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# Conceptual Robustness in Simultaneous Engineering: An Extension of Taguchi's Parameter Design

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**Abstract.** *Simultaneous engineering processes involve multi-functional teams; team members simultaneously make decisions about many parts of the product–production system and aspects of the product life cycle. This paper argues that such simultaneous distributed decisions should be based on communications about sets of possibilities rather than single solutions. By extending Taguchi's parameter design concepts, we develop a robust and distributed decision-making procedure based on such communications. The procedure shows how a member of a design team can make appropriate decisions based on incomplete information from the other members of the team. More specifically, it (1) treats variations among the designs considered by other members of the design team as* conceptual noise; *(2) shows how to incorporate such noises into decisions that are robust against these variations; (3) describes a method for using the same data to provide preference information back to the other team members; and (4) provides a procedure for determining whether to release the* conceptually robust *design or to wait for further decisions by others. The method is demonstrated by part of a distributed design process for a rotary CNC milling machine. While Taguchi's approach is used as a starting point because it is widely known, these results can be generalized to use other robust decision techniques.*

**Keywords.** Engineering design; Simultaneous engineering; Concurrent engineering; Robust design; Distributed optimization

## 1. Introduction

### 1.1. Motivation

Clark and Fujimoto (1991) observed that some Japanese motor companies designed new models in much less time than their American counterparts. The Japanese motor companies overlapped the die design and the body design through frequent communications. For the American companies, the die design was not started until the body design was frozen. Despite the overlapping, Japanese motor companies experienced about 10% design changes, while the American companies experienced about 30% design changes. The Japanese approach saved about a year in the development cycle. The traditional sequential design approach used until recently by many American companies attempts to take one step at a time–feasibility study, preliminary design, detail design, manufacturing process design, production, distribution, etc. Information is not communicated until it is as specific as possible: for example, body drawings are not released to the die designers until they are complete. If conflicts occur in the later stages, time-consuming iterative changes are required.

Conversely, the simultaneous decision process described by Clark and Fujimoto incorporates all aspects of the product life cycle simultaneously in the early design stages. Ward *et al.* (1994) demonstrate that engineers at Toyota, in particular, communicate about sets of possible designs long before final decisions are made, while concepts are still vague and uncertain. This simultaneous engineering process results in better products with less time, because fewer iterations are needed, more people work in parallel, and upstream decisions are based on better information from downstream. This is not a simple matter of critique from downstream: the critique is meaningful because the downstream decisions are being made at the same time.

Formal simultaneous engineering may have been common in electrical/electronic engineering, because interfaces can be more rigorously defined (by authorized organizations such as the IEEE) than in

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mechanical engineering. Examples are numerous: network developing, logic circuits, etc. In modern industry, concurrency between the design of products and manufacturing systems is only the most visible aspect of concurrency in design. It seems to us only rarely possible to identify an unambiguous sequence for making design decisions: most decisions involve interdependence.

Despite the clear success of simultaneous engineering, it lacks a theoretical basis. Multi-functional teams must communicate and make decisions that take into account other aspects of the system, but:

1. Each communication abstracts from information possessed by the communication source; how should this abstraction be done?
2. How should they make the decisions?
3. How can these communications and decisions be given a mathematical expression?

### 1.2. Concepts

Because the teams must make interdependent decisions simultaneously, we argue that they should communicate about sets of possibilities and make *conceptually robust* decisions: that is, decisions that are robust against variations in the part of the designs done by other team members. If we treat variations as *conceptual* noises, then we can use any optimization technique for producing designs that are robust against physical variations. In this paper we use the statistical methods for approximating optima that have been popularized by Taguchi. We necessarily also introduce an economic criterion to guide the engineer in *deciding when to decide*, thereby eliminating the common tendency for all members of the team to wait for all the other members.

Based on these concepts, this paper will define our approach based on the notion of *conceptual noise* in Section 3. Section 3.1 describes how a member of the design team, an *agent*, can use an extension of Taguchi's parameter design to make decisions that are *conceptually robust*. Section 3.2 describes how team members can use the same experiments (physical or computational) to identify the *best* values from *their own perspective* for parameters they share with others and to estimate the marginal cost of variation from those values. Section 3.3 outlines a procedure for deciding whether to release the conceptually robust design or to wait for further information from others. Section 3.4 lists the steps of the process in detail.

In addition to the approach, this paper also contains generally related work, a brief introduction to the Taguchi method, the need for conceptually robust design, and an illustrative example.

### 1.3. Related Work

The Taguchi method was introduced to American academia by Kackar (1985). Several books on the Taguchi method were published later (Phadke 1989, Dehnad 1989, Logothetis and Wynn 1989), as well as English translations of Taguchi's Japanese books (Taguchi 1986, Taguchi 1987). Taguchi (1986) gives good introductory descriptions of quality loss and parameter design. For complete treatments of the Taguchi method including examples and experimental designs, see Taguchi (1987). Taguchi's work is based on statistical design of experiments (Khuri and Cornell 1987, Box, Hunter and Hunter 1978). Taguchi uses orthogonal arrays to lay out the experiments and signal-to-noise ratios to design robust products against noise. Taguchi and Clausing (1990) give clear descriptions of quality loss, robustness, and orthogonal arrays. Their discussion assumes some background in Taguchi's methods.

Wilde (1990, 1991), Otto and Antonsson (1993), and Michelena and Agogino (1991) have extended Taguchi's work within the standard optimization framework. It seems certain that their methods can (and should) also be applied to the extensions proposed here.

Other related issues include set-based processes, quality loss, value of information, and timeliness. Ward (1992) expands the argument made here that set-based reasoning is essential for simultaneous engineering. The labelled interval calculus (LIC) is another mechanism for such reasoning, which can be used to narrow the set of possibilities by eliminating infeasible regions (Ward and Seering 1993a, 1993b). Ward *et al.* (1994) show that the first and best practitioner of concurrent engineering, the Toyota Motor Company, uses a highly set-based process. Krishnan *et al.* (1991) define a *quality loss* to capture the decrease in freedom of choice as a cooperative sequential design process progresses. Bradley and Agogino (1991), on the other hand, introduce the idea of the value of information to the catalog selection problems, and assert that the designer should make a selection when the expected value of perfect information is negligible. They do not define negligibility. Ulrich *et al.* (1993) argue that in addition to the design and manufacturing costs, the cost of time should be included in the decision-making process.

### 1.4. Taguchi Method

Taguchi has introduced to the design community three important ideas that are used in this paper. First, he suggests that designers should minimize *quality loss*, a quadratic function of the deviation of performance parameters from desired values.

Second, he advocates designing products to be *robust* against manufacturing and environment variations (physical noise). Products are subject to deterioration, different users and environments, and manufacturing errors. These variations are inevitable and beyond the control of product designers. Good-quality products should perform their intended functions regardless of these noises. Taguchi sets design decision variables to be robust against noise by experimenting with trial designs of various settings of decision variables under various noise settings.

Third, he uses partial–factorial *orthogonal arrays* to run experiments, a procedure borrowed from traditional experimental design, but previously little used by engineers. According to Taguchi and Clausing (1990), a group of automobile steering engineers identified 13 critical variables governing steering performance. If the engineers were to compare three levels of values for each critical variable, they would have 1,594,323 design options. Instead of a *one-factor-at-a-time* approach, Taguchi uses orthogonal arrays (similar to fractional factorial matrices) to lay out experiments, changing several factors simultaneously. A small number of experiments are enough to identify the average effects of the factors–for the steering problem, 27 experiments ($L_{27}$ orthogonal array) instead of about 1 million. He then selects the value for each factor that maximizes performance averaged over all the tested combinations of values for the other design variables and noises.

## 2. The Need for Conceptually Robust Design

In the conventional sequential design approach and in many prescriptions for simultaneous engineering, decisions about variables that influence multiple components of a product (for example, the space available for an engine) or both the product and its manufacturing processes are made by a higher-ranking manager or by one of the several involved parties based on informal consultation. This approach often results in conflicts in the later stages of product development, because decisions are made with insufficient data. Iterations are required to resolve the conflicts.

To remedy the defects of the sequential approach, there emerged the simultaneous engineering approach to incorporating all aspects of the product life cycle in early design stages. However, mathematical and computing tools to support simultaneous engineering are not yet fully developed, nor do we yet have mathematical models of the process. We believe that the tools enabling simultaneous engineering should support set-based communications and distributed decision-making, allowing the product development process to progressively narrow the design possibilities rather than making iterative changes. This is consistent with Clark and Fujimoto (1991), and with Ward *et al.* 1994, who show that at Toyota specifications are fixed very late in the design process, and as a result of communications about the set of possibilities rather than by executive fiat.

Since every agent is allowed to make decisions simultaneously in the course of narrowing the set of design possibilities, the decisions should be robust against others' decisions. If we consider a complex product design problem as an example, several agents will design the components. Each component design agent needs to proceed with the design regardless of the design status of the neighboring components, so that no time is wasted waiting for others' decisions. Some decision variables may be dependent on several components. We need to develop a tool to help the component design members to proceed with their designs, despite indecision about the interdependent decision variables. The tool should also be able to help designers decide the best values for the interdependent decision variables in terms of the integrated system design. Component designs done using the tool should be robust against the variations of the neighboring component designs, or conceptually robust.

## 3. Conceptually Robust Design Using the Extended Taguchi Method

This section will address the issues raised in Section 2, using the idea that variations of the neighboring component design concepts constitute *conceptual noise*. We will provide a procedure based on Taguchi's parameter design method for designing a component to be robust against not only physical noise but also conceptual noise; show a method for the agent to show his preference for a conceptual noise factor in designing a component; and develop a criterion for deciding whether to eliminate the designs that are sensitive to conceptual noise or keep them until there is a reduction in the conceptual noise (that is, a decision by others).

Taguchi uses signal–noise ratios as objective functions. In this paper, for the sake of simplicity, we minimize average quality loss.

### 3.1. Conceptually Robust Design

Taguchi argues that a high-quality product should successfully perform its intended functions under varying conditions (physical noise). He designs a high-quality product by finding values for design decision variables that are robust against noise. The steps are as follows: (1) Identify the product's performance characteristic, design decision factors, noise factors, and the range of factor variation. (Rather than performance characteristic, we have chosen to use *quality loss*, a quadratic function.) (2) Use orthogonal arrays for trial designs (inner array) and noise factors (outer array). (3) Perform experiments on the trial designs under the noise conditions specified in the outer array. (4) Identify values of the design decision variables giving the lowest average quality loss. He calls this design process *parameter design.*

Let $\boldsymbol{d}$ be the vector of decision variables and $\boldsymbol{n}$ be the vector of noise variables, each of which may be assigned several different values. For each element of $\boldsymbol{d}$, Taguchi attempts to find the value that minimizes the quadratic quality loss function. He normally assumes that engineering judgment has been used to pick parameters that are reasonably independent, so that the couplings among them can be ignored. The problem, if of the *nominal-the-best* type, can be formulated as follows:

for each $\quad d_i \in \boldsymbol{d}, \quad$ find $\quad d_i^j,$

such that

$$L_i = \frac{1}{N_i^j} \sum_{\substack{\text{Experiments in} \\ \text{which } d_i = d_i^j}} k \cdot [y(\boldsymbol{d}, \boldsymbol{n}) - y_d]^2$$

is minimized,

where $d_i^j$ is the $j$th level of $d_i$, $L_i$ is the average quality loss associated with $d_i$, $N_i^j$ is the number of experiments involving $d_i^j$, $k$ is a proportionality constant relating monetary loss to the squared units of the physical parameter that reflects the quality loss caused by deviation, $y(\boldsymbol{d}, \boldsymbol{n})$ is the performance value of the experiment, and $y_d$ is the desired performance value (here, we consider only constant $y_d$). For *smaller-is-better* and *larger-is-better* types, the quality loss will have the forms $k \cdot y(\boldsymbol{d}, \boldsymbol{n})^2$ and $k/[y(\boldsymbol{d}, \boldsymbol{n})^2]$, respectively. Also, we assume that every level is equally likely to be selected. Note that in Taguchi (1986), instead of fixing $\boldsymbol{d}$ all at once, Taguchi establishes the robust level for each element of $\boldsymbol{d}$, namely, $d_i$, separately. There are two possible arguments for this procedure. First, it may reduce search time. Second, it may increase the robustness of the solution against variations that have not been modeled. These arguments need to be analyzed in a greater detail.

When a component designer designs a part without final decisions having been made about interdependent variables by the rest of the team, the variations of the interdependent decision variables are also uncontrollable to the component designer. For example, *conceptual noise* for a car body design may include the engine height. We propose that a component designer include conceptual noise factors in the noise orthogonal array and carry out Taguchi's parameter design process. The performance of the resulting design will be satisfactory regardless of the final design of neighboring components. We call the resulting design a *conceptually robust* design. In the above formulation, the interdependent decision variables are included in $\boldsymbol{n}$ rather than $\boldsymbol{d}$. We will denote the average quality loss *for each agent* on the decision variable $d_i$, $d_i \in \boldsymbol{d}$, as $L_{d,i}^j$, and the loss associated with the conceptually robust level as $L_{d,i}^{\bar{j}}$

$$L_{d,i}^j = \frac{1}{N_i^j} \sum_{\substack{\text{Experiments in} \\ \text{which } d_i = d_i^j}} k \cdot [y(\boldsymbol{d}, \boldsymbol{p}, \boldsymbol{c}) - y_d]^2 + L_{\Delta,i}^j, \tag{1a}$$

$$L_{d,i}^{\bar{j}} = \min_{\text{levels of } d_i} (L_{d,i}^j), \tag{1b}$$

where $j$ is the level index, $\bar{j}$ is the (conceptually robust) level with the lowest average quality loss, $N_i^j$ is the number of experiments that involve $d_i^j$, the $j$th level of $d_i$, and $\boldsymbol{p}$ and $\boldsymbol{c}$ denote the physical and conceptual noise, respectively ($\boldsymbol{p}$ combines with $\boldsymbol{c}$ to form $\boldsymbol{n}$, the total noise vector). $L_{\Delta,i}^j$, which will be formalized in next section, represents the quality loss to other agents if $d_i^j$ is selected.

### 3.2. Marginal Quality Loss

In Section 3.1, the interdependent decision variables belonging to neighboring components are regarded as (conceptual) noise factors. However, component designers also need to provide feedback to the designers of neighboring components about their preferred values for the connecting variables and the cost of deviations from those values. This can be done by considering the conceptual noise factors as design decision variables and identifying the best values for conceptual noise factors in the component design.

We use the same experimental data obtained in the

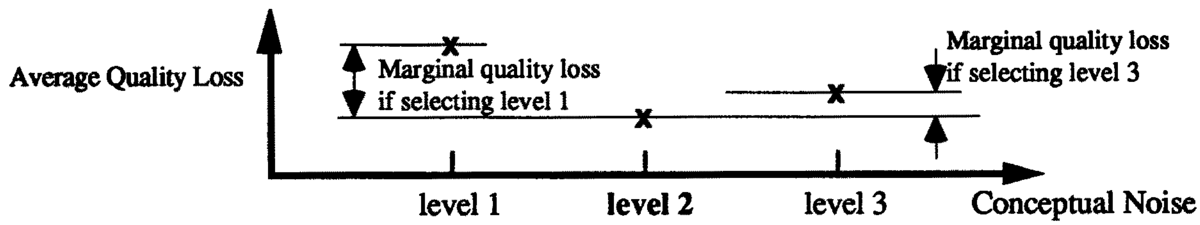


**Fig. 1.** The best value and marginal quality loss for a conceptual noise factor.

conceptually robust design of a component to identify the best values for conceptual noise factors. We regroup the experimental data according to the level of the conceptual noise factor. The level of a conceptual noise factor corresponding to the *lowest average quality loss* is identified as the *best* value for the conceptual noise factor. The increase in expected average quality loss for the levels of the conceptual noise factor, defined as *marginal quality loss*, provides a measure of the importance of this factor to the component designer (as in Fig. 1). The designer of neighboring components can then take this into account.

Equation (2) expresses the marginal quality loss associated with the $j$th level of the $i$th conceptual noise (denoted as $c_i^j$):

$$l^j_{\Delta,i} = \frac{1}{N^j_i} \sum_{\substack{\text{Experiments in} \\ \text{which } c_i = c_i^j}} k \cdot [y(\boldsymbol{d}, \boldsymbol{p}, \boldsymbol{c}) - y_d]^2 - L^{\bar{j}}_{c,i}, \quad (2)$$

where

$$L^{\bar{j}}_{c,i} = \min_{\text{levels of } c_i} \left( \frac{1}{N^j_i} \sum_{\substack{\text{Experiments in} \\ \text{which } c_i = c_i^j}} k \cdot [y(\boldsymbol{d}, \boldsymbol{p}, \boldsymbol{c}) - y_d]^2 \right) \quad (2a)$$

represents the minimum average quality loss associated with $c_i$ (at the $\bar{j}$th level), and $N_i^j$ is the number of experiments that involve $c_i^j$.

Similarly, for each level of $d_i$, every other agent has a corresponding marginal quality loss, ${}^{\alpha}l^j_{\Delta,i}$. Once this has been communicated to the agent controlling $d_i$, $L^j_{\Delta,i}$ can be computed using

$$L^j_{\Delta,i} = \sum_{\alpha=1}^{m-1} {}^{\alpha}l^j_{\Delta,i}, \quad (3)$$

where $\alpha$ denotes the agents and there are $m$ agents in total.

### 3.3. Decision on Whether to Eliminate the Conceptually Sensitive Design

The conceptually robust design involves a tradeoff. It will allow designers to design a product sooner, but it may not produce the best possible design. That is, by waiting until the other members of the team have made their decisions, an agent may reduce the quality loss associated with the component below the conceptually robust design level. However, this can lead to paralysis, with everyone waiting for others' decisions. We therefore need an approximate cost computation method to enable each agent to decide whether to *eliminate* conceptually *sensitive* choices, in favor of the conceptually robust choice, or to wait for more information. We will estimate the cost of eliminating the conceptually sensitive choices on each element $d_i$ of $\boldsymbol{d}$ by comparing (1) the quality loss associated with the conceptually robust level of $d_i$ ($L^{\bar{j}}_{d,i}$), (2) the lowest quality loss that might be achieved by waiting to decide $d_i$ ($L^j_{\text{WAIT},i}$, *for every* $j$), and (3) the cost of the time lost due to the failure to make a decision on $d_i$ ($L_{\text{TIME},i}$). If the cost of eliminating a specific conceptually sensitive choice is negative (we gain rather than lose), then we should drop that conceptually sensitive choice for $d_i$. The cost of eliminating the conceptually sensitive choice $j$ for $d_i$ is estimated as

$$\$^j_i = L^{\bar{j}}_{d,i} - (L^j_{\text{WAIT},i} + L_{\text{TIME},i}). \quad (4)$$

While $L^{\bar{j}}_{d,i}$, as well as the conceptually robust design ($\bar{j}$), can be obtained using the average quality loss for every level of $d_i$ using equation (1), $L^j_{\text{WAIT},i}$ can be approximated by the average quality loss associated with level $j$ ($L^j_{d,i}$) and the possible marginal gain (over the average value) under the condition that the best level for each $c_u$ is selected. (Results are still subject to physical noise $\boldsymbol{p}$.) Equation (5) gives the formulation:

$$L^j_{\text{WAIT},i} = L^j_{d,i} - \frac{1}{\|c\|} \sum_{r=1}^{\|c\|} \left\{ \frac{1}{\#\,\text{levels}} \sum_{v=1}^{\#\,\text{levels}} \bar{L}^v_{u,d_i^j} - \min_{\text{levels of } c_u} (\bar{L}^v_{u,d_i^j}) \right\}, \quad (5)$$

where

$$\bar{L}^v_{u,d_i^j} = \begin{pmatrix} \text{Averaged quality loss over experiments} \\ \text{in which } d_i = d_i^j \text{ and } c_u = c_u^v \end{pmatrix}$$

$$= \frac{1}{N^v_u} \sum_{\substack{\text{Experiments in} \\ \text{which } d_i = d_i^j \\ \text{and } c_u = c_u^v}} k \cdot [y(\boldsymbol{d}, \boldsymbol{p}, \boldsymbol{c}) - y_d]^2, \quad (5a)$$

$N_u^v$ is the number of experiments that involve both $c_u^v$ and $d_i^j$, and $\|\bullet\|$ is the dimension of the vector.

Ulrich *et al.* (1993) embed the cost of time in a profit model in which the rate of sale, the unit price, the unit cost, etc., are time-dependent. The model is complex, and varies from case to case. In this paper, we estimate the cost of the time lost in waiting explicitly on the basis of the following criteria:

1. Cost must increase with delay to guarantee convergence. For simplicity, a quadratic function is used here to approximate the cost: $L_{\text{delay}} = k_t \cdot t^2$.
2. One must consider the different completion times assigned to different agents by determining an appropriate coefficient for the quadratic function.
3. The marginal cost of delay at an agent's time limit equals the cost of delaying the *entire* project ($\hat{L}$, estimated by marketing).

If the design team has weekly ($t_0 = 1$ week) meetings and for agent $\alpha$ the time limit is $t_\alpha$, the coefficient can be determined according to criterion (3):

$$\left.\frac{dL_{\text{delay}}}{dt}\right|_{t_\alpha} = 2k_t t_\alpha = \hat{L} \quad \Rightarrow \quad k_t = \frac{\hat{L}}{2t_\alpha}.$$

Thus, let $t$ be the time *now* (counting from the start of this component design) and $L_{\text{TIME},\,i}$ be the cost caused by delay (from *now* to the *next meeting*) in choosing $d_i$. We have

$$\begin{aligned} L_{\text{TIME},\,i} &= L_{\text{delay}}(t + t_0) - L_{\text{delay}}(t) \\ &= \frac{\hat{L}}{2t_\alpha} \cdot [(t + t_0)^2 - t^2] \\ &= \frac{\hat{L}}{2t_\alpha}(2t \cdot t_0 + t_0^2). \end{aligned} \tag{6}$$

### 3.4. Procedure

The procedure to follow in implementing a conceptually robust design using extended Taguchi's parameter design may be summarized as follows. For each design agent concurrently:

1. Define the problem by establishing the objective, relations of variables, and time available.
2. Determine the decision variable vector $\boldsymbol{d} = \{d_1, d_2, d_3, \ldots, d_{\|d\|}\}$ and possible levels of $d_i$. Each $d_i$ should be as independent as possible.
3. Determine the physical and conceptual noise factors and their possible levels through communication:
   Physical: $p_i$, $i = 1, 2, 3, \ldots, \|\boldsymbol{p}\|$;
   Conceptual: $c_i$, $i = 1, 2, 3, \ldots, \|\boldsymbol{c}\|$.
4. Use the extended Taguchi parameter design method.
   (a) Set up an inner array ($L_{in}$) of $\boldsymbol{d}$.
   (b) Set up an outer array ($L_{out}$) of both $\boldsymbol{p}$ and $\boldsymbol{c}$.
   (c) Run the experiments (*in* × *out*).
5. For $c_i$, $i = 1, 2, 3, \ldots, \|\boldsymbol{c}\|$:
   (a) For each level of $c_i$, compute the average quality loss.
   (b) Identify the best level for $c_i$ and estimate the corresponding *marginal quality loss* ($l_{\Delta,\,i}$'s) for levels of $c_i$ using equation (2).
   (c) Transmit $l_{\Delta,\,i}$'s to the agent that controls $c_i$.
   For $d_i$, $i = 1, 2, 3, \ldots, \|\boldsymbol{d}\|$,
   (a) Obtain ${}^{\alpha}l_{\Delta,\,i}^j$, $\alpha = 1, 2, 3, \ldots, m-1$, for every $j$ through communication.
   (b) Compute $L_{\Delta,\,i}^j$ for every $j$ using equation (3).
6. Compute $L_{d,\,i}^{\bar{j}}$, $L_{\text{WAIT},\,i}^j$, and $L_{\text{TIME},\,i}$
   (a) For $d_i$, $i = 1, 2, 3, \ldots, \|\boldsymbol{d}\|$, identify the robust level $\bar{j}$ and $L_{d,\,i}^{\bar{j}}$ against both the physical and conceptual noise using equation (1).
   (b) For each level of $d_i$, $i = 1, 2, 3, \ldots, \|\boldsymbol{d}\|$, find $L_{\text{WAIT},\,i}^j$ using equation (5).
   (c) Find $L_{\text{TIME},\,i}$ using equation (6).
7. For each (except the $\bar{j}$th) level of $d_i$, $i = 1, 2, 3, \ldots, \|\boldsymbol{d}\|$,
   (a) Compute $\$_i^j$ using equation (4).
   (b) If $\$_i^j \le 0$, eliminate the $j$th level of $d_i$.
8. Repeat steps (2) to (7) until each $d_i$ has only **one** level remaining.

## 4. A Simple Illustrative Example

The example will be shown by following the steps described in Section 3.4.

### 4.1. Problem Description and Definition (Steps 1 and 2)

The example partially designs a two-axis CNC milling machine using a rotary configuration (Rohlfs 1994). By assuming that its two moving axes are identical, the milling machine can be partitioned into the following subsystems: machine frame, actuators, transmissions, spindle assembly, working table, and the control system. As this machine is in a revolute configuration, a rotary transmission, the Roto-Lok cable drive (a product of Sagebrush Technology Inc., Albuquerque, New Mexico), replaces ball screws. Figure 2 shows schematically the feed-drive system, which includes an actuator and a cable drive, together with a spindle assembly.

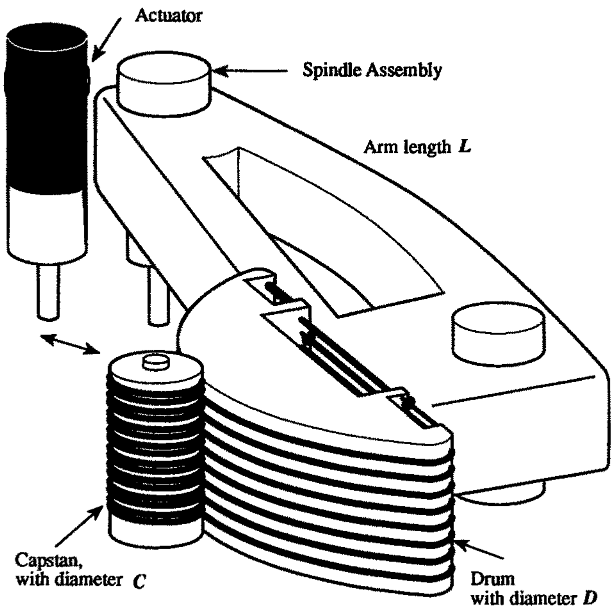


**Fig. 2.** Schematic diagram of a rotary feed-drive (from an artist's view).

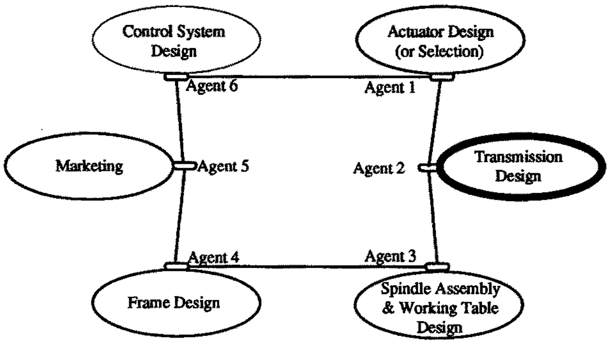


**Fig. 3.** Schematic diagram of the distributed design network.

We will illustrate the proposed robust design approach using a design network of six agents, human or computational (Fig. 3). Links are provided for bi-directional communications between any two agents. Each design agent will make decisions in the design or selection of a particular subsystem. She will have control of the design parameters of that subsystem and be interested in design parameters that affect her design objective, yet are controlled by other agents. The local objective will be to minimize the quality loss from her point of view. In addition to the design agents for the subsystems of the machine, a marketing agent is introduced to help the design agents build up their utility functions for design evaluation.

In this example, for the sake of simplicity, we will demonstrate the design procedure by focusing on

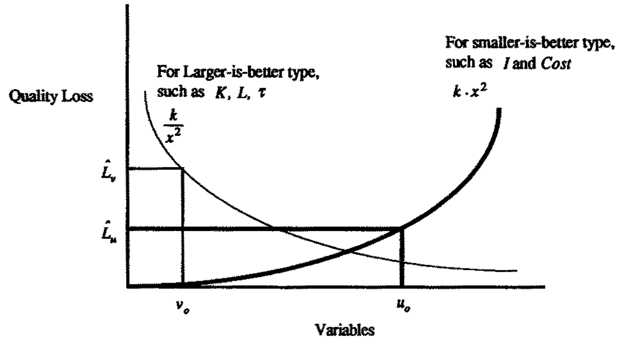


**Fig. 4.** Quality loss functions.

agent 2, who is responsible for the transmission design; namely, to decide the values for $C$ and $D$, the diameters of the capstan and drum respectively, as well as the material used to make these parts. (The major concern here will be the density, $\rho$, of the material.) We have made other simplifying assumptions; this example should not be taken as evidence about the feasibility or appropriate design of revolute machine tools.

*Simplifying assumptions*:

1. Functions describing relations will be assigned their simplest forms.
2. The design of the control system has been fixed.
3. The transmission contributes to the over all machine performance in *stiffness* ($K$), *inertia*($I$), *size* ($L$), *torque capacity* ($\tau$), and *cost*.
4. The mechanism of the transmission is fixed to be a cable drive. Its power loss is negligible, as claimed by Sagebrush Technology Inc.
5. The marketing agent provides the information as required to fix the constants ($k$'s) in the quality loss functions. As in Fig. 4,

$$k = \hat{L}_u/u_0^2 \quad \text{for } \textit{smaller-is-better} \text{ type,} \tag{7a}$$

$$k = \hat{L}_v \cdot v_0^2 \quad \text{for } \textit{larger-is-better} \tag{7b}$$

6. Agent 2 is interested in the following parameters (incoming interface variables):

   From agent 1 (designing the actuator): $K_1$, its stiffness; $I_1$, its inertia.

   From agent 3 (designing the spindle assembly): $m_3$, its mass.

   From agent 5 (marketing):

   $\hat{L}$, the loss for the entire project delay; $t_\alpha$, the time limits; and the constants ($k$'s) for the quality loss function in equation (8), together with their estimation errors ($\delta k$'s). We assume the marketing information is a statistical result, with deviations.

Other agents are interested in $C$, $D$, $\rho$, as well as induced characteristics such as the stiffness, $K_2$, the inertia, $I_2$, etc. (outgoing interface variables).

The problem for agent 2 can then be summarized as:

*Quality characteristic*:

$$\textit{Quality loss} = k_K \cdot 1/K^2 + k_1 \cdot I^2 + k_L \cdot 1/L^2 + k_\tau \cdot 1/\tau^2 + k_{\text{cost}} \cdot \text{cost}^2, \qquad (8)$$

where $k_K$, $k_I$, $k_L$, $k_\tau$ and $k_{\text{cost}}$ are provided by agent 5 (marketing), and for $K$, $L$ and $\tau$ the loss is *larger-is-better* type; for $I$ and cost, it is *smaller-is-better* type.

*Decision variables*: $C$, $D$, and $\rho$ (values shown in Table 1).

*Physical noise factors*: $C'$, $D'$, $\rho'$, $\delta k_K$, $\delta k_I$, $\delta k_L$, $\delta k_\tau$, and $\delta k_{\text{cost}}$ (values shown in Table 2). (Note that although $\delta k_K$, $\delta k_I$, $\delta k_L$, $\delta k_\tau$ and $\delta k_{\text{cost}}$ are interface variables, no one can control these variations ($\delta k$'s).)

*Conceptual noise factors:* $K_1$, $I_1$ and $m_3$.

*Project loss*: $\hat{L} = \$10{,}000$.

*Time limit*: $t_2 = 20$ weeks ($\alpha = 2$ for agent 2), time period: $t_0 = 1$ week.

*Internal governing equations* (characteristics of a cable drive):

$$R = D/C.$$

$$K_2 = 3.105 \times 10^9 \cdot D^{1.5} \cdot C^{1.82} \text{ N}\cdot\text{m/rad},$$

$$I_2 = \left(\frac{7 + 3\pi}{24}\right) \cdot \frac{\rho \cdot h \cdot t}{R^2} \cdot D^3 \text{ kg}\cdot\text{m}^2,$$

where $h$ is the height of the drive, 0.15 m, $t$ is the thickness of the drive, 0.01 m (to produce an appropriately stiff drum).

$$K = \frac{1}{2} \cdot \frac{1}{\dfrac{1}{K_1 \cdot R^2} + \dfrac{1}{K_2}} \cdot \left(\frac{2}{D}\right)^2 \text{ N/m}.$$

$$I = I_1 + I_2 + \frac{m_3 \cdot D^2}{4R^2} \text{ kg}\cdot\text{m}^2.$$

$$L = D/2 \text{ m (assume the drum rotation} = 60°).$$

$$\tau = 14\,187 \cdot \frac{D^{3.16}}{R^{2.23}} \text{ N}\cdot\text{m}.$$

Cost = 2 (unit price $\cdot$ volume $\cdot\, \rho$ + casting and machining costs).

### 4.2. Communication on Interface Variables (Step 3)

Communication provides the possible values for interface variables. These values then are used to construct the inner and outer arrays for Taguchi's parameter design. In this example, agent 2 has more than 20 interface variables, in and out. In addition to decision variables and noise factors, both physical and conceptual, agent 2 also has the constants, $k_K$, $k_I$, etc. obtained from agent 5:

$$k_K = 1.225 \times 10^{15}, \quad k_I = 25, \quad k_L = 0.36,$$
$$k_\tau = 2500, \quad k_{\text{cost}} = 2.5 \times 10^{-7}$$

Estimating these constants is a crucial topic, which is not emphasized in this paper. We arbitrarily specify values by assuming they are from a marketing specialist.

### 4.3. Applying Extended Taguchi's Parameter Design Method (Step 4)

Three decision variables, ($C$, $D$ and $\rho$) and their possible levels are set in Table 1. Assuming at the very beginning, other agents have **no** preference over the levels of the decision variables, the corresponding marginal quality loss is zero.

Then, eight physical noise factors ($C'$, $D'$, $\rho'$, $\delta k_K$, $\delta k_I$, $\delta k_L$, $\delta k_\tau$ and $\delta k_{\text{cost}}$) and three conceptual noise factors ($K_1$, $I_1$ and $m_3$) are set out in Table 2. Values in Tables 1 and 2 are assigned on the basis of our intuition.

**Table 1.** The levels of the decision variables.

| *variable* | *level 1* | *level 2* | *level 3* |
|---|---|---|---|
| $D$ (m) | 0.25 | 1 | 2.5 |
| $C$ (m) | 0.075 | 0.125 | 0.2 |
| $\rho$ (kg/m$^3$) | 2700 (aluminum) | 7850 (steel) | n/a |

**Table 2.** The levels of the noise factors (information on $K_1$ and $I_1$ are from Mectrol Co., Salem, New Hampshire; others are our estimates).

| *factor* | *level 1* | *level 2* | *level 3* |
|---|---|---|---|
| $D'$ (%) | −0.5 | 0 | 0.5 |
| $C'$ (%) | −0.5 | 0 | 0.5 |
| $\rho'$ (%) | −5 | 0 | 5 |
| $K_1$ (N m/rad) | 3,390 | 16,950 | 45,200 |
| $I_1$ (kg m$^2$) | $6.554 \times 10^{-5}$ | $1.8532 \times 10^{-4}$ | n/a |
| $m_3$ *(kg)* | 30 | 50 | 80 |
| $\delta k_K$ (%) | −10 | 0 | 10 |
| $\delta k_I$ (%) | −10 | 0 | 10 |
| $\delta k_L$ (%) | −10 | 0 | 10 |
| $\delta k_\tau$ (%) | −10 | 0 | 10 |
| $\delta k_{\text{cost}}$ (%) | −10 | 0 | 10 |

With these decision variables and noise factors, we use an $L_9$ orthogonal array as an inner array and assign $C$, $D$, and $\rho$ to the columns 1, 2 and 3, respectively. The outer array, on the other hand, is an $L_{27}$ orthogonal array. Noise factors are assigned to the array columns in the order of Table 2. Interactions between the factors are assumed to be zero for both inner and outer arrays. While experimenting, the levels in the inner array will be replaced by the corresponding actual values and then those in the outer array will be fitted with the values or induced values from Table 2 and the inner array.

The quality loss for each experiment is computed using Eq. (8). The values of decision variables will be determined for 9 different combinations given in the row of the inner array. Corresponding to one row of the inner array, the values of the whole outer array will be determined. Since one row of the outer array means one experiment, there will be 243 ($9 \times 27$) experiments.

### 4.4. Experimental Data Analysis by Regrouping (Step 5)

We want to analyze the effect of the conceptual noise factor by regrouping the data according to the levels of conceptual noises. This analysis will enable agent 2 to show her preference over the conceptual noises in the next communication in the form of marginal quality losses.

For example, by regrouping the data using equation (2), we have the results associated with the three levels of $K_1$, $l_1$, and $m_3$ shown in Table 3. In this case, agent 2 can notify *agent 3* that she would prefer $m_3$ to be fixed at level 1, and if level 2 or level 3 is selected then the associated quality loss, with respect to level 1, will be $576 or $1097, respectively.

While sending out the preference to other agents, agent 2 can receive others' preferences over her decision variables $D$, $C$ and $\rho$. Obtaining ${}^{\alpha}l^{j}_{\Delta,i}$ through communication and computing $L^{j}_{\Delta,i}$ using Eq. (3). We have arbitrarily specified the results shown in Table 4.

**Table 3.** Agent 2's preference (${}^{2}l_{\Delta}$'s) over conceptual noise factors.

| *variable* | $K_1$ | $l_1$ | $m_3$ |
|---|---|---|---|
| level 1 | $16,605 | $12 | <u>$0</u> |
| level 2 | $578 | <u>$0</u> | $576 |
| level 3 | <u>$0</u> | n/a | $1,097 |

**Table 4.** Sum of marginal quality loss ($L^{j}_{\Delta,i}$'s) for levels of the decision variables.

| *variable* | $D$ | $C$ | $\rho$ |
|---|---|---|---|
| level 1 | $1254 | $412 | $35 |
| level 2 | $785 | $157 | $706 |
| level 3 | $906 | $1051 | n/a |

**Table 5.** $[L^{j}_{\mathrm{WAIT},i}, L^{j}_{d,i}]$ of controllable factors (underlined values indicate the robust levels against noises).

| *variable* | $D$ | $C$ | $\rho$ |
|---|---|---|---|
| level 1 | [$5,013, $7,107] | [$630, <u>$740</u>] | [$3,784, <u>$5,881</u>] |
| level 2 | [$4,524, <u>$6,620</u>] | [$1,635, $2,457] | [$4,464, $6,561] |
| level 3 | [$4,661, $6,761] | [$10,609, $15,967] | n/a |

### 4.5. Computation of $L^{\bar{j}}_{d,i}$'s, $L^{j}_{\mathrm{WAIT},i}$'s, and $L_{\mathrm{TIME},i}$ (Step 6)

To identify the robust levels for the decision variables, we compute the mean of the average quality loss values for each decision variable level using Eq. (1). The right-hand side (RHS) numbers in Table 5 are $L^{j}_{d,i}$'s, the average quality loss associated with the $j$th level of $d_i$. The underlined numbers represent the robust level and $L^{\bar{j}}_{d,i}$.

The LHS numbers in the brackets are $L^{j}_{\mathrm{WAIT},i}$'s associated with levels of decision variables computed from Eq. (5).

To compute the cost of time, we arbitrarily assign the following: $\hat{L} = \$10{,}000$, $t_2 = 20$ weeks, $t = 0$, and $t_0 = 1$ week. Then, $L_{\mathrm{TIME},i}$ for every level of all the decision variables will be $250 according to Eq. (6).

### 4.6. Cost of Eliminating the Conceptually Sensitive Design (Step 7)

For $D$, as the second level is the robust design, we will examine levels 1 and 3 using equation (4).

$$\$^{1}_{D} = L^{2}_{d,D} - (L^{1}_{\mathrm{WAIT},D} + L_{\mathrm{TIME},D})$$
$$= \$6620 - (\$5013 + \$250) = \$1357;$$
$$\$^{3}_{D} = L^{2}_{d,D} - (L^{3}_{\mathrm{WAIT},D} + L_{\mathrm{TIME},D})$$
$$= \$6620 - (\$4661 + \$250) = \$1709.$$

Shown above, both the costs of eliminating levels 1 and 3 are *positive*, which implies that agent 2 *should not* abandon any level of $D$.

On $C$, the sensitive levels are the second and third which will be examined by

$$\$_C^2 = L_{d,C}^1 - (L_{\mathrm{WAIT},C}^2 + L_{\mathrm{TIME},C})$$
$$= \$740 - (\$1635 + \$250) = -\$1145;$$
$$\$_C^3 = L_{d,C}^1 - (L_{\mathrm{WAIT},C}^3 + L_{\mathrm{TIME},C})$$
$$= \$740 - (\$10{,}609 + \$250) = -\$10{,}119.$$

With the result above, agent 2 can abandon both levels 2 and 3; that is, $C$ is fixed to its first-level value: 0.075 $m$.

We now check whether level 2 of $\rho$ can be eliminated by computing:

$$\$_\rho^2 = L_{d,\rho}^1 - (L_{\mathrm{WAIT},\rho}^2 + L_{\mathrm{TIME},\rho})$$
$$= \$5881 - (\$4464 + \$250) = \$1167.$$

The result suggests that agent 2 should keep both levels for the next iteration.

Failing to make a decision (by eliminating all the conceptually sensitive levels), agent 2 will redo the process starting from the step described in Section 4.2.

### 4.7. Second Iteration (Step 8)

Assume that the levels of decision variables and noise factors, both physical and conceptual, are changed to the values listed in Tables 6 and 7 on the second time period ($t = 1$). Running the experiments and communication gives the results in Tables 8, 9 and 10.

**Table 6.** The levels of the decision variables (2nd iteration).

| *variable* | *level 1* | *level 2* | *level 3* |
|---|---|---|---|
| $D$ (m) | 0.25 | 1 | 2.5 |
| $C$ (m) | 0.075 | fixed (0.075) | fixed (0.075) |
| $\rho$ (kg/m$^3$) | 2700 (aluminum) | 7850 (steel) | n/a |

**Table 7.** The levels of the noise factors (2nd iteration).

| *factor* | *level 1* | *level 2* | *level 3* |
|---|---|---|---|
| $D'$ (%) | −0.5 | 0 | 0.5 |
| $C'$ (%) | −0.5 | 0 | 0.5 |
| $\rho'$ (%) | −5 | 0 | 5 |
| $K_1$ (N m/rad) | 3,390 | 16,950 | 45,200 |
| $I_1$ (kg m$^2$) | $1.8532 \times 10^{-4}$ | fixed ($1.8532 \times 10^{-4}$) | fixed ($1.8532 \times 10^{-4}$) |
| $m_3$ (kg) | 30 | 50 | 80 |
| $\delta k_K$ (%) | −10 | 0 | 10 |
| $\delta k_I$ (%) | −10 | 0 | 10 |
| $\delta k_L$ (%) | −10 | 0 | 10 |
| $\delta k_\tau$ (%) | −10 | 0 | 10 |
| $\delta k_{\mathrm{cost}}$ (%) | −10 | 0 | 10 |

**Table 8.** Agent 2's preference ($^2l_\Delta$'s) over conceptual noise factors (2nd iteration).

| *variable* | $K_1$ | $I_1$ | $m_3$ |
|---|---|---|---|
| level 1 | \$16,605 | no choices | \$0 |
| level 2 | \$578 | n/a | \$30 |
| level 3 | \$0 | n/a | \$57 |

**Table 9.** Sum of marginal quality loss ($L_{\Delta,i}^j$'s) for levels of the decision variables (2nd iteration).

| *variable* | $D$ | $C$ | $\rho$ |
|---|---|---|---|
| level 1 | \$769 | no choices | \$27 |
| level 2 | \$315 | n/a | \$506 |
| level 3 | \$684 | n/a | n/a |

**Table 10.** $[L_{\mathrm{WAIT},i}^j,\ L_{d,i}^j]$ of controllable factors (2nd iteration) (underlined values indicate the robust levels against noises).

| *variable* | $D$ | $C$ | $\rho$ |
|---|---|---|---|
| level 1 | [\$1006, \$1114] | no choices | [\$242, \$352] |
| level 2 | [\$520, \$631] | n/a | [\$724, \$835] |
| level 3 | [\$895, \$1008] | n/a | n/a |

In this case ($t = 1$), $L_{\mathrm{TIME},i} = \$750$ according to Eq. (6). With Eq. (4), we have

$$\$_D^1 = L_{d,D}^2 - (L_{\mathrm{WAIT},D}^1 + L_{\mathrm{TIME},D})$$
$$= \$631 - (\$1006 + \$750) = -\$1125;$$
$$\$_D^3 = L_{d,D}^2 - (L_{\mathrm{WAIT},D}^3 + L_{\mathrm{TIME},D})$$
$$= \$631 - (\$895 + \$750) = -\$1014;$$
$$\$_\rho^2 = L_{d,\rho}^1 - (L_{\mathrm{WAIT},\rho}^2 + L_{\mathrm{TIME},\rho}\Psi$$
$$= \$352 - (\$724 + \$750) = -\$1122.$$

Based on these results, all the conceptually sensitive levels will be dropped at this run and we can conclude that the conceptually robust design is the combination of $D = 1$ m, $C = 0.075$ m, and $\rho = 2700$ Kg/m$^3$ (aluminum).

### 4.8. Summary

We have demonstrated the steps of the proposed design procedure. The example illustrates a problem setup, the operation on data, and the shrinking of design possibilities. By following the procedure described in Section 3.4, agent 2 finishes her design in two weeks, allowing other agents who rely on $D$, $C$

or $\rho$ to continue their work. Also, the evaluation results show that most of the decision variables can be determined without much waiting.

## 5. Conclusion and Future Work

An approach to simultaneously designing components of both products and their manufacturing systems has been demonstrated using an extension of Taguchi's parameter design method. Each component designer identifies both physical and conceptual noises – those parameters that affect her component, but are not under her control. She performs experiments, which may be physical or computational, as organized using Taguchi's orthogonal arrays, and identifies the conceptually (and physically) robust levels for the parameters she controls. She then computes for other levels the relative costs of eliminating them immediately, or waiting until decisions have been made by other members of the team, taking into account the affect her decisions will have on others. The design processes converge because of a satisfactory result or time pressure to approximately minimize the overall cost.

This work has several goals. First, the procedure we define appears reasonably practical for use in designing medium scale systems, at least if software is developed to make it easier for team members to manage. By medium scale, we mean systems comprising a number of well-defined components, each of which is independently of appropriate complexity for treatment using Taguchi's methods. Since Taguchi's methods are fairly well known in industry, we hope to achieve an industrial application fairly soon. Because these ideas are aimed at problems too large to solve in a centralized way, no small scale test can be very convincing.

The work also raises a number of theoretical issues. For example, we believe (but have not argued here) that utility theory cannot be used effectively between different agents in the design process because it is essentially individual, and have substituted the somewhat vague notion of quality loss. We believe that the economic information exchanged between agents ultimately will need to use both *cost* and *revenue* categories, as in market economics. That is, we expect agents to *trade* on interface variables to maximize their internal profits.

In the paper, we assumed that the communication contains limited (or discrete) levels of the possible values for interface variables and they have equal weighting. This should be extended by estimating the probability that each noise level will be selected (Otto and Antonsson 1993). We also expect to address the case of continuous variables, using other optimization techniques.

The significance of this paper does not lie in its details. Many details, such as the use of Taguchi methods, are somewhat arbitrary. Rather, this represents a first step toward a novel theory of distributed optimization, which does not assume the existence of an overall model which can be decomposed to form sub-problems, and which does not assume a single common starting point for the various agents. This step rests on two individually simple legs:

1. Uncertainty about other people's decisions can be treated as a noise, exactly like physical noises, except that
2. The cost of waiting for the elimination of the conceptual noise must be taken into account.

We hope that these ideas will prove a fruitful source of interesting research and effective design tools.

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