For presentation at the 1991 Conference
of the American Association of Cost Engineers

Designing For Cost
by
Edwin B. Dean and Resit Unal

THE MENTAL PROCESS OF DESIGNING FOR COST

Designing for cost is a state of mind. Of course, a lot of technical knowledge is required and the use of appropriate tools will improve the process.

Unfortunately, the extensive use of weight based cost estimating relationships has generated a perception in the aerospace community that the primary way to reduce cost is to reduce weight. Wrong! Based upon an approximation of an industry accepted formula, the PRICE H™ [1] production-production equation, Dean [7] demonstrated theoretically that the optimal trajectory for cost reduction is predominantly in the direction of system complexity reduction, not system weight reduction. Thus the phrase "keep it simple" is a primary state of mind required for reducing cost throughout the design process.

How do we keep a system simple? Korda [9] gives us one clue. His quantification of the PRICE H™ manufacturing complexity [1] for structural components is

$$Mx = 4.3\ PLTFM^{0.32}\ NP^{0.04}\ (1+(.06\ (N - MATUR))) / (1.35\ PRECI^{0.081}\ MI^{0.024})$$

where PLTFM is the specification level, NP is the number of parts, MATUR is the relative assembly tolerance, PRECI is the machining tolerance, MI is the machinability index of the material, and N = 3 if PLTFM < 2 else 4.

Additional equations exist for machining hog out and surface finish.

An analysis of these equations for structural components indicates that to reduce system complexity we need to reduce specification difficulty, reduce part count, relax assembly tolerance requirements, relax component machining tolerances, use more machinable materials, relax surface finish requirements, and use near net shape raw stock to minimize machining. In other words, "keep it simple."

Webb [21] has demonstrated that the industrial culture within the United States is valuing performance increases far more than cost reduction. In virtually every category of system examined, cost has increased over time, as each new system in each category is produced, at a rate well above inflation. His measured technology escalation rates are hypothesized to represent the difference between performance induced increased system complexity and decreased system production complexity due to improvements in manufacturability.

If these trends of cost increase are to be reduced, serious attention must be given to reductions in system performance increases or major improvements in system produceability.

How can we reduce performance induced cost?

First, we must define what the cost driving performance requirements are. This can be accomplished by implementing activity based [19] parametric [6] accounting from which parametric equations which relate system cost to system requirement parameters, system performance parameters, or engineering process parameters can be derived. Next, we assess the sensitivity of cost to the parameters by examining the magnitude and sign of the partial derivatives, ∂cost/ ∂parameter. The objective of designing for cost is to reduce cost. Thus, through design, subject to constraints on the system, we wish to move each parameter in the direction which provides a negative cost differential; that is, reduce cost. Finally, we must define how we can realistically accomplish this task through design. This will be discused in the following section on robust design.

How can we increase system produceability? The example above is appropriate. Also, Sjovold et. al. [14] provide an example. They indicate the cumulative average unit cost at quantity Q of a liquid rocket engine is estimated by

$$C_{pq} = 0.00124\, Q^{-0.251}\, R^{-0.132}\, W^{0.618}\, (P_{si}\, N)^{0.347}$$

and the cost of developing the engine is estimated by

$$C_d = 52.947\, C_{p150}^{0.939}\, P_{ro}^{0.618}$$

where R is the annual production rate, W is the engine mass, P_{si} is the pump discharge pressure, N is the number of coolant passages, C_{p150} is the cumulative average unit cost at the 150th engine, and P_{ro} is the number of development prototypes.

Q and R are programmatic variables determined by program requirements. The heuristic guidance from these equations is that both development and unit production cost will be reduced if we purchase the largest number of engines within the requirements. This, however, leads to a higher total system cost. The equations indicate that we should produce as many engines per year as possible within production capacity constraints.

W is a design variable. In current form, these equations suggest we should reduce weight as much as possible to reduce cost. This is possibly an incorrect deduction since another variable, μ, implicitly exists in the production equation. To make this variable explicit, the production equation becomes

$$C_{pq} = e^{\mu}\, Q^{-0.251}\, R^{-0.132}\, W^{0.618}\, (P_{si}\, N)^{0.347}$$

where μ is a generalized production complexity [7]. For the liquid rocket engine historical data base we have the special case

$$\mu = \ln(0.00124) \ .$$

Since production complexity and weight are related, this relationship must be considered. In the aerospace industry weight reduction, at best, reduces cost minimally because of the associated increase in production complexity required to reduce weight. Since μ is dominant over weight in reducing cost [7], it is appropriate to ask how to reduce production complexity. This will be discussed below.

P_{si} and N are also design variables. The guidance provided here is to reduce the pump discharge pressure as much as possible and to use as few coolant passages as possible. Both should lead to system simplicity.

The development cost equation is best examined by defining the development equation as

$$C_d = e^{\beta} C_{p150}^{0.939} P_{ro}^{0.618}$$

where ß is a generalized development complexity. For the liquid rocket engine historical data base we have the special case

$$\beta = \ln(52.947).$$

Since the effects of C_{p150} have already been discussed, the advice deduced is to reduce ß and P_{ro}. It makes sense that to reduce either development complexity or the number of prototypes will reduce cost. It could be argued, however, that reducing the number of prototypes could increase risk; and hence, even increase cost. Thus, a method of reducing prototypes without increasing risk is required. It turns out that the Japanese have been developing processes which require fewer prototypes, reduce production complexity, and reduce development complexity.

One particularly promising technique is an emerging method of design optimization for performance, quality, and cost, called Robust Design [12], which was pioneered by Dr. Taguchi [17]. The objective in Robust Design is to select the best combination of controllable design parameters so that the system is robust to noise factors in manufacturing and operational environments. Robust Design has been used successfully in Japan and the United States in designing reliable, high quality products at low cost in less time in such areas as automobiles and consumer electronics [5, 10, 12, 15, 20].

THE ROBUST DESIGN PROCESS FOR COST

Background

The product or process design has the greatest impact on life cycle cost and quality [8, 16, 17]. The three major steps in designing a quality product/process are system design, parameter design, and tolerance design [3, 12, 16, 17].

System design involves innovation and technical knowledge of the engineer to develop an initial feasible design architecture. The initial design may be functional, but it may be far from optimum in terms of quality and cost.

After the system architecture is determined, parameter design begins. Parameter design selects near optimum levels for the controllable design parameters such that the system is functional, exhibits a high level of performance under a wide range of conditions, and is robust to noise factors. Studying the design variables one at a time or by trial and error is a common approach to design optimization [3, 12]. The result is usually a long and expensive time span for design completion or a premature termination of the design process with a product design which is far from optimal.

In contrast, Taguchi's robust design method provides a systematic and efficient approach for determining a near optimal configuration of design parameters for performance and cost [3, 8, 10, 11, 12]. Robust design uses orthogonal arrays (OA) from design of experiments theory to significantly reduce the number of experimental configurations to be studied. OA's are not unique to Taguchi. They were discovered considerably earlier [3]. However, Taguchi simplified their use by providing tabulated sets of standard OA's and corresponding linear graphs to fit a specific project [2, 3, 12].

To evaluate the quality of the product, robust design uses a statistical measure of performance called signal-to-noise (S/N) ratio from electrical control theory. The S/N ratio developed by Dr. Taguchi is a performance measure for choosing control levels that best cope with noise [3, 4, 12]. The S/N ratio takes both the mean and variability into account. In its simplest form, the S/N is the ratio of mean (signal) to the standard deviation (noise).

Making use of OA and S/N ratios, robust design improves the efficiency of generating the information necessary to design systems which are robust to variations in operating conditions, variations in manufacturing processes, and system degradation due to to deterioration of parts. As a result, development time can be shortened, R&D costs can be reduced, and a near optimum choice of parameters can result in wider tolerances so that low cost components and production processes can be used. In addition, important design factors affecting operation, performance, and cost can be identified. Also, manufacturing and operations costs can be greatly reduced [3, 10, 12].

The third step, tolerance design, is only required if robust design can not produce the required performance without costly special components or high process accuracy. It involves tightening tolerances on parameters where their variability could have a large negative effect on the final system. Typically, tighter tolerances leads to higher cost [9, 12].

Most American and European engineers focus on system and tolerance design to achieve performance. The common practice in aerospace design appears to be basing the first feasible design on an initial prototype, studying the reliability and stability against noise factors, and then correcting any problems by requesting better, costlier components, and elements with tight tolerances [5, 12]. In other words, parameter design is largely overlooked. As a result, the opportunity to improve quality without increasing cost is missed.

The use of Taguchi's methods has been increasing in the U.S: the application of the methods is expected to become widespread in the coming decade [8, 12] .

Steps in Robust Design

Optimizing a product or process design means determining the best system architecture, best control factor settings, and most relaxed tolerances. Robust design involves eight steps [12]:

Step 1. Define the problem,
Step 2. Define the noise factors,
Step 3. Define the objective function to be optimized,
Step 4. Define the control factors and their alternative levels,
Step 5. Design the matrix experiment and the data analysis procedure,
Step 6. Conduct the matrix experiment,
Step 7. Analyze the data and determine near optimum levels for the control factors,
Step 8. Predict the performance under these levels.

The first five steps are used for planning the experiment. In the sixth step the experiment is conducted. In steps seven and eight the experiment results are analyzed and verified. The steps will be demonstrated using a fuel cost minimization problem.

An Example: Fuel Storage Purchasing Problem

step 1: define the problem

One of the problems encountered in fuel purchasing is to determine how many liters of each item to purchase for a minimum cost policy. System costs for this example are described by the following equation [13]:

$$\text{Minimize} \quad C(x) = \sum (F_i W_i / X_i + H_i X_i / 2)$$

where F_i = fixed cost for ith item
W_i = withdrawal rate per unit of time for ith item
H_i = holding cost per unit time for ith item
C(x)= total storage cost.

Assume that the following costs are determined:

Item	F_i($)	W_i	H_i($)
1	9.60	3	0.47
2	4.27	5	0.26
3	6.42	4	1.71

The problem is to determine how many thousand liters of each item (X_i) to purchase for minimum cost, subject to storage space availability.

step 2: define the noise factors

Noise factors are those variables which can not be controlled or are too expensive to control [12]. Variations due to noise factors affect purchasing decisions. Therefore, one should identify as many noise factors as possible. Engineering judgement should be used to decide the more important ones to be considered in the analysis. We will assume that the withdrawal rates (W_i) for the three items under consideration are uncertain.

The first noise factor N_1 is the withdrawal rate for item 1. It can range from 2 to 3 units, depending on demand. The second noise factor N_2 is the withdrawal rate for item 2. Experience shows it could be higher (up to 6 units) rather than its expected rate of 5 units. The last noise factor N_3 is the withdrawal rate for item 3. It could be higher than the expected rate of 4 units (up to 5 units).

step 3: define the objective function to be optimized

Minimum cost is the objective. The objective function to be optimized is total system cost C(x) subject to storage space constraints. The objective is to find the combination which provides a near minimal C(x), considering the uncertainty due to the cited noise factors.

step 4: define the control factors and their alternative levels

The amounts in thousands of liters for each fuel (X_1, X_2, X_3) are the control factors since they can be changed to determine the total storage cost. Under zero noise conditions, a preliminary study determined the initial control parameter values in liters to be

$$X_1 = 9, \qquad X_2 = 11, \qquad \text{and} \qquad X_3 = 7.$$

As a next step, the cost and design engineers want to study alternative levels for the controllable design parameters, considering the uncertainty due to noise factors. In robust design, two or three levels are selected for each factor. The level of a test parameter refers to how many test values of the parameter are to be analyzed. Commonly, one of these levels is taken to be the initial operating condition.

Three alternative levels were identified for the controllable design factors (Figure 1a). These factor levels define the experimental region for study. All of these levels satisfy power and storage constraints. Level one represents the initial setting (base line).

Control Factor Levels

	1	2	3
X_1	9	11	13
X_2	11	13	15
X_3	7	9	11

Initial Setting

(a)

Noise Factor Levels

	1	2
N_1	48	56
N_2	24	27
N_3	95	100

Initial Setting

(b)

Figure 1: Factor Levels for the Optimization Problem

Two levels of noise were identified (Figure 1b). Level one represents the initial setting.

step 5: design the matrix experiment and the data analysis procedure

Next, the matrix experiment is designed and the appropriate orthogonal arrays are selected for the control and noise factors. Taguchi provides tabulated sets of standard orthogonal arrays and corresponding linear graphs to fit specific projects [2, 3, 12]. To select the appropriate orthogonal array, we count the total degrees of freedom to find the minimum number of experiments which must be performed [2, 12]. One degree of freedom is associated with the overall mean, regardless of the number of control factors. We must add the degrees of freedom associated with each control factor, which is equal to one less than the number of levels. We have a total of 7 degrees of freedom; therefore, we need to conduct at least 7 experiments. This fits Taguchi's standard L_9 array, shown in Figure 2a. The L_9 array has 8 degrees of freedom and can handle four factors at 3 levels.

Having only three control factors, one of the columns of the array will be left empty. Orthogonality is not lost by keeping one or more columns of an array empty [2, 12].

	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

(a): $L_9(3^4)$

	A	B	C
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

(b): $L_4(2^3)$

Figure-2: Orthogonal Arrays

The L_4 array (Figure 2b) was selected for the three noise factors from the tabulated standard orthogonal arrays [18].

step 6: conduct the matrix experiment

The next step is to define a procedure to simulate the variation in cost due to the noise factors. Taguchi proposes orthogonal array based simulation to evaluate the mean and the variance of a products response resulting from variations in noise factors [4, 12, 17]. Orthogonal arrays are used to sample the domain of noise factors. The diversity of noise factors are studied by crossing the orthogonal array of control factors by an orthogonal array of noise factors [3], as shown in Figure 3. The results of the experiment for each combination of control and noise array experiment are denoted by $Y_{i,j}$.

We can now study the design against four different combinations of noise factors by running only 36 experiments.

The matrix experiment is conducted using the appropriate system of mathematical equations for cost and storage space constraints [13]. The response ($Y_{i,j}$), the total cost in dollars, is computed for each combination of control and noise matrix experiments. The results are displayed in Figure 3. Note that column D in the control orthogonal array was left empty since we had three control factors.

Noise Matrix

	1	2	3	4
N1	3	3	2	2
N2	5	6	5	6
N3	4	5	5	4

Control Matrix

	X1	X2	X3	D
1	9	11	11	
2	9	13	13	
3	9	15	15	
4	11	11	11	
5	11	13	13	
6	11	15	15	
7	13	11	11	
8	13	13	13	
9	13	15	15	

Y1	Y2	Y3	Y4
14.49	15.80	14.34	13.81
14.24	15.29	13.89	13.51
14.38	15.24	13.89	13.60
14.17	15.27	14.01	13.69
14.22	15.13	13.93	13.68
14.38	15.58	14.42	13.79
14.33	15.30	14.18	13.98
14.41	15.65	14.58	14.00
14.24	15.24	14.22	13.78

Figure 3: Results of the Matrix Experiment

step 7: analyze the data and determine near optimum levels for the control factors

Traditionally, with data from a designed experiment, only the mean response is analyzed [4]. Robust design employs a signal to noise (S/N) ratio to include response variation.

The S/N ratio developed by Dr. Taguchi is a performance measure for choosing control levels which best cope with noise [3, 4, 12]. The S/N ratio accounts for both the mean and variability. The S/N equation depends on the optimization criterion. While there are many different S/N ratios, the smallest-is-best S/N ratio is used below since the objective is to minimize cost [2, 4, 12].

$$\text{S/N} = -10 \log (\text{Mean square deviation})$$
$$= -10 \log \left(1/n \quad \Sigma y_i^2\right) .$$

The S/N ratios for the data are computed and displayed in Figure 4a.

Control Matrix

	X1	X2	X3	D	S/N
1	1	1	1	1	-23.30
2	1	2	2	2	-23.08
3	1	3	3	3	-23.10
4	2	1	2	3	-23.11
5	2	2	3	1	-23.07
6	2	3	1	2	-23.26
7	3	1	3	2	-23.20
8	3	2	1	3	-23.32
9	3	3	2	1	-23.16

(a) Signal-to Noise Ratio

	Average S/N		
	X1	X2	X3
1	-23.16	-23.20	-23.29
2	-23.14	-23.15	-23.11
3	-23.33	-23.17	-23.12

(b) Response Table

Figure 4: Signal-to-Noise Ratios and the Response Table

Graphing the S/N ratios visually identifies the factors which appear to be significant [2, 4, 12, 17]. Since the experimental design is orthogonal, it is possible to separate the effects of each factor [4]. The average S/N ratios for each level of the three control factors are displayed in the response table given in Figure 4b. The average S/N ratios shown in the response table are calculated by taking the average from Figure 4a, for a parameter, at a given level, every time it was used. For example, X_2 was at level two in experiments 2, 5, and 8. The average of corresponding S/N ratios is -23.15 which is shown in the table under X_2 at level 2.

The average S/N ratios from the response table are plotted in Figure 5. The graphs reveal that control parameter X_3 has a greater effect on cost than X_1 and X_2. Level two appears to be the best choice for parameters (X_1, X_2, X_3) since it corresponds to the largest average S/N ratio.

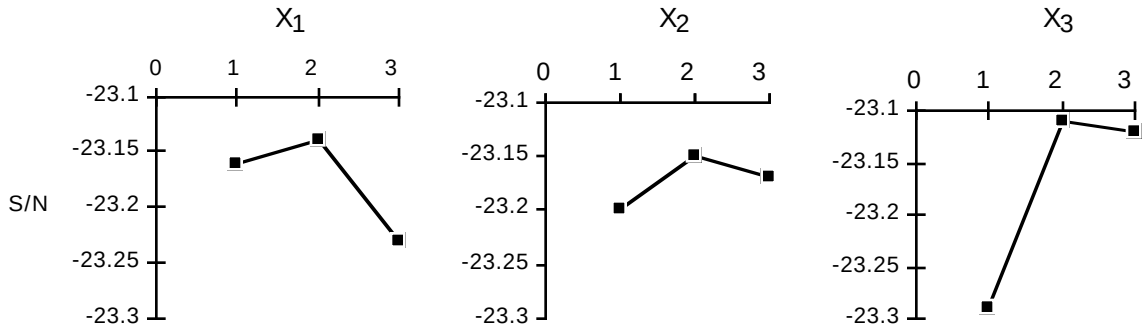

Figure-5: S/N Ratios

The near optimum levels for the three controllable parameters are

Test Parameters:	X_1	X_2	X_3
Best Level:	2	2	2
Parameter Setting :	1 1	1 3	9

Note that this combination was not actually an experiment carried out. In robust design the predicted optimum setting need not correspond to one of the rows of the matrix experiment. This is often the case when highly fractioned designs are used [4].

step 8: predict the performance under these levels

The initial settings for the control parameters were

Test Parameters:	X_1	X_2	X_3
Parameter Level:	2	2	2
Parameter Setting :	2 8	3 9	3 8

These settings correspond to an initial average cost of $14.61 with a S/N of -23.30. Selected best parameter levels after robust design provide an average cost of $14.21 with a S/N of -23.06. In this case, robust design resulted in a cost saving of about 3%.

CONCLUSIONS

Parametric cost analysis is defined as the generation and application of equations to cost analysis. When equations exist which define cost as a function of system requirement parameters, system performance parameters, or engineering process parameters, a tool exists to enable designing for cost. Cost sensitivity is expressed through the partial derivatives of these functions. This provides insight into the magnitude and direction of cost change for given parameter changes. This information can be used to provide heuristic design-for-cost guidelines.

The robust design method is a systematic and efficient approach for determining the near optimum set of design parameters for cost. Principal benefits include considerable time and resource savings; determination of important factors affecting operation, performance, and cost; quantitative measures of the robustness (sensitivity) of the design results; and quantitative recommendations for design parameters which achieve lower cost.

Robust design moves cost considerations to the design stage where the greatest benefits can be realized. Also, the robust design approach aids integration of cost and engineering functions.

Results suggest that the robust design method offers improvements in engineering productivity and system cost.

REFERENCES

1. Anonymous, 1988. **PRICE H™ Reference Manual**. Moorestown NJ: General Electric Price Systems.

2. Anonymous, 1989. **Taguchi Methods: Implementation Manual**. Dearborn, MI: American Supplier Institute Inc.

3. Bendell, A., 1988. Introduction to Taguchi Methodology . **Taguchi Methods: Proceedings of the 1988 European Conference**. London, England: Elsevier Applied Science.

4. Bryne, D. and S. Taguchi, 1986. The Taguchi Approach to Parameter Design . **American Society of Quality Control Quality Congress Transactions**. Anaheim, CA, p 168.

5. Cullen, J. and J. Hollingum, 1987. **Implementing Total Quality**. New York, N.Y: Springer-Verlag.

6. Dean, E., 1989. Cost Analysis Research Directions . Presented at the **Second Joint National Conference of the National Estimating Society and the Institute of Cost Analysis**. 5-7 July, Washington DC.

7. Dean, E. ,1990. The Design-to-Cost Manifold . Presented at the **International Academy of Astronautics Space Systems Cost Estimation Methodologies and Applications.** 10-11 May, San Diego CA. IAA-CESO-11(90).

8. Kackar, R., 1985. Off-Line Quality Control, Parameter Design, and the Taguchi Method . **Journal of Quality Technology**. Vol. 17, No.4, pp. 176-188.

9. Korda, P., 1982. MCPLXS Generation for Complex Structures . Proceedings of the **Fourth Annual Conference of the International Society of Parametric Analysts**. Virginia Beach VA.

10. Logothetis N. and J. Salmon, 1988. Tolerance Design and Analysis of Audio Circuits . **Taguchi Methods: Proceedings of the 1988 European Conference**, pp. 161-175. London, England: Elsevier Applied Science.

11. Meisl, C. J., 1990. Parametric Cost Analysis in the TQM Environment . Presented at the **Twelfth Annual Conference of International Society of Parametric Analysts**. San Diego, CA.

12. Phadke, S., 1989. **Quality Engineering Using Robust Design**. Englewood Cliffs, NJ: Prentice Hall.

13 Ravindran A., D. Phillips, and J. Solberg, 1987. **Operations Research, Principles and Practices**. New York NY: John Wiley and Sons.

14 Sjovold, A., and D. Morrison, 1989. Rocket Propulsion Cost Modeling. Gulledge, T. and L. Litteral, eds., **Cost Analysis Applications of Economics and Operations Research**. New York, NY: Springer-Verlag.

15. Sullivan, L., 1987. The Power of Taguchi Methods . **Quality Progress**. June, pp 76-79.

16. Taguchi, G., E. Elsayed, and T. Hsiang, 1989. **Quality Engineering in Production Systems**. New York, NY: McGraw Hill.

17. Taguchi, G., 1986. **Introduction to Quality Engineering**. Asian Productivity Organization (Distributed by American Supplier Institute Inc., Dearborn, MI).

18. Taguchi, G. and S. Konishi, 1987. **Orthogonal Arrays and Linear Graphs**. Dearborn, MI: American Supplier Institute Inc.

19. Turney, P., 1991. How Activity-Based Costing Helps Reduce Cost . **Cost Management**. Winter, pp 29-35.

20. Wille, R., 1990. Landing Gear Weight Optimization Using Taguchi Analysis , Presented at the **49th Annual International Conference of Society of Allied Weight Engineers Inc**. 14-16 May, Chandler AZ.

21. Webb, D. ,1990. Cost Complexity Forecasting: Historical Trends of Major Systems . Presented at the **Twelfth Annual International Conference of the International Society of Parametric Analysts**. 10-11 May, San Diego CA.