Application of Design for Six Sigma Processes of an Aero Gas Turbine

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Abstract

Gas turbines are highly complex systems with many competing and increasingly onerous requirements, for example: lower emissions, improved availability and lower running costs. This means that future designs will be driven to be lighter in weight, operate at higher and higher temperatures and speeds to reduce fuel burn, whilst at the same time maintaining acceptable life and overall performance characteristics. However, it is important to recognise that all of these requirements must also be robust (insensitive) to the effects of variation ("noise") to which the gas turbines will be subjected throughout their lives.

In order to better identify solutions to these requirements a number of new technologies are being developed in research programmes and then applied in full engine programmes. As an example of this improvement activity, Design for Six Sigma (DFSS) has been applied to the design of a specific component – a High Pressure Turbine (HPT) disc – the result of which will then provide a template for a generic robust design process going forward that can produce better designs faster.

The aim of this paper is to show how DFSS was applied, using a "DCOV" methodology, to result in a quantitatively robust HPT disc design. An overview of the DCOV methodology will be given including usage of some of the key tools, such as:

Quality Function Deployment (QFD), Design of Experiments, Surrogate modelling, Analytic Hierarchy Process (AHP), Monte Carlo simulation, Data Mining and parameter design. This will be followed by a review of the DCOV process for the HPT disc example.

Keywords: *Six Sigma, Aero Gas Turbine, High Pressure Turbine, Design for Six Sigma (DFSS)*

INTRODUCTION

Although predictive techniques for engineering design (such as statistical tolerancing) have been in widespread use for many years, the methodology "Design for Six Sigma" (DFSS) was popularised by General Electric in the late 1980s. The intent of DFSS is to gain quantitative confidence in the design stage that a design will perform as intended, obviating the need for costly re-design after the product, service or process is realised.
Six Sigma product and process improvement via the DMAIC methodology has become reasonably standard, although there are variants of it that incorporate "pre-define" and "knowledge transfer" phases. DFSS, on the other hand, is less well understood and less widely applied. As a consequence, DFSS is less standardised in its implementation than Six Sigma, resulting in several variants of the most widely recognised methodologies: IDOV (Identify, Design, Optimise, Verify) and DMADV (Define, Measure, Analyse, Design, Verify).

In this aerospace equipment manufacturing firm (aero engine, power generation and marine propulsion sectors), the methodology of choice is DCOV (Define, Characterise, Optimise and Verify). The following paragraphs explain the objectives and tools & techniques that are typically used in each of these phases of the process.

DEFINE

The first objective of Define phase is to elicit, understand and prioritise the customer requirements for the design. Prioritisation is achieved by the use of AHP (Analytic Hierarchy Process) (Saaty, 1999). In AHP all the requirements at any level in the hierarchy are formed in to a triangular matrix as shown in figure 1.

The row items are compared to the column items and the following question is answered in each case: "is the row item more, equally, or less important than the column item in fulfilling the requirement at the level above?" If the row item is deemed more important the comparison is scored between 2 and 9; if less important it is scored between 2 a score of 1 is given – see figure 2.

At level 1 (the highest level) in the hierarchy, requirements are compared for their importance relative to the operational definition of the system. If we consider the example of a domestic toaster, such an operational definition would be "toast bread products safely"

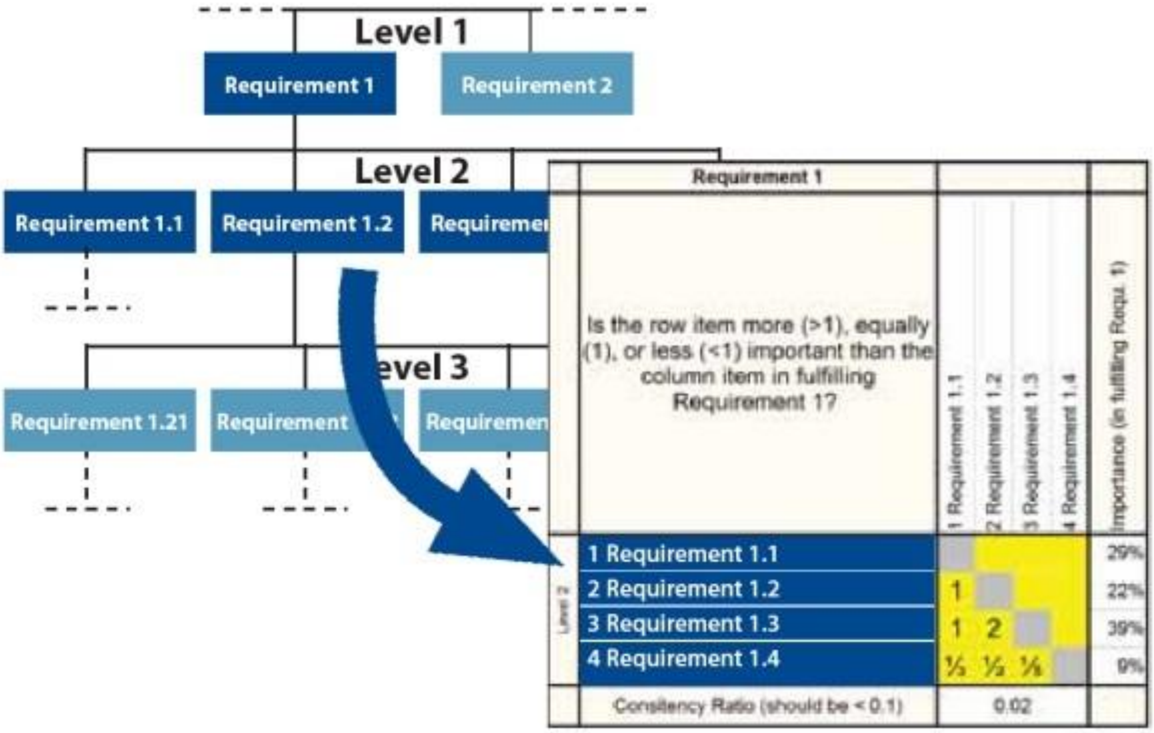


Figure 1*: Requirements Hierarchy and Prioritisation Using AHP*

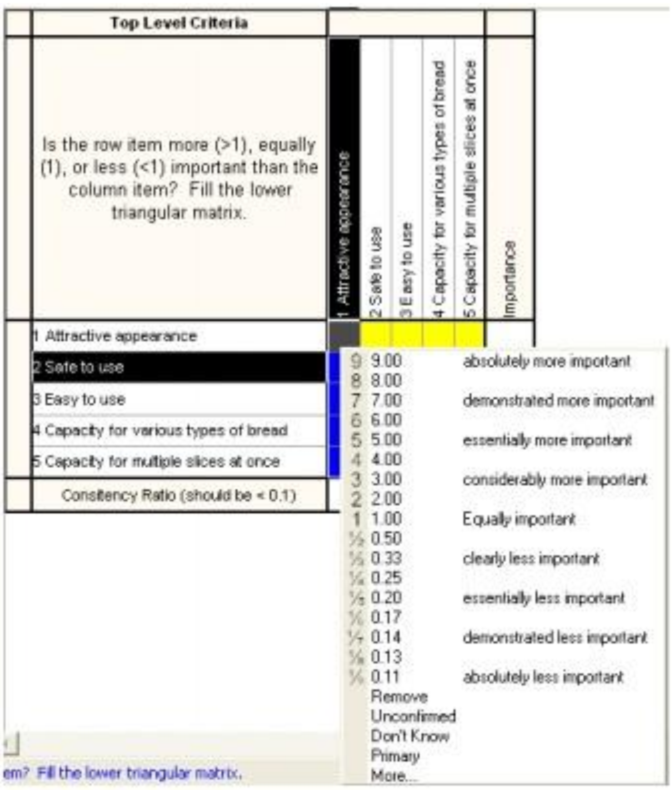


Figure 2*: Scoring Comparisons in AHP*

Notwithstanding the benefits of the discussion that AHP stimulates, another benefit of using AHP is the Consistency Ratio that is calculated as part of the process. This informs us as to whether the set of comparisons (within a group at any level) is self-consistent. A high value (greater than 0.10) indicates inconsistency such that the scores could plausibly have been generated randomly. The result of this process is that we have an importance weighting on a continuous scale of all requirements, rather than a simple ordinal ranking. We can therefore make meaningful ratio comparisons between any two requirements – impossible with ranked data.

Requirements are then translated into a technical (functional) specification for the design using Quality Function Deployment (QFD) – see figure 3 for a simple example of “QFD1” for a domestic toaster, create in Qualica (see Ref. Error! Reference source not found.). Note that the suffix ‘1’ attached to QFD indicates that there are a number of QFD matrices in the requirements translation - flow-down - process, this being the first.

It is important to understand that the functional specification should be concept invariant – thus allowing more scope for innovation in proposed design solutions. To illustrate this point, using the domestic toaster example, some of the functions of a toaster are to: load bread products, generate heat, apply heat, monitor toasting, remove from heat, and unload toast. This functionality would be the same whether we were using an electric toaster or a toasting fork! Thinking of the functionality in these generic terms allows us to ask the question “how might we fulfil this function?” Systems Engineering tools – such as morphological analysis for concept generation and Pugh matrices (or again AHP) for concept selection – can be used here.

Once a high level concept has been selected, the next objective in the Define phase is to establish a detailed nominal design. In this context, a nominal design is one that, prior to understanding the effects of variation on performance, meets all nominal requirements. In this company design processes are heavily simulation-based; involving computationally intensive and complex calculations of air flow, structural stresses, temperatures etc. For this reason the only efficient and effective means of understanding the design space is to perform these simulations systematically according to a Design of Experiments (DOE) scheme, as

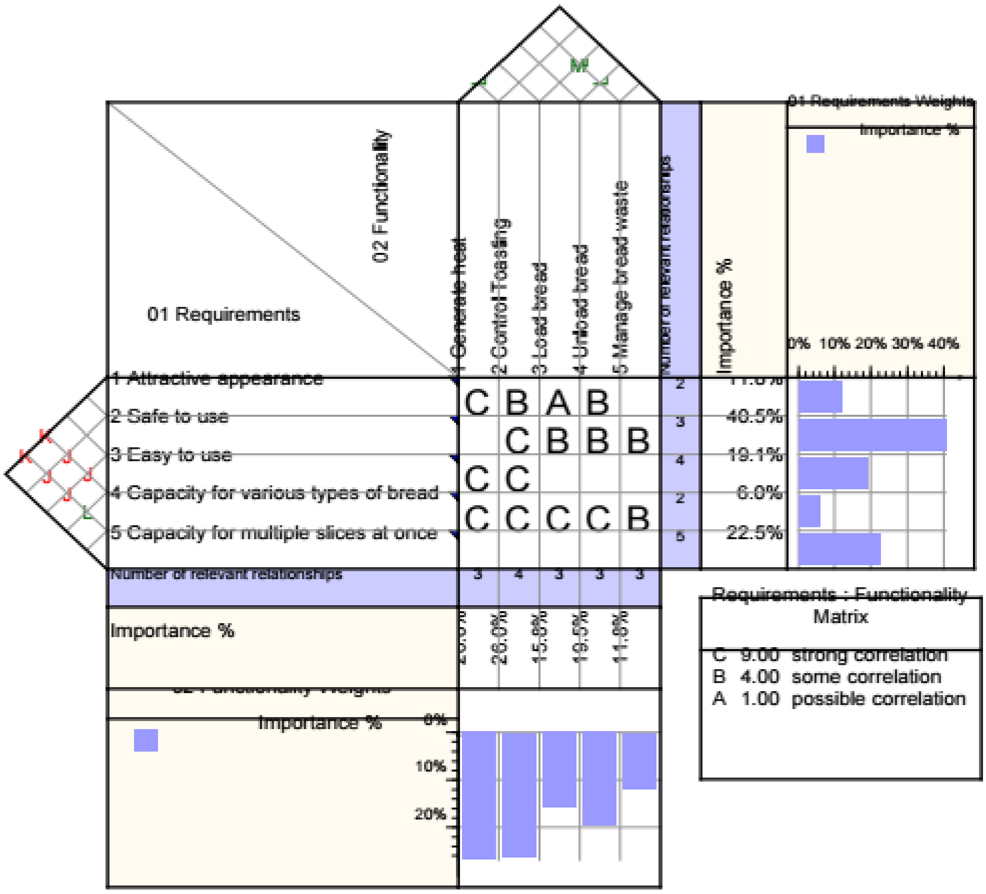


Figure 3*: Simplified QFD1 for a Domestic Toaster*

opposed to a trial and error (sometimes known as "engineering judgment") approach. Figure 4 explains diagrammatically how the judicious use of DOE allows us to evolve our understanding of the design space whilst minimising computational effort.

Once the nominal design has been established, the final objective in the Define phase is to understand what might influence the robustness of the design. In this context, robustness doesn't mean "bigger, stronger, harder etc.", rather it refers to a design's ability to perform consistently in the presence of unavoidable sources of variation ("noise"). In order to achieve this objective it is first necessary to identify, prioritise and quantify the causes of variation in the key design performance metrics - the CTQs (Critical To Quality characteristics). We must therefore pose the question "what things will cause the CTQs to deviate from their target values either directly or through affecting the values of the design parameters themselves?"

An example of the latter type of noise (referred to as "type A" noise) is wear – when something wears its physical characteristics change. These changes transmit variability to the outputs that are driven by the design parameter in question. An example of the former type of noise (referred to as "type B" noises) is road surface condition; its effect on stopping distance (the CTQ for a vehicle's braking system) is direct: an icy road will influence stopping distance but it will not change the physical characteristics of the braking system itself.

In order to collate both the control factors that influence the performance characteristics of the product by design and the noise factors (sources of variation) that may inhibit the ability of those parameters to deliver the desired performance, P-diagrams are employed. Shown in generic form in figure 5, a P-diagram elegantly captures and categorises these factors and equates the performance CTQ (labelled "output Y") of the design as a function of Signal, Control and Noise factors. Incidentally, a signal factor is one whose values are set by the system user in real time with the intent of achieving a desired output; an example for the braking system would be pressure applied to the brake pedal by the driver – by exerting more force on the brake pedal, the driver desires the car to stop more quickly.

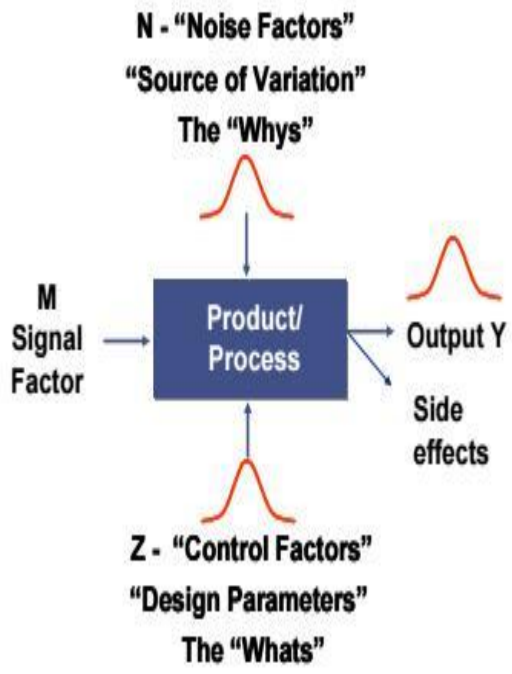
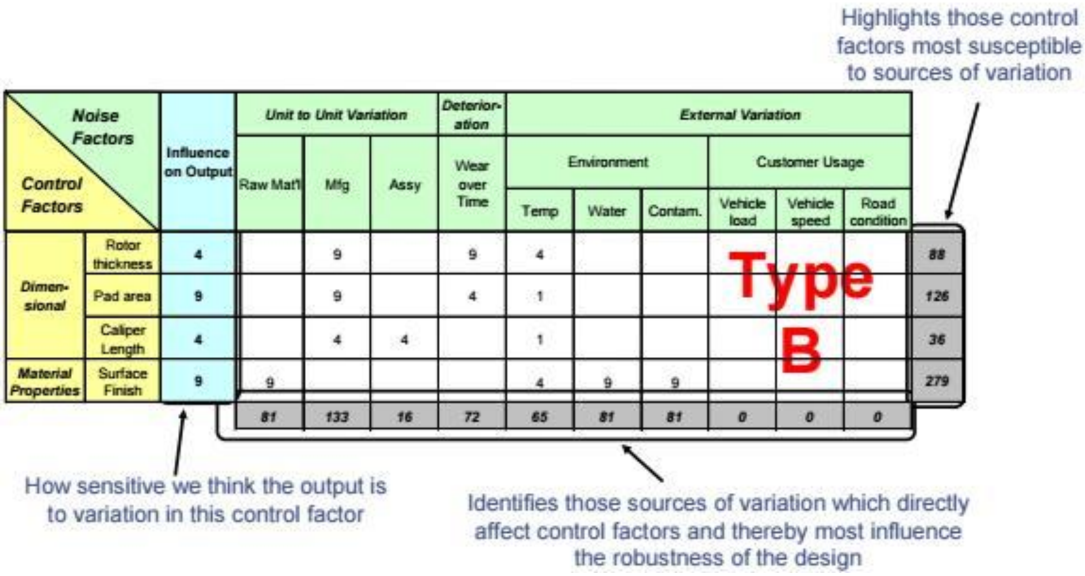


***Figure 5**: A Generic P-diagram*

This exercise can reveal many more design parameters and sources of variation than may otherwise have been identified. Although in principle all of these factors will be modelled probabilistically in the Characterise phase of DCOV it is necessary to prioritise which sources of variation will be modelled using real-world data since this is often difficult and expensive to collect.

To achieve this prioritisation a "What-Why table" is employed (see figure 6). This involves making both subjective and



Control Factors \ Noise Factors		Influence on Output	Unit to Unit Variation: Raw Mat'l	Mfg	Assy	Deterioration: Wear over Time	External Variation: Environment: Temp	Water	Contam.	Customer Usage: Vehicle load	Vehicle speed	Road condition	
Dimensional	Rotor thickness	4		9		9	4						88
	Pad area	9		9		4	1						126
	Caliper Length	4		4	4		1						36
Material Properties	Surface Finish	9	9				4	9	9				279
			81	133	16	72	65	81	81	0	0	0	

***Figure 6**: A Sample What-Why Table*

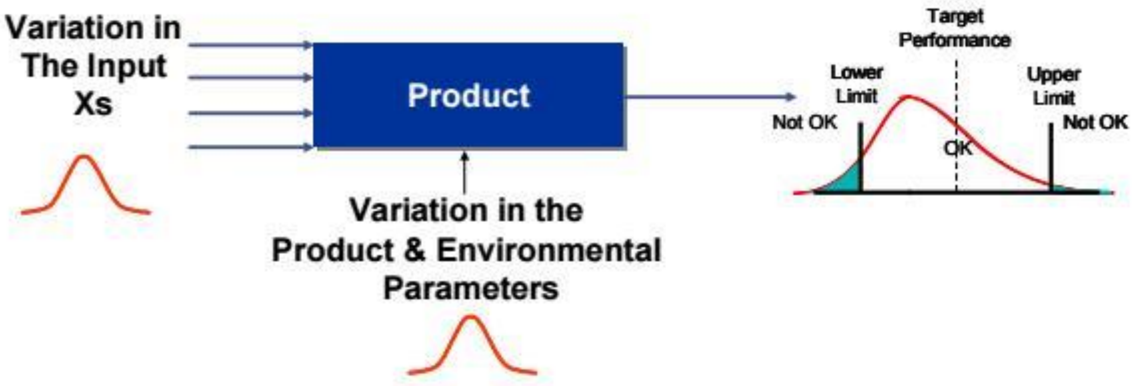


Figure 7: Transmission of Variation from Input to Output
Transmission of Variation from Input to Output

(preferably) objective assessments of the contribution of noise factors to design parameter variability (type A) and CTQ variability (type B). It results in a set of design parameters that are most influenced by noise, and a set of noises that cause most of the variability.

CHARACTERISE

"Characterise" is the phase in DCOV in which variability in the CTQs is quantified. Combined with mean performance of the CTQs their variability in the presence of noise variation measures the robustness of the design, as shown in figure 7.

There are several methods and metrics available in DCOV that can be used to quantify the robustness of a design. The choice of both method and metric is driven largely by the knowledge and nature of the input variation, but also the speed of the simulation code and the ability to automate the simulation workflow parametrically to calculate the CTQs for which a quantification of robustness is required.

The simplest of these robustness metrics is called “Delta Y”(Y) : if a change to noise factor is made of a magnitude that is to be expected in the real world we can measure (for hardware) or calculate (for software) the change induced in the CTQ. For any given noise factor j, this is called Yj are varied by their expected amounts one at a time and all resulting individual Y values are summed. If the result is of the same order of magnitude as the tolerance width for the CTQ then the design is unlikely to be robust in practice.

Although not a statistically rigorous robustness metric, Delta Y can be used as both a ‘rough cut’ assessment and to determine which noise factors have the most impact. It can also be used to compare alternative design concepts. An alternative robustness metric (with statistical meaning) is the variance of the CTQ; y2. If one has an explicit equation (an explicit transfer function) linking the noise factors n and the control factors z to the CTQ of the form y = f(n,z) then one can generate a variance transmission equation (VTE) from partial differentiation of the transfer function with respect to the noise factors to approximate y2 . For example, the VTE derived from a first order Taylor series approximation, for two independent noise factors is:

$$\sigma_y^2 \approx \sigma_{n_1}^2\left(\frac{\partial y}{\partial n_1}\right)^2 + \sigma_{n_2}^2\left(\frac{\partial y}{\partial n_2}\right)^2 \quad (1)$$

Kapur & Feng (2005) gives a more accurate higher order approximation, but oftenKapur & Feng (2005) gives a more accurate higher order approximation, but often will suffice. Remember that for type A noise, the noise factor and the control factor are the same variable, so one would differentiate with respect to z for such factors.

If the explicit transfer function is generated from a designed experiment, rather than from theoretical standpoint,

$$\sigma_y^2 \approx \sigma_{n_1}^2\left(\frac{\partial y}{\partial n_1}\right)^2 + \sigma_{n_2}^2\left(\frac{\partial y}{\partial n_2}\right)^2$$

Equation 1 will be supplemented by the model error (Myers and Montgomery, 1995).

Another way to obtain an approximation for y (an implicit "black box" transfer function) is via the technique of simple differences when the transfer function exists but cannot be written down explicitly.

This method utilises the first order approximation as in

$$\sigma_y^2 \approx \sigma_{n_1}^2\left(\frac{\partial y}{\partial n_1}\right)^2 + \sigma_{n_2}^2\left(\frac{\partial y}{\partial n_2}\right)^2$$

Equation 1, but in the simplified form (again shown for two noise factors):

$$\sigma_y^2 \approx (\Delta y)_1^2 + (\Delta y)_2^2 \quad \text{Equation 2}$$

This simplification is made possible by three assumptions: the transfer function is approximates to linearity over the small region of design space being perturbed by the noise factors, the noise factors are independent and the change in noise factors n is defined to be the standard deviation, n rather than the infinitesimally small amount represented by ∂n, then since . If we represent small (tangible) changes in the noise factors by n, rather than the infinitesimally small amount represented by ∂n, then since

$$_n^{2}/(\ n)^2 = 1,\ \sigma_y^2 \approx \sigma_{n_1}^2\left(\frac{\partial y}{\partial n_1}\right)^2 + \sigma_{n_2}^2\left(\frac{\partial y}{\partial n_2}\right)^2$$

Equation 1 reduces to Equation 2, so that y2 is simply the summation of the squares of the changes in the CTQ (yj) away from its nominal value when each noise factor is varied in turn by one standard deviation. This can be surprisingly accurate, but if desired higher order approximations can be made to refine the estimate. In long running simulation codes with a large number of noise factors k, simple differences can be very efficient, since it requires only k + 1 runs.)

The final method we shall discuss here is Monte Carlo Simulation (MCS), of which there are several variants. The metric we shall focus on is Pc, the probability of conformance for the CTQ. We shall limit our discussion to "simple MCS", the basic form. MCS requires a transfer function to exist, but it need not be explicit. As we have already said, variation in noise factors causes variation in the response (CTQ). If we can model the probability density function (PDF) of the noise factors through data fitting (or experience or

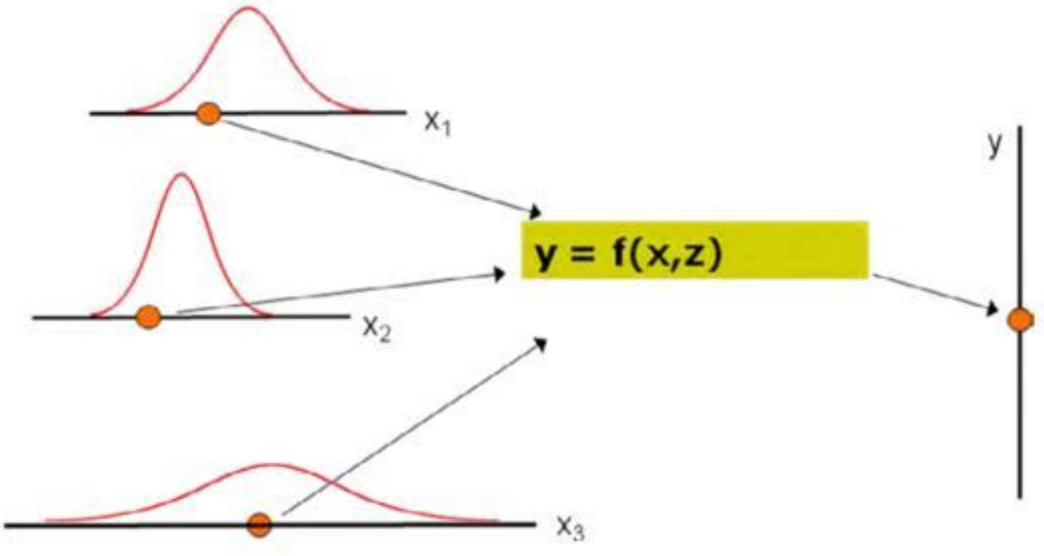


Figure 8*: Single Random Sample from Input PDFs to Predict Single Result from Transfer Function*

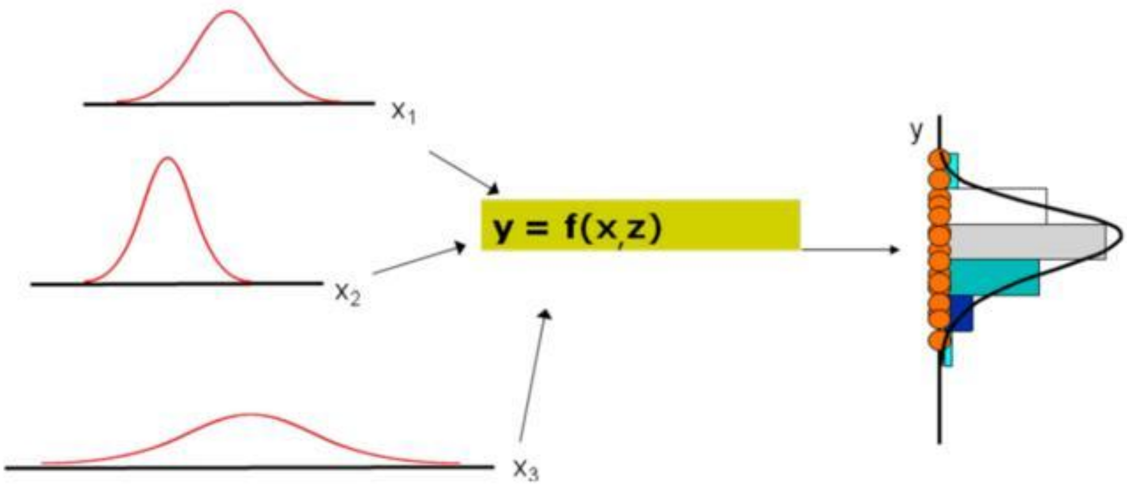


Figure 9*: Multiple Random Samples from Input PDFs to Predict PDF of Result from Transfer Function*

judgment to be begin with), then these distributions can be sampled one at a time at random to produce a random value of the CTQ via the transfer function, as shown in figure 8.

This can be repeated many times to produce a probability distribution for the CTQ itself, as shown in figure 9.

The CTQ data can be fitted to a PDF, which may then be used to compute the probability of conformance, Pc to the specification for the CTQ. The beauty of this method, of course, is that it gives a complete picture of the variation of the CTQ without having to perform mathematics, or use approximations. Disadvantages are that MCS is only relevant to simulations, whereas the previous two methods could also be performed on hardware, and additionally a large number of runs of the simulation code are needed to form a smooth picture of the CTQ variation.

When performing Monte Carlo simulation another important consideration to make is whether or not there is correlation between input parameters. This is important as a strong correlation between any of the factors may have a profound influence on the evaluation of robustness for the design. Clearly if two parameters are correlated then not all combinations of them are sensible.

However, applying Monte Carlo simulation in the usual fashion does not account for this – any combination of values is possible and may therefore be selected by the sampling process. Omission of the effects of so- called 'covariance' between inputs can result in over- or under-estimation of the output variance.

Whether there is under- or over-estimation depends upon the direction of the correlation between the inputs and the signs of their gradients in the design space (also referred to as 'sensitivity coefficients') at the point in the design space at which we are interested in quantifying the robustness of the design.

The magnitude of the covariance effect depends upon the strength of the correlation, the magnitude of the sensitivity coefficients and the variance of the inputs themselves. Scatter plots can identify correlations, which can then be statistically justified through hypothesis tests.

Figure 10 shows an example of a collection of scatter plots (called a 'matrix plot' in Minitab) that suggest the presence of significant correlations between three pairs of input noise parameters used in the case study described in the next section.

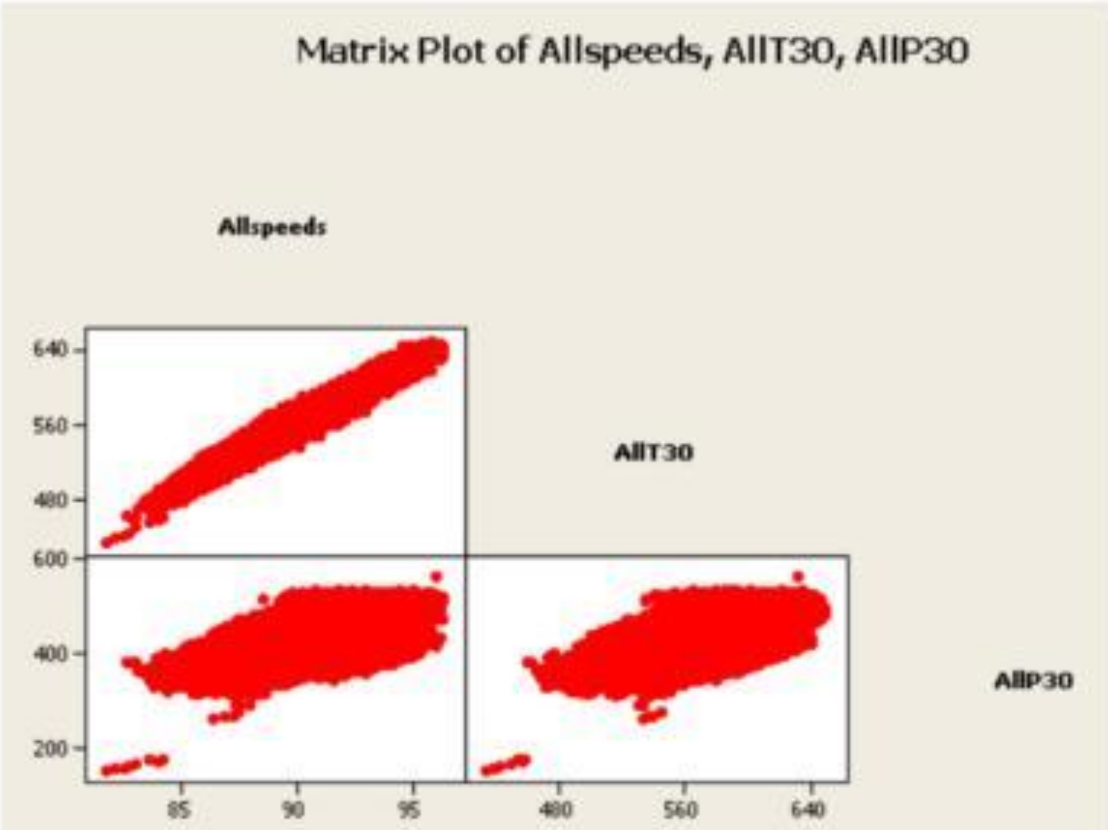


Figure 10: Matrix Plot Showing Correlations between Input Parameters, and Statistical Quantification of Correlation Coefficients with Statistical Significance.

The results shown in figure 6.10 include values for the correlation coefficient, which can have values between -1 and +1 with values closer to these extremes indicating a stronger correlation. The confidence in these correlations is supported by an associated p-value (shown below the correlation coefficients). This is the probability of observing such behaviour shown in the scatter plot if there is actually no correlation between the variables in reality. A value of 0.000 therefore indicates a very high confidence that the actual correlation coefficient is non-zero.

In many situations the simulations required to be performed are relatively long-running (perhaps taking even days to complete for a single analysis), making MCS impractical. In this instance, either one of the other metrics may be used, or alternatively a surrogate model (a synthesised transfer function) for the source code can be created.

Using a suitable software package (such as iSIGHT-FD) in conjunction with a Designed Experiment approach a data set can be generated on which to “train” a surrogate model. Depending on the peakedness of the response surface the surrogate models may take the form of Polynomial equations, Kriging models or Radial Basis Functions. Once created, the surrogate model must be validated. This involves testing the ability of the surrogate to predict the value of the CTQs at other, randomly selected, points throughout the design space.

The benefit of these surrogate models is that they run extremely quickly, regardless of the complexity of the model and the number of parameters involved, allowing robustness to be evaluated everywhere in the design space. In fact, through judicious application of DOE in the Define phase, the same model that was used to generate a good nominal design can be re-used for robustness assessment – and even optimisation. An output from Characterise is also an understanding of the sensitivity of the CTQs to input variation: which sources of variation contributed most to the observed variation in the CTQs?

In the simplified case depicted in figure 11, a single CTQ is determined by two design parameters, each affected by type A noise. In this case, the CTQ is not robust to the expected extent of variation in X1 equally sensitive to both sources.

OPTIMISE

Any shortcomings in robustness revealed in the Characterise phase give rise to the need for the Optimisation phase. Alternatively, an “overly robust” design can be made less (but still sufficiently) robust in order to gain benefits in other performance metrics (e.g. reduced weight or cost).

This is important to understand, since many, if not all, engineering problems involve satisfying multiple objectives simultaneously.

A variety of sophisticated techniques are available to deliver robustness without necessarily incurring cost associated with the common practice of achieving robustness through tightening tolerances or increasing design margin as illustrated in figure 12 and figure 13 respectively.

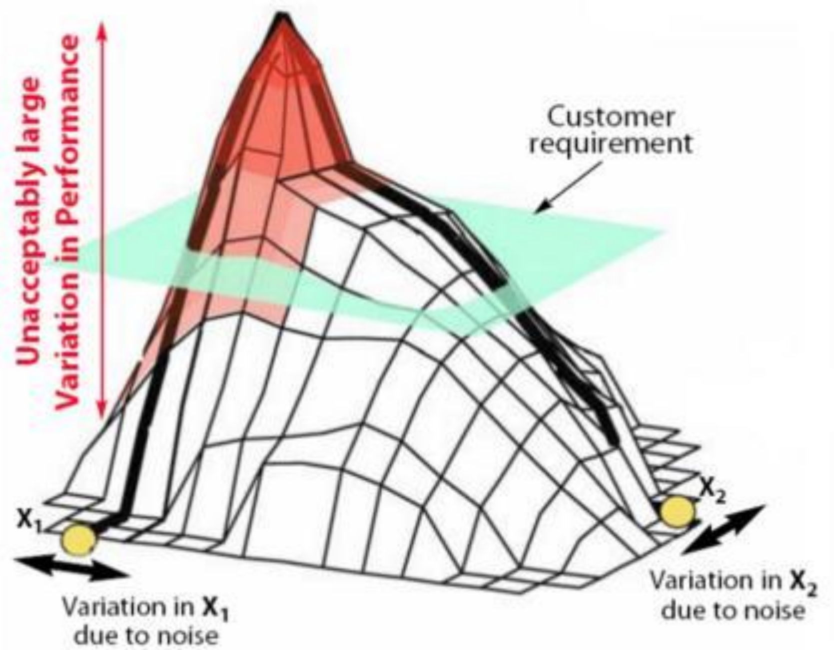


Figure 11*: A Non-robust, Sensitive Design*

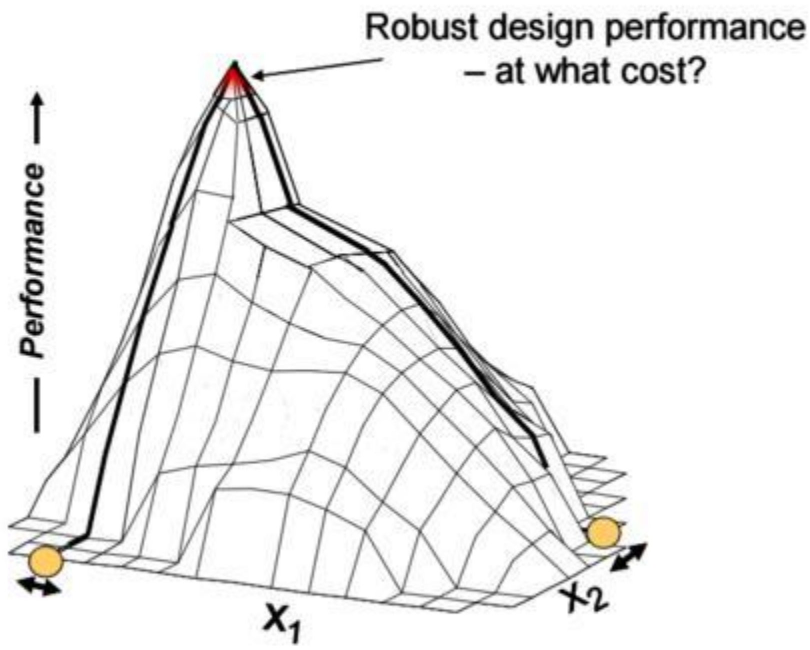


Figure 12*: Achieving Robustness through Tightening Tolerances*

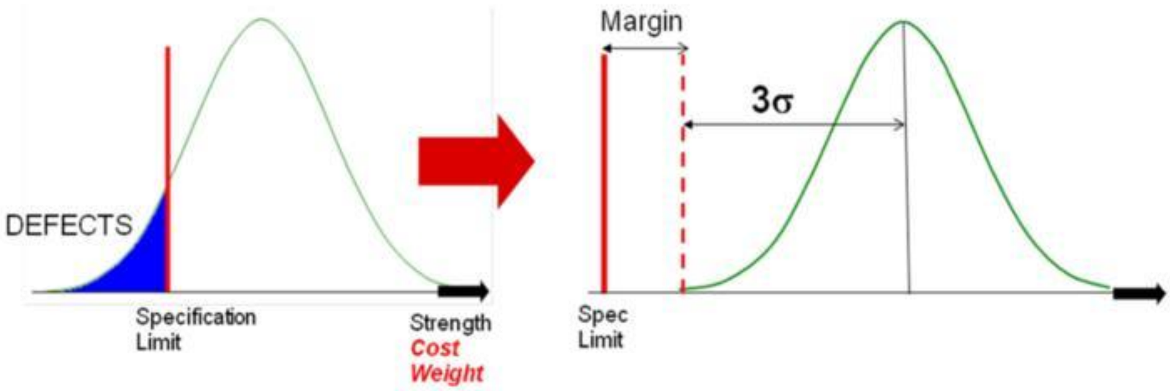


***Figure 13**: Achieving Robustness through Increasing Margin*

Figure 13 illustrates the design margin approach to a problem whereby the strength of the component is insufficient. The design margin solution is to “beef up” the design. Although this works, it increases weight and material cost.

Parameter Design and Tolerance Design are two strategies that can be applied to deliver a required robustness improvement, either separately or in combination, as part of the Optimise phase of DCOV. Parameter Design is a method to reduce the transmission of input variation to the CTQs by simultaneously adjusting the nominal values of a combination of design parameters. In this strategy the sources and extent of noise variation remain unchanged. Rather we exploit the underlying non-linearity in the relationship between CTQs and design parameters to achieve robustness of the CTQs. Figure 14 illustrates this type of Parameter Design approach.

Tolerance Design is a strategy that modifies the amplitude of the noise affecting the CTQs to achieve the same result: improved design robustness (see figure 15).

However, it is important to understand that this is not the same as the simple approach of tolerance tightening; Tolerance Design is achieving the appropriate balance between tightening some tolerances while at the same time loosening others according to the sensitivity of the CTQ to each source of variation. Hence Tolerance Design can result in cost savings!

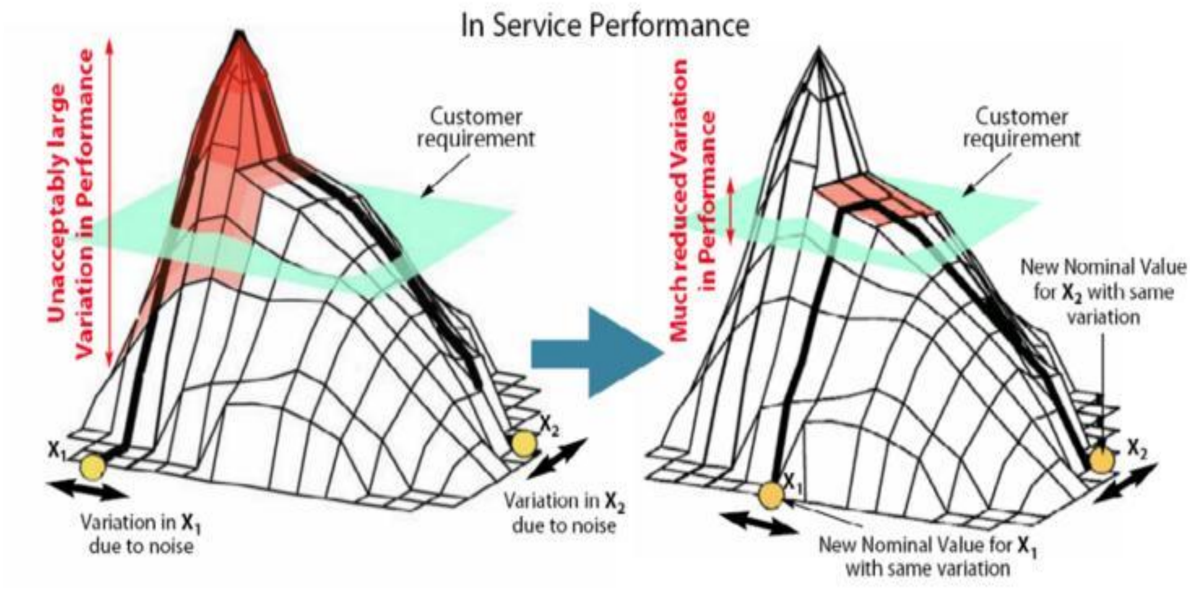


***Figure 14**: PARAMETER DESIGN- changing the nominal settings of the design parameters to achieve design robustness*

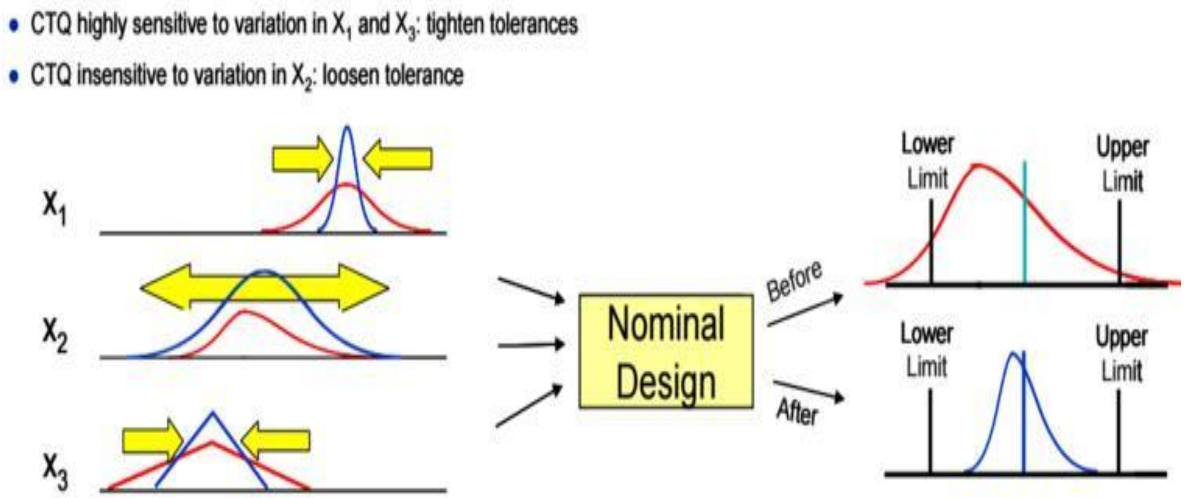


***Figure 15**: TOLERANCE DESIGN- changing the tolerances of the design parameters to achieve design robustness*

Target Mean (centre line for Xbar chart)	Target Short-Term Standard Deviation	±Tolerance in Units of Measure	Short-Term Capability to which ±Tolerance Refers (C_{pk})	SPC Subgroup Size, *N*
20.400	0.500	2.000	1.333	5
Average Range, Rbar	**Lower Control Limit for Range Chart, LCL_R**	**Upper Control Limit for Range Chart, UCL_R**	**Lower Control Limit for Xbar Chart, LCL_{Xbar}**	**Upper Control Limit for Xbar Chart, UCL_{Xbar}**
1.163	0.000	2.460	19.730	21.070

Table 1*: Statistically-based Specifications for key design parameters*

The results of the Optimise phase are confident predictions of design robustness, an understanding of the drivers of robustness and statistically-based specifications for design parameters. An example of such a specification is shown in table 1 (Rowe, 2006).

Here we can see that rather than the traditional “goalpost” specifications of a nominal with plus/minus tolerancing (20.400±2.000 in the above case), we have a statistical process control specification defining a required process capability, Cpk. This gives manufacturing a gauge by which to better assess actual ongoing process performance manifestly linked to design performance via the analysis chain created during the DFSS process – something that is not possible with traditional tolerancing!

VERIFY

The Verify phase assures us that the predictions made during Characterise and Optimise are both accurate and trustworthy. This means collecting production, hardware testing and in-service data in order to perform statistically-designed tests of confidence that the assumptions used to predict robustness were correct.

The Verify phase also assures us that the statistically-based specifications are being consistently achieved. This involves monitoring the process and comparing to the control limits and target lines for Statistical Process Control (SPC) charts defined in the Optimise phase, an example of such is shown in figure 16.

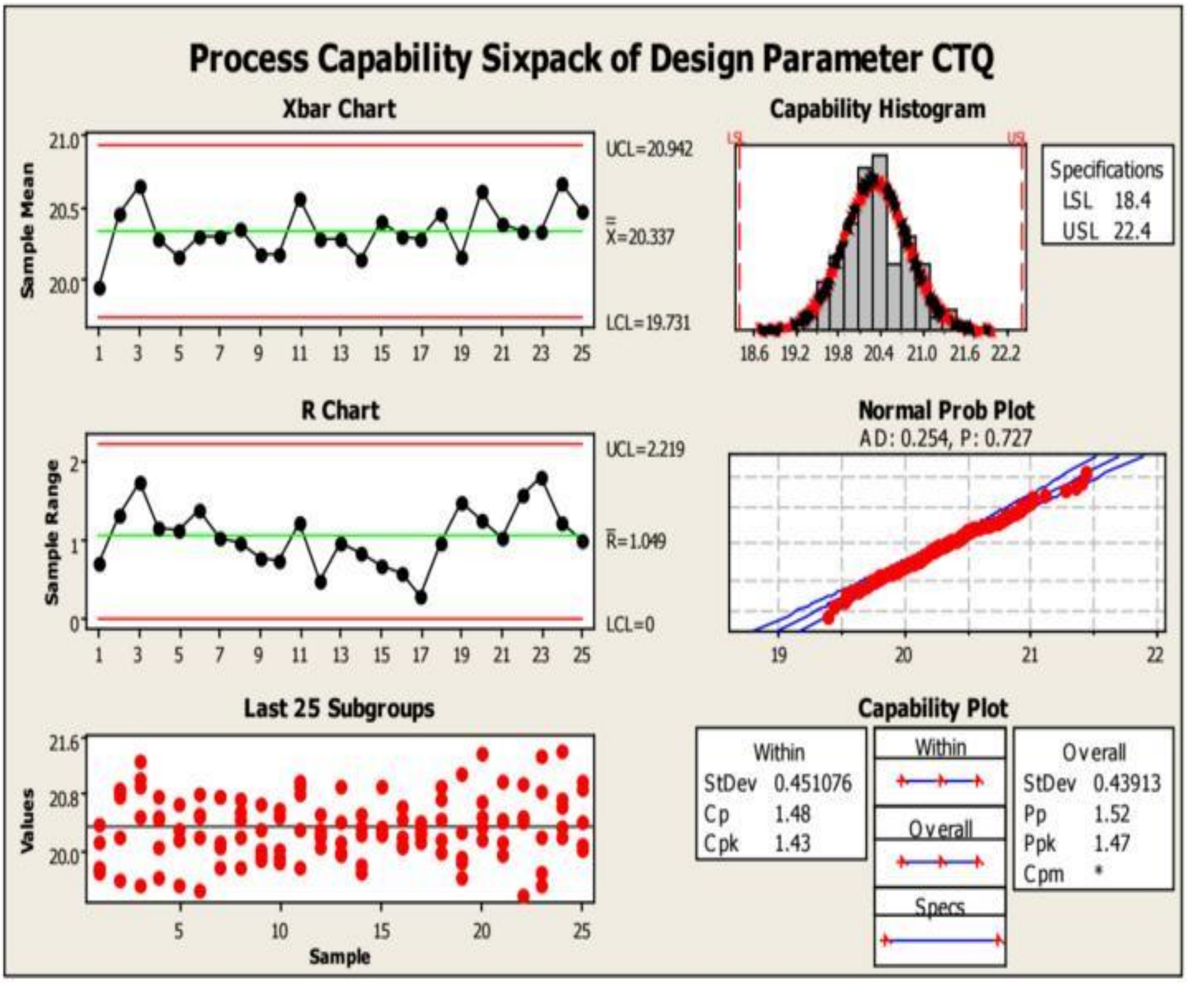


Figure 16: *Statistical Process Control chart to demonstrate conformance to statistical design specifications (Minitab "Capability Six Pack")*

In figure 16, we can see that the process is in control and exceeding the required capability of Cpk = 1.33.

This data can be fed back to design, along with data for all the other CTQs for the system so that we can re-assess the robustness of the design on an on-going basis.

CONCLUSIONS

- This paper has set out not only to clearly describe a practical implementation of DFSS using the DCOV methodology, but also to highlight the demonstrated benefits of the approach, specifically:

- A more thorough exploration of the design space is achieved than would otherwise be possible. This means that many more feasible options are made available to the designer for evaluation, enabling a design solution to be chosen that best meets the competing demands of low cost and consistent high performance.

- A quantified estimation of Pc (probability of conformance) for the design – hence greater confidence in the consistency of delivery for actual in-service performance.

- The application of Parameter Design – rather than traditional "Tolerance Tightening" – to fix robustness issues thereby avoiding extra cost and pain.

- Much of the data and associated models of variation, the automated analysis chain and surrogate models, QFD matrices, P-diagrams, What-Why tables, etc. used in this project can be re-used in future projects where a similar design concept is to be evaluated in a new application – thereby further speeding up design cycle times and improving quality.

- Through its team-based activities such as QFD, P-diagram and What-Why table creation, development of a multi-disciplinary analysis chain, DFSS promotes better cross-functional cooperation leading to a higher overall awareness of all design issues that exist. This improves the quality of decision making throughout the design process.

- Adapting individual methods and tools that form part of the overall "DFSS toolkit" to the needs of the engineering task at hand (in particular tools such as QFD and DOE) so they are less burdensome in application but still highly beneficial in progressing the engineering design process and hence encourage its adoption as a framework within which to solve engineering problems.

- With the computational power that is available today, it is possible to achieve design optimality (including robustness) through fully automated "black box" optimisation techniques. However, the more "hands on" approach as described in this paper is often more desirable, since it imparts a greater knowledge of the design space and the factors that influence both nominal performance and robustness to the design team.

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