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ORIGINAL ARTICLE

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Optimization of multi-response processes using the VIKOR method

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Abstract Design of experiments and Taguchi methods are extensively adopted as off-line quality improvement techniques in industry. However, these methods were developed to optimize single-response processes. In many situations, multiple responses must be optimized simultaneously, since some product designs, especially in the integrated circuit industry, are becoming increasingly complex to meet customers' demands. Although several procedures for optimizing multi-response processes have been developed in recent years, the associated quality measurement indices do not consider variations in the relative quality losses of multiple responses. These procedures may therefore result in an optimization in which quality losses associated with a few responses are very small but those associated with others are very large, even if the overall average quality loss is small. Such an optimization with a large variation of quality losses among the responses is usually unacceptable to engineers. Accordingly, this study employs the VIKOR method, which is a compromise ranking method used for multicriteria decision making (MCDM), to optimize the multi-response process. The proposed method considers both the mean and the variation of quality losses associated with several multiple responses, and ensures a small variation in quality losses among the responses, along with a small overall average loss. Two case studies of plasma-enhanced chemical vapor deposition and copper chemical mechanical polishing demonstrate the effectiveness of the proposed method.

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1 Introduction

The Taguchi method [1] is a commonly implemented off-line experimental technique for improving quality in industry. Taguchi used an orthogonal array to perform experiments and employed the signal-to-noise (SN) ratio as the quality measurement index, with simultaneous consideration of the mean and variability of the quality characteristic, to determine the optimal setting of process parameters. The effectiveness of the Taguchi method for improving quality in industry has been extensively verified. However, most of the method applications optimize only a single response. When more than one response is to be optimized, engineers usually set the optimal factor-level combination from their experience. Such behavior is neither objective nor systematic. Some procedures have been developed for optimizing multi-response problems in recent years; however, these procedures cannot explain the variation in quality losses among multiple responses. The optimal factor-level combination, determined using these procedures, may result in small quality losses associated with some responses but very large losses associated with others, even if the average quality loss is sufficiently small. Engineers sometimes cannot accept such a result of optimization. Additionally, some methods for optimizing several responses have been developed that use complex statistical models and are impractical for application by engineers who do not have a strong background in mathematics. Therefore, this study proposes a new approach for solving the optimization problem for multi-response processes using the VIKOR method taken from multicriteria decision making (MCDM). The MCDM procedure can be employed to determine the optimal solution among several alternatives with conflicting and compromising multicriteria. In this study, the VIKOR

Table 1 Quality losses for five responses in two experimental runs

	Response 1	Response 2	Response 3	Response 4	Response 5	Total loss
Experiment 1	10	10	10	10	10	50
Experiment 2	8	8	8	8	16	48

(*VlseKriterijumska Optimizacija I Kompromisno Resenje* in Serbian) method [2–4] is applied to derive an integrated quality measurement of several conflicting and compromising responses. Firstly, the ideal and negative-ideal solutions are initially determined from the quality loss. Secondly, the utility measure and the regret measure of each alternative are determined according to the weight of each criteria. Thirdly, the VIKOR index of each experimental run is obtained using the corresponding utility and regret measures. Finally, the main effect of the VIKOR index is determined and the optimal factor-level combination is thus obtained. Two cases, one of plasma-enhanced chemical vapor deposition (PECVD) and one of copper chemical mechanical polishing (Cu-CMP), are presented to demonstrate the effectiveness of the proposed method.

2 Literature review

2.1 Optimizing multiple responses

Derringer and Suich [5] defined a desirability function to transform several response variables into a single response. Khuri and Conlon [6] simultaneously optimized various responses using polynomial regression models. They firstly defined a distance function by considering the ideal solution, and then determined the optimal condition by minimizing this function. Logothetis and Haigh [7] demonstrated the use of the multiple regression method and the linear programming approach, to optimize a multi-response process using Taguchi experiments. Phadke [8] implemented the conventional Taguchi method to optimize individually the number of surface defects, and the thickness of the wafer and the rate of deposition in an IC manufacturing process. The optimal condition is determined by separately optimizing each response. When conflicts arise in determining the optimal level of a factor, the engineer draws upon his own knowledge to determine the best factor-level combination. Su and Hsieh [9] and Tong and Hsieh [10] applied artificial neural networks (ANN) to find the optimal solution to the multi-response type of problem. Su and Tong [11] and Antony [12] utilized principle component analysis (PCA) to analyze multi-response problems. The PCA technique can transform several related original variables into a smaller number of uncorrelated principal components, which are linear combinations of the original variables. The optimal factor-level combination is determined using these uncorrelated principal components. Vining and Myers [13] developed algorithms for obtaining the optimal solutions of a dual-response surface system (DRSM). Their method assumed that the DRSM includes a primary response, y_p and a constraint response, y_s. y_p and y_s can both be fitted using a quadratic regression model. The DRSM seeks parameter settings that can optimize $\widehat{y}_p$ under the constraint $\widehat{y}_S = c$, where c is a constant.

Table 2 Control factors and their levels

Control factor	Level 1	Level 2	Level 3
A. Cleaning method	No	<u>Yes</u>	
B. Chamber temperature	<u>100°C</u>	200°C	300°C
C. Run number after chamber has been cleaned	1st	<u>2nd</u>	3rd
D. Flow rate of S_iH_4	6%	<u>7%</u>	8%
E. Flow rate of N_2	30%	<u>35%</u>	40%
F. Chamber pressure	160 motorr	<u>190 motorr</u>	220 motorr
G. R.F. power	30 watt	<u>35 watt</u>	40 watt
H. Deposition time	11.5 min	<u>12.5 min</u>	13.5 min

The current levels are identified by underlining

The features of the above multi-response optimization methods can be summarized as follows.

1. Most procedures neglect the variation in quality losses for multiple responses. The optimal factor-level combination may result in very small quality losses associated with some responses, but very large quality losses associated with others, even when the average quality loss is acceptably small.
2. The optimal condition obtained from some procedures is determined by separately optimizing each response. When conflict arises in determining the optimal levels of factors, the optimal factor-level combination is determined from the engineer's knowledge. Since each engineer's experience is subjective, addressing of the same problem by various engineers may yield inconsistent results.
3. Some procedures used complex mathematics or statistical methods, such as PCA, ANN or the dual-response approach or linear programming. These approaches are difficult to implement by individuals with little background in statistics and so are of little practical use.
4. Some procedures for developing an optimization model cannot easily determine the optimal learning structure or assign the best values of the learning parameters.
5. Some methods can set parameters optimally, but nothing can be learned about the relationship between

Table 3 Summary of experimental data

Experimental run	Control factor								Average		VIKOR value
	A	B	C	D	E	F	G	H	DT	RI	
1	1	1	1	1	1	1	1	1	730.6	2.033	0.1620
2	1	1	2	2	2	2	2	2	874.2	2.224	0.0124
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
17	2	3	2	1	3	2	2	3	818	1.914	0.0000
18	2	3	3	2	1	3	3	1	738.8	2.021	0.0932

the control factors and the responses during the optimization process.

This study proposes a novel approach based on the VIKOR method from MCDM to solve some of these problems.

2.2 MCDM and the VIKOR method

The MCDM method is an extensively applied tool for determining the best solution among several alternatives with multiple criteria or attributes. An MCDM problem can be expressed using a decision matrix as follows:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} x_1 & x_2 & \cdots & x_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & & x_{mn} \end{bmatrix} \end{array} \quad (1)$$

where A_i represents the ith alternative, i = 1, 2, …, m; x_j represents the jth criterion, j = 1, 2, …, n, and x_{ij} is the performance of alternative A_i with respect to the jth criterion. The procedures for determining the best solution to an MCDM problem include computing the utilities of alternatives and ranking these utilities. The alternative solution with the greatest largest utility is considered to be the optimal solution. For details of MCDM methods refer to Zeleny [14].

The VIKOR method includes the following steps.

Step 1. Determine the normalized decision matrix.

The normalized decision matrix can be expressed as follows:

$$F = [f_{ij}]_{m\times n} \quad (2)$$

where $f_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$, i = 1,2, …, m; j = 1, 2, …,n; and x_{ij} is the performance of alternative A_i with respect to the jth criterion.

Step 2. Determine the ideal and negative-ideal solutions.

The ideal solution **A*** and the negative ideal solution $\mathbf{A}^-$ are determined as follows:

$$\begin{aligned} A^* &= \left\{ \left(\max f_{ij} | j \in J\right) or \left(\min f_{ij} | j \in J'\right) | i = 1, 2, \cdots, m \right\} \\ &= \left\{ f_1^*, f_2^*, ..., f_j^*, .. f_n^* \right\} \end{aligned} \quad (3)$$

$$\begin{aligned} A^- &= \left\{ \left(\min f_{ij} | j \in J\right) or \left(\max f_{ij} | j \in J'\right) | i = 1, 2, \cdots, m \right\} \\ &= \left\{ f_1^-, f_2^-, \cdots, f_j^-, \cdots, f_n^- \right\} \end{aligned} \quad (4)$$

where $J = \{ j = 1, 2, ..., n | f_{ij}$, a larger response is desired$\}$
$J' = \{ j = 1, 2, ..., n | f_{ij}$, a smaller response is desired$\}$

Step 3. Calculate the utility measure and the regret measure.

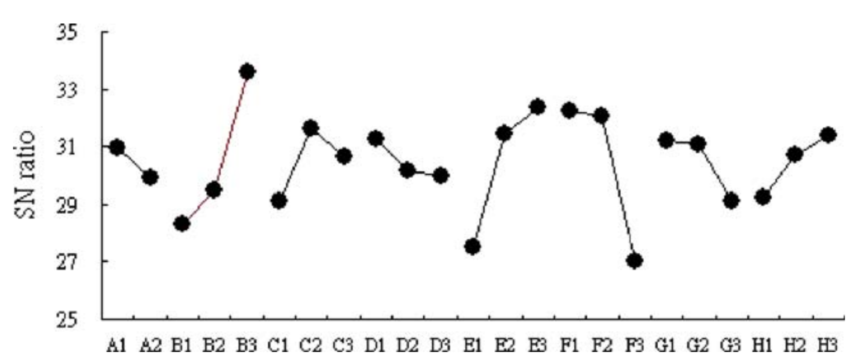
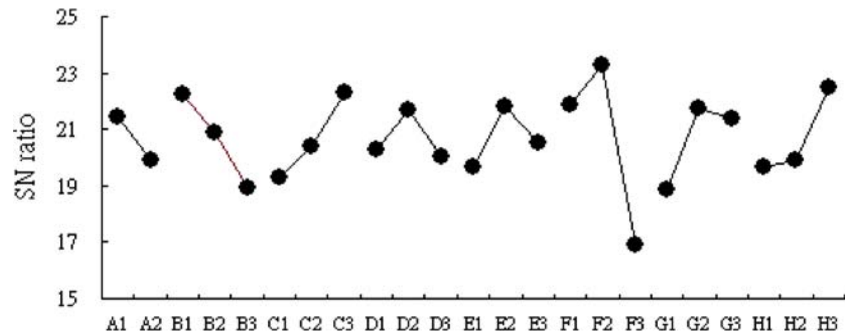


Fig. 1 Factor effects of RI response on SN ratios

Fig. 2 Factor effects of DT response on SN ratios



The utility measure and the regret measure for each alternative are given as

$$S_i = \sum_{j=1}^{n} w_j \left(f_j^* - f_{ij}\right) \Big/ \left(f_j^* - f_j^-\right) \tag{5}$$

$$R_i = \underset{j}{Max}\left[w_j \left(f_j^* - f_{ij}\right) \Big/ \left(f_j^* - f_j^-\right)\right] \tag{6}$$

where S_i and R_i represent the utility measure and the regret measure, respectively, and w_j is the weight of the jth criterion.

Step 4. Calculate the VIKOR index.

The VIKOR index can be expressed as follows:

$$Q_i = \nu\left[\frac{S_i - S^*}{S^- - S^*}\right] + (1-\nu)\left[\frac{R_i - R^*}{R^- - R^*}\right] \tag{7}$$

where Q_i represents the ith alternative VIKOR value, i=1, …, m; $S^* = \underset{i}{Min}S_i$, $S^- = \underset{i}{Max}S_i$, $R^* = \underset{i}{Min}R_i$, $R^- = \underset{i}{Max}R_i$ and ν is the weight of the maximum group utility (and is usually set to 0.5 [1–3]).

Step 5. Rank the order of preference.

The alternative with the smallest VIKOR value is determined to be the best solution.

The advantage of the VIKOR method, enabling it to be applied in situations with multiple criteria, follows from the use of the Lp metric in the compromising programming method [14, 15]. It can be described as follows:

$$L_{P,i} = \left\{\sum_{j=1}^{n}\left[w_j \left(f_j^* - f_{ij}\right) \Big/ \left(f_j^* - f_j^-\right)\right]^p\right\}^{1/p} \tag{8}$$

where $1 \le p \le \infty$; i =1, 2,…, m.

The utility function of the VIKOR method is an aggregate of $L_{1,i}$ and $L_{\infty,i}$. $L_{1,i}$ is interpreted as 'concordance' and can provide decision makers with information about the maximum 'group utility' or 'majority'. Similarly, $L_{\infty,i}$ is interpreted as 'discordance' and provides decision makers with information about the minimum individual regret of the 'opponent'.

Of the many MCDM tools, the VIKOR method has the following characteristics.

1. The best alternative determined by the VIKOR method is nearest to the ideal solution and farthest from the negative-ideal solution.
2. The best alternative according to the VIKOR method has the maximum group utility for decision makers and ensures the least regret.
3. The VIKOR method considers two distance measurements, $L_{1,i}$ and $L_{\infty,i}$, based on the Lp metric in the compromising programming method to provide information about utility and regret.
4. The VIKOR method considers two weights in decision-making. One is that of the criteria, the other that of the maximum group utility.

2.3 VIKOR method for multi-response optimization

The VIKOR method can be applied to optimize the multi-response problem, because it accounts for the variation among quality losses associated with multiple responses. It also simultaneously accounts for the utility and regret measures in an experimental run. For instance, two experimental runs are completed and the quality losses for five responses are obtained as in Table 1.

From the traditional perspective, in which smaller losses are better, experiment 2 apparently yields a higher quality measurement than experiment 1, since its total loss is smaller. However, from an engineering perspective, experiment 2 is worse than experiment 1 because the loss of response 5 is too large. A good quality measurement index must reflect this fact. By the VIKOR method, the utility

Table 4 Main effects on VIKOR values

Factor	Level 1	Level 2	Level 3	Max−Min
A	0.174	0.227		0.054
B	0.269	0.125	0.208	0.144
C	0.214	0.246	0.142	0.103
D	0.269	0.153	0.180	0.116
E	0.321	0.143	0.138	0.184
F	0.108	0.107	0.387	0.280
G	0.170	0.166	0.266	0.101
H	0.171	0.290	0.141	0.148

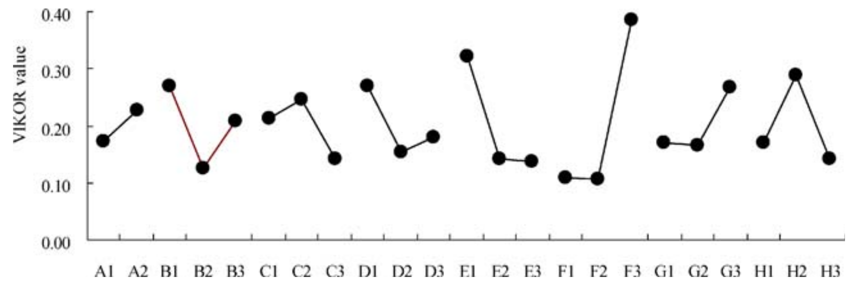


Fig. 3 Factor effects on VIKOR values

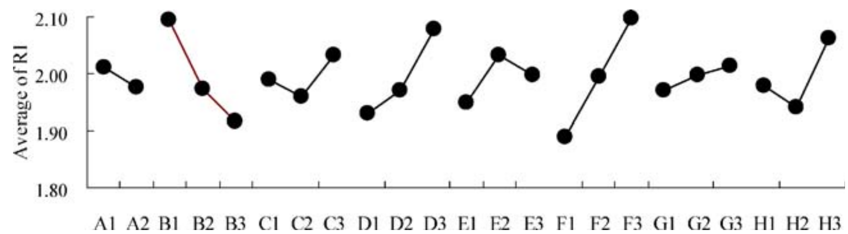


Fig. 4 Factor effects on the average of RI response

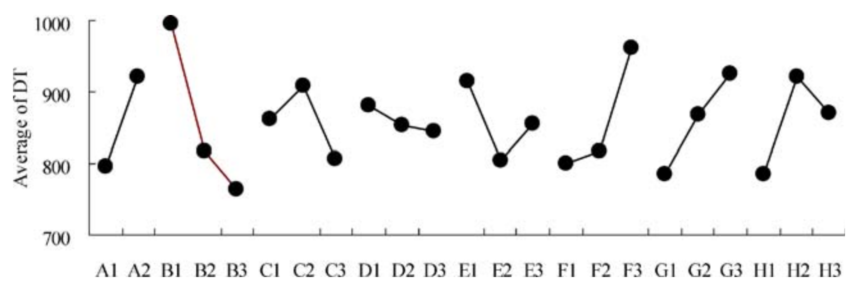


Fig. 5 Factor effects on the average of DT response

measure in experiment 1 is 50 and the regret measure of experiment 1 is 10, while the utility measure in experiment 2 is 48 and the regret measure is 16. By simultaneously considering both concordance and discordance, the VIKOR method determines that experiment 1 is better than experiment 2.

3 Proposed procedure

Although some methods have been developed to solve simultaneous optimizing multi-response problems, they neglect the variation among quality losses associated with the various responses. The optimal factor-level combination may generate an inconsistent quality loss among responses that is unacceptable to customers. A systematic multi-response optimization procedure is presented herein to solve this problem. The VIKOR method in MCDM is employed to optimize the solution to the multi-response problem. The proposed procedure firstly calculates the ideal and negative-ideal solutions of each experimental run by considering the quality loss and weight of each response, and then the corresponding utility and regret measures can be determined. The VIKOR index is obtained by weighting the utility and regret measures of each experimental run. The developed VIKOR index can help engineers to determine the optimal setting of parameters. The proposed optimization procedure is as follows.

Step 1. Calculate the quality loss.

Taguchi [8] defined three formulae for quality loss, based on the desirability of each quality characteristic, as follows.

(a) For a smaller-is-better response:

$$L_{ij} = k_1 \times \frac{1}{r}\sum_{k=1}^{r} y_{ijk}^2 \tag{9}$$

Table 5 Results of confirmatory experiment

Response	Index	Starting condition	Optimal condition (prediction)	Optimal condition (confirmation)	Improvement
Refractive index	SN	32.09	33.21	38.53	6.44
	Average	2.0216		1.8714	
	Variance	0.00198		0.000491	
Deposition thickness	SN	22.58	27.99	31.13	8.55
	Average	1043.267		1124.35	
	Variance	6000.8		974.54	

(b) For a larger-is-better response:

$$L_{ij} = k_2 \times \frac{1}{r}\sum_{k=1}^{r}\frac{1}{y_{ijk}^2} \tag{10}$$

(c) For a nominal-is-better response:

$$L_{ij} = k_3 \times \left(\frac{S_{ij}}{\overline{y}_{ij}}\right)^2 \tag{11}$$

where L_{ij} is the quality loss associated with the jth response in the ith experimental run; y_{ijk} is the observed kth repetition datum for the jth response in the ith experimental run; r is the number of repetitions for each experimental run, $\overline{y}_{ij} = \frac{1}{r}\sum_{k=1}^{r} y_{ijk}$, and $S_{ij}^2 = \frac{1}{r-1}\sum_{k=1}^{r}\left(y_{ijk} - \overline{y}_{ij}\right)^2$; and k_1, k_2 and k_3 are quality loss coefficients, for i= 1, 2, …, m; j= 1, 2, …, n; k= 1, 2, …, r.

Step 2. Calculate the normalized quality loss (NQL) of each response in each experimental run.

The NQL can be obtained as follows:

$$f_{ij} = \frac{L_{ij}}{\sqrt{\sum_{i=1}^{m} L_{ij}^2}}, i = 1, 2, ..., m; j = 1, 2, ..., n \tag{12}$$

where f_{ij} represents the NQL of the jth response in the ith experimental run.

Step 3. Determine the ideal and negative-ideal solutions.

A smaller NQL is preferred, so the ideal and negative-ideal solutions which represent the minimum and maximum NQL of all experimental runs are as follows:

$$A^* = \left\{\min f_{ij} | i = 1, 2, ...m\right\} = \left\{f_1^*, f_2^*, ..., f_j^*, ..., f_n^*\right\} \tag{13}$$

$$A^- = \left\{\max f_{ij} | i = 1, 2, ...m\right\} = \left\{f_1^-, f_2^-, ..., f_j^-, ..., f_n^-\right\} \tag{14}$$

Step 4. Calulate the utility and regret measures for each response in each experimental run.

The utility and regret measure of each response in each experimental run can be obtained using Eqs. 5 and 6.

Step 5. Calculate the VIKOR index of the ith experimental run.

Substituting S_i and R_i into Eq. 7 yields the VIKOR index of the ith experimental run as follows. A smaller VIKOR index produces better multi-response performance.

Table 6 Summary of experimental data

Experimental run	Control factor					Response			VIKOR value
	A	B	C	D	E	RR	NU	TaN/Cu	
1	1	1	1	1	1	294	14.3	4	0.7058
2	1	2	2	2	2	289	15.7	4.3	0.6240
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
17	3	2	1	3	1	580	15.1	4.6	0.3490
18	3	3	2	1	2	651	5	5.8	0.0000

Table 7 Main effects of factors on VIKOR values

Factors	Level 1	Level 2	Level 3	Max−Min
A	0.691	0.367	0.257	0.434
B	0.618	0.490	0.207	0.114
C	0.514	0.400	0.401	0.080
D	0.419	0.408	0.488	0.080
E	0.431	0.449	0.435	0.018

Table 8 Confirmatory experimental result

Response	Starting condition	Optimal condition (prediction)	Optimal condition (confirmation)	Improvement
RR	52.7071	56.2585	57.0861	4.3790
NU%	−18.0167	−16.8302	−14.8440	3.1727
TaN/Cu	12.9393	14.8497	19.3768	6.4375

Step 6. Determine the optimal factor-level combination.

The multi-response quality scores for each experimental run can be determined from the VIKOR index obtained in step 5, and the effects of the factors can be estimated from the VIKOR values. The optimal combination factor-level combination is finally determined, based on the fact that a smaller VIKOR value indicates a better quality.

Step 7. Perform the confirmatory experiment.

A confirmatory experiment should be performed to ensure that the optimal condition actually yields improvement. If the predicted and observed SN ratios are close to each other, the effectiveness of the optimal condition is ensured. The optimal condition can then be applied to the production line and expected to yield a robust result. If the predicted and observed SN ratios are not comparable, then the additive model is suspected to have failed and the interactions of factors are to be significant. Consequently, the entire experimental design must be reviewed to obtain a successful additive model and an optimal condition.

4 Illustrative examples

4.1 Optimizing the PECVD process

The following case study [16] demonstrates the effectiveness of the proposed optimization procedure. The case illustrates the improvement of a PECVD process used in fabricating an IC. Two major responses (nominal is the best) in the multi-response process are of interest, i.e., the refractive index (RI) and the deposition thickness (DT).

Following a discussion with process engineers, eight control factors were chosen to be optimized. Table 2 lists these factors and their levels. The standard orthogonal array L_{18} is selected to plan the experiment. Table 3 summarizes the experimental data. The relative importance of RI and DT was determined to be 2:1 in the discussion with the engineers. The target values of the two responses are 2 and 1000 Å, respectively.

4.1.1 Conventional Taguchi method

The following study illustrates the difficulty of determining the optimal condition of the multi-response process using the conventional Taguchi method. Figures 1 and 2 show the factor effects of responses RI and DT on SN ratios, respectively. These two Figures illustrate the conflicts among the conditions for some factors.

A larger SN ratio reflects better quality, so the following optimal factor-level combination for each response can be found as follows.

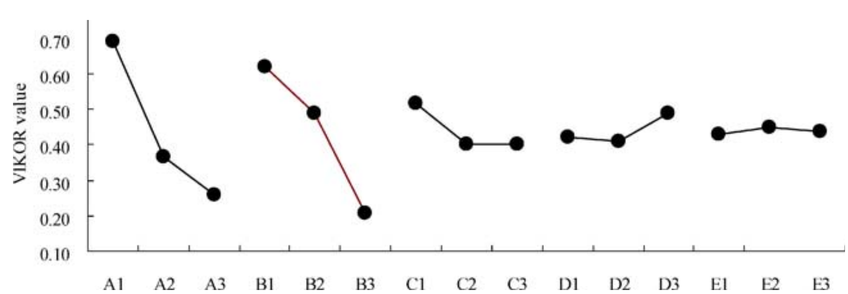
– RI: A_1 B_3 C_2 D_1 E_3 F_1 G_1 H_3
– DT: A_1 B_1 C_3 D_2 E_2 F_2 G_2 H_3

The two responses can be optimized by setting factor A to level 1 and setting factor H to level 3. However, determining the optimal settings of factors B, C, D, E, F and G is difficult. For instance, setting factor C to level 2 is advantageous for the RI response, but not for the DT response. In contrast, setting factor C to level 3 is advantageous for the DT response, but not for the RI response. This conflicting situation reveals the difficulty of optimizing factor-level combination by separately optimizing the two responses.

4.1.2 Proposed optimization procedure

By applying the procedure proposed, the values of the VIKOR index can be obtained, as presented in the last column of Table 3. Table 4 summarizes the VIKOR values of factor effects. Figure 3 plots the corresponding effects of

Fig. 6 Effects of factors on VIKOR values



these factors. The order of the strength of the effects of control factors on the VIKOR value is F, E, H, B, D, C, G and A. A smaller VIKOR value means a better quality, so the optimal condition is $A_1B_2C_3D_2E_3F_2G_2H_3$.

Figures 4 and 5 plot the factor effects on the averages of responses RI and DT, respectively. The flow rate of S_iH_4 (Factor D) is selected as the factor to be adjusted to optimize the RI response, because it only weakly affects the VIKOR value of the RI response and the average DT response, whereas it more strongly affects the average RI response. Similarly, the R.F. power (factor G) is selected to be adjusted to optimize the DT response, because it only weakly affects the VIKOR value of DT response and the average RI response, but more strongly affects the average DT response. If the average RI is not satisfactory, the flow rate of S_iH_4 can be adjusted to the target value of RI. Similarly, if the average of DT is not satisfactory, the R.F. power can be adjusted to the target value of DT.

The optimal condition was verified by performing a confirmatory experiment. Table 5 compares the optimal condition $A_1B_2C_3D_2E_3F_2G_2H_3$ with the starting condition $A_2B_1C_2D_2E_2F_2G_2H_2$. The optimal condition represents an improvement of 6.44 dB (with a decline in variance to 25%) in the RI response and 8.55 dB (with a decline in variance to 16%) in the DT response.

4.2 Optimizing the Cu-CMP process

The Cu-CMP process [17] is optimized using the VIKOR method to demonstrate the effectiveness of the procedure. As advanced IC technology develops, devices are becoming smaller. As the speed and performance of IC devices are increased, reducing the width of the metallic lines and increasing the resistance may delay signal propagation. Such a delay is a major concern. Additionally, increasing the speed of IC operation may also increase current densities in smaller interconnections. Copper is an appropriate material for metalizing advanced interconnections since it has lower resistivity and higher electromigration resistance than aluminum alloy interconnects. Accordingly, Cu-CMP is a promising method for fabricating multilevel Cu interconnections and performing planarization.

This process optimization case concerns a Taiwanese integrated circuit (IC) manufacturer. In a discussion with engineers, the following three important responses were identified.

1. Removal rate (RR): larger is better
2. Non-uniformity (NU): smaller is better
3. Selectivity of TaN/Cu: larger is better

Five control factors (A to E) were selected and included in an orthogonal array L_{18}. The starting levels of all control factors were set to 2. For reasons of confidentiality, no detailed information about the factors or levels is presented. Table 6 summarizes the experimental data.

4.2.1 Proposed optimization procedure

The last column of Table 6 lists the VIKOR values for each experimental run, obtained by the proposed procedure. Table 7 summarizes the main effects on the VIKOR values, and Fig. 6 plots their effects of the corresponding factors. The optimal factor-level combination is determined as $A_3B_3C_2D_2E_1$ and the order of the strengths of the effects of the control factors on the VIKOR value is A, B, C, D and E.

Table 8 presents the predicted and confirmed results. The optimal condition provides an improvement of 4.379 dB in RR, 3.1727 dB in NU% and 6.4375 dB in TaN/Cu. This great improvement demonstrates the effectiveness of the proposed method.

5 Conclusions

Most applications of the Taguchi method concern only the optimization of a single-response problem. When more than one response is considered, engineers generally optimize based on their subjective experience. Although some systematic procedures for optimizing multi-response problems have been developed in recent years, the quality indices associated with these procedures are concerned primarily with optimizing the utility of the multi-response process, and they neglect the variation in quality loss among the various responses. In this study, a systematic procedure is developed that involves applying the MCDM compromise ranking method VIKOR to optimize the multi-response process. The procedure consists of the following steps: (a) computing the quality loss; (b) determining the VIKOR value; (c) determining the optimal condition; (d) performing and analyzing the results of a confirmatory experiment. Theoretical analysis herein revealed that the quality concepts of Taguchi's SN ratio and VIKOR index are compatible. Taguchi's SN ratio simultaneously considers the mean and variation of a quality characteristic and can be applied to optimize the single-response process, while the VIKOR index simultaneously considers the utility and regret measure to optimize the multi-response process. Two case studies of plasma-enhanced chemical vapor deposition and copper chemical mechanical polishing demonstrate the effectiveness of the proposed method.

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