Robust Design Optimization in virtual prototyping - Promises and Challenges

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Summary:

The speed of product innovation and the rising requirements for product optimization demands more than ever CAE-based product development and CAE-based product optimization. Here CAE-based Robust Design Optimization (RDO) is the key technology to optimize product performance while at the same time proving the quality requirements of product reliability and robustness.
Looking to the obvious necessity and the possible benefits of CAE-based Robust Design Optimization in virtual prototyping, the fact that still only a rare number of publications about successful applications for daily use exist may surprise. Is CAE-based RDO seen to be a luxury? Or if not, where are the challenges and bottlenecks for implementation at a daily base of virtual product development.

The paper discussed some challenges of introducing CAE-based RDO into virtual prototyping as well introduced the main algorithmic parts of and successful RDO workflow. After discussing a lot about challenges, necessary amount of input and verification of course after a successful RDO flow is implemented in virtual prototyping the benefits in time to market, resulting product robustness and reliability and cost-effective product development are huge, documented with some industrial applications examples.

Keywords:

robust design optimization, robustness evaluation, sensitivity analysis, optimization

1 Introduction

Due to a highly competitive market, the development cycles of increasingly complex structures must be constantly reduced while the demand regarding performance, cost and safety is rising. The development of innovative, high quality products within a short time frame which are able to succeed in competitive markets is only possible by using CAE-based virtual prototyping. Herein one of the greatest challenges is the rising number of numerical simulation of large test and analysis programs including CAE-based optimization and CAE-based stochastic analysis while reducing the number of hardware tests. Looking at the obvious necessity of CAE-based Robust Design Optimization in virtual prototyping, the fact that only a rare number of publications about successful applications for daily use exist may surprise. Is the CAE-based RDO seen to be a luxury? Or if not, where are the bottlenecks at implementation. In the paper we discuss the status of application at industrial examples including the challenges and possible barriers or bottle necks.

CAE-based optimization has a long tradition in engineering. The goal of optimization is often the reduction of material consumption while pushing the design performance to the boundaries of allowable stress, deformations or other critical design responses. At the same time safety margins are asked to be reduced and products should be cost-effective and not over-engineered. Of course, a product should not only be optimal under one possible set of parameter realizations. It also must function with sufficient reliability under scattering environmental conditions. In the virtual world we can prove that e.g. with a stochastic analysis, which leads to CAE-based robustness evaluation. If CAE-based optimization and robustness evaluation is combined, we are entering the area of Robust Design Optimization (RDO) which is also called Design for Six Sigma (DFSS) or just Robust Design (RD).
The main idea behind that methodology is that uncertainties are considered in the design process. These uncertainties may have different sources like, in the loading conditions, tolerances of the geometrical dimensions and material properties caused by production or deterioration. Some of these uncertainties may have a significant impact on the design performance which has to be considered in the design optimization procedure.
Before entering the introduction of the different algorithmic parts of a RDO workflow we would like to point out some main challenges when introducing RDO into virtual prototyping.

2 Challenges for introducing RDO in virtual prototyping

2.1 RDO is not just a small extension of an optimization workflow

Often, in marketing or scientific publications the RDO task is simplified by assuming that the robustness space is a subspace of the optimization space defined by the optimization parameters. The suggested RDO strategies based on this simplification allow recycling CAE solver runs from the optimization algorithms for the robustness evaluation and reducing the additional effort of RDO compared to deterministic optimization to a minimum. Unfortunately, for real world engineering applications outside the scatter of the optimization parameters also other important uncertain parameters like loading conditions or material properties must be considered to obtain a meaningful robustness assessment. Consequently, we often need to deal with different variable spaces of optimization and the robustness parameters. Thus, usually design runs in the optimization domain cannot be recycled directly to estimate the robustness criteria and vice versa.
Therefore, we should expect that substantial RDO applications always need to consider a significant amount of additional information compared to a deterministic optimization task and will need significant additional CPU requirements. The most important additional input is information about uncertainties, which will start with many uncertain parameters. Therefore, double checking of availability of the knowledge about the uncertainties and their best representation in an uncertainty model, the careful planning of a suitable algorithmic RDO workflow and careful checking of suitable measures for design robustness are recommended.

Often it is recommended to start with an iterative RDO approach using decoupled optimization and robustness steps including an initial sensitivity analysis in the domain of the optimization parameters as well as a subsequent robustness evaluation in the domain of uncertain parameters. This iterative approach helps to better understand the variable importance and the complexity of the RDO task to adjust the necessary safety margins. Only with this knowledge and if the iterative approach did not converge successfully a simultaneous RDO task should and can be defined. The iterative approach and the simultaneous approach will be illustrated at industrial examples.

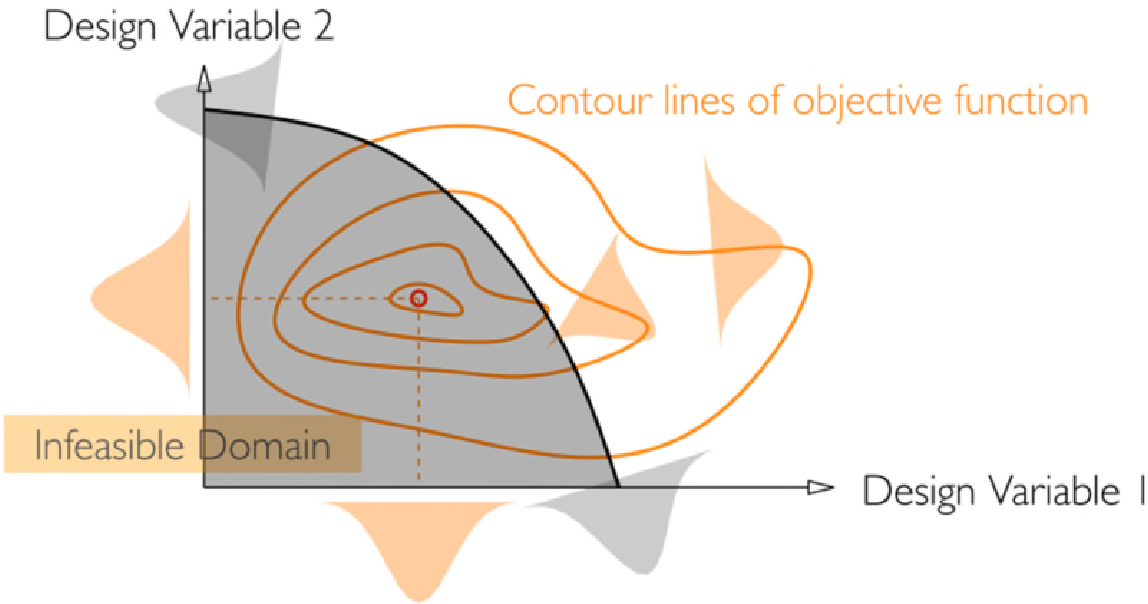

Figure 1: Robust Design Optimization (RDO) optimizes the design performance with consideration of scatter of design (optimization) variables as well as other tolerances or uncertainties. Because of uncertainties, the location of the optima as well as the contour lines of constraints varies.

2.2 Garbage in, Garbage out, danger to a meaningful stochastic analysis

When asking the question about the influence of uncertainties we need to collect the best available knowledge about expected uncertainties with the best possible translation into the statistical definition of the CAE-model. Illustrating that with a translation to a stress calculation: Nobody would question that a reliable stress calculation can only be achieved by using a reliable value of the Young's modulus, otherwise the calculated stress value is not confident. The same question arises for the stochastic analysis itself. If we have no trustable information on the input uncertainties and no suitable approach to translate this information into adequate definitions of the scattering parameters, we should not perform a stochastic analysis. In such a case most likely this stochastic analysis would lead to useless estimates of the variations, sensitivities etc.

2.3 Start with conservative estimations about all known important uncertainties

Discussing how to formulate a suitable uncertainty model we should note one of the most important differences between CAE-based optimization and CAE-based robustness evaluation. When simplifying an optimization task while using just a small subset of optimization parameters and a tiny parameter range, we might miss the goal to improve the design significantly. Nevertheless, any variation is a valid space of the optimization parameters and gives you valid information about the optimization potential corresponding to this investigated design space. There is no risk obtaining unconfident or even dangerous predictions. To say it with other words, in a deterministic optimization task the user can reduce almost arbitrary large and complex parametric spaces to a handful of parameters with small ranges without loss of confidence of the obtained optimization results.

In sharp contrast to that, the verification of product safety with a simplified robustness evaluation is only possible, if the unimportance of the neglected uncertain inputs is proven or their effect is covered sufficiently by additional safety factors. If we neglect significant important effects during the stochastic analysis, the robustness assessment based on this insufficient information may be much too optimistic and the results pretend an artificial safety. For that reason, we recommend addressing an RDO problem by starting with a robustness evaluation of a reference design by introducing all possibly affecting uncertainties and translating all knowledge in conservative assumptions about the expected scatter ranges. Here, we must study which uncertainty is important and which degree of discretization is necessary to introduce the uncertainty into the CAE model. Then we can make sure that the uncertainty quantification and representation is appropriate. So, we can answer the following questions:
Is it sufficient to check a variation window of uncertain parameters by assuming a conservative upper and lower bound within a uniform distribution or do we have to identify the distribution type more in detail?
Is it sufficient to define single independent scattering parameters or introducing scalar parameters with pair-wise correlations, or is an even more sophisticated spatial correlation model, which we call

random fields [15], necessary to represent the properties and spatial distribution of the uncertainties. Please find more discussion about the necessary degree of discretization of uncertainties in [1,10,11,12,13].

2.4 We need to define confident robustness measures

By defining an RDO task measures of variation will be included into the optimization objectives and/or constraints. These statistical measures like mean value, standard deviation, safety margins or probabilities of exceeding a critical event are outcomes of the stochastic analysis. Note that all these measures are estimates and their confidence must be proven. This is like the verification of the mesh quality of a finite element analysis: the verification of variance estimates is necessary to trust in the predicted robustness of an investigated design. Everybody agrees that evaluating only 10 sample points will not lead to a confident assessment of a six-sigma design. A six-sigma design requires proof that the probability of its failure is not larger than three out of a million realizations. 10 sample points are sufficient only to estimate roughly a mean value and a standard deviation, but the projection to a small event probability related to a six-sigma design has an almost unpredictable large error. At the same time, it is a challenge for any real world RDO problem to balance between the numbers of design runs spent on the estimation of the variation and the necessary accuracy of the robustness measures to drive the design in the right direction. Therefore, all RDO strategies need to estimate variation values with a minimal number of solver calls. To reach this goal, some methods make assumptions about the linearity of the problem or use response surface approximations in the space of the scattering parameters whereby the final proof of robustness, using alternative methods of CAE-based reliability analysis is of urgent need to prove the targeted robustness and reliability requirements.
If the knowledge is vague about important uncertainties and their best available representation in a CAE model, a verification of the robustness at current product lines is strongly recommended before extrapolating robustness measures to future designs.

2.5 Non experts of stochastic analysis need to be able to perform RDO

Chapters 2.1 to 2.4 discuss the importance of reliable definition of uncertainties and reliable robustness measures to be able to define a successful RDO task. Same kind of importance is the “ease” and “safety” of using RDO workflows for non experts of stochastic analysis. Although optiSLang [14], our general purpose software tool for CAE-based RDO, had all pieces of technology available since multiple years we learned it is necessary to come up with easy to use workflows, which safeguards users in selecting automatically most effective RDO algorithms, which safeguards user to check and proof estimation of variance at the end of an RDO cycle as well as safeguard users in the post processing before non experts of stochastic analysis feel comfortable to perform RDO and to trust the results.

3 Main algorithmic parts of the RDO workflow

3.1 Deterministic Optimization

In parametric optimization, the optimization parameters are systematically varied by mathematical algorithms to get an improvement of an existing design or to find a global optimum. The design parameters are defined by their lower and upper bounds or by several possible discrete values. In real world industrial optimization problems, the number of design parameters can often be very large. Unfortunately, the efficiency of optimization algorithms usually decreases with an increasing number of optimization parameters. With the help of sensitivity analysis, the designer can identify the parameters which contribute most to a possible improvement of the optimization goal. Based on this identification, the number of design parameters may be dramatically reduced, and an efficient optimization can be performed. Additional to the information regarding important parameters, a sensitivity analysis may help to decide whether the optimization problem is formulated appropriately and if the numerical CAE solver behaves as expected. Please find more discussion about effective sensitivity analysis in [2,3]. After the sensitivity analysis all the knowledge is created or verified to select the most effective optimization strategy out of Gradient-based optimization algorithms, Natural inspired optimization algorithms with or without the help of Response Surface approximations.

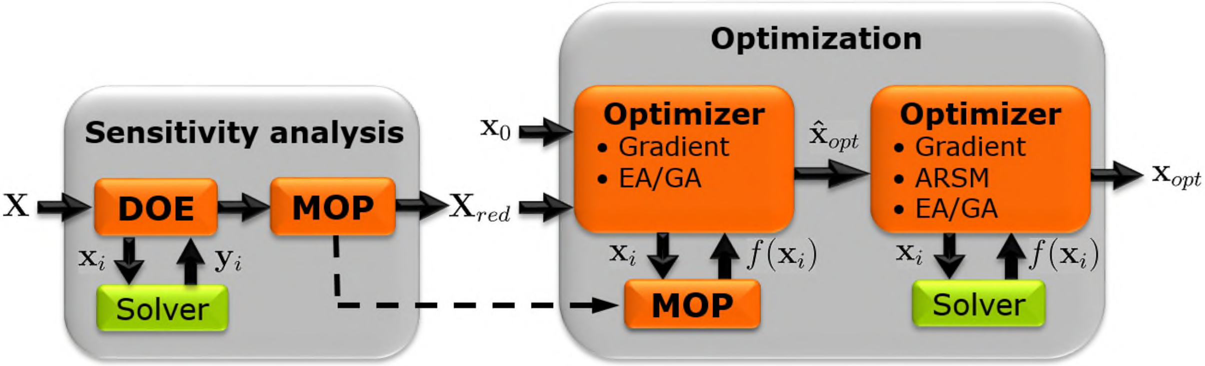

Figure 2: Recommended workflow for a single-objective optimization: from a full parameter set $\mathbf{X}$ the sensitivity analysis identifies the important parameters $\mathbf{X}_{\mathrm{red}}$; together with the start design $\mathbf{x}_0$ the optimization is performed and an optimal design $\mathbf{x}_{\mathrm{opt}}$ is found.

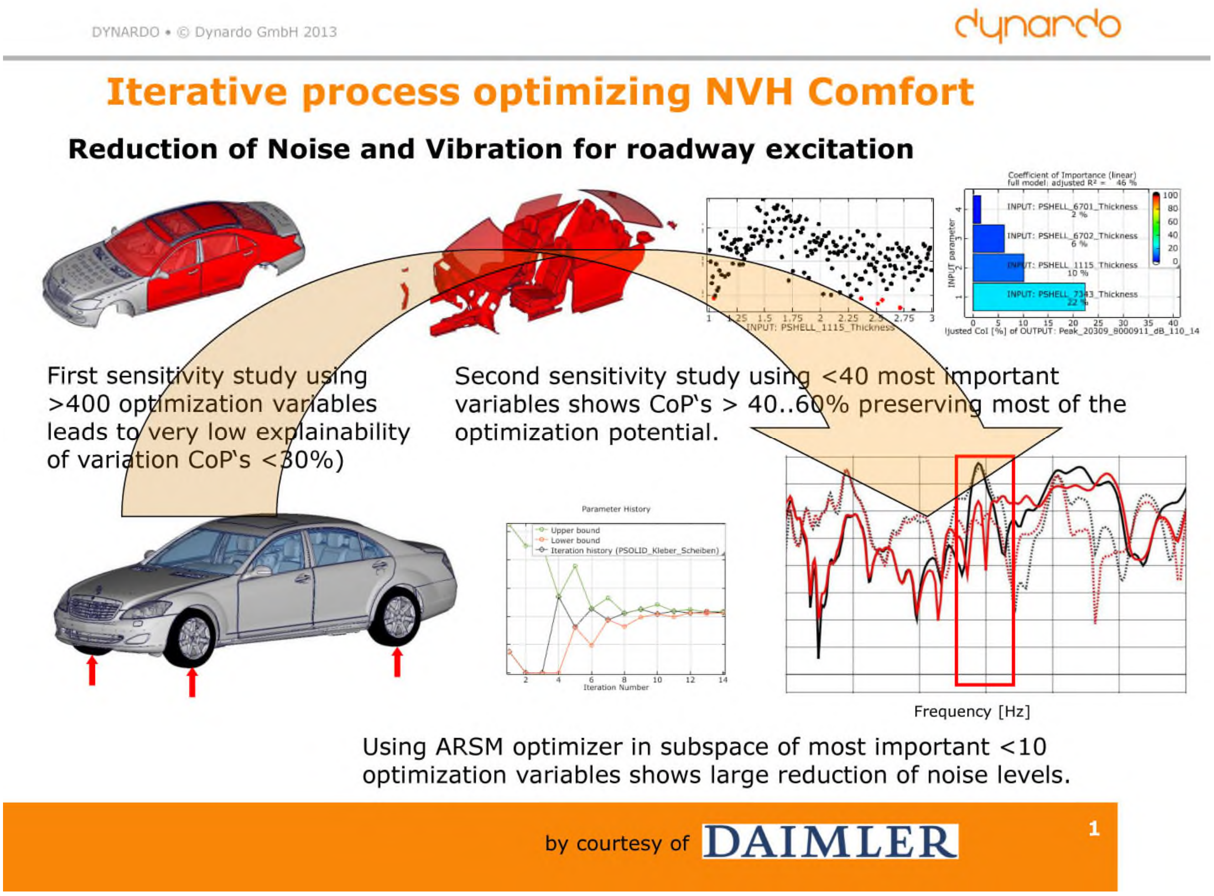

Figure 3: Industrial Example of iterative optimization approach using sensitivity analysis to identify the most important parameter for the optimization potential and finally run the optimization using Adaptive Response Surface optimization Method (ARSM).

3.2 Robustness evaluation

Optimized designs may become sensitive to scatter e.g. in geometry and material parameters, boundary conditions and loads. Therefore, it becomes necessary to investigate how the optimized design is affected by scattering model input parameters. Design robustness can be checked by applying stochastic analysis, like Latin Hypercube Sampling, based on a randomly generated sample set and a suitable definition of the scattering parameters. Therefore, robustness measures as mean value, standard deviation, safety margins to failure criteria or the probability of failure need to be introduced. In terms of using variation-based measures we call the approach variance-based robustness evaluation. In terms of using probability-based measures we call such a procedure probability-based robustness evaluation, also known as reliability analysis. Please find more discussion about the necessary balance between reliability of the definition of scattering parameters, the reliability of the stochastic analysis and the reliability of the robustness measures for CAE-based robustness evaluations for industrial applications in [1, 5, 8, 9, 10, 11, 13].

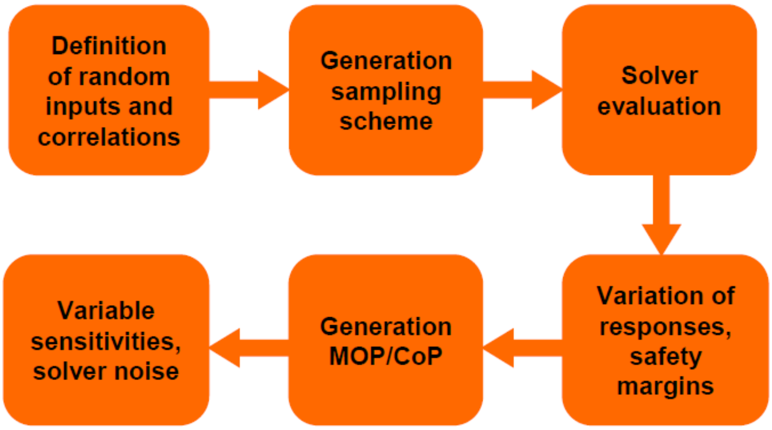

Figure 4: Flowchart of the variance-based robustness evaluation with an included sensitivity analysis

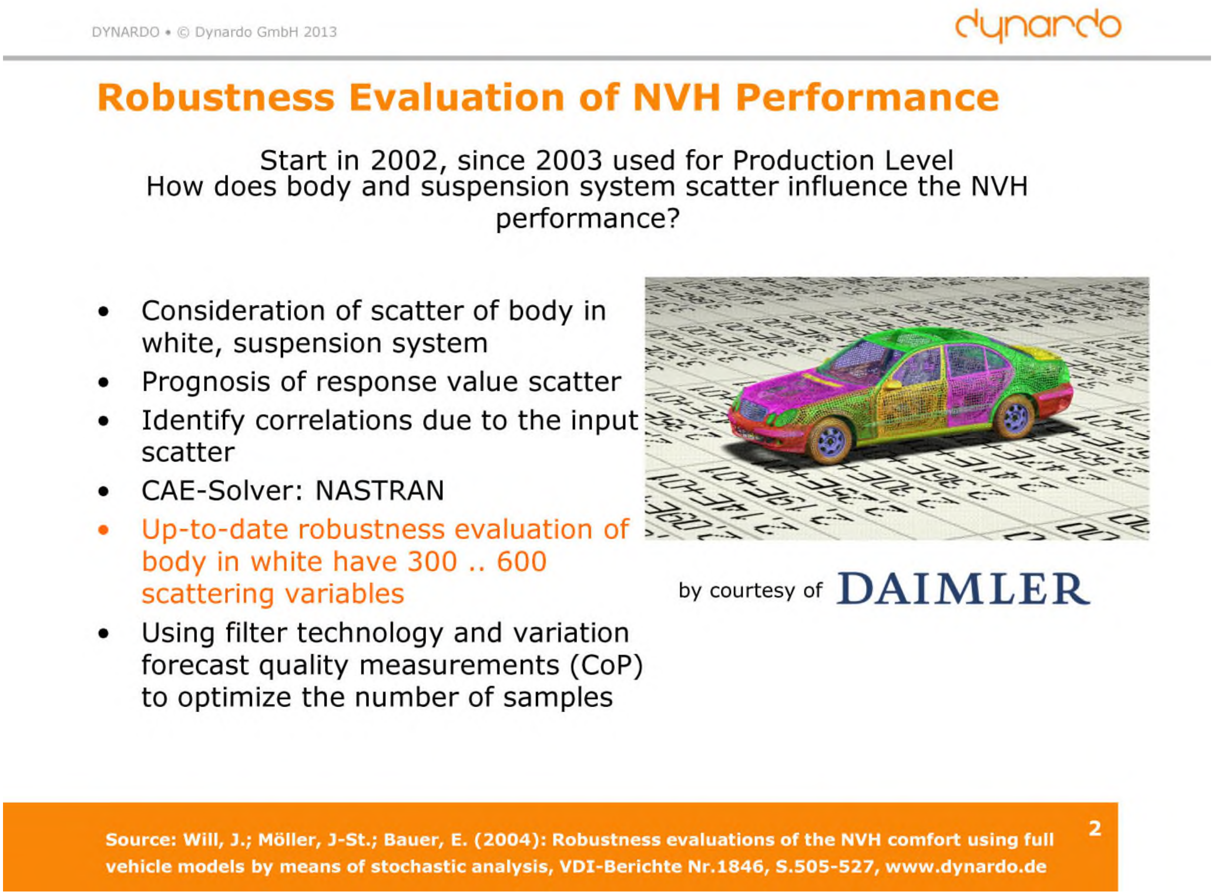

Figure 5: Industrial Example of a robustness evaluation of the NVH performance of a passenger car [8]

3.3 Robust Design Optimization

Talking about the combination of robustness evaluation and optimization, the frequency of coupling and interaction of both tasks must be defined. We call it an iterative Robust Design Optimization (RDO) when deterministic optimization is combined with variance-based robustness analysis at certain points during the optimization process. Of course, this requires the introduction of safety factors, which should ensure that a sufficient distance to the failure criteria is given during the deterministic optimization. These safety factors may be adjusted iteratively during the iterative RDO process, and a final robustness and reliability proof is mandatory at least at the end of the procedure. This procedure is state-of-the-art in most publications on real world RDO projects like [6,7].

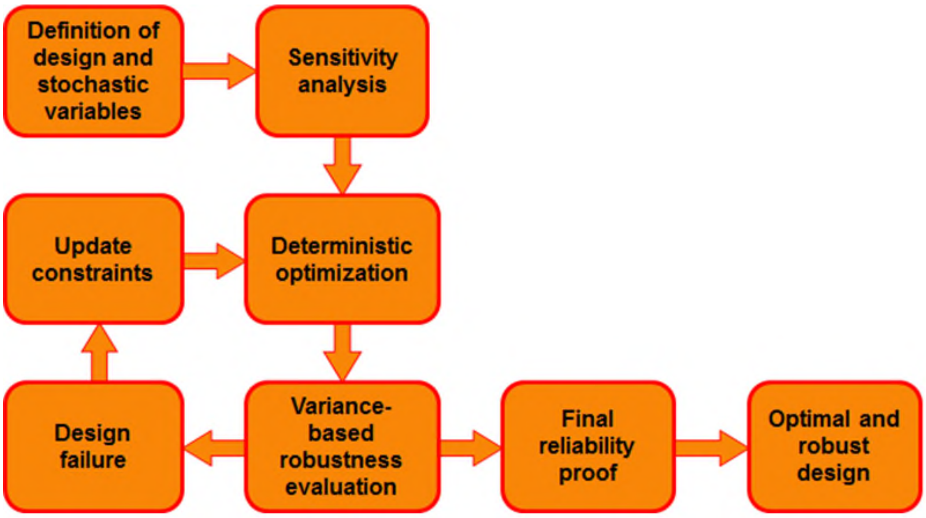

Figure 6: Flowchart of an iterative Robust Design Optimization with final reliability proof

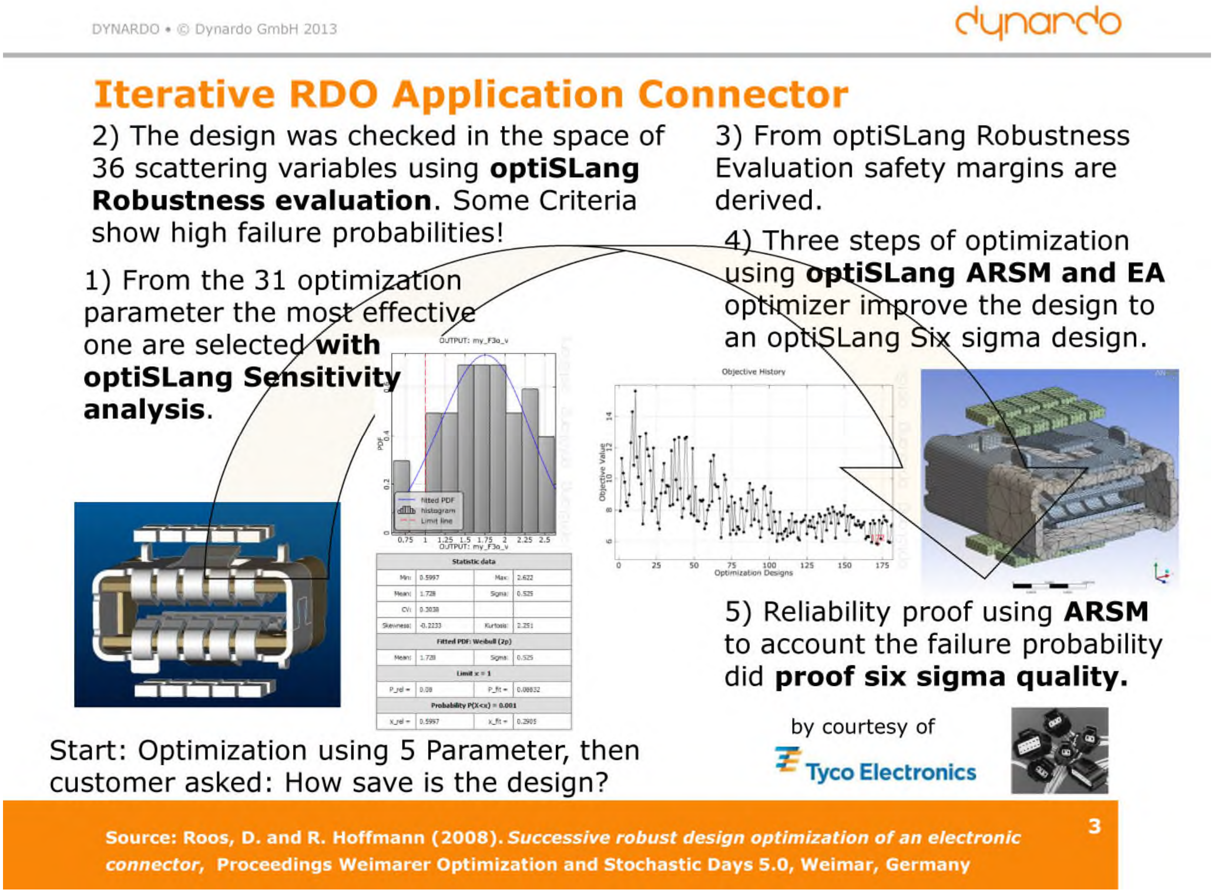

Figure 7: Industrial Example of iterative Robust Design Optimization of a Design for Six Sigma development process of an electric connector [6]

If the safety margins fluctuate within the optimization domain, e.g. due to several interacting failure phenomena, an iterative procedure may require many iterations. Because of very fluctuating safety distances to the main robustness criteria, one candidate for simultaneous RDO is the minimization of brake noise excitation [5,10]. In such a case, an automatic approach where the robustness criteria are estimated for every candidate in the optimization domain, a so-called nominal design, may be more efficient with respect to the CPU requirements compared to iterative RDO. That procedure we call simultaneous RDO approach. Since the robustness evaluation is performed as an internal loop within the global optimization loop, this approach is sometimes also called “loop in loop” RDO. Especially when probability-based measures are used to quantify design robustness and safety the numerical effort significantly increase when for every candidate in the optimization loop the robustness or reliability is measured. Therefore, the simultaneous RDO approach can be found more frequently when the single CPU run of a design evaluation is relatively inexpensive like for system simulation [4].

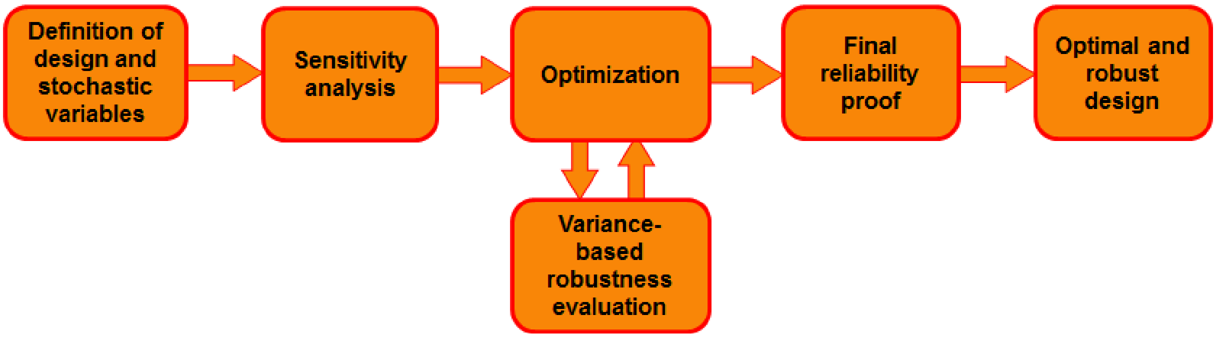

Figure 8: Flowchart of simultaneous variance-based Robust Design Optimization approach with final reliability proof

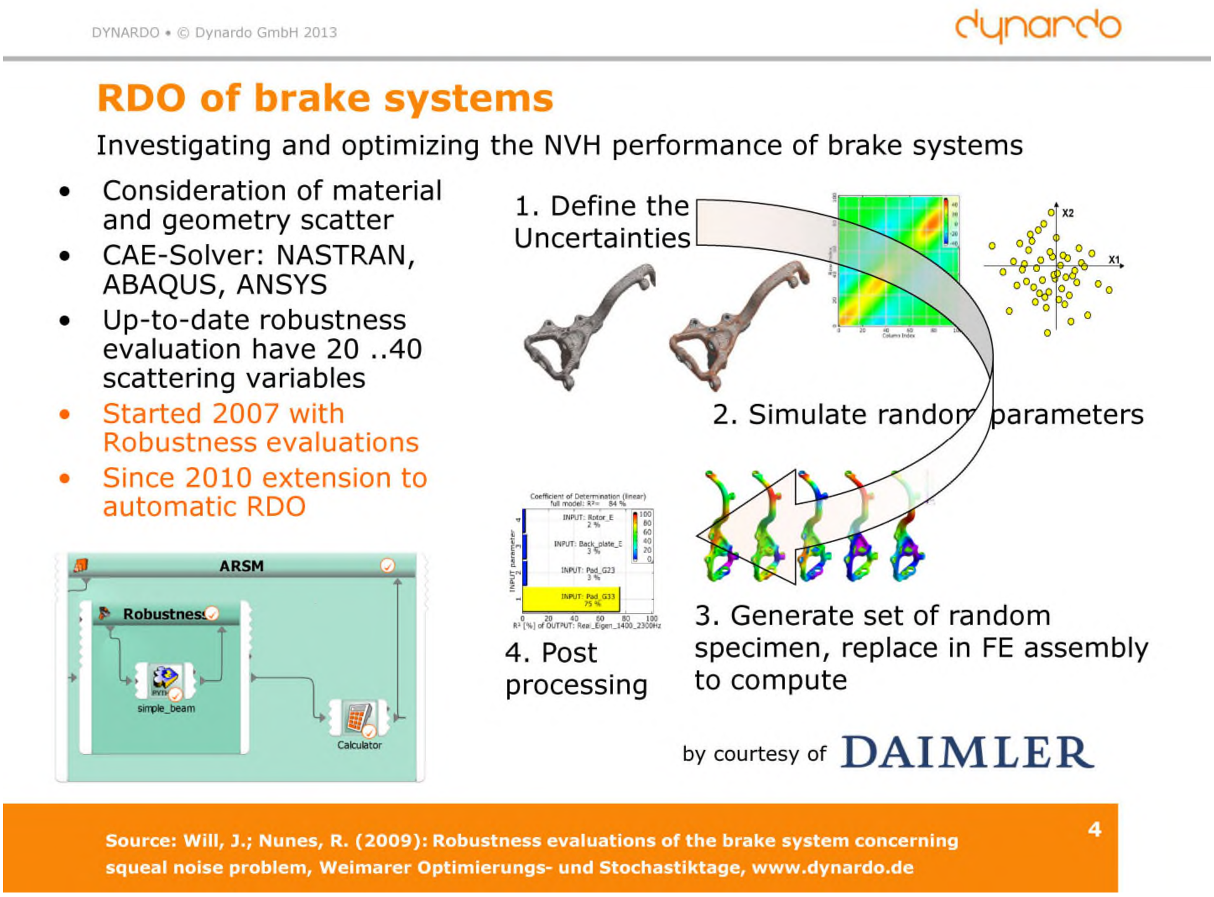

Figure 9: Industrial Example of simultaneous variance-based Robust Design Optimization of brake systems [5]

4 Summary

Successful integration of RDO strategies into industrial CAE-based virtual product development cycles needs an RDO strategy which is in balance with the available knowledge about uncertainties of scattering variables, with available criteria to reliably quantify robustness or safety of designs as well as with the dimensionality and non-linearity of the RDO task.

For definition of successful objectives and criteria for robust designs sensitivity analysis in the design space of optimization as well as in the space of scattering variables are very helpful. Any kind of design space defined by a hand full or hundreds of optimization parameters is a valid space to optimize the design. In contrast to that for real world RDO applications we must expect that at least in the robustness space we have to start with a large number of potentially important scattering variables. In contrast to the design space of optimization the variable reduction in robustness space starting from all possible influencing variables is only possible with know how about unimportance of scattering variables. The number of variables which need to be considered is crucial for selection of appropriate optimization as well as stochastic algorithms. Also, for the task of reducing to the most effective optimization variables as well as most important scattering variables sensitivity analysis is the key.

If the RDO task is defined with appropriate robustness measures and safety distances multiple optimization strategies can be performed successfully to drive the design in the direction of being optimal and robust. If a design evaluation needs significant time the balance between the number of CAE design runs and the accuracy of robustness measures is a challenge for all RDO strategies, iterative or simultaneous. Then all of them try to minimize the number of design evaluations to estimate the robustness measures. If small failure probabilities (like smaller than 1 out of 100) need to be proven, algorithms of reliability analysis have to apply, at least at the end of an RDO process to prove the reliability of the optimal design.

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