Time to Quality

Design/Simulation Council

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PRODUCT LIFECYCLE MANAGEMENT ROAD MAP™

CPDA: Collaborative Product Development Associates, LLC

CPDA's Product Lifecycle Management (PLM) research programs target the critical decisions in Product Lifecycle Management challenging Design, Engineering, Manufacturing, and Information Technology managers and executives. CPDA's PLM collaborative research programs provide in-depth analysis of strategies, products, issues, processes, technologies, trends, case studies, and surveys for assessing technology, business goals and objectives, and implementation road maps.

The cohesive suite of collaborative programs clarifies and evaluates new capabilities, standards for frameworks, and development issues; it highlights the most advanced uses of leading technologies, and it links the technical effort to the realization of business value. The four collaborative research programs include:

Design Creation and Validation*:* A bottom-up view of engineering requirements from the desktop across the enterprise. Advanced computer-aided design (CAD), engineering analysis, manufacturing technologies, collaboration, and visualization software serve as springboards for gaining a competitive advantage. The Design Creation and Validation service applies CPDA's structured methodology to the evaluation of new products and processes as well as to current projects in client organizations. A critical focus, the emerging technology of knowledge engineering with templates and rule-based architectures focuses on delivering the needed tools into the hands of product developers to capture knowledge, and to formalize its use. The use of direct geometry access and manipulation, data translation technology, XML alternatives, and JT options are also assessed for their ability to deliver interoperability across the diverse and disparate business and technical applications.

Design/Simulation Council*:* The Council promotes a standard framework employing common terminology to integrate and optimize the diverse and divergent specialist activities currently fragmenting design efforts. CAE must fully integrate with design, up front, to close the chasm between design and analysis. Analysts must actively participate continuously in design decisions and enter the mainstream. The impending breakthrough in CAE will rest on knowledge reuse, process capture, and streamlining.

PLM Integration / Product Definition: A top-down view provides a conceptual framework for collaboration across different product development perspectives, bridging customer needs, systems engineering and tradeoffs, design solutions, and fulfillment and manufacturing. Integration and interoperability in complex PLM environments pose substantial hurdles. The rapid transition to cross-enterprise collaboration, at all levels of design and supply, intensifies the pressure on existing, inwardly focused IT architectures to support and enable new modes of doing business.

Product Value Management: Common processes for design, development, and product introduction across the supply chain may be validated with reference models such as SCOR (Supply Chain Operational Reference model), or VCOR (Value Chain Operational Reference model). The first step, business process modeling (BPM), facilitates the building of consensus around a common understanding and terminology, across organizations and functional silos. Mapping BPM to a service-oriented architecture based on open standards represents a critical second step. An IT integration infrastructure in a Federated Enterprise Reference Architecture™ (FERA) supports a loose coupling between enterprises extending across the supply chain.

Collaborative Product Development Associates was formed by the PLM research team of D.H. Brown Associates, Inc. (DHBA).

Time to Quality

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Dr. Andreas Vlahinos has been instrumental in rapid product development through the implementation of Design for Six Sigma (DFSS) and Computer-Aided Concurrent Engineering for several government agencies, including NASA and DOE, and for industry partners such as Alcoa, Allison Engine Company, Ford Motor, General Dynamics, IBM, Lockheed Martin, Mechanical Dynamics, PTC, Solar Turbines, and Toyota, among others.

Dr. Vlahinos teaches Structural Mechanics and Computer-Aided Structural Engineering at the University of Colorado, and has received the Professor of the Year Award several times. He has authored over 100 publications covering structural stability, structural dynamics, and design optimization, and has received R&D Magazine's R&D 100 award. Dr. Vlahinos received his Ph.D. in Engineering Science and Mechanics from the Georgia Institute of Technology.

This report is derived from Dr. Vlahinos' presentation at Collaborative Product Development Associates' annual conference, PLM Road Map™.

EXECUTIVE SUMMARY

Design for Six Sigma (DFSS) strategies are transforming our methodologies for improving quality from inspecting defects after-the-fact to building quality into a product from the beginning of its design. The approach considers the statistical contribution of the design parameters to the critical requirements. The effects of variation can be identified, understood, and forecast during the design cycle. Adoption of the DFSS process mitigates the risks and costs of poor quality.

How can DFSS be implemented? In general, by making the cost of poor quality part of the design equation, including the warranty, liability, recall, lost customer, and rework costs. The cost of the product must include all of the quality issues, in addition to direct development costs. Optimize for total cost, including quality, up front early in the design. In terms of specific steps, seven prerequisites should be fulfilled to support process integration and design optimization, as summarized in Table 1 on the following page.

Most critically, the CAE analyses should include a robust assessment of known sources of variation. The sigma quality level must be calculated given the target performance and variation. Place the power of DFSS in the hands of every design engineer, not just those with advanced degrees. And finally, automate DFFS into

your design process. Mainstream software products greatly facilitate a DFSS implementation.

Table 1: Prerequisites for a Highly Effective Design Process	
1.	Clarify and document the desired design decision process.
2.	Create a design environment tailored to the desired design process and workflow management.
3.	Develop a repository of design and manufacturing rules to govern the design process.
4.	Simplify and automate tool usage for standard analyses.
5.	Automate and simplify data integration, to make the right data available on the first attempt to access the information.
6.	Augment the experts by automating large portions of the design process with approaches such as workbench wizards.
7.	Take full advantage of the new class of PIDO tools including DesignXplorer (ANSYS), Universal Engineering Model [UEM] (CoMeT Solutions), OPTIMUS (Noesis/LMS), VisualDOC (Vanderplaats Research & Development), iSIGHT (Engineous), modelFRONTIER (ESTECO, in Italy), HyperStudy (Altair), Model Center (Phoenix Integration), KollabNet (KollabNet Corporation), Tool Integration Environment [TIE] (Technosoft), Enductive (Enductive Solutions), and BMX [Behavioral Modeling Extension] (PTC).

This paper summarizes current modeling processes and tradeoffs to automatically create optimum robust designs, including three examples of probabilistic design and optimization. It covers reusable workflow processes, as well as the challenges and rewards for successful DFSS implementations.

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INTRODUCTION TO DFSS, ROBUST DESIGN, AND PIDO

Successful organizations realize that probabilistic design techniques have enormous positive impact on time-to-quality. Time-to-market often becomes irrelevant when the total costs of poor quality factor into the analysis. Liability costs for some products even exceed the development budget. Consider as well the rework costs on recalls, warranty payments, and lost customers from a negative brand image. Too often, companies simply make mistakes, or overreact and build in superfluous safety factors.

Design must directly consider the noise factors of variation, recognizing that not all bad outcomes happen at the same time. Variation in manufacturing must be measured, as well as factored into design tradeoffs. Applying direct statistical techniques derived from Six Sigma, companies may compare the mean and the standard deviation for any outcome with the targeted performance. Then an assessment of the quality level must consider the costs incurred as well. With this approach, design can rationally achieve the targeted level of cost.

Design for Six Sigma (DFSS) methodology considers the statistical contribution of the design parameters to the critical requirements. The effects of variation can be identified, understood, and forecast during the design cycle. Adoption of the DFSS process mitigates the risks and costs of poor quality. DFSS, robust design, and a new class of tools fall under the umbrella of PIDO – Process Integration and Design Optimization. As illustrated in the consideration of three actual design problems, to deal effectively with variation, the workflow is very similar across most designs. Moreover, today that workflow may be effectively integrated in the product development process.

Time-to-market is not good enough.

Regardless of the industry, we all face the same challenges, which may begin with contradictory design requirements. As more complex design requirements surface involving issues such as cost, performance and safety, quality, time-to-market, environmental impact, and aesthetics, the need for innovative tools becomes ever more apparent and urgent.

Many organizations emphasize quality and reputation. For the automotive sector out of Detroit, in particular, the perception of poor quality drives the need to fight to overcome the reputation. Product quality in turn involves managerial, technological, and statistical capabilities across all the major functions of an organization.

What degrades quality, what is its enemy? The enemy is variation, which comes from such factors as thickness, loads, material properties, and surface finish. Of several dozen different approaches for dealing with variation, one of the most practical includes the design of experiments. A second, Design for Six Sigma, involves a set of tools for analyzing, allocating, and optimizing variability. The statistics from finite element analysis (FEA) provide valuable input for the analysis as well.

PROCESS INTEGRATION AND DESIGN OPTIMIZATION (PIDO)

How do we do all of these things today? The best approach relies on PIDO tools that follow four major steps:

1. Process Automation
2. Design Exploration
3. Design Optimization
4. Robust Design

PROCESS AUTOMATION

The first step, process automation, ensures that the task and events in simulation flow automatically. It is necessary to automate one run or one simulation completely. For example, with a car, the solver must have the ability to change the parameters. There should be a human interface that can direct the solver to run a few results by pointing the mouse, obtaining the result and target, and automatically designating the result as a design or a response variable. But, note that for some older PIDO tools an XML team is needed to help build the particular XML link to the PIDO model. Moreover, with those tools that same team may have to return later towards the end of any project to rebuild the links as some of the tools have not fully matured to deal fully and effectively with changes.

DESIGN EXPLORATION

With the process defined, design exploration, the second step, then addresses the need to run combinations of parameters and different ranges of values, as well as perform Design of Experiments. The ability to quickly and effortlessly solve for variations in parameters supports the exploration needed to identify the best solution and allows users to perform quick and accurate what-if scenarios to test design ideas. Just by dragging a mouse, the software can display the number of screening variables that are changing, which is particularly useful with a large design space involving many variables, and makes it easy to understand how design variation can affect system performance.

DESIGN OPTIMIZATION

Design optimization, the third step, has been around for years; it is the selection of the best alternative available within the acceptable range of performance variables. How do we address this design optimization today? Knowledge, tradition, and experience govern the design choices. The optimization typically sets those design parameters right up to the limits of a constraint. But finding the best solution is not necessarily good enough. If you push the design a little bit past the constraint, problems may occur. In a perfect world, this would be the optimum. In the real world, which includes variation, half of the products could easily fall on the other side of the constraint. Half of your products would be recalled. Why do we need to deal with the variability? Because variation exists in all systems, sub-systems, and components.

ROBUST DESIGN

This leads to step four: robust design. Robust design delivers customer expectations at acceptable cost and profitable levels regardless of:

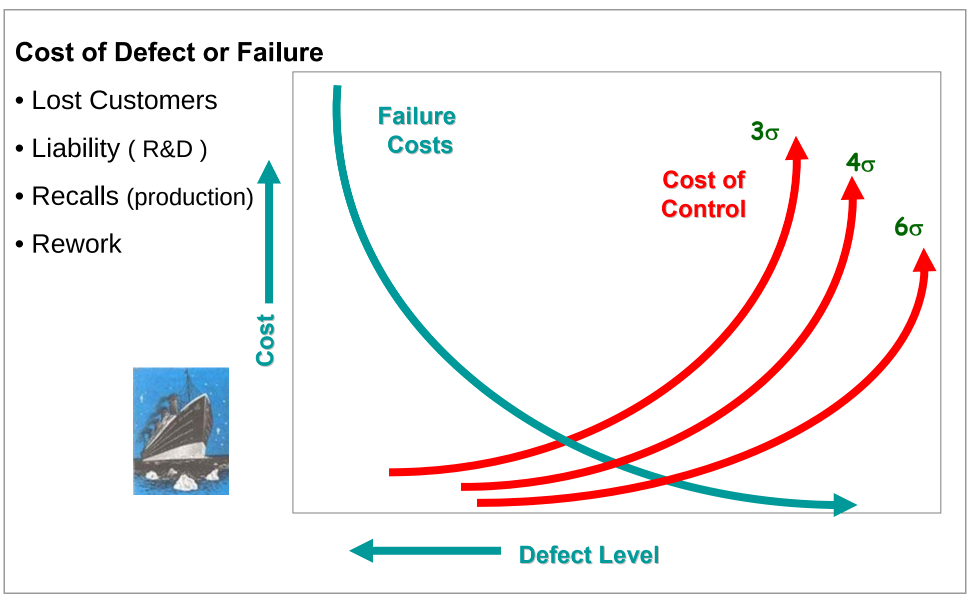
- customer usage;
- variation in manufacturing ;
- variation in suppliers;
- variation in distribution, delivery, and installation;
- degradation over product life.

Customer usage cannot be dictated. Ideally, drivers should avoid potholes, but they will inevitably go through them. The same is true for variation in manufacturing. You cannot ask a customer to just bear with you if you change manufacturers and the material is now a bit weaker. The customer cannot be expected to keep buying the products.

We understand the presence of variations. So what do we do as designers? Shift the performance mean for the target value, and shrink the product's performance variability.

The cost of the product is more realistic if we include the cost of poor quality, defects, lost customers, or liability claims. When budgeting, the costs of buying new software or new training tools, or of hiring a consultant, must also be included. Determine if that budget is sufficient by trying to determine internally the cost of poor quality. Failure costs increase with the defect level. With more control on quality, total cost drops, as illustrated below in Figure 1.

FIGURE 1
Improved Quality and Reduced Total Cost



How do we control quality? There are two classes of parameters involving both noise and control. Noise parameters represent factors that are beyond the control of the designer. For example, there is nothing a designer can do about the variability of material properties. There are also manufacturing process limitations, such as those related to accuracy and tolerance with ejection molding, for example. Environmental variables such as temperature and humidity levels may also be classified as noise parameters. For example, a hybrid car battery gets hot. Does that mean you do not sell this car in Palm Springs? Or vice versa, would you not sell it in Buffalo, New York because the fuel cell freezes in the wintertime?

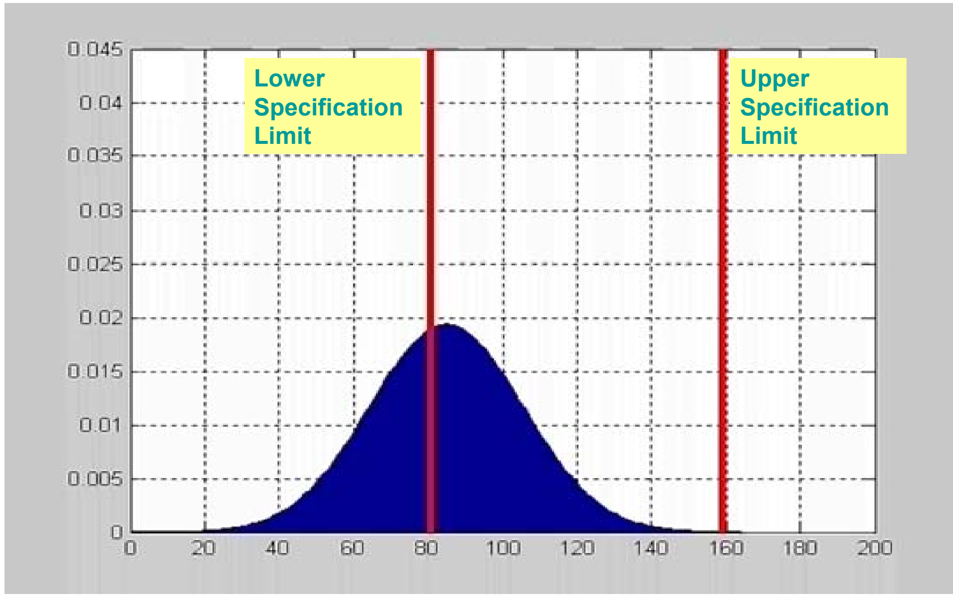
The control parameters for the designer include geometric design variables (width, thickness), material selection (aluminum-steel), design configuration (flat, corrugated, or ribbed panel), manufacturing process settings, as well as several other factors.

What tools are available to account for variability? As shown on Table 2 below, there is the design of experiments, the response surface method, and six sigma design.

Table 2: Tools for Robust Design
Design of Experiments
Exploits nonlinearities and interactions between noise and control parameters to reduce the variability of product performance
Full factorial, fractional factorial, Monte-Carlo, LHC
Response Surface Methods
Central Composite Design
Box-Bhenken Design
Six-Sigma Design
Identifying and qualifying causes of variation
Centering performance on specification targets
Achieving Six Sigma-level robustness on the key product performance characteristics with respect to the quantified variation

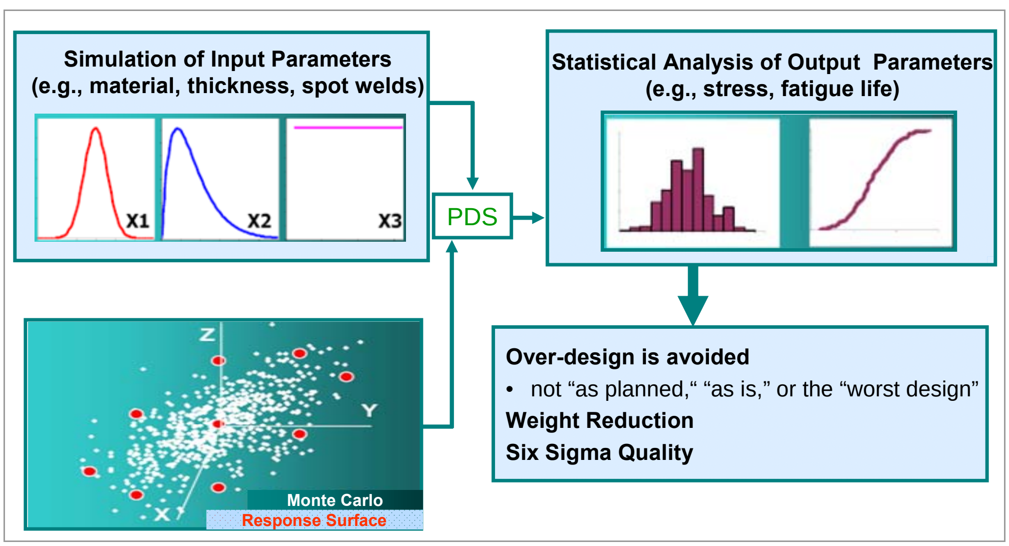
Shift-and-shrink comes into play here. Referring to Figure 2 on the following page, there is a lower and an upper limit in our attributes. The mission is to shift the distribution from the left out to the middle, and then shrink or squeeze the distribution so it will fit between the upper and lower bounds of the specification to meet the targets.

FIGURE 2
Shift and Shrink



How is this done in a simulation? By using a mean value and a standard deviation, instead of giving a single-point estimate as the targeted numerical value. Using a sampling technique, a pair of random variables is run in the simulation. This is then repeated with other pairs until there may be results from a thousand random runs. There will then be a thousand random outputs that define the mean and standard deviation.

FIGURE 3
Key Performance Parameters: Statistical Design Performance Simulation



As illustrated in Figure 3 above, three variables such as material, thickness, and spot welds may be considered. In this case, the variation of the key performance parameters follows various distributions. For example the material variation follows a Weibull distribution, the thickness follows a normal distribution, and the loads follow a log-normal distribution. With spot welds, the distribution can be uniform, as any can fail with equal probability.

Once the information on both the mean and standard deviation is available with the distribution of the critical performance variables, combinations of variables can be assessed with a smart Monte Carlo approach to assemble the data for simulation. Hundreds or even thousands of runs might be completed to support the statistical analysis of output parameters.

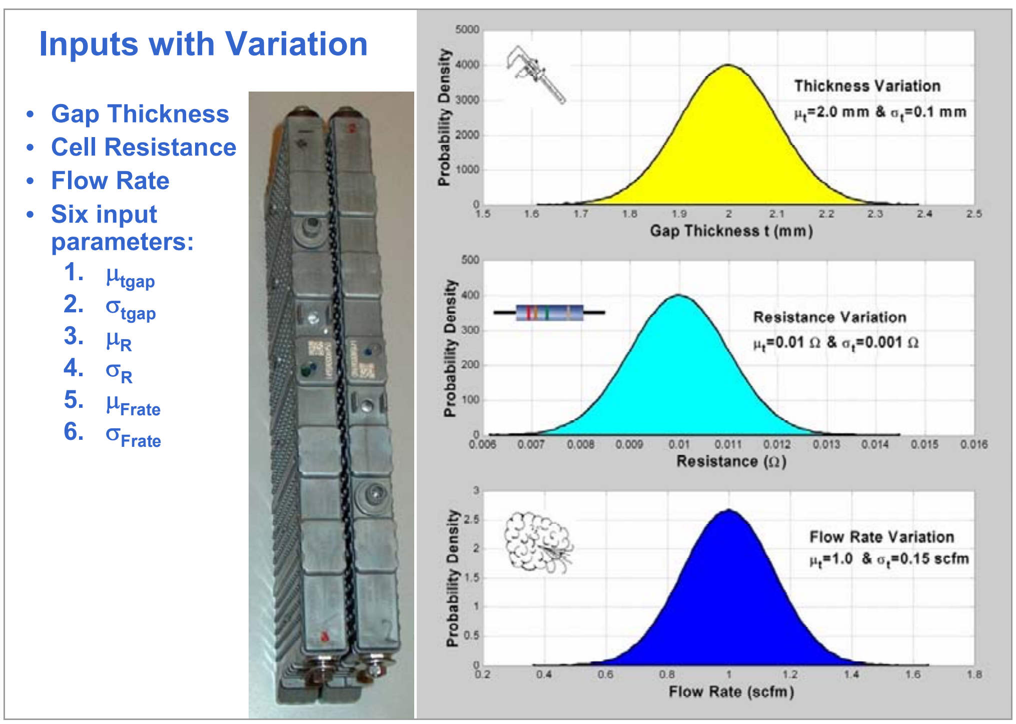
To illustrate how DFSS applies in design, three examples will be considered – thermal management for a battery, design of an SUV door, and gasket configurations for fuel cells.

1. APPLYING SIX SIGMA DESIGN TO BATTERY THERMAL MANAGEMENT

The first example involves a hybrid electric vehicle battery, which has evolved with many design improvements over time. The battery cell is, practically speaking, handmade. It has layers of copper and aluminum that are put in a cavity and filled with electrolytes. However, there is a great deal of variation involved, particularly in the thickness of the gaps between the layers, which leads to significant variation in the overall electrical resistance.

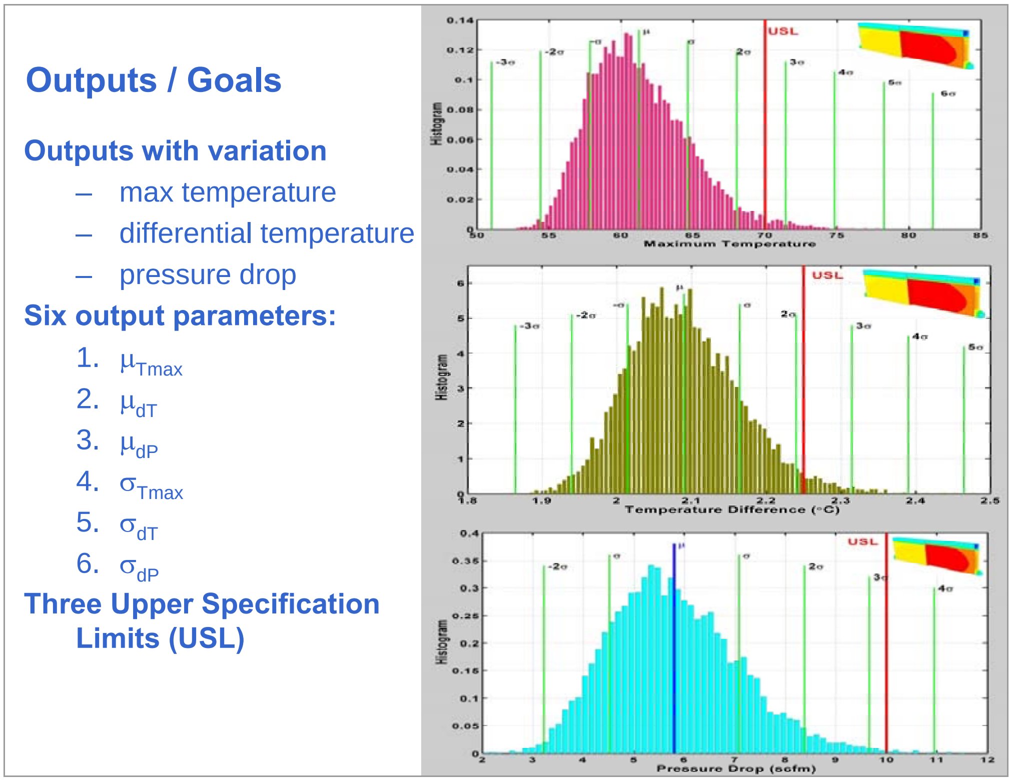
Most companies cannot afford to design for the worst case of uncertainty for all variables. That leads to an over-designed configuration. The limits must be analyzed and defined statistically. Variation must be assessed in the design for the mean and deviation of gap thickness, cell resistance, and flow rates, as summarized in the figure below.

FIGURE 4
Applying Six Sigma to Battery Thermal Management



To statistically analyze the variation, a good modeling tool is required. In this case, the tool processed the inputs to estimate the target outputs for three variables: the maximum temperature, the differential temperature, and the pressure drop, as summarized in Figure 5 below.

FIGURE 5
Statistical Analysis of Variation



The supplier cares about the temperature because the life of the battery correlates with the maximum temperature, the differential temperature within the cell, and the level of pressure of pressure drop of the cooling system. Empirical data indicates how long the battery will last. If that battery were to fail before the end of the guarantee period, the company pays for the battery. It becomes critical to make sure the battery lasts, supported by a well informed financial business decision. Do I release this product before I know how many will fail the warranty?

One approach popular in the automotive sector is the sigma quality level, which measures the distance between the mean value and the specification limit in terms of the standard deviation. Today this is measurement is fully automated within the ANSYS/Workbench environment.

To assess failure rates for the battery statistically, the tradeoffs covering the maximum temperature, the differential temperature, and the pressure drop must be considered together. Very little can be done about the variation of standard deviation, but the mean values can be shifted. Figure 6 (on the following page) summarizes data for the maximum temperature given the mean value of the air flow and the mean value of the gap between cells, while Figure 7 presents the data on differential temperature for the same design space. In both cases, the area to the top left in brown represents six sigma results, while the red designates five sigma, yellow, four sigma, and so on. Figure 8 considers the level of pressure drop given the air flow and the gap, however, which presents very different tradeoffs. Optimizing for all three variables, which are in conflict, the best that can be accomplished is sigma two quality, as summarized in Figure 9. Minimizing the impact of one variable such as temperature would boost the variance of the other. The tradeoffs for all three must be considered together.

The result implied too many failures per million would occur. The executive decision was made at that time not to release the battery. The vehicle was released slightly late as a result, but another iteration of the battery design was able to cool itself.

FIGURE 6
Temperature

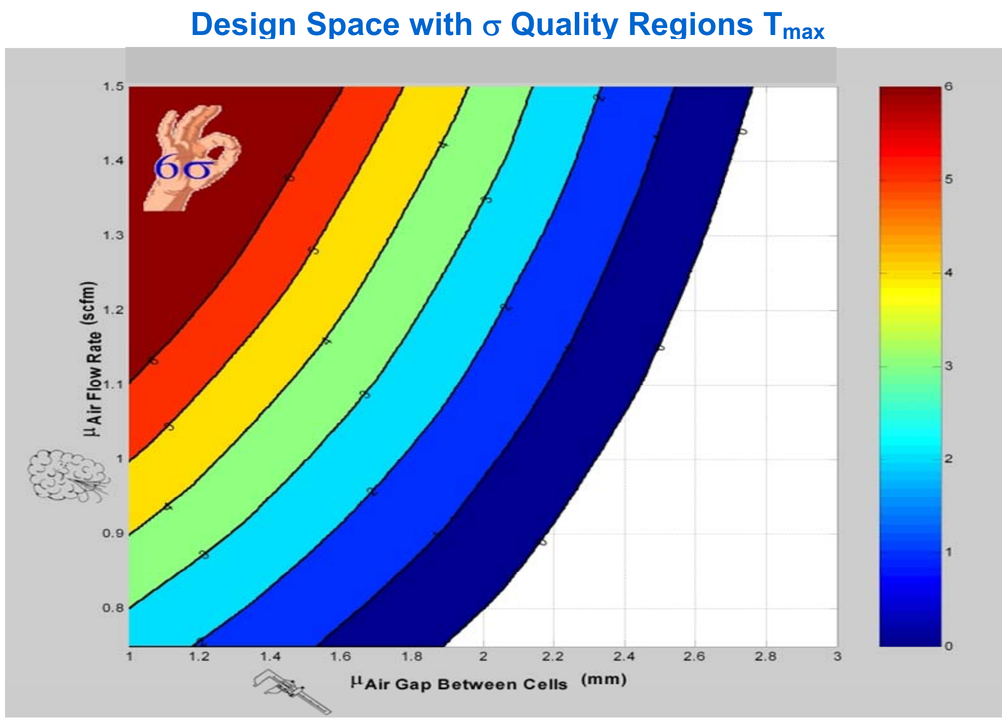


FIGURE 7
Temperature Differential

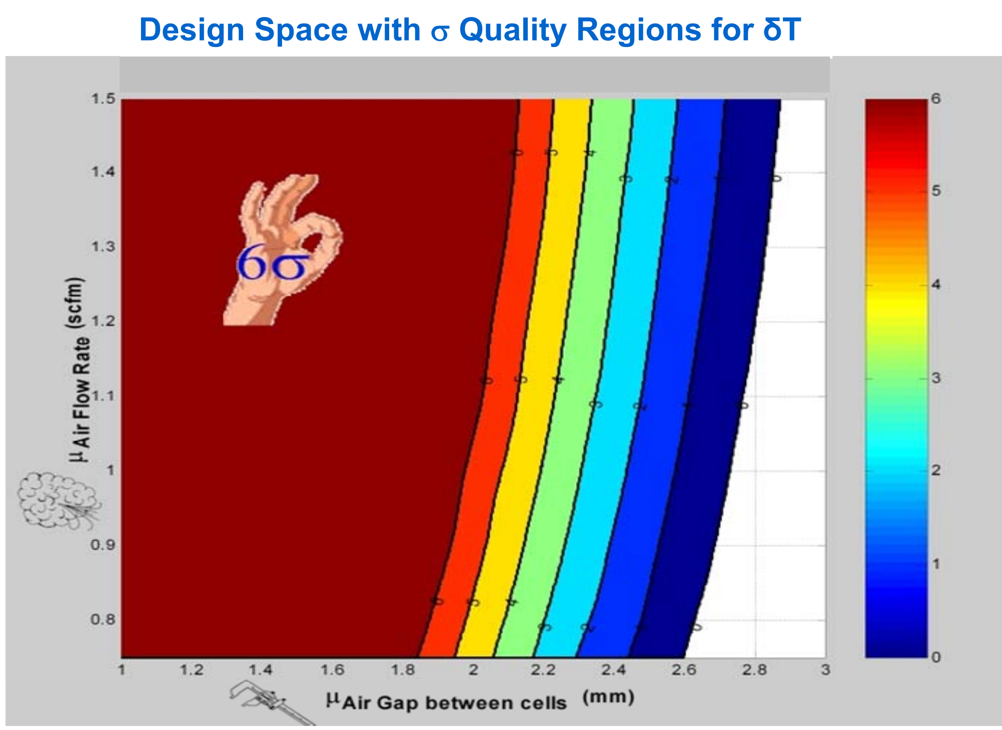


FIGURE 8
Pressure Differential

Design Space with σ Quality Regions for Pressure Drop

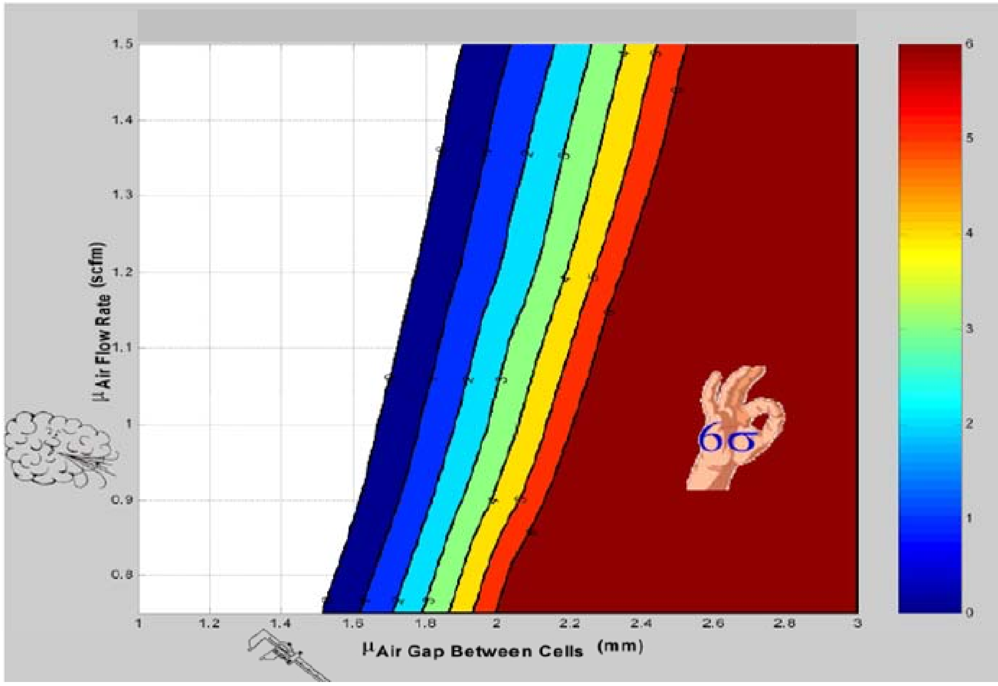
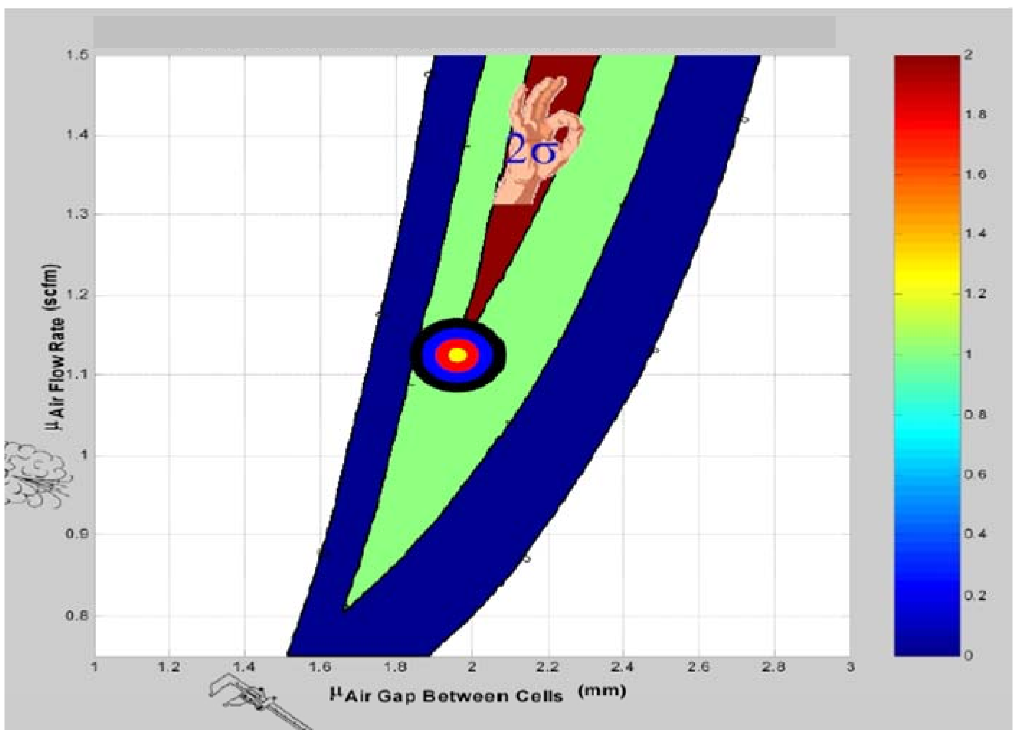


FIGURE 9
Design Tradeoffs across All Three Parameters

Design Space with σ Quality Regions for All Criteria



Some companies compute the sigma quality level based on empirical data after the fact, from actual results such as a recall or physical tests. Unfortunately, the design mistakes that do not account for variation in environment may only be discovered after the fact when it is too late. Even with physical tests, the prototypes or early production may be thrown out as scrap when they don't meet criteria. Designing up front to account for variation with analytical models involving FEA may determine the sigma quality level and calculate the full effects of variation. By calculating the deviation of the mean in terms of the standard deviation, the results convert statistically to dollars, since it is known how many will fail. Quality cost tradeoffs may be explicitly identified.

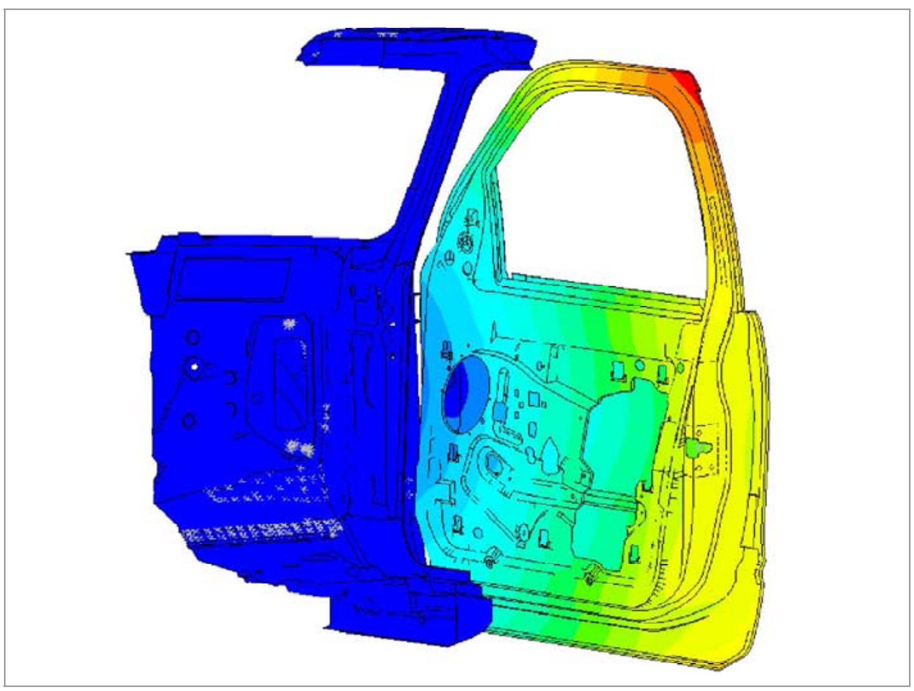
Considering the example of the battery cell with sigma quality level 2, the only industry that has more than 6 sigma is North American Airlines, which is 6.2 sigma on fatalities. A company with 3 sigma in the airlines sector would incur six flights crashing a day, clearly catastrophic. In the airline industry, 99% is not good enough.

But in the power industry, 99.9% power uptime means forty-five minutes a month there is no power, which may be considered acceptable. Some products can be tolerated with less than six sigma. The North American auto industry quality level is around four sigma level across in most categories.

2. SIX SIGMA PERFORMANCE TARGETS FOR A DOOR ASSEMBLY

The next example involves the design of an SUV door to meets specifications and performance criteria. The focus here is on the door sag and snap-through buckling. The door should not sag too much; it should not have to be lifted in order to close it. Door sag may still be seen in older cars, but today that is not acceptable. What is more, no one wants to get dents from door impact when they park. To deal with the challenge, the effect of thickness and material variation on six sigma performance targets must be analyzed for the door assembly, as illustrated in Figure 10.

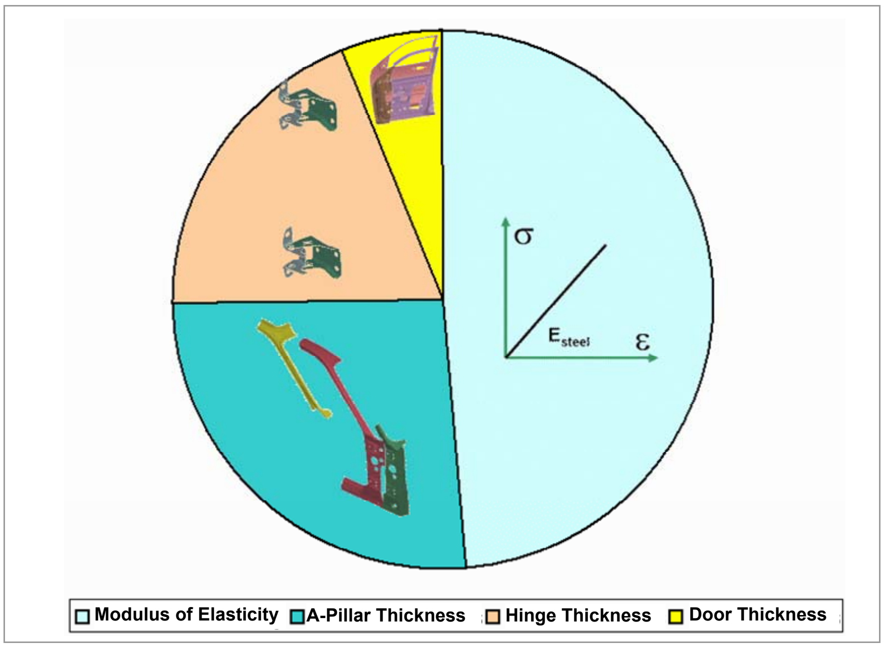
FIGURE 10
Door Assembly:
Door Sag Displacement Distribution



The American Institute of Steel Construction provides guidelines that help in assessing the variation on blanks during manufacturing. A part is put on a blank, and then a press squeezes it down. With use, the press warms up and oil drips onto it, causing any parts manufactured at the end of the day, when the press is warm, to have a different thickness from those manufactured in the morning. Furthermore, using the same equipment, the difference becomes even greater after a month.

There are many variables to consider in a car door, such as the thickness of the door, and the hinges. In this example, which is from personal experience, I did not understand why the hinges should be considered in the analysis of thickness and material variation, as they are the smallest piece. Take all the inputs – the thickness of the A-pillar components, the thickness of the door components, the thickness of the door hinges, and the modulus of elasticity. Calculate the mean and standard deviation of the door sag relative to the maximum sag specification. The process is the same for each of the targets. The result summarizes the sensitivity of the door sag to each of the design variables, illustrated in the figure below.

FIGURE 11 Sensitivity to Design Variables on Door Sag Deflection



The beauty of the approach relates to the ability to run the analysis quickly, and a sensitivity analysis is also provided. This analysis identifies the most important variables, so we know where we need to focus next time. The door thickness was originally thought to be the most important variable. But as shown in the figure above, the hinges and the A-pillar components contributed the most to door sag. The next time, it will not be necessary to even bother considering door thickness.

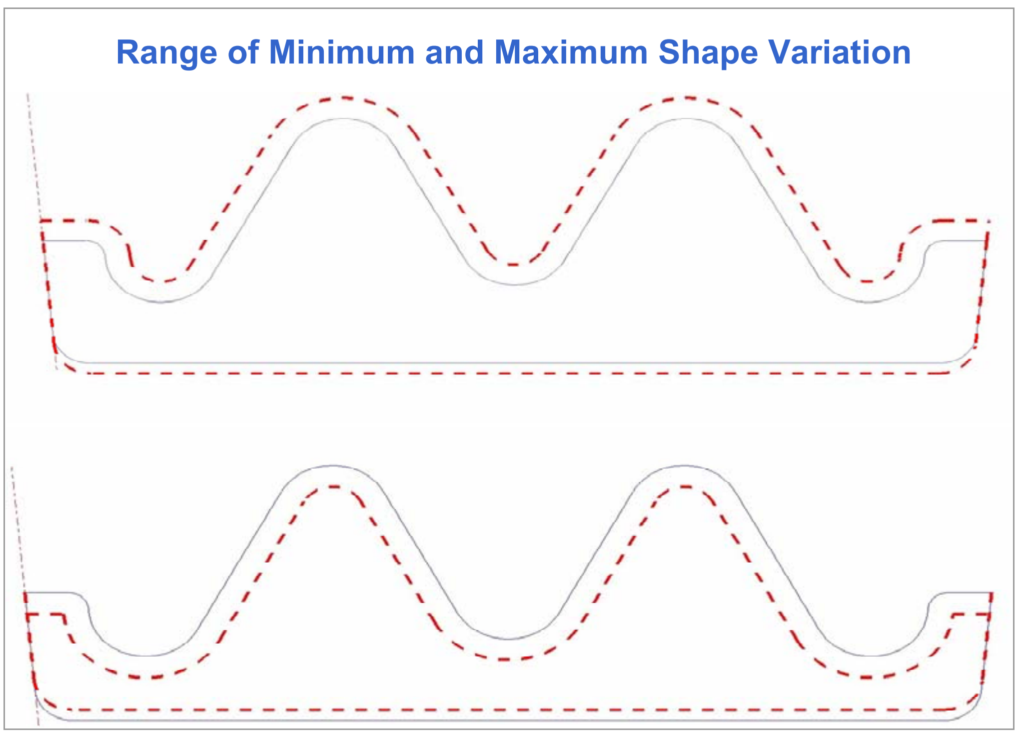
As an aside, an important point to keep in mind relates to the realities of decision making across disciplines in any organization. Each department wants to make the decisions, to be the "king." In the auto industry, packaging and cost are "kings" If it cannot be fit, nor be produced at a reasonable cost, it does not matter if you are the most brilliant engineer in design. Brilliance in engineering does not count if the cost and packaging do not work.

3. FUEL CELL GASKET CONFIGURATIONS

The last example involves fuel cell gasket configurations of cooler and cell interfaces to support robust sealing. In typical PEM (proton exchange membrane) fuel cells, a compressed gasket provides a sealing barrier between the cell and cooler bipolar plate interfaces. The gasket initially bears the entire bolt load and its resisting reaction load depends on the cross-sectional shape of the gasket, the bipolar plate's groove depth, and the hyper-elastic properties of the gasket material. Each fuel cell has approximately 200 plates with several gaskets. In an effort to obtain optimum robust design that is not sensitive to variations in noise parameters, such as manufacturing tolerances, material properties, process capability, or tooling wear, a probabilistic FEA analysis was performed.

This particular company desired a high sigma quality level for the fuel cells that would potentially be used in both stationary and mobile applications. They also insisted that the tolerances in manufacturing be controlled as much as possible, and we would have to live with that variation. That meant changing the design, and we put in two thick sections on the gaskets, as shown in the figure below.

FIGURE 12
Fuel Cell Gasket Variation



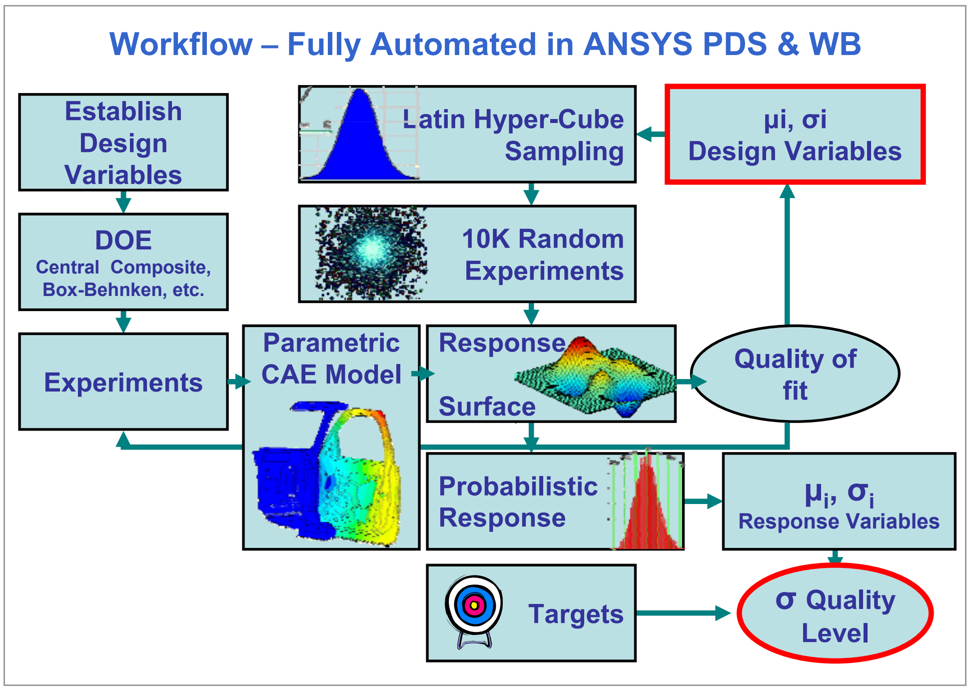
With an assessment of robustness, the first – and hardest – task is to assess the variation. The original deterministic shape is shown on Figure 12 showing the minimum and maximum shape variation. The assessment of robustness then randomly varied four key parameters:

1. The gasket profile

2. The gasket groove depth
3. The recessed opposing plate's pocket groove depth
4. The interface gap

The response surface of the contact force per unit length of the gasket was determined in terms of the probabilistic input variables. The sensitivity of each of the input variables on the contact force was found. The probability density function of the contact force was determined and compared to the various upper and lower specification limits of cell and cooler interfaces. The sigma quality level for each target is determined and the methodology for implementing robust design used in this research effort is summarized in a reusable workflow diagram shown in Figure 13.

FIGURE 13
Workflow Automation



WORKFLOW AUTOMATION

Although three examples of the battery, car door, and fuel cell involve very different design challenges, the workflow is similar for all three. First, you need to identify the design variables. Then in sampling, is it necessary to perform 10,000 runs to be realistic? Not at all. Indeed, an analysis that follows the principles of the design of experiments provides a mathematical framework for changing the key parameter simultaneously to evaluate variation with a relatively limited number of runs. With a CAE-automated project, running multiple analyses provides the outputs to determine the quality of the fit. If the fit is not good, run more experiments. When the fit is good, assess the probabilistic design variables, find the mean and standard deviation of the probabilistic response, compare the target, and find the quality level.

The approach may seem like a lot of work, but it can now be fully automated. A workflow of the process is depicted in Figure 13 above, using ANSYS PDS (Probabilistic Design Systems) and Workbench. The mean and standard deviation of the design parameters represent the input, and the sigma quality level is the output. Feed the mean and standard deviation of your design variables into the workflow and you get to the sigma level. Then optimize for the sigma level. A high level of integration now automates a process once completed manually. If you have a higher level optimizer covering this problem, it is called a DesignXplorer. Today, the workflow can be executed in a single day because of the tools available.

Design for Six Sigma strategies are transforming our methodologies for improving quality from *inspecting defects* to *building quality in.*