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Achieving Robust Designs with Six Sigma

Dependable, Reliable, and Affordable

Developing "best-in-class" robust designs is crucial for creating competitive advantages. Customers want their products to be dependable—"plug-and-play." They also expect them to be reliable—"last a long time." Furthermore, customers are cost-sensible; they anticipate that products will be affordable. Becoming *robust* means seeking win–win solutions for productivity and quality improvement. So far, robust design has been a "road less traveled." Very few engineering managers and professionals are aware of robust design methods; even fewer of them have hands-on experience in developing robust designs. As a breakthrough philosophy, process, and methodology, Six Sigma offers a refreshing approach to systematically implement robust designs. This chapter outlines a process for engineering robust designs with Six Sigma and provides a road map.

1.1 Six Sigma and Robust Design

Six Sigma is a rigorous and disciplined methodology that uses data and statistical analysis to measure and improve a company's operational performance. It identifies and eliminates "defects" in product development, manufacturing, and service-related processes. The goal of Six Sigma is to increase profits by eliminating variability, defects, and waste that undermine customer loyalty.

A *best-in-class* robust design starts with three categories of static response metrics: the smaller-the-better, the nominal-the-best, and the larger-the-better. Each of these characteristics should be measurable on a continuous scale.

- A *smaller-the-better* response is a measured characteristic with an ideal value of zero. As the value for this type of response decreases, quality improves.
- A *nominal-the-best* response is a measured characteristic with a specific target (nominal) value that is considered ideal.
- A *larger-the-better* response is a measured characteristic with an ideal value of infinity. As the value for this type of response increases, quality improves.

Besides static responses, dynamic responses are also encountered when developing engineering products. A *dynamic response* is a characteristic that, ideally, increases along a continuous scale in proportion to input from the system. Dynamic responses should be related to the transfer of energy through the system. To develop robust products, dynamic formulations are recommended for the maximum benefit of the application of a Parameter Design methodology (see Chapter 7). Using a dynamic response provides the greatest long-term benefits, but it requires the most engineering know-how.

The Six Sigma approach for engineering robust designs depends heavily on formulating the Voice-of-Customers (VOCs) and Critical-to-Quality (CTQ) characteristics through experiments. The following steps provide a thorough, organized framework for planning, managing, conducting, and analyzing robust design experiments.

1. Identify project and organize team
2. Develop VOC models
3. Formulate the CTQs based on VOCs
4. Control the energy transformation for each CTQ
5. Determine control and noise factors for each CTQ
6. Establish the control factor matrix

These steps, although specified sequentially, should not be used as a "cookbook approach" to experimentation; instead, they should be used in an iterative way. During each stage of development, consider the decisions that were made in earlier steps. Your team may need to revisit previous steps in light of insights gained farther along in the process.

1.2 Identify Project and Organize Team

Six Sigma provides a product development team with the tools to improve design capability. The first step in the robust design process is to identify the project (Figure 1-1) and organize a team. This section shows how to develop the project-selection criteria and successful project characteristics.

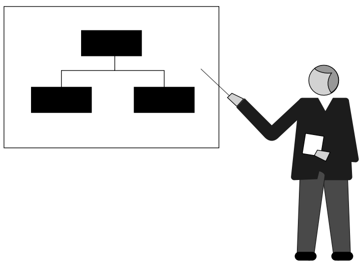


Figure 1-1 Identify a robust design project.

As with any project, effective planning and selection of the right team can make the difference between success and failure. Project selection should be based on the potential for increasing customer satisfaction, increasing reliability, incorporating new technology, reducing cost, reducing warranty service, and achieving best-in-class.

The characteristics of a successful project are (1) a clear objective, including the desired outcome; and (2) a cross-functional team that includes suppliers, thorough planning, and management support. Management sponsorship and support is critical for team success. Management's role is to provide necessary resources, empower the team, and remove obstacles to progress.

1.3 Develop VOC Models

The *Voice-of-Customer* process is used to capture the requirements and/or feedback from customers (internal or external) to provide them with the best-in-class service or product quality. This process is all about being proactive and constantly innovative in order to capture the changing requirements of customers over time. The second step in the robust design process is to begin to develop VOC models. The following are several key requirements and inputs of a Voice-of-Customer model:

- Perceived result
- Customer intent
- Customer and engineering metrics
- Intended function
- Response criteria

Customer requirements are the starting point for determining what to measure in an experiment. But, customer performance metrics are sometimes vague, usually subjective, and typically expressed in nontechnical

- ➢ Identify customer needs
- ➢ Perform surveys
- ➢ Communicate with focus groups
- ➢ Turn customer data into VOC models

Figure 1-2 Establish Voice-of-Customer models.

terms. So, to produce quality products, the engineer must translate customer performance metrics into measurable, objective engineering metrics (Figure 1-2).

For example, the VOCs convey to the engineer what customers want and how they perceive what they actually get. The Voice-of-Customer model is the engineers' interpretation, in engineering terms and functions, of customers' *perceived result*. But the perceived result is a subjective perception of what customers get from the product. Together, these represent the customer's world. When the perceived result doesn't match her or his voice, the customer is disappointed.

Traditionally, the mismatch between the voice of the customer and the perceived result has been addressed by attempting to "solve the problem" when it becomes evident. It would be preferable, however, to anticipate customers' expectations and design products to meet them proactively.

The term *Voice-of-Customer* is used to describe the stated and unstated needs or requirements of the customer, and there are a variety of ways to capture VOCs:

- Direct discussion or interviews
- Surveys

- Focus groups
- Customer specifications
- Observation
- Warranty data
- Field reports
- Complaint logs
- And so on . . .

To design robust products, the engineer must determine which system or subsystem to study and establish technical metrics that quantify the system's ability to satisfy the VOC. The Voice-of-Customer model ultimately determines what is critical to quality—the focus of the next section.

1.4 FORMULATE CRITICAL-TO-QUALITY CHARACTERISTICS

CTQs (*Critical-to-Quality*) are the key measurable characteristics of a product or process whose performance standards or specification limits must be met to satisfy the VOCs (Figure 1-3). They align improvement or design efforts with customer requirements.

➢ *Metric* means measurement
➢ Measure product quality levels
➢ Help understand design tradeoffs
➢ Develop based on VOC modeling

Figure 1-3 CTQ: An engineering metric.

CTQs represent the product or service characteristics defined by the customer (internal or external). They can include the upper- and lower-specification limits or any other factors related to the product or service. A CTQ item usually must be determined from a qualitative customer statement and “translated” into an actionable, quantitative business specification.

In robust design, a Critical-to-Quality characteristic should be related to the perceived result. In a robust design experiment, the measured output of the system is the CTQ. The CTQ performance is frequently inconsistent with the ideal perceived result because of noise. When determining what to measure in an experiment—the CTQ—first consider the customer’s perspective of system functionality.

For example, customers use their brakes with the intent of slowing down or stopping the car. The ideal perceived result is for the car to smoothly slow down or come to a stop every time the brakes are applied. With this in mind, the team must now determine which portion of the brake system to focus on and establish a CTQ, in engineering metrics, that quantifies the functionality of that system.

For nonrobust brake systems, the perceived result is often conveyed in terms that describe unintended results, such as noisy or rough. Optimizing a CTQ related to brake functionality—the distance to stop—minimizes unintended results. This philosophy represents a change in the way the engineer approaches the design process.

In sum, a CTQ is an engineering metric that quantifies the system’s functionality (i.e., its ability to meet the VOCs). Critical-to-Quality characteristics drive efforts to control energy transformation within a product or system.

1.5 CONTROL ENERGY TRANSFORMATION FOR EACH CTQ CHARACTERISTIC

To fulfill the intent of the system, the customer does something that initiates a transfer of energy, which produces a CTQ that might be categorized as either the intended result or the unintended result (error state). Because energy transfer creates CTQs, the system must be studied in terms of this transfer. Such a study will help the team identify a response that quantifies the system's production of intended results. It is important to consider the following:

- Energy can neither be created nor destroyed.
- Energy can be transformed into various states.
- Only one energy state is intended, or ideal.

Maximizing the amount of energy used to produce an intended result will minimize the amount available to produce unintended results, or error states (Figure 1-4). Robust design shifts from examining the error states and searching for remedies, to studying the functional intent of the system and exploring ways of optimizing it.

➢ Energy: Mechanical, thermal, electrical, chemical, . . .
➢ Target or ideal state: 100 percent energy utilization
➢ Avoid error states; that is, energy is transferred smoothly

Figure 1-4 Control energy transformation effectively.

Engineering robust products with Six Sigma requires a shift from measuring the symptoms of poor quality to measuring the transformation of energy. This philosophy requires a shift in thinking by the engineer. Robust design enhances quality through a focus on optimizing the system's intended functions—the efficient transfer of all energy.

To depict the intended function in terms of engineering metrics, study the underlying physics of a system, which should yield an engineering metric that quantifies the amount of energy used to produce a result. Use this metric as the Critical-to-Quality characteristic. Maximizing such a CTQ will optimize system functionality.

Clearly, CTQ characteristics depend on the system chosen for study. Many systems are composed of several subsystems and related processes, each with its own intended function. Therefore, what to study must be determined before the team can identify the transfer function and the related CTQs.

The following are the three types of metrics commonly used in industry:

- *Customer metrics*—usually subjective and expressed in nontechnical terms
- *Management metrics*—typically related to productivity or economics
- *Engineering metrics*—quantitative, objective, and physics-based

All of these metrics have their place in the development of quality products and processes. In experimentation though, engineering metrics will provide more useful and reproducible information than either management or customer metrics.

Levels are the different settings a factor can have. For example, if you want to determine how the response (speed of data transmittal) is affected by the factor (connection type), you need to set the factor at different levels (e.g., modem and local area network).

EXAMPLE 1.1

Consider a robust design experiment with the objective to reduce the production of defective donuts. Suppose the management metric yield is the CTQ and the factors (time and temperature) are both tested at two levels.

Yield is the percentage of a product that is free of defects (i.e., the percentage of defect-free products over the total number of products produced). At the low temperature, B_1, increasing time (from A_1 to A_2) increases yield; whereas, at the high temperature, B_2, increasing time (from A_1 to A_2) decreases yield.

A: Time	B: Temperature
A_1 = 5 minutes	B_1 = 200°F
A_2 = 8 minutes	B_2 = 260°F

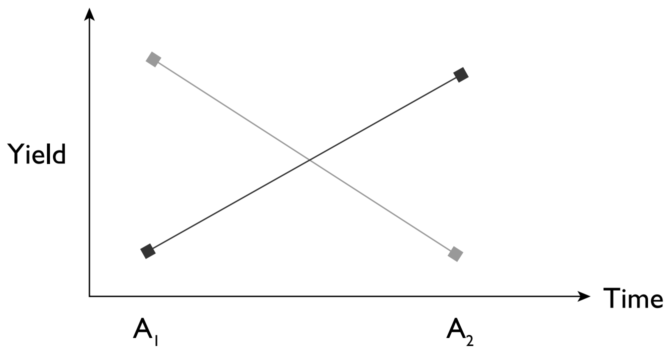


Figure 1-5 Time and temperature interact with respect to yield.

So, the effect of cook time (on yield) depends on the temperature level. This implies that cook time and temperature interact, as is indicated by the nonparallel nature of the lines on the interaction plot of level combinations (see Figure 1-5). An interaction occurs when the response achieved by one factor depends on the level of the other factor. On the interaction plot, when lines are not parallel, there's an interaction.

Suppose, instead, that the CTQ is defined as "color." With color as the CTQ, increasing cook time increases color at either temperature, and increasing temperature increases color at either level of cook time. An interaction occurs when the response achieved by one factor depends on the level of the other factor. On the interaction plot, when lines are not parallel, there's an interaction. As shown in Figure 1-6, the factors interact little, if at all, with respect to

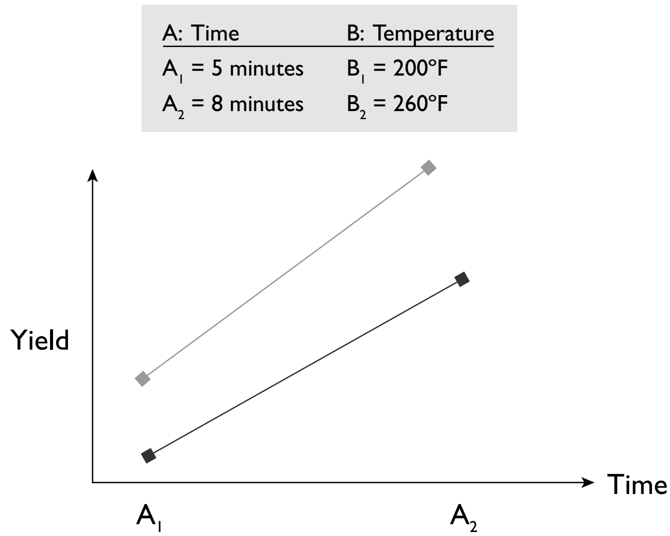


Figure 1-6 The interaction between color and temperature; the effect of cook time is to increase color at either temperature.

the color engineering metric. Similar results would follow if the CTQ were another engineering metric such as moisture or density. In this example, with an engineering metric as Critical-to-Quality rather than a customer metric as Voice-of-Customer, the size of interactions can be reduced.

In sum, the Voice-of-Customer is what the customer wants. Systems transform the intent into the perceived result for VOCs. The perceived result is what the customer gets. A Critical-to-Quality characteristic is an engineering metric that quantifies the output of the system. A VOC is expressed in nontechnical terms and is frequently subjective. CTQ characteristics are expressed in technical terms and should (1) be related to the perceived results for VOCs, (2) quantify energy transfer, and (3) be an engineering metric.

1.6 Determine Control and Noise Factors

To make products affordable, engineers need to determine how to control the CTQ characteristics at minimal cost. The fifth step in the robust design process is to develop a list of control and noise factors for each CTQ. This section covers the following:

- Definition of control factors
- Definition of noise factors
- Sources of noise

In robust design, engineering parameters related to CTQs are categorized as either control factors or noise factors (see Figure 1-7). The Engineered System, or P-Diagram (see Chapter 6), for a product or process is a diagram that shows the relationship among system (or subsystem) parts, the CTQ, and the control and noise factors.

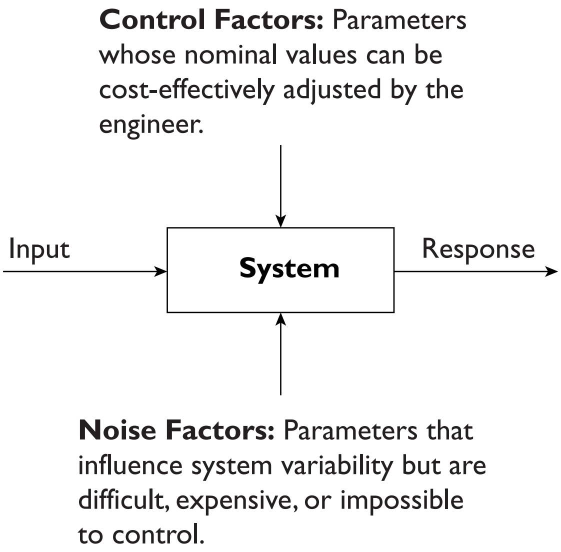
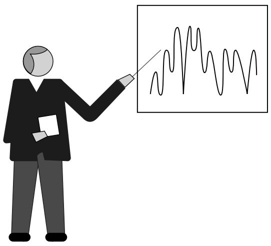


Figure 1-7 Control and noise factors.

Brainstorming is a useful tool for developing an initial list of control and noise factors. Further investigation may be needed to research creative ideas that result or to discover additional factors. If the list of influential control and/or noise factors becomes prohibitively long, consider narrowing the scope of the study to a simpler subsystem. Then, you may need to redefine the response to establish a complete situational understanding of a wide range of data where several control factors may be interacting at once to produce an outcome.

Determining whether a factor is a noise or a control one often depends on the team's objective or the scope of the project. A factor considered control in some cases might be considered noise in others. For example, consider the material hardness factor (measured in Rockwell units). Design engineers focus on the product, so they may categorize material hardness as a control factor. However, process engineers focus on the process, so they may categorize material hardness as a noise factor; from their perspective, the process needs to be insensitive to the hardness of the material.

There are many sources of noise. Figure 1-8 shows five broad noise factor categories. Frequently, customer usage creates the most variability; but when developing a noise strategy, consider all possible sources to ensure that influential noise factors are not overlooked. Typically, control factors are obvious to the engineer because they relate directly to system design. On the other hand, it is easy to overlook some noise factors because they are often external to system design. Examining the five potential sources of noise can help engineers develop a thorough list of noise factors.



- ➢ Internal environment as a result of neighboring subsystems
- ➢ Part-to-part, or piece-to-piece, manufacturing variation
- ➢ Customer usage and duty cycle
- ➢ External environment
- ➢ Age, or deterioration

Figure 1-8 Source of noise factors.

In sum, control factors are parameters whose nominal values can be adjusted by the engineer, ideally with minimal impact on cost. A noise factor is a source of variability, either internal or external to the system. A noise factor disrupts the transfer of energy to the intended function.

1.7 Assign Control Factors to the Inner Array

The sixth step in the robust design process is to assign control factors to an inner array. Orthogonal arrays are efficient tools for multifactor experimentation. The orthogonal array of control factors is called the inner array. The *inner array* specifies the combinations of control factor levels to be tested. When running a designed experiment, the present design (or other reference design) should be included, allowing comparison of the current process to alternatives based on common testing conditions.

Figure 1-9 shows a sample orthogonal array. Genichi Taguchi (1992, 1999, 2000) made a significant contribution by adapting fractional factorial

Test Runs	Control Factors A	B	C	D	E	F	F	Response Results
1	1	1	1	1	1	1	1	(R_1)
2	1	1	1	2	2	1	2	(R_2)
3	1	2	2	1	1	1	2	(R_3)
4	1	2	2	2	2	1	1	(R_4)
5	2	1	2	1	2	1	2	(R_5)
6	2	1	2	2	1	1	1	(R_6)
7	2	2	1	1	2	1	1	(R_7)
8	2	2	1	2	1	1	2	(R_8)

Figure 1-9 An orthogonal array.

orthogonal arrays (balanced both ways) to experimental design so that time and cost of experimentation are reduced while validity and reproducibility are maintained.

Taguchi's approach is disciplined and structured to make it easy for quality engineers to apply. Use of orthogonal arrays has been demonstrated to produce efficient robust designs that improve product development productivity. A full factorial design with seven factors at two levels would require $2^7 = 128$ experiments. Taguchi's L_8 orthogonal array requires only eight experiments. Typically, orthogonal arrays include a configuration in which all factors are set at Level 1. When using these arrays, the team may elect to let Level 1 represent the present design so that no testing beyond that specified in the inner array is necessary. Other teams may prefer to assign levels in increasing order of the factor settings so that it is easy to interpret the response tables and plots relative to the settings.

When testing at only two levels, the team may opt to test at levels above and below the present level. If this is preferred, the reference design should be run in addition to those specified in the inner array. Although the reference design statistics will be used for comparison to the selected optimal, they should not be included when developing response tables and plots.

Based on their relative impact on the system and on available resources, the team must now select the control factors for experimentation. They should then identify each factor's level and assign the factors and levels to the inner array. Previous experience, studies, or screening experiments can be used to help prioritize the brainstormed list of control factors.

Parameter Design experiments should be conducted with low-cost alternatives to present design settings (see Chapter 7). (Higher-cost alternatives are considered in Chapter 8, Tolerance Design, which emphasizes cost and quality tradeoffs.) As many factors as possible should be identified to enhance improvement potential. Control factors are usually tested at two or three levels in orthogonal array experiments; however, techniques are available to accommodate more levels.

The range of levels should be broad but still maintain system function. If the system ceases to function at a combination of factor levels designated by the inner array, data will be unavailable for a run. As a result, balance will be lost and all affect estimates will be biased.

In this book, control factor levels are denoted with numerals. Thus, for Level 2 factors, the levels are denoted 1 and 2 (or for Factor A, A_1 and A_2); and for Level 3 factors, the levels are denoted 1, 2, and 3 (or for A_1, A_2, and A_3).

EXAMPLE 1.2

Let's say you are an engineer working on the ball-swirling line at the Marion Bearing Manufacturing plant. As a cost-saving measure, management would like to loosen the ball bearing diameter's tolerance. As shown in Figure 1-10, the swirl-time variation has a significant impact on bearing quality.

- ➢ Short design life
- ➢ Poor damping, leading to high amplification factors
- ➢ Poor load-carrying capacity
- ➢ Limited maximum rotation speed

Figure 1-10 Quality problems caused by variations in swirl time.

The Six Sigma project champion has assigned your team the task of establishing process parameter nominal values at which the swirl time in the swirling machine's funnel will be robust to variation in ball bearing diameter in order to achieve a target in 10 seconds. After lab or project group assignments have been made, your team will be given an experimental apparatus with which to take data.

For each run, one group member will release the ball, another will time the ball with a stopwatch, and a third will record the result on paper. The experimental apparatus consists of a funnel mounted on a stand, a ramp mounted above the funnel, and a ball bearing. Your task in this lab is to conduct an experiment to determine how long it takes the ball bearing to roll down the funnel. Teams will perform one set of three runs with each possible pairing of group members. In other words, if there are four in your group, 12 sets of 3 runs each will be done.

A data sheet on which to record the observations is provided. For each run, you record the set number, the name of the persons releasing and timing, the order of the run in the set (1 to 3), and the time. Table 1-1 shows the control factors and levels that are most likely to impact energy transfer in the ball-swirling process. Levels are the different settings a factor can have. For example, if you want to determine how the response (swirl time) is affected by the

Table 1-1 Control Factors for Ball-Swirling Line

Control Factors	Level 1	Level 2
L: Run length	900mm	600mm
A: Ramp-to-funnel angle	30 degrees	45 degrees
H: Run end height	500mm	600mm
C: Clamping (unscrewed)	0.0 turns	0.5 turns
O: Operator training	Yes	No

Run No.	A	H	O	C	C5	C6	L
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

Figure 1-11 Use of an L_8 orthogonal array for a swirling machine's robust design.

factor (run length), you would need to set the factor at different levels (e.g., 900mm and 600mm).

For maximal test efficiency, this particular team elected to use the L_8 array for the inner array of their experimental plan. As shown in Figure 1-11, the ramp-to-funnel angle was assigned to column 1 to limit the number of changes necessary. It was believed that operator training would not interact with any of the other factors, so it was assigned to column 3, which then keeps the other four main effects free from confounding by any potentially real control-by-control interactions.

As Figure 1-11 shows, an L_8 orthogonal array enables selection of up to seven factors for testing with only eight runs. In comparison, a 2^K full factorial design of experiment (DOE)[1] requires 128 runs. A full factorial

1. A *design of experiment* is a structured, organized method for determining the relationship between design factors (*X*s) affecting a product and the output of that product (*Y*).

DOE measures the response of every possible combination of factors and factor levels. These responses are analyzed to provide information about every main effect and every interaction effect.

A full factorial DOE is practical when fewer than five factors are being investigated. Testing all combinations of factor levels becomes too expensive and time-consuming with five or more factors. Orthogonal arrays include selected combinations of factors and levels. It is a carefully prescribed and representative subset of a full factorial design. By reducing the number of runs, orthogonal arrays will not be able to evaluate the impact of some of the factors independently. In general, higher-order interactions are confounded with main effects or lower-order interactions. Because higher-order interactions are rare, usually the assumption is that their effect is minimal and that the observed effect is caused by the main effect or lower-level interaction.

If more than seven factors were selected for testing, it may have been more practical to use the L_{12} array, which is described in Chapter 2. As discussed there, use of L_{12}, L_{18}, L_{36}, or L_{54} orthogonal arrays is recommended. These arrays allow for testing many factors and share the quality that only fractions of interaction effects confound the main effects in any column.

1.8 SUMMARY AND ROAD MAP

The road map for engineering robust products with Six Sigma is shown in Figure 1-12. Chapters 2, 3, and 4 discuss in detail how to establish the Voice-of-Customer models and how to convert them into CTQs, design concepts, and design controls. CTQs represent the product or service characteristics that are defined by the customer (internal or external), which may include the upper- and lower-specification limits or any other factors related to them. A CTQ characteristic—what the customer

Define project goals, deliverables, and customer needs
(Chapter 2: The Kano Model)

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Measure and flow-down customer needs and specifications
(Chapter 3: Quality Function Deployment)

↓

Generate design concepts and process options to meet customers' needs
(Chapter 4: Theory of Inventive Problem Solving)

↓

Perform design risk assessment and management
(Chapter 5: Failure Mode and Effect Analysis)

↓

Laying out a robust design strategy for control and noise factors
(Chapter 6: The P-Diagram)

↓

Optimize design parameters for control factors
(Chapter 7: Parameter Design)

↓

Optimize tolerances for critical design parameters
(Chapter 8: Tolerance Design)

↓

Verify design capability for long-term customer satisfaction
(Chapter 9: Reliability Design)

Figure 1-12 Road map for engineering robust products with Six Sigma.

expects of a product—usually must be translated from a qualitative customer statement into an actionable, quantitative business specification. It is up to engineers to convert CTQs into measurable terms using Six Sigma tools.

Six Sigma robust design starts with the voices of the customers, which reflect their spoken and unspoken needs and/or requirements. The Kano model, which is discussed in Chapter 2, helps engineers identify VOCs systematically.

Based on VOCs, a House of Quality can be built using a Six Sigma methodology called Quality Function Deployment (QFD). Within the House of Quality, customer requirements are converted into Critical-to-Quality characteristics. QFD enables identification and prioritization of the CTQs. A case study example in Chapter 3 illustrates the six steps to construct a House of Quality. The QFD process can also identify technical contradictions, which are the basis for applying the Theory of Inventive Problem Solving (TRIZ—the Russian acronym for the theory) to generate creative design concepts that can eliminate contradictions (see Chapter 4).

Critical-to-Quality characteristics reveal a main difficulty for developing robust designs. However, being able to integrate value-added features using TRIZ enables engineers to determine the final robust design concept. As illustrated with a practical example in Chapter 4, the quality of the design concept is the design's *DNA,* which drives product robustness.

Starting with Chapter 5, the focus shifts from control factors to noise factors, which are the process inputs that consistently cause variation in the output measurement that is random and expected and, therefore, not controlled. Strategies to manage noise (e.g., white noise, random variations, common-cause and special-cause variations, uncontrollable variables) are discussed in detail in Chapters 5, 6, 7, 8, and 9.

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