DESIGN FOR SIX SIGMA

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ABSTRACT

This article provides a step by step process of executing analytical or computer based Design for Six Sigma using a Sliding Door project as an example. It comprises of identification of Voice Of the Customer (VOC), transformation of VOC to what it is called Critical To Quality characteristics (CTQs), modeling of system transfers function, optimal and robust solutions, and tolerance design approach

Keywords: VOC, CTQ, DMAIC, DFSS

1. INTRODUCTION

The goal in product design or business process engineering is to create products or processes that are insensitive to the sources of variation that inhibit their intended function. Design phase in the product development process is always crucial activity since most downstream production and quality problems are locked during that activity. As a consequence, a successful DMAIC (define, measure, analyze, improve, control) Six Sigma programs for operations or production evolve into what is now known as design for Six Sigma (DfSS) for product or process development.

As a contrast to Six Sigma program whose steps are known as DMAIC, DFSS has different names in its steps, e.g. 4D (Define, Design, Develop, Demonstrate), (DCOV Design, Characterize, Optimize, Verify), DMADV (define, measure, analyze, design, verify), IDOV (Identify, Design Optimize, Validate), DCCDI (define, customer, concept, design, implementation), etc. However, those different step names are essentially the same.

DfSS integrates Marketing, Engineering and Production information into the design world. DfSS focuses on preventing defects by optimizing a transformation of what is wanted and perceived in the customer domain to what can be produced in engineering and the process domain. Therefore, DFSS starts by defining a problem in the customer domain to understand the voice of the customer (VOC) and the customer's use of the products or transactions. Models of the problem related system must then be developed in the engineering or process domain with the help of functional Parameter Diagram and Quality Function Deployment (QFD)-like techniques. The model must be a translation of the voice of the customer into a system that can be engineered. Understanding design variable interactions and sensitivity of system performances relative to system variables are the ultimate goal of this step.

Having understood the behaviour of the system, the next steps are to find optimal and robust solutions and then verify the solutions in customer and production conditions. Typically, DfSS deals with multiple objectives in the optimization step and then stack-up tolerance analysis and degradation or key life testing in the verification step. Robustness and optimal solutions will ensure the product meets the customer's intended use and is delivered on time and at a lower cost--eventually improving the company's profitability.

2. ROLE OF COMPUTER-BASED EXPERIMENTATION IN DfSS

Complexity of the product or process and the fast pace schedule to bring product to the market demands DfSS to take the advantages of the computer based analysis. Computer based analysis needs analytical, either mathematical or simulation, models called Transfer Function and analytical optimization. Transfer function can be derived from 1st principle of physics, engineering drawing of stack-up processes, Finite Element Method based simulation such as Computer Aided Engineering (CAE), regression analysis of empirical or observational data, and/or response surface from computer experimental designs. When the analytical models do not include comprehensive Noise Factors such as piece-to-piece variation, changes in dimension or strength over time/cycle, customer usage and duty cycle, external operating environment, and internal operating environment /interaction with neighbouring subsystems, they can be represented by the variability of the existing variables or parameters in the models.

More complete understanding of transfer functions eliminates the waste of over-design and cost of under-design, resulting in efficient designs that satisfy customers. To have complete understanding Transfer Function needs sequential efforts from a model that is still under development requires further correlation before usage to a model that can be used as the sole determiner of Sign Off of a product or process release.

Analytical optimizations for functional and multiple objective problems rely heavily on computer based experimentation. The goal of computer based experimentation is multiple, one of them is to develop simple approximation that is fast-to-compute and accurate enough within a certain design space, especially for time consuming CAE models. Computer based experiment logistics are often straightforward so that relatively large number of runs may be feasible and parameters can be adjusted in software. A large number of runs allow variable sampling over many levels instead of just fewer runs with limited variable sampling, e.g. 2 or 3 in hardware experimentation. Many level sampling can capture high order and nonlinear models. As responses from computer are deterministic, there is no random error and replication and randomization do not have value. Therefore, flexible alternatives to standard arrays, e.g., Uniform Design and Latin Hypercube Designs are suitable to running computer based experimentation.

Here, we illustrate a step by step process of executing analytical or computer based DFSS. This includes identifying voice of the customer, translating VOC to critical to quality characteristics (CTQ) using QFD, modeling system transfers function using engineering drawing, finding optimal and robust solutions using graphical approach and mathematical programming based on computer experimentation, and finally indicating tolerance design approach. As a case study we show how to find optimal and robust designs of a sliding door. Sliding door project is chosen with the hope that this example can reach wider readers who have different backgrounds and business processes. We will show that we can run this study using available commercial package software such as MS Excel, Minitab, Crystal Ball and DOE PRO XL. This step-by-step example can be easily adapted to different product design and business process engineering, included transactional products and processes. The essential difference between engineering and transactional processes is that natural laws, such as conservation of energy or mass, govern engineering and manufacturing processes, but man-made laws, such as regulations, govern transactional processes.

3. IDENTIFYING VOC

Side and top views of a sliding door consists of a sliding panel, a roller and a track is shown in Figure 1. The following are what customers want:

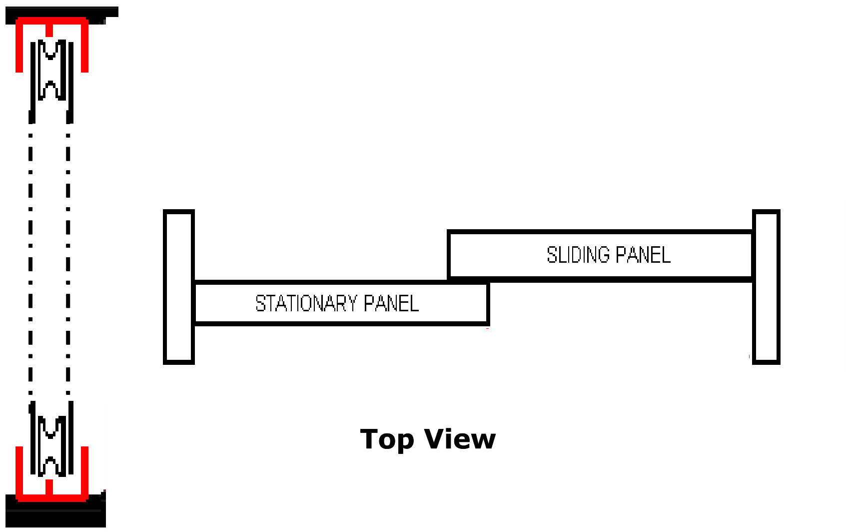

Figure 1. Side and Top Views of A Sliding Door.

- Good value for money and image.
- Reliable/Durable design for various material and condition.
- Low noise and rattle level.
- Ergonomic features, easy to use with minimum effort to open.
- Safety features to prevent from accidental operations.

Customers complained about the noise and rattle levels of the existing door

3.1 Translating VOC to CTQ

QFD in the form of house of quality translates VOC to CTQ as shown in Figure 2. The house of quality shows that noise and rattle levels are related to the clearance between track and roller of the door. When the clearance is too big, the rattle level will increase, but when it is too tight, the noise level will increase.

The detail functional relation between design variables or parameters (Signal, Control and Noise Factors) and the system performance or CTQ, i.e. Clearance is captured in the Parameter-Diagram (see Figure 3).

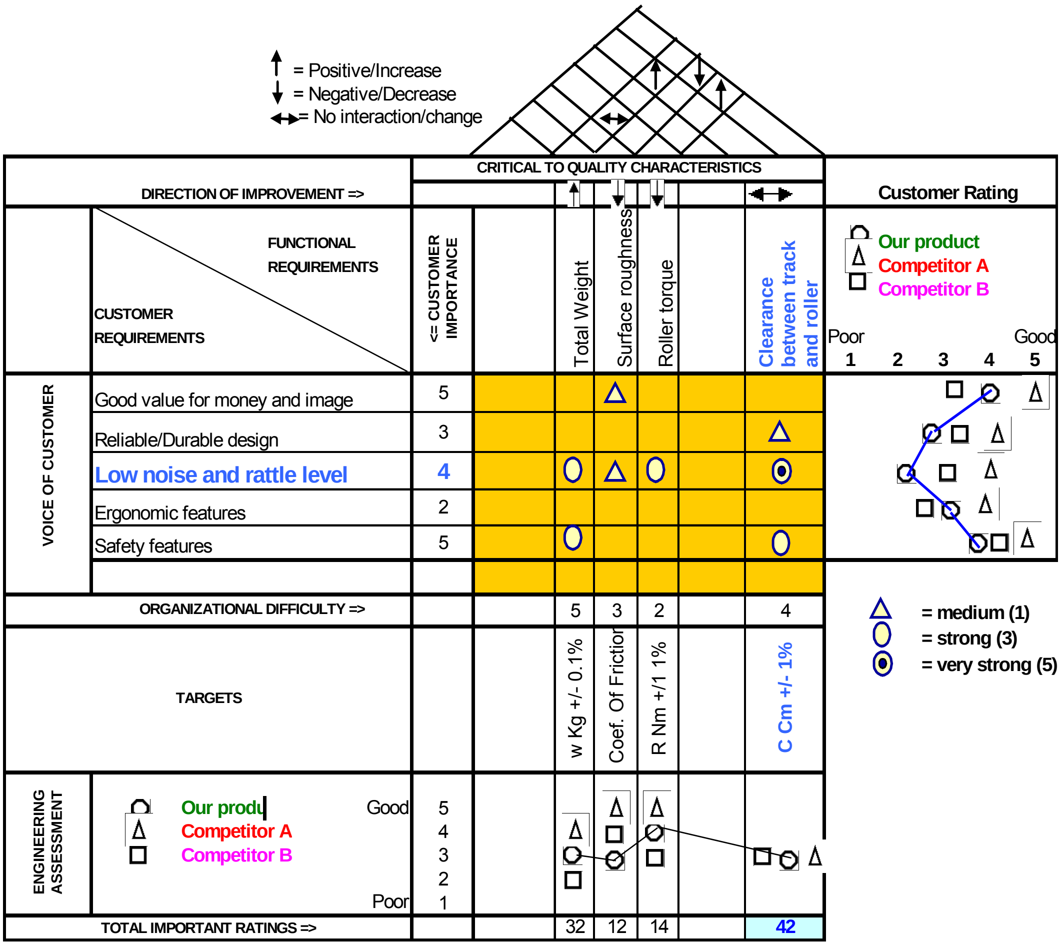

Figure 2. Quality Function Deployment of A Sliding Door.

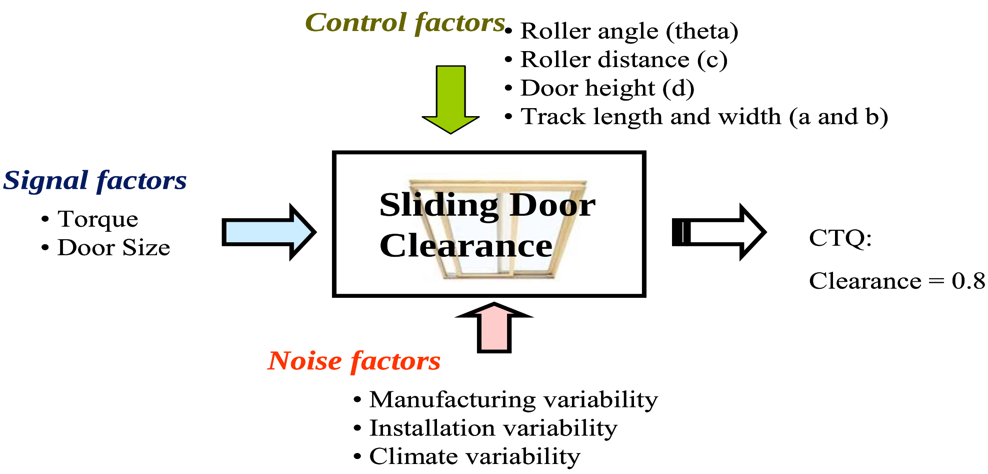

Figure 3. Parameter Diagram of A Sliding Door.

The base line design, i.e. a = 0.3, b = 1, c = 9, d = 13 and theta = 600 gives Clearance = 1.6 with standard deviation = 2.9. The objective to get a low noise and rattle level is Clearance = 0.8.

4. MODELING SYSTEM TRANSFER FUNCTION

Let **P** be the set of control factors (*a, b, c, d and theta*), **M** be the signal factor (*torque, door size*), **Z** be the set of observable noise factors (*variability of a, b, c , d and theta*). The signal can be considered as a part of noise factors, if it is fixed at one value. Let Y be the system performances, i.e. *Clr*. Assume the system follows an additive noise model, i.e. the location-dispersion or mean-variance model as follows:

$$Y = f(\mathbf{P}, \mathbf{Z}, M) + \varepsilon \tag{1}$$

$f(.)$ is the deterministic performance mean derived from the 1st principle of Physics, engineering drawings, regression or response surface methods. ε is the random error caused by the uncontrollable noise factors whose expectation and variance are $E(\varepsilon) = 0$ and $\mathrm{var}(\varepsilon) = \sigma^2(\mathbf{P},\mathbf{Z},M)$, respectively. In many cases, the variation of ε (or the performance variability) is close enough to the variance of linear approximation of Y since the linear approximation of Y is around the small area between its mean and variance.

As the computer experimentation output is deterministic the performance variability, i.e. standard deviation of Clr, can be estimated through Taylor Series expansion of f and the variance of each design variable at a neighborhood of a certain fixed value of the design variables, $\mathbf{x}_0$:

$$\sigma_{\mathbf{y}}^2 \approx \left(\left. \frac{\partial f}{\partial x_1} \right|_{\mathbf{x}_0} \right)^2 \sigma_{x_1}^2 + \left(\left. \frac{\partial f}{\partial x_2} \right|_{\mathbf{x}_0} \right)^2 \sigma_{x_2}^2 + \ldots + \left(\left. \frac{\partial f}{\partial x_n} \right|_{\mathbf{x}_0} \right)^2 \sigma_{x_n}^2 + \ldots \tag{2}$$

For $\mathbf{x}$ is a set of design variables or parameters or factors. Approximation of σ_y is "good" when y is approximately linear in a 2σ- - 3σ neighborhood of x_0.

Robust design can be obtained by minimizing the performance variability, i.e. σ^2_y. This can be done either by either minimizing the sensitivities, i.e. derivatives of f(x), or minimizing variability of design variables, i.e. $\sigma_{x1}, \ldots, \sigma_{xn}$. *Optimal design* can be obtained by selecting nominal values of other certain design variables, i.e. $x_1, \ldots, x_n$, to bring the system performance mean to its target. Minimizing design variables or parameter sigma by improving process capability is mainly part of DMAIC Six Sigma. Minimizing the sensitivities by selecting nominal values of design variables, i.e. $x_1, \ldots, x_n$, is mainly part of DFSS.

Following mean-variance model above and applying Vector Loop Technique for stack-up analysis, we can derive the transfer function of the transformation from Radial to of Cartesians of Clearance and its variance as shown in Figure 4.

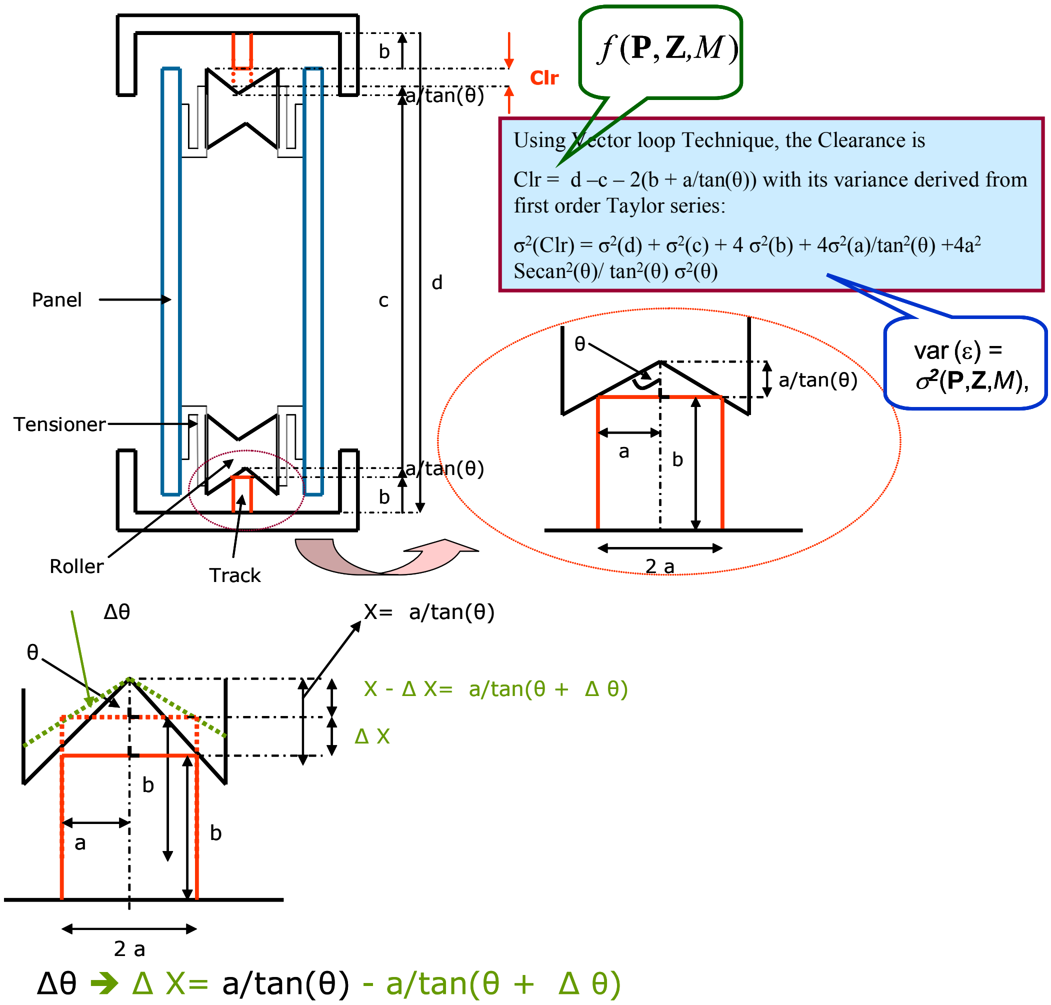

Figure 4. Transfer Function of A Sliding Door Derived From Vector Loop Technique

4.1. Finding Optimal and Robust Design

Here, we will find the best setting of certain design variables that can minimize performance variability and of others than already chosen design variables that can adjust performance mean to target. This kind of approach was originated by Dr. Genichi Taguchi. The following is the steps to execute this approach.

DOE

Choosing design space and number of levels or settings of the design variables in experimental design need to include engineering and production knowledge (see Table 1). The baseline and benchmark values should also be considered in choosing the design space. To explore high order interaction effect or the nonlinearity relationship between a specific design variable and its system performance we need to choose more number of levels of that variable as for variables *a* and *theta* The standard deviation of each design variables should be obtained from a stable and under control process.

Table 1. Design Space of A Sliding Door

Variables	Minimum	Maximum	Levels	StDev
a	0.1	0.4	4	0.03
b	0.5	1.5	3	0.03
c	8	10	3	0.08
d	12	14	3	0.1
θ	45	80	5	4

After choosing design space, number of levels and standard deviation of each variable, we then create an appropriate experiment matrix. Since we have analytical expressions of the system performance and its variation, the outputs of the experiment are obvious. In our case we apply a full factorial design generated from DOE Pro XL or Minitab and then generated the values of Clearance and its standard deviation using their explicit formulas in MS Excel.

Global Sensitivity Analysis

Having got experimental outputs, we analyze the sensitivity of the Clearance and its standard deviation in relation to the design variables on their chosen design space. Global Sensitivity analysis is very important to rank the important of the design variables, especially in sequential design of experiments to identify the effective design variables included in design. ANOVA is one tool to get the Global Sensitivity of the system performance, as shown in Table 2 obtained from DOE PRO XL:

Table 2. ANOVA Analysis of A Sliding Door DOE

ANOVA TABLE

	Clr						StDev(Clr)				
Source	SS	df	MS	P	% Contrib	Source	SS	df	MS	P	% Contrib
a	10.7	3	3.6	0.000	0.96%	a	638.4	3	212.8	0.000	86.63%
b	360.0	2	180.0	0.000	32.39%	b	0.0000	2	0.0000	1.000	0.00%
c	360.0	2	180.0	0.000	32.39%	c	0.0000	2	0.0000	1.000	0.00%
d	360.0	2	180.0	0.000	32.39%	d	0.0000	2	0.0000	1.000	0.00%
theta	17.2	4	4.3	0.000	1.55%	theta	82.1	4	20.5	0.000	11.14%
AE	3.4487	12	0.2874	0.000	0.31%	AE	16.5	12	1.4	0.000	2.24%
Error	0.000	514	0.000		0.00%	Error	0.000	514	0.000		0.00%
Total	1111.398	539				Total	737.013	539			

The ANOVA table shows that *a* and *theta* have about 98% influence to minimize performance variability (StDev(Clr)) and b, c and d have about 97 % influence to optimize the performance mean (Clr). Small interaction between *a* and *theta* occurs to both of the performance variability and mean.

Graphical Approach:

The direction to find the best settings of the variables can be searched through the main effect and interaction plots of the experimental results as shown in Figure 5 which was obtained from Minitab.

The plots give directions that decreasing *a* and increasing *theta* will minimize performance variability and selecting settings for b, c and d will adjust the performance mean to target, but they don't affect the performance variability. This approach is called Graphical Approach. As a note: in order to optimize the base line design to its target, without considering robustness, we would intuitively increase *a* and decrease *theta*. This would get an optimal solution, but the solution would not be necessarily robust.

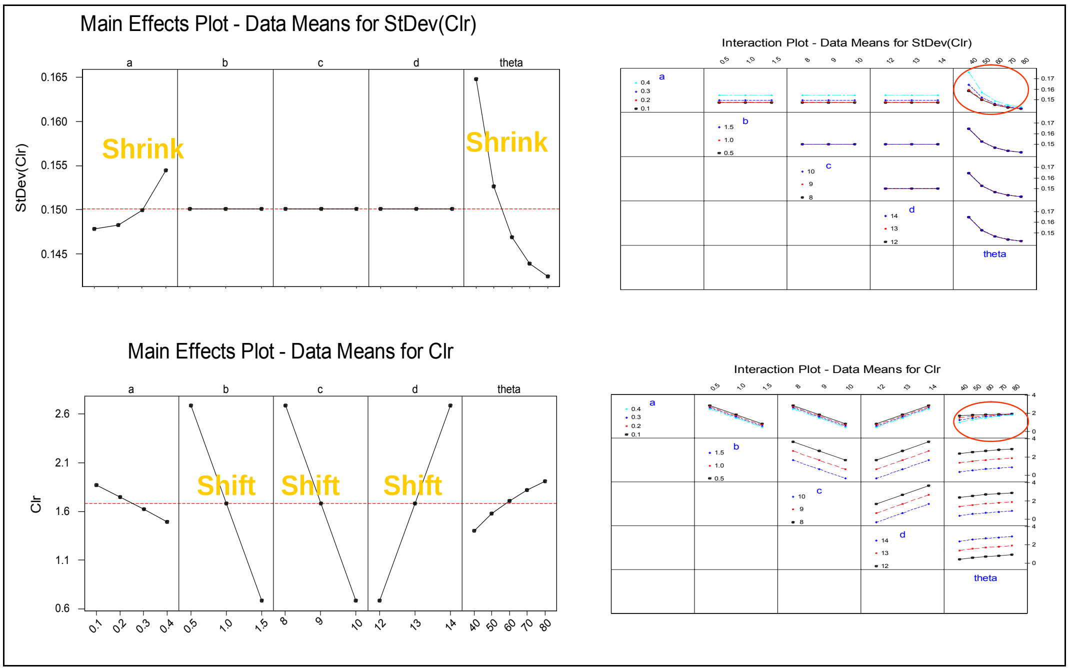

Figure 5. Main Effect and Interaction Plots of A Sliding Door DOE

Mathematical Programming

Graphical Approach cannot provide an easy way to find optimal and robust solutions when we have multiple performances or the interactions among the design variable are significant. In such kind of situation, we need to apply what is called Mathematical Programming Approach, e.g. Dual Response Optimization for performance mean and variability problems or Desirability Function Method like approaches for multiple performances.

Dual Response Optimization is to minimize StDev(Clr) subject to Clr on target and the design variables in design space. This can be implemented by using add-in MS Excel Solver.

In many cases each performance has different magnitudes. One way to normalize each performance into values between 0 and 1 is to implement Desirability Function Method. Optimizing Clr is to find its best nominal values. Optimizing σ(Clr*)* is to minimize σ(Clr*).*

Once performances are converted into individual desirability which has values between 0 and 1, weighted geometric mean aggregate methods may be used to combine the individual desirability. Finally, optimize the aggregate value is equivalently to optimize each individual performance, i.e. Clearance and its standard deviation. Multiple objective optimizations will generally end up with what are called Pareto Optimal Solutions. These solutions are suitable to satisfy family of products whose performance targets are various.

The baseline design results compared to the optimal and robust design results using Minitab Optimizer which is based on Desirability Function method are given in Figure 6.

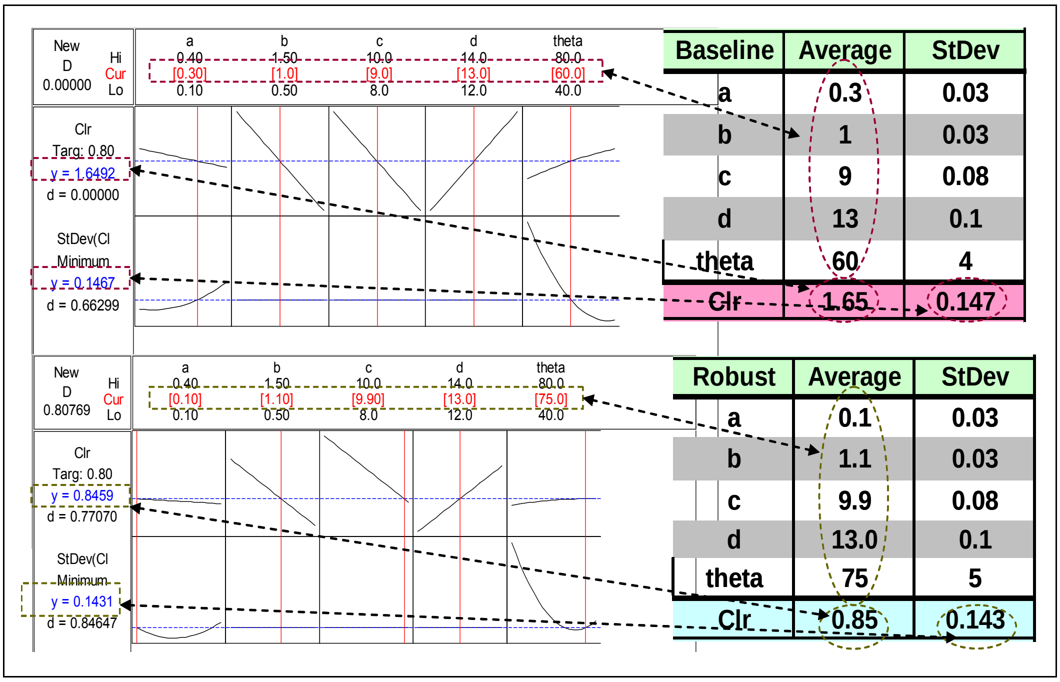

Figure 6. Baseline and Robust Results of A Sliding Door.

The Robust Design gives performance mean close to the target, i.e. 0.8 with the performance variability is only 0.83. The design is robust about 2.7 % than the base line design. Moreover, the Robust Design relaxes the theta tolerance from StDev = 4 to StDev = 5.

Guide for Manufacturing and Quality Process

From the equation of the variance of y for a point $\mathbf{x}_0$ above, the local sensitivity of the design variables is defined as

$$S(x_i)=\frac{\left(\frac{\partial f(xo)}{\partial x_i}\sigma(x_i)\right)^2}{\sigma^2(y)}\text{ x }100\% \qquad (3)$$

The local sensitivity of the Robust Design using Crystal Ball Version 7 is given in Figure 7. It shows that Roller distance (c) and door height (d) are the most sensitive variables in relation to the system performance mean, as their influence to Clearance is as much as 80%. Track length (a) and roller angle (theta) are the only influential variables to the system performance variability. Those results can be applied as early identification to allow, e.g.: Quality Assurance people focus on variables *c* and *d* in their control process and Manufacturing or Supplier people to plan for variables *c* and *d* in their facility and tooling upfront.

The Robust Design also identifies that variables *a* and *theta* have minimum influence to optimal performance mean. Therefore, the tolerance of both variables can be relaxed without loosing significantly the optimal and robust design.

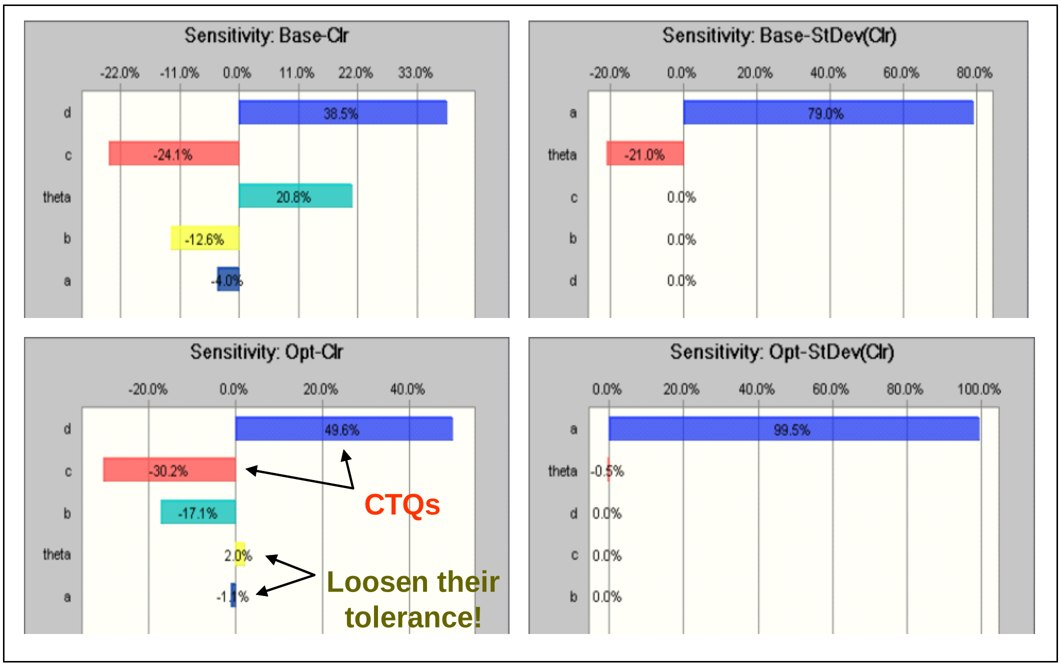

Figure 7 Local Sensitivity Analysis of Baseline and Robust Designs of A Sliding Door.

Monte Carlo Simulation

In our case we have the explicit transfer functions of Clearance and its standard deviation and we know the distribution of the design variables, i.e. normal. With this information, we can use Monte Carlo simulation package software to find the best setting of the design variables for Robust Design. Figure 8 and Table 3 are the Monte Carlo simulation results of base line and robust designs obtained by using Crystal Ball version 7 for 10,000 trials. Opt-Clr is the average of the robust design result and Opt-StDev(Clr) is the standard deviation of the robust design result. BaseLine-Clr is the average of the base line result and BaseLine-StDev(Clr) is the standard deviation of the baseline result.

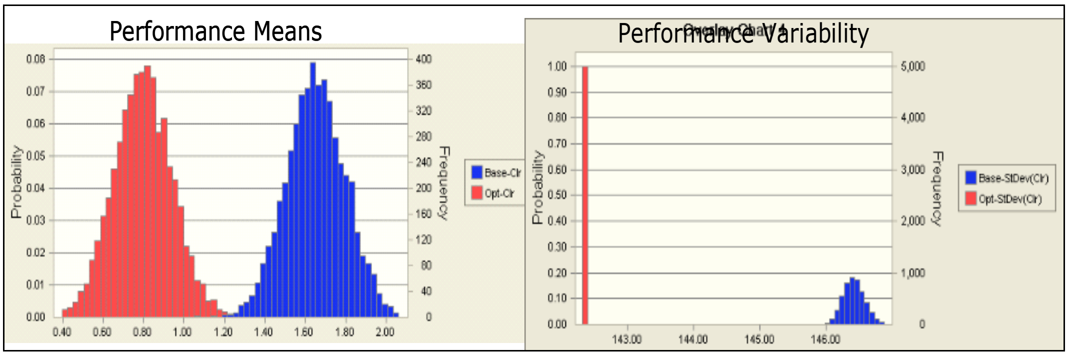

Figure 8.Monte Carlo Simulation Results of Baseline and Robust Designs of A Sliding Door.

Table 3. ummary Statistics of Monte Carlo Simulation Results of Baseline and Robust Designs of A Sliding Door.

Statistics (mm)	BaseLine-Clr	Opt-Clr	BaseLine-StDev(Clr)	Opt-StDev(Clr)
Average	1.65	0.85	0.147	0.143
StDev	0.15	0.14	0.16	0.01

Table 3 shows that the robust design give an optimal average value, i.e. 0.85 mm and smaller and consistent (robust) standard deviation. i.e. 0.143 mm. The robust standard deviation (Opt-StDev) is 16 times more consistent than base line standard deviation (BaseLine-StDev).

4.2 Designing Tolerance

The similar process shown above can be repeated to get the optimal tolerance for each design variables. This is about how to economically allocate the performance tolerance to the tolerance of the controllable and un-controllable variables. The algorithm is to fix the design variables at values to get the optimal and robust design and then to change the deviation of the variables. In this example we choose 5 levels of standard deviations, i.e. the baseline, baseline-50% of the baseline, baseline-25% of the baseline, baseline+25% of the baseline and baseline+50% of the baseline (see Table 4).

Table 4.Design Space For Tolerance Design of A Sliding Door.

Variables	Mean Values	Standard Deviation				
	Robust Design	B-50%*B	B-25%*B	Baseline(B)	B+50%*B	B+100%*B
a	0.1	0.015	0.023	0.030	0.045	0.060
b	1.1	0.015	0.023	0.030	0.045	0.060
c	9.9	0.04	0.06	0.08	0.12	0.16
d	13	0.05	0.08	0.10	0.15	0.20
theta	75	2.50	3.75	5.00	7.50	10.00

The main effect plot (see Figure 9) and the sensitivity analysis (see Table 5) derived from the results of full factorial design experiments show that a and theta are insensitive to the changing of their tolerance and the most sensitive variable is door height (d), i.e. 61.18%. The process control should focus on this variable.

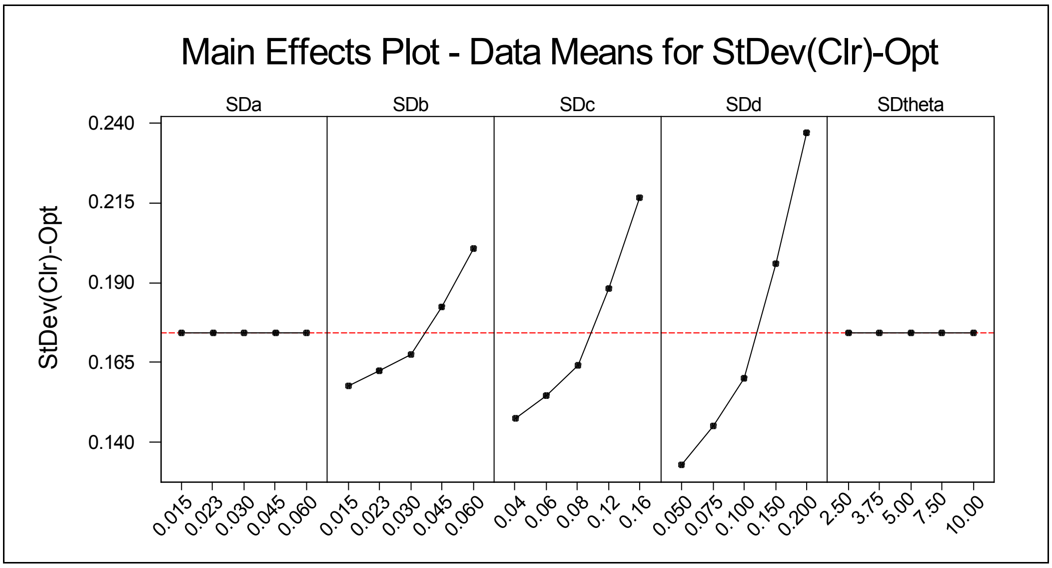

Figure 9. Main Effect Plot of Tolerance Design of A Sliding Door

Table 5. ANOVA Analysis of Tolerance Design of A Sliding Door

Source	SS	Si %	TS(i)%	Adj. TS(i)%	Total Main Effect	Total Interaction
SDa	0.000	0.00	0.00	0.00	98.30	1.70
SDb	0.770	10.46	11.17	10.98		
SDc	1.993	27.06	28.33	27.84		
SDd	4.476	60.78	62.26	61.18		
SDtheta	0.000	0.00	0.00	0.00		
SDb*SDc	0.017	0.22				
SDb*SDd	0.032	0.43				
SDc*SDd	0.073	0.99				
SDb*SDc*SDd	0.004	0.06				
SDa*SDtheta	0.000	0.00				
Total	7.364	100.00	101.76			

5. CONCLUSIONS

- The ultimate goal of DfSS is to have products or processes which are insensitive to the sources of variation that inhibit their intended function. This means that DfSS produces consistent products or processes within or, even, beyond customer's quality expectation.
- DfSS comprehends the relationship between the product or process performances and the product or process controllable and uncontrollable variables. This provides a guide to Product Development Process to avoid over or under designs and drive focus on design essentials. Thus, DfSS shortens the product development cycles and reduces cost.

- DfSS shows early identification of customer critical and un-critical factors (characteristics) that allows manufacturing to plan for those factors in their facility and tooling upfront. This provides a guide to manufacturing and quality processes. Thus, DfSS speeds up delivery, improves quality and prevent cost of poor quality.
- Once the functional subsystem is completely understood DfSS provides a quality opportunity with replication of the methodologies on other applications. Thus, DfSS improves organizational design knowledge.

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