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A Desirability Function Approach to the Robust Design for Multiple Quality Characteristics

호감도함수 접근법을 이용한 다수품질특성치의 강건설계

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Abstract

We often have multiple quality characteristics to develop, improve and optimize industrial processes and products. It is not easy to find optimal control factor setting when there are multiple quality characteristics, since there will be conflict among the selected levels of the control factors for each individual quality characteristic. In this paper we propose a desirability function approach and devise a scheme which gives a systematic way of solving mutiple quality characteristic problems. A numerical example is provided.

1. Introduction

Parameter design, also called robust design, is one of the three design phases wherein the best nominal values of the product or process parameters are determined (Taguchi(1978)). The basic steps of parameter design for identifying optimal settings of design parameters are as follows: (1) identify controllable factors and noise factors, (2) construct the design and noise matrices, (3) conduct the parameter design experiment and evaluate the signal-to-noise(S/N) ratio for each test run of the design matrix, (4) determine new settings of the design parameters using the S/N ratio values, and (5) conduct confirmation experiments (Kackar(1985)).

An assumption implicitly employed in the standard procedure described above is that there exists only one performance or quality characteristic whose mean and variance are simultaneously considered by the S/N ratio in steps (3) and (4). This assumption is not always justified. A common problem in product or process design is the selection of optimal factor levels which essentially involves simultaneous consideration of multiple conflicting quality characteristics. For example, to assemble a connector to a nylon tube in automotive engine components, we have two quality characteristics invloved, namely, assembly effort and pull-off force(Byrne and Taguchi(1987)). Generally, the customers' perception of the quality of a product is determined by multiple performance characteristics (Hauser and Clausing(1988)).

Till now the levels for the control factors have been

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selected in an ad-hoc manner. And there is only one systematic approach based on loss functions in determining the optimal levels of the control factors. Tong(1991) derives a weighted loss function by extending Taguchi's loss function into multiple dimensions assuming that the quality characteristics are not correlated. Pignatiello(1993) develops a more general loss function which considers correlation among characterstics. Recently, Lee(1996) investigates the loss functions suggested by Tong and Pignatiello and proposes a new loss function. In these work, the optimal setting is determined by minimizing the expected loss. This approach is attractive in the sense that it reduces a complicated multiple characteristic problem to a simple univariate optimization problem. However, the responses are expressed in terms of expected loss which includes the controversial cost parameter in the loss function formula. Another difficulty of this approach is that high costs are required to estimate the covariance structure.

The purpose of this paper is to extend Taguchi's parameter design into the multiple quality characteristic case using the desirability function approach and to develop a single aggregate measure of the performance of the multiple quality characteristics based on fuzzy multicriteria optimization method(Yager(1977), Zimmermann(1976), Zimmermann(1978)). The approach proposed in this paper can easily be understood and applied by practitioners. A brief review on the desirability function approach is given in Section 2. In Section 3, using the desirability function approach, a robust design procedure for multiple quality characteristics is proposed. An example from a surface mount technology is provided in Section 4. Section 5 discusses two different types of dimensionality reduction strategies. Finally, summary and concluding remarks are made in Section 6.

2. Desirability Function Approach

Suppose a designed experiment is performed and the value of m quality characteristics $y = (y_1, y_2, ..., y_m)$ is observed at a set of process or design parameters $x = (x_1, x_2, ..., x_p)$. A general multiple response problem can then be defined as

$$y_j = f_j(x_1, x_2, ..., x_p), j = 1, 2, ..., m,$$

where $f = (f_1, f_2, ..., f_m)$ represents the functional relationship between the process or design parameters and responses. The exact form of f is usually unknown, but can be estimated using model building techniques such as regression or response surface methodology.

One popular approach to dealing with multiple characteristics has been the use of a dimensionality reduction strategy, which converts a multiple characteristic problem into one with a single aggregate characteristic and solves it using conventional techniques for a single characteristic problem.

The early work by Harrington (1965) has been extended and applied by a number of authors in conjunction with classical response surface methodology. The desirability function approach first transforms estimated response on each quality characteristic j ($\hat{y}_j$) to a scale-free value d_j, called desirability. d_j is a value between 0 and 1 and increases as the desirability of the corresponding response increases. The individual desirabilities (d_j's) are combined into an overall desirability value D. Then the objective is to find the optimal solution x^* which maximizes the value of D, i.e., the parameter setting which achieves the optimal compromise among multiple quality characteristics. Harrington suggests various types of transformations. As a transformation from individual d_j's to the overall desirability D, Harrington suggests the use of the geometric mean of d_j's, i.e.,

$$D = (d_1 d_2 ... d_m)^{1/m}, \tag{1}$$

and treats it as though it were a measure of a single quality characteristic.

Derringer and Suich(1980) modify Harrington's approach by employing a different transformation scheme from $\hat{y}_j$ to d_j. For a larger-the-better(LTB) type quality characteristic, they consider the transformation given by

$$d_j = \begin{cases} 0, & \hat{y}_j \le y_j^{min}, \\ \left[\dfrac{\hat{y}_j - y_j^{min}}{y_j^{max} - y_j^{min}} \right]^r, & y_j^{min} < \hat{y}_j < y_j^{max}, \\ 1, & \hat{y}_j \ge y_j^{max}, \end{cases} \qquad (2)$$

where y_j^{min} and y_j^{max} denote the minimum acceptable value and the highest value of $\hat{y}_j$, respectively. The value of r, specified by the user, would indicate the degree of stringency of the characteristic. A larger value of r is used to make the desirability curve steeper if it is very desirable for $\hat{y}_j$ to be close to y_j^{max}. Eq. (2) can be easily modified for the smaller-the-better(STB) or nominal-the-best(NTB) type quality characteristics. Once D is constructed using individual d_j's as in (1), they employ an existing univariate search technique to maximize D over the process parameter (x) domain. Later, Derringer(1994) modifies the overall desirability function D. The new form of D is still based on the concept of a (weighted) geometric mean;

$$D = \left[d_1^{w_1} d_2^{w_2} \dots d_m^{w_m} \right]^{1/\sum w_j}, \qquad (3)$$

where w_j's are relative weights among m quality characteristics, j = 1, 2, ..., m. If all w_j's are set to 1, (3) is reduced to (1).

Harrington(1965) argues that the individual d_j can and should be self-weighting, which is manifested by the larger (or smaller) value of r for more (or less) important quality characteristic in (2). On the other hand, Derringer (1994) uses a different approach by incorporating the weights directly in the functional form of D, as given in (3). This would reduce the cognitive burden required on users by separating the weights from the shape of desirability functions. However, the value of D given in (3) still does not allow a clear interpretation, except the principle that a higher value of D is preferred. As an example, if the overall desirability D at x_1 ($D(x_1)$) is higher than D at x_2 ($D(x_2)$), then x_1 is considered a better design point than x_2, but it is generally impossible to assign a physical meaning to the desirability values $D(x_1)$ and $D(x_2)$ as well as the difference $D(x_1) - D(x_2)$.

3. Robust Design for Multiple Characteristics Using Desirability Function Approach

A robust design procedure for multiple characteristics is proposed in this Section. Suppose there are m quality characteristics, n control factor level combinations, and q noise level combinations for each of the n control factor level combinations. y_{ijk}(i=1, 2, ⋯, n; j=1, 2, ⋯, m; k=1, 2, ⋯, q) denotes the response value of the j-th quality characteristic obtained at the i-th factor level combination and the k-th noise level combination. For example, the matrix of the response values for the first factor level combination can be described as

$$\begin{bmatrix} y_{111} & y_{112} & \cdots & y_{11q} \\ y_{121} & y_{122} & \cdots & y_{12q} \\ \vdots & \vdots & \ddots & \vdots \\ y_{1m1} & y_{1m2} & \cdots & y_{1mq} \end{bmatrix} \qquad (4)$$

where the row denotes the quality characteristic and the column denotes the noise level. From this matrix we can calculate a matrix of individual desirabilities using desirability functions as

$$\begin{bmatrix} d_{111} & d_{112} & \cdots & d_{11q} \\ d_{121} & d_{122} & \cdots & d_{12q} \\ \vdots & \vdots & \ddots & \vdots \\ d_{1m1} & d_{1m2} & \cdots & d_{1mq} \end{bmatrix} \qquad (5)$$

To calculate an individual desirability d_{ijk} we use a linear transformation of y_{ijk}. We can see that d_{ijk} is more meaningful than y_{ijk}, since it incoporates the boundary conditions of each quality characteristic as shown in the Eqs.(6)-(8). For the LTB case, the individual desirability is given by

$$d_{ijk}=\begin{cases} 0, & y_{ijk} \le y_j^{min}, \\ \dfrac{y_{ijk}-y_j^{min}}{y_j^{max}-y_j^{min}}, & y_j^{min} < y_{ijk} < y_j^{max}, \\ 1, & y_{ijk} \ge y_j^{max}, \end{cases} \qquad (6)$$

and for the STB case,

$$d_{ijk}=\begin{cases} 0, & y_{ijk} \ge y_j^{max}, \\ \dfrac{y_j^{max}-y_{ijk}}{y_j^{max}-y_j^{min}}, & y_j^{max} > y_{ijk} > y_j^{min}, \\ 1, & y_{ijk} \le y_j^{min}. \end{cases} \qquad (7)$$

When the quality characteristic is the NTB type, d_{ijk} is given by

$$d_{ijk}=\begin{cases} 0, & y_{ijk} \ge y_j^{max} \text{ or } y_{ijk} \le y_j^{min}, \\ \dfrac{y_j^{max}-y_{ijk}}{y_j^{max}-T_j}, & y_j^{max} > y_{ijk} \ge T_j, \\ \dfrac{y_{ijk}-y_j^{min}}{T_j-y_j^{min}}, & T_j \ge y_{ijk} > y_j^{min}. \end{cases} \qquad (8)$$

In Eq.(8), T_j is the target value of the j-th quality characteristic. Desirability functions for the three types of quality characteristics are depicted in Figure 1.

From the k-th column of the matrix in (5) we can calculate the overall desirability of the k-th noise level for the first factor level combination as

$$D_{1k}=\min_{1\le j\le m}\left\{ d_{1jk}^{w_j} \right\}, \qquad (9)$$

where w_j is the relative importance of the j-th characteristic satisfying $\sum_{j=1}^{m} w_j = m$. Depending on the design situation, we can use another type of the overall desirability measure, which is discussed later in Section 5. For the first factor level combination we can have a row vector with overall desirabilities as

$$(D_{11}, D_{12}, \ldots, D_{1q}) \qquad (10)$$

Similarly we can have row vectors like (10) for the other control factor level combinations. A matrix of the overall desirabilities can then be given by

$$D = \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1q} \\ D_{21} & D_{22} & \cdots & D_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ D_{n1} & D_{n2} & \cdots & D_{nq} \end{bmatrix} \qquad (11)$$

From the matrix D we can have a performance measure for each factor level combination. In this paper, the classical S/N ratio is used as the performance measure. However, any other kind of performance measure can be employed as appropriate without additional effort or complication. (For a discussion on the proper use of Taguchi's S/N ratio and other performance statistics, see Nair(1992)).

Since each overall desirability values are bounded by $0 \le D_{ik} \le 1$, we adopt an S/N ratio as given by Eq. (12) which is a modification of the S/N ratio used for fraction defective (Phadke(1989), Taguchi(1987));

$$SN_i = -10\log_{10}\left\{ \frac{1}{q-1}\sum_{k=1}^{q}\left(\frac{1-D_{ik}}{D_{ik}}\right)^2 \right\}. \qquad (12)$$

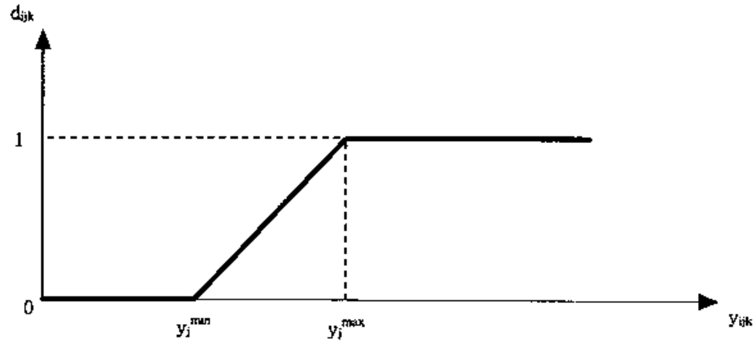
In Eq.(12), when $D_{ik} = 0$, we can replace 0 by a very small value like 10^{-5}, which makes the SN_i to have a very low value. Then the procedure of analyzing multiple characteristics data is as follows.

<u>Step 1</u> Calculate individual desirability d_{ijk} from the multiple characteristics data y_{ijk}, i=1, 2, ..., n, j=1, 2, ..., m, k=1, 2, ..., q.

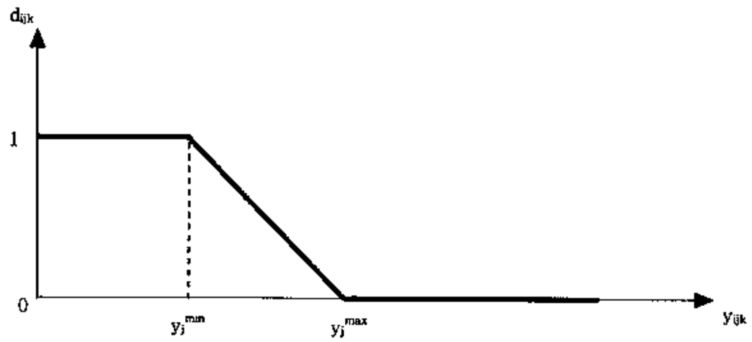
<u>Step 2</u> For the i-th control factor level combination and k-th noise level combination, obtain the overall desirability D_{ik} as follows:

$$D_{ik} = \min_{1\le j\le m}\left\{ d_{ijk}^{w_j} \right\},$$

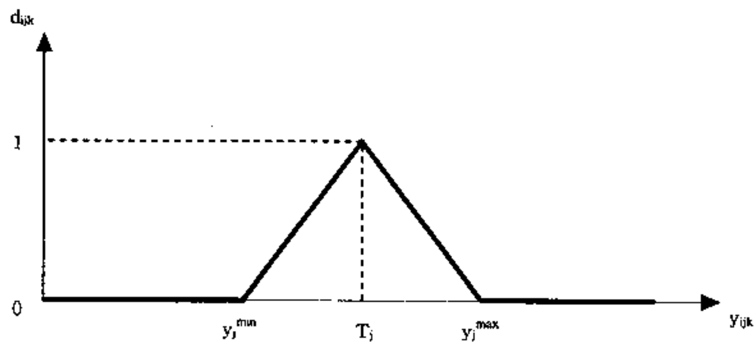
i=1, 2, ..., n, k=1, 2, ..., q,



(a) Larger-the-better case



(b) Smaller-the-better case



(c) Nominal-the-best case

Figure 1. Desirability Functions

where w_j is the relative importance of the j-th characteristic, and w_j's are scaled so that $\sum_{j=1}^{m} w_j = m$.

Step 3 Calculate S/N ratios using Eq.(12).

Step 4 Estimate the effect of each control factor on the S/N ratio. Identify important control factors on the S/N ratio, and determine the optimal levels of the factors.

Step 5 Conduct confirmation experiments and plan future actions.

In Step 2, the relative importance values of multiple characteristics can be assessed by simply assigning weights directly or by using an eigenvector method which is widely used weight elicitation method among practitioners (Yager(1977)).

4. An Example

A double-sided surface mount technology(SMT) for electronic assembly operation was studied by Peace(1993). Solder paste is screened onto the pads on the top side of the circuit board for placement of components. Glue is applied to the bottom side for attaching electronic components. Prior to entering the infrared reflow stage, solder paste screening on the top side is checked by weighing the assemblies and measuring solder paste height. A pull force test is also performed on the bottom side of the circuit board to check glue adhesion. Three quality characteristics are considered: solder paste weight (y_1), solder paste height (y_2), and glue torque (y_3). y_1 and y_2 are NTB type with target values 4.2 and 10, respectively. y_3 is LTB type. Minimum acceptable values and highest values of each characteristics are assumed to be

$$y_1^{min} = 1.7, \quad y_1^{max} = 6.7,$$
$$y_2^{min} = 5, \quad y_2^{max} = 15,$$
$$y_3^{min} = 10, \quad y_3^{max} = 20.$$

$L_8(2^7)$ orthogonal array is used for the control factors. This array is crossed with a 2^2 factorial design for two noise factors. The full experimental design and the observed values of the quality characteristics are reproduced in Table 1.

Using Eqs.(6) and (8), individual desirabilities are computed and given in Table 2. Overall desirabilities and S/N ratios are also computed and given in the last two columns of Table 2. To compute the overall desirabilities, the relative importances of the quality characteristics are assumed to be equal, that is $w_1 = w_2 = w_3 = 1$. Later in this section, we will present the results of sensitivity analysis in terms of the relative importances of the characteristics.

The control factor effects on the S/N ratio are summarized in Table 3 and the half-normal probability plot of these effects are shown in Figure 2. From the figure, we can see that factors A, C, and D have significant effect on the S/N ratio, while the effects of the other factors are only negligible. Optimal design setting is $A_1C_1D_2$.

We see that the optimal design setting is $A_1C_1D_2$, when $w_1 = w_2 = w_3 = 1$. To see the influence of the relative importance of the three quality characteristics, i. e., solder paste weight, solder paste height, and glue torque, we investigate the effects of different values of w_1, w_2, and w_3 on the optimal design setting. Since glue torque is supposed to be more important than the other two charateristics, we perform sensitivity analysis using the following values of w_1, w_2, and w_3:

$$w_1 : w_2 : w_3 = 1 : 1 : \alpha$$
$$w_1 + w_2 + w_3 = 3$$

which are equivalent to

$$w_1 = \frac{3}{2+\alpha},\ w_2 = \frac{3}{2+\alpha},\ w_3 = \frac{3\alpha}{2+\alpha},$$

Table 1. Double-Sided SMT Assembly Experiment(Peace(1993))

Experimental Run#								Solder Paste Weight*				Solder Paste Height*				Glue Torque*			
								M_1**		M_2		M_1		M_2		M.		M_2	
	A	B	A×B	C	D	E	F	N_1**	N_2	N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2
1	1	1	1	1	1	1	1	4.15	3.42	3.95	3.80	11.00	10.62	8.85	11.00	15.90	12.95	11.60	13.55
2	1	1	1	2	2	2	2	4.13	4.46	4.13	3.33	9.23	9.56	9.23	7.73	15.33	13.66	13.50	10.70
3	1	2	2	1	1	2	2	3.15	3.12	2.97	2.02	11.28	11.58	9.13	9.78	15.02	13.29	10.74	10.39
4	1	2	2	2	2	1	1	2.99	2.29	2.63	2.64	11.15	10.80	11.15	11.15	16.55	13.60	14.70	14.20
5	2	1	2	1	2	1	2	4.22	4.52	4.87	4.07	11.97	11.92	12.27	10.77	19.35	19.70	20.80	18.00
6	2	1	2	2	1	2	1	5.74	6.73	6.53	6.38	8.90	9.55	7.05	9.20	18.48	20.11	17.46	19.41
7	2	2	1	1	2	2	1	4.72	5.70	5.35	5.35	13.19	13.84	13.49	13.49	20.95	22.58	22.38	21.88
8	2	2	1	2	1	1	2	3.27	3.57	4.07	3.12	5.72	5.67	3.87	4.52	12.92	13.27	11.92	11.57

* quality characteristics

** noise factors

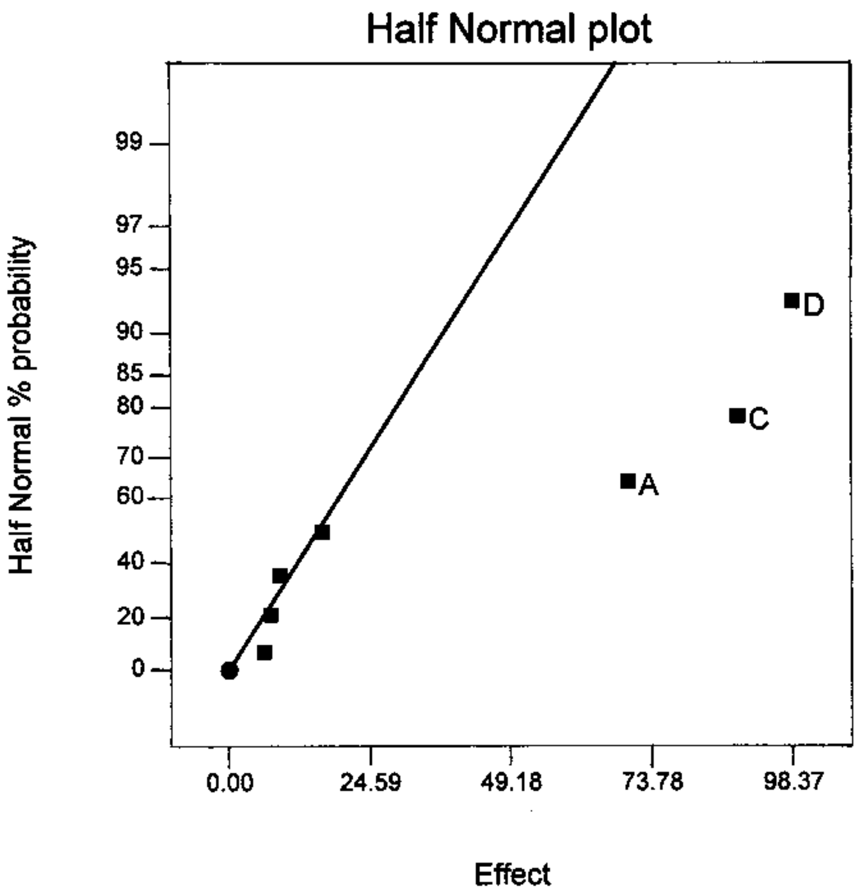


Figure 2. Half-Normal Probability Plot

Table 2. Double-Sided SMT Assembly Experiment: Individual Desirabilities, Overall Desirabilities and S/N Ratios

Level	Noise level*	Weight	Height	Torque	D_{ik}	SN_i
1	1	0.980	0.800	0.590	0.590	-10.918
	2	0.688	0.876	0.295	0.295	
	3	0.900	0.770	0.160	0.160	
	4	0.840	0.800	0.355	0.355	
2	1	0.972	0.846	0.533	0.533	-17.871
	2	0.896	0.912	0.366	0.366	
	3	0.972	0.846	0.350	0.350	
	4	0.652	0.546	0.070	0.070	
3	1	0.580	0.744	0.502	0.502	-24.088
	2	0.568	0.684	0.329	0.329	
	3	0.508	0.826	0.074	0.074	
	4	0.128	0.956	0.039	0.039	
4	1	0.516	0.770	0.655	0.516	-7.524
	2	0.236	0.840	0.360	0.236	
	3	0.372	0.770	0.470	0.372	
	4	0.376	0.770	0.420	0.376	
5	1	0.992	0.606	0.935	0.606	2.825
	2	0.872	0.616	0.970	0.616	
	3	0.732	0.546	1	0.546	
	4	0.948	0.846	0.800	0.800	
6	1	0.384	0.780	0.848	0.384	-95.229
	2	0	0.910	1	0	
	3	0.068	0.410	0.746	0.068	
	4	0.128	0.840	0.941	0.128	
7	1	0.792	0.362	1	0.362	-9.164
	2	0.400	0.232	1	0.232	
	3	0.540	0.302	1	0.302	
	4	0.540	0.302	1	0.302	
8	1	0.628	0.144	0.292	0.144	-98.239
	2	0.748	0.134	0.327	0.134	
	3	0.948	0	0.192	0	
	4	0.568	0	0.157	0	

* Noise level : 1=M_1N_1, 2=M_1N_2, 3=M_2N_1, 4=M_2N_2

for α = 1.1, 1.2, . . ., 4.0. $A_1C_1D_2$ continues to be optimal until α = 1.8. When $\alpha > 1.8$, the factor A becomes insignificant and the optimal setting is C_1D_2.

Table 3. Factor Effects on the S/N Ratio

Level	A	B	A×B	C	D	E	F
1	-15.100	-30.298	-34.048	-10.336	-57.118	-28.464	-30.709
2	-49.952	-34.754	-31.004	-54.716	-7.933	-36.588	-34.343
Effect	-34.852	-4.456	3.044	-44.380	49.185	-8.124	-3.634

5. Discussion

In Section 3, we employ D_{ik} as a measure of the overall desirability. We see that D_{ik} is the minimum value of the individual desirabilities of the q the noise level combinations at the i-th factor level combination. For the evaluation of the overall desirability, we can also employ another type of measure which is based on the weighted mean of the individual desirabilities (Keeney and Raiffa (1976)):

$$V_{ik}=\sum_{j=1}^{m} w_j d_{ijk},\ i = 1, 2, \ldots, n,\ k=1, 2, \ldots, q. \tag{13}$$

Here again, w_j is the relative importance of the j-th quality characteristic satisfying $\sum_{j=1}^{m} w_j = m$.

D_{ik} is a noncompensatory overall desirability measure in the sense that a low desirability value in one quality characteristic cannot be offset by a high desirability in some other characteristic. However, V_{ik} is a compensatory measure meaning that it allows desirability tradeoffs among charateristics. The choice between two measures depends on the specific design situation. In general, D_{ik} is useful in the early design stage where it is crucial to screen out low-performing design points. V_{ik} is a good choice in a situation where a poor performance in one quality characteristic can be compensated by other characteristics with high performance. V_{ik} would be preferred in later design stage or for the improvement of current manufacturing process where the quality of the product or process is perceived by its totality as an holistic system rather than by the performance of each individual characteristic.

6. Summary and Concluding Remarks

A common problem in product or process design is to determine the optimal parameter setting when there exist multiple quality characteristics, which may be conflicting with each other. Most of the work on parameter design so far, however, has been concerned with the single quality characteristic case. This paper extends Taguchi's parameter design into the multiple quality characteristic case using the desirability function approach. We perform a linear transformation of the original quality characteristic value to obtain an individual desirability. The individual desirability is more meaningful than the original characteristic value, since it incoporates the boundary conditions of each quality characteristic. An example from a double-sided surface mount technology(SMT) for electronic assembly operation is also included.

The experimental and computational procedure of our approach is virtually unaffected by the number of quality characteristics considered. Moreover, our approach can easily accommodate any combination of larger-the-better, smaller-the-better, or nominal-the-best type characteristics.

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