Tuning Parameters in Engineering Design*

Kevin N. Otto†
Erik K. Antonsson‡
Engineering Design Research Laboratory
Division of Engineering and Applied Science
California Institute of Technology

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Abstract

In the design and manufacture of mechanical devices, there are parameters whose values are determined by the manufacturing process in response to errors introduced in the device's manufacture or operating environment. Such parameters are termed *tuning parameters*, and are distinct from *design parameters* which the designer selects values for as a part of the design process. This paper introduces tuning parameters into the design methods of: optimization, Taguchi's method, and the method of imprecision [10]. The details of the mathematical formulation, along with a design example, are presented and discussed. Including tuning parameters in the *design process* can result in designs that are more tolerant of variational noise.

1 Introduction

In the design, development, and manufacture of mechanical devices, parameter values are determined by different mechanisms. The device's geometry, power, etc. are chosen during the design process. However, there are usually variations on these values which are determined by mechanisms such as random manufacturing errors. There are also variations in the device's operating environment which are operator induced. But there are also parameters whose values are set during the manufacturing process in response to the previous variations. We denote these parameters as *tuning parameters*. Though they are common to the practicing industrial engineering community, we have found no formal models which incorporate their behavior.

As an example of a tuning parameter, consider the design of a uni-directional accelerometer, which indicates accelerations above a threshold with a switch closure. It can be modeled as a simple mass spring system, as shown in Figure 1. Under specified accelerations, the accelerometer mass must contact a switch within specified time durations.

*EDRL-TR 91a: Manuscript accepted for publication in the *ASME Journal of Mechanical Design*.
†Graduate Research Assistant
‡Associate Professor of Mechanical Engineering, Mail Code 104-44, Caltech, Pasadena, CA 91125

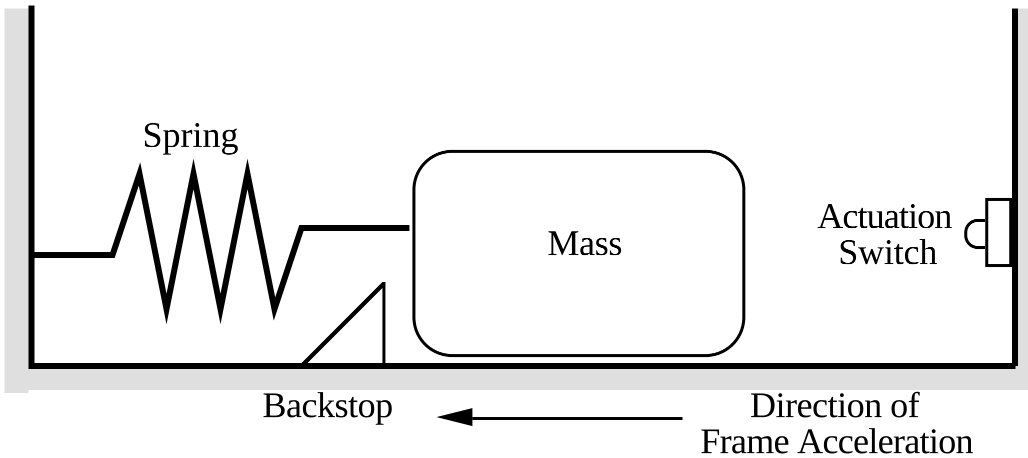

Figure 1: Accelerometer design.

However, suppose the spring is a plate manufactured by a stamping procedure. The inaccuracies introduced by the stamping manifest themselves as an inaccurate value for k, the spring constant. This uncertainty occurs randomly. Hence due to the manufacturing process, it is difficult to set precise actuation times (time for the mass to touch the actuation switch). However, the design has a method to overcome these manufacturing errors in the spring. Specifically, during manufacturing, the backstop of the mass can be adjusted to compensate for variations in k. This backstop positioning distance is a tuning parameter of the design. During manufacture, the spring constant of every accelerometer is measured, and the backstop of each accelerometer is positioned accordingly to meet the specified actuation times.

This example demonstrates what is meant by a tuning parameter. Tuning parameters are also observed in other engineering problems such as: automotive carburetor idle positioning, radio or television signal tuning circuit adjustments, etc. They are characterized by the tuning parameter's ability to compensate for noise.

Note that the term "noise" is used in the sense of Taguchi [8], meaning that there are three types of noise observed: external, internal, and variational. External noise errors are due to environmental fluctuations, such as operating temperatures, humidities, etc. Internal noise errors are inherent in the design, such as wear, storage deterioration of materials, etc. Variational noise errors are due to variations in the supplied materials and manufacturing processes.

Tuning parameters are those which are introduced to overcome the confounding influences of the noise parameters. Tuning parameters are characterized by being set *after* the confounding effects of the noise have occurred. This distinguishes tuning parameters from design parameters, which are set *before* the noise has occurred. Hence design engineers do not set the values of tuning parameters, the manufacturing engineer (or even the customer) sets their values. But when the design parameter values are chosen, the design engineer should take into consideration that a tuning parameter can later be adjusted.

Given such an inherently common concept of engineering, it is surprising that none of the formal techniques of engineering design incorporate tuning parameters. It is the objective of this paper to introduce tuning parameters, and to demonstrate how they can be modeled in various existing formalized methods of engineering design. We will demonstrate how optimization [4], Taguchi's method [1], and the method of imprecision [10, 11] can incorporate tuning parameters.

2 Modeling Tuning Parameters

In addition to tuning parameters, two other types of parameters are used in the design process: design parameters and noise parameters. Design parameters are those for which the designer selects values as a part of the design process. When the design is finished, exact nominal values are specified for design parameters. Noise parameters, on the other hand, confound the ability of the designer to specify nominal values for the design parameters. As stated earlier, noise parameters model uncertainty in the design, they behave randomly. Typically, parameters in a design will have both a design and a noise parameter aspect. That is, a designer will specify a nominal value, and there will be (manufacturing) noise associated with trying to achieve the specified value.

In the design process, the design parameter values are chosen such that the design goals are maximized despite the noise parameter actions. In the accelerometer example, the design parameters (the nominal spring constant K and the mass M) would be chosen such that the desired performance is achieved as often as possible. This is the extent to which formal techniques such as Taguchi's method [1] and probabilistic optimization [6] currently model parameter types: select the design parameter values which maximize the output despite the noise.

With tuning parameters, however, more freedom is provided to the designer. The above techniques choose the design parameters to maximize the output despite the expected noise. Tuning parameters, however, are set after the noise has occurred, and are set to overcome the noise parameters' influences.

Utilizing this observation, we can introduce tuning parameters into three current formal methods of engineering design: optimization, Taguchi's method, and the method of imprecision. The first requirement is to establish (or determine) the order in which the various parameters are fixed. We refer to this order as the *precedence relation* between tuning and noise parameters. This order is important because not all tuning parameters are set before all of the probabilistic noise has occurred.

Consider again the accelerometer design. There were manufacturing errors in the spring constant k which could be overcome by the backstop position tuning. However, if the spring material is sensitive to the operating temperature, k will also vary with the operating temperature. Temperature is another noise parameter. Yet the tuning parameter (backstop positioning) cannot be adjusted to overcome this noise, the backstop is already positioned. All that can be done is to adjust the tuning parameter to maximize the performance across the *expected* temperatures, paralleling what a designer does when selecting design parameters. Hence relative to this component of the noise (temperature), the tuning adjustment is not a tuning parameter, but rather a "design parameter" of the manufacturing engineer. It's value is set (by the manufacturing engineer) to maximize the expected performance over the temperature noise. So the precedence relation in this design is: the manufacturing noise occurs, then the tuning parameter adjustment occurs, and then the temperature noise occurs.

Having made this observation, that the precedence relation must be known among tuning and noise parameters, different formal engineering design methods will now be extended to model tuning parameters. Section 3 will then formalize the accelerometer example to demonstrate tuning parameters.

2.1 Optimization

Consider a single objective function $f(\vec{x}, \vec{p}, \vec{t})$ to be minimized, where $\vec{x}$ are the design parameters, $\vec{p}$ are the noise parameters, and $\vec{t}$ are the tuning parameters. The problem is to choose values for $\vec{x}$ which minimize f, given that there is random noise $\vec{p}$ which varies according to specified probability distributions, and that there are tuning parameters $\vec{t}$ which can be adjusted after the noise has occurred (in their proper precedence). Also, consider constraint equations $\vec{g}(\vec{x}, \vec{p}, \vec{t})$ which all must be less than or equal to zero. This problem is an extended form of a probabilistic non-linear programming problem [6].

To use tuning parameters within optimization, observe that tuning parameter values are determined based on noise parameter values. That is, given values for the noise parameters, a value for each tuning parameter is selected. This can be directly formalized into the following statement. Find:

$$\vec{x}^* = \min_{\vec{x}} \left[\int_{\vec{p}|\vec{x}} \min_{\vec{t}|\vec{x},\vec{p}} \left[f(\vec{x}, \vec{p}, \vec{t}) \right] dPr(\vec{p}|\vec{x}) \right] \tag{1}$$

subject to:

$$Pr\left(\vec{g}(\vec{x}, \vec{p}, \vec{t}) \leq \vec{0} \right) \geq D \tag{2}$$

where the $\vec{x}$, $\vec{p}$, and $\vec{t}$ used to evaluate the constraints $\vec{g}$ are also used simultaneously in evaluating f.

In Equation 1, the inner *min* minimizes the objective function across the tuning parameters: the best tuning parameter arrangement is used. The integral across the noise parameters finds the expected value of the minimized objective function (over the tuning parameters), thus the average case of performance is considered (as in traditional probabilistic optimization [6]). The outer *min* minimizes the expected performance across the design parameters.

In Equation 2, the Pr in the expression of $\vec{g}$ is the probability that any of the constraints are less than or equal to zero (*i.e.*, are satisfied). D is a specified probability requirement to satisfy the constraints. The solution will therefore be the set of design parameters which minimize the expected f and satisfies the constraints D % of the time, given that the tuning parameters can be adjusted. Within the constraint equations $\vec{g}$ will be the bounds on allowable ranges of $\vec{x}$ and $\vec{t}$.

The differences between tuning, noise, and design parameters are as follows. Noise parameters confound the solution, and their modeling requires an expectation process. Design parameters values are selected to minimize the objective function. Tuning parameters, on the other hand, are adjusted to minimize the output after the noise is set. Hence the tuning $\vec{t}$ variation occurs inside the expectation integral across the noise $\vec{p}$. Notice that at the end of the designer's nominal design process, values for $\vec{x}$ have been selected. But values for the tuning parameters $\vec{t}$ have not; this will occur subsequently after the noise has occurred (and will be selected by the manufacturing engineer). But the design engineer has incorporated the fact that the tuning parameters can be adjusted when the selection was made for the design parameters $\vec{x}$. Also notice that there may be environmental or operating noise that occurs after the tuning parameters are set. This is noise for which the tuning parameters cannot compensate, they can only be chosen to minimize the objective function.

Thus, it is not always the case that all of the tuning parameters t_k in the tuning parameter vector $\vec{t}$ will be chosen after the all of the noise parameters p_i in the noise vector $\vec{p}$ have been set. Some p_i will perhaps occur after all of the $\vec{t}$, and hence the expectation across that p_i must occur inside the minimization across $\vec{t}$ as well. In the accelerometer example, the expectation across the temperature effects will occur inside the tuning parameter (backstop positioning) adjustment minimizations. Hence the order among the expectation integrals of $\vec{p}$ and the minimizations of $\vec{t}$ depends on the precedence relation among the variables.

For example, if the precedence relation in a problem was: $\vec{p_1}$ $\vec{t_1}$ $\vec{p_2}$ $\vec{t_2}$ (noise $\vec{p_1}$ is compensated by tuning parameters $\vec{t_1}$, then noise $\vec{p_2}$ occurs and is compensated by $\vec{t_2}$), then first the $\vec{p_1}$ integral would be expressed, within which the $\vec{t_1}$ would be minimized, and likewise for $\vec{p_2}$ and $\vec{t_2}$. The objective function would then be

$$\int_{\vec{p_1}|\vec{x}} \left\{ \min_{\vec{t_1}|\vec{x},\vec{p_1}} \left[\int_{\vec{p_2}|\vec{x},\vec{p_1},\vec{t_1}} \left(\min_{\vec{t_2}|\vec{x},\vec{p_1},\vec{t_1},\vec{p_2}} \left[f(\vec{x},\vec{p},\vec{t}) \right] \right) dPr(\vec{p_2}|\vec{x},\vec{p_1},\vec{t_1}) \right] \right\} dPr(\vec{p_1}|\vec{x}) \quad (3)$$

Notice that the formulation is flexible enough to incorporate any order of noise and tuning.

2.2 Taguchi's Method

Having extended the formulation of probabilistic optimization to include tuning parameters, extending Taguchi's method is also possible. Taguchi's method selects among different design parameters arrangements (DPAs) determined by considering nominal values of a design, and perturbations from these nominal values. The method also considers different noise parameter arrangements (NPAs), and selects the DPA which minimizes variance across the NPAs. See [1] or [5].

The basic Taguchi method selects the DPA defined by:

$$DPA^* = \max_{DPA} \left[-10 \log \left[\sum_{NPA} \left(f(DPA, NPA) - \tau \right)^2 \right] \right] \quad (4)$$

for a design in which an objective f must be maintained as close to τ as possible.

With tuning parameters, however, the output can be maximized after the noise has occurred, or after the NPA has been set. Therefore, Taguchi's method can also be extended by forming a tuning parameter array, similar to the inner array (design parameter array) and outer array (noise parameter array) [1]. The tuning parameter array would list tuning parameter values versus tuning parameter arrangements (TPAs). Then, the extended Taguchi method would select the DPA defined by:

$$\max_{DPA} \left[-10 \log \left[\sum_{NPA} \min_{TPA} \left[\left(f(DPA, NPA, TPA) - \tau \right)^2 \right] \right] \right] \quad (5)$$

The example in Section 3 will be solved using Taguchi's method with tuning parameters, and will demonstrate the method. Note that the order of the summation across the NPAs and the minimization across the TPAs varies according to the precedence relation in the same fashion as with optimization, where the precedence order varied the order of integrations across the p_i and minimizations across the t_k. In Taguchi's method, the precedence relation requirement means that the noise parameters and tuning parameters cannot be simply formed into single arrays. Rather, each must be split into sub-arrays according to the precedence relation.

For example, if the precedence relation in a problem was: $\vec{p}_1$, $\vec{t}_1$, $\vec{p}_2$, $\vec{t}_2$, then first the $\vec{p}_1$ would be formed into an array, with NPAs denoted NPA$_1$, then the $\vec{t}_1$ would be formed into an array, with TPAs denoted TPA$_1$, and likewise for $\vec{p}_2$ and $\vec{t}_2$. The solution would then be the DPA with the maximum of

$$-10\log\left[\sum_{NPA_1}\min_{TPA_1}\left[\sum_{NPA_2}\left(\min_{TPA_2}\left[\left(f(DPA,NPA,TPA)-\tau\right)^2\right]\right)\right]\right] \tag{6}$$

2.3 Method of Imprecision

The method of imprecision determines design parameter values based on maximizing designer preferences (as introduced and developed by Wood and Antonsson [10, 11]). It has a much richer set of modeling capabilities than the two methods previously described, and can model tuning parameters in a more detailed fashion. With the method of imprecision, tuning parameters are modeled as possibilistic uncertainties. Tuning parameters have a range over which they can vary, and any value within that range can be used, yet the designer does not specify their values. This is by definition a possibilistic uncertainty [12]. Further, degrees of possibility can be introduced. That is, not only is a range of possibility given for tuning parameters, but every value within the range is given a normalized rank indicating how possible the value is.

The method of imprecision as a preliminary design methodology is presented in [9, 10, 11]. Design parameters values are ranked, by the designer, as to the degree to which they are preferred. These design parameter preferences are then propagated into preferences on multiple performance parameters. The formalism considers multiple uncertainty forms: imprecision (uncertainty in choice), probability (stochastic uncertainty), and possibility (uncertainty due to freedom). Each uncertainty form is propagated from the design parameters into performance parameter uncertainty via their respective mathematics: imprecision and possibility use the fuzzy mathematics, and probability uses the probabilistic mathematics.

Inclusion of tuning parameters within the formalism requires no modification of the calculation procedures, since tuning parameters are forms of possibilistic uncertainty. Thus the method of imprecision can easily be extended to incorporate tuning parameters. The only change required is a modification of how the results of the calculations are interpreted. The possibilistic uncertainty from tuning parameters is uncertainty which can *improve* the solution, *i.e.*, among the possibilistic variations, the design can use the best among the variation. This is different from basic possibilistic uncertainty (not caused by tuning parameters) which is a possible variation *away* from the nominal.

For example, consider a design which has a possibilistic uncertainty from the tuning parameters which is greater than the probabilistic uncertainty, as shown in Figure 2. The spread of the possibilistic uncertainty π is larger than the spread of the probabilistic uncertainty pdf. Hence no matter what the probabilistic uncertainty, the possibilistic uncertainty can overcome the probabilistic uncertainty. Therefore the designer can confidently use the values of μ.

On the other hand, consider a design where the possibilistic uncertainty from the tuning parameters is less than the probabilistic uncertainty, as shown in Figure 3. The spread of the probabilistic uncertainty pdf is larger than the spread of the possibilistic uncertainty π. Hence no matter how much tuning occurs, there will always be some residual probabilistic uncertainty error remaining. The tuning parameter's range is not sufficient to overcome all the probabilistic error. In this case, the designer can use the values of μ only to within the difference between the probabilistic uncertainty pdf and the tuning parameter's correcting ability π.

3 Example

Consider again the accelerometer design introduced earlier. There is a mass M attached to a spring k attached to the ground. The ground is accelerated. With sufficient acceleration, the mass must displace a specified distance to make contact with a switch. There is also a backstop placed against the mass, to which the spring k pulls against with pre-load P under no acceleration. Refer to Figure 4.

There are two goals in this design: to maintain a specified preload P, and to close the switch in time τ under a specified acceleration. The parameter τ reflects the desired actuation time, and the pre-load P reflects the desired insensitivity to weak accelerations. As a part of these goals, the designer needs to determine whether the design can be made sufficiently tolerant to variational noise to satisfy the customer.

There are two design parameters, mass M and spring constant K. There is, however, uncertainty in the manufacture of the spring: a random variation on K, denoted δk. Finally, to assist in maintaining the targets on the goals, the manufacturing line can position the backstop based on measurements made of the total spring constant ($k = K + \delta k$) of each accelerometer. This backstop distance is denoted x_0, and is a tuning parameter. The switch distance is denoted x_c. The position of the mass at any given time is denoted x. The mass is to make contact with the switch when subjected to acceleration a.

To determine the time to actuate the switch, the differential equation of motion of the mass must be solved. It is:

$$M(\frac{d^2x}{dt^2} + a) \times H(x - x_0) + kx = P \times H(x_0 - x) \tag{7}$$

where H is a step function, $x(0) = x_0$, and $\dot{x}(0) = 0$. This can be solved for the time to actuation:

$$\tau = \sqrt{\frac{M}{k}} \times \arccos\left(\frac{Ma - (x_c - x_0)k}{Ma}\right) \tag{8}$$

This solution assumes, of course, a is sufficiently large to move the mass (i.e., the *arccos* is defined). The other goal is the pre-load P, whose equation is:

$$P = kx_0 \tag{9}$$

Maintaining a specific pre-load helps eliminate spurious switch closures.

3.1 Optimization Solution Formulation

Having formulated the problem, it can now be solved by optimization methods. The problem shall be formulated using an objective function consisting of a weighted sum of the two goals: time to actuation and spring pre-load. Both the target actuation time variation and the target pre-load variation shall be simultaneously minimized, and hence there is a relative coefficient needed between the two goals to ensure the variances are of the same order. The relative weighting coefficient used here was $\sqrt{5}$. Determining weighted sum coefficients is incidental to the tuning parameter formulation, refer to [2, 7] for multi-objective function optimization formulations. Substituting Equations (8) and (9) into (1) produces the problem to be solved as:

$$M^*, K^* = \min_{M,K} \left[\int_{\delta k} \min_{x_0} \left[\frac{|\tau - \tau_s|}{\tau_s} + \sqrt{5} \times \frac{|P - P_s|}{P_s} \right] \times pdf(\delta k) d\delta k \right] \tag{10}$$

subject to:

$$0.0135 \leq x_0 \leq 0.0165 \tag{11}$$

$$0.0125 \leq M \leq 0.0175 \tag{12}$$

$$1.625 \leq K \leq 2.375 \tag{13}$$

where $\tau_s = 5$ milliseconds is a specified actuation time under an acceleration of $a = 20$ g's, $P_s = 0.02$ N is the specified preload under no acceleration. The results of the formulation will be shown below.

3.2 Taguchi's Method Solution Formulation

The problem can also be formulated in a Taguchi method formulation. Consider a 3 factorial design. The inner (design parameter) array is shown in Table 1. The outer (noise parameter) array is shown in Table 2. The tuning parameter array is shown in Table 3. Unfortunately, the experimental matrix cannot be drawn, since it would have to be three dimensional, with the new tuning parameter arrangement dimension.

Substituting Equations (8) and (9) into (5) produces the problem to be solved as:

$$M^*, K^* = \max_{DPA} \left[-10 \log \left[\sum_{NPA} \min_{TPA} \left[\left(\frac{|\tau - \tau_s|}{\tau_s} \right)^2 + 5 \times \left(\frac{|P - P_s|}{P_s} \right)^2 \right] \right] \right] \tag{14}$$

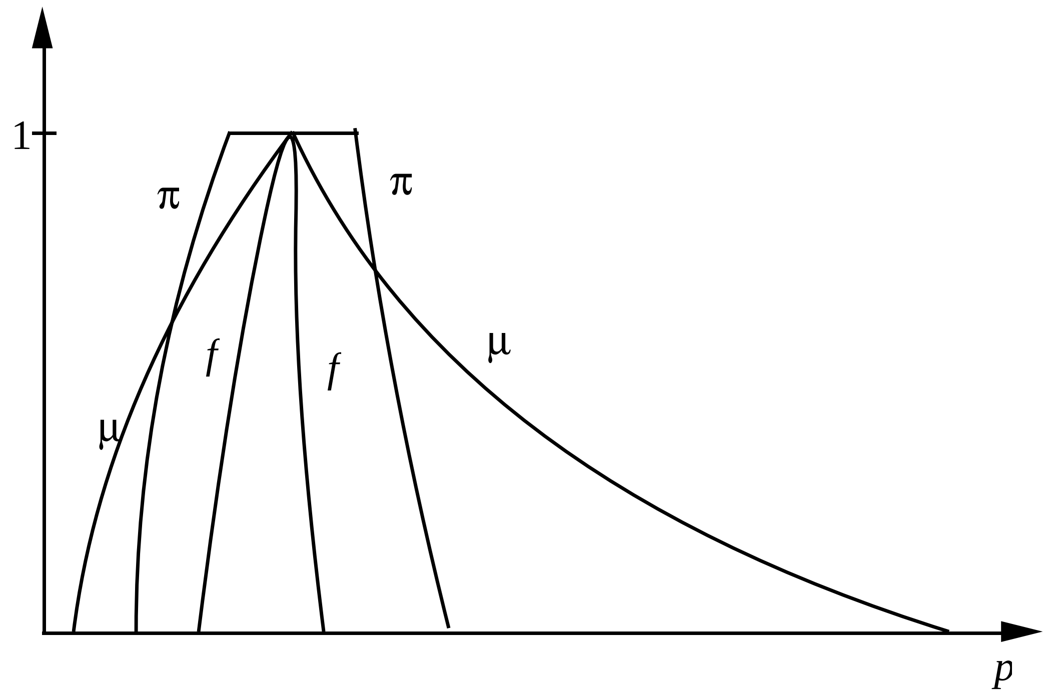

Figure 2: Method of Imprecision: Tuning parameters completely overcome the noise.

	M (kg)	K (N/m)
DPA_1	0.013	1.75
DPA_2	0.013	2.0
DPA_3	0.013	2.25
DPA_4	0.015	1.75
DPA_5	0.015	2.0
DPA_6	0.015	2.25
DPA_7	0.017	1.75
DPA_8	0.017	2.0
DPA_9	0.017	2.25

Table 1: Inner (design parameter) array.

	δk (N/m)
NPA_1	-0.15
NPA_2	0.0
NPA_3	0.15

Table 2: Outer (noise parameter) array.

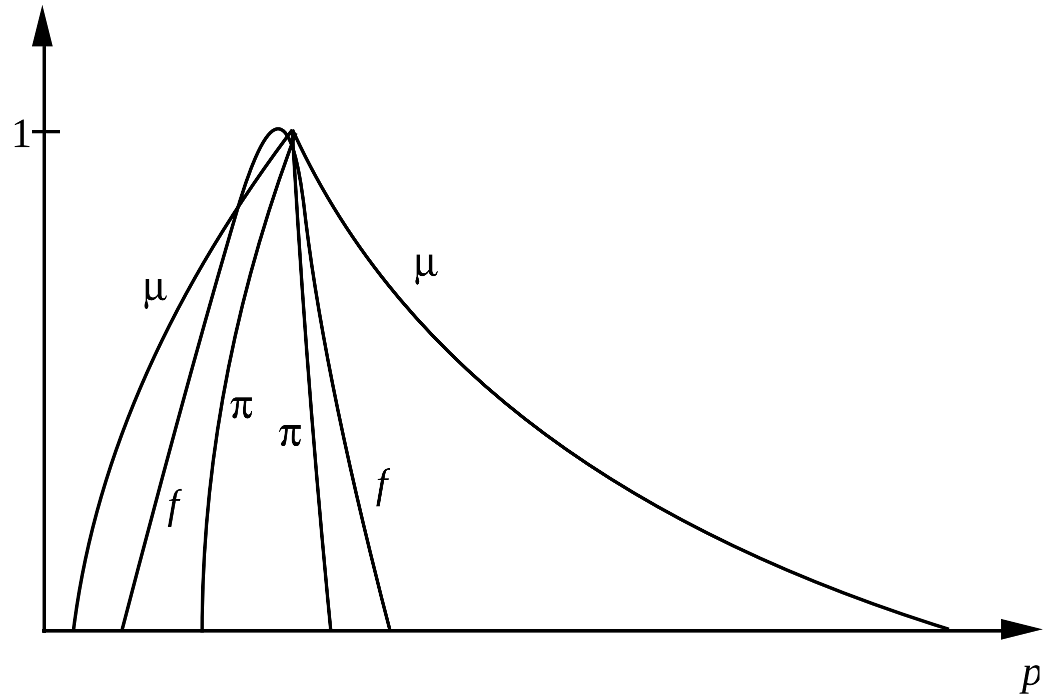

Figure 3: Method of Imprecision: Tuning parameters fail to completely overcome the noise.

	x_0 (m)
TPA_1	0.014
TPA_2	0.015
TPA_3	0.016

Table 3: Tuning parameter array.

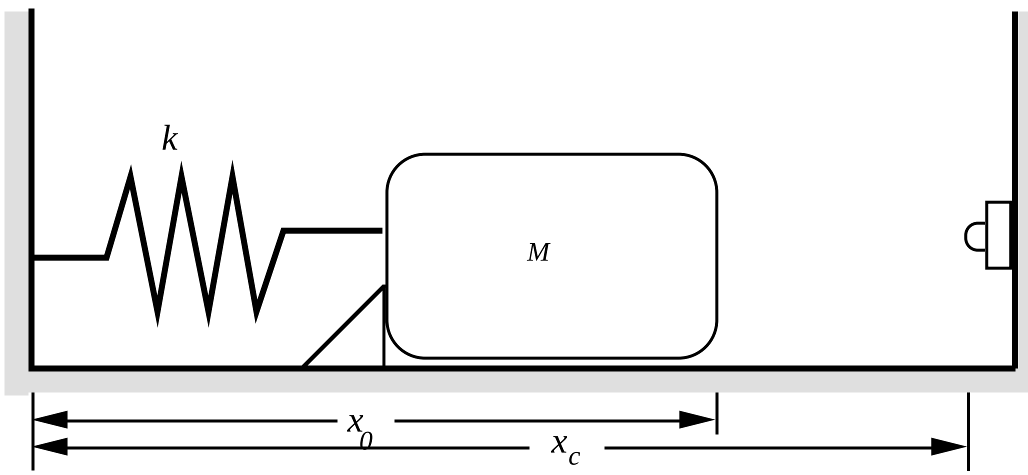

Figure 4: Accelerometer model.

3.3 Modeling without Tuning Parameters

The designer might instead model the backstop position as a design parameter, rather than a tuning parameter. This more traditional formulation will be presented below, and the results will show that the variation in performance (due to the variational noise) will be greater. Substituting Equations (8) and (9) into a traditional probabilistic optimization formulation [6], the model of this problem would be:

$$M^*, K^*, x_0^* = \min_{M,K,x_0} \left[\int_{\delta k} \left(\frac{|\tau - \tau_s|}{\tau_s} + \sqrt{5} \times \frac{|P - P_s|}{P_s} \right) \times pdf(\delta k) d\delta k \right] \tag{15}$$

subject to:

$$0.0135 \leq x_0 \leq 0.0165 \tag{16}$$
$$0.0125 \leq M \leq 0.0175 \tag{17}$$
$$1.625 \leq K \leq 2.375 \tag{18}$$

Similarly, Substituting Equations (8) and (9) into the traditional Taguchi's method formulation (4), the model of this problem would be:

$$M^*, K^*, x_0^* = \max_{DPA} \left[-10 \log \left[\sum_{NPA} \left(\frac{|\tau - \tau_s|}{\tau_s} \right)^2 + 5 \times \left(\frac{|P - P_s|}{P_s} \right)^2 \right] \right] \tag{19}$$

These solutions will be compared with the tuning parameter formulation.

3.4 Results

The solutions for the Taguchi and optimization formulations are shown in Figure 5. Both methods pick the same solution region. This is due to the fact that both use the same multi-objective function (which Taguchi's method simply transformed through a -10*log*).

Taguchi's method picked the closest experimental point to the optimal solution. Different results would have occurred if the optimization formulation used either P or τ as a constraint equation (using the aspiration level), and a single objective function optimization performed. Taguchi's method, of course, cannot incorporate constraint equations [3].

But one additional important question is the tolerance of the device to variational noise. Modeling with tuning parameters allows for more variability in δk, since x_0 can be tuned to keep P and τ on target. Modeling x_0 as a tuning parameter shows that with ± 0.2 N/m variation in δk, the pre-load P was within 0.006 N, and that the time to actuation τ was within 5 milliseconds. A traditional model in which x_0 is treated as a design parameter showed that the pre-load P was within 0.008 N, and that the time to actuation τ was within 6 milliseconds. Therefore a traditional model without tuning parameters results in a needlessly tight tolerance on δk.

4 Conclusion

This paper has introduced a formalization of tuning parameters common in engineering design. Tuning parameters are characterized by being set after the effects of noise have occurred. Tuning parameters are set to overcome these noise effects. The formal models of optimization and Taguchi's method have been extended to include tuning parameters. The method of imprecision inherently incorporates a modeling scheme for tuning parameters (using possibility).

One important observation regarding tuning parameters is that they are not under the direct control of the designer. Their values are, in the case of manufacturing noise, set by the manufacturing engineer. Therefore care must be used by the designer when incorporating tuning parameters into a design model.

In the case of variational noise (noise due to variations in supplied material, manufacturing, etc.), the use of tuning parameters is justifiable – the designer can ensure that tuning will occur, and the assumption of finding the best performance across the tuning parameters' ranges is correct. In the case of external noise (noise due to environmental or user fluctuations) and internal noise (noise due to wear or storage deterioration), the modeling of tuning parameters which can overcome these noises may not be justifiable (in general). The tuning *must* occur for the tuning parameter model to be correct. In the case of a closed loop controller, for example, the control response is a valid tuning parameter. Operator adjustment variables, on the other hand, perhaps should not be modeled as tuning parameters, even though they can be adjusted to increase performance. The designer cannot ensure that tuning will occur. Hence adjustment variables should only be modeled as tuning parameters when the designer is certain the adjustment will occur.

A final point should also be made with respect to modeling tuning parameters in Taguchi's method. Doing so is counter to the Taguchi philosophy, which states that one should eliminate tuning parameters altogether (by proper selection of the design parameters), since these are aspects of tolerancing design [8] and increase cost. This is indeed true; tuning parameters do increase cost. It is almost always the case that the manufacturing process should be kept as simple as possible, *i.e.*, that one should not use tuning parameters. However, if it is known that the design goals cannot be achieved by proper selection of the design parameter values and that tuning parameters will be required, then this fact should be incorporated into

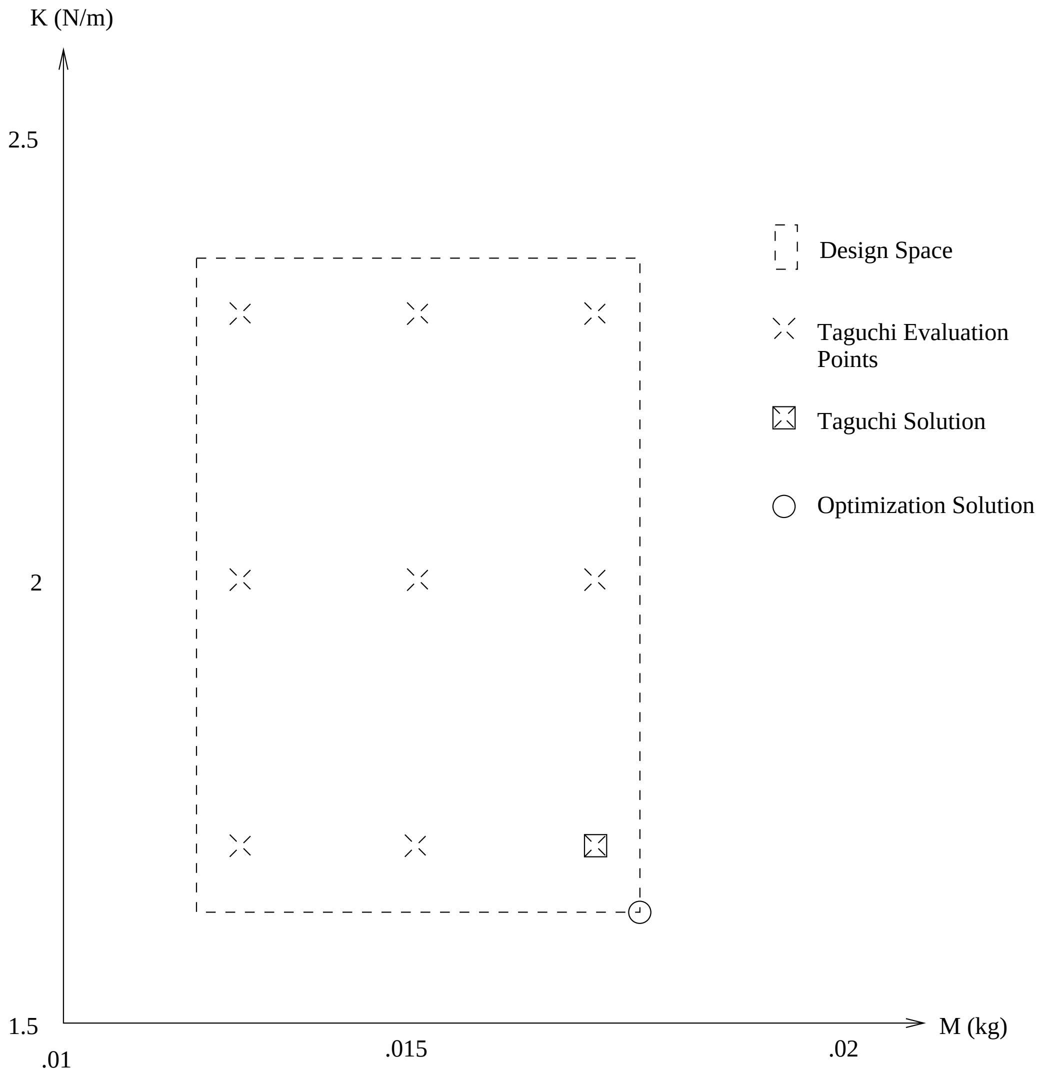

Figure 5: Design space K,M with results from the different solution procedures.

the design process. Doing so can allow for the selection of less expensive design parameters and tolerances, given that the design will be tuned during manufacture. Hence this is a more complete formulation of Taguchi's method, incorporating into the method the effects of tolerancing design on the design parameter selection.

This paper has introduced tuning parameters into formal methods of engineering design. Including tuning parameters in the design process can result in designs that are more tolerant of variational noise.

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