A Quality Engineering-Based Approach to the Simultaneous Engineering of Products and their Manufacturing Processes

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SYNOPSIS This paper presents several concepts and methods which aid in the realization of the goal of simultaneous engineering of products and their manufacturing processes. A quality engineering approach, based on Taguchi's loss function, is shown to be a valuable performance measure in the selection of design parameters. An example is presented which integrates these concepts and methods into a unified framework to solve a specific parameter design problem.

1 INTRODUCTION

In recent years many U.S. companies have begun to carefully examine new directions which must be cultivated to significantly improve competitive position in the long term. Companies have sought to develop an overarching quality philosophy that can be implemented through policy and operating procedures to insure that customer needs can be met competitively. One thing that has become clearly evident is the need to push the quality issue farther and farther upstream so that it becomes an integral part of every aspect of the product life cycle, e.g., marketing, product design and engineering, process engineering, production, etc.

The concepts of Design for Manufacturability and Design for Assembly have been the subject of considerable research in recent years. Numerous specific models have been proposed and refined and will not be discussed here. All of this work is aimed at overcoming the difficulties precipitated by the traditional "over-the-wall" design philosophy. The magnitude of the problem with the over-the-wall approach to design and manufacturing can perhaps be to measure in terms of the number of times the drawing is thrown back and forth over the wall! As we proceed from the initial design concept through prototype testing and development to final design detailing and ultimately to the initiation of production and beyond, the number of design interactions has, in the past, been too high. Sullivan [17] has contrasted the typical Japanese and US companies in this regard through a figure similar to Fig 1.

Presently, a great deal of attention is being given to the development of concepts and methods for product and process design and engineering. It is recognized by many that it is through engineering design that we have the greatest opportunity to influence the ultimate delivery of products which meet customer needs and expectations. Recently, the term "simultaneous engineering" has been used to describe the process by which the design of products and their associated manufacturing processes is considered jointly rather than in a serial way [4]. It is well recognized that such an approach should be more cost effective over the entire product life cycle as lead times are reduced, more manufacturable product designs are created, and more reliable products are passed to the customer.

Central to the successful refinement of Simultaneous Engineering is the advancement of mathematical modeling and computer simulation of both product and process designs. For some time, product design activities have benefited greatly from the development of sophisticated math modeling methods for the analysis of product performance. Techniques such as finite element modeling make it possible to understand more about dynamic performance and the heat transfer characteristics of complex designs such as an engine block, for example. As a result, engineers can examine the consequences of particular design configurations and identify critical design characteristics very early in the product design life cycle. The development of mathematical process models has been much slower although in the last several years considerable progress has been made. Process models which predict performance, "well ahead of the first cut" so to speak, when merged with product models will enable the simultaneous engineering discipline to evolve in a substantial way.

The purpose of the simultaneous engineering concept is to give increased consideration to manufacturing system design and the impact of manufacturing on product design at the earliest stages of product design. It is well recognized that lead times can be significantly reduced and a more globally optimal product and process combination can be obtained through interactive simultaneous design rather than a more sequentially-based design strategy. Fig 2 provides a simultaneous engineering conceptual framework.

The complete simultaneous engineering framework is composed of four models, three of which describe the product and the process while the fourth represents the design process itself.

Product Design Model: The product design model may take several forms. Its purpose is to reduce the design to a set of parameters which are related to relevant performance measures. Simple performance measures might include size, weight, and/or shape. A finite element model may be used to define the values of the relevant structural dynamics of the product.

Macro-Level Process Model: The macro-level process model is a large-scale systems representation of the processing system under design. The elements of the system, e.g., machines, conveyors, robotic manipulators, and gaging devices, could be modeled in a structure which allows for the simulation of the operation of the entire system. Simulation languages and models such as SLAM [14] and SIMAN [11] may be usefully employed to build up such a macro-level process model.

Micro-Level Process Model: The micro-level process model provides a representation of an individual process, for example, in machining, the process might be face milling, boring, turning, or drilling. Such a model is capable of simulating a cut or series of cuts with full consideration of the process geometry, tool geometry, part geometry, and the cutting mechanism itself. Models such as those which will be described later in this paper are novel at this modeling level. Machine tool characteristics and fixturing are also part of the micro-level process model.
Design Process Model: The design process model provides a framework and methodology to facilitate rapid convergence to a quality product and manufacturing process. Several design process models have been proposed. Among these are the techniques of design optimization as discussed by Reklaitis, Ravindran, and Ragsdell [16] and the techniques of Taguchi [21-24]. The Taguchi design concepts, when merged with the classical methods of experimental design, provide a particularly useful model for simulation work. Phadke [12] has recently applied and discussed these ideas and techniques.

The element in Fig 2 which holds the key to the successful refinement of simultaneous engineering is the design process model. Much has been proposed and written in recent years about how the design process should evolve, what concepts and methods should drive this evolution, and the extent to which creativity in design can be formalized and projected methodologically. For many, it is this last point - design creativity, which may be clouding the overall issue and inhibiting progress on the formalization of the science of design.

In the last few years, the role of statistical methods for quality and productivity improvement have received considerable attention. The work of Taguchi has been particularly appealing in an engineering design context because it provides both a conceptual framework and a set of tools and methods to improve quality through design. At the center of this framework is the interpretation of quality as measured by loss due to functional variation in the performance of a product or process. This definition encourages the continual pursuit of performance variation reduction through the identification and elimination of sources of variation. Taguchi stresses the design process as a fundamental countermeasure against the forces of variation to improve product quality as it is measured during field use.

As the simultaneous engineering approach to product/process design matures, it is becoming clear that its successful application lie with the use of several important concepts and method. In particular with:

1. The use of simulation through mathematical models of both the product and the process to optimize a design.
2. The use of design of experiments methods as a framework for performance evaluation through simulation, and,
3. The concept of "robust design" wherein levels of the design/control parameters of the product/process are sought which minimize the functional variation in performance induced by variation sources referred to as noise factors.

2 TAGUCHI'S CONTRIBUTION TO QUALITY DESIGN

The Taguchi approach to quality design has a number of significant strengths which may be successfully exploited. In particular, Taguchi places a great deal of emphasis on the importance of minimizing variation as a means to improve quality and of centering product/process performance at the design-mandated target. In fact, Taguchi defines quality as loss due to functional variation and provides a basis for making this "definition of quality" operational through the loss function. Furthermore, the idea of designing products, the performance of which, is insensitive to environmental conditions and making this happen at the design stage through the use of design of experiments have been cornerstones of the Taguchi methodology for quality engineering. The strengths of Taguchi's approach lie in the following areas:

1. Focus on the engineering design process.
2. Emphasis on variation reduction.
3. Classification of variables in accordance with the roles they play in influencing product/process performance.
5. The parameter/robust design concept.

Taguchi methods have strong engineering orientation and focus primary attention on the engineering design process, in particular, the projection of a three-stage design process model of system design, parameter design, and, tolerance design. In the initial stage, System Design, the available science, technology, and, experience bases are used to develop/select the basic design alternative to meet customer needs. A variety of techniques may be useful in specifically mapping the relationship between customer needs and the selection of design configuration and parameters which will effectively meet those needs.

At the Parameter Design stage interest focuses on the selection of the specific nominal values for the important design parameters. The overarching selection criterion is to "identify those nominal values which minimize the transmission of functional variation to the output performance as a result of the presence of noise factors operating in the environment in which the product and/or process is functioning." That is, we select the nominal values which produce the most robust/least sensitive design to noise variation. It is at the parameter/robust design stage that Taguchi strongly advocates the use of design of experiments methods. Taguchi proposes the use of performance measures which he calls signal-to-noise ratios during this stage in order to minimize the average/expected loss.

The Tolerance Design stage of the design process concentrates on the selection of the allowable tolerances for the important design parameters. The loss function concept of quality is used to provide a basis for striking the proper economical trade-off in the selection of design specifications.

The technique of parameter design described above has been applied in many product and process design situations. For such situations, design/control variables have been selected which parametrically describe the product/process, and noise variables have been selected which characterize the environmental disturbances which affect the performance of the product/process in the field. Parameter design suggests that levels for the control variables should be sought which are robust to the effects of the noise variables. A technique suggested by Taguchi to examine different levels of the control variables in pursuit of a robust combination employs an experimental design with an "inner" (control) design and an "outer" (noise) design structure. Such an experimental design may be referred to as an Inner/Outer Array design structure. For each point in the Inner Array, a signal-to-noise ratio is calculated. Then, the design/control variables that have a significant effect on the signal-to-noise ratio are determined via statistical methods. Finally, the design/control variables that have a significant effect are set to the levels that maximize the signal-to-noise ratio, while the design/control variables that have no significant effect are set to their most economical or productive levels.

While Taguchi's overall approach to improving quality/performance is sound from an engineering design standpoint, the statistical tools that Taguchi prescribes do have their shortcomings. Some of these are:

1. The signal-to-noise ratio and loss function confound location/mean and spread/dispersion/variability effects. In other words, the signal-to-noise ratio and the loss function contain information concerning both the mean and the variability, and the singular effect of variables on these two measures cannot be assessed.
2. In some cases it is unclear that maximizing the signal-to-noise ratio minimizes the average/expected loss. In particular, for a "nominal is best" situation, it "has not been" shown, for the general case, that maximizing the signal-to-noise ratio minimizes the average/expected loss.

3. In order to use the Inner/Outer Array design structure, the variables must be classified as design/control or noise variables prior to data analysis. In view of the "degree of control" concept, to be discussed later, a variable, which may be classified as either a noise or control variable, will require separate data analyses for each classification. The notion of a-priori variable classification does not take into account the issue of economic control.

4. Orthogonal arrays (sometimes referred to as "Taguchi" designs) are the experimental designs recommended by Taguchi. In these designs, interaction effects are assumed to be negligible unless they are explicitly recognized. In addition, the generally accepted method of creating these designs does not always achieve optimum design resolution to mitigate the problem of effect confounding. These designs may be more effectively dealt with in a more generalized framework which includes a more rigorous selection process.

5. The results obtained using these methods are not truly optimal in most cases because optimization methods are not employed. In addition, the sequential nature of experimental investigation is not pursued. Once a combination of design variables from the orthogonal array is selected, no further improvement is sought.

3 THE NOTION OF DEGREE OF CONTROL

Taguchi and his colleagues [1,5,7,8,10,13,15] have classified the variables which influence the performance of a product or a process in accordance with the precise ways in which performance is affected and from the standpoint of the ability to control or manipulate the variables at will. Factors have been defined in the following ways:

1. Signal Factors: These are the factors which may be adjusted by the user/operator to attain the target performance. Steering angle is a signal factor for the steering mechanism of an automobile.

2. Control Factors: The control factors are the product/process design parameters the values of which are to be determined during the design process. The purpose of the design activity is to select the "best" levels of the control factors according to an appropriate design criterion.

3. Noise Factors: The noise factors, as defined previously, are the factors which vary in a more random fashion in the environment in which the product or process is functioning and are generally considered uncontrollable.

4. Scaling/Leveling Factors: These factors are special cases of control factors. They are factors which may be easily adjusted to achieve a desired functional relationship between a signal factor and the output response. For example, the gear ratio in a steering mechanism can be easily adjusted to achieve a desired relationship between the turning radius and the steering angle.

Signal factors are those variables adjusted to attain the target/nominal performance. The control factors are those variables under the control of the designer. The selection of the nominal values for the control factors is the primary role of parameter design. Noise factors describe those variables which are difficult or impossible to control but whose variation is transmitted through the design - as described by the transfer function - to the output.

Since Taguchi defines the these factors as either being noise factors or factors under the control of the designer he generally responds to them in a design of experiments sense through the use of a structure which is referred to as an inner array/outer array design. In this structure the control variables are arranged in the inner array while the noise variables are arranged in the outer array. The complete outer array is conducted for each unique combination of the variables in the inner array. At first glance it would appear that this structure is quite appealing. But upon further study we find that it is unnecessarily restrictive and in efficient. One of the reasons for this is because of the notion of "degree of control". There are other reasons which will be discussed later.

Often, the matter of control of a given factor is an economic one. Factors which appear to be capable of being treated as control factors might be treated as noise factors for the purpose of gaining economic advantage. This notion is particularly appealing in a simultaneous/concurrent engineering framework when product design and processing considerations are being jointly dealt with. The design for manufacturability concept can be served in a quantitative fashion by seeking levels for the control factors which minimize the transmitted variability to product performance of conditions present during processing - the manufacturing process.

Sometimes the identification of a factor as a noise factor is clear from the outset of the study. Only as product and process design/maturity may it be possible to clearly understand the economic ramifications of the control of certain factors. Other times, such is only revealed as the study progresses and data from experiments comes to light. The opportunity to consider a factor as not needing to be actively controlled, or controlled at a lower level, may come to light only through the identification of nonlinear relationships which may exist between or among two or more variables.

4 DESIGN OF EXPERIMENTS STRATEGY

It has been previously mentioned that Taguchi has proposed an experimental design structure to respond to his classification of variables which is sometimes referred to as an inner array/outer array structure. A simple example of the inner array/outer array experimental design structure is considered in Figure 3. In this situation we have two control factors, each at two levels, and two noise factors, each also at two levels. The inner array would be defined by a $2^2$ factorial and the outer array would also be a $2^2$ factorial. Taguchi's use of this design structure suggests that for each trial in the inner array we conduct the complete outer array of experiments.

To examine the robustness of the product/process over the range of the two control factors as the two noise factors vary we would conduct the outer array experiment for each of the four test conditions of the inner array. In this way we can see the variation in the response at each point in the inner array which results from the variation in the noise factors purposely created by the varying conditions of the outer array. Therefore, a total of sixteen trials or tests would need to be conducted.

When the number of control and/or design factors becomes large and it is still desirable to examine each factor at only two levels then Taguchi suggests the use of "orthogonal arrays" for either an inner array or an outer array or for both.

There are at least three major disadvantages of using the inner/outer array structure advocated by Taguchi. These are:

1. The used of this structure requires that the distinction between control and noise factors be made prior to the conduct of the experiment. As will be shown in this paper such is contrary to the notion of degree of control and unnecessarily constrains the problem.
2. The use of this structure generally leads to the need to run a rather large number of experiments since two separate designs are developed and then combined. As a result there is a tendency to use very low resolution fractional factorials with associated dense effect confounding.

3. The use of this structure makes it impossible to explicitly determine and hence interpret the interactions (nonlinearities) which may arise between control factors and noise factors. Yet it is these interdependencies, as will be seen in this paper, which may be exploited to gain economic advantage.

In the following section, a methodology will be presented for robust design which is not restricted to the inner/outer array design structure. Instead, the methodology makes use of the general class of two-level full and fractional factorial designs.

5 MODELS FOR QUALITY IMPROVEMENT

In [6], it was shown that mathematical models for the mean and variability could be used to characterize the loss for a quality characteristic of interest. In this paper, the goal is to develop mathematical models to predict the average performance/quality, the variation in performance/quality, and the average loss due to variation in performance/quality of a product design as a function of those variables controlled by the designer in a simultaneous engineering framework.

We will consider \( Y \) to be the variable quantity for the performance/quality characteristic of interest. It is assumed that there exist a finite number of variables \( X_C, X_N, X_U \) and a function \( f \) such that

\[
Y = f(X_C, X_N, X_U)
\]  

(1)

where \( X_C, X_N \), and \( X_U \) denote vectors of control variables, noise variables, and unrecognized noise variables, respectively.

Control and noise variables are, defined in the previous section, are controlled in the experimental design. Unrecognized noise variables are those variables which affect performance but are not included in the experimental design. They may be unknown to the experimenter or, if known, are simply too difficult or expensive to control even in the experiment.

5.1 Models for the Mean and Variance

In the experimental design, \( Y \) is measured given specific values for only \( X_C \) and \( X_N \). It is impossible to predict \( Y \) exactly since no information about \( X_U \) is included. In other words, there is a distribution of \( Y \) for each given \( X=\{X_C, X_N\} \). The average/expected value and variance of \( Y \) given \( X \) will be denoted, respectively, by

\[
E(Y|X) = \eta(X)
\]  

(2)

and

\[
\text{Var}(Y|X) = \sigma^2(X).
\]  

(3)

It is assumed that the true value of \( Y \) given \( X \) is equal to the sum of \( \eta(X) \) and a random residual error \( \varepsilon \) given \( X \). This can be written as

\[
(Y|X) = \eta(X) + (\varepsilon|X).
\]  

(4)

where the only assumption made about the residuals is that \( E(\varepsilon|X) = 0 \). Mathematical models can be fit to the \((Y|X)\) data in order to predict \( \eta(X) \). For the general case, an iterative weighted least squares scheme may be employed for this purpose. In weighted least squares it is assumed that \( E(\varepsilon_i|X_i) = 0 \) and \( \text{Var}(\varepsilon_i|X_i) = \sigma_i^2 \) for test condition \( i \). The values for the model parameters are then determined that minimize \( \sum \left( \frac{1}{\sigma_i^2} (Y_i(X) - \hat{\eta}(X_i))^2 \right) \).

The variance of \( Y \) given \( X \) may be written as

\[
\sigma^2(X) = E\{((Y|X) - \eta(X))^2\}.
\]  

(5)

It is seen from Eq. (4) that this is equivalent to

\[
\sigma^2(X) = E(\varepsilon^2|X).
\]  

(6)

Mathematical models may be fit to the calculated \((\varepsilon^2|X)\) data in order to predict \( \sigma^2(X) \). Alternatively, when an experiment is replicated, the sample variance or sample standard deviation may be modeled in order to predict \( \sigma^2(X) \) or \( \sigma(X) \), respectively.

Now that models for predicting the mean and variance of \( Y \) given \( X \) are available, the question is how do you use them? The objective of parameter design is to determine specific values of the control variables that optimize the final design. These specific values will be denoted by \( x_C \). In order for the models of the mean and variance of \( Y \) to be useful, they must be a function only of the control variables. Given some knowledge about the behavior of the noise variables in the product environment, such as their mean and variance, the mean and variance of \( Y \) as a function of \( x_C \) may be determined from the equations that follow. The mean of \( Y \) as a function of \( x_C \) is given from

\[
E(Y) = E(\eta(X))
\]  

(7)

The variance of \( Y \) as a function of \( x_C \) is given from

\[
\text{Var}(Y) = E(\sigma^2(X)) + \text{Var}(\eta(X)).
\]  

(8)

The mean and variance of \( Y \) as a function of \( x_C \) are thus approximated by

\[
E(Y) = E(\hat{\eta}(X))
\]  

(9)

and

\[
\text{Var}(Y) = E(\hat{\sigma}^2(X)) + \text{Var}(\hat{\eta}(X)).
\]  

(10)

An important point to make here is that the fitting of the conditional models is done as a function of all of the variables included in the experimental design. Then, the models as a function of \( x_C \) are determined by simply taking appropriate expectation of the conditional models. The advantage here is that you may tentatively consider different classifications of variables as noise or control variables according to the "degree of control" concept and yet only one set of models will need to be fit to the data.

5.2 Models for the Average Loss

There are three cases to be considered. They are smaller is better, larger is better, and nominal/target is best quality/performance characteristics. A quadratic form of the loss function is assumed here as suggested by Taguchi. For smaller is better, the loss function, \( L(Y) \), is given by

\[
L(Y) = kY^2
\]  

(11)

where \( k \) is a constant. The objective is to minimize the average/expected loss (also known as risk) which is given by
\[ E(L(Y)) = kE(Y^2) \]  \hspace{1cm} (12)

Since \( k \) is a positive constant, the average loss is minimized by minimizing only \( E(Y^2) \). An estimate of \( E(Y^2) \) as a function of \( x_c \), obtained from Eqs. (9) and (10), is

\[ E(Y^2) = E(\hat{Y}^2(X)) + \text{Var}[\hat{Y}(X)] + \{E[\hat{Y}(X)]\}^2. \]  \hspace{1cm} (13)

The loss function for larger is better is given by

\[ L(Y) = k(1/Y^2). \]  \hspace{1cm} (14)

Again since \( k \) is a positive constant, the average loss is minimized by minimizing only \( E(1/Y^2) \).

The loss function for nominal/target is best is given by

\[ L(Y) = k(Y-Y_0)^2 \]  \hspace{1cm} (15)

where \( Y_0 \) is the nominal/target value. The average loss in this case is minimized by minimizing \( E((Y-Y_0)^2) \). An estimate of \( E((Y-Y_0)^2) \) as a function of \( x_c \), obtained from Eqs. (9) and (10), is

\[ E((Y-Y_0)^2) = E(\hat{Y}^2(X)) + \text{Var}[\hat{Y}(X)] + \{E[\hat{Y}(X)] - Y_0\}^2. \]  \hspace{1cm} (16)

6 MACHINING PROCESS SIMULATION MODELS

In this paper the quality engineering methods described above will be applied in a simultaneous engineering framework using computer simulation. A machining process model will be used to study the effect of the manufacturing process on the product quality characteristic of interest. Some brief background on the machining process model used herein follows.

Over the last several years, research has been carried out to develop mechanistic models for a variety of machining processes, including end milling, face milling, turning, and boring, with much of this work being summarized in [19]. These models have been employed in a number of design, process and operations planning, and process control settings.

The models have been used to predict cutting forces under a wide variety of conditions which include varying cutting conditions, tool geometries, cut geometries, tool condition, and process irregularities such as cutter or insert runout. In addition, model predicted forces have in turn been used to determine energy and power requirements, surface error including flatness in face milling, cylindricity in cylinder boring, and surface flatness in peripheral milling. The models have incorporated system dynamics to predict levels of forced vibration and process stability as well as surface texture. In addition, the models have been used to identify important excitation frequencies in force signatures for highly irregular workpiece geometries, particularly those with thin walled sections.

These process models all have three common elements; 1) a model which describes the tool, workpiece, and process geometry, 2) a relationship between cutting forces and chip load, and 3) a model for the machine tool system structure. These three elements, when integrated, as shown in Fig 4, form a machining process simulation model that may be used for cutting force system prediction. It can be seen in Fig 4 that the basic model contains feedback, that is, the effect of system compliance is an integral part of the machining system model.

The models developed for the simulation of machining processes focus on the cutting force system as the primary measure of process performance. Knowledge of the cutting forces allows for the subsequent determination of secondary process performance measures which provide the basis for realizing the goal of simultaneous engineering. These include such things as cutter and workpiece deflections which provide the basis for the calculation of machined surface error. Further, given knowledge of the dynamics of the system elements, issues such as forced vibration and chatter may also be examined.

As mentioned previously, a model has been developed for the end milling process [2,3,9,18,20]. In [9] it was shown how such an end milling force model could be used to predict machined surface error. Surface error in this context refers to the deviation of the machined surface from the surface that would be produced by a completely rigid machining system. Thus, surface error predictions acknowledge the inherent flexibility within the machining system. Fig 5 depicts the surface error which may result from a peripheral end milling cut of a given radial and axial depth. It is noted that the surface has an "s" shaped characteristic profile which can be explained by considering the relationship between the instantaneous cutting force and the position of the force center as it moves along the axis of the end mill [9]. The cutter deflection was calculated based on a cantilever beam model, while the workpiece deflection was determined using an influence coefficient model obtained through the use of a finite element model. It is this end milling process and the associated surface errors as described above which will be used herein to demonstrate the simultaneous engineering concepts projected in this paper.

7 SIMULTANEOUS ENGINEERING ILLUSTRATION

To illustrate the methodology described in this paper, an illustration is employed in which an end milling operation is to be performed on the part feature shown in Fig 6. To design the feature and the end milling process to manufacture it, the computer-based end milling process model described above was employed as would be the case in the simultaneous engineering framework. The quality characteristic of interest is the final part feature thickness. Due to the flexibilities in the part and the cutting tool it is known that the cutting force system will produce deflection and hence error in this part feature. The design process objective is to minimize the mean error and minimize the variation in the error about the mean. The modeling approach outlined in the previous section will be employed for this purpose using design of experiments.

For the purposes of this example, the part feature shown in Fig 6 may be considered to be limited by the following design constraints:

1. The part height must be greater than or equal to 44.45 mm (1.75 inches), and less than or equal to 57.15 mm (2.25 inches).
2. The final part thickness must be greater than or equal to 5.08 mm (0.20 inch), and less than or equal to 7.62 mm (0.30 inch).
3. The product of the part width and the final wall thickness must be equal to 161.29 mm² (6.25 in²).

To achieve a satisfactory surface finish on the machined part, the following process constraints were also imposed:

1. The feedrate must be between 0.0762 and 0.1524 mm/tooth (0.003 and 0.006 inch/tooth).
2. The cutter diameter must be between 12.7 and 19.05 mm (0.50 and 0.75 inch).

For this scenario, the mean surface error was predicted for a number of different settings of product, process, and noise variables. Referring to Fig 6, the product design variables considered for the simulation were the final part thickness (FPT) and part height (PH). Process design variables considered for the simulation were the feedrate (FEED), cutter projection length (PL), cutter diameter (DIA), and initial part thickness (IPT). The levels for two additional process variables, the axial depth of cut, and radial depth of cut were set based on the part height.
and the difference between the initial and final part thicknesses respectively. During the simulations, noise was added to the material properties associated with both the cutter and the workpiece to reflect the variation in those properties from workpiece to workpiece and from tool to tool. In addition, noise in the form of parallel axis offset runout was also introduced into the simulator.

A replicated (4 runs for each unique combination of the independent variables) 2^6 full factorial design was performed using the product and process variables described above. The variables using their coded names along with the low and high levels for each are given in Table 1. For each of the 2^6 experimental trials the cutter and part feature deflections were determined from the model predicted cutting forces and the associated average surface error was calculated. These responses were then used to estimate the variable effects associated with the models for both the mean response and the sample standard deviation of the response. Table 2 provides the least squares estimates of the variable effects that were deemed to be statistically significant. It should be noted that the effects in Table 2 have been determined based on coded levels for the independent variables, i.e., ±1 levels.

Table 1  Variable Settings for the 2^6 Factorial Design.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Low Level (-1)</th>
<th>High Level (+1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PH</td>
<td>44.45 mm (1.75 in)</td>
<td>57.15 mm (2.25 in)</td>
</tr>
<tr>
<td>2. IPT</td>
<td>8.89 mm (0.35 in)</td>
<td>11.43 mm (0.45 in)</td>
</tr>
<tr>
<td>3. FPT</td>
<td>5.08 mm (0.20 in)</td>
<td>7.62 mm (0.30 in)</td>
</tr>
<tr>
<td>4. FEED</td>
<td>0.0762 mm (0.003 ipt)</td>
<td>0.1524 mm (0.006 ipt)</td>
</tr>
<tr>
<td>5. DIA</td>
<td>12.70 mm (0.50 in)</td>
<td>19.05 mm (0.75 in)</td>
</tr>
<tr>
<td>6. PL</td>
<td>63.5 (2.50 in)</td>
<td>76.2 (3.00 in)</td>
</tr>
</tbody>
</table>

Table 2  Estimates of the Variable Effects for the Replicated 2^6 Full Factorial Design.

<table>
<thead>
<tr>
<th>Significant Effects for the Mean Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1 = 13.50</td>
</tr>
<tr>
<td>E2 = 8.70</td>
</tr>
<tr>
<td>E3 = -10.50</td>
</tr>
<tr>
<td>E4 = 8.86</td>
</tr>
<tr>
<td>E5 = -17.10</td>
</tr>
<tr>
<td>E6 = 8.18</td>
</tr>
<tr>
<td>E25 = -6.22</td>
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</tbody>
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<tr>
<th>Significant Effects for the Standard Deviation Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1 = 1.78</td>
</tr>
</tbody>
</table>

For the significant effects given in Table 2, the associated models for the mean and standard deviation are:

\[
\hat{Y}(X) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 
+ b_{25}X_2X_5 + b_{26}X_2X_6 + b_{34}X_3X_4 + b_{35}X_3X_5 + b_{36}X_3X_6 + b_{45}X_4X_5 + b_{56}X_5X_6
\]

and

\[
\hat{\sigma}(X) = \alpha_0 + \alpha_5X_5
\]

where, \( \alpha_0 = E_1, \alpha_2 = E_2^2, \alpha_3 = E_3^2, \ldots, \alpha_5 = E_5^2 \) and \( \alpha_5 = D_5^2 \). It should be noted that variable 1, the part height, was found to have no significant effect, either singularly or through its interactions, on the response.

In this design exercise the degree of control concept may be employed by allowing the process design/variables to exhibit varying levels of noise, reflective of the actual conditions that are likely to be encountered in the part feature manufacturing processes. For example, the wall height and initial wall thickness may be treated as random variables with an amount of variability produced by the casting process used to create the feature. Similarly, cutter projection length and cutter diameter may also be treated as random variables, reflecting variation in tool setting and variation due to the regrind condition of the tool. Table 3 lists the variability associated with each of the independent variables in the actual processing environment.

Table 3  Standard Deviation Associated with the Independent Variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standard Deviation (Actual Units)</th>
<th>Standard Deviation (Coded Units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PH</td>
<td>0.254 mm (0.01 in)</td>
<td>0.04</td>
</tr>
<tr>
<td>2. IPT</td>
<td>0.254 mm (0.01 in)</td>
<td>0.20</td>
</tr>
<tr>
<td>3. FPT</td>
<td>Negligible</td>
<td>-</td>
</tr>
<tr>
<td>4. FEED</td>
<td>Negligible</td>
<td>-</td>
</tr>
<tr>
<td>5. DIA</td>
<td>0.254 mm (0.01 in)</td>
<td>0.08</td>
</tr>
<tr>
<td>6. PL</td>
<td>0.508 mm (0.02 in)</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Based on the models for the mean and standard deviation (Eqs. (17) and (18)), an equation of the form of Eq. (13) may be developed, which describes the loss as a function of the independent variables for this smaller is better criterion. After considerable simplification of Eq. (13), the average loss may be expressed as:

\[
\text{Average Loss} = a_0^2 + 2a_0a_5 + a_5^2 (\mu_2 + \sigma_2^2) + \frac{(b_2 + b_5 + b_6 + b_{25})^2 \sigma_2^2 + (b_0 + b_5 + b_6 + b_{25})^2 \sigma_2^4 + (b_0 + b_5 + b_6 + b_{25})^2 \sigma_2^6}{(b_0 + b_5 + b_6 + b_{25})^2 \sigma_2^6 + (b_0 + b_5 + b_6 + b_{25})^2 \sigma_2^4 + (b_0 + b_5 + b_6 + b_{25})^2 \sigma_2^2 + (b_0 + b_5 + b_6 + b_{25})^2 \sigma_2^0}
\]

(19)

As is evident from an examination of Eq. (19), terms associated with the standard deviations of variables 3 and 4 (FPT and FEED) are absent, because the variability associated with these two variables is very small. Eq. (19) was used to prepare Table 4, which displays the predicted average loss associated with 32 unique combinations of the five variables found to be significant in the factorial design. Note that, since in general, there is noise associated with these variables in the product/process environment, Table 4 displays the average loss as a function of the mean settings for these random variables. Due to the non-linear nature of the Eq. (19), there is no guarantee that the minimum loss will occur at one of the 32 variable level combinations shown in Table 4. The true minimum of this constrained nonlinear optimization problem was found using a GRG (generalized reduced gradient) algorithm. The average loss was found to be minimized with the following settings for the five important variables: \( \mu_2 = -1, \mu_3 = +1, \mu_4 = -1, \mu_5 = 1, \) and \( \mu_6 = 0.457 \). The mean setting for the part height, \( \mu_1 \), which does not significantly affect the average loss, should be selected based on other factors such as cost or productivity.
Table 4  Predicted Average Loss for 32 Unique Combinations of Variables 2, 3, 4, 5, and 6.

<table>
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<tr>
<th>Combination</th>
<th>u2</th>
<th>u3</th>
<th>u4</th>
<th>u5</th>
<th>u6</th>
<th>Avg Loss</th>
</tr>
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<td>-1</td>
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<td>-1</td>
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<td>-1</td>
<td>-1</td>
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<td>-1</td>
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<td>43.31</td>
</tr>
</tbody>
</table>

One might reason that the same optimal settings for the independent variables may have been obtained by using only the model for the mean surface error, or alternatively through the application of common sense and sound engineering judgement. Unfortunately, such approaches would only reveal the best possible combination for the independent variables, and opportunities like those described in Fig 7, where the feedrate/productivity may be increased without damage to the loss, would be missed. This global mapping of a function which characterizes the effect of both mean and variability on the average loss is a strength of the quality-engineering based approach to parameter design presented in this paper. Furthermore, this approach is not in conflict with the iterative approach to experimentation often practiced through techniques such as Response Surface Methodology. Such an iterative approach permits continued reduction in the average loss through exploration of the region outside the original experimental design. Finally, the approach described herein permits the simple evaluation of other processing alternatives. The average loss function could easily be re-examined under the assumption that the part feature was generated initially by a forging rather than a casting process. The variability associated with the initial part thickness ($\sigma_2$) in Eq. (19) need only be modified to reflect the reduced variability in that random variable when it is generated by a forging process.

7 SUMMARY

This paper has reviewed and presented a number of concepts and techniques which are key elements in the simultaneous engineering of products and processes:

1. Taguchi's model of the design process, and the role of parameter design in a simultaneous engineering framework.

2. The notion that for many design variables an economic decision must be made about the "degree-of-control" that is required.

3. The role of design of experiments techniques to study the effects of design parameters on a performance measure of interest.

4. A methodology which characterizes the quality of a product/process using the loss function concept. This approach describes the performance of the product/process in both an average and in a variability sense through the use of models developed as a function of design and noise variables. Such a formulation permits the evaluation of the product/process performance for any combination of the design parameters.

5. The role of process models in the design of products/processes well upstream in the design process. The fact that these process models describe the process performance as a function of both product and process design parameters is a key to achieving the goal of simultaneous engineering.

As is apparent from an examination of Fig 7, the average loss does not appear to be too sensitive to changes in either the feedrate or projection length near the indicated optimal point. Thus, the level for the feedrate may be set to its high level without sacrificing much in terms of the loss function. A detailed examination of the residuals associated with the model for the mean surface error (Eq. (17)) revealed that the one of the largest model residuals (over-predicted value for the mean) was associated with the low levels for both the feedrate and projection length, with the levels of the other variables held constant at the values used to create Fig 7. The magnitude of this residual suggests that either a model inadequacy or estimation errors are responsible for the larger predicted average losses at the shorter projection lengths in Fig 7.
8 REFERENCES


Fig 1  Comparison of Japanese and US Product Design Life Cycles

Fig 2  A Model for the Simultaneous Engineering Process.
N1: Noise Factor 1
N2: Noise Factor 2
\[ 2^2 \times 2^2 = 16 \]
Tests are Required

Control Factor 1

Fig 3  Example of an Inner/Outer Array Design Structure

Cutting Tool and Workpiece Geometry and Material
Cutting Speed, Feed, and Depth of Cut
Displacement of Cutting Tool Relative to Workpiece

Geometry Model
Cutting Force - Chip Load Relationship
Model for Machine Tool System Structure

Fig 4  Block Diagram of a Machining Process Simulation Model
Fig 5 Surface Error Produced by an End Milling Process

Fig 6 Part Feature of Interest in the Simultaneous Engineering Application
Fig 7  Contours of Constant Predicted Average Loss for $\mu_2=-1$, $\mu_3=+1$, and $\mu_5=1$