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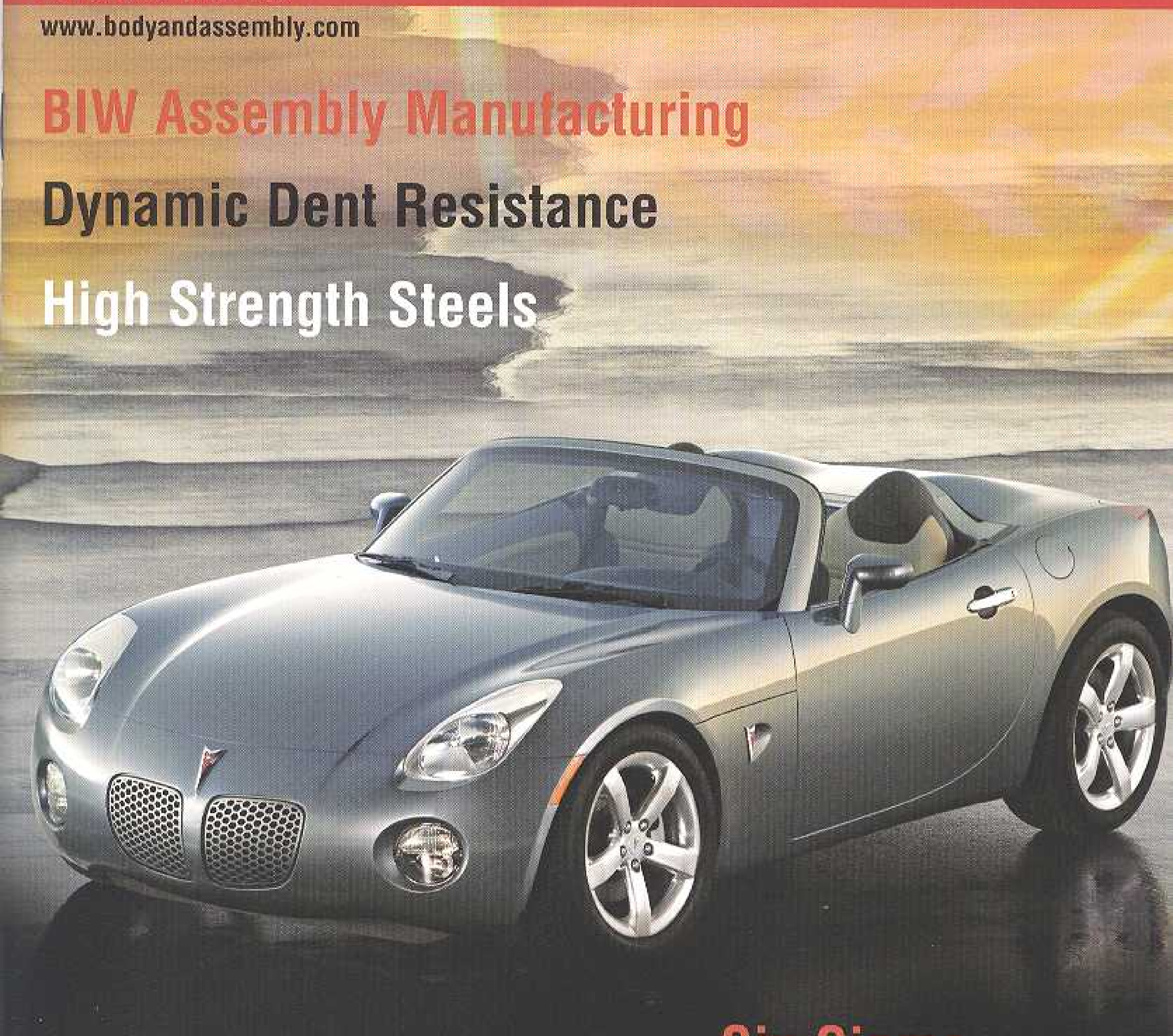

Six-Sigma Door Assembly

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Effect of Thickness and Material Variations on Six-Sigma Performance Targets of a Door Assembly

Andreas Vlahinos ▪ *Advanced Engineering*
Subhash Kelkar ▪ *Ford Motor Company*

FEATURE

Abstract

A design is robust when it is not sensitive to variations in noise parameters such as manufacturing tolerances, material properties, loading, etc. In recent years, several robust design concepts have been introduced to develop optimum designs and to minimize the variation in the performance characteristics. In this study, a probabilistic FEA analysis was performed on a door assembly in order to identify the effect of thickness and material property variation on performance targets such as drop-off, sag, and snap-through buckling. The thickness of the inner and outer panels, the thickness of the hinges, and the modulus of elasticity were considered as randomly varying parameters with a given mean and an assumed standard deviation. The performance targets were determined corresponding to the probabilistic input variables, and sigma quality regions are determined in the design space. The methodology for implementing robust design used in this research effort is summarized in a reusable workflow diagram.

Introduction

Most organizations address the quality issue by focusing on implementation of Six Sigma in their management and manufacturing environments. Most of the manufacturing cost over the life cycle of a product is determined by its initial design, therefore quality issues must be addressed early in the design cycle with robust design methodologies.

The goal of robust design is to deliver customer expectations at affordable cost regardless of customer usage, degradation over product life and variation in manufacturing, suppliers, distribution, delivery and installation. Since randomness and scatter are a part of reality everywhere, probabilistic design techniques are necessary to engineer quality into designs. Traditional deterministic approaches account for uncertainties through the use of empirical safety factors. The safety factors are derived based on past experience [Ref 5]; they do not guarantee satisfactory performance and do not provide sufficient information to make optimal use of available resources, frequently resulting in overdesign. The probabilistic design process has not been widely used because it has been intimidating and tedious due to its complexity. In recent years, CAD and FEA codes have introduced integrated design space exploration (PTC's Behavioral Modeling [14]), and Probabilistic Systems (e.g. ANSYS' PDS [1, 3, 5 and 7]) that make probabilistic analysis easy to setup if the con-

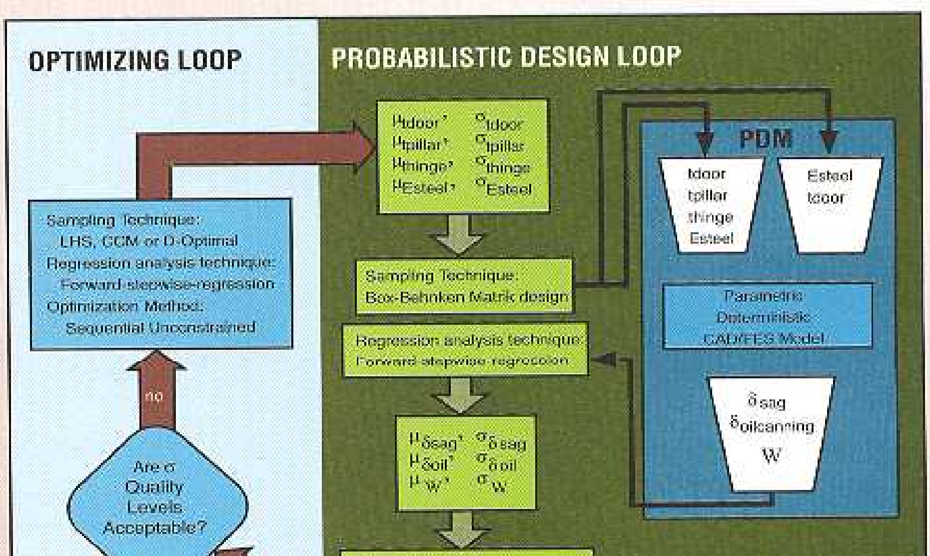

FIGURE 1: Workflow for Robust Optimization

trol and the noise parameters are identifiable [1]. Control parameters are those factors which the designer can control, such as geometric design variables, material selection, design configurations, manufacturing process settings, etc. [8]. Noise parameters on the other hand are factors that affect the design's functionality and are beyond the control of the designer or too expensive to control or change. Examples of noise parameters are material property variability (gauge, yield strength, percent elongation, etc.), manufacturing process limitations (part-to-part, run-to-run, and begin-end variations) [2], environmental loading, temperatures, humidity, component degradation with time, etc. One of the keys to finding optimal and robust designs is exploring the nature of the design space. The goal is to identify the key design parameters that have the most impact on the product attributes. This paper describes a design for a six-sigma technique that integrates FEA, probabilistic and robust design tools within the Computer Aided Design (CAD) environment. An example of an SUV door assembly is used and the effects of material and manufacturing variations on the assembly's behavior are identified.

Robust Design Process

The robust design process shown in Figure 1 has been implemented to evaluate the effect of component thickness and modulus of elasticity on some of the door assembly attributes. All of the symbols and processes will be described in subsequent sections. A sensitivity analysis of the random inputs on door assembly attributes is also presented.

In a typical design, we need to meet several design requirements such as sag, drop-off, window frame rigidity, door seal loading, beltline rigidity, flutter, outer panel oil canning, weight, etc. In this example, three of these targets were considered: the sag displacement of the door latch, the outer panel oil canning local deflection and the weight target. The robust optimization workflow includes three different processes: the parametric deterministic model (PDM), the probabilistic design loop, and the design optimization loop.

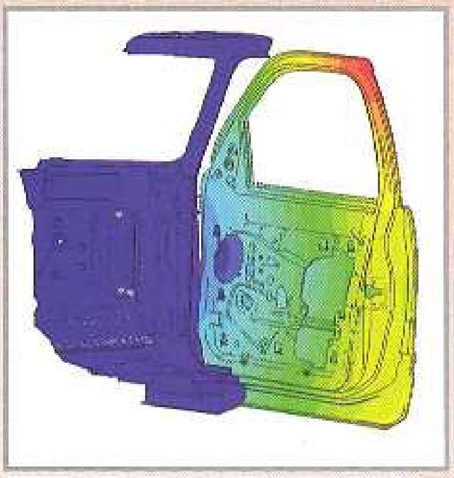

FIGURE 2: Displacement Distribution of the Door Sag Analysis Model

FIGURE 3: Displacement Distribution of the Door Sag Analysis Model

The Parametric Deterministic FEA Model

The parametric deterministic FEA model consists of an assembly of twenty body components that contain the A pillar, the hinge and the front door assemblies. The model contains approximately 45,000 nodes, 43,000 elements, and 14,000 constraint equations that represent the spot welds and bolted connections. The model is subject to gravity loading and the sag displacement of the door latch and the total weight are computed. Figure 2 shows the displacement distribution of the door sag analysis model. A portion of this model that consists only of the outer door panel is subjected to a load normal to the door panel and panel "oil canning" local deflection is computed. Figure 3 shows the outer door panel deflection under the second load case.

The A-pillar, hinge and door thicknesses as well as the modulus of elasticity were

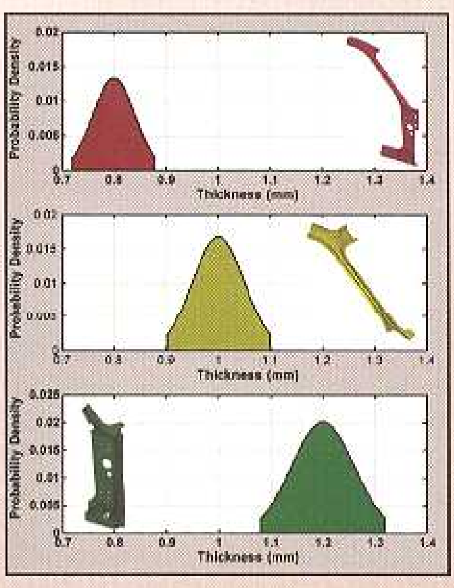

FIGURE 4: Probability Density Functions of A-pillar Components

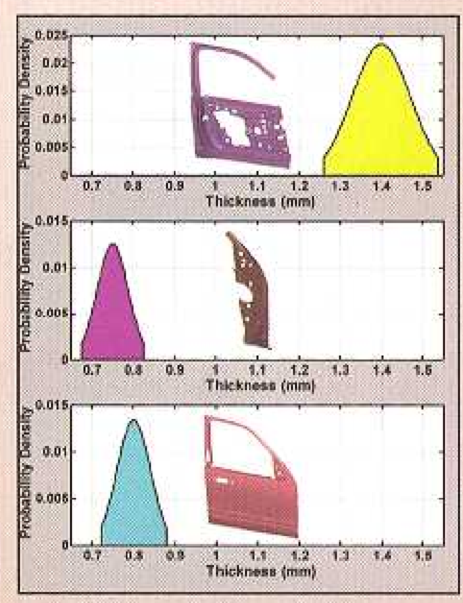

FIGURE 5: Probability Density Functions of Door Components

considered parameters. The thicknesses of the three components, shown in figure 4, of the A-pillar assembly were considered correlated parameters in such a way that their thickness ratios always remain the same. Similarly the three door components shown in figure 5 were considered correlated. In other words, they are assigned the maximum mean values at the same time. Proprietary observations and implementation details are omitted from this paper.

The Probabilistic Design Loop

All four parameters of the deterministic model were considered as having variation. The distributions of the mean dimensions are approximately normal [2]. It was assumed that all three thickness variables exhibit truncated normal distribution with given mean, standard deviation, minimum and maximum values. The mean value of the door panel thickness μ_{tdoor}, the mean value of the A-pillar thickness $\mu_{tpillar}$ and the mean value of the hinge thickness μ_{thinge} were considered as control variables. The mean value of the modulus of elasticity and all the standard deviations were considered as noise parameters. The standard deviation of each parameter

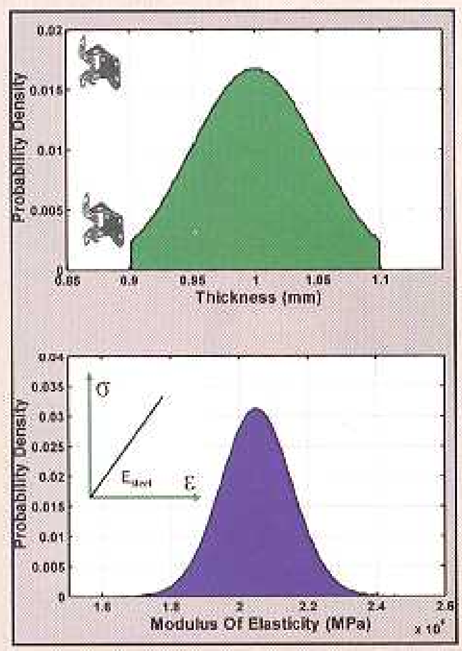

FIGURE 6: Probability Density Functions (a) of Hinge Thickness and (b) Elasticity Modulus

was assumed to be five percent of the mean value. The maximum and minimum values of each distribution were assumed to be ten percent of the mean value. Typically allowed ranges are essentially the tolerance of the process and material input variables [2]. Figure 4 shows the probability densities of the three A-pillar components with $\mu_{tpillar}$ = 1.0 mm. Figure 5 shows the probability densities of the three door components with μ_{tdoor} = 0.8 mm. Figure 6a shows the probability density of the hinge thickness. It was assumed that the modulus of elasticity variable exhibits normal distribution with given mean and standard deviation. Figure 6b shows the probability density of the modulus of elasticity for μ_{Esteel} = 205,000 MPa.

For a given set of the mean values of these input design variables and the assumed distributions one may easily generate a large set of random numbers for each variable. Several sampling techniques are available to generate combination sets of these design variables such as Monte Carlo, Latin Hypercube Sampling (LHS), Central Composite, Box-Behnken Matrix, etc. If the "experiment" is fast and inexpensive Monte Carlo and LHS sampling techniques work well. In this case the "experiment" is a structural finite element analysis. If the "experiment" is time consuming and expensive, a Box-Behnken Matrix in combination with the response surface technique is preferred. In this example, the Box-Behnken Matrix sampling was used in combination with Forward-stepwise-regression. The probabilistic design loop is fully automated and if one views this loop as a transfer function, the mean values of the four design variables can be considered as inputs ($\mu_{tpillar}$, μ_{tdoor}, μ_{thinge} and μ_{Esteel}) and the mean (μ_{sag}, $\mu_{oil\_canning}$, μ_W) and standard deviation (σ_{sag}, $\sigma_{oil\_canning}$, σ_W) of the attributes (the sag displacement of the door latch, the outer panel oil canning local deflection and the weight target) can be considered as outputs. Figure 1 shows a graphical representation of the data flow for this loop.

Figure 7 shows the histogram of the door sag deflection of the optimized case corresponding to input values in Figures 4-6. Vertical lines corresponding to the mean value and the various sigma levels (1-6) of the door sag deflection are shown in this figure. One may observe that in this case the upper specification limit (USL) is farther away from the six sigma range indicating that this design, practically speaking, will always satisfy the upper specification limit. Figure 8 shows the histogram of the oil canning deflection and the upper specification limit. A similar conclusion can be made since the upper specification limits is farther away from the six-sigma range. Figure 9 shows the histogram of the weight distribution corresponding to input values Figures 4-6. In this case the upper specification limit is close to the six-sigma level.

An alternative way to quantify the quality of the design is to determine the sigma level by solving for "n_i" in the following equations.

Equation 1

$$\mu\delta sag - \mathbf{n}\,\delta sag \ast \sigma\,\delta sag \le \delta SagTarget$$

Equation 2

$$\mu tdoor - \mathbf{n}\,tdoor \ast \sigma\,tdoor \le \delta SagTarget$$

Equation 3

$$\mu tpillar - \mathbf{n}\,tpillar \ast \sigma\,tpillar \le \delta SagTarget$$

Figure 10 shows the sigma quality levels $n_{\delta sag}$, n_{tdoor}, $n_{tpillar}$ versus the mean value of the door panel thickness μ_{tdoor}. Each one of the three curves corresponds to a specific performance target. To meet the weight target with six-sigma quality level the mtdoor must be less than 0.8 mm and in order to meet the oil-canning target with six-sigma quality level the μ_{tdoor} must be greater than 0.73 mm. One may observe form this figure that to achieve a six-sigma quality level the mtdoor must be between 0.73 and 0.8 mm.

If the desired sigma level of quality is achieved the first time, the designer can stop at this point. If the desired sigma level of quality is not achieved the

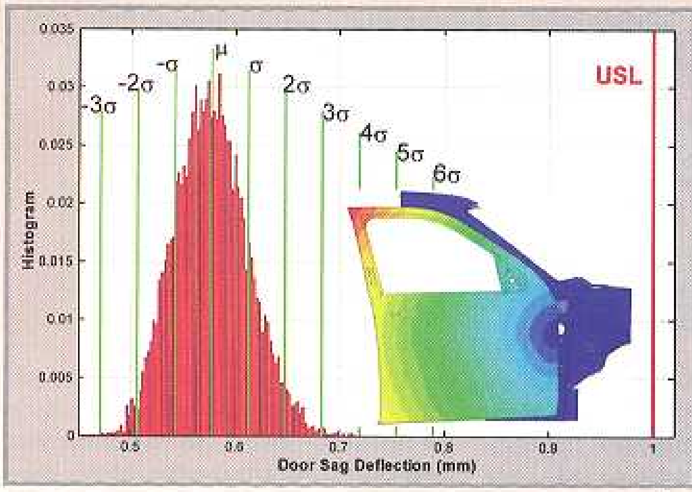

FIGURE 7: Histogram of the Door Sag Deflection (Response Attribute)

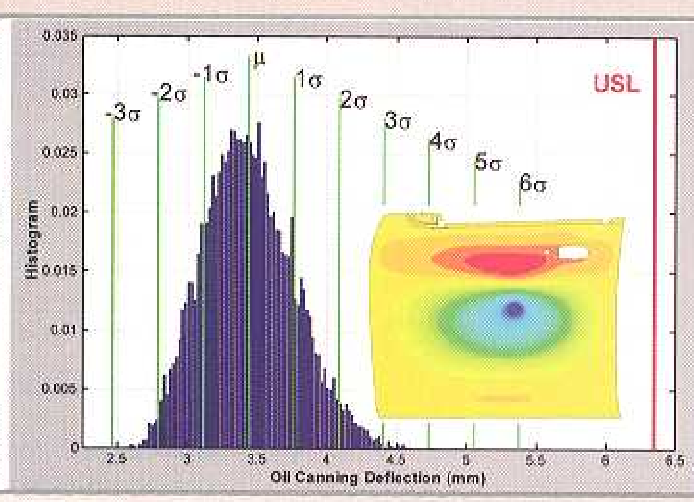

FIGURE 8: Histogram of the Oil-Canning Deflection (Response Attribute)

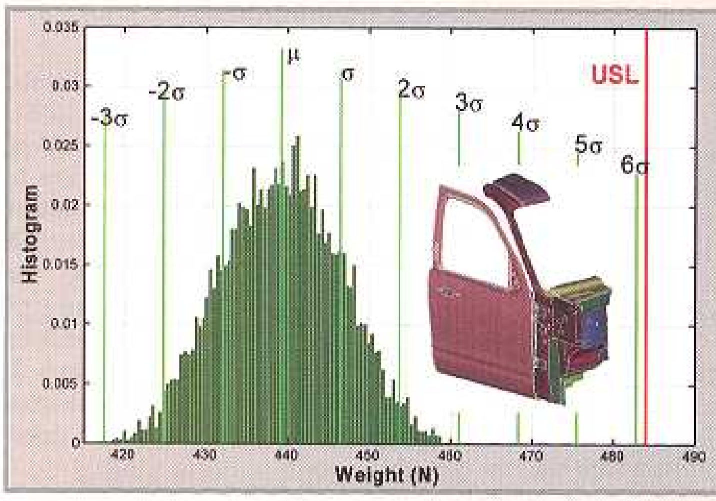

FIGURE 9: Histogram of the Assembly Weight (Response Attribute)

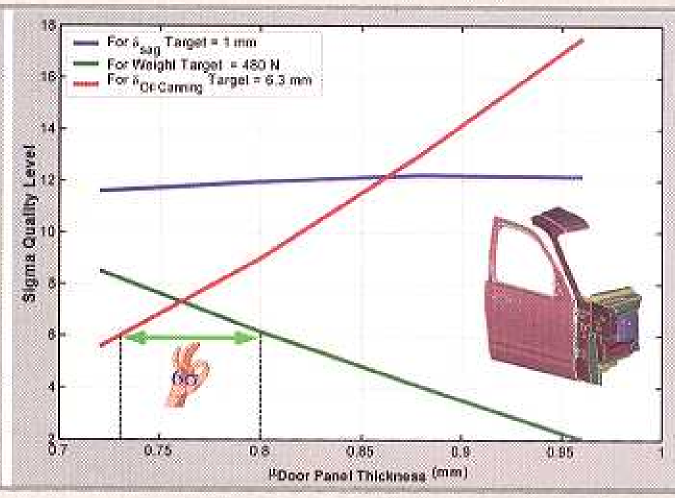

FIGURE 10: Sigma Quality Levels versus Door Panel Thickness

designer needs to adjust the inputs of the probabilistic design loop ($\mu_{tpillar}$, μ_{tdoor}, μ_{thinge} and μ_{Esteel}) and rerun his analysis. This adjustment can be automated with a design optimization loop

The Design Optimization Loop

The three main control variables used as inputs of the probabilistic design loop are mean values of the three design variables ($\mu_{tpillar}$, μ_{tdoor}, μ_{thinge}). The three main outputs of that loop are the sigma quality levels of each one of the three targets. The designer's goal is to select the appropriate sets of values for the design variables ($\mu_{tpillar}$, μ_{tdoor}, μ_{thinge}) that maximizes the minimum value of the three sigma quality levels. The optimization setup in mathematical form is:

Find the values of $\mu_{tpillar}$, μ_{tdoor}, μ_{thinge} that

Maximize the min $[n_{\delta sag}, n_{tdoor}, n_{tpillar}]$

where:

$0.70 \text{ mm} < \mu_{tpillar} < 2.00\text{mm}$

$0.70 \text{ mm} < \mu_{tdoor} < 2.00\text{mm}$

$0.70 \text{ mm} < \mu_{thinge} < 2.00\text{mm}$

This task has been fully automated with the design optimization loop [11]. Since each "experiment" of this loop is computationally expensive, the D-optimal sampling technique was selected to select the initial set of trials. The Sequential Unconstrained minimization technique was selected as the optimization method. Figure 1 shows the workflow for the optimization loop. If the geometry is very challenging, the design optimization loop can be automated using PTC's Behavioral Modeling. The Behavioral Modeling Extension of Pro/Engineer is an additional module that has the capability of generating analysis and optimization study features. The external analysis feature sends certain information to an external program, executes it, retrieves some predefined results from the output information and generates Pro/Engineer parameters. These parameters can be optimized using the optimization feature [13].

Sensitivity Analysis

Figures 11-13 show the sensitivity of the various design variables corresponding to the design requirements of Door Sag, Oil Canning, and Weight, respectively. The results are summarized in Table 1.

For Door Sag, the door panel thickness has the smallest contribution (i.e. 6%). This contribution is small because though a higher thickness does increase the stiffness of the door panel, it also increases the gravity loading (weight). The hinge thickness contribution is 19.3%, the A-pillar thickness contributes 26%, and the Modulus of Elasticity contributes 48.7%. The range that these variables are allowed to fluctuate in influences the contribution of each design variable.

Figure 12 shows the sensitivity of the design variables corresponding to oil canning deflection. As expected, only the outer door panel thickness and the Modulus of Elasticity have an effect. The Modulus of Elasticity contributes 62% and the outer door panel contributes 38% to the oil canning deflection.

Figure 13 shows the sensitivity of the design variables corresponding to the weight requirement. The hinge thickness contribution is 6%, the A-pillar contribution is 30%, and the door thickness contribution is 64% as expected, since the surface area of the door is much larger than that of the A-pillar and the hinges.

		SENSITIVITY CONTRIBUTION				
FIGURE	REQUIREMENT	MODULUS OF ELASTICITY	DOOR PANEL THICKNESS	HINGE THICKNESS	A-PILLAR THICKNESS	COMMENTS
11	Door Sag	48.7%	6.0%	19.3%	26.0%	Door Panel thickness contributes positively to resisting sag, but negatively to minimizing weight
12	Oil Canning	62.0%	38.0%	0.0%	0.0%	Local Effect: Hinge Pillar, A-Pillar and Door Inner Panel Thickness have no contribution
13	Minimum Weight	0.0%	64.0%	6.0%	30.0%	Based on relative volume of each component; Modulus of Elasticity has no effect

TABLE 1: Summary of Sensitivity Results

Conclusions

• The example presented demonstrates that with probabilistic design and optimization integration, engineers are able to develop designs that better meet performance objectives and are less sensitive to manufacturing variations.

• The methodology for implementing robust design used in this research effort is presented in a practical, reusable workflow diagram with the proposed DOE and response surface algorithms.

• Modern CAD and FEA software tools that have incorporated probabilistic design allow distributed computing that enables the implementation of this computer intensive technology.

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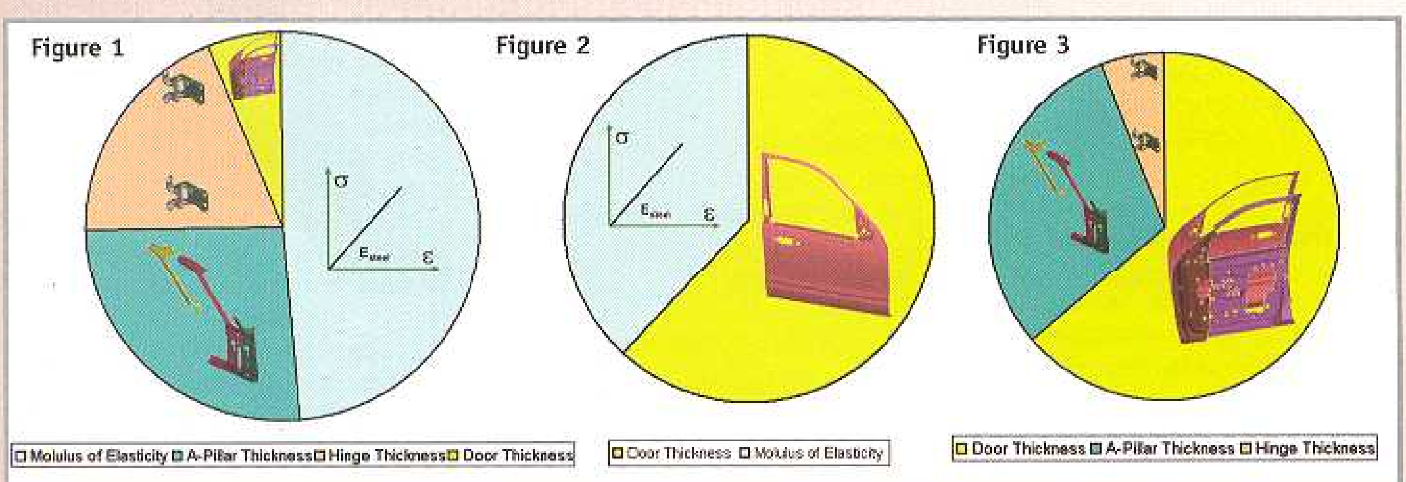

FIGURE 11: Sensitivity of Design Variables on Door Sag Deflection
FIGURE 12: Sensitivity of Design Variables on Oil-Canning Deflection
FIGURE 13: Sensitivity of Design Variables on Assembly Weight Deflection

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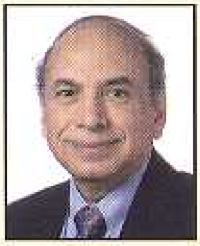
John R. Brockenbrough, PhD
Alcoa
Dr. John R. Brockenbrough is a Senior Staff Engineer at the Alcoa Technical Center working on R&D related to durability and fracture of aluminum alloys and product design. His background included development in resistance spot welding for automotive sheet applications and microstructural influences on durability in aluminum castings.

Donald Dixon
Gage Products Company
Mr. Dixon is president of Gage Products Company, a leading supplier of test fuels, paint solvents and closed-loop paint-system recycling technology for the automotive industry. He is a graduate of Michigan Technological University. Mr. Dixon joined Gage Products in 1971 as a sales engineer and went on to hold a series of key management positions, including executive account manager and vice president, prior to becoming the company's president in 1991.



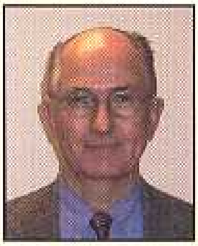
Subhash Kelkar, PhD
Ford
Dr. Subhash Kelkar is Technical Leader, Durability CAE at Ford Motor Company. He has published numerous international and external technical publications. Dr. Kelkar received his Ph.D. in Mechanical Engineering from the University of Missouri-Rolla in 1973 and has been employed by Ford Motor Company since 1977. He has developed and taught several technical courses related to CAE within Ford Motor Company.

Ron Krupitzer
American Iron and Steel Institute
Mr. Krupitzer is a Senior Executive Director of AISI's Automotive Applications Committee (AAC). He began his career in 1968 at the Republic Steel Research Center and later became section chief of flat rolled and tubular products research. He was promoted to process development manager at Republic/LTV Steel's Cleveland Works in 1982 and he joined Chrylser Corporation in 1985. In 1992 he was promoted to stamping senior manager in the Chrysler Stamping Division. Mr. Krupitzer earned a Bachelor's Degree in Metallurgy from Case Institute of Technology and a Master's Degree in Metallurgy and Materials Science from Case Western Reserve University, both in Cleveland, Ohio.

Dinesh Seksaria
Alcoa
Dinesh Seksaria P.E. is a Senior Technical Consultant in Alcoa's Automotive Business Unit. He has more than 35 years experience in development of automotive products and has more than 20 patents in the field published several papers in SAE and in industry publications. His current activities include developing automotive body and suspension related products using aluminum sheet and other product forms.

Herman Tang, PhD
DaimlerChrysler
Dr. He (Herman) Tang is with Advance Manufacturing Engineering of DaimlerChrysler Corporation. His technical interests are in process development, lean manufacturing, dimensional control and welding, and research experiences on NVH, FEA, CAPP and machinery diagnosis. He published 25 technical papers. Dr. Tang holds a Doctorate degree from University of Michigan, a Master's degree and a Bachelor's degree from Tianjin University, China, all in Mechanical Engineering. Dr. Tang is a member of SAE, AWS and ASME.

Dennis Urban
Ispat Inland, Inc.
Mr. Dennis Urban is Director of Product Applications for Ispat Inland Research & Development, a position he has held for the past six years. After completing his education in Metallurgical Engineering at the Illinois Institute of Technology, Mr. Urban joined the former Inland Steel Company, now Ispat Inland Inc. With 33 years of experience, he has held a variety of engineering and management positions in operations, technology, quality control, planning and commercial areas.



Dennis A. Wilmer
United States Steel
Mr. Witmer has served the steel industry for over 40 years. He began his career at Bethlehem Steel as a Research Engineer, and later was involved with the sales and marketing of coated and specialty sheet steel products. In 2002, he was named to his current position, Technical Marketing Manager t U.S. Steel's Automotive Center in Troy, Michigan. Mr. Witmer holds a Bachelor of Science degree in Engineering from the University of Maryland, and a Masters of Science degree in Metallurgy and Materials Science from Lehigh University. He has published several articles on the physical metallurgy of low carbon sheet steels.

Andreas Vlahinos, PhD
University of Colorado
Dr. Andrea Vlahinos is the Principal of Advanced Engineering Solutions. He has been Professor at the University of Colorado and has over 100 publications. He has been instrumental in rapid product development through the implementation of CAE and DFSS for several Government agencies such as NASA, NREL and DOE and industry partners such as IBM, Coors, Lockheed Martin, Alcoa, Allison Engine Comp., Solar Turbines, Ball, Futech, American Standard, Kohler, Varian, Stewart & Stevenson, TDM, PTC, MDI, Ford.