Variable Complexity Modeling for Speeding Up Multi-Run-Design-Tasks with Computationally Expensive Simulations

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Summary:

Optimization and the improvement of robustness and reliability in the early stages of the product development is often attempted today using simulation methods together with algorithms that run these simulations in an automated manner.

In this context the need often arises, to run the simulation models with small changes of the geometry hundreds to tenth of thousands times. If these simulations are computationally expensive, like a full vehicle crash analysis, the wall clock time to perform the runs is often prohibitively large. Even the usage of big compute clusters cannot always remedy this problem.

For this reason approximation methods are often used. But no matter what actual technique is employed, polynomial approximations, radial basis functions, kriging or support vector machines, these techniques are purely mathematical and don't have any knowledge about the physical problem they approximate.

This paper presents a different approach. Here the same physical phenomenon is modeled using two different simulation models. One is very accurate but computationally expensive, the other is less accurate but computes faster. Both models are used to simulate the baseline design and the difference is recorded either as an additive correction delta or multiplicative correction factor. Then the multiple runs of the optimization algorithm or stochastic technique are performed using only the low fidelity quick code, and the correction is applied. When the baseline point is sufficiently far away from the actual point the correction delta or factor needs to be updated.

This methodology is explained on a Taguchi Robust Design study for a full vehicle side crash using LS-Dyna. The focus of this paper is to explain the methodology, not to discuss the results.

Keywords:

Approximations, Optimization, Robust Optimization, Variable Complexity Modelling.

1 Introduction

Approximation concepts were introduced in structural design optimization by in the late 1970s [1].

Many types of approximations, also referred to as behavior models, have been used in engineering design exploration. One of the primary reasons for using approximation models is to reduce the computational expense of performing optimization.

Some of the most widely used approximation methods are briefly mentioned below.

1.1 Polynomial Response Surface Models

Response Surface Models (RSM) typically use polynomials of low order to approximate response of an actual analysis code. A number of exact analyses using the simulation code(s) have to be performed initially to construct a model, or alternatively a datafile with a set of analyzed design points can be used. The model then can be used in optimization and sensitivity studies with a very small computational expense, since evaluation only involves calculating the value of a polynomial for a given set of input values. Accuracy of the model is highly dependent on the amount of data used for its construction (number of data points), the shape of the exact response function which is approximated, and the volume of the design space in which the model is constructed. In a sufficiently small volume of the design space, any smooth function can be approximated by a quadratic polynomial with good accuracy. For highly non-linear functions, polynomials of 3rd or 4th order can be used. If the model is used outside of the design space where it was constructed, its accuracy is impaired, and refining of the model is required.

1.2 Kriging Models

Kriging has its roots in the field of geostatistics and is useful for predicting temporally and spatially correlated data. Kriging meta models are extremely flexible due to the wide range of correlation functions which can be chosen for building the meta model. Furthermore, depending on the choice of the correlation function, the meta model can either “honor the data,” providing an exact interpolation of the data, or “smooth the data”, providing an inexact interpolation [2].

Kriging postulates a combination of a polynomial model and departures of the following form:

$y(x) = f(x) + Z(x)$

where y(x) is the unknown function of interest, f(x) is a known polynomial function of x, and Z(x) is the realization of a stochastic process with mean zero, variance , and non-zero covariance. The f(x) term in the previous equation is similar to the polynomial model in a response surface, providing a “global” model of the design space. In many cases f(x) is simply taken to be a constant term. While f(x) “globally” approximates the design space, Z(x) creates “localized” deviations so that the kriging model interpolates the n_s sampled data points. The covariance matrix of Z(x) which dictates the local deviations is as follows: $Cov[Z(x_i),Z(x_j)] = var(Z) ([R(x_i,x_j)])$ where R is the correlation matrix, and R(xi,xj) is the correlation function between any two of the $0(n_s)$ sampled data points x_i and x_j . R is a n_s x n_s symmetric, positive definite matrix with ones along the diagonal.

1.3 Radial Basis Functions

Radial Basis Functions are a type of neural network employing a hidden layer of radial units and an output layer of linear units, and characterized by reasonably fast training and reasonably compact networks. Weissinger [3] was the first to use numerical potential flow to calculate the flow around wings. The potential flow equations are a radial basis function. [4] realized that the same concept could be used to fit geophysical data to geophysical phenomena. Broomhead, D. S., and D. Lowe [5] renamed this technology “neural nets” and it was subsequently used to approximate all types of behavior.

How good RBF models fit to a given physical problem depends on the form of the kernel $g(|| x – x_j||)$, where $|| x – x_j ||$ is the Euclidean distance between the sample points and the interpolation point x.

Generally RBF models are better suited to capture strong local gradients than polynomial methods.

1.4 Variable Complexity Model

Variable Complexity Models use two computational tools modeling the same physical phenomenon with different degrees of fidelity (e.g., a more accurate higher cost simulation code, and a less accurate computationally inexpensive simulation code). Both codes have to do the same type of analysis, but with different levels of accuracy. An example of two such computational tools are a Navier-Stokes CFD flow solver taking hours of CPU time for one analysis, and an Euler CFD code taking minutes, or tens of minutes, of CPU time for one analysis. Both flow solvers can be used for aerodynamic flow analysis of a body providing the same information, but with different levels of accuracy, with the first one being more accurate due to accounting for viscous flow effects. Obviously, both computational tools (simulation codes or other) must take the same input parameters, and output the same output parameters. The higher fidelity tool in this case constitutes the Exact Analysis of a Variable Complexity Model approximation. During approximate analyses, a Variable Complexity Model approximation runs the lower fidelity tool, and then adjusts the output values obtained from that analysis using correction factors. That way, the results of the analysis are closer to the expected results of the more expensive, higher fidelity tool. This allows you to take advantage of the lower computational cost of the lower fidelity tool, while preserving the accuracy of the analysis at the level close to that of the higher fidelity tool. Correction factors are computed at the baseline design, so that the results of both computational tools match exactly at that design point. At other design points, away from the baseline design, the correction factors will not provide the exact match of the outputs. The farther away the design point is from the baseline, the less accurate the approximate analysis of a Variable Complexity Model approximation. During optimization with a Variable Complexity Model, as the optimization progresses farther away from the initial design point, recalculation of the correction factors (updating of the Variable Complexity Model approximation) is required to keep the accuracy of the model at an acceptable level.

Initialization and updating processes are equivalent for a Variable Complexity Model approximation, and consist of executing both the higher fidelity tool and the lower fidelity tool at the same design point; then, calculating the correction factors. Two different types of correction can be used by a Variable Complexity Model approximation

- additive (delta) type
- multiplicative (scale) type

A Variable Complexity Model with additive type of correction simply calculates the difference between the output values of both computational tools, and then during approximate analyses adds the difference to the outputs of the lower fidelity tool. A Variable Complexity Model with the multiplicative type of correction calculates the ratio (scaling factor) between the values of the outputs of the two computational tools, and then during approximate analyses multiplies the outputs of the lower fidelity tool by that ratio. Each output parameter has an individual correction factor associated with it in a Variable Complexity Model.

The big advantage of the VCM method compared with the other approximation techniques is, that it still keeps the physics in. Therefore highly nonlinear physical behavior can be taken into account, provided the low fidelity model can capture these phenomena.

2 Robust Design of Side Impact Using VCM

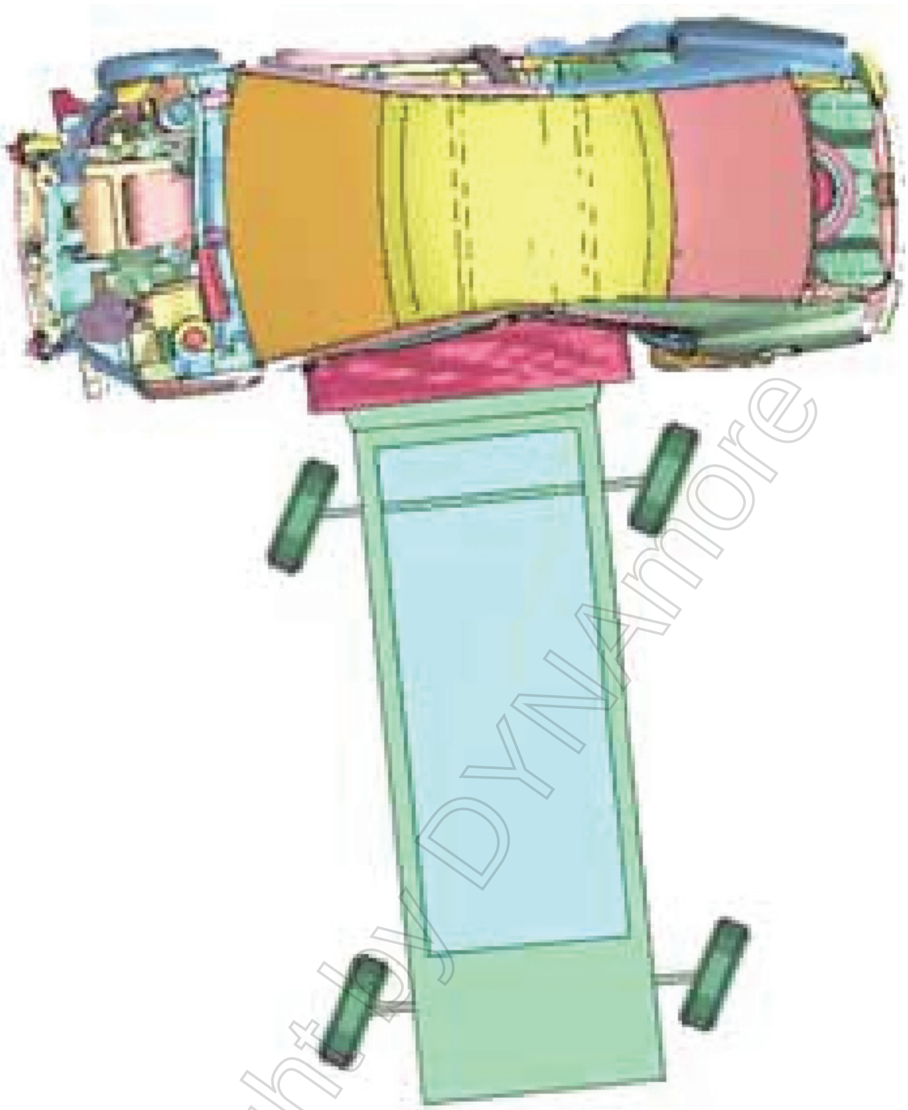


Figure 1: Physical Model

The physical problem to be simulated is the North American SINCAP (Side Impact NCAP) test for passenger cars, see Figure 1. LS-DYNA is used as the FE-solver.

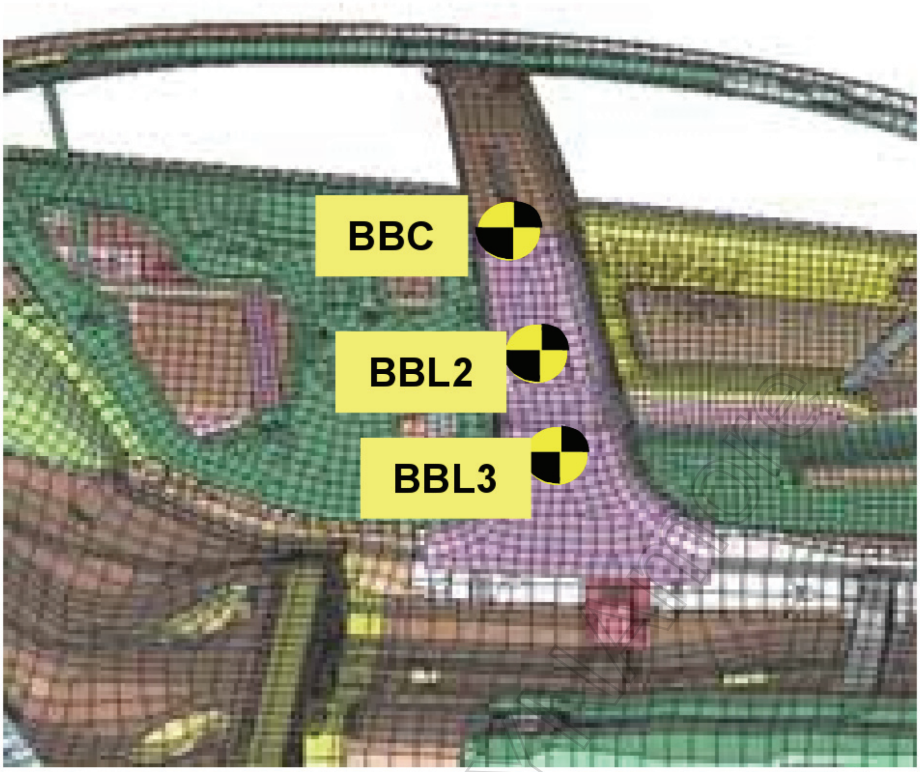
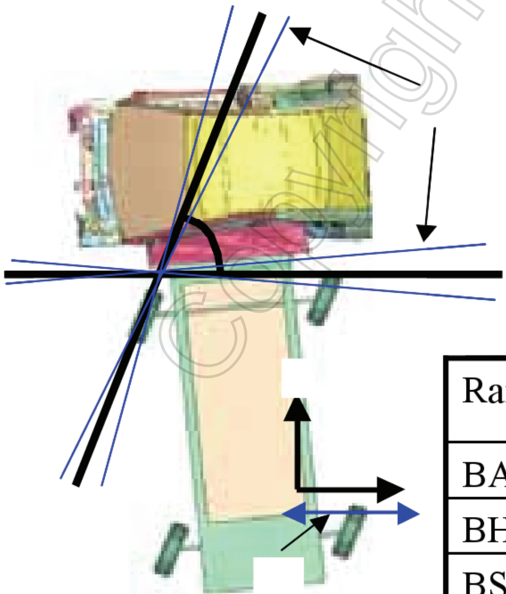
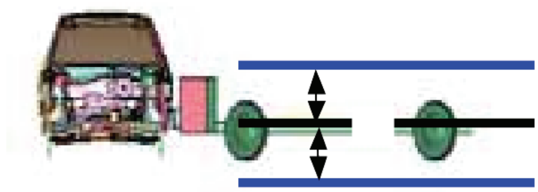


Figure 2 Robust objectives

The robust design study formulated for this simulation is the reduction of both the mean and the variance of the intrusion of the center pillar into the passenger compartment. The intrusion of three measure points is used as the goal function, see Figure 2. The total mass of the car should stay the same, or should be increased only marginally.





Random Variables		Base	Lower	Higher
BA	Angle(deg)	0	-5	5
BH	Height(mm)	0	-25	25
BS	Shift(mm)	0	-25	25

Figure 3: Random Variables

Three parameters that describe the Movable Deformable Barrier (MDB) are selected as random variables, see Figure 3, while 25 shell thicknesses of the car body are used as design variables. For a sensitivity analysis, these variables are sorted into 4 different groups, that are expected to have only minimal interaction effects, see Figure 4. More Details can be found in [6].

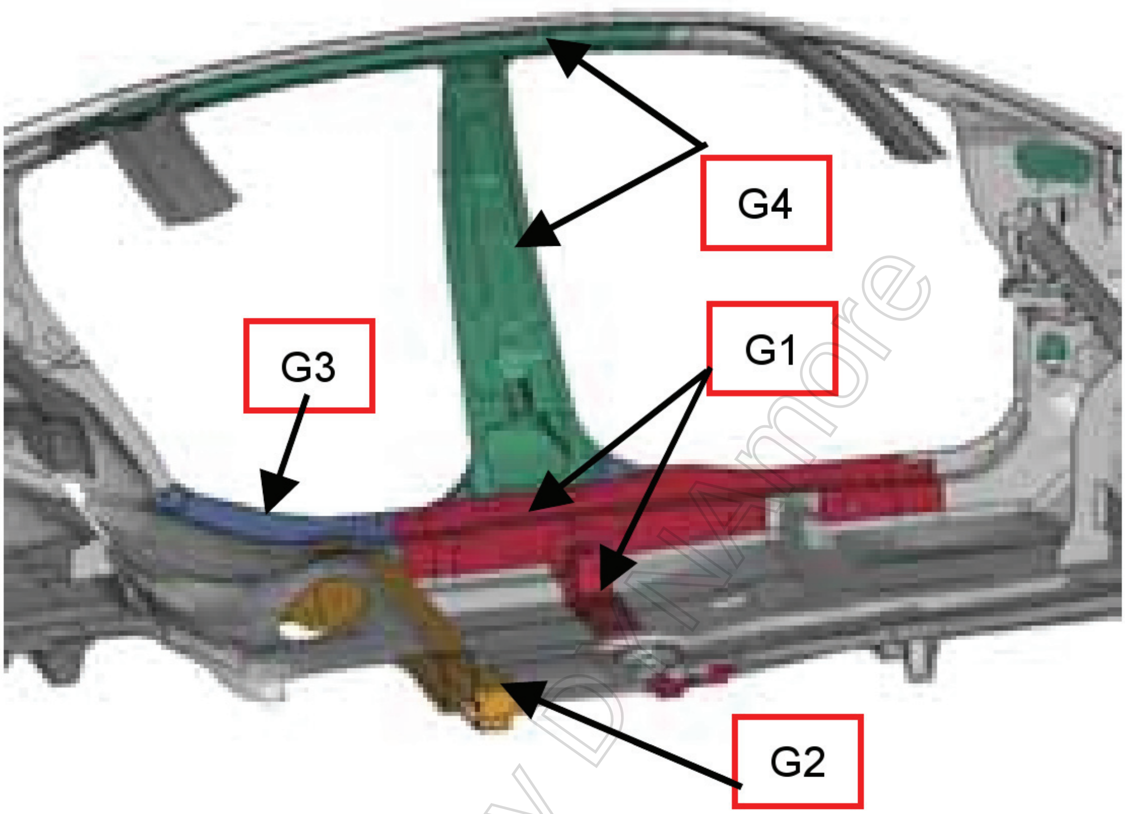


Figure 4: Design Variables

2.1 VCM approach

The low fidelity model that is used in the VCM approximation, is constructed from the full LS-DYNA model through the following steps:

1. Reduce model size by coarsening mesh. (300K shell elements to 100K shell elements)
2. Reduce model size by taking out areas of low impact
3. Reduce simulation time (80 ms to 40 ms)

While the high fidelity model runs 36 hours, the low fidelity model runs 6 hours, both on 4 CPUs.

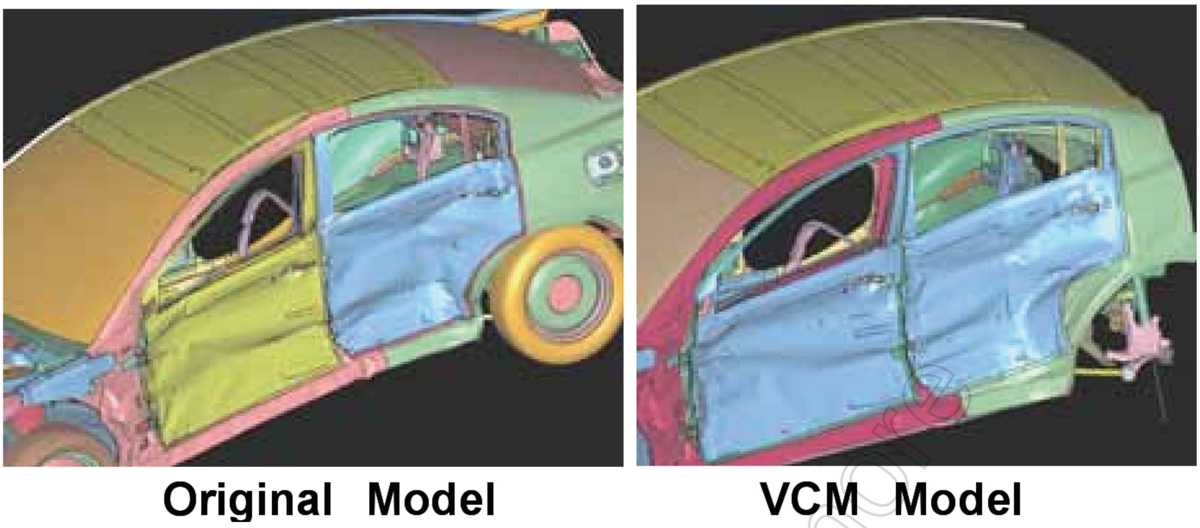


Figure 5: Comparison of High vs. Low Fidelity Model

For the baseline design a run with the high fidelity and the low fidelity model are performed. The deformation modes of the center pillar, the door panel and the side sill are similar in both cases, so the fundamental physics are captured in both cases, see Figure 5.

The intrusion of the measure points are found to be smaller with the VCM model, so scale factors are defined that map the VCM results to the results with the full model. These scale factors are kept constant throughout the remainder of this study.

2.2 Robust Design Strategy

With the VCM model first a sensitivity study is performed to determine the most important random variables. This analysis shows that the height of the barrier has highest impact, with the shift position possessing a non negligible contribution. Only these two variables will be incorporated in the robust improvement.

Next the important design variables are selected. For each group of design variables a Taguchi robustness study is employed, and only the most important contributors from each group are taken into further account. Then number of design variables could be reduced from 25 to 9.

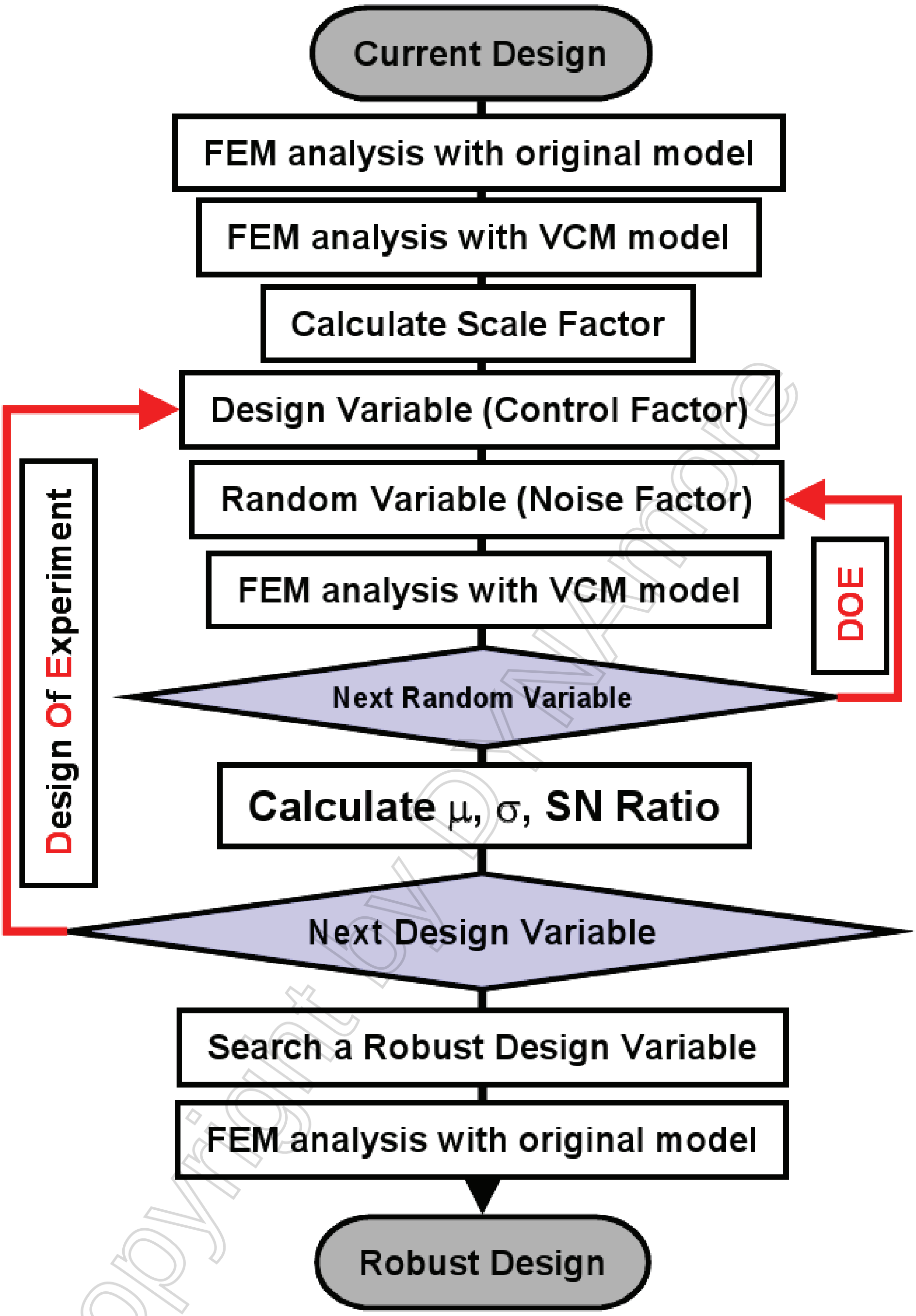


Figure 6: Taguchi Robust Design with VCM

With this information the final Taguchi Robust Design Method is performed. Within a full factorial DOE at two levels for each of the two important random variables, an Orthogonal Array L27 DOE study is executed for the 9 selected design variables. Then the experiment that gives the best result for the mean and the variance of the goal functions is selected as the robust optimum, see Figure 6.

2.3 Results

The results of the Taguchi Robust Design Method are verified by an additional parameter study, where the most important random variable, the height of the barrier, is varied for both the baseline design and the robust optimum. The results show that the variance of the goal functions decrease by 19% and the mean decrease by 7% to 13%. the mass increases by 0.45%.

Finally the VCM model is validated. At the robust optimum, the full model is run once again, and the deviations between the prediction of the VCM model, with the scale factors applied, and the full result lies between 7% and 2%, giving an good level of accuracy.

3 Conclusion

This study shows that it is feasible to perform robust optimization studies with Variable Complexity Models. While VCM doesn't reduce the wall clock time per run as dramatically as the pure mathematical meta models they take the physics into account and can be applied in extremely nonlinear cases that are intractable by other approximation methods. One challenge in applying VCM is the construction of the low fidelity model, which must capture the relevant physics of the problem.

The VCM approach can be used to make design improvement studies feasible, which would be too computationally expensive if full models would be applied.

Recent and future studies with VCM try to update the scale factors in a more dynamic way, depending on the distance to the starting point.

4 Literature

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