven that the optimized design is a so called Six Sigma Design.

5 Summary

Robust design optimization can provide multiple benefits. It permits the identification of those design parameters that are critical for the achievement of a certain performance characteristic. A proper adjustment of the thus identified parameters to hit the target performance is supported. This can significantly reduce product costs. The effect of variations on the product behaviour and performance can be quantified. Moreover, robust design optimization can lead to a deeper understanding of the potential sources of variations. Hence, a minimization of the effect of variations (noise) is made possible, and appropriate steps to desensitize the design to these variations can be determined. Consequently, more robust and affordable product designs can be achieved.

For the presented variance and probability-based robust design optimization of the electronic connector with in total *n*=36 random CAD parameters the resulting system failure probability could be reduced to zero. Additional result of the optimization procedure is a Six Sigma Design without numerical outliers. In summary, *N*=950 parallel finite element calculations are needed with a total calculation time of 1 week on 8 Xeon 2.66 GHz CPUs. In this sense, the provided successive robust design optimization approach is applicable for Design for Six Sigma Analysis of real world applications with highly efficiency.

References

BUCHER, C.: Basic concepts for robustness evaluation using stochastic analysis. In: *Proceedings of the EUROMECH Colloquium 482.* London, September 10-12, 2007

CHEN, W.; LIU, H.; SHENG, J.; GEA, H.C.: Application of the sequential optimization and reliability assessment method to structural design problems. In: *Ptoceedings of DETC’03, ASME 2003 Design Engineering Technical Conference and Computers and Information in Engineering Conference*. Chicago, USA, 2003

ROOS, D., Adam, U., Bayer, V.: Design Reliability Analysis . In *Proceedings of the 24th CAD-FEM USERS' Meeting 2006, International Congress on FEM Technology with 2006 German ANSYS Conference*, Stuttgart, Schwabenlandhalle, Germany, October 26-27, 2006.

ROOS, D.: Advanced methods of stochastic and optimization in industrial applications. In *Proceedings of the 7th International Conference and Workshop on Numerical Simulation of 3D Sheet Metal Forming Processes*, Numisheet 2008, September 1-5 – Interlaken, Switzerland

optiSLang - the optimizing Structural Language, *An Users' Manual - Version 3.0.1*, DYNARDO GmbH, Weimar, 2009

ABOUT TYCO ELECTRONICS

Tyco Electronics Ltd. is a leading global provider of engineered electronic components, network solutions, specialty products and undersea telecommunication systems, with fiscal 2009 sales of US$10.3 billion to customers in more than 150 countries. We design, manufacture and market products for customers in a broad array of industries including automotive; data communication systems and consumer electronics; telecommunications; aerospace, defense and marine; medical; energy; and lighting. With approximately 7,000 engineers and worldwide manufacturing, sales and customer service capabilities, Tyco Electronics' commitment is our customers' advantage. More information on Tyco Electronics can be found at http://www.tycoelectronics.com/.