Robust Design – An Important Tool For Business Success

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This paper addresses the need and usage of an innovative design tool called robust design that could be employed during the whole product lifecycle management (PLM) to facilitate the business success for the long run. Quality in itself is an important business strategy for the long-term success. Many quality failures can be traced back to the design deficiencies, which must be addressed using robust design approaches very early in the design cycle. VR&D, over the last 15 years, has been developing and providing a number of tools that could be used to improve productivity and quality in product development. This paper will address the development of a framework for performing a robust design approach called Design For Six Sigma (DFSS). It will describe strategies and tools that can be used to successfully implement a robust design approach The VisualDOC optimization software system will provide the necessary software tools for implementing the proposed framework.

I. Introduction

The most challenging issue in today's business is not only how to be successful, but also how to stay successful over a long run [Ref. 1]. Over the years we have seen many successful companies with their "15 minutes of fame", and then they have gradually faded away. To be successful over the long run, you must have continuously evolving strategies that are superior to the ones employed by your competitors.

This paper addresses the need and usage of innovative design tools that could be employed during the whole product lifecycle management (PLM) to facilitate the business success for the long run. The important design requirements such as cost of ownership, performance, quality, safety, time-to-market, environmental impacts etc. need to be addressed at the very beginning of the development cycle. As time-to-market is gradually shrinking due to tremendous market pressure, particularly in automotive and many consumer products, it is very important that designs do not get bogged into trial-and-error approach of design and simulation. There is a need to approach the whole design cycle with mathematically sound design methods.

Quality in itself is an important business strategy for the long-term success. It also needs to be addressed early in the design cycle for the maximum benefit. Many quality failures can be traced back to the design deficiencies, which must be addressed using robust design approaches very early in the design cycle.

The goal of the robust design is to produce designs that consistently meet key performance characteristics or targets, while being very insensitive to factors, such as humidity levels, changes in the raw material properties, product aging, operating temperature, etc., that are difficult to control [Ref. 2]. The traditional deterministic approach where uncertainties of factors are handled through the use of safety factors, are not very robust because the safety factors are mainly determined based on past experience. Hence the design approach should not only address deterministic design optimization but also random variable considerations. Numerical design optimization

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techniques allow us to make best use of the resources while satisfying certain deterministic targets, while probabilistic approaches can address uncertainty issues related to random variables.

VR&D has developed a number of design optimization tools over the last 15 years. These tools combined with certain design strategies, such as robust design, can be effectively used to design products that can provide sustainable success in business. The remaining sections of this paper will describe how these tools could be effectively used to achieve robust designs.

II. The General Optimization Problem

Mathematically the optimization problem [Ref. 3] is stated as follows.

Minimize or maximize,

$\mathrm{F}(\mathbf{X})$ Objective Function

Subject to:

$g_j(\mathbf{X}) \le 0$ where j=1, NCON Inequality Constraints

$h_k(\mathbf{X}) = 0$ where k=1,NECON Equality Constraints

$\mathbf{X}_i^L \le \mathbf{X}_i \le \mathbf{X}_i^U$ where i=1, NDV Side Constraints

Here $\mathrm{F}(\mathbf{X})$ is the objective function, **X** is a vector of unknown input parameters, typically called design variables. $\mathrm{F}(\mathbf{X})$ could be a linear, nonlinear, explicit or non-explicit function of the design variable vector **X**. In engineering, we generally deal with $\mathrm{F}(\mathbf{X})$ which are nonlinear functions of **X**. There may be a number of inequality [$g_j(\mathbf{X})$] and constraints [$h_k(\mathbf{X})$] constraints. The aim here is to find the design vector, **X**, that will maximize or minimize the objective function, $\mathrm{F}(\mathbf{X})$. $\mathbf{X}_i^L$ and $\mathbf{X}_i^U$ are the lower and upper bounds on design variables to specify a design space.

The above mathematical problem can be solved using a number of numerical algorithms. Some of the algorithms are based on computation of the gradient of the objective and constraints, and are therefore called gradient-based algorithms. Another group of algorithms, such as the ones based on genetic algorithms (GA), simulated annealing (SA), particle swarms optimization (PSO) etc., do not require the calculation of gradients of objective and constraints, and are called non-gradient based algorithms.

No matter what optimization algorithm you use to solve the above problem, they all require a number of function evaluations or calls to simulation programs. If the simulations are expensive, the cost of solving optimization problems can become large. Techniques such as design of experiments (DOE), response surface method (RSM) can be used to reduce the number of simulation calls in optimization. As computer power increases on a daily basis, analysts and designers are attempting to solve problems with 1000s of design variables and constraints [Refs. 4, 5]. Hence there is a need to look for robust algorithms that can handle such large problems.

III. Related VR&D Tools

VR&D develop and market a number of design optimization tools. These are briefly described in the following sections to help readers understand the rest of the discussion in this paper.

VisualDOC® Design Optimization Software Systems [Ref. 6]. VisualDOC is graphics based design optimization software system, which simplifies addition of design optimization capabilities to any simulation code. It provides all the necessary design optimization algorithms, user interfaces to setup up the optimization problem, process integration tools to link your simulation with the optimizer, and post-process the design optimization runs. VisualDOC provides both gradient and non-gradient based algorithms along with response surface approximations, and design of experiments (DOE) modules. VisualDOC API allows developers to embed VisualDOC functionality in their applications.

DOT® Design Optimization Tools [Ref. 7]. DOT is a general-purpose gradient-based design optimization tool for solving primarily nonlinear optimization problems. Typically application programs call DOT as a subroutine or function to perform optimization. Currently DOT supports only continuous variable optimization. DOT is one of the optimization engines for gradient based optimization in VisualDOC.

BIGDOT™ Very Large Scale Design Optimization Tool [Ref. 5]. BIGDOT has been recently added to the suite of VR&D optimization products. BIGDOT allows solution of very large, nonlinear, constrained optimization problems where gradients are available. The algorithm in BIGDOT is based on Sequential Unconstrained Minimization Technique (SUMT). BIGDOT is capable of solving continuous, discrete/integer, or mixed variable problems. The techniques in BigDOT are intended to efficiently obtain a near optimum discrete solution very efficiently. BIGDOT is also used by VisualDOC.

GENESIS® Structural Analysis & Optimization Software [Ref. 8]. GENESIS is a fully integrated finite element analysis (FEA) and design optimization software. Analysis is based on the finite element method for static, normal modes, direct and modal frequency analysis, heat transfer, and system buckling calculations. Optimization is based on the advanced approximation concept approach to find an optimum design efficiently and reliably. Actual optimization is performed either by the DOT and/or BIGDOT optimizer. GENESIS typically requires less than ten detailed finite element analyses, even for large and complex design tasks. Shape, sizing and topology optimization are the optimization options available to the user.

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IV. Robust Design

The objective of the robust design is to create products that are robust to environmental conditions, component variations, and that minimize the variability of key performance target(s) [Ref. 2]. There are two types of parameters involved in a product design, namely controllable parameters (control factors), and uncontrollable parameters, also called noise factors. The environmental parameters such as humidity levels, operating temperatures, raw materials, product aging, are examples of noise parameters. The examples of control parameters are the factors, which can be controlled, such as geometric parameters, materials, design configurations, manufacturing process etc. The aim in robust design is to find the appropriate levels of the controlled parameters such that the final design is insensitive (or robust) to changes in a set of noise factors. The word *robust* is used to signify that the product performs consistently on target, and is relatively *insensitive* to factors that are difficult to control (noise factors).

In robust design, the controlled factors are treated as deterministic design variables while noise factors are treated as random design variables. Hence robust design approach must combine the traditional deterministic optimization with probabilistic analysis. Over the years, we have seen ample application of deterministic optimization in the design cycle. Probabilistic analyses have not been widely used because of its perceived complexity and computational cost.

V. A Framework Of Robust Design With VisualDOC Software

In this section, we will provide a framework for performing a robust design approach called Design For Six Sigma (DFSS). The VisualDOC optimization software system [Ref. 10] will provide the necessary software tools for implementing the proposed framework.

The Figure 1 shows how VisualDOC communicates with the external analysis code.

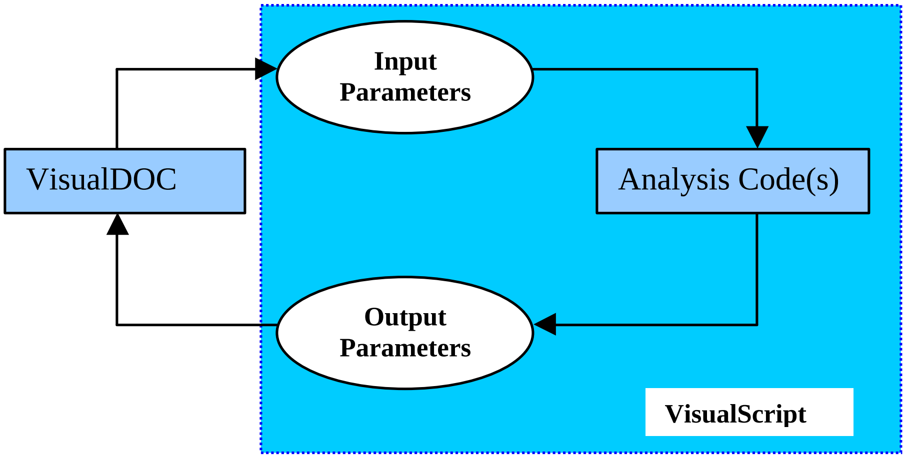

Figure 1: VisualDOC Communications with External Codes

Any analysis code that accepts ASCII input file(s), and generates one or more ASCII output file(s) can be graphically linked with VisualDOC optimization system using standalone software called VisualScript. VisualScript is the process-integration software provided along with the VisualDOC software package. VisualScript allows users to graphically select/tag a number of input parameters from the input file. The input parameters could be potential design variables for optimization. Similarly the output file could be opened to select/tag a number of output parameters. These output parameters are later used as objective function(s) and constraint(s). VisualScript allows more than one-analysis codes for interfacing with the VisualDOC. VisualScript will be used extensively to interface the external analysis and probabilistic codes for the robust design.

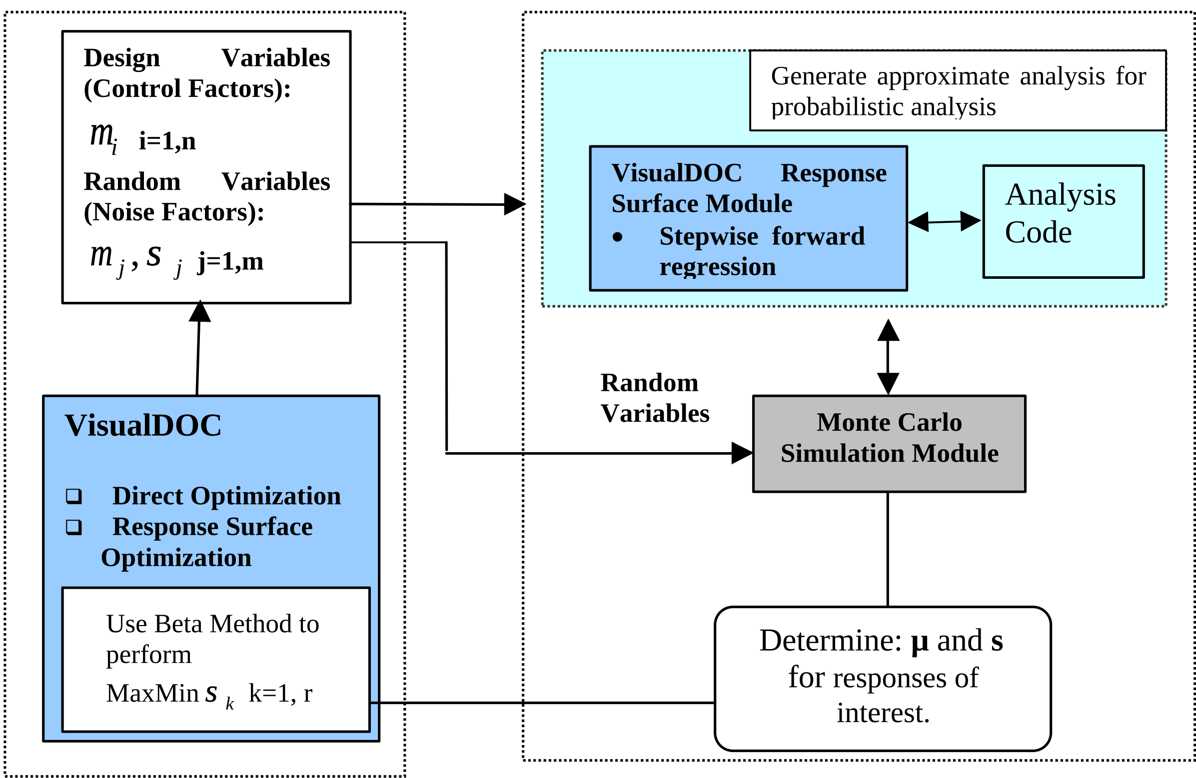

Figure 2: VisualDOC Framework for Robust Design

The first step in the robust design is to identify the important design variables. Some of these design variables are going to be deterministic in nature (control factors), and others are going to be random in nature (noise factors). For each design variable, specify realistic initial values, and the upper and lower bounds. One important success factor in robust design is to identify the design parameters that are sensitive. It may involve exploring the design space, and performing a sensitivity study. For each random variable, we will need to specify the mean, standard deviation, and the distribution type. It may not always be possible to specify the actual standard deviations. In that case, the standard deviation of a random variable could be specified as a percentage (say, 10%) of the mean value.

Before performing probabilistic analysis, it is recommended that we perform one deterministic optimization to get "optimal" starting design points for the optimization-probabilistic analysis. During this deterministic optimization process, the random variables could be treated as constants (equal to their mean values).

As shown in Figure 2, the probabilistic analysis is treated as a regular analysis in the optimization loop. Given a set of design variables, and random variables, Monte Carlo Simulation could be used to generate the random output responses. If the analysis is not expensive, we can perform "exact" analysis during the Monte Carlo Simulation. That may not always be the case, particularly analysis that involves expensive FEA simulations. In that case, an "approximate" analysis model will be used. The VisualDOC response surface module could be called in advance to create an approximate analysis model. A step-wise forward regression model coupled with an appropriate design of experiment (central composite, Box-Behnken, Latin Hyper Cube, etc) will be used to create the approximate model. This approximate model will created only once, and be used for the probabilistic analysis within the outer optimization loop.

One important aspect in the DFSS is to come with a set of SMART (Simple, Measured, Agree to, Reasonable, Time-based) goals and targets [Ref. 9]. If reasonable target values can be chosen, they can be used simply as "Target Values" on the output random variables for the optimization loop to satisfy. Alternatively, given the target values, the Sigma level of each output random variable can be calculated using the following equation [Ref. 11].

$$s_i = \frac{m_i - m_i^T}{s_i}$$

where

S_i is the current Sigma level of random response i

m_i is the current mean value of random variable i

m_i^T is the target mean value of random variable i

s_i is the current standard deviation of random variable i

Now the optimization can be based on either specifying target value on the individual sigma levels (S_i), or by specifying a single sigma level (S_T) for all random responses of interest. In that case, we can use a constraint such as $S_i \geq S_T$. S_T is equal to 6 for DFSS. Another approach is to maximize the minimum levels (S_i). While using this approach, one may be tempted to just pick the minimum of the S_i values, and them provide that to the optimizer for maximization. However, this is not a good approach because at any point where two or more response functions are equal, we will have a discontinuous derivative. A better approach is to add a new design variable, ß, to the already existing design variables as

$$m = \{m_1, m_2, ..., m_n, b\}^T$$

Now, we can simply maximize ß while requiring that all $S_i \geq b$. This lead to the following optimization problem:

Maximize ß
Subject to:

$$S_i \geq b \quad \text{i=1, Number of random responses of interest}$$

This approach, also called *Beta Method* [Ref. 3], allows us to find the highest sigma level that is achievable in the current design space.

VII. Conclusions

The importance of robust design in product development is now well recognized. Although there still exist some hesitations in fully implementing optimization and probabilistic approaches in the CAE community, we have started to see growing interest in using these technologies. This paper described strategies and tools that can be used to successfully implement a robust design approach.

References

1. Pande, P., Neuman, R., and Cavanagh, R. The Six Sigma Way: How GE, Motorola, and Other Top Companies Are honing Their Performance, McGraw-Hill, New York, 2000.
2. Myers, Raymond and Montgomery, Douglas, Response Surface Methodology – Process and Product Optimization Using Designed Experiments, John Wiley & Sons, Inc., New York, 1995.
3. Vanderplaats, G., Numerical Optimization Techniques for Engineering Design: With Applications, Vanderplaats Research & Development, Colorado Springs, CO, 2003.
4. Vanderplaats, G., "Very Large Scale Optimization", presented at the 8th AIAA/USAF/NASA/ISSMO Symposium at Multidisciplinary Analysis and Optimization, Long Beach, CA September 6-8, 2000.
5. BIGDOT – Very Large Scale Design Optimization Tools, V 1.0 User's Manual, Vanderplaats Research & Development, Inc., Colorado Springs, CO, 2002.
6. VisualDOC Design Optimization Software System, V 4.0 User's Manual, Vanderplaats Research & Development, Inc., Colorado Springs, CO, 2004.
7. DOT Design Optimization Tools, V 5.1 User's Manual, Vanderplaats Research & Development, Inc., Colorado Springs, CO, 2001.
8. GENESIS V 7.2 Reference Manual, Vanderplaats Research & Development, Inc., Colorado Springs, Colorado, 2002.
9. Breyfogle, F., Cupello, J., Meadows, B., Managing Six Sigma: A Practical Guide to Understanding, Assessing, and Implementing the Strategy That Yields Bottom-line Success, John Wiley, New York, 2001.
10. Balabanov, V., Charpentier, C., Ghosh, D. K., Quinn, G., Vanderplaats, G. and Venter, G., "VisualDOC: A Software System for General Purpose Integration and Design Optimization", presented at the 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, Atlanta, GA, September 4-6, 2002.
11. Vlahinos, A., Kelly, K., Pesaran, A., and Penney, T., "Empowering Engineers to Generate Six-Sigma Quality Designs", American Society for Quality (ASQ) Automotive Division Council Meeting, Troy, MI, January 13, 2003.