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SIMULTANEOUS OPTIMIZATION OF ROBUST DESIGN WITH QUANTITATIVE AND ORDINAL DATA

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The Taguchi method traditionally focused on one quality characteristic to optimize the control factor settings, yet most products have more than one quality characteristic. Several studies have presented approaches optimizing the multiple quantitative quality characteristics design. Due to the inherent nature of the quality characteristic or the convenience of the measurement technique and cost-effectiveness, the data observed in many experiments are ordinal data. Few published articles have focused primarily on optimizing the multiple quality characteristics involving quantitative and ordinal data. This paper presents a simple approach to optimizing this problem based on the quality loss function. A numerical example of the polysilicon deposition process for minimizing surface defects and achieving the target thickness in a very large-scale integrated circuit can demonstrate the proposed approach's effectiveness.

Significance: The experimental data of robust design may simultaneously include quantitative and ordinal data. This article presents an effective method to optimize such problem.

Keywords: Taguchi method, Multiple quality characteristics, Quantitative data, Ordinal data, Quality loss function.

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1. INTRODUCTION

Many industries have employed the Taguchi method over the years to improve product or process performance. In confronting a product or process with multiple quality characteristics, it is difficult to determine the optimal control factor settings for each of the quality characteristics, as each usually varies according to different combinations of control factor settings. The choice of quality characteristic often plays an important role in robust design. To choose quantitative (continuous) variables as quality characteristics and try to use the appropriate measurement technique are the guidelines for selecting quality characteristics. However, data observed in many experiments are ordinal (ordered categorical) data owing to the quality characteristics or the convenience of the measurement technique and cost-effectiveness. For example, in the attachment of rubber gaskets to the body portion of automobile hood hinges, the rubber gasket was glued to the hinge with a contact adhesive. The defects were classified into five categories: gasket melted, gasket slightly melted, target (adhesion to both sides and no melting), adhesion to one side only and no adhesion. When the experimental responses involve quantitative and ordinal data, an appropriate and efficient method has rarely been proposed to optimize such problem. In this paper, a quality loss-based approach is proposed to optimize the multiple quality characteristics design involving quantitative and ordinal data.

This paper is organized as follows: Section 2 reviews literature related to the optimization of multiple quantitative quality characteristics or ordinal data; Section 3 defines the average quality loss for quantitative and ordinal data and proposes a parameter design optimization procedure; Section 4 provides an illustrative example to demonstrate the proposed approach's effectiveness. A numerical analysis of the model is provided and the results are compared with those of prior approaches; Section 5 contains the conclusions of this paper.

2. LITERATURE REVIEW

Several publications reveal approaches for addressing multiple quantitative quality characteristics. Derringer and Suich (1980) proposed desirability function models, which turned the multiple quality characteristics into a single characteristic problem by maximizing the combined desirability. Khuri and Conlon (1981) used the distance function based on a polynomial regression model to optimize the multiple quality characteristics. Logothetis and Haigh (1988) presented a two-stage procedure for optimizing multiple quality characteristics. The multiple regression and linear programming are employed in their procedure. Pignatiello (1993) derived the expression of expected loss function to minimize the function for the multiple quality characteristics. Elsayed and Chen (1993) provided a multiple characteristics model based on the loss function, which is similar to Pignatiello's approach. Su and Tong (1997) presented an approach based on the principal component analysis. Tong and Su (1997) also employed the Fuzzy theorem to optimize the parameter design. Tong, Su and Wang (1997) presented an approach to standardizing the loss of each characteristic by setting standardization values between 0 and 1. Chen (1997) built a multiple quality characteristics model based on the SN ratio instead of the quality loss function. He transformed each SN ratio into a commensurable value between 0 and 1 to represent the designers' degree of satisfaction with each quality characteristic. Vining (1998) proposed a compromise approach based on the distance function to optimizing the multiple quality characteristics problem. Tsui (1999) extended Pignatiello's approach and created a new model, which is more complex in computation than Pignatiello's approach. Chiao and Hamada (2001) considered experiments with correlated multiple quality characteristics and then proposed a multiple polynomial regression model to optimize this problem. In this model, they did not consider the loss coefficient of a single characteristic and correlated loss coefficient between two characteristics. Lu and Antony (2002) used a fuzzy-rule based inference system to optimize the multiple quality characteristics design. Wu and Chyu (2004) proposed a mathematical programming model to optimize the correlated multiple quality characteristics with asymmetric loss function.

To analyze the ordinal data, Taguchi (1991) primarily developed the accumulation analysis method to optimize the factor settings. The AA method consists of three steps for determining the optimal control factor settings in the case of ordinal data. The first step is to define the corresponding cumulative categories. The second step is to determine the effects of the factor levels on the probability distribution by the categories. Finally, the optimal control factor settings are determined by the desired cumulative category. The drawback of the accumulation analysis method is that it detects only the location effects and comments about the accumulation analysis method can be found in Agresti (1986), Box and Jones (1986), Hamada and Wu (1986), McCullagh (1986), Hamada and Wu (1990), Koch et al. (1990). Nair (1986) presented two scoring schemes (SS) to identify the location and dispersion effects separately. An investigation recommended using the mean square to identify a prominent effect. The optimal factor settings of location and dispersion effects can be obtained by the contribution of both effects of each control factor. The final optimal factor settings are obtained by adjusting between the location and dispersion effects. Jeng and Guo (1996) proposed a weighted probability-scoring scheme (WPSS) to avoid the computational complexity of Nair's scoring scheme. The location and dispersion effects were merged into a single mean square deviation. The expected mean square deviation for each category can be obtained according to the definition of the categories. The optimal factor settings are then obtained by selecting the minimum mean square deviation. Chipman and Hamada (1996) proposed a Bayesian model for the ordinal data. They employed the combination of a generalized linear model (GLM) with Bayesian estimation techniques to optimize the factor settings. The computational complexity is more than that of Nair's scoring scheme. Hsieh and Tong (2001) presented an approach based on artificial neural network to optimizing the multiple quantitative and qualitative characteristics; unfortunately this method is difficult to be employed to industries.

3. AVERAGE QUALITY LOSS FOR QUANTITATIVE AND ORDINAL DATA

Taguchi (1991) gives the following definitions for the average quality loss when n units of a product are measured.

$$\overline{L(y)} = \begin{cases} k \cdot \left(\dfrac{1}{n} \sum_{i=1}^{n} y_i^2 \right) & \text{for Smaller-the-Better Characteristic} \\ k\mu_0^2 \cdot \left(\dfrac{s^2}{\bar{y}^2} \right) & \text{for Nominal-the-Best Characteristic (after adjustment)} \\ k \cdot \left(\dfrac{1}{n} \sum_{i=1}^{n} \dfrac{1}{y_i^2} \right) & \text{for Larger-the-Better Characteristic} \end{cases} \quad \cdots \quad (1)$$

Figure 1: Percentage employment of working-age people (ages 21-64) categorized by the disability status in US

where k is quality loss coefficient, y_i is a measurable statistic of quality characteristic, μ_0 is the target value for nominal-the-best characteristic, $\bar{y}$ is the sample mean of n units and $s^2 = \sum_{i=1}^{n} \left(y_i - \bar{y} \right)^2 \Big/ (n-1)$ is the unbiased estimator of process variance (σ^2).

According to the concept of Taguchi's quality loss function, a weighted average quality loss was defined for ordinal data. Suppose that the assigned weight for each category is proportional to the quality loss and then the ordinal data can be treated as continuous variables. Let f_{ij}, j=1, 2,…, J, be the observed frequency of the jth category for the ith run. The determined weight (ω_j , j=1, 2,…, J) according to the defined categories is the lower bound of each category. The weighted average quality loss for ordinal data is defined by

$$\overline{L(y)} = k \cdot \left(\frac{1}{n} \sum_{j=1}^{J} \omega_j^2 f_{ij} \right) \quad \dots \quad (2)$$

The proposed optimization approach for multiple quality characteristics with quantitative and ordinal data is given in the following steps:

Step 1: Compute the total average quality loss, Q, for each experiment combinations based on the additive model.
Step 2: Transform the Q into the Signal-to-noise ratio (SNR), η, in decibels by the following equation.

$$\eta = -10 \log_{10} Q \quad \dots \quad (3)$$

Step 3: Evaluate the effects of the control factors under consideration on η. The optimal factor settings are obtained by selecting the maximum η.

4. ILLUSTRATIVE EXAMPLE

The effectiveness of the proposed optimization approach is shown in this section by using the case of polysilicon deposition process, which was described by Phadke (1989). The experimental data set for manufacturing VLSI circuits for optimal parameter design of the polysilicon deposition process is tested. The control factors are deposition temperature (factor A), deposition pressure (factor B), nitrogen flow (factor C), silane flow (factor D), setting time (factor E) and cleaning method (factor F), each factor has 3 alternate levels and are listed in Table 1.

Table 1. Control factors and their levels of polysilicon deposition process

Factor \ Levels	1	2	3
A. Deposition temperature (□)	T_0-25	T_0	T_0+25
B. Deposition pressure (mttor)	P_0-200	P_0	P_0+200
C. Nitrogen flow (sccm)	N_0	N_0-150	N_0-75
D. Silane flow (sccm)	S_0-100	S_0-50	S_0
E. Setting time (min)	t_0	t_0+8	t_0+16
F. Cleaning method	None	CM_2	CM_3

There are three quality characteristics for this polysilicon deposition process. The first is surface defects (smaller-the-better type), and the surface defect count should not exceed 10 per square centimeter. The second is thickness (nominal-the-best type) with target value of 3600 Å, and the specifications are that the thickness should be within ± 8% of the target thickness. The third is deposition rate (larger-the-better type). In this case, the thickness can use the deposition time needed to achieve the target value of 3600 Å. The deposition time was a scaling factor, that is, for every surface area where polysilicon was deposited, (thickness) = (deposition rate)×(deposition time). Hence, there are only two quality characteristics to be considered in this process: surface defects and thickness. An L_{18} orthogonal array was used and the factors were assigned to column 2, 3, 4, 5, 6 and 8. The starting condition is $A_2B_2C_1D_3E_1F_1$. The assignment of control factors is shown in Table 2 and the experimental data is shown in Table 3~4.

Suppose, due to the inconvenience of counting the number of surface defects, the experimenters had decides to record the data in the following subjective categories, list in progressive undesirable order: practically no surface defects, very few defects, some defects, many defects, and to many defects. Take the observations form Table 3 listed in Table 5 and associate with them categories I through V as follows:

I : 0 — 3 defects
II : 4 — 30 defects
III : 31 — 300 defects
IV : 301 — 1000 defects
V : 1001 and more defects

Hence, the determined weights according to the lower bound of each defined category are 0, 4, 31, 301 and 1,001 for categories I through V, respectively. The number of observations in the categories for the eighteen experiments is listed in Table 5.

Table 2. L_{18} orthogonal array and factor assignment

Expt. No.	Column Numbers and Factor Assignment							
	1	2	3	4	5	6	7	8
	e	A	B	C	D	E	*e*	F
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

Table 3. Surface defect data (defect/unit area)

Expt. No.	Surface Defect								
1	1	0	1	2	0	0	1	1	0
2	1	2	8	180	5	0	126	3	1
3	3	35	106	360	38	135	315	50	180
4	6	15	6	17	20	16	15	40	18
5	1720	1980	2000	487	810	400	2020	360	13
6	135	360	1620	2430	207	2	2500	270	35
7	360	810	1215	1620	117	30	1800	720	315
8	270	2730	5000	360	1	2	9999	225	1
9	5000	1000	1000	3000	1000	1000	3000	2800	2000
10	3	0	0	3	0	0	1	0	1
11	1	0	1	5	0	0	1	0	1
12	3	1620	90	216	5	4	270	8	3
13	1	25	270	810	16	1	225	3	0
14	3	21	162	90	6	1	63	15	39
15	450	1200	1800	2530	2080	2080	1890	180	25
16	5	6	40	54	0	8	14	1	1
17	1200	3500	3500	1000	3	1	9999	600	8
18	8000	2500	3500	5000	1000	1000	5000	2000	2000

Table 4. Thickness data

Expt. No.	Thickness								
1	2029	1975	1961	1975	1934	1907	1952	1941	1949
2	5375	5191	5242	5201	5254	5309	5323	5307	5091
3	5989	5894	5874	6152	5910	5886	6077	5943	5962

4	2118	2109	2099	2140	2125	2108	2149	2130	2111
5	4102	4152	4174	4556	4504	4560	5031	5040	5032
6	3022	2932	2913	2833	2837	2828	2934	2875	2841
7	3030	3042	3028	3486	3333	3389	3709	3671	3687
8	4707	4472	4336	4407	4156	4094	5073	4898	4599
9	3859	3822	3850	3871	3922	3904	4110	4067	4110
10	3227	3205	3242	3468	3450	3420	3599	3591	3535
11	2521	2499	2499	2576	2537	2512	2551	2552	2570
12	5921	5766	5844	5780	5695	5814	5691	5777	5743
13	2792	2752	2716	2684	2635	2606	2765	2786	2773
14	2863	2835	2859	2829	2864	2839	2891	2844	2841
15	3218	3149	3124	3261	3205	3223	3241	3189	3197
16	3020	3008	3016	3072	3151	3139	3235	3162	3140
17	4277	4150	3992	3888	3681	3572	4593	4298	4219
18	3125	3119	3127	3567	3563	3520	4120	4088	4138

Table 5. The number of observations by categories

Expt. No.	Number of Observations by Categories				
	I	II	III	IV	V
1	9	0	0	0	0
2	5	2	2	0	0
3	1	0	6	2	0
4	0	8	1	0	0
5	0	1	0	4	4
6	1	0	4	1	3
7	0	1	1	4	3
8	3	0	2	1	3
9	0	0	0	4	5
10	9	0	0	0	0
11	8	1	0	0	0
12	2	3	3	0	1
13	4	2	2	1	0
14	2	3	4	0	0
15	0	1	1	1	6
16	3	4	2	0	0
17	2	1	0	2	4
18	0	0	0	2	7

Assume that the loss coefficients of surface defects and thickness are equal (k=1). Therefore, the total average quality loss is represented as

$$Q = \frac{1}{9}\left(\sum_{j=1}^{5} \omega_j^2 f_j + \sum_{i=1}^{9} 3600^2 \cdot \left(\frac{s^2}{\overline{y}^2} \right) \right) \qquad \ldots \qquad (4)$$

From the data of Tables 4 and 5, the total average quality loss can be computed using equation (4). Then, we take log transform of quality loss and express the SNR in decibels using equation (3). Table 6 shows the quality loss and SNR for the ordinal data of surface defect and thickness for the 18 experiments.

For example, the SNR of experiment No.2 is calculated as follows:

The quality loss of ordinal data for surface defect is

$$\overline{L(y)} = \frac{0^2 \cdot 5 + 4^2 \cdot 2 + 31^2 \cdot 2 + 301^2 \cdot 0 + 1001^2 \cdot 0}{9} = 217.11 \qquad \ldots \qquad (5)$$

Table 6. Quality losses and SNRs of experiments for polysilicon deposition process

Expt. No.	Factor Assignment A	B	C	D	E	F	Quality Loss of Surface Defect	Quality Loss of Thickness	SNR (*db*)
1	1	1	1	1	1	1	0.00	3891.72	-35.901
2	1	2	2	2	2	2	217.11	3445.12	-35.637
3	1	3	3	3	3	3	20774.22	3240.08	-43.805
4	2	1	1	2	2	3	121.00	773.51	-29.516
5	2	2	2	3	3	1	485602.67	93144.08	-57.625
6	2	3	3	1	1	2	344494.22	6626.77	-55.455
7	3	1	2	1	3	3	374376.00	94025.96	-56.706
8	3	2	3	2	1	1	344280.67	67382.48	-56.145
9	3	3	1	3	2	2	596934.33	11293.84	-57.841
10	1	1	3	3	2	1	0.00	26759.42	-44.275
11	1	2	1	1	3	2	1.78	1706.76	-32.326
12	1	3	2	2	1	3	111659.11	2027.98	-50.557
13	2	1	2	3	1	2	10283.89	8047.10	-42.632
14	2	2	3	1	2	3	432.44	598.83	-30.134
15	2	3	1	2	3	1	678176.00	2337.35	-58.328
16	3	1	3	2	3	2	220.67	8451.46	-39.381
17	3	2	1	3	1	3	465469.11	81513.62	-57.380
18	3	3	2	1	2	1	799467.67	186309.33	-59.938

The quality loss of thickness is

$$\overline{L(y)} = \mu_0^2 \cdot \frac{s^2}{\bar{y}^2} = 3600^2 \cdot \frac{7340.19}{5254.78^2} = 3445.12 \qquad \cdots \qquad (6)$$

Hence, the SNR for experiment No.2 is

$$\eta = -10 \cdot \log_{10}\left(3662.23\right) = -35.637 \ \ (db). \qquad \cdots \qquad (7)$$

From Table 6, the main effects (*db*) of factor levels are tabulated in Tables 7.

Table 7. Effects of the control factors under consideration on η.

Level \ Factor	A	B	C	D	E	F
Level 1	-40.417	-41.402	-45.215	-45.077	-49.678	-52.035
Level 2	-45.615	-44.875	-50.516	-44.928	-42.890	-43.879
Level 3	-54.565	-54.321	-44.866	-50.593	-48.029	-44.683

As seen in Tables 7, the optimal factor settings are $A_1B_1C_3D_2E_2F_2$ by selecting the maximum η. According to the regression model proposed by Wu and Chyu (2004), the predicted mean and variance are 0.291, 0.236 for surface defect, and the predicted mean and variance are 3361.53 and 451.86 for thickness based on the proposed optimal factor settings $A_1B_1C_3D_3E_2F_2$, respectively. The optimal factor settings for Phadke (1989), Su and Tong (1997), and Tong et al. (1997), Wu and Chyu (2004) are $A_1B_2C_1D_3E_2F_2$, $A_2B_1C_3D_2E_3F_2$, $A_1B_1C_3D_2E_3F_2$ and $A_1B_1C_3D_2E_3F_2$ based on the original data for surface defect, respectively. The result among published techniques using this case is displayed in Table 8.

Table 8. Result of among methods published

Optimal Control Factor Settings	Surface Defect $\hat{\mu}$	Surface Defect $\hat{\sigma}^2$	Thickness $\hat{\mu}$	Thickness $\hat{\sigma}^2$
Phadke ($A_1B_2C_1D_3E_2F_2$)	3.68	23.71	3845.94	2156.78
Su and Tong ($A_2B_1C_3D_2E_3F_2$)	10.67	146.80	2531.20	499.68
Tong, Su and Wang ($A_1B_1C_3D_2E_3F_2$)	0.44	0.56	3622.90	780.70
Wu and Chyu ($A_1B_1C_3D_2E_3F_2$)	0.44	0.56	3622.90	780.70
Proposed ($A_1B_1C_3D_2E_2F_2$)	0.29	0.24	3361.53	451.86

From Table 8, although the obtained thickness for proposed method is lower than the target value of 3600 Å, the thickness can use the deposition time needed to achieve the target value.

5. CONCLUSION

Robust design is a widely employed methodology in many different industries for improving product quality and process performance at low cost. A real problem in a product or process usually has multiple quality characteristics. The optimization methods of multiple quality characteristics design have thus become important issues for many manufacturers. Furthermore, the data of experiments for multiple quality characteristics design may simultaneously include quantitative and ordinal data. The published methods cannot be directly applied to optimize such multiple quality characteristics design. This article presents an effective method based on Taguchi's quality loss function to simultaneously optimize the multiple quality characteristics involving both quantitative and ordinal data. The proposed method does not require a complicated computation. An illustrative example demonstrates the proposed method effectiveness.

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BIOGRAPHICAL SKETCH

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