Taguchi's Approach to Robust Parameter Design: A New Perspective

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Abstract

Adjustment factors play a crucial role in Taguchi's approach to robust parameter design. However, the notion of adjustment factors is not well defined and ambiguities exist in the selection of those factors. In this article, we propose a criterion for selecting adjustment factors. This new criterion can be used to explain and extend Taguchi's approach. The concept is illustrated using two examples.

1. Introduction

Taguchi has proposed various performance measures known as Signal-to Noise (SN) ratios for evaluating the performance of engineering systems (see Taguchi and Wu (1980), and Taguchi (1991a)). Most of them are criticized in the literature (see Box (1998), Nair (1992), Bérubé and Wu (2000), and Montgomery (2004), among many others). The recommendation was to use data-driven performance measures instead of the SN ratios. Although the SN ratios can be shown to be incorrect under some modeling assumptions, Taguchi's approach has a merit which was not easy to appreciate because of the lack of a rigorous framework. In this article we provide a new perspective to his approach.

A certain type of control factors, namely "adjustment factors", play a crucial role in Taguchi's approach. The SN ratios are supposed to be performance measures independent of these adjustment factors, so that the optimization of the system can be conveniently split into two steps, the first being to maximize the SN ratio and the second being some adjustments using the adjustment factors. Leon, Shoemaker, and Kacker (1987) gave a mathematical foundation to this approach and proposed the concept of performance measures independent of adjustment (PerMIA). Using this concept, SN ratios can be justified under some modeling assumptions, whereas they are inappropriate under other modeling assumptions. However, the notion of adjustment factors is not well defined and thus deriving PerMIAs can be ambiguous (see the discussions by various researchers accompanying the paper of Leon, Shoemaker and Kacker (1987)).

We argue that Taguchi's motivation for using adjustment factors is mainly to simplify

the experiment than to simplify the optimization. Based on this we propose a criterion for selecting adjustment factors from the set of control factors. The new criterion clarifies several ambiguities about Taguchi's approach and enables one to develop better approaches to robust parameter design.

The article is organized as follows. The new criterion about the adjustment factors is proposed in Section 2. In Section 3, two examples are presented to illustrate the advantages of the new criterion and some concluding remarks are given in Section 4.

2. Adjustment Factors

Taguchi's SN ratio for a nominal-the-best characteristic is given by $SN = \mu^2/\sigma^2$, where μ and σ^2 are the mean and variance of the response. In order to minimize the expected value of the quadratic loss function, he proposed to perform the optimization in two steps: first to find the setting of control factors to maximize the SN and then to use an adjustment factor to adjust the mean to target. According to his approach an adjustment factor is a control factor that has a large effect on μ but not on SN. Others, who criticized the use of SN ratios suggested to replace the SN in the first step by σ^2. Therefore, in their approach an adjustment factor is the one having a large effect on μ but not on σ^2. Clearly the two definitions of an adjustment factor are in contradiction. Then, what is actually an adjustment factor?

The approach of Leon, Shoemaker, and Kacker (1987) can be explained as follows (see also the discussion by Easterling (1987)). Let Y be the response and $L(Y)$ be a quality loss function. Divide the control factors into two groups $(\boldsymbol{X}, \boldsymbol{M})$, where $\boldsymbol{M}$ denotes the

set of adjustment factors. Then, the minimization of the $E\{L(Y)\} = R(\boldsymbol{X}, \boldsymbol{M})$, where the expectation is taken with respect to the distribution of noise factors, can be done in two steps:

1. Minimize $PM(\boldsymbol{X}) = R(\boldsymbol{X}, \boldsymbol{M}^*(\boldsymbol{X}))$ with respect to $\boldsymbol{X}$, where $\boldsymbol{M}^*(\boldsymbol{X}) = arg\min_{\boldsymbol{M}} R(\boldsymbol{X}, \boldsymbol{M})$. Denote the solution by $\boldsymbol{X}^*$.

2. Adjust $\boldsymbol{M}$ to $\boldsymbol{M}^*(\boldsymbol{X}^*)$.

$PM(\boldsymbol{X})$ is called a PerMIA. Leon, Shoemaker, and Kacker (1987) further showed that if Y has a multiplicative error model with error depending only on $\boldsymbol{X}$, then minimizing $PM(\boldsymbol{X})$ is equivalent of maximizing the SN ratio, whereas if Y has an additive error model with error depending only on $\boldsymbol{X}$, then minimizing $PM(\boldsymbol{X})$ is equivalent of minimizing the variance of Y. According to them the adjustment factors are selected from the set of control factors to make the product/process design more flexible. Adjustment factors are easy-to-change factors which can be adjusted to meet with a change in the product's design requirement. Because a PerMIA is used for finding the optimal setting of $\boldsymbol{X}$ which are hard-to-change factors, their settings will not be affected by the design changes. Even with this explanation, many questions remain unanswered. What is the connection between an easy-to-change factor with the type of model, such as multiplicative error or additive error model? When only one adjustment is necessary, what prevents us from using a hard-to-change factor in the adjustment step? Note that if frequent adjustments are necessary due to the changes in design or customer requirements, then a different type of control factor known as signal factor should be used for adjustments (see Taguchi 1991a; Miller and Wu 1996; and Joseph

and Wu 2002a).

On the other hand, Box (1998) among many others advocated using data-analytic methods to identify adjustment factors. The approach was to use transformations on the response to achieve separation between location and dispersion effects. Then, the factors that affect the location but not the dispersion are termed as adjustment factors, which are used in the second step of the two-step optimization procedure. The drawback of this approach is that the adjustment factors are treated as part of the factors used in the experiment. This either ignores the prior knowledge about such factors or increases the experimental effort by including such factors as part of the experiment.

In this article, we take a different point of view about adjustment factors. We propose that these factors should be selected from a set of factors where a fair amount of knowledge exists about how they affect the mean of the response. Therefore, these factors can be used for adjusting the mean, even when they are not included in the experiment. This approach, thus takes advantage of our engineering knowledge about the product/process during optimization without causing any additional experimental burden. A general strategy for implementing this approach is given below.

Divide the control factors into two groups denoted by $\boldsymbol{M}$ and $\boldsymbol{X}$, where the effect of $\boldsymbol{M}$ on the mean response is known based on the engineering/physical knowledge, whereas the effect of $\boldsymbol{X}$ is unknown. For example, in an electro plating process, the plating time and current can be selected as factors in $\boldsymbol{M}$ because their effect on the mean plated thickness is known from Faraday's law, whereas factors such as distance between the cathode and anode, concentration, pH, and temperature of electrolyte can be taken as factors in $\boldsymbol{X}$. Let μ be the

mean of the response. The engineering/physical models are mostly deterministic and thus it makes sense to state the relationship in terms of μ than Y. Thus we have $\mu = f(\boldsymbol{M}, \boldsymbol{\beta})$, where the functional form of f is known up to a set of parameters $\boldsymbol{\beta}$. Because of the presence of noise factors, Y is random and has a distribution with mean μ. Let the distribution be $p(y; \mu, \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a set of unknown parameters. Now $\boldsymbol{X}$ enters in the model through the unknown parameters $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$. Thus the complete model can be written as

$$Y \sim p(y; f(\boldsymbol{M}, \boldsymbol{\beta}(\boldsymbol{X})), \boldsymbol{\theta}(\boldsymbol{M}, \boldsymbol{X})).$$

Note that $\boldsymbol{\beta}$ is a function of $\boldsymbol{X}$ only, because the functional form f is assumed to be correct with respect to $\boldsymbol{M}$. A factor from $\boldsymbol{M}$ or all of $\boldsymbol{M}$ can be used for adjustment if the optimization can be conveniently divided into two steps as described in Leon, Shoemaker, and Kacker (1987).

Physical experiments can be performed to estimate $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ as functions of $\boldsymbol{M}$ and $\boldsymbol{X}$. Because the engineering knowledge about $\boldsymbol{M}$ is already incorporated into the modeling, the experiments can focus more on $\boldsymbol{X}$ than $\boldsymbol{M}$. This strategy helps in reducing the experimental cost and time, because the investment for obtaining the exact effect of $\boldsymbol{M}$ is smaller. We will not get into the details of how such experiments can be performed; instead we want to motivate Taguchi's approach of using adjustment factors in the light of the foregoing strategy. It is explained with two examples in the next section.

3. Examples

3.1 *Example 1: Tile Experiment*

Consider the famous Ina tile experiment of Taguchi (see Taguchi and Wu, 1980). The experiment was performed to optimize the manufacturing process with respect to the tile dimension. As described in the previous section, the set of control factors in the process can be divided into $\boldsymbol{M}$ and $\boldsymbol{X}$. What can be the factors in $\boldsymbol{M}$? In order to answer this question, we need to know about the manufacturing process. It is easy to understand about the effect of one control factor, namely the mold dimension (M). Clearly, the mean tile dimension should be proportional to the mold dimension. Thus, we must have $\mu = \beta M$. Assume a normal distribution for the tile dimension. Because the tile dimension should be proportional to M irrespective of the other control and noise factors in the process, it is reasonable to assume that $var(Y) \propto M^2$. Therefore the following model can be used

$$Y \sim \mathcal{N}(\beta(\boldsymbol{X})M, \theta^2(\boldsymbol{X})M^2).$$

Suppose we choose the quadratic loss function: $L(Y) = c(Y-T)^2$, then

$$E\{L(Y)\} = c\left(\{\beta(\boldsymbol{X})M - T\}^2 + \theta^2(\boldsymbol{X})M^2\right).$$

Minimizing this with respect to M, we obtain

$$M^* = T\frac{\beta(\boldsymbol{X})}{\beta^2(\boldsymbol{X}) + \theta^2(\boldsymbol{X})}.$$

The PerMIA can be obtained by substituting this in $E\{L(Y)\}$. We obtain,

$$PM(\boldsymbol{X}) = \frac{cT^2}{1 + \beta^2(\boldsymbol{X})/\theta^2(\boldsymbol{X})}.$$

Thus, minimizing $PM(\boldsymbol{X})$ is equivalent of maximizing

$$\frac{\beta^2(\boldsymbol{X})}{\theta^2(\boldsymbol{X})} = \frac{E^2(Y)}{var(Y)},$$

which is the same as the SN ratio. It can be estimated from an experiment by keeping the mold dimension fixed, say at M_0. Therefore only $\boldsymbol{X}$ has to be varied in the experiment. This significantly simplifies the experimentation. In addition, using the above approach we are able to incorporate the engineering knowledge about the process into the modeling and optimization. This is clearly superior to those that use only experimental information.

3.2 *Example 2: Chemical Experiment*

In this section we discuss the robust parameter design of a chemical process. First, we explain the problems associated with the traditional approach using a hypothetical experiment and then present an intriguing SN ratio proposed by Taguchi. Then we explain how to derive a PerMIA based on the physical knowledge of the process and demonstrate the usefulness of adjustment factors.

3.2.1 *The Problem*

A first order consecutive chemical reaction in two steps is given by

$$A \rightarrow^{k_1} B \rightarrow^{k_2} C,$$

where the initial chemical A converts to B at a reaction rate k_1 and B converts to another chemical C at a reaction rate k_2. Suppose B is the desired chemical, in which case C is an unwanted byproduct. A typical plot of the concentrations of the three chemicals against time is given in Figure 1. We can see that as time passes, A depletes to 0; B increases, attains a maximum, and then decreases to 0; whereas C monotonically increases to 1 (assuming the

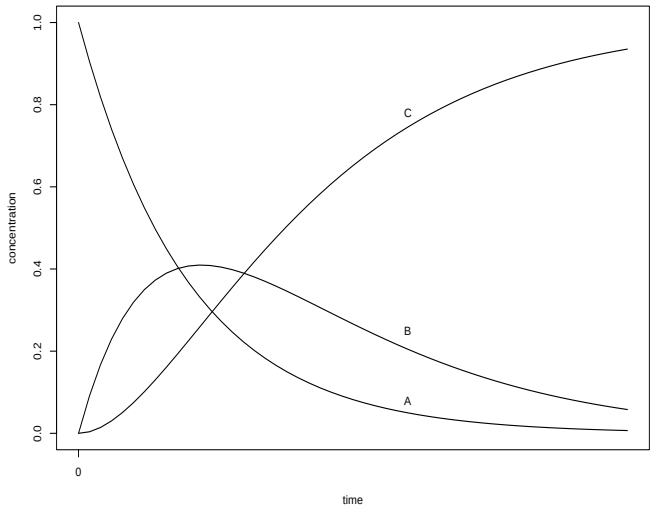

Figure 1: Plot of the concentrations of the chemicals A, B, and C against time.

initial concentration of A to be 1). There are many control factors in the process such as reaction time, temperature, pressure, cooling rate, and stirring rate in the reaction tank. They can be set to maximize the concentration of B. For simplicity of presentation, suppose an experiment is performed by changing only one control factor (say, pressure) keeping all the other control factors fixed. Let Y_1, Y_2, and Y_3 denote the concentrations of the three chemicals A, B, and C respectively and let x denote the pressure. The data from the experiment are given in Table 1 (a similar example is given by Fowlkes and Creveling (1995)).

We would like to find out the best setting for x that maximizes Y_2. At first sight all of them look equally good, as they give the same concentration of 0.6 for the chemical B. Looks can be deceiving! We will show that by treating the reaction time as an adjustment factor, $x = 10$ is the best setting in terms of maximizing the concentration.

3.2.2 *Taguchi's Approach*

Taguchi (1991b) proposed an SN ratio for optimizing consecutive chemical reactions

Table 1: Chemical Experiment and Data

Run	x	Y_1	Y_2	Y_3
1	10	0.3	0.6	0.1
2	15	0.2	0.6	0.2
3	20	0.1	0.6	0.3

(see also Fowlkes and Creveling (1995), Section 5.5.2, for details). To derive the SN ratio, Taguchi first made some transformations. Define $u_1 = Y_1$, $u_2 = Y_1+Y_2$, and $u_3 = Y_1+Y_2+Y_3$. Because $u_3 = 1$ for all t, the process can be optimized by simultaneously minimizing u_1 and maximizing u_2. Therefore, u_1 is considered as a smaller-the-better (STB) characteristic and u_2 a larger-the-better (LTB) characteristic. For a fraction defective variable (p), Taguchi defined the SN ratio as

$$SN = -10 \log \frac{p}{1-p}.$$

See Phadke (1989, page 113) for some intuitive arguments for using the above SN ratio. Because the concentrations are also variables in $[0, 1]$, the SN ratios for the two characteristics are given by

$$SN_1 = -10 \log \frac{u_1}{1-u_1} \text{ and } SN_2 = 10 \log \frac{u_2}{1-u_2}.$$

Note that maximizing the SN ratios will minimize u_1 and maximize u_2. Now the SN ratio for the process is defined as the sum of the SN ratios for the STB and LTB characteristics (similar to the case of operating window SN ratio, see Joseph and Wu (2002b)). Thus

$$SN = SN_1 + SN_2$$

$$
\begin{aligned}
&= 10 \log \left\{ \frac{u_2(1-u_1)}{u_1(1-u_2)} \right\} \\
&= 10 \log \left\{ \frac{(Y_1+Y_2)(1-Y_1)}{Y_1(1-Y_1-Y_2)} \right\}.
\end{aligned}
$$

For the experiment given in the previous section, the three SN ratios are 13.2, 12, and 13.2 respectively. Thus, according to the SN ratio the setting $x = 15$ is bad, whereas $x = 10$ and $x = 20$ are equally good. This can be explained as follows. Since $Y_1 = Y_3$ at $x = 15$, there is not much scope for improvement. Whereas at $x = 10$, the process can be run for some more time, so that more of A can be converted to B thereby increasing its concentration. In the same way the reaction time can be reduced at $x = 20$ to increase the concentration of B. Thus SN ratio is a measure that assesses the performance of the process independent of the adjustment. As shown in the next section that a better performance measure can be derived using chemical kinetics. However, Taguchi's motivation for using reaction time as an adjustment factor is clear and correct.

3.2.3 *Performance Measure*

We can treat the reaction time (M) as an adjustment factor, because its relationship with the concentrations can be easily obtained using the well established laws of chemical kinetics (see for example Steinfeld, Francisco, and Hase (1999), Section 2.1.3). For this example, we denote the adjustment factor reaction time by t instead of M. Let $E\{Y_i\} = \mu_i(t)$. Then, assuming the initial concentration of A to be 1, we obtain

$$\mu_1(t) = e^{-k_1 t}, \tag{1}$$

$$\mu_2(t) = \frac{k_1}{k_1 - k_2}(e^{-k_1 t} - e^{-k_2 t}), \tag{2}$$

and $\mu_3(t) = 1 - \mu_1(t) - \mu_2(t)$, where k_1 and k_2 are the reaction rates. Note that, in terms

of the notation used in Section 2, $\boldsymbol{\beta} = (k_1, k_2)$. For the case $k_1 = k_2 = k$, (2) becomes $\mu_2(t) = kt\exp(-kt)$.

The responses are random due to the presence of noise factors in the process (such as impurities in the chemical, variations in pressure and temperature). Because $Y_i \geq 0$ and $\sum_{i=1}^{3} Y_i = 1$, we may use the Dirichlet distribution to model these random variables (Kotz, Balakrishnan, and Johnson (2000)), whose probability density function is given by

$$p(\boldsymbol{Y}) = \frac{\Gamma(\alpha_1 + \alpha_2 + \alpha_3)}{\Gamma(\alpha_1)\Gamma(\alpha_2)\Gamma(\alpha_3)} Y_1^{\alpha_1} Y_2^{\alpha_2} Y_3^{\alpha_3}.$$

We have

$$\mu_i(t) = \frac{\alpha_i}{\sum_{j=1}^{3} \alpha_j}, \tag{3}$$

for $i = 1, 2, 3$. Note that the μ_i's are functions of both t and $\boldsymbol{X}$, but for simplicity, we have suppressed the notation on $\boldsymbol{X}$.

The next step is to specify a loss function. Suppose we terminate the process after time t. Then the loss may be taken as proportional to the amounts of the chemicals A and C left in the reaction tank after the termination of the process. Thus, let $L(\boldsymbol{Y}) = c_1 Y_1 + c_3 Y_3$, where c_1 and c_3 are some cost coefficients. Similar type of quality loss functions are discussed in Joseph (2004). Our objective is to find a control factor setting that minimizes the expected value of the loss function. We have

$$E\{L(\boldsymbol{Y})\} = c_1\mu_1(t) + c_3\mu_3(t).$$

Assume $c_1 = c_3 = c$. Then, $E\{L(\boldsymbol{Y})\} = c\{1 - \mu_2(t)\}$. Thus the expected loss can be minimized by maximizing $\mu_2(t)$.

The foregoing optimization can be simplified using the concept of PerMIA. To obtain the PerMIA, first we should maximize $\mu_2(t)$ with respect to t. Consider the case with $k_1 \neq k_2$. Solving for t from

$$\frac{d}{dt}\mu_2(t) = \frac{k_1}{k_1 - k_2}(-k_1 e^{-k_1 t} + k_2 e^{-k_2 t}) = 0,$$

we obtain

$$t^* = \frac{1}{k_2 - k_1} \ln \frac{k_2}{k_1}. \tag{4}$$

Substituting t^* back in $\mu_2(t)$ we get the PerMIA. Let $\eta = k_2/k_1$. Then for $\eta \neq 1$, we obtain $\mu_2(t^*) = \eta^{\eta/(1-\eta)}$. Similarly for $\eta = 1$, we obtain $t^* = 1/k$ and $\mu_2(t^*) = e^{-1}$. It is easy to show that $\mu_2(t^*)$ is a decreasing function of η. Therefore, for simplicity η can be taken as the performance measure. It can be minimized to obtain the best control factor setting (note that η is a function of $\boldsymbol{X}$).

Suppose the experiments are performed by fixing the reaction time at t_0. Let (Y_{1j}, Y_{2j}, Y_{3j}), $j = 1, \cdots, n$ be the data at some experimental run, where $\sum_{i=1}^{3} Y_{ij} = 1$ for all j. To do the performance measure modeling, we need to estimate the performance measure for each run. The parameters in the Dirichlet distribution can be estimated using maximum likelihood method. Unfortunately there are no explicit expressions for the estimates. They have to be solved numerically. The estimates of Dirichlet parameters can then be substituted into (3) to get the maximum likelihood estimate of $\mu_i(t_0)$. A much easier approach is to use the sample moment estimation. Then, the estimate of $\mu_i(t_0)$ is $\hat{\mu}_i = \sum_{j=1}^{n} Y_{ij}/n$. Eliminating t from (1) and (2) we obtain

$$\hat{\mu}_1^{\eta} - \hat{\mu}_1 = (1 - \eta)\hat{\mu}_2.$$

Thus η is a solution of the function $f(\eta) = \hat{\mu}_1^{\eta} - \hat{\mu}_1 + (\eta - 1)\hat{\mu}_2$. This equation can be solved numerically to obtain the value of η. For this function, $\eta = 1$ is always a solution. It is easy to show that the function has one more solution different from 1 provided $\hat{\mu}_1 \ln \hat{\mu}_1 + \hat{\mu}_2 \neq 0$. Once we obtain η for each experimental run, it can be modeled as a function of the control factors. Let $\hat{\eta}(\boldsymbol{X})$ be the estimated relationship from the experiment. We need one more relationship to implement the adjustment step. We have, from (4) $t^* = \ln \eta/(k_1(\eta - 1))$ and from (1) $k_1 t_0 = -\ln \mu_1(t_0)$. Therefore, define

$$\lambda = \frac{\ln \eta}{(1 - \eta) \ln \hat{\mu}_1},$$

so that $t^* = \lambda t_0$. We can compute λ for each experimental run and model it with respect to $\boldsymbol{X}$. Denote the estimated relationship by $\hat{\lambda}(\boldsymbol{X})$. Now we can perform the following two-step optimization:

1. Find $\boldsymbol{X}^*$ by minimizing $\hat{\eta}(\boldsymbol{X})$.

2. Adjust the time to $t_1 = \hat{\lambda}(\boldsymbol{X}^*)t_0$.

Now consider the experiment given earlier. We obtain $\hat{\mu}_i = Y_i$ for $i = 1, 2, 3$. The performance measures η and λ are evaluated for the three experiments and are given in Table 2. Because there is only one control factor (x) and three data points, it is unnecessary to fit linear regression models for η and λ. We can simply look at Table 2 and pick the best. We see that $x = 10$ is the best setting (because it gives the smallest η). The adjustment step is to increase the time by 61.8% from the existing level (because $\lambda = 1.618$). The mean concentration of B after the optimal time adjustment is also given in the table. The

concentration at $x = 10$ is 0.654 whereas that of $x = 20$ is 0.617. Thus the setting $x = 20$ is not as good as the setting $x = 10$, which could not be realized using Taguchi's SN ratio.

Table 2: Performance Measures

Run	x	$\hat{\mu}_1$	$\hat{\mu}_2$	$\hat{\mu}_3$	η	λ	$\mu_2(t^*)$
1	10	0.3	0.6	0.1	0.218	1.618	0.654
2	15	0.2	0.6	0.2	0.293	1.079	0.602
3	20	0.1	0.6	0.3	0.269	0.780	0.617

Note that t is chosen as an adjustment factor not because it is a factor that affects the location without affecting the dispersion. In fact, it affects both the location and the dispersion. Also t is not selected neither to make the process design flexible nor because it is an easy-to-change factor. Instead, t is selected because we knew its relation with the responses based on the engineering/physical knowledge of the process. Thus, the new perspective given to the adjustment factors was critical behind this application.

If we had not used the reaction time as an adjustment factor, then all the three settings would have deemed identical because all of them have equal values for the concentration of B. We knew the relationship of concentration with t before the experiment itself. We incorporated this knowledge into the modeling and optimization and thus able to find a better process setting. Note that we could have achieved the same results by using t also as an experimental factor. For such an experiment, at least three levels of t should be chosen because of the nonlinearity. Then the number of experiments will be increased to 9, three

times more than used here.

4. Conclusions

In the literature, there are ambiguities regarding the role of an adjustment factor. We tried to clarify that an adjustment factor is a control factor that can be used for adjusting the mean response. The definition of an adjustment factor should not be accompanied by statements such as "a factor that do not affect the dispersion", because given the model and loss function, a performance measure independent of adjustment can be derived using the procedure described in Leon, Shoemaker, and Kacker (1987). We also recommended that whenever possible, an adjustment factor should be selected from those factors which can be related to the response based on the engineering/physical knowledge of the system. Of course, this does not rule out the possibility of identifying an adjustment factor through data analysis, but we stress the importance and advantages of identifying an adjustment factor before the experiment.

The use of engineering knowledge of the system in modeling not only helps in simplifying the experiments but also helps in improving the estimation. For example, the data may suggest a quadratic relationship between the mold dimension and the tile dimension, but by imposing a linear relationship between them, this can be detected as due to the noise in the data. Clearly, such conclusions are valid only if our knowledge of the process is correct.

In the examples presented here and in many of Taguchi's work, the parameters in the model could be efficiently estimated by keeping the adjustment factor at a fixed value. This cannot be done always. In such cases, the adjustment factor also needs to be varied in the

experiment. For examples, see the application of adjustment factors in operating window experiments (Joseph and Wu 2002b) and failure amplification method (Joseph and Wu, 2004). Here, although adjustment factors do not help in simplifying the experiment, they help in improving the estimation of model parameters.

There are cases where one cannot use a factor selected based on engineering knowledge for adjustments. Consider for example a consecutive process in three steps, in which the PerMIA cannot be derived explicitly and thus the two-step procedure cannot be easily implemented. However, it is possible to use the chemical kinetics equations and directly minimize the expected loss. Therefore, although reaction time cannot be used to simplify the optimization, it can be used to simplify the experiment. Thus the idea of using engineering knowledge in experimentation is valuable and much broader than the concept of using adjustment factors. A general strategy for integrating engineering knowledge with experiments needs to be developed which we leave as a topic for future research.

Acknowledgements

The author would like to thank two referees and Tirthankar Dasgupta for their valuable comments and suggestions. The research was supported by the U.S. National Science Foundation grant DMI-0448774.

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