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Andreas Vlahinos
Principal, Advanced Engineering Solutions, LLC

Subhash Kelkar
Staff Technical Specialist, Ford Motor Company

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ABSTRACT

A design is robust when it is not sensitive to variations in noise parameters such as manufacturing tolerances, material properties, environmental temperature, humidity, etc. In recent years several robust design concepts have been introduced in an effort to obtain optimum designs and minimize the variation in the product characteristics [1,2]. In this study, a probabilistic design analysis was performed in order to develop a robust design with the mean value of the resulting stress at target, and minimum standard deviation. The methodology for implementing robust design used in this research effort is summarized in a reusable workflow diagram.

INTRODUCTION

Currently, to account for manufacturing variations, auto body designs are based on the nominal or worst case scenario values, which leads to over-designed components. If the scatter in material properties, thickness and dimensions is accounted for in the finite element analysis stress prediction, it is expected that lighter designs will be produced. This type of stochastic approach can be used to investigate the robustness and sensitivity of a proposed solution and to minimize the risk of failing corporate and consumer tests. In addition, it can potentially reduce the cost by allowing more variation in components that are not critical to performance requirements.

In this research effort, probabilistic modeling of manufacturing variations for a structural auto body component (battery tray of an SUV) is performed to determine the sensitivity and the response distribution (stress, stiffness, fatigue life) due to the scatter of the random variables. The scatter of the modulus of elasticity and the thickness and loading are defined in terms of probability distribution functions. Monte Carlo and response surface sampling techniques are implemented in determining the response distribution. Six sigma design criteria are established to size the component and compare this design to the one developed using the traditional nominal value criteria.

The Parametric Deterministic FEA Model

For this study, the battery tray (FE model shown in figure 1) was selected. The tray is made from a composite material SMC and is supporting the battery (FE model shown in figure 2).

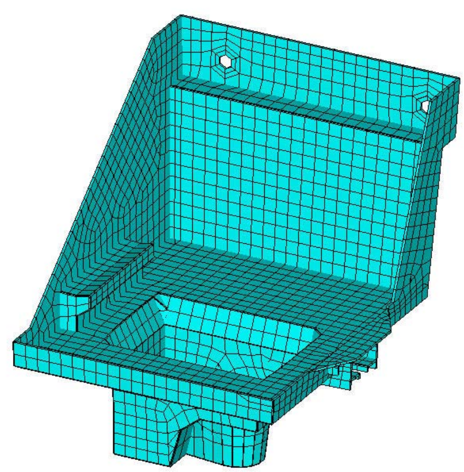

Figure 1. FE Model Of The Battery Tray

The battery is modeled with an elastic isotropic material of uniform density appropriately adjusted to produce the battery weight. The battery is supported by the tray with a set of springs at appropriate locations. The parametric model contains 2105 shell, 324 solid and 48 spring elements.

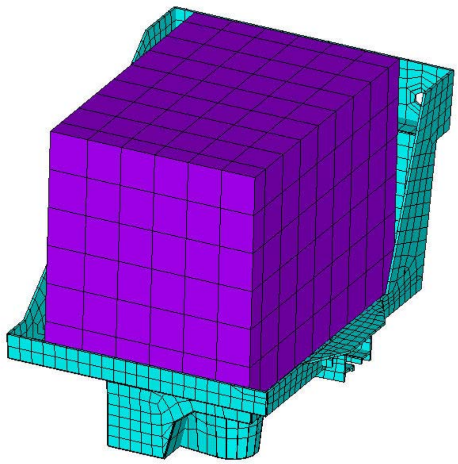

Figure 2. FE Model of the Battery and Tray Assembly

It is assumed that the tray is rigidly fixed at the support locations. The input parameters of the FEA model can be any dimension, material property and loading. For this study three parameters were considered: the wall thickness (t), the modulus of elasticity (E) and the vertical loading (q). We call these ***model parameters*** and for any set of values of the three model parameters a solution of the FEA model can produce two model output variables: the maximum Von Mises stress (max $_e$) and the maximum equivalent strain (max $_e$).

The Probabilistic FEA Model

Uncertainty in the input parameters of the FEA model can be introduced by assuming certain randomness in the input parameters. In this study, it was assumed that the thickness (t), and the modulus of elasticity (E) are characterized by a Gaussian distribution and that the vertical loading (q) is characterized by a lognormal distribution. These assumptions are based on historical data. The distribution parameters (mean values and standard deviations) can be specified to define a set of random values for the model parameters. The mean value of the thickness was considered as a *controllable* parameter and it was declared as an ***optimization design variable***. The rest of the distribution parameters (mean values of E & q) and the standard deviation of t, E and q were considered uncontrollable or noise parameters. Figures 3, 4 and 5 show the probability distributions and the probability of the input variables, namely, thickness, modulus of elasticity and vertical loading. The ANSYS[3] probabilistic Design System was used to generate the values from the distribution parameters. A set of 100 points from these distributions was used to perform FEA analysis on the tray. It was assumed that the thickness exhibits a Gaussian distribution with a mean value of 3.0 mm and a standard deviation of 0.3 mm. In the optimization model, the mean value of the thickness was an unknown design variable. It was also assumed that the modulus of elasticity exhibits a Gaussian distribution with a mean value of 5723 N/mm^2 and a standard deviation 570 N/mm^2.

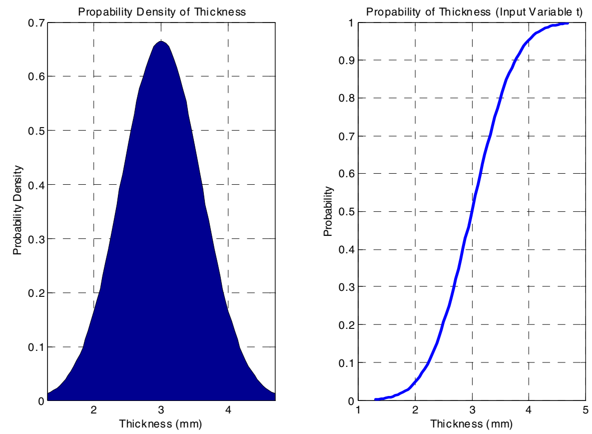

Figure 3. Probability Distribution of Thickness t (input variable)

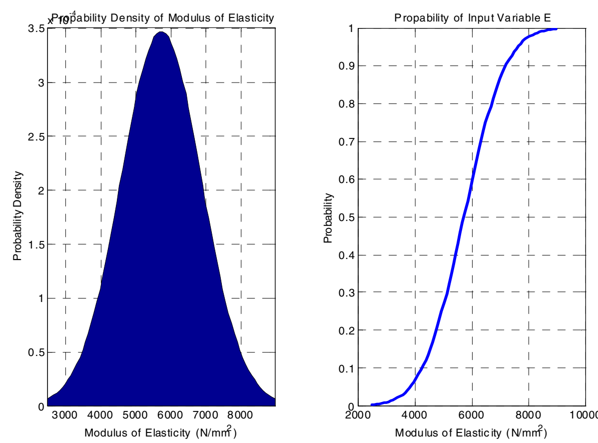

Figure 4. Probability Distribution of Modulus of Elasticity E (input variable)

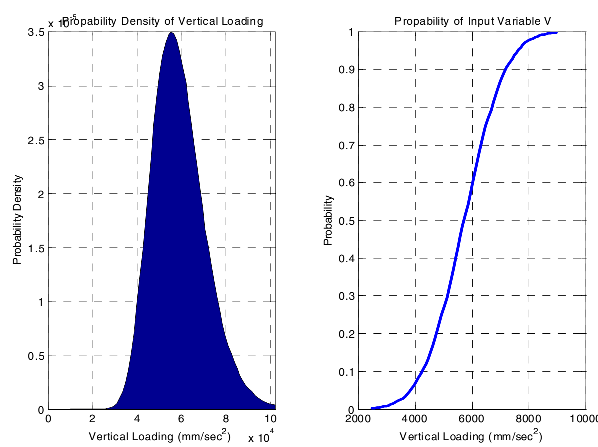

Figure 5. Probability Distribution of Vertical Loading q (input variable)

The lognormal distribution with a mean of 58842 m/sec^2 and standard deviation of 12000 m/sec^2 was considered for the vertical loading.

The following four sampling techniques were used to combine the input variables and produce a set of output variables max $_e$ and max $_e$:

1. Direct Monte Carlo Sampling
2. Latin Hypercube Sampling
3. Central Composite Design with response surface
4. Box-Behnken Matrix Design with response surface

Using one of the four sampling techniques, the probabilistic model determines a set of designs (unique values of the model input parameters), uses the parametric FEA model and computes a set of output variables. By post-processing the output variables, the probabilistic model computes the distribution parameters of the output variables.

Direct Monte Carlo Sampling

Figure 6 shows a scatter plot of the input variables t and E using the direct Monte Carlo sampling technique. Figure 7 and 8 show the effect (and scatter) of the thickness variation on the max equivalent strain and stress respectively. Figures 9 and 10 show the histogram of the max equivalent strain and stress respectively. The mean (average) value of the max Von Mises stress is 40.80 N/mm^2 and the standard deviation is 19.57 N/mm^2. The mean (average) value of the max strain is 1.0545846e-002 and the standard deviation is 6.1042144e-003.

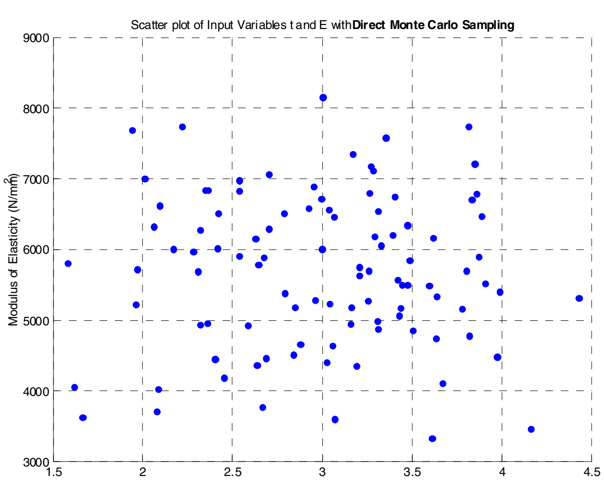

Figure 6. Scatter Plot of the Input Variables t and E using Direct Monte Carlo Sampling

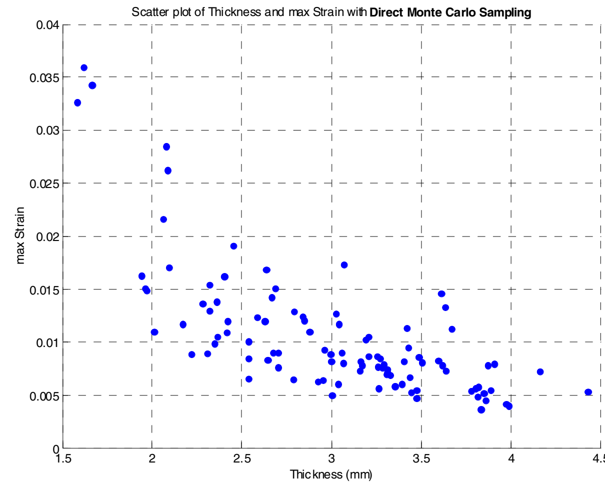

Figure 7. Scatter Plot of the Input Variables t and max strain using Direct Monte Carlo Sampling

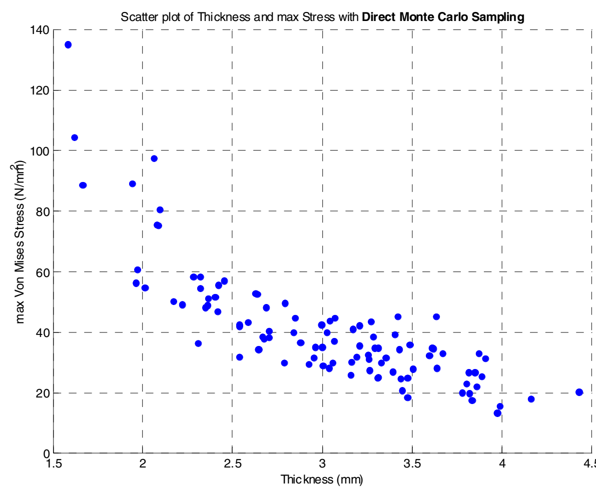

Figure 8. Scatter Plot of the Input Variables t and max stress using Direct Monte Carlo Sampling

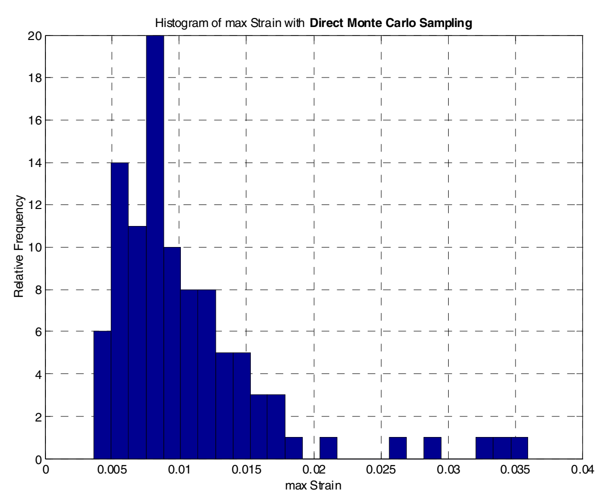

Figure 9. Histogram of max strain using Direct Monte Carlo Sampling

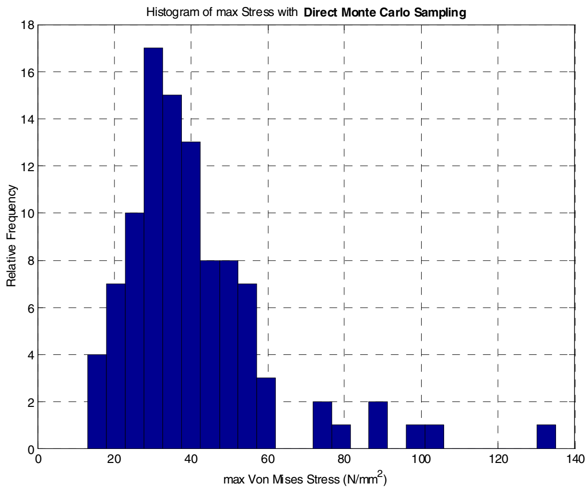

Figure 10. Histogram of max stress using Direct Monte Carlo Sampling

Latin Hypercube Sampling

Figure 11 shows a scatter plot of the input variables t and E using the Latin Hyper Cube Sampling technique. Figures 12 and 13 show the effect (and scatter) of the thickness variation on the max equivalent strain and stress respectively. Figures 14 and 15 show the histogram of the max equivalent strain and stress respectively. The mean (average) value of the max Von Mises stress is 40.18 N/mm^2 and the standard deviation is 19.40 N/mm^2. The mean (average) value of the max strain is 1.0358670e-002 and the standard deviation is 5.9027582e-003.

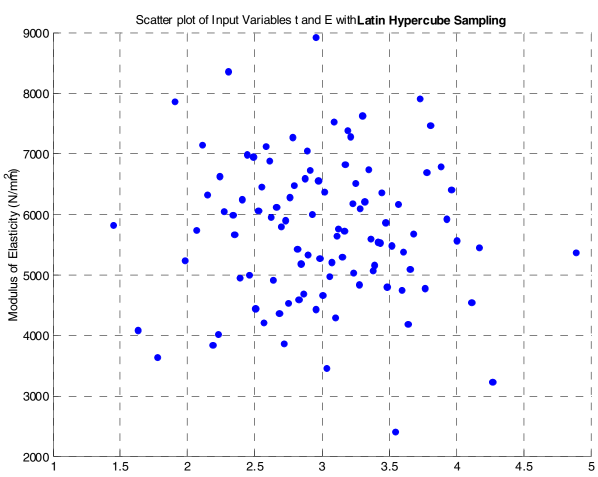

Figure 11. Scatter Plot of the Input Variables t and E using Latin Hypercube Sampling

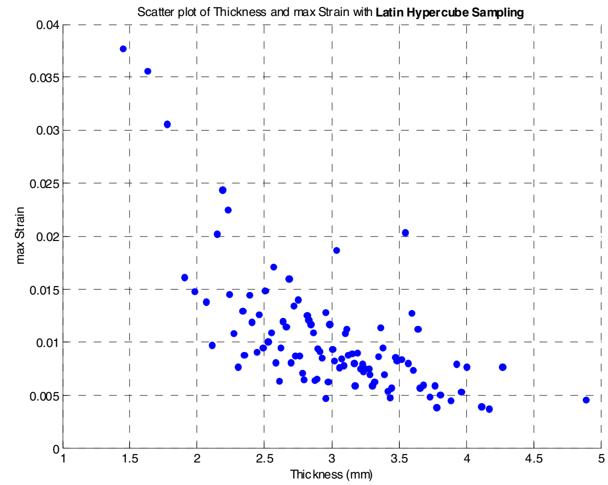

Figure 12. Scatter Plot of the Input Variables t and max strain using Latin Hypercube Sampling

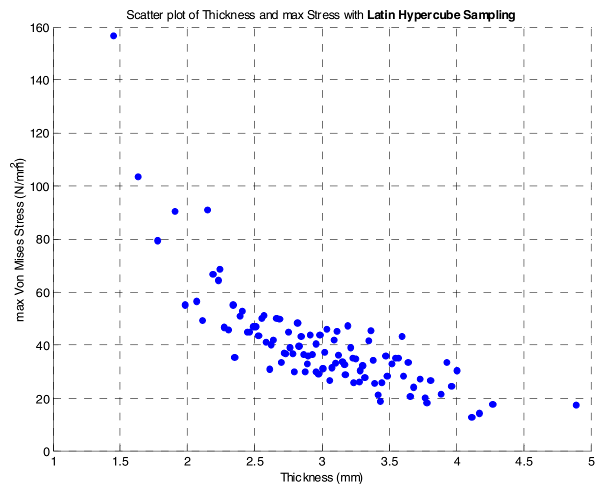

Figure 13. Scatter Plot of the Input Variables t and max stress using Latin Hypercube Sampling

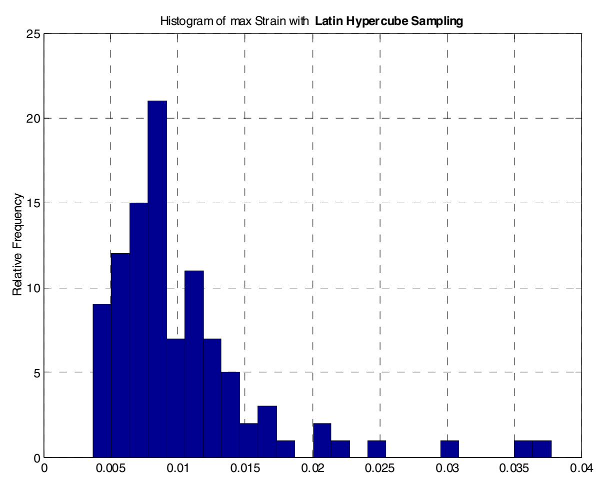

Figure 14. Histogram of max strain using Latin Hypercube Sampling

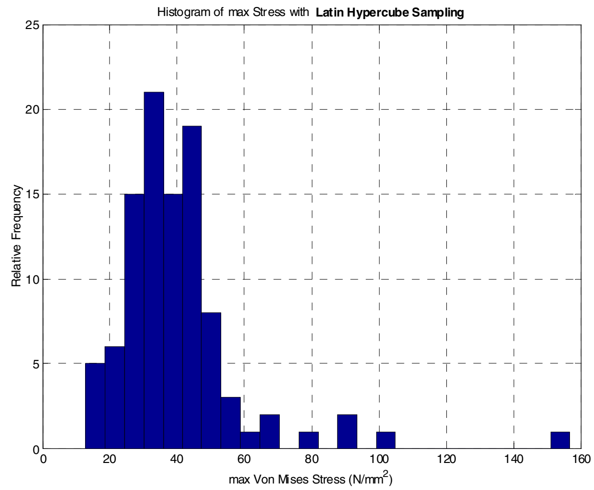

Figure 15. Histogram of max stress using Latin Hyper Cube Sampling

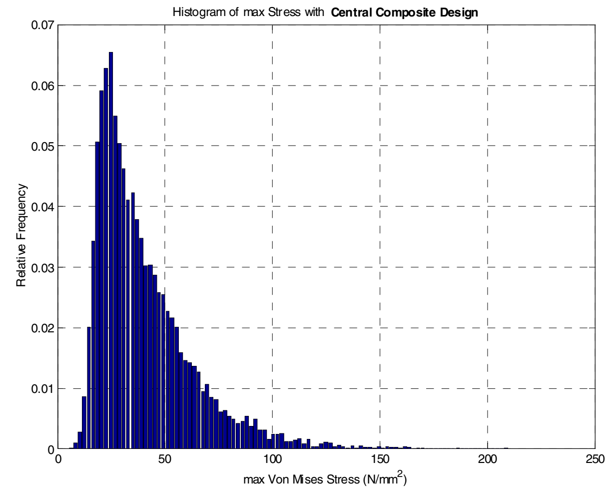

Figure 17. Histogram of max stress using the Central Composite Design

Central Composite Design

Figures 16 and 17 show the histogram of the max equivalent strain and stress respectively. The mean (average) value of the max Von Mises stress is 39.98 N/mm^2 and the standard deviation is 22.08 N/mm^2. The mean (average) value of the max strain is 1.3305926e-002 and the standard deviation is 4.8547397e-003.

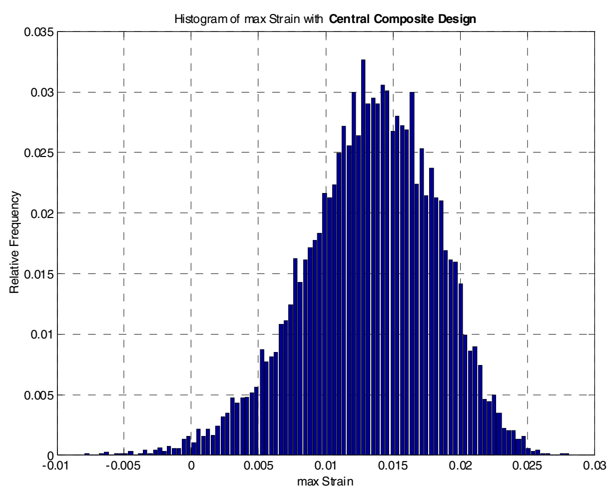

Figure 16. Histogram of max strain using the Central Composite Design

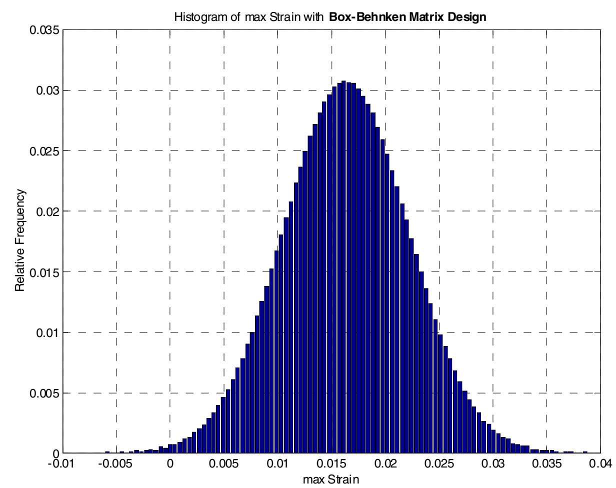

Figure 18. Histogram of max strain using the Box-Behneken Matrix Design.

Box-Behnken Matrix Design

Figures 18 and 19 show the histograms of the max equivalent strain and stress respectively. The mean (average) value of the max Von Mises stress is 40.95 N/mm^2 and the standard deviation is 24.60 N/mm^2. The mean (average) value of the max strain is 1.6345224e-002 and the standard deviation is 5.8322964e-003.

Designing for Six Sigma quality with Probabilistic Design and Optimization

Factors like geometric dimensions (mean value of thickness) of a part can be controlled by designers in a typical automotive design. Uncontrollable or noise factors such as manufacturing imperfections (standard deviation of the thickness), environmental variables (loading), product deterioration (material properties) are sources of variations whose effects cannot be eliminated. The goal of a robust design is to reduce a product's variation by reducing the sensitivity of the product to the sources of variation rather than by controlling these sources. An effort was made to reduce response variation by selecting appropriate settings for controllable parameters to dampen the effects of hard-to-control noise variables. The methodology for implementing robust design used in this research effort is summarized in a workflow diagram shown in Figure 20.

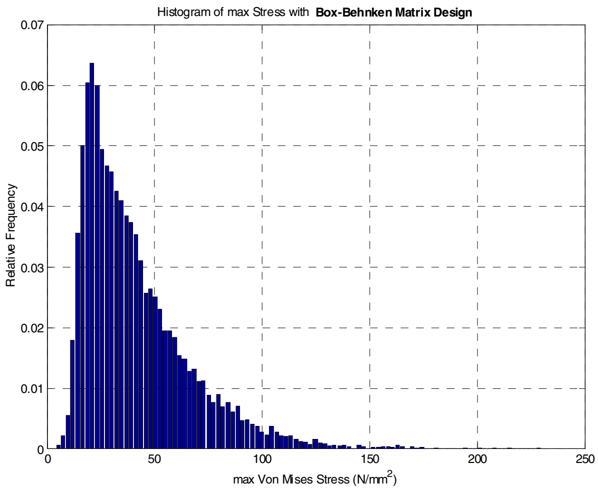

Figure 19. Histogram of max stress using the Box-Behneken Matrix Design

The objective is to select automatically the mean value of the geometric design variables that minimize variation and produce a design that meets a target value. To automate this, we can set up an optimization loop that uses as design variables the mean values of thickness. For a given set of mean values (using the probabilistic model) this approach can produce the mean and standard deviation of the response. In this case the mean max Von Mises stress and its standard deviation. The next step is to compute the value of the

$_{con}$ = mean (max $_e$) + 3 * std dev of (max $_e$),

compare it to a target value and select the mean values of the design variables that minimize the standard deviation subject to $_{con}$ < $_{Target}$

The problem can be expressed in mathematical terms as:

Select the **mean values** of the model design variables within a given range:

t_{min} < mean t_i < t_{max}

that minimize the standard deviation of the response

minimize [std. dev of (max $_e$)]

subject to the constraint:

[mean (max $_e$) + 3 * std dev of (max $_e$)] < $_{Target}$

The ANSYS script files to implement this process are available upon request.

CONCLUSIONS

- The example presented demonstrates the advantage of using an automated probabilistic design process.
- The sampling technique has a negligible effect on the mean values of the response and a small effect on the standard deviation of the response.
- For this component and number of design variables, the Box-Behneken Matrix design technique is recommended since it produces the same quality of results as the other techniques, but with the minimum number of FEA runs.
- The above conclusion may not be valid if a large number of design variables forms a highly non-linear problem. In that case, the Latin Hypercube and Box-Behneken Matrix should be used to validate the "goodness" of the Box-Behneken Matrix technique.
- With the probabilistic design and optimization approach, engineers are enabled to identify better designs that meet the performance objectives and are less sensitive to manufacturing variations.
- FEA software tools have incorporated probabilistic design and allow distributed computing that enables the implementation of this technology.
- By incorporating the physical scatter into the model, the risk of failing legal or consumer tests can be minimized

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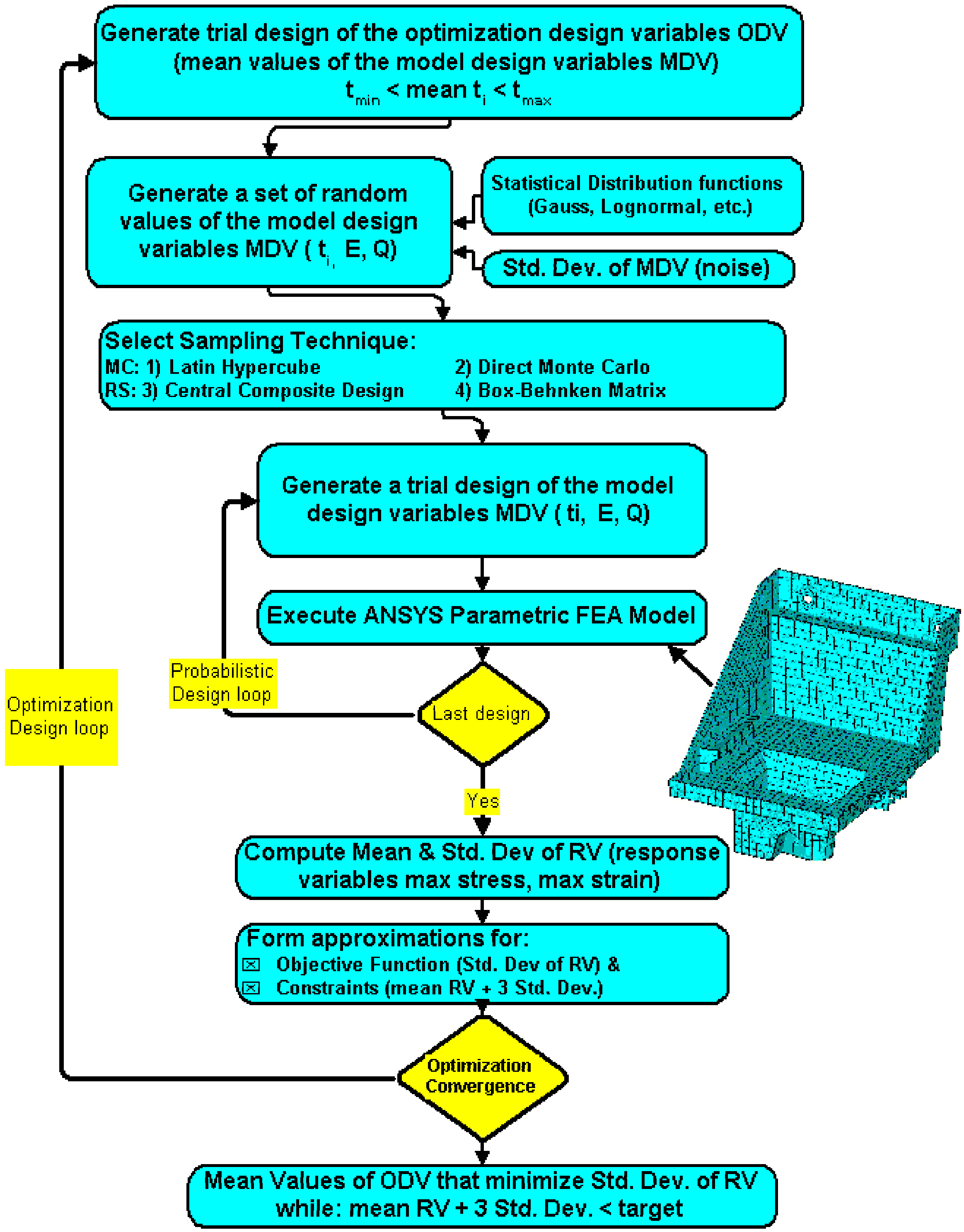

Figure 20 Reusable workflow template that determines the mean values of design variables that produce robust design

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5. Stefan Reh, Personal communications ANSYS Inc.

CONTACT

Andreas Vlahinos, Ph.D. email: andreas@aes.nu