

Optimization of Multiple Responses Using Data Envelopment Analysis and Response Surface Methodology

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Abstract

Multiple responses must usually be considered when designing or developing complex products/processes. Therefore, simultaneously optimizing multiple responses is of priority concern for manufacturers hoping to gain a competitive advantage. Design of experiments (DOE) is extensively adopted in industry for determining an optimal parameter-setting or enhancing product quality. However, DOE can only be applied to optimize a single response. Moreover, when using DOE to identify the most significant factors in optimizing a single response, the optimal parameter setting for continuous factors can be determined by using the response surface methodology (RSM). The number of response surfaces increases with an increasing number of responses. Consequently, the trade-off between numerous response surfaces simultaneously is complex. Restated, determining the optimal parameter-setting is a complex task when numerous responses must be considered simultaneously. Thus, this study presents a novel optimization procedure for multiple responses by using data envelopment analysis (DEA), which can efficiently analyze data with multiple inputs and multiple outputs, and RSM. By combining DEA and RSM, the proposed procedure optimizes multiple responses simultaneously, and overcomes the limitations of RSM when dealing with a large number of responses. An experiment involving an etching process demonstrates the effectiveness of the proposed procedure.

Key Words: Optimization, Multiple Responses, Data Envelopment Analysis, Response Surface Methodology, Design of Experiments

1. Introduction

Product/Process design is typically complex due to varying customer demands and technology advances. Several responses must generally be considered in complex product/process designs. Therefore, simultaneously optimizing multiple responses is of priority concern among manufacturers.

Design of experiments (DOE) is extensively adopted in industry to improve processes, product design or obtain

an optimal parameter-setting for process parameters. When utilizing DOE, response surface methodology (RSM) is frequently employed to obtain the optimal parameter-setting following analysis of variance (ANOVA) for identifying significant factors. Through RSM, an equation (i.e., response surface) representing the approximate relationship between a single response and control factors can be obtained based on experimental data. A contour plot is used to characterize the response surface graphically and determine the optimal parameter-setting. When multiple responses are considered, the optimal parameter-setting is obtained by observing overlay contour plots.

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Because RSM constructs response surfaces for each response, the overlay contour plots are complex when many responses are considered. In this case, determining the optimal parameter-setting is difficult. A conventional means of optimizing multiple responses in DOE is to formulate a multi-response problem as a constrained optimization problem [1]. The response surface of a concerned response is selected as the objective function, and the remaining response surfaces are selected as constraint functions. Mathematical programming is then utilized to acquire the problem solution. Another approach for optimizing multiple responses in DOE is the Derringer-Suich method via a desirability function [2]. A geometric mean of desirabilities calculated using desirability functions is used to transform several response variables into a univariate variable. Koksoy [3] utilized the Derringer-Suich method to optimize dual responses. Allen and Yu [4] enhanced RSM using novel low-cost response surface methods (LCRSMs). These LCRSMs are generated according to the selection of regression models with a minimum sum of squares error (SSE).

These approaches for optimizing multiple responses must construct equations for each response. Restated, the number of equations increases with an increasing number of response variables. Optimizing numerous equations simultaneously is difficult. Thus, determining an optimal parameter-setting for a multi-response problem is complex when numerous responses must be considered simultaneously.

This study presents a novel optimization procedure that combines data envelopment analysis (DEA) with RSM to optimize multiple responses. Because DEA is an efficient means of analyzing data with multiple inputs and multiple outputs, this study analyzes the designed experimental data with multiple responses by using DEA. Multiple responses are evaluated via DEA to acquire relative efficiency for each experimental run. RSM is then used to generate the optimal parameter-setting according to the relative efficiencies. Consequently, through the combination of DEA and RSM, multi-responses problem can be simply modeled in a single equation. Accordingly, difficulties associated with the simultaneous trade-off between numerous equations can be avoided. Therefore, the proposed optimization scheme can overcome the limitations of existing approaches when the number of responses is large. Finally, an etching experiment un-

dertaken in a semiconductor company located in Hsinchu Science-based Industrial Park, Taiwan, demonstrates the effectiveness of the proposed procedure.

2. Data Envelopment Analysis

Notably, DEA has been widely adopted in recent years to assess the performance of a group of units. These measured units are called decision making units (DMUs). Based on the concept of an efficiency frontier, Charnes et al. [5] first modeled DEA through mathematical programming. Thus, DEA can measure the relative efficiency of DMUs with multiple inputs and outputs. The DEA model introduced by Charnes et al. [5] is called the CCR model. The CCR model utilizes a virtual multiplier to integrate multiple inputs and outputs into a single index. The virtual multiplier – generated as the sum of weighted outputs divided by the sum of weighted inputs – is utilized to represent the efficiency of each DMU. The CCR model selects the input and output weights that maximize relative efficiency of each measured DMU. The relative efficiency of the t th DMU analyzed by the CCR model is obtained by Eq. (1).

$$\begin{aligned} \max E_{tt} &= \frac{\sum_y u_y O_{ty}}{\sum_x v_x I_{tx}} \\ \text{s. t. } \frac{\sum_y u_y O_{wy}}{\sum_x v_x I_{wx}} &\leq 1, \quad w = 1, \dots, L \\ u_y &\geq 0, \quad v_x \geq 0 \end{aligned} \quad (1)$$

where E_{tt} is the relative efficiency of the t th DMU, u_y is the y th output weight, v_x is the x th input weight, O_{wy} and I_{wx} are the y th output and x th input, respectively, for the w th DMU, and $w = 1, \dots, L$, L is the number of measured DMUs.

A DMU with a unity efficiency score is considered the best performer among measured DMUs. However, from experience, many DMUs occasionally have this efficient status. In this case, cross-evaluation is applied to rank the best performers. Cross-evaluation was first proposed by Sexton et al. [6]. Doyle and Green [7] extended cross-evaluation and further developed a cross-efficiency method to discriminate between efficient DMUs. They regarded the relative efficiency in the CCR model as a

self-appraisal measure. Considering input and output weights of DMUs in the reference set for the CCR model can generate a peer-appraisal efficiency. Peer-appraisal efficiency is determined from the cross-efficiency. For instance, the cross-efficiency of the s th DMU with weights determined by the t th DMU (i.e., E_{ts}) can be expressed as

$$E_{ts} = \frac{\sum_y (u_{ty} O_{sy})}{\sum_x (v_{tx} I_{sx})} \quad (2)$$

where u_{ty} is the weight of the y th output determined by evaluating the t th DMU, v_{tx} is the weight of the x th input determined by evaluating the t th DMU, O_{sy} is the value of the y th output for the s th DMU, and I_{sx} is the value of the x th input for the s th DMU.

Subsequently, the cross-efficiency value can be obtained using Eq. (3).

$$\begin{aligned} & \min \sum_y (u_{ty} \sum_{s \neq t} O_{sy}) \\ & \text{s. t. } \sum_x (v_{tx} \sum_{s \neq t} I_{sx}) = 1 \\ & v_{tx} \text{ and } u_{ty} \geq 0 \\ & E_{ts} \leq 1 \text{ for all DMUs } s \neq t \\ & \sum_y O_{ty} u_{ty} - E_{tt} \sum_x I_{tx} v_{tx} = 0 \end{aligned} \quad (3)$$

where I_{tx} is the value of the x th input for the t th DMU, and O_{ty} is the value of the y th output for the t th DMU. The first constraint in Eq. (3) can avoid the objective function having a fractional format, and is helpful in obtaining a solution for the goal programming procedure. The second constraint in Eq. (3) restricts the DEA model to yield a positive weight, while the third constraint ensures that the relative efficiency value does not exceed 1. The last constraint in Eq. (3) represents the self-appraisal measure (i.e., E_{tt} in Eq. (1)).

Finally, the peer-appraisal efficiency without self-appraisal of the s th DMU (i.e., e_s), which is obtained by averaging cross-efficiency, can be expressed as

$$e_s = \frac{1}{(L-1)} \sum_{s \neq t} E_{ts} \quad (4)$$

3. Response Surface Methodology

Response surface methodology is an empirical sta-

tistical approach for modeling problems in which several variables influence a response of interest. In RSM, an approximate relation between a single response and multiple variables is modeled as a polynomial equation obtained through regression analysis. The equation is called a response surface and is generally represented graphically on a contour plot for analyzing an optimal solution. Usually, a low-order polynomial in some regions of variables is used [8]. Assume that y denotes the response and x_g denotes the variables, $g = 1, \dots, N$. When a linear function of variables can effectively model a response, then the response surface is a first-order model, as follows.

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \dots + \hat{\beta}_N x_N \quad (5)$$

where β_g is the regression coefficients, $g = 1, \dots, N$. When specifying curvature of a response surface, a polynomial of a high order is appropriate for the response surface. For instance, a second-order model of the response surface is

$$\hat{y} = \hat{\beta}_0 + \sum_{g=1}^N \hat{\beta}_g x_g + \sum_{g=1}^N \hat{\beta}_{gg} x_g^2 + \sum_{g < f} \hat{\beta}_{gf} x_g x_f \quad (6)$$

The fitted response surface is an adequate approximation of the true response function when an appropriate model is selected. Furthermore, model parameters are estimated effectively when proper experimental designs are used to obtain experimental data. Details of experimental designs for fitting response surfaces are found in Khuri and Cornell [9] and Montgomery [8].

4. Optimization Procedure

This study presents a novel procedure that simultaneously optimizes multiple responses for designed experiments. First, an appropriate experimental design is selected to construct the experiments. Both DEA and RSM are then applied to analyze experimental data. Finally, the parameter-setting with the highest efficiency is selected as the optimal parameter-setting. The proposed procedure has the following five steps.

Step 1. Design and perform the experiment

Control factors, response variables and quality characteristics (i.e., larger-the-better (LTB), nominal-the-

best (NTB) or smaller-the-better (STB)) of response variables are determined according to expert opinions or screening experiments. An appropriate experimental design (e.g., a central composite design (CCD), a face-centered cube design or a computer-generated design) is then utilized to construct the experiment. After performing the experiments, associated response values for each experimental run are recorded. Let y_{ij} represent the record of the j th response under the i th experimental run, $i = 1, \dots, m, j = 1, \dots, n$.

Step 2. Normalize the experimental data

To mitigate the effects of various measuring units of responses on relative efficiency analysis in DEA, experimental data are normalized. Response values y_{ij} for the j th response variable are transformed to y'_{ij} using Eq. (7), $j = 1, \dots, n$.

$$y'_{ij} = \begin{cases} \frac{(y_{ij} - y_j^+)}{(y_j^- - y_j^+)}, & \text{if the } j\text{th response variable belongs to a STB variable} \\ \frac{(|y_{ij} - \text{target}| - y_j^{++})}{(y_j^{--} - y_j^{++})}, & \text{if the } j\text{th response variable belongs to a NTB variable} \\ \frac{(y_{ij} - y_j^-)}{(y_j^+ - y_j^-)}, & \text{if the } j\text{th response variable belongs to a LTB variable} \end{cases} \quad (7)$$

where $y_j^- = \min\{y_{ij} | \forall i\}, j = 1, \dots, n$, when the j th response variable belongs to a STB or LTB variable; $y_j^+ = \max\{y_{ij} | \forall i\}, j = 1, \dots, n$, when the j th response variable belongs to a STB or LTB variable; $y_j^{--} = \min\{|y_{ij} - \text{target}| | \forall i\}, j = 1, \dots, n$, when the j th response variable belongs to a NTB variable; $y_j^{++} = \max\{|y_{ij} - \text{target}| | \forall i\}, j = 1, \dots, n$, when the j th response variable belongs to a NTB variable.

Step 3. Determine the efficiency of each experimental run using DEA

As DEA can analyze multiple inputs and outputs simultaneously, DEA can be utilized to analyze experimental data with multiple inputs and outputs. Additionally, cross-evaluation is utilized to construct the DEA model for differentiating between efficient experimental

runs. In this study, each experimental run is considered as a DMU when using DEA. Let ϵ be an extremely small positive value (i.e., 10^{-6}); ϵ is regarded as the input in DEA. Notably, y'_{ij} obtained in Step 2 plus ϵ are regarded as DEA outputs. Equation (8) is then applied to derive the cross-efficiency of each experimental run. Consequently, the peer-appraisal efficiency without self-appraisal for the measured s th DMU (i.e., e_s) is acquired, using Eq. (9). A high e_s value represents superior performance among experimental runs. Therefore, e_s can be considered an index of quality performance for the parameter-setting used in the measured s th DMU.

$$\begin{aligned} \min & \sum_j (u_{ij} \sum_{s \neq i} (y'_{sj} + \epsilon)) \\ \text{s. t. } & v_i \sum_{s \neq i} I_s = 1 \\ & \sum_j (u_{ij} (y'_{sj} + \epsilon)) - v_i I_s \leq 0 \\ & \sum_j (u_{ij} (y'_{ij} + \epsilon)) - E_{ii} v_i I_i = 0 \\ & v_i, u_{ij} \geq 0 \\ & \forall s \neq i, \forall I_i \in \{\epsilon\} \end{aligned} \quad (8)$$

where v_i is the input weight determined by evaluating the i th DMU; u_{ij} is the weight of the j th response determined by the evaluating the i th DMU; I_i is the input value for the i th DMU; y'_{ij} is the value obtained in Step 2, $i = 1, \dots, m, j = 1, \dots, n$.

$$e_s = \frac{1}{(m-1)} \sum_{s \neq i} \left(\frac{\sum_j (u_{ij} (y'_{sj} + \epsilon))}{v_i I_s} \right) \quad (9)$$

Step 4. Establish the response surface of efficiency using RSM

The e_s values and corresponding parameter-settings are analyzed using RSM to determine the response surface of efficiency. The appropriate polynomial model of efficiency is determined based on lack-of-fit test results. When a quadratic model is appropriate, the response surface of efficiency can be expressed as

$$\hat{e}_s = f(x) = \hat{\beta}_0 + \sum_{g=1}^N \hat{\beta}_g x_g + \sum_{g=1}^N \hat{\beta}_{gg} x_g^2 + \sum_{\substack{g=1 \\ g < f}}^N \sum_{f=1}^N \hat{\beta}_{gf} x_g x_f \quad (10)$$

where x_g represents the control factors designed in Step

$1, g = 1, \dots, N.$

Step 5. Determine the optimal parameter-setting

The optimal parameter-setting can be obtained using Eq. (11) according to the response surface of efficiency acquired in Step 4.

$$\max_{x \in \Omega} \hat{e}_s = f(x) \tag{11}$$

where Ω is the feasible region.

5. Illustrative Example

An experiment involving an etching process demonstrates the effectiveness of the proposed optimization procedure. Experimental data were provided by a semiconductor company located in Hsinchu Science-based Industrial Park, Taiwan.

Etching is an important process in manufacturing semiconductors. Specifically, plasma etching is widely applied in semiconductor manufacturing. Plasma etching involves using a glow discharge with a solid material to produce chemically reactive species from relatively inert molecular gases [10]. Radiation caused by ions, electrons and photons enhances the reaction to form volatile compounds that are to be removed. Selective etching, reaction rate and uniformity are three important factors in the etching process. The desired parameter-setting is to have highly selective etching, a high reaction rate and high uniformity in the etching process. Therefore, experimental responses were determined according to these criteria and are denoted as y_1 (LTB), y_2 (STB), y_3 (STB), y_4 (STB) and y_5 (LTB). Both y_1 and y_3 signify erosion rate; y_2 and y_4 are indices of uniformity; y_5 is the capability of selective etching. Figure 1 shows the location of the Si_3N_4 layer and oxide layer in the etching process. Furthermore, five control factors, determined according to screening experiments, are denoted by x_1, x_2, x_3, x_4 and x_5 . The current operational setting for control factors is $(x_1, x_2, x_3, x_4, x_5) = (175, 125, 0, 67, 0)$.

Face-centered CCD is utilized to construct the experiments and, then, experimental observations are normalized using Eq. (7). Normalized data are then analyzed using DEA via Eqs. (8) and (9). Table 1 lists the efficiency values after calculation. Additionally, a response surface of efficiency is established using RSM.

Based on lack-of-fit test results (by Design-Expert software, version 6, Stat-Ease, Minneapolis, USA) (Table 2), the quadratic model is selected as follows.

$$e_s = 0.61 + (4.3 \times 10^{-4}) \times x_1 + (1.9 \times 10^{-3}) \times x_2 - (6.8 \times 10^{-4}) \times x_3 + (3.4 \times 10^{-3}) \times x_4 + 0.02 \times x_5 - (7.1 \times 10^{-7}) \times x_1^2 - (1.3 \times 10^{-5}) \times x_2^2 + (2 \times 10^{-5}) \times x_3^2 + (3 \times 10^{-6}) \times x_4^2 - (1.1 \times 10^{-3}) \times x_5^2 + (3.5 \times 10^{-6}) \times x_1 \times x_2 - (9.2 \times 10^{-6})$$

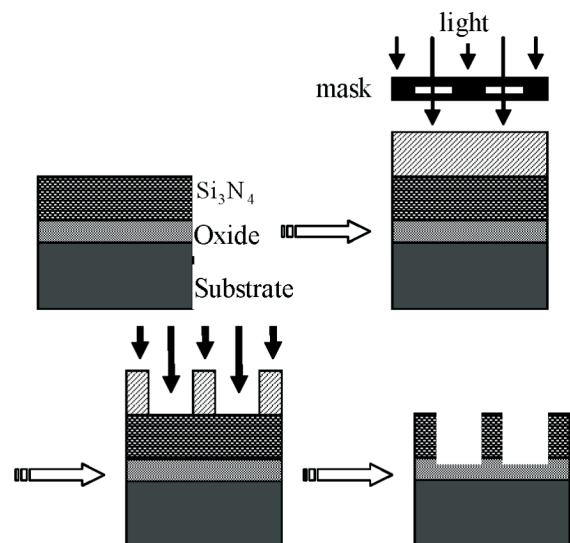


Figure 1. Etching process.

Table 1. Efficiency score values

Run	Control factors					e_s
	x_1	x_2	x_3	x_4	x_5	
1	400	200	70	20	0	75.81%
2	80	50	70	20	0	81.56%
3	240	125	35	50	8	86.57%
⋮	⋮	⋮	⋮	⋮	⋮	⋮
30	400	200	0	80	0	73.45%
31	80	200	0	20	0	53.43%
32	80	50	0	80	0	91.40%

Table 2. Summary of lack of fit tests

Source	S.S.	d.f.	M.S.	F value	
Linear	0.32	21	0.02	784.95	
2FI	0.15	11	0.01	685.89	
Quadratic	0.01	6	0.00	103.43	Suggested
Cubic	0.00	1	0.00	37.17	Aliased
Pure Error	0.00	5	0.00		

$$\begin{aligned} & \times x_1 \times x_3 - (8.2 \times 10^{-8}) \times x_1 \times x_4 + (2 \times 10^{-5}) \times x_1 \times x_5 \\ & + (1.3 \times 10^{-5}) \times x_2 \times x_3 - (2.1 \times 10^{-5}) \times x_2 \times x_4 + (2.9 \\ & \times 10^{-5}) \times x_2 \times x_5 - (2.5 \times 10^{-8}) \times x_3 \times x_4 + (8.5 \times 10^{-6}) \\ & \times x_3 \times x_5 - (1.9 \times 10^{-4}) \times x_4 \times x_5 \end{aligned} \quad (12)$$

Finally, the optimal parameter-setting for the Si₃N₄ etching process is obtained using Eq. (11). The optimal parameter-setting of the proposed procedure is (400, 50.69, 0, 80, 5.26).

To compare further the responses of the proposed procedure with those of the current operation, response surfaces for each response are generated to predict response values. The conventional RSM is utilized to construct response surfaces for each response based on original experimental observations. The response surfaces obtained by the conventional RSM are as follows.

$$\begin{aligned} y_1 = & -694.60 + 5.67 \times x_1 - 11.53 \times x_2 + 14.99 \times x_3 + 46.55 \\ & \times x_4 + 34.27 \times x_5 - 0.01 \times x_1^2 + 0.04 \times x_2^2 - 0.08 \times x_3^2 \\ & - 0.52 \times x_4^2 - 0.03 \times x_5^2 + 0.03 \times x_1 \times x_2 + 0.02 \times x_1 \times x_3 \\ & + 0.11 \times x_1 \times x_4 - 0.15 \times x_1 \times x_5 - 0.09 \times x_2 \times x_3 + 0.07 \\ & \times x_2 \times x_4 - 0.10 \times x_2 \times x_5 - 0.10 \times x_3 \times x_4 + 0.86 \times x_3 \times x_5 \\ & - 0.67 \times x_4 \times x_5 \end{aligned} \quad (13)$$

$$\begin{aligned} y_2 = & 26.05 - 0.06 \times x_1 - 0.08 \times x_2 - 0.03 \times x_3 - 0.21 \times x_4 \\ & - 0.71 \times x_5 + (8.7 \times 10^{-5}) \times x_1^2 + (7.3 \times 10^{-4}) \times x_2^2 - (2.7 \\ & \times 10^{-4}) \times x_3^2 + (5.1 \times 10^{-4}) \times x_4^2 - (1.4 \times 10^{-3}) \times x_5^2 \\ & - (2.7 \times 10^{-4}) \times x_1 \times x_2 + (5.7 \times 10^{-4}) \times x_1 \times x_3 + (1.5 \\ & \times 10^{-5}) \times x_1 \times x_4 + (5.8 \times 10^{-4}) \times x_1 \times x_5 - (5.8 \times 10^{-4}) \\ & \times x_2 \times x_3 + (4.4 \times 10^{-4}) \times x_2 \times x_4 + (2.7 \times 10^{-4}) \times x_2 \times x_5 \\ & - (9 \times 10^{-5}) \times x_3 \times x_4 - (2 \times 10^{-3}) \times x_3 \times x_5 + 0.01 \times x_4 \\ & \times x_5 \end{aligned} \quad (14)$$

$$\begin{aligned} y_3 = & -278.40 + 10.25 \times x_1 - 13.85 \times x_2 + 11.62 \times x_3 + 8.49 \\ & \times x_4 - 31.05 \times x_5 - 0.02 \times x_1^2 + 0.04 \times x_2^2 - 0.05 \times x_3^2 \\ & - 0.12 \times x_4^2 + 7.00 \times x_5^2 + 0.01 \times x_1 \times x_2 + 0.02 \times x_1 \times x_3 \\ & + (7.3 \times 10^{-4}) \times x_1 \times x_4 - 0.21 \times x_1 \times x_5 - 0.08 \times x_2 \times x_3 \end{aligned}$$

$$\begin{aligned} & + 0.12 \times x_2 \times x_4 - 0.14 \times x_2 \times x_5 - 0.15 \times x_3 \times x_4 + 0.07 \\ & \times x_3 \times x_5 + 0.30 \times x_4 \times x_5 \end{aligned} \quad (15)$$

$$\begin{aligned} y_4 = & 13.69 - 0.03 \times x_1 + 0.09 \times x_2 - 0.12 \times x_3 - 0.14 \times x_4 \\ & - 0.09 \times x_5 - (2 \times 10^{-4}) \times x_1 \times x_2 - (1.1 \times 10^{-7}) \times x_1 \times x_3 \\ & + (5.2 \times 10^{-4}) \times x_1 \times x_4 + (4.5 \times 10^{-4}) \times x_1 \times x_5 + (4.3 \\ & \times 10^{-4}) \times x_2 \times x_3 - (1.1 \times 10^{-4}) \times x_2 \times x_4 - (1.7 \times 10^{-3}) \\ & \times x_2 \times x_5 + (2.6 \times 10^{-3}) \times x_3 \times x_4 + (4.3 \times 10^{-3}) \times x_3 \times x_5 \\ & - (3.6 \times 10^{-3}) \times x_4 \times x_5 \end{aligned} \quad (16)$$

$$\begin{aligned} y_5 = & 0.81 - 0.02 \times x_1 + 0.03 \times x_2 - (3.6 \times 10^{-3}) \times x_3 + 0.04 \\ & \times x_4 + 0.09 \times x_5 + (4.2 \times 10^{-5}) \times x_1^2 - (4.6 \times 10^{-5}) \times x_2^2 \\ & - (1.1 \times 10^{-5}) \times x_3^2 - (3.1 \times 10^{-4}) \times x_4^2 - 0.01 \times x_5^2 - (5.4 \\ & \times 10^{-5}) \times x_1 \times x_2 - (5.6 \times 10^{-5}) \times x_1 \times x_3 + (3 \times 10^{-5}) \times x_1 \\ & \times x_4 + (4.7 \times 10^{-4}) \times x_1 \times x_5 + (1.4 \times 10^{-4}) \times x_2 \times x_3 \\ & - (5.3 \times 10^{-5}) \times x_2 \times x_4 - (3 \times 10^{-4}) \times x_2 \times x_5 + (3.6 \\ & \times 10^{-4}) \times x_3 \times x_4 - (2.2 \times 10^{-4}) \times x_3 \times x_5 - (2.1 \times 10^{-3}) \\ & \times x_4 \times x_5 \end{aligned} \quad (17)$$

The predicted responses for the parameter-setting generated by the proposed procedure and current operations are acquired using Eqs. (13) to (17), respectively. Table 3 summarizes the prediction results of the proposed procedure and the existing methods (Derringer and Suich [2], Koksoy [3] and Allen and Yu [4]). Table 4 shows the optimal parameter-setting of these methods. According to Table 3, the parameter-setting of the proposed procedure yields a better performance for each response than that of the current operation. Consequently, the proposed procedure is an effective means of optimizing multiple responses simultaneously.

6. Conclusion

This study presents a novel procedure that optimizes products/processes with multiple responses. Because DEA is used to simultaneously analyze experimental data with

Table 3. Comparison of proposed procedure with current operation and existing methods

Response	Quality characteristic	Current operation	Proposed procedure	Derringer and Suich (1980)	Allen and Yu (2002)	Koksoy (2005)
y ₁	LTB	2349.35	3561.16	3800.05	4121.98	1634.93
y ₂	STB	5.56	0	0.07	-1.83	3.72
y ₃	STB	1244.51	954.54	1090.78	1343.10	1821.34
y ₄	STB	11.34	5.61	6.33	5.15	7.04
y ₅	LTB	2.47	2.98	3.08	2.84	0.12

Table 4. Optimal parameter-setting of proposed procedure and existing methods

Control factors	Current operation	Proposed procedure	Derringer and Suich (1980)	Allen and Yu (2002)	Koksoy (2005)
x_1	175	400	400	400	224.41
x_2	125	50.69	71.42	107.87	50.02
x_3	0	0	8.48	0.01	34.69
x_4	67	80	75.26	80.00	20
x_5	0	5.26	5.5	6.04	16

multiple inputs and outputs, the drawback that the number of response surfaces increases with an increasing number of responses in RSM can be avoided. Moreover, by combining DEA and RSM, the proposed procedure can simultaneously evaluate several responses to acquire a satisfactory parameter-setting for all responses. When encountering a complex product/process design with numerous responses, the proposed procedure avoids difficulties associated with subjective trade-off settings. The illustrative example of the etching process at a semiconductor company demonstrates the effectiveness of the proposed procedure. Analytical results indicate that the parameter-setting obtained using the proposed procedure satisfies the quality requirements of each response.

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