Reliability Based Design Optimization of Sub-systems / Component using Monte Carlo Simulation of Isight

Sastry Bonala

Tata Consultancy Services Ltd, Bangalore – 560 066, India

Abstract: *With the advent of CAE high fidelity simulations, both non parametric and parametric optimization methods are gaining rapid momentum in order to find the optimum design that satisfies the performance requirements. Usually, each input design variable such as material property, load and manufacturing processes of a component / sub-system will have uncertainties which have to be accounted while performing the optimization. Since, the output parameters of mechanical sub-systems are highly nonlinear and sensitive to variation of input design variables. The Monte Carlo Simulation (MCS) method of Isight has been used to define variation of input design variables thereby to assess the risk factor of the optimum design. With the help of MCS method, the product designer was able to quantify risk involved in the optimum design instead of a qualitative assessment of the design. This paper also compares Robust Design Optimization (RDO) and Reliability Based Design Optimization (RBDO) formulations. This paper will summarize benefits of evaluating risk factor of the optimum design.*

Keywords: Parametric Optimization, Risk factor, Reliability, Robust design and Uncertainty

1. Introduction

Higher fuel economy, "Go Green" and better engine performance along with stringent emission regulations set by the government for gasoline engines are challenges for automotive manufacturers. To achieve these goals, mass / weight reduction has become an important attribute of component / sub-system design process without compromising the functional performance parameters such as frequency, stiffness, durability and structural integrity. Since few decades, virtual validation of a design using simulation tools such as Abaqus has become part of the product design process. OEMs are continuously developing high fidelity standard CAE work flows, which had been correlated with prototype testing. With the help of these standard work flows, the cost of prototype testing has been reduced significantly. To a certain extent, parametric and non-parametric optimization methods have become standard tool in the design process of automotive industry. However, these non-parametric optimization methods such as topology, shape and size optimizations are executed independently in the organization by various departments such as durability, dynamic stress and structural integrity to reduce weight of the component or to improve the stiffness of the component by varying the design variables (DV) such as operational load and material property.

In the design process, uncertainties are introduced from various sources, variability in material properties, manufacturing tolerance and operational load variation etc. These uncertainties may be involved in different stages of product life cycle as shown in Fig. 1 (Kang, 2005)

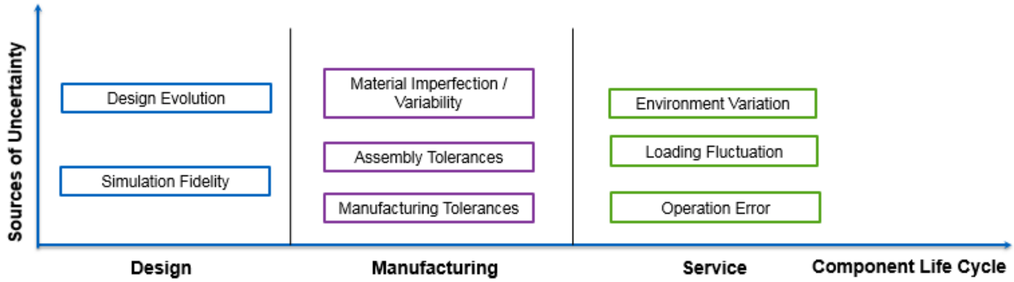

Figure 1. Sources of uncertainties

These uncertainties need to be accounted and quantified for achieving the optimum design. Traditionally, these uncertainties are accounted in the design process by applying factor of safety. The factor of safety value is mainly determined by design codes or practicing engineers based on their field failure correlation experience, which may be too conservative or too dangerous. The design variables are considered as deterministic in the traditional design process. In certain component / sub-system designs, the output performance parameters are highly sensitive to input design variables as shown in Fig. 2. In such scenarios, slight variation in input design variable can lead to a significant loss of component / sub-system performance.

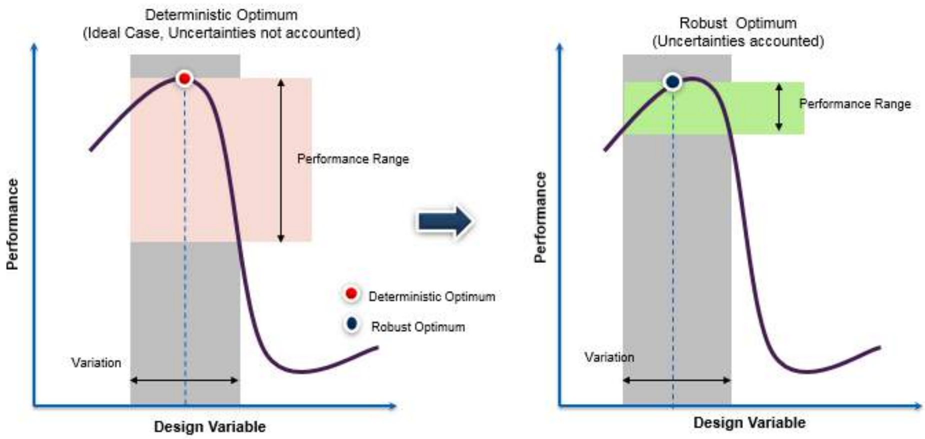

Figure 2. Deterministic optimum & robust optimum

As shown in Fig. 2, at robust optimum the output performance parameter is less sensitive to the input design variables, which is called as robust design. Therefore, design variable uncertainty and variability have to be considered in the design optimization process. However, these uncertainties in design variables can be modeled as stochastic variables which allows to predict risk factor or probability of failure. With the new technology advancements in high performance computing in CAE, it is possible to conduct sensitivity analysis studies by defining probability density function for the design variables to estimate the performance variation.

2. Parametric Optimization using Isight

The design spaces are always multi-dimensional and searching optimum design which satisfies all requirements is a very challenging task in today's global scenario. Usually, parametric optimization methods are adopted to conduct RBDO, where the design variables are identified based on engineering judgment or by conducting screening Design of Experiments (DOE). After identifying the design variables, DOE frame work available in Isight is used as a scheduler for conducting DOE runs on High Performance Computing (HPC). Then, the Response Surface Methodology (RSM) of Isight has been used to construct a global approximate mathematical model (Surrogate Model) for the design space. The developed RSM and transfer function need to be validated with CAE analysis i.e., performing the analysis at few design points in the design space considered for DOE. This RSM can be correlated with prototype test results, which enhances the confidence level of CAE work flow. The RSM has been used to replace Abaqus Finite Element Method model and it works well when number of design variables are less.

- Using the RSM, sensitivity analysis is conducted to evaluate the gradient of performance with respect to the design variables
- Design search tool of Isight provides greater flexibility for designers to select the best design that satisfies all requirements

The generated RSM is used in structural optimization, to identify optimum point in the design space. Isight has a good collection of optimization algorithms and the selection of algorithm depends upon output response characteristics and problem. The output responses of sub-systems / component of automotive engine such as durability, stiffness and structural integrity are highly non-linear.

2.1 Monte Carlo Simulation using Isight

The Monte Carlo method is still the most robust method for reliability and response analysis of uncertain systems. This technique is widely used in the industry to define probability distribution for design variables and quantify uncertainty using mean and standard deviation. The accuracy of Monte Carlo method depends upon the number of sampling points and increases with increasing sampling size. The sampling points are randomly selected based on the probability distribution function. In this paper, Monte Carlo Simulation (MCS) of Isight has been used to evaluate probability of failures P (f), which is also referred as "Risk factor" of the optimum design. Reliability, R is referred as inverse factor of probability of failures. Therefore, R can be expressed as R = 1- P (f). Both these factors can be expressed as percentages instead of a factor.

2.2 Reliability Based Design Optimization (RBDO) and Robust Design Optimization (RDO)

Compared with RBDO, robust design is relatively new concept in structural optimization. Both of formulations aim at incorporating random performance variations into the optimal design process. Therefore, the difference between RBDO and RDO are not clearly distinguished in the literature. However, these two approaches differ in basic aspects. The comparison between two methods are listed in Table 1 as shown below (Kang, 2005)

Table 1. A Comparison between RBDO and Robust Design

Parameter	RBDO	Robust Design
Description of input	PDF / CDF	Mean and Variability
Design Objective	Minimize Objective	Reduce Variability
Analysis Type	Reliability Analysis	Variation Analysis

Robust design optimization is also called "Design for Six Sigma (DFSS), which also deal with improving the quality of the process / product by improving the process capability of design. As shown in Fig. 3, the optimum design (non-robust design) may be satisfying all requirements, but its performance is uncertain, when there are variation in design variables. In RBDO, the reliability of optimum design is predicted using MCS of Isight.

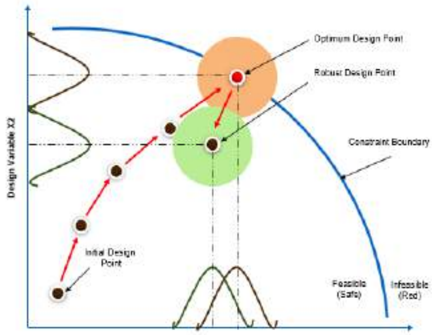

Figure 3. Robust design

3. Case Study

The optimization process was developed and implemented on various industry problems. To demonstrate MCS work flow, an illustrative example as shown in Fig 4 was considered. This problem consists for two pipes and the pipe flanges are connected with few bolts. A gasket was used to seal the joint between two pipe flanges. Usually, the flange joint always should be closed during application of operation loads such as fluid pressure. The loads acting on this system were as given below

- Bolt pretension
- Pressure in the pipe & load deflection curve of the gasket
- Temperature of fluid flowing in the pipe

Usually, the bolt pretension is applied to keep the both flanges compressed together, which compresses the gasket. Thus, the gasket in turn applies pressure on the flange, which causes bending of the pipe flanges. The flange thickness and bolt load plays an important role in determining joint behavior.

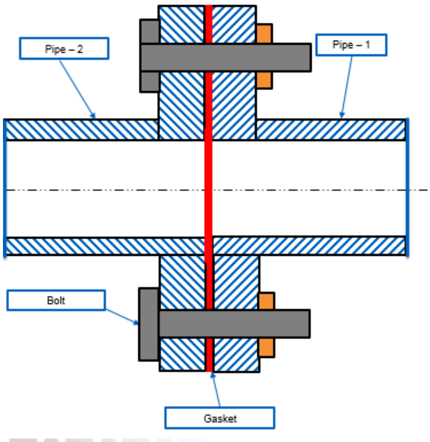

Figure 4. Schematic diagram of pipe flange

To conduct parametric optimization, five important design variables DV1, DV2, DV3, DV4 and DV5 were considered, which are either related to geometry or operation load. Two output responses R1 and R2 were considered for output responses and measure, which are function of design variables. The following four steps were followed to calculate reliability of the system.

- Step 1 : Setting up DOE
- Step 2 : RSM approximation
- Step 3 : Parametric optimization
- Step 4 : RBDO using MCS of Isight

In Step 1, the DOE has been conducted using full factorial method, 32 analysis runs were executed for different set of design variables using analysis work flows, which were automated partially. The output responses R1 and R2 were calculated for all 32 analysis runs. This design matrix data was fed to Isight to fit mathematic RSM and transfer function.

In Step 2, RSM has been validated by performing the CAE analysis at an arbitrary design point. The normalized response values predicated form RSM approximation and CAE analysis are tabulated in Table 2. As the percentage of error with reference to Abaqus is less, the RSM has been validated, which can be used to replace the conventional CAE workflow. This RSM mathematical approximation was used in optimization and MCS

Table 2. Validation of RSM with Abaqus

Parameter	RSM	Abaqus
Response (Normalized)	0.957	0.9
% of Error with reference to Abaqus	6.3 %	

In step 3, parametric optimization was carried out to search optimum design in the design space. The optimization goal is to target response (R1) to a normalized value of 1.0 while keeping the response (R2) under the design requirements. The obtained design point from optimization has been validated by running the analysis with optimum values for design variables.

In RBDO using MCS, the normal probability distribution was considered for design variables with a mean value and standard deviation. Initially, MCS process was started with defining 5% variation for all design variables and reliability factor was calculated. The same process was repeated for defining 1% and 2.5 % variation for all design variables.

3.1 RBDO Results and Discussion

The MCS module of Isight provides various plots such as interaction plots, pareto plots, probability distribution plots and probability tables. CAE engineers have to interpret the data accurately and feed RBDO summary to product design team. The designers are mainly interested in risk factor of design due to uncertainties and the key design variables effecting output response. The praeto plot provides sensitivity of each design variable on the output response, these plots help designer to identify the design variables, which have to be improved in order to change the reliability factor as shown in Fig. 5.

- DV5, DV2 and DV1 are effecting the response significantly than other variables.
- Cross interaction of two design variables is very low.
- The uncertainties for DV4 may not effect reliability of system significantly.

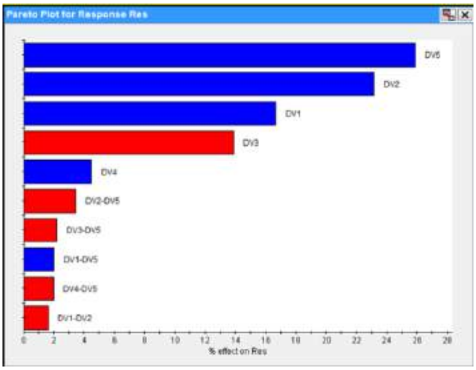

Figure 5. Pareto plot of design variables

The MCS provides reliability factor or number of safe designs for a specified variation of the design variables. The MCS probability table is as shown Fig. 6.

Monte Carlo Probability Table

	lower	upper	between
Res	0.67895		0.67895

Figure 6. Monte Carlo probability table

From the cumulative probability distribution plot, the number of designs that are meeting target value in the number of sampling points as shown in Fig 7. This plot also provides minimum and maximum response values on horizontal axis.

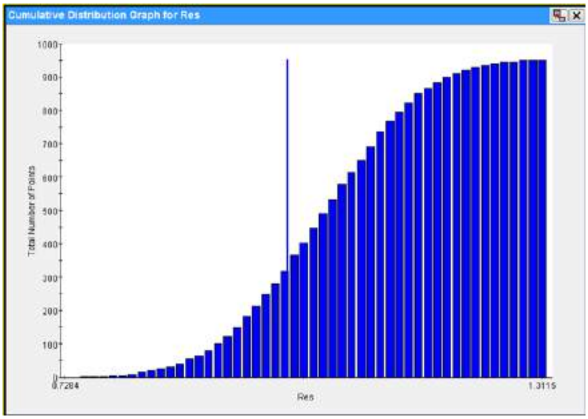

Figure 7. Cumulative probability distribution for response

A sensitivity analysis was carried out on existing MCS model for different variations of design variables. Reliability and risk factor in percentage for three different variations are calculated and shown in Table 3. The reliability factor is decreasing non-linearly with increase in the variation of design variables.

Table 3. Reliability & Risk factor for different variations

#	Variation of design variables (%)	Distribution Type	Reliability factor (%)	Risk factor (%)
1	1%	Normal distribution	99 %	1 %
2	2.5%		81 %	19 %
3	5%		68 %	32 %

4. Summary & Discussion

In this paper, RBDO using MCS of Isight are discussed along with numerical problem. Uncertainty of design variable is a very important factor that has to be considered in design process. In the robust optimum design, the output variables are less sensitive to design variables and the output performance variation is very less. In the RBDO, the reliability of optimum design for a specific probability distribution of design variables has been evaluated. The RBDO can implemented on high fidelity CAE based work flows and these work flows should be validated and correlated with prototype testing. On the other hand, the RBDO requires lot of analysis runs, which is computationally more expensive. This scientific quantification will be helpful for designer to assess the risk involved in the design due to uncertainties.

5. Acknowledgements

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6. References

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