Int J Adv Manuf Technol (2005) 27: 407–414
DOI 10.1007/s00170-004-2157-9

ORIGINAL ARTICLE

Lee-Ing Tong · Chung-Ho Wang · Hung-Cheng Chen

Optimization of multiple responses using principal component analysis and technique for order preference by similarity to ideal solution

Received: 3 December 2003 / Accepted: 25 February 2004 / Published online: 7 July 2004

Abstract Optimizing multi-response problems has become an increasingly relevant issue when more than one correlated product quality characteristic must be assessed simultaneously in a complicated manufacturing process. This study proposes a novel optimization procedure for multiple responses based on Taguchi's parameter design. The signal-to-noise (SN) ratio is initially used to assess the performance of each response. Principal component analysis (PCA) is then conducted on the SN values to obtain a set of uncorrelated components. The optimization direction for each component is determined based on the corresponding variation mode chart. Finally, the relative closeness to the ideal solution resulting from the technique for order preference by similarity to ideal solution (TOPSIS) is determined as an overall performance index (OPI) for multiple responses. Engineers can easily employ the proposed procedure to obtain the optimal factor/level combination for multiple responses. A case study involving optimization of the chemical-mechanical polishing of copper (Cu-CMP) thin films from an integrated circuit manufacturer in Taiwan is also presented to demonstrate the effectiveness of the proposed procedure.

Keywords Multi-response problems · Optimization · Principal component analysis · Taguchi method · TOPSIS

L.-I. Tong (✉)
Department of Industrial Engineering and Management,
National Chiao Tung University,
Hsinchu, Taiwan, R.O.C. 300

C.-H. Wang
Department of General courses, Chung Cheng Institute of Technology,
National Defense University,
Taoyuan, Taiwan, R.O.C.

H.-C. Chen
Enterprise Operation Planning Division,
United Microelectronics Corporation,
Hsinchu, Taiwan, R.O.C. 300

1 Introduction

The method that Taguchi developed in 1960 for enhancing product quality has been widely implemented throughout industry to upgrade manufacturing products/processes [9]. The Taguchi method evaluates product quality by applying the signal-to-noise (SN) ratio and, in doing so, the optimal factor/level combination obtained from the Taguchi method can be determined to reduce simultaneously the quality variation and bring the mean close to the target value. Despite its widespread industrial applications, the Taguchi method can only be used for optimizing single-response problems. When the product design becomes increasingly complicated, more than one response must be optimized. Because these responses are usually moderately or highly correlated, developing procedures capable of optimizing simultaneously multi-response problems has become increasingly important, particularly in high-tech industries. However, most available procedures do not consider the correlations among the responses and they are too mathematically complicated for engineers to use in practice. Additionally, the possible correlations among responses may cause difficulty in optimizing multiple responses simultaneously.

This study develops a novel multi-response optimization procedure capable of resolving the correlation problems among responses, and reducing the computational complexity. The SN ratio is initially used to assess the performance of each response. The PCA is then conducted on SN values to obtain a set of uncorrelated principle components, which are linear combinations of the original responses. The variation mode chart is plotted to interpret the variation mode (or principal component variation) resulting from PCA. Based on the engineering requirements, engineers can determine the optimization direction for each principal component using the variation mode chart. Finally, TOPSIS is employed to derive the OPI for multiple responses. The optimal factor/level combination is determined by the maximum OPI value. A case study involving the optimization of the chemical-mechanical polishing of copper (Cu-CMP) thin films, from an integrated circuit manufacturer in Taiwan, is presented to demonstrate the effectiveness of the proposed procedure.

2 Literature review

Many Taguchi practitioners have used engineering knowledge to resolve multi-response optimization problems. For example, Phadke [9] combined engineering knowledge with relevant experience to optimize three responses, i.e. surface, wafer thickness, and deposition rate, in a very-large-scale integrated (VLSI) circuit-manufacturing process. Other techniques, as proposed by Logothetis and Haigh [8], suggested that multi-response data must be transformed before determining the noise performance statistic (NPS) and the target performance statistic (TPS) for each response. The optimal factor/level combination and adjustment factors are determined based on the NPS and TPS values. Elsayed and Chen [4] distinguished between the control factor and adjustment factor by the performance measure independent of adjustment (PerMIA). The performance measure for quality (PerMQ) is calculated based on the selected adjustment factor. Chang and Shivpuri [2] established a regression model for each response for control factors and applied the procedure of multiple-attribute decision making (MADM) to determine an optimal factor/level. Tong and Su [10] used fuzzy theory and the MADM technique to resolve a multi-response problem. Ames et al. [1] adopted the response surface method (RSM) to resolve a multi-response problem. Despite their contributions, the above multi-response optimization methods share the following limitations:

1. The optimal factor/level combination for multiple responses is determined based on pure engineering experience but the correlations among responses are not considered. Because the engineer's judgment often leads to uncertainty during decision making, different engineers may produce conflicting results when addressing the same problem; and
2. These procedures are developed based on the linear programming technique or other complicated mathematical algorithms, thereby making them impractical for many engineering applications.

3 PCA and TOPSIS

3.1 PCA

Pearson and Hotelling [5] initially developed PCA to explain the variance-covariance structure of a set of variables by linearly combining the original variables. The PCA technique can account for most of the variation of the original p variables via k uncorrelated principal components, where $k \leq p$. Restated, let $\mathbf{x} = x_1, x_2, \ldots, x_p$ be a set of original variables with a variance-covariance matrix $\mathbf{\Sigma}$. Through the PCA, a set of uncorrelated linear combinations can be obtained in the following matrix:

$$\mathbf{Y} = \mathbf{A}^{\mathrm{T}}\mathbf{x} \tag{1}$$

where $\mathbf{Y} = (Y_1, Y_2, \ldots, Y_P)^{\mathrm{T}}$, Y_1 is called the first principal component, Y_2 is called the second principal component and so on; $\mathbf{A} = (a_{ij})_{P\times P}$ and $\mathbf{A}$ is an orthogonal matrix with $\mathbf{A}^{\mathrm{T}}\mathbf{A} = \mathbf{I}$. Therefore, $\mathbf{x}$ can also be expressed as follows:

$$\mathbf{x} = \mathbf{AY} = \sum_{j=1}^{p} \mathbf{A}_j Y_j \tag{2}$$

where $\mathbf{A}_j = [a_{1j}, a_{2j}, \ldots, a_{pj}]^{\mathrm{T}}$ is the j^{th}eigenvector of Σ.

3.2 Variation mode chart

The variation mode chart [11] is an effective means of analysing the variation mode (or principal component variation) obtained from PCA. Analysing this chart can provide further insight into the different variation types for each variation mode. Therefore, the portion of variation contributed by the original variables $(x_1, x_2, \ldots, x_p)$ in each mode can be obtained. The calculation process for establishing a variation mode chart is given as follows: Let $\mathbf{z}_j = \mathbf{A}_{.j} Y_j = [a_{1j}, a_{2j}, \ldots, a_{pj}]^{\mathrm{T}} Y_j = [z_{1j}, z_{2j}, \ldots, z_{pj}]^{\mathrm{T}}$, Eq. 2 can be rewritten as follows:

$$\mathbf{x} = \mathbf{z}_1 + \mathbf{z}_2 + \ldots + \mathbf{z}_p \tag{3}$$

where $\mathbf{z}_j$ is a product of a random scalar Y_j and a deterministic vector $\mathbf{A}_{.j}$; $\mathbf{z}_j$ can be defined as a geometrical variation mode. The mean, variance and standard deviation of z_{ij} are given as follows:

$$E(z_{ij}) = E(a_{ij} \times Y_j) = a_{ij} E(Y_j) = 0 \tag{4}$$

$$\mathrm{Var}(z_{ij}) = \mathrm{Var}(a_{ij} \times Y_j) = a_{ij}^2 \mathrm{Var}(Y_j) = a_{ij}^2 \lambda_j \tag{5}$$

$$\sigma(z_{ij}) = |a_{ij}|\sqrt{\lambda_j} \tag{6}$$

Figure 1 plots the variation mode chart based on a three-sigma zone $(u \pm 3\sigma)$ that describes the pattern and magnitude for each variation mode. In this figure, the solid line denotes the variation extent limit (VEL_1), which is equal to $3\sigma(z_{ij})$ as shown in Eq. 7. The dotted line denotes the variation extent limit (VEL_2), which is equal to $-3\sigma(z_{ij})$ as shown in Eq. 8.

$$VEL_1(z_j) = (3a_{1j}\sqrt{\lambda_j}, \ldots, 3a_{pj}\sqrt{\lambda_j}) \tag{7}$$

$$VEL_2(z_j) = (-3a_{1j}\sqrt{\lambda_j}, \ldots, -3a_{pj}\sqrt{\lambda_j}) \tag{8}$$

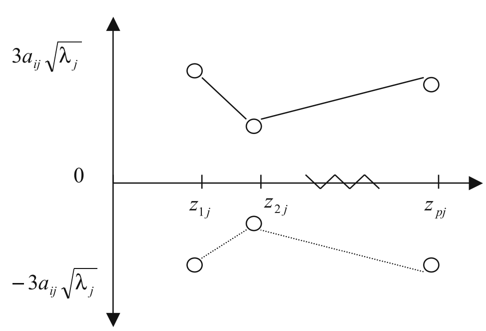

Fig. 1. Variation mode chart

The following example, including four variables $\mathbf{x} = (x_1, x_2, x_3, x_4)$, illustrates how to use a variation mode chart to characterize the exact pattern and magnitude of a variation mode. In this example, assume that the eigenvalue $\lambda_1 = 33.62$ and $A_{.1} = (0.503, 0.332, -0.455, -0.656)$. The $VEL_1(z_1) = (8.75, 5.77, -7.91, -11.4)$ and the $VEL_2(z_1) = (-8.75, -5.77, 7.91, 11.4)$ are accordingly obtained using Eqs. 7 and 8. Thus, the variation mode chart for mode 1 is presented in Fig. 2.

Clearly, when x_1 and x_2 vary in the positive direction, then x_3 and x_4 vary in the negative direction. As x_1 moves in the positive direction up to 8.75, x_2 moves in the positive direction up to 5.77, and x_3 and x_4 move in the negative direction up to 7.91 and 11.4, respectively. Therefore, analysis of the variation mode chart can provide further insight into the variation pattern of various variables. Doing so can facilitate the reduction of the origins of variable variations.

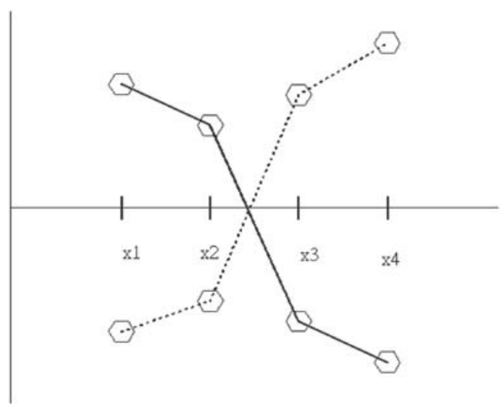

Fig. 2. An example of variation mode chart

3.3 TOPSIS

Hwang and Yoon [6] developed TOPSIS to assess the alternatives before multiple-attribute decision making. TOPSIS considers simultaneously the distance to the ideal solution and negative ideal solution regarding each alternative, and also selects the most relative closeness to the ideal solution as the best alternative. That is, the best alternative is the nearest one to the ideal solution and the farthest one from the negative ideal solution. The procedure of TOPSIS is summarized as follows:

1. Establish an alternative performance matrix. The structure of the alternative performance matrix is expressed as follows:

$$\mathbf{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdot \\ A_i \\ \cdot \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} X_1 & X_2 & X_j & X_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdot & x_{1j} & \cdot & x_{1n} \\ x_{21} & x_{22} & \cdot & x_{2j} & \cdot & x_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{i1} & x_{i2} & \cdot & x_{ij} & \cdot & x_{in} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{m1} & x_{m2} & \cdot & x_{mj} & \cdot & x_{mn} \end{bmatrix} \end{array} \tag{9}$$

   where A_i denotes the possible alternatives, $i = 1, \ldots, m$; X_j represents attributes relating to alternative performance, $j = 1, \ldots, n$; and x_{ij} is the performance of A_i with respect to attribute X_j.

2. Normalize the performance matrix. The normalized performance matrix can be obtained using the following transformation formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{10}$$

   where r_{ij} represents the normalized performance of A_i with respect to attributeX_j. The matrix form of r_{ij} is given as follows:

$$\mathbf{R} = [r_{ij}] \tag{11}$$

   where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots n$.

3. Multiply the performance matrix by its associated weights. Each column of matrix $\mathbf{R}$ is multiplied by weights associated with each attribute. The weighted performance matrix $\mathbf{V}$ is obtained as follows:

$$\mathbf{V} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdot & w_j r_{1j} & \cdot & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdot & w_j r_{2j} & \cdot & w_n r_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ w_1 r_{i1} & w_2 r_{i2} & \cdot & w_j r_{ij} & \cdot & w_n r_{in} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ w_1 r_{m1} & w_2 r_{m2} & \cdot & w_j r_{mj} & \cdot & w_n r_{mn} \end{bmatrix} = \begin{bmatrix} v_{11} & v_{12} & \cdot & v_{1j} & \cdot & v_{1n} \\ v_{21} & v_{22} & \cdot & v_{2j} & \cdot & v_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ v_{i1} & v_{i2} & \cdot & v_{ij} & \cdot & v_{in} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ v_{m1} & v_{m2} & \cdot & v_{mj} & \cdot & v_{mn} \end{bmatrix} \tag{12}$$

   where w_j represents the weight of attribute X_j and v_{ij} represents the weighted normalized performance of A_i with respect to X_j for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

4. Determine the ideal and negative ideal solution. The ideal value set $\mathbf{V}^+$ and the negative ideal value set $\mathbf{V}^-$ are determined as follows:

$$\begin{aligned} \mathbf{V}^+ &= \{(\max v_{ij} \,|\, j \in \mathbf{J}) \text{ or } (\min v_{ij} \,|\, j \in \mathbf{J}'),\ i = 1, 2, \ldots, m\} \\ &= \{v_1^+, v_2^+, \ldots, v_n^+\} \\ \mathbf{V}^- &= \{(\min v_{ij} \,|\, j \in \mathbf{J}) \text{ or } (\max v_{ij} \,|\, j \in \mathbf{J}'),\ i = 1, 2, \ldots, m\} \\ &= \{v_1^-, v_2^-, \ldots, v_n^-\} \end{aligned}$$

   where

$$\mathbf{J} = \{j = 1, 2, \ldots, n \,|\, v_{ij}, \quad \text{a larger response is desired}\}$$

$$\mathbf{J}' = \{j = 1, 2, \ldots, n \,|\, v_{ij}, \quad \text{a smaller response is desired}\}$$

5. Calculate the separation measures. The separation of each alternative from the ideal solution (S_i^+) is given as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{13}$$

The separation of each alternative from the negative ideal solution (S_i^-) is as follows:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{14}$$

Calculate the relative closeness to the ideal solution and rank the preference order. The relative closeness C_i to the ideal solution can be expressed as follows:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{15}$$

where C_i lies between 0 and 1. The closer C_i is to 1, the higher the priority of the i^{th} alternative.

4 Proposed procedure

This study proposes an optimization procedure for multiple responses based on Taguchi's parameter design. Because multiple responses always contain moderate or high correlations, the PCA is initially performed on the SN values obtained from each response to integrate the dimension of multiple responses to a smaller number of uncorrelated components. The variation mode charts for components obtained from PCA are then used to investigate the variation pattern of various integrated responses. Finally, TOPSIS is used to determine the optimal factor/level combination for multiple responses. The symbols used in this study are summarized in Table 1.

The proposed procedure for optimizing multi-response problems includes the following seven steps:

Step 1. Calculate the SN ratio for each response.

Phadke [9] details the SN ratio formula.

Step 2. Conduct the PCA on normalized SN ratios.

The SN ratio for each response is normalized by the following formula:

$$\frac{SN_{ij} - \overline{SN_j}}{S_{SN_j}} \tag{16}$$

where SN_{ij} denotes the SN ratio of the j^{th} response in the i^{th} experimental run; $\overline{SN_j}$ and S_{SN_j} represent the mean and standard deviation of the SN ratio for the j^{th} response, respectively.

Table 1. List of symbols

Symbols	Notation
SN_{ij}	The signal-to-noise (SN) ratio of the j^{th} response under the i^{th} experimental run.
$\overline{SN_j}$	The mean of the SN ratio of the j^{th} response.
S_{SN_j}	The standard deviation of the SN ratio for the j^{th} response.
v_j^+	The ideal solutions of the j^{th}response.
v_j^-	The negative ideal solutions of the j^{th} response.
C_i	The overall performance index (OPI) of multiple responses under the i^{th} experimental run.

The eigenvalues and eigenvectors for each principal component are obtained after conducting PCA on the normalized SN ratios.

Step 3. Determine the number of principal components retained and establish the variation mode charts.

Some principal components are selected for further analysis based on the significance of the linear correlation between the responses and principal components and the cumulative variation of the responses accounted for by the selected principal components. The corresponding variation mode charts are also established using Eq. 7 and Eq. 8.

Step 4. Determine the optimization direction of the selected principal components.

The optimization direction of each selected principal component is determined according to the variation mode chart. According to Fig. 2, if responses x_1 and x_2 are more important than responses x_3 and x_4, the first principal component score is determined since a larger value is desired. In this case, optimizing (or maximizing) the first principal component increases response x_1 and x_2 by 8.75 and 5.77, respectively, and decreases x_3 and x_4 by 7.91 and 11.4, respectively. When responses x_3 and x_4 are more important than responses x_1 and x_2, the first principal component score is determined, as a smaller value is desired. In this case, optimizing (or minimizing) the first principal component decreases responses x_1 and x_2 by 8.75 and 5.77, respectively and increases x_3 and x_4 by 7.91 and 11.4, respectively. When more than one principal component is selected for further analysis, the first principal component initially determines the optimization direction. Thereafter, the optimization direction of the second principal component is determined, and so on for the remaining selected components.

Step 5. Conduct TOPSIS to obtain the OPI for multiple responses.

According to the optimization direction of the selected principal components obtained from Step 4, TOPSIS is used to determine the OPI. The experimental runs are treated as alternatives; and the selected principal components are treated as attributes and a quality performance matrix is formed. The weighted quality performance matrix can be obtained using Eqs. 9–12, where the weights are the eigenvalues associated with each principal component. If a larger value is desired, the ideal and negative ideal solutions representing the maximum and minimum principal component scores of all experimental runs are expressed in Eq. 17 and Eq. 18, whereas if a smaller value is desired, the ideal and negative ideal solution representing the minimum and maximum principal component scores of all experimental runs are expressed in Eq. 19 and Eq. 20. Correspondingly, the OPI values (or C_i values for $i = 1, 2, \ldots, m$) for each experimental run are derived using Eqs. 13–15.

$$v_j^+ = \max\{v_{1j}, v_{2j}, \ldots, v_{mj}\} \tag{17}$$

$$v_j^- = \min\{v_{1j}, v_{2j}, \ldots, v_{mj}\} \tag{18}$$

$$v_j^+ = \min\{v_{1j}, v_{2j}, \ldots, v_{mj}\} \tag{19}$$

$$v_j^- = \max\{v_{1j}, v_{2j}, \ldots, v_{mj}\} \tag{20}$$

Step 6. Determine the optimal factor/level combination.

The main effects on OPI are determined based on the C_i values. Thus, the corresponding diagram plots the factor effect on OPI. The optimal factor/level combination produces the maximum OPI value.

Step 7. Conduct the confirmation experiment.

According to the optimal factor/level combination, confirmation experiments are performed to verify whether the experimental results can be reproduced. The predicted SN value for each response is compared with the associated actual SN value obtained from the confirmation experiments. If the predicted SN values and the actual SN values differ only slightly then the experiment can be reproduced. If the predicted SN values and the actual SN values differ substantially, the experimental result cannot be reproduced. In this case, suitable quality characteristics, control factors, or signal factors must be reselected, and return to step 1 of the proposed procedure to start all over again.

5 Illustrative example

The effectiveness of the proposed procedure is demonstrated using a chemical-mechanical polishing process of copper thin-film provided by a Taiwanese integrated circuit (IC) manufacturer. With the scaling down in size of integrated circuit devices and the increasing number of devices on the chip, on-chip interconnections play a dominant role in determining IC performance. Although scaling down the size of the device enhances the device speed, the interconnection delays the signal propagation. Consequently, interconnect delay severely limits circuit performance. The interconnection RC-delay increases rapidly in sub-micron regions because the resistance of the metal line increases with the decreasing line width while the parasitic capacitance of metal lines increases with decreasing line spacing. Higher operating frequencies for IC chips increase current densities in smaller interconnection features. Consequently, a stable metal like copper is highly promising for the metallization of advanced interconnection owing to its lower resistivity and enhanced electromigration resistance compared to current aluminum alloy interconnects [3, 7]. A dual damascene process is initially developed to pattern the inter-layer dielectric (ILD) to form trenches and vias. These trenches and vias are then filled with copper, followed by chemical-mechanical polishing to flatten the wafer surface until the only remaining copper is in the trenches, and the vias have recessed into the ILD. Since CMP leaves the wafer surface globally planar, this sequence can be repeated to add multiple metal layers. Furthermore, Cu-CMP is essential in successfully implementing the dual damascene process for multilevel Cu-interconnects. Thus, multilevel Cu-interconnection using the dual damascene process is a viable alternative for ULSI manufacturing. The proposed procedure is verified via the optimization steps of removing the TaN barrier layer of the Cu-CMP process. Based on the engineering requirements, the following quality characteristics are determined as the process responses:

1. Removal rate (RR): a larger value is desired.
2. Non-uniformity (NU): a smaller value is desired.
3. TaN/Cu selectivity: a larger value is desired.

Among these responses, NU is the most important quality characteristic, TaN/Cu is the next important one and RR is the least important one. Five control factors (A to E), each with three levels, are allocated sequentially to a L_{18} orthogonal array. Owing to engineering confidentiality, the names of the factors and the contents of each level are omitted. The experiments are conducted randomly.

The experimental data was analysed by following the proposed procedure strictly. Table 2 displays the experimental observations and SN ratios for each response resulting from Taguchi's SN ratio formula. Tables 3 and 4 display the eigenval-

Table 2. Experimental observations and SN ratio

Ex. no.	Control factor					Response			SN ratio		
L_{18}	A	B	C	D	E	RR	NU	TaN/Cu	RR	NU	TaN/Cu
1	1	1	1	1	1	294	14.3	4.0	49.37	-23.11	12.04
2	1	2	2	2	2	289	15.7	4.3	49.22	-23.92	12.67
3	1	3	3	3	3	314	23.2	5.6	49.94	-27.31	14.96
4	2	1	1	2	2	375	12.1	3.7	51.48	-21.66	11.36
5	2	2	2	3	3	437	8.7	4.9	52.81	-18.79	13.80
6	2	3	3	1	1	498	6.5	6.1	53.94	-16.26	15.71
7	3	1	2	1	3	481	8.99	4.2	53.64	-19.08	12.46
8	3	2	3	2	1	588	11.8	4.3	55.39	-21.44	12.67
9	3	3	1	3	2	660	12.4	5.3	56.39	-21.87	14.49
10	1	1	3	3	2	242	16.2	4.6	47.68	-24.19	13.26
11	1	2	1	1	3	268	26.9	4.1	48.56	-28.60	12.26
12	1	3	2	2	1	340	10.5	5.3	50.63	-20.42	14.49
13	2	1	2	3	1	377	16.9	3.9	51.53	-24.56	11.82
14	2	2	3	1	2	434	5.06	4.7	52.75	-14.08	13.44
15	2	3	1	2	3	494	7.08	5.4	53.87	-17.00	14.65
16	3	1	3	2	3	483	8.76	5.2	53.68	-18.85	14.32
17	3	2	1	3	1	580	15.1	4.6	55.27	-23.58	13.26
18	3	3	2	1	2	651	5.0	5.8	56.27	-13.98	15.27

Table 3. The eigenvalues and explained percentage of variation for principal components

Components	Eigenvalue	Difference	Percentage	Accumulative percentage
First component	1.99107	1.36858	0.663689	0.66369
Second component	0.62249	0.23604	0.207496	0.87118
Third component	0.38645	–	0.128816	1.00000

Table 4. The eigenvectors for principal components

Response	First component	Second component	Third component
Removal rate (RR)	0.589389	−0.487698	0.644028
Non-uniformity (NU)	0.610704	−0.252885	−0.750393
Selectivity (TaN/Cu)	0.528830	0.835583	0.148792

ues and eigenvectors arising from PCA conducted by employing the SAS statistical software package (many other statistical soft packages such as SPSS, Minitab or STATISTICA can also be used to conduct PCA).

Based on Tables 3 and 4, all three principal components are retained, since the first two principal components only account for 87% of the variation of the original variables. The three principal components are uncorrelated and can account for 100% of the variation of original variables. Fig. 3 displays the variation mode charts for each principal component. Clearly, the directions of variation mode for responses RR, NU and TaN/Cu is consistent and their variation contributions do not significantly differ for the first principal component. Therefore, the first principal component is determined, as a larger value desired integrated response. The SN ratios of each response can be enhanced simultaneously when optimizing the first principal component. The directions of variation mode for responses RR and TaN/Cu are opposite and the variation contributed by response NU is insignificant in the second principal component. Therefore, the second principal component is determined as a larger value desired integrated response since the response TaN/Cu is more important than the response RR. Similarly, the third principal component is determined as a smaller value desired integrated response since NU is the most important response and the directions of variation mode for responses RR and NU are opposite in the third principal component. Thus, decreasing the SN ratio of response RR by 1.2 can increase the SN ratio of NU by 1.39 and the SN ratio of TaN/Cu is nearly unchanged.

Table 5 lists the OPI values, which are measures of relative closeness to the ideal solution resulting from TOPSIS. Accordingly, a response diagram on OPI values is established as shown in Fig. 4. According to this figure, the optimal factor/level combination is determined as A_3 B_3 C_3 D_1 E_3.

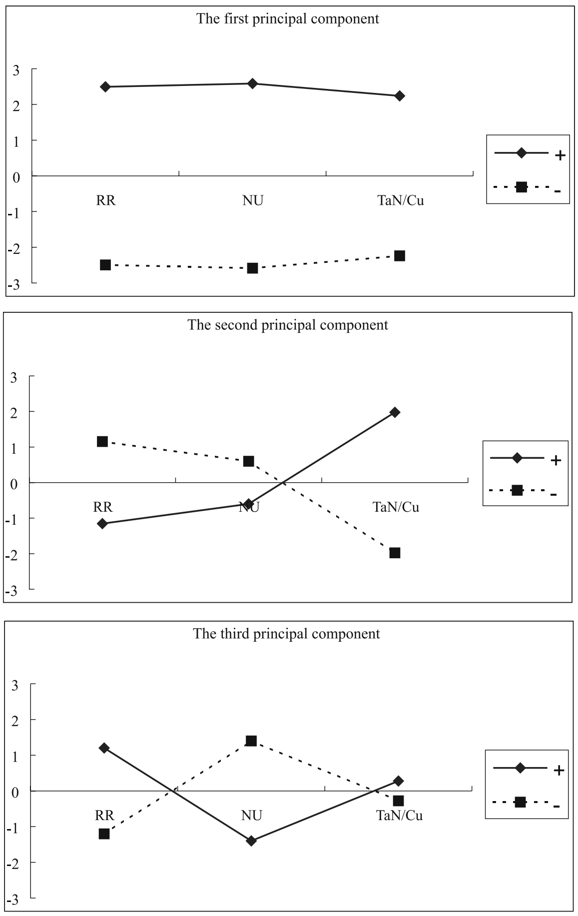

Fig. 3. The variation mode chart

Table 5. The overall performance index

Experimental runs	OPI
1	0.23
2	0.26
3	0.39
4	0.26
5	0.57
6	0.83
7	0.47
8	0.48
9	0.64
10	0.28
11	0.15
12	0.53
13	0.21
14	0.65
15	0.72
16	0.64
17	0.47
18	0.83

Table 6. Summary of the predicted SN value and the actual improvement

Response	*Starting condition	Optimal condition (prediction)	Optimal condition (confirmation)	Actual improvement
Removal rate (RR)	52.7071	55.9256	56.9391	4.2320
Non-uniformity (NU)	−17.3205	−16.260	−12.8691	4.4514
Selectivity (TaN/Cu)	12.9393	16.0201	21.0076	8.0683

* Starting condition are at level 2 for all factors.

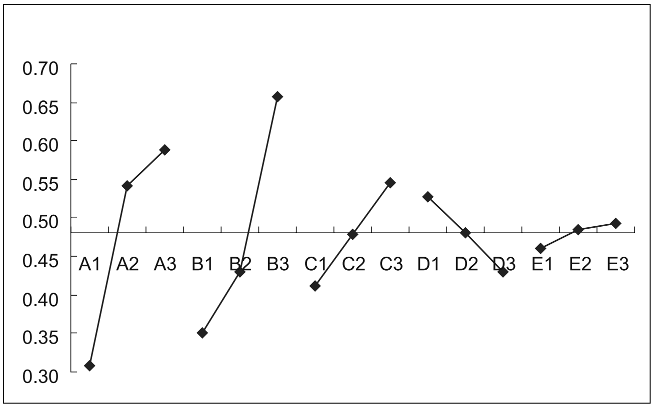

Fig. 4. Factor effects on OPI

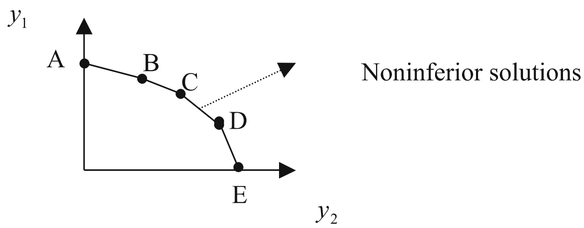

Fig. 5. The diagram of non-inferior solutions

The confirmation experiments are performed under the optimal factor/level combination to verify whether the optimum condition is reproduced. Table 6 summarizes the computations of the predicted SN values for all three responses, revealing that the actual SN values slightly differ from the predicted SN values. The SN ratio for RR is improved by 4.2320 dB, NU is improved by 4.4514 dB and TaN/Cu is improved by 8.0683 dB. This finding confirms that the optimal factor/level combination can be reproduced and the proposed procedure for optimizing multiple responses can enhance the product/process quality efficiently.

6 Conclusion

This study utilizes PCA to simplify multi-response problems and determines the optimization direction by using a variation mode chart. The optimal factor/level combination is also determined based on the overall performance index for multiple responses obtained from TOPSIS. A case study in which the chemical-mechanical polishing process of copper thin films is optimized confirms the effectiveness of the proposed procedure.

The proposed procedure has the following merits:

1. The proposed procedure is relatively simple and does not involve much complicated mathematical processing, thus making it quite feasible for engineers to use without much statistical background.
2. Most of the multi-response optimization procedures developed in previous studies provided non-inferior solutions. In addition, these procedures do not consider the relative importance of each response. The proposed procedure can identify the optimization direction via the variation mode chart, which reflects the relative importance of each response, to obtain a real optimal solution. To address this point, as illustrated in Fig. 5, assuming two responses, say y_1 and y_2, with the larger values desired for both responses, the solid line represents the collection of all non-inferior solutions. The optimization solution for multiple responses obtained from previous studies falls anywhere in the interval between A and E. However, the optimization solution falls only in the interval between C and E if the response y_2 is more important than y_1. Whereas when the response y_1 is more important than y_2, the optimization solution falls in the interval between A and C.
3. The proposed procedure transforms the correlated multiple responses into uncorrelated components through PCA, thereby simplifying the optimization process.
4. The proposed procedure can also resolve the multi-response problems in a dynamic system with some modification.

References

1. Ames AE, Mattucci N, Macdonald S, Szonyi G, Hawkins DM (1997) Quality loss functions for optimization across multiple response surfaces. J Qual Technol 29:339–346
2. Chang SI, Shivpuri R (1995) A multiple-objective decision-making approach for assessing simultaneous improvement in die life and casting quality in a die casting process. Qual Eng 7:371–383
3. Hu CK, Harper JME (1998) Copper interconnections and reliability. Mater Chem Phys 52:5–16
4. Elsayed EA, Chen A (1993) Optimal levels of process parameters for products with multiple characteristics. Int J Prod Res 31:1117–1132
5. Hotelling H (1933) Analysis of a complex of statistical variables into principal components. J Educ Psych 24:471–441, 498-520
6. Hwang CL, Yoon K (1981) Multiple Attribute Decision Making-Method and Applications, A State-of-the-Art Survey. Springer-Verlag, New York

7. Lakshminarayanan S, Steigerwald J, Price D, Chow TP, Gutmann RJ, Murarka SP (1995) CMOS devices and multilevel interconnections with dual damascene copper metallization. Proceddings of IEEE VMIC, pp337–339, June 27-29
8. Logothetis N, Haigh A (1988) Characterizing and optimizing multi-response processes by the Taguchi method. Qual Reliability Eng Int 4:159–169
9. Phadke MS (1989) Quality Engineering Using Robust Design. Prentice-Hall, NJ
10. Tong L-I, Su C-T (1997) Optimizing multi-response problems in the Taguchi method by fuzzy multiple attribute decision making. Qual Reliability Eng Int 13:25–34
11. Yang K (1996) Improving automotive dimensional quality by using principal component analysis. Qual Reliability Eng Int 12:401–409