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Empowering Engineers to Generate Six-Sigma Quality Designs

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ABSTRACT

Although great advances have been made over the last two decades in the product development process, tradition and experience still govern many design decisions. The need for innovative tools is apparent now more than ever as the design team tries to cope with multiple requirements such as cost, performance, six-sigma quality, styling, packaging, safety, durability, environmental impact, etc.

A DFSS technique that integrates FEA and probabilistic and robust design tools within the CAD environment is presented. An example from the automotive industry that demonstrates the process and how engineering quality into designs positively impacts the bottom line is presented.

INTRODUCTION

The need for innovative tools is apparent now more than ever as more complex design requirements are surfacing such as cost, performance, safety, quality, time to market, short life cycle, environmental impacts, WOW aesthetics and major changes in industries' business models. Moreover, the automotive industry's cycle development time from concept to production is being compressed significantly. Some of the changes in the automotive industry's business model include: vehicle designs are tailored to focused markets; vehicles are being manufactured more on a global scale; and vehicles are designed increasingly through multiple engineering sites around the world.

Quality issues can 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 achieve optimal use of available resources. 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 [Ref 14]) and probabilistic systems (e.g. ANSYS' PDS [Ref 1, 3, 5 and 7]) that makes probabilistic analysis setup simple if the control and the noise parameters are identifiable [Ref 1]. Control parameters are those factors which the designer can control, such as geometric design variables, material selection, design configurations and manufacturing process settings [Ref 8]. Noise parameters on the other hand are factors that affect the design's function and are beyond the control of the designer or too expensive to control or change. Examples of noise parameters are material property variability, manufacturing process limitations, environmental 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 six-sigma technique that integrates FEA, probabilistic and robust design tools within the CAD environment.

PROCESS FOR ROBUST DESIGN

An example of cooling a battery pack of a hybrid/electric vehicle is used to describe the robust design process. Due to the large amount of energy exchanged between the propulsion/charging system and the battery pack, the thermal management of the hybrid/electric vehicles' batteries is a challenging task.

The Parametric the Deterministic Model

Figure 2 shows a typical battery pack of a hybrid/electric vehicle. A parametric finite element model that can predict the maximum temperature ($T_{max)}$ and the maximum differential temperature within the pack (dT) was built. The gap spacing (t_{gap}) between he battery cells, the cooling fan flow rate (F_{rate}) and the internal electric resistance (R) of the cells were considered input design variables. If one views the parametric deterministic FEA model as a transfer function the three design variables gap, flow rate, and internal resistance can be considered as input variables. The maximum temperature, the differential temperature, and the pressure drop can be considered as the output variables. Typical tight integration between CAD and FEA systems enables rapid generation of this type of transfer function. Figure 1 shows the data flow for the parametric deterministic FEA model.

The Probabilistic Design Loop

All three design variables were considered as having variation. It was assumed that all three design variables exhibit normal distribution with given mean (?$_{tgap,}$?$_{R,}$?$_{Frate}$) and standard deviation (?$_{tgap,}$?$_{R}$ and ?$_{Frate}$) values. The mean values of the air gap and flow rate were considered control variables. The mean value of the internal resistance and the standard deviations of all three input design variables were considered as noise variables since they were out of the control of the battery pack designer. The mean value of the gap (?$_{tgap)}$ was allowed to vary within a range of 1 mm and 3mm. The standard deviation of the gap was 5% of the mean value ?$_{tgap}$ = 0.05*?$_{tgap}$. The mean value of the electric

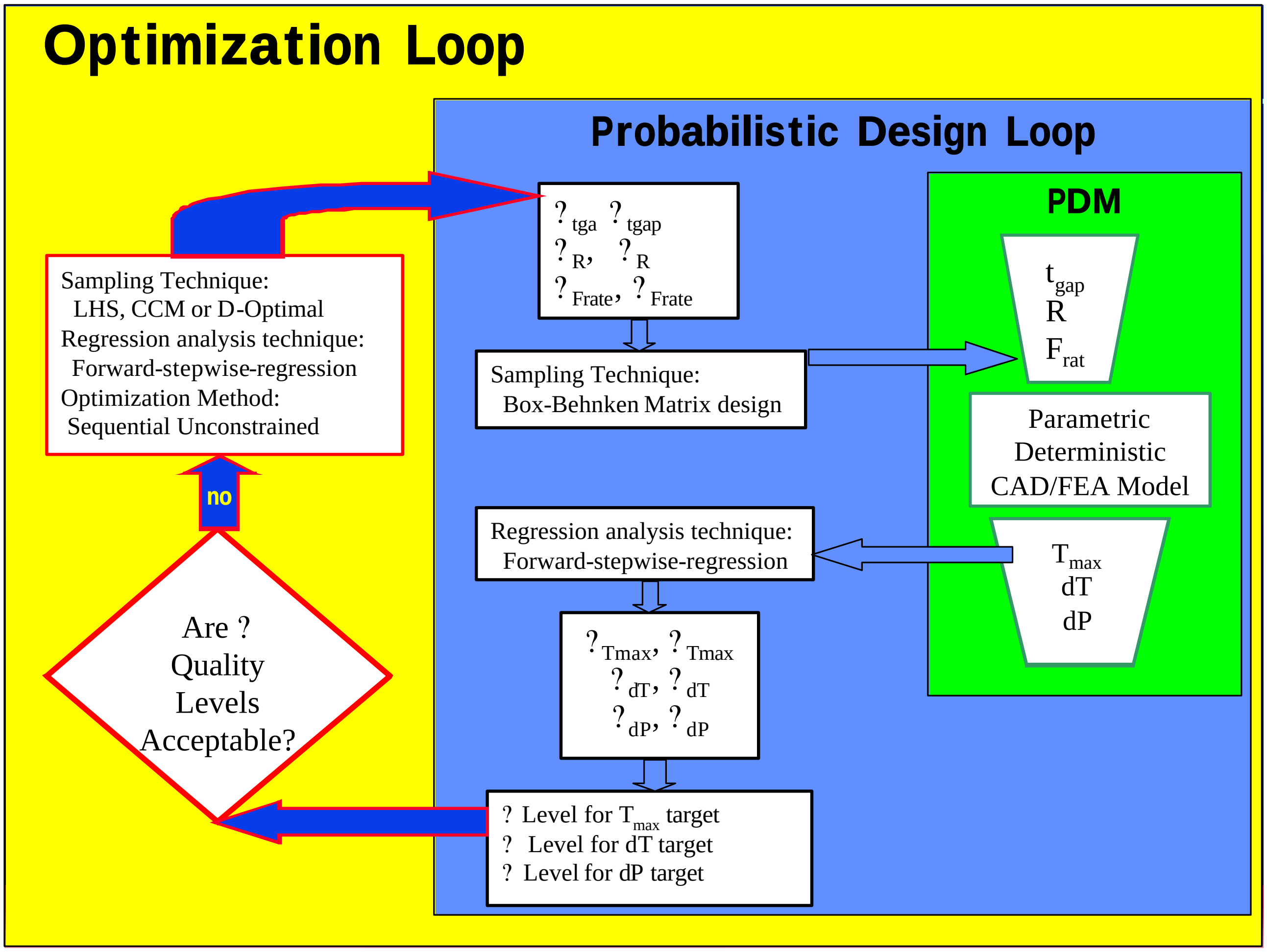

Figure 1 Workflow for Robust Optimization

resistance of the cells was allowed to vary within a range of 0.01 - 0.03 ohms. The standard deviation of the resistance was assumed to be 10% of the mean value, ?$_{R}$ = 0.10*?$_{R}$. The mean value of the flow rate was allowed to vary within a range of 0.25 to 1.5 scfm. The standard deviation of the flow rate was assumed to be 15% of the mean value, ?$_{Frate}$ = 0.15*?$_{Frate}$.

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 thermal finite element analysis. If the "experiment" is time consuming and expensive Box-Behnken Matrix in combination with the response surface technique is preferred. In this example 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 three design variables can be considered as inputs ($?_{tgap,}$ $?_{R,}$ $?_{Frate}$) and the mean ($?_{Tmax}$, $?_{dT,}$ $?_{dP}$) and standard deviation ($?_{Tmax}$, $?_{dT,}$ $?_{dP}$) of the attributes (max temperature, differential temperature, and pressure drop) can be considered as outputs. Figure 1 shows a graphical representation of the data flow for this loop.

Consideration should be given to crafting insightful metrics and establishing a set of SMART (Simple, Measurable, Agree to, Reasonable, Time-based) goals and targets [Ref 2]. All financial, performance, and innovation perspectives need to be considered to produce a well-balanced scorecard. If a target value, upper/lower limits or process capability indices are defined for the attributes one may easily determine the design performance using the probabilistic loop's output variables. In our design example the T_{Target} = 55?C, dP_{Target} = 10 scfm and dT_{Target} = 2.25?C. A graphical representation of the results can indicate the need for shifting the mean value of the response or squeezing the response's variation.

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

$$?_{Tmax} - n * ?_{Tmax} \ ? \ T_{Target} \qquad \text{Eq(1)}$$

If the desired sigma level of quality is achieved the first time the lucky designer can stop at this point. If the desired sigma level of quality is not achieved the designer needs to adjust the inputs of the probabilistic design loop ($?_{tgap,}$ $?_{R,}$ $?_{Frate}$) and rerun his analysis. This adjustment can be automated with a design optimization loop.

The Design Optimization Loop

The two main control variables used as inputs of the probabilistic design loop are the mean value of the air gap and the flow rate. 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 ($?_{tgap,}$ $?_{R,}$ $?_{Frate}$) that maximizes the minimum value of the three sigma quality levels. This task has been fully automated with design optimization loop [Ref 11]. Since each "experiment" of this loop is computationally expensive the D-optimal sampling technique was selected to choose 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 [Ref 13].

RESULTS

Experimental Work

The National Renewable Energy Laboratory (NREL) purchased a 2001 model year hybrid electric Toyota Prius to evaluate its battery thermal performance. The Prius NiMH battery was removed from the vehicle and instrumented with thermocouples and voltage and current sensors. Measurements of the pack coolant fan power and air flow rate were also made. Experimental testing by NREL included chassis dynamometer driving of the vehicle, on-road driving cycles, off-board cycling of the battery pack, and heat capacity and heat generation measurements at the Lab's calorimeter. This testing gave NREL a good understanding of the battery thermal characteristics and response to various power demands required by the vehicle.

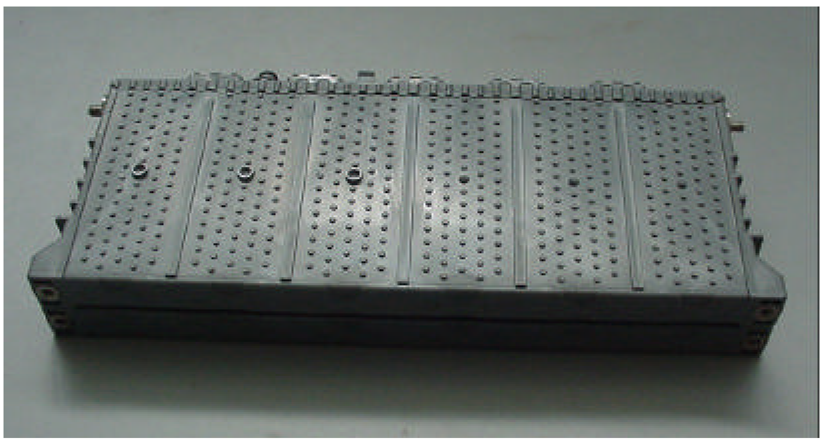

Figure 2 Battery Module

The Prius battery pack is a NiMH design that consists of 38 prismatic modules, each having six 1.2 V cells. The total pack nominal voltage is 273.6 V. Figure 2 shows part of the Prius pack with the 2 of the 38 prismatic modulus. Forced cabin air flows around and between the modules in air spaces between each module. Variable cross-sectional area air plenums are used to maintain constant airflow rates to all the modules.

The Parametric FEA Model

A parametric FEA model of the battery module was developed for thermal analysis. The physical properties defined in the model are shown in table 1. The boundary conditions applied to the model include convection on the top and two flat sides of the module. The heat transfer coefficient for the top and side areas was calculated based on the airflow rate. A heat transfer coefficient of 5.0 W/m^2 K was applied at the bottom and two ends of the module. The inlet air temperature was assumed to be 25 C and varied linearly along the height of the module, with the outlet temperature calculated from:

$$T_{out} = q/mc_p + T_{in}$$

Heat generation (q) inside the core of the battery was calculated based on internal resistance (R) and input current (i).

$$q = i^2 R$$

The input current was assumed constant at 15 amps. This is based on the average current levels measured during several different vehicle driving cycles. The nominal internal resistance, based on measured values, was 0.02 ohms.

Table 1. Physical Parameters of the Parametric Finite Element Model

Battery Core Properties		
Thermal conductivity	15	W/m K
Density	2327	kg/m3
Heat capacity	810	J/kg K
Internal resistance	0.02	ohms
Battery current	15	amps
Air gap between modules	0.002	m
Module Plastic Coating		
Thermal conductivity	0.17	W/m K
Density	1930	kg/m3
Heat capacity	910	J/kg K
Air Properties		
Thermal conductivity	0.0258	W/m K
Density	1.1	kg/m3
Specific heat	1013	J/kg K
Dynamic viscosity	1.97E-05	N s/m2
Air inlet temperature	25	C

Results of the probabilistic analysis

A typical set of the probability density functions of the parametric FEA input model are shown in figure 3.

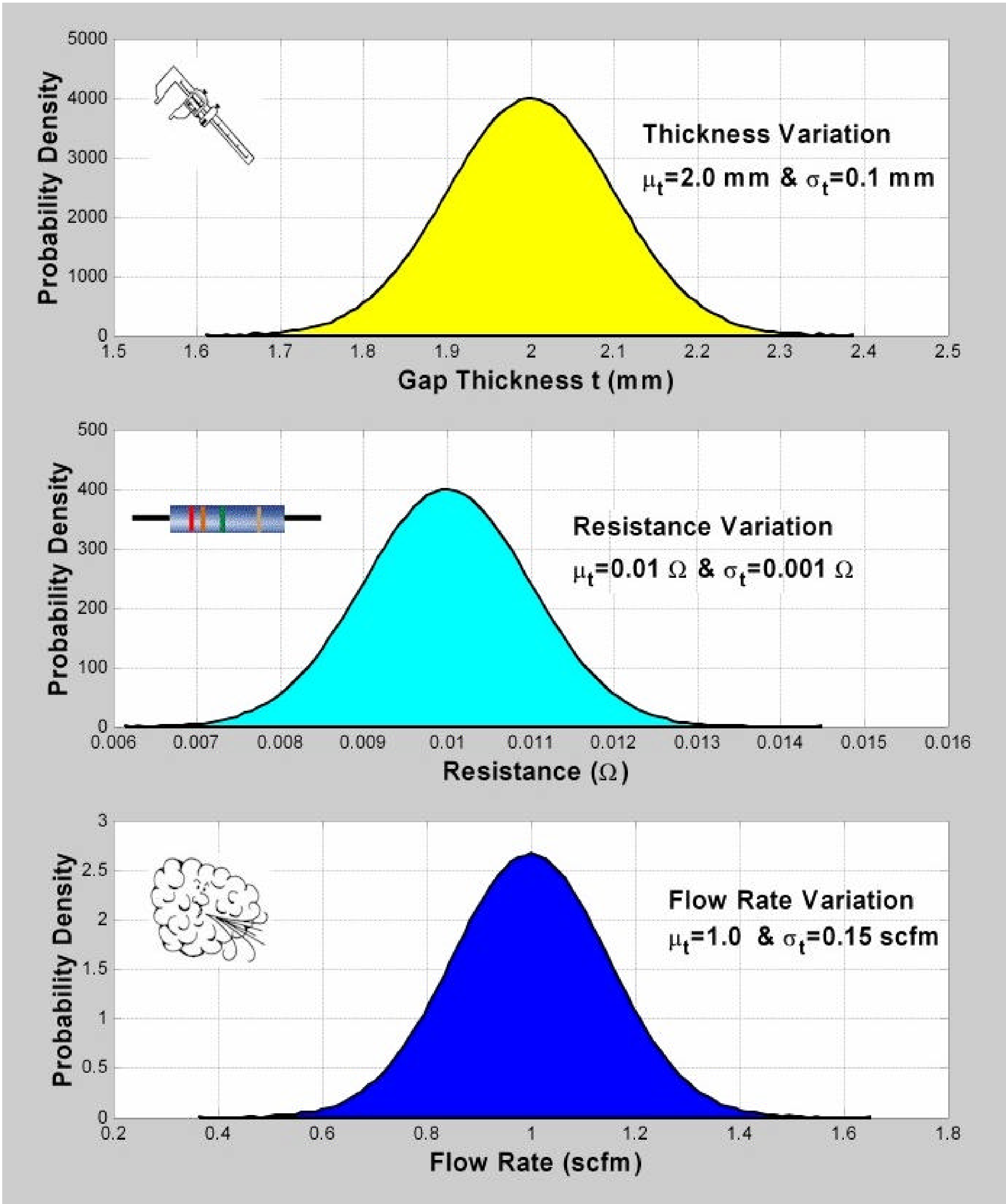

Figure 3 Probability density functions of input variables

Execution of the probabilistic design loop will result in a probabilistic distribution of the response attributes (maxT, dT, dP). Figure 4 shows the histograms of the attribute values for this probabilistic design loop.

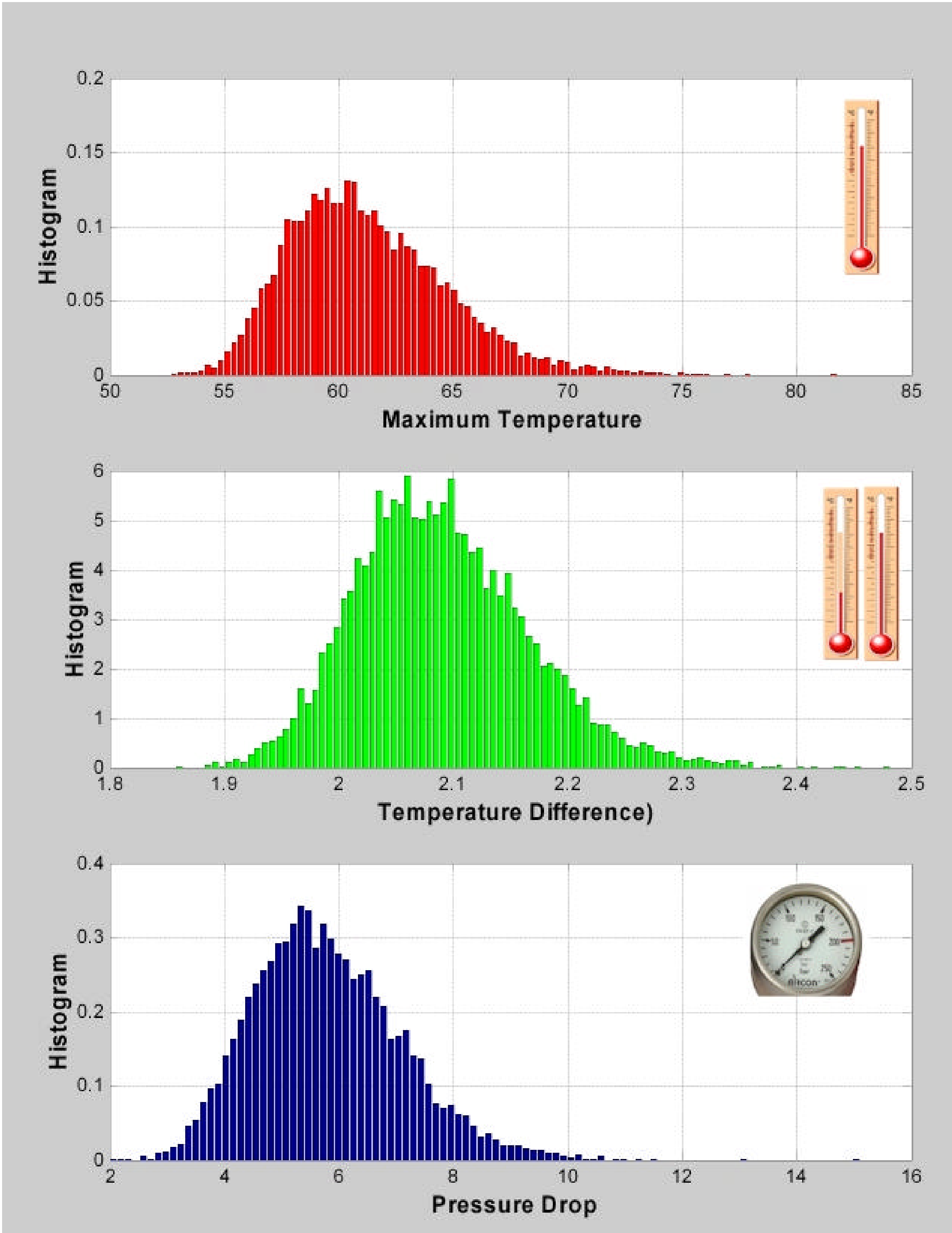

Figure 4 Histograms of the Response Attributes

Figure 5 shows the sensitivity of the design variables on the response attributes. It is apparent that the flow rate has the most impact on the maximum temperature. All three input design variables have about equal effect on the temperature differential. The internal battery resistance has no effect on the pressure drop.

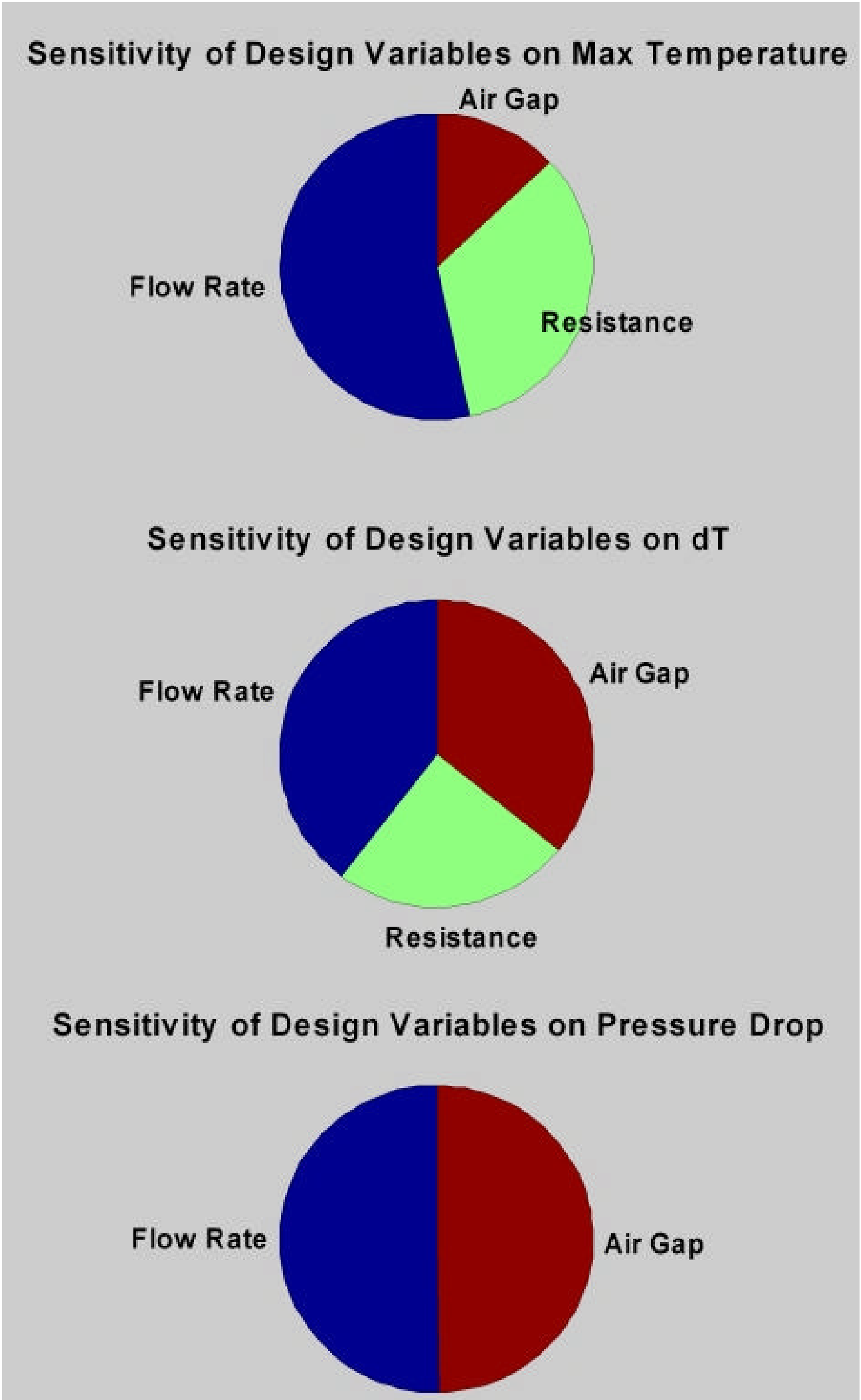

Figure 5 Sensitivity of the Design Variables on The Response Attributes

Figure 6 shows the design space with sigma quality regions for the maxT. If that was the only criteria one can quickly declare victory since the top left region of the design space will provide six-sigma level quality. Figure 7 shows the design space with sigma quality regions for the dT. The entire left side of the design space appears to provide six-sigma level quality. Figure 8 shows the design space with sigma quality regions for the dP. Figure 6 through 8 illustrates a case of contradicting design requirements. The smaller air gap provides lower maxT and dT but at a cost of higher dP. The minimum value of the sigma quality level for all criteria is shown in figure 9. One may observe a point at the center of the design space will be the best choice for the mean value of the flow rate and the air gap. Only a two-sigma quality level was achievable within the range of the design variables. In a similar study [Ref 14] probabilistic modeling of manufacturing variations coupled with optimization can avoid over-design (deterministic analysis) and reduce the component weight by 17%.

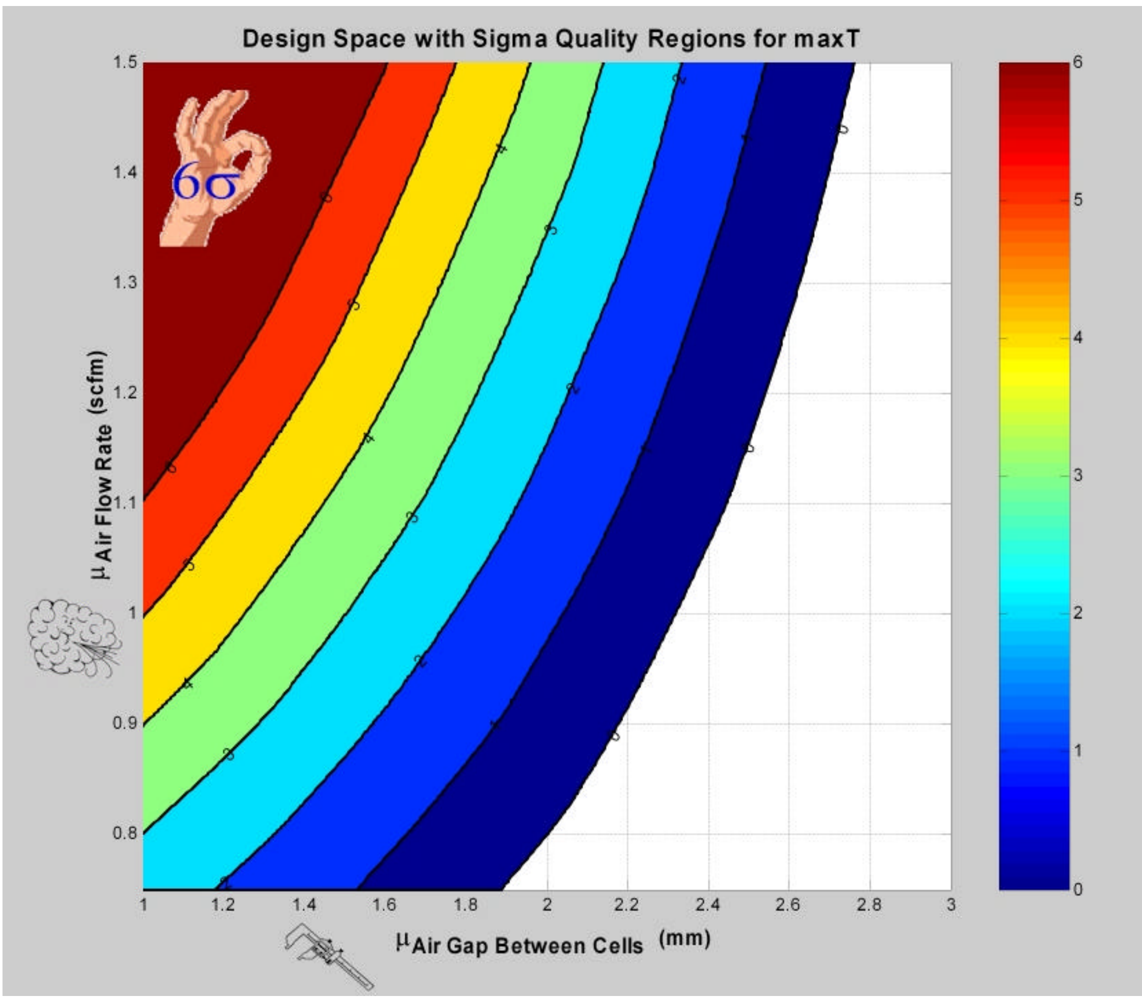

Figure 6 Design Space With Sigma Quality Regions for the maxT

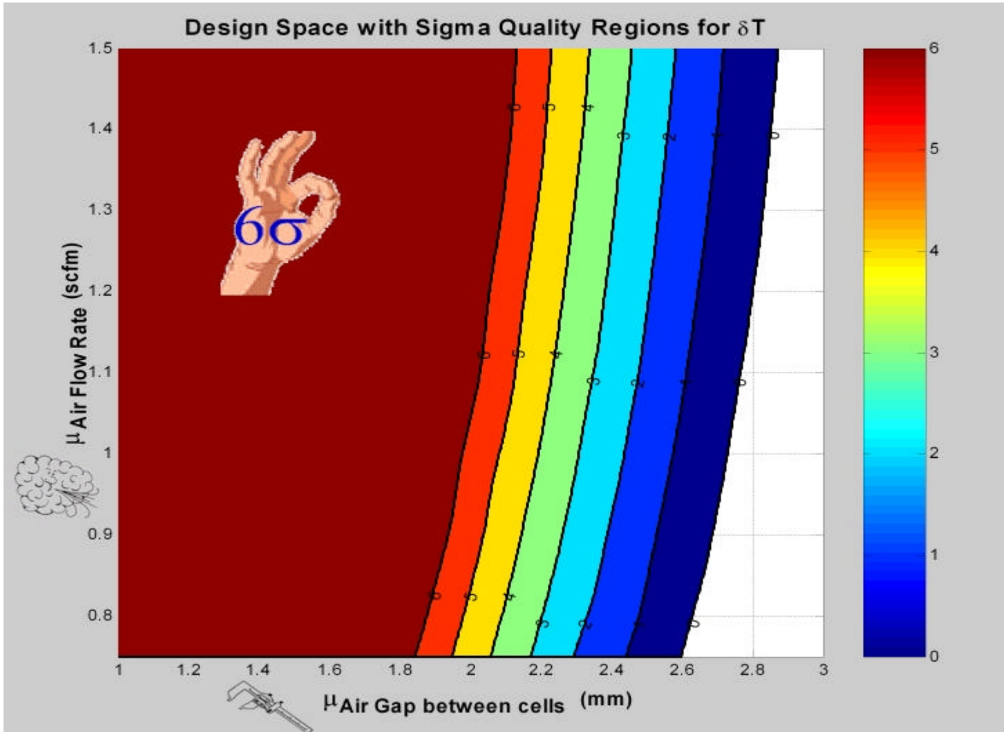

Figure 7 Design Space With Sigma Quality Regions for the dT

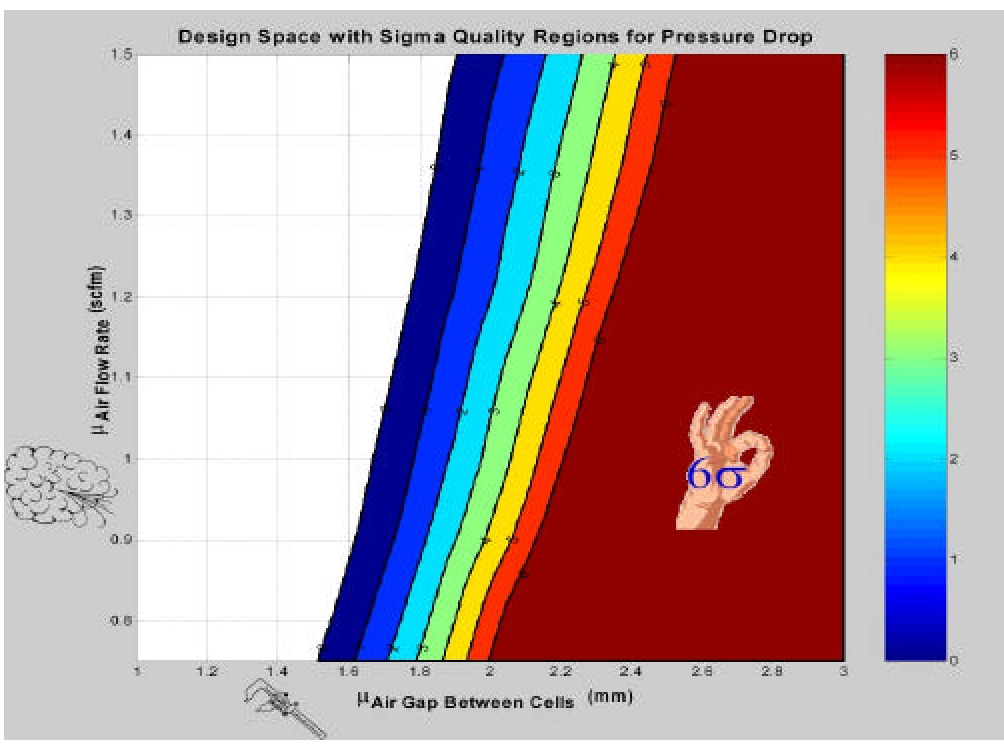

Figure 8 Design Space With Sigma Quality Regions for the dP

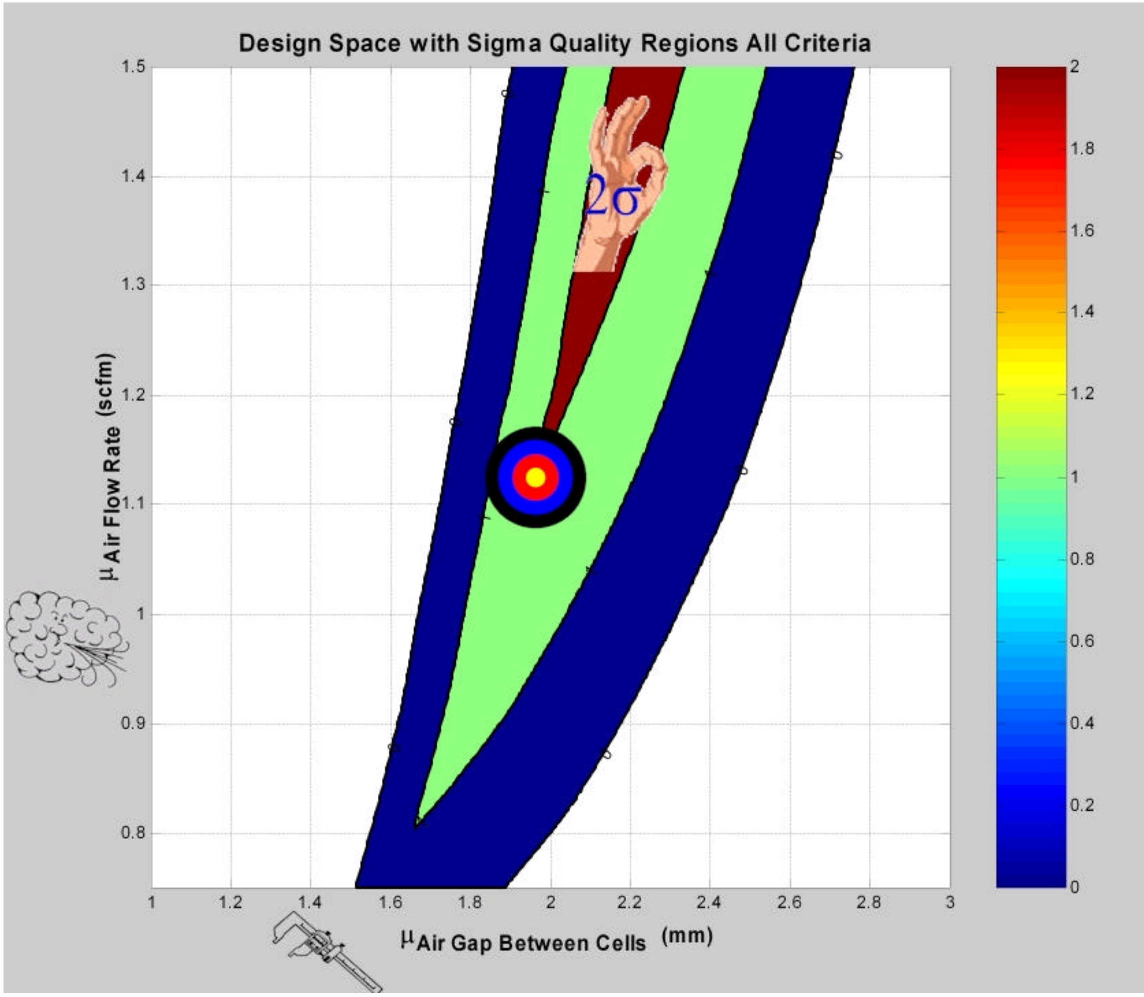

Figure 9 Design Space With Sigma Quality Regions for all criteria

OVERCOMING THE IMPLEMENTATION CHALLENGES

The design automation described passes the drudgery of multiple simulation runs to the computer. Therefore substantially greater portions of engineers' time can be spent on fundamental engineering. This enables engineers to spend more time understanding customer requirements and focusing on design constraint definitions (QFD).

Unfortunately implementation of these methodologies has not "taken off" due to several technical and organizational challenges. Some of the technical challenges are that:

? The design process remains unstructured or unplanned.

? There is insufficient number of experts for product design attribute prediction.

? Product attributes have not been formalized and managed early enough.

? The CAD/CAE tool set is not tailored to the design environment.

- ? Data are not readily available to feed the analysis.

Some of the organizational challenges are:

- ? There is a lack of clear metrics and success stories.
- ? There is an expectation that consensus on the methods to be used is required.
- ? There is a lack of custom capabilities that integrate commercially available software (CAD, FEA, PDS, Optimization).
- ? There is a lack of an organization's commitment to product development excellence.

Steps for realizing the expected gains from the integrated product development process are to identify the right organization, identify the right project, and implement solutions strategies. One should select the right organization within the company that is committed to product development excellence, willing to change, able to make decisions and willing to bypass consensus when needed. One should also select a project that is repetitive and measurable and currently is a bottleneck. This project should be of short duration, high value and have objective measurable requirements. The management should clarify and document the desired decision process early in the design cycle. An effort should also be made to simplify and automate the tool usage for standard analyses by creating a design environment tailored to the design process. Augmentation of the experts by automating a large portion of the design process is necessary. The development of a repository of design and manufacturing rules that govern the design process is also required. The development of this repository will increase the use of existing designs and will capture and reuse the design knowledge.

CONCLUSIONS

The objectives of this research effort are to demonstrate a process that empowers engineers to generate Six-Sigma quality designs early in the design process, to identify the implementation challenges and to offer solution strategies to overcome them. Some of the conclusions are:

- ? By incorporating the physical scatter into the modeling, the risk of failing legal or consumer tests can be minimized.
- ? The example presented demonstrates that with the probabilistic design and optimization integration, engineers are enabled to identify better designs that meet the performance objectives and are less sensitive to manufacturing variations.
- ? Modern CAD and FEA software tools that have incorporated probabilistic design, allow distributed computing that enables the implementation of this computer intensive technology.

SYMBOLS

CAD Computer aided Design

DFSS	Design for six sigma
FEA	Finite Element Analysis
QFD	Quality Function Development
$\mathbf{c_p}$	heat capacity
$\mathbf{dP_{Target}}$	target for deferential module temperature
$\mathbf{dT_{Target}}$	target for pressure drop
i	input current
$\mathbf{T_{in}}$	inlet air temperature
$\mathbf{T_{out}}$	outlet air temperature
$\mathbf{T_{target}}$	target for maximum cell temperature
$?_{\mathbf{tgap}}$	mean value of air gap between modulus
$?_{\mathbf{R}}$	mean value of internal cell resistance
$?_{\mathbf{Frate}}$	mean value of flow rate
$?_{\mathbf{Tmax}}$	mean value of maximum module temperature
$?_{\mathbf{dT}}$	mean value of deferential module temperature
$?_{\mathbf{dP}}$	mean value of pressure drop
$?_{\mathbf{tgap}}$	standard deviation of air gap
$?_{\mathbf{R}}$	standard deviation of cell resistance
$?_{\mathbf{Frate}}$	standard deviation of flow rate
$?_{\mathbf{Tmax}}$	standard deviation of maximum module temperature
$?_{\mathbf{dT}}$	standard deviation of deferential module temperature
$?_{\mathbf{dP}}$	standard deviation of pressure drop

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