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ORIGINAL ARTICLE

Uniformity and signal-to-noise ratio for static and dynamic parameter designs of deposition processes

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Abstract In this paper, the relationship between the uniformity measure (U) and the Taguchi signal-to-noise ratio (SNR) for parameter design (or robust design) is investigated with a focus on the deposition process. For the static parameter design, it can be easily shown that U is directly related to the Taguchi SNR, and, as such, U can be interpreted as a measure directly related to the expected loss after the mean thickness is adjusted to the target. For the dynamic parameter design in which the target of a characteristic (e.g., the target thickness for a deposition process) changes, the Taguchi SNR is conditional on the signal parameter values (e.g., the deposition times) used in the parameter design experiment. Therefore, a new performance measure is developed considering a general distribution of the target thickness, and it is shown that U is also equivalent to this new performance measure. In summary, U can be used as a valid performance measure for the dynamic as well as static parameter design of a deposition process. Based on these findings, static and dynamic parameter design procedures for a deposition process are developed considering not only U but also the deposition rate, and the proposed dynamic procedure is illustrated with an example case study.

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1 Introduction

The uniformity measure (U) has been used to assess the variation of deposition, coating, or growth thickness, etched depth, amount removed in chemical mechanical polishing, etc. [1–3]. In this paper, the relationship between U and the Taguchi signal-to-noise ratio (SNR) for parameter design (or robust design) is investigated with a focus on the deposition process.

Let y be the thickness of the deposited material. Then, U is usually defined as the ratio of the standard deviation to the mean of y [1] (often called percent of standard deviation in the literature). In addition to U, engineers are also concerned with the deposition rate (r) for productivity. A deposition process is then optimized by determining settings of process design parameters such that r is large and U is small. Finally, the mean of y is adjusted to the target thickness by manipulating the deposition time.

Concerning U, engineers frequently ask such questions as “What is the meaning of U?”, “Why is U, instead of the standard deviation, minimized?”, etc. Answers to these questions are closely related to the SNR in the Taguchi parameter design methodology. In this paper, the meaning of the Taguchi SNR for a nominal-the-best (NB) quality characteristic (e.g., deposition thickness) is explained, and the meaning of U is clarified based on the relationship between U and *SNR*.

Another important feature to consider when optimizing a deposition process is that it is highly desirable to design the process to adequately deal with the situation where the target thickness varies from product to product or from step to step within a product. In other words, a deposition process should be optimized over a certain range of the target thickness, not for a specific target value only, and thereby, can be effectively used under varying production requirements. This feature can be adequately handled using the Taguchi dynamic parameter design approach [4]. On the other hand, the Taguchi SNR is conditional on the signal parameter values (e.g., deposition times) included in the parameter design experiment. Therefore, a new performance measure is developed in this paper considering a general distribution of the target thickness, and it is shown that the usual uniformity measure is also directly related to this new performance measure. The new approach proposed for the dynamic parameter design of a deposition process is illustrated with an example case study.

2 Static formulation

2.1 SNR and U

Let y be an NB characteristic and m be the target value of y. The cost incurred when y deviates from m is represented by the following loss function [5].

$$L(y) = k(y-m)^2$$

where k is a constant. The expected loss (L) is then given by

$$L = E_y[L(y)] = k\left[\sigma^2 + (\mu - m)^2\right]$$

where μ and σ^2 are the mean and variance of y, respectively. In the case of an NB characteristic, the existence of an adjustment parameter is assumed, the role of which is to adjust the mean of y to m. Taguchi [5] states that in many cases the effect of the adjustment on y can be mathematically represented as:

$$y_a = \frac{m}{\mu} y \tag{1}$$

where y_a is the characteristic after adjustment with its mean (μ_a) and variance $\left(\sigma_a^2\right)$ being given by m and $(m/\mu)^2\sigma^2$, respectively. Then, the expected loss after adjustment is given by:

$$L_a = k\left[\sigma_a^2 + (\mu_a - m)^2\right] = km^2\frac{\sigma^2}{\mu^2}. \tag{2}$$

Since k and m are common to all designs, the superiority of a design over the others can simply be based on σ^2/μ^2, namely, the ratio of the variance to the squared mean of y for a design before adjustment. Taguchi takes the logarithm of the reciprocal of σ^2/μ^2 and defines the true SNR as:

$$\eta = 10\log\left(\mu^2/\sigma^2\right) \tag{3}$$

As mentioned earlier, $\sigma_a^2 = (m/\mu)^2\sigma^2$ under the relationship in Eq. 1. This can be rewritten as:

$$\frac{\sigma_a^2}{m^2} = \frac{\sigma^2}{\mu^2} \Leftrightarrow \frac{\sigma_a^2}{\mu_a^2} = \frac{\sigma^2}{\mu^2}.$$

In other words, under the relationship in Eq. 1, σ^2/μ^2 is constant, and therefore,

$$\sigma = c\mu \tag{4}$$

where the proportionality constant c depends on the settings of the design parameters. On the other hand, for a given design, c is independent of μ. Note that the SNR in Eq. 3 can be rewritten as

$$\eta = 10\log\left(\mu^2/\sigma^2\right) = -10\log\left(\sigma/\mu\right)^2 = -10\log c^2 \tag{5}$$

The uniformity U for a deposition process is usually defined as [1, 6–8]:

$$U = \sigma/\mu. \tag{6}$$

Then, from Eq. 5,

$$\eta = -10\log c^2 = -10\log U^2.$$

That is, U is directly related to the Taguchi SNR, η, in that maximizing η is the same as maximizing ($-10\log U^2$), which is in turn directly related to the loss after the mean is adjusted to the target (see Eq. 2). As such, U is independent of μ for a given design, although it changes from design to design.

Other uniformity measures appeared in the literature and used in practice include:

(1) Sample standard deviation (s) of y [9],
(2) $V = y_{\max} - y_{\min} = \text{Range}$ [10], and
(3) $W = \frac{y_{\max} - y_{\min}}{\bar{y}} = \frac{\text{Range}}{\bar{y}}$.

From the Taguchi point of view, s in (1) is justified if the adjustment of the mean of y to the target can be mathematically represented as (compare with Eq. 1):

$$y_a = y + (m - \mu). \tag{7}$$

Since $E(y_a) = \mu_a = m$ and $\text{Var}(y_a) = \sigma_a^2 = \text{Var}(y) = \sigma^2$ under the relationship in Eq. 7, the expected loss after adjustment is given by:

$$L_a = k\left[\sigma_a^2 + (\mu_a - m)^2\right] = k\sigma^2,$$

and the corresponding SNR by $-10\log\sigma^2 = -20\log\sigma$, which can be estimated as $-20\log s$ In other words, the uniformity measure s in (1) is equivalent to the SNR under the additive model in Eq. 7. V in (2) is in essence equivalent to s in (1). For instance, E (range) is proportional to σ for a normally distributed y. Since the standard deviation and mean of the deposition thickness y usually behave as in Eq. 4 (e.g., see Fig. 6 for the example case study in Section 4, the uniformity measure in Eq. 6 is preferred to the one in (1) or (2) for the deposition thickness.

To assess the relationship between U and W in (3), 100 samples, each of which consists of nine measurements of y from Normal $(3000, 45^2)$, were randomly generated and U and W were calculated for each sample. Figure 1 shows the scatter plot of U and W. Notice that W has a strong linear relationship with U, implying that W is equivalent to U except for sampling variation. In practice, however, U is usually recommended since W, which is based on the range statistic, is sensitive to extreme observations.

2.2 Optimization

For an experimental optimization of a system with an NB characteristic, Taguchi suggests the following two-step procedure [5].

(1) At each experimental design condition, observe y's under various noise conditions.

(2) At each experimental design condition, estimate the SNR and sensitivity (S) as follows.

$$\widehat{\eta} = 10\log\left(\overline{y}^2/s^2\right)$$

$$\widehat{S} = 10\log\overline{y}^2$$

where $\overline{y}$ and s^2 are the sample mean and variance of y at a design condition, respectively.

(3) Analyze $\widehat{\eta}$ and $\widehat{S}$ (using the analysis of variance (ANOVA) technique for instance) and classify the design parameters as follows.

  (a) Dispersion parameters which have a significant effect on $\widehat{\eta}$.

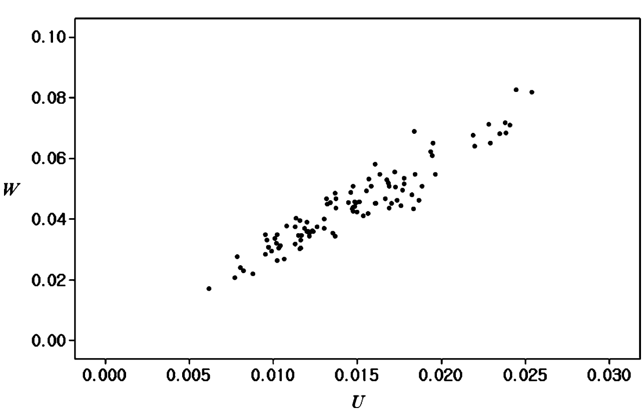

Fig. 1 The relationship between uniformity measures W and U

  (b) Adjustment parameters which have a significant effect on $\widehat{S}$, but not on $\widehat{\eta}$.

(4) An optimal design condition is obtained by determining the value of each dispersion parameter such that $\widehat{\eta}$ is maximized and adjusting the mean of y to its target using the adjustment parameters.

For a deposition process, the deposition time is usually used as an adjustment parameter in steps (3) and (4) above, and therefore, finding an adjustment parameter through the analysis of $\widehat{S}$ is unnecessary. In addition, as previously shown, maximizing the Taguchi SNR is the same as maximizing $(-10\log U^2)$. Furthermore, the deposition rate is also of interest in addition to the thickness. As a result, the above two-step procedure is modified as follows for a deposition process.

(1) At each experimental design condition, thickness values y_k, $k=1, 2, \cdots, K$ are observed under various noise conditions.

(2) At each experimental design condition, estimate U and mean deposition rate as follows.

$$\widehat{U} = s/\overline{y}$$
$$\overline{r} = \frac{1}{K}\sum_{k=1}^{K} r_k, \quad r_k = y_k/t \tag{8}$$

where $\overline{y}$ and s are respectively the sample mean and standard deviation of y, r_k is an observed deposition rate, and t is the deposition time.

(3) Analyze $\left(-10\log\widehat{U}^2\right)$ and $\left(10\log\overline{r}^2\right)$ (using the ANOVA technique for instance) and classify the design parameters as follows.

  (a) Parameters which have a significant effect on $\left(-10\log\widehat{U}^2\right)$ only.

  (b) Parameters which have a significant effect on $\left(10\log\overline{r}^2\right)$ only.

  (c) Parameters which have a significant effect on both $\left(-10\log\widehat{U}^2\right)$ and $\left(10\log\overline{r}^2\right)$.

(4) An optimal design condition is obtained by determining: (1) the value of each parameter in (3a) such that $\left(-10\log\widehat{U}^2\right)$ is maximized; (2) the value of each parameter in (3b) such that $\left(10\log\overline{r}^2\right)$ is maximized; and (3) the value of each parameter in (3c) based on engineering judgment and/or using a multi-characteristic optimization technique [11]. The last scheme also applies when no parameters satisfy the condition in (3a or b).

(5) Let $\overline{r}_0$ be the deposition rate for the optimal design condition determined in (4), and m be the target of y. Then, the deposition time is determined as $m/\overline{r}_0$.

In the above procedure, it is recommended to analyze $\left(-10\log\widehat{U}^2\right)$ and $\left(10\log\overline{r}^2\right)$, instead of $\widehat{U}$ and $\overline{r}$, to enhance the additivity of design parameter effects. Some authors [12] considered the deposition rate uniformity U_r

instead of the thickness uniformity U in optimizing a deposition process. Notice, however, that

$$U_r = \frac{\sigma_r}{\mu_r} = \frac{\sigma/t}{\mu/t} = U \tag{9}$$

where μ_r and σ_r^2 are the mean and variance of r, respectively. The second equality in Eq. 9 follows from Eq. 8. In other words, the deposition rate uniformity is equal to the thickness uniformity, and therefore, they can be used interchangeably.

3 Dynamic formulation

In a dynamic parameter design problem, the target value of y changes from time to time, and the so-called signal parameter is manipulated to attain the varying target values of y. In the case of a deposition process, the deposition time (t) is usually used as a signal parameter (see Fig. 2).

Let y and t are related as follows (see Fig. 5 for the example case study).

$$y = rt + \varepsilon \tag{10}$$

where r is the deposition rate and ε is a random error distributed with mean 0 and variance $c^2(rt)^2$. That is, it is assumed that the mean of y (=rt) changes linearly with respect to t, and the standard deviation of y (=crt) is proportional to its mean, which is consistent with the assumption for the static parameter design in Section 2 (see Eq. 4 and Fig. 6 for the example case study).

The concept of adjustment also exists in a dynamic parameter design problem, although its purpose is to adjust the slope of the linear relationship between y and t to an appropriate value r_a (see Fig. 3). Assume that the effect of the adjustment can be mathematically represented as:

$$y_a = \left(\frac{r_a}{r}\right)y = r_a t + \left(\frac{r_a}{r}\right)\varepsilon = r_a t + \varepsilon_a$$

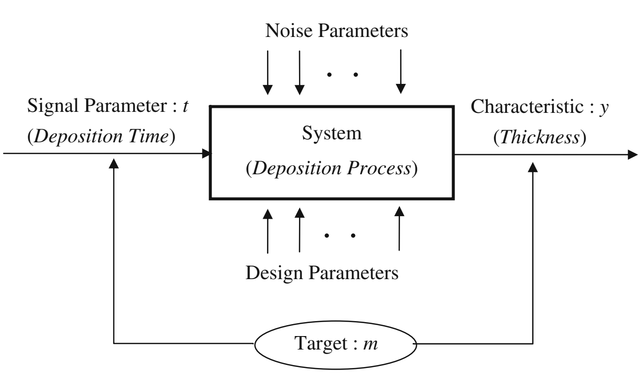

Fig. 2 A process diagram for dynamic parameter design

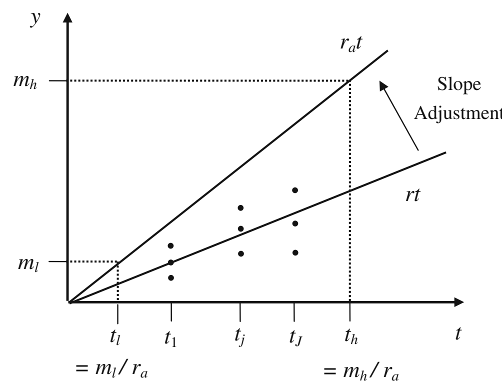

Fig. 3 Slope adjustment, target range, and signal parameter range for a deposition process

where $\varepsilon_a = (r_a/r)\varepsilon$. Note that

$$\varepsilon_a \sim \left(0,\ c^2 r_a^2 t^2\right).$$

Suppose that the target value of y follows a known distribution over the region $[m_l,\ m_h]$ with the density function $f(m)$. The distribution of m can be translated into the corresponding distribution of the signal parameter t over the region $[t_l$ and $t_h]$ (see Fig. 3). Let $g(t)$ be the density function of t. It can be shown that

$$g(t) = r_a f(r_a t),\ t_l \le t \le t_h. \tag{11}$$

The expected loss after adjustment is then given by

$$\begin{aligned} L_a &= E_t E_y\left[(y_a - r_a t)^2\right] \\ &= E_t E_y\left(\varepsilon_a^2\right) \\ &= E_t\left(c^2 r_a^2 t^2\right) \\ &= c^2 r_a^2 \int_{t_l}^{t_h} g(t) t^2 \mathrm{d}t \\ &= c^2 \int_{t_l}^{t_h} r_a f(r_a t)(r_a t)^2 \mathrm{d}t. \end{aligned}$$

Integration by change of variables using the relationship $m = r_a t$ yields

$$\begin{aligned} L_a &= c^2 \int_{m_l}^{m_h} m^2 f(m) dm \\ &= c^2 \tau. \end{aligned}$$

If m follows a discrete distribution, then so does t, and, in Eq. 11, $g(t)$ represents the probability mass function of t and the subsequent integrations are replaced with summations over the support of the distribution. Note that L_a is independent of r_a. In other words, to whatever value the slope is adjusted, the expected loss after adjustment is unchanged. Since τ is common to all designs, the superiority of a design over the others can be based on c^2 or c. That is, the uniformity measure U (=c) can still be used as a performance measure for the dynamic parameter design of a deposition process. Although r_a is not involved in the expected loss, it needs to be also considered in the optimization of a deposition process since it is desired to have a high r_a to reduce the time for deposition.

At each design condition in a dynamic parameter design experiment, multiple measurements of the thickness are made at several deposition times (see Fig. 4) to obtain y_{jk} for j=1, 2, ···, J and k=1, 2, ···, K where j represents the deposition time and k represents the measurement at each j. The corresponding model is given as:

$$y_{jk} = rt_j + \varepsilon_{jk}, \varepsilon_{jk} \sim \left(0,\ c^2r^2t_j^2\right) \tag{12}$$

for j=1, 2, ···, J and k=1, 2, ···, K. To estimate c^2 and r, Eq. 12 is modified as:

$$y'_{jk} = y_{jk}/t_j = r + \varepsilon'_{jk}, \varepsilon'_{jk} \sim \left(0,\ c^2r^2\right)$$

for j=1, 2, ···, J and k=1, 2, ···, K. Then, r and c^2r^2 are respectively estimated as:

$$\begin{aligned} \widehat{r} &= \sum_{j=1}^{J}\sum_{k=1}^{K} y'_{jk}/(JK), \\ \widehat{c^2r^2} &= \sum_{j=1}^{J}\sum_{k=1}^{K} \left(y'_{jk} - \widehat{r}\right)^2/(JK-1). \end{aligned} \tag{13}$$

Finally, a natural estimator of c^2 is given as:

$$\widehat{c^2} = \sum_{j=1}^{J}\sum_{k=1}^{K} \left(y'_{jk} - \widehat{r}\right)^2 / \left[\widehat{r}^2(JK-1)\right] \tag{14}$$

Dynamic parameter design procedures for a deposition process can be summarized as follows.

(1) Construct a design matrix (e.g., see Fig. 4).
(2) At each experimental condition, observe thickness measurements at several deposition times.
(3) At each experimental condition, calculate $\left(10\log\widehat{r}^2\right)$ and $\left(-10\log\widehat{c^2}\right)$.
(4) Analyze $\left(10\log\widehat{r}^2\right)$ and $\left(-10\log\widehat{c^2}\right)$ using, for example, the ANOVA technique.
(5) Classify the design parameters into:
   (a) Parameters that have a significant effect on $\left(-10\log\widehat{c^2}\right)$ only,
   (b) Parameters that have a significant effect on $\left(10\log\widehat{r}^2\right)$ but not on $\left(-10\log\widehat{c^2}\right)$, and
   (c) Parameters that have a significant effect on both $\left(10\log\widehat{r}^2\right)$ and $\left(-10\log\widehat{c^2}\right)$.
(6) Same as the schemes in (4) in Section 2.2 except that $\widehat{U}$ and $\overline{r}$ are replaced with $\widehat{c^2}$ and $\widehat{r}$, respectively.
(7) Let $\widehat{r}_0$ be the deposition rate at the optimal design condition, and m be the target of y for a specific product or at a specific step. Then, the deposition time is determined as $m/\widehat{r}_0$.

In the above procedure, it is also recommended to analyze $\left(-10\log\widehat{c^2}\right)$ and $\left(10\log\widehat{r}^2\right)$, instead of $\widehat{c^2}$ and $\widehat{r}$, to enhance the additivity of design parameter effects. Since c^2 or c can be estimated in the static parameter design of a deposition process, one may argue that the dynamic formulation is unnecessary. However, a more accurate and valid estimate of c^2 or c over the range of the deposition time can be obtained using the dynamic formulation (see Eq. 14 and Fig. 6 for the example case study).

In the Taguchi approach to dynamic parameter design [4], the SNR is estimated as:

$$\widehat{\eta} = 10\log\frac{\widehat{r}^2}{V_e}, \widehat{r} = \frac{\sum_{j=1}^{J}\sum_{k=1}^{K} y_{jk}t_j}{K\sum_{j=1}^{J} t_j^2}, V_e = \frac{1}{JK-1}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(y_{jk} - \widehat{r}t_j\right)^2.$$

Note that $\widehat{\eta}$ is conditional on the signal parameter values t_j's included in the parameter design experiment. No distribution of the target thickness, and hence, of the signal parameter is considered.

Fig. 4 An experimental setup for dynamic parameter design

					t_1	t_2	• • •	t_J
No.	A	B	C	D	1, 2, • • •, K	1, 2, • • •, K	• • •	1, 2, • • •, K
1	Design Matrix				Experimental Data			
2								
•								
•								
•								
I								

No.: experimental condition, $A \sim D$: design parameters,

t_j: signal parameter value, 1, 2, • • •, K: noise conditions

4 Example case study

Hsia and Hwan [13] presented a case study in which a new PECVD system for a low temperature oxide process was optimized using the Taguchi dynamic parameter design approach. The film thickness was considered as a performance characteristic (y) and the deposition time as a signal parameter (see Fig. 2). Design parameters are *temperature*, *pressure*, *RF power*, *gas 1 flow*, *gas 2 flow*, and *gas 3 flow*.

In the dynamic parameter design experiment, each design parameter has three levels except that *temperature* has two. Each design parameter is assigned to an appropriate column of an L_{18} orthogonal array [14] (i.e., L_{18} is the design matrix in Fig. 4). The signal parameter (deposition time) has three levels (i.e., J=3 in Fig. 4). No noise parameters were explicitly considered in the experiment. Instead, the effects of variations in the gas flows, power and temperature on y were captured at nine positions in a wafer (i.e., K=9 in Fig. 4). Then, at the ith set of design parameter settings (i.e., at the ith run of the design matrix) and for the jth deposition time, y is measured at the kth position to obtain y_{ijk} for i=1, 2, ⋯, 18, j=1, 2, 3, and k=1, 2, ⋯, 9. In the case study, the three deposition times are given as $3.8s$, $7.4s$, and $11s$ with s being unknown. In the present investigation, s is arbitrary set to 5 to obtain three deposition times as 19, 37, and 55. What value of s is used does not affect the statistical significance/insignificance of a design parameter to $\left(-10\log\widehat{c^2}\right)$ or $\left(10\log\widehat{r}^2\right)$, although it affects the magnitude of the estimate of r, which is not of major concern.

The experimental data in the case study is re-analyzed in this paper under the proposed framework in Section 3. Firstly, the data are plotted as shown in Fig. 5 to assess the validity of the model in Eq. 10. Notice that for all 18 design conditions the average relationship between y and t can be well described by a straight line through the origin. Next, for each i, the sample standard deviation s_{ij} and sample mean $\bar{y}_{ij}$ for j=1, 2, 3 are plotted as shown in Fig. 6. Except at several design conditions, a straight line relationship through the origin is evident, and therefore, the proportional relation between the standard deviation and mean of y can be generally accepted for the given data.

At each i, $\widehat{r}$ and $\widehat{c^2}$ are calculated using Eqs. 13 and 14, respectively, and $\left(10\log\widehat{r}^2\right)$ and $\left(-10\log\widehat{c^2}\right)$ analyzed using the ANOVA technique (see Tables 1 and 2). Effects of design parameters on $\left(-10\log\widehat{c^2}\right)$ and $\left(10\log\widehat{r}^2\right)$ are also plotted in Figs. 7 and 8, respectively.

The significance of an effect can be based on the corresponding P value in the ANOVA table (see Tables 1 and 2). That is, if $P<\alpha$ where α is the significance level, then the corresponding effect is declared to be significant. For α=0.10, *gas 1 flow* is regarded as significant for $\left(-10\log\widehat{c^2}\right)$ (see Table 1), while *pressure*, *RF power*, *gas 1 flow*, and *gas 2 flow* are regarded as significant for $\left(10\log\widehat{r}^2\right)$ (see Table 2). Then, the design parameters are classified as:

(1) Those parameters that have a significant effect on $\left(-10\log\widehat{c^2}\right)$ only: None

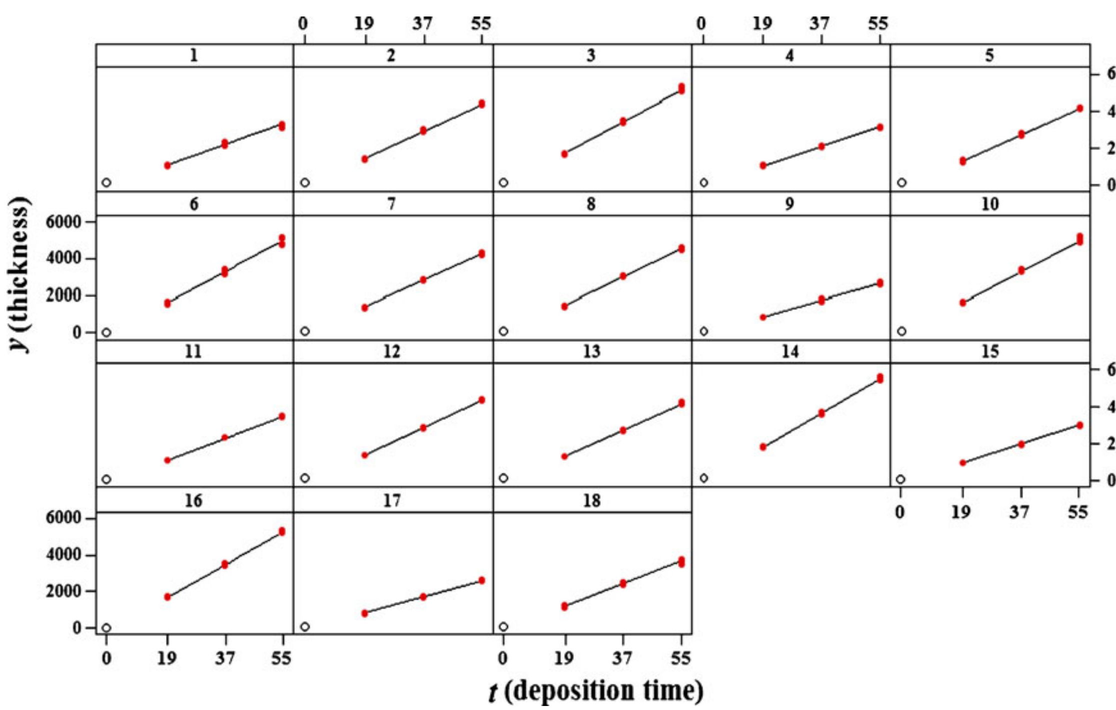

Fig. 5 Relationships between thickness and deposition time for experimental conditions (*empty circles* origin)

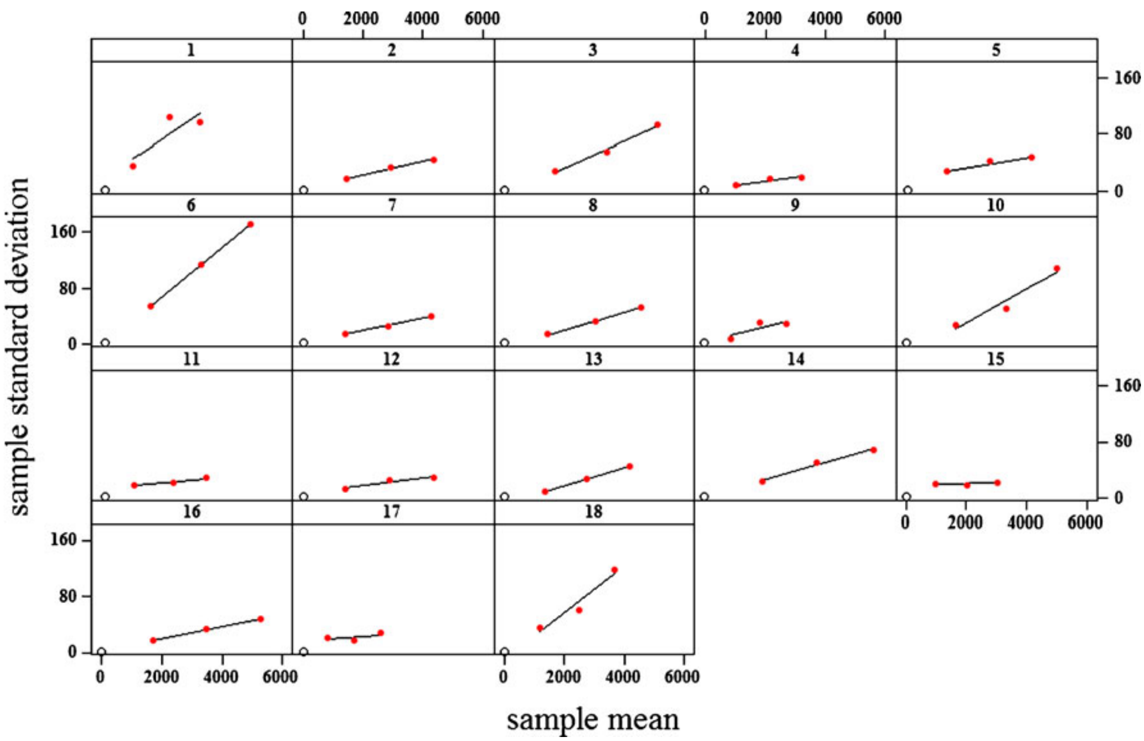

Fig. 6 Relationships between sample standard deviation and sample mean for experimental conditions (*empty circles* origin)

(2) Those parameters that have a significant effect on $\left(10\log\widehat{r}^2\right)$ only: *pressure*, *RF power*, *gas 2 flow*

(3) Those parameters that have a significant effect on both $\left(-10\log\widehat{c^2}\right)$ and $\left(10\log\widehat{r}^2\right)$: *gas 1 flow*

For *pressure*, *RF power*, and *gas 2 flow*, the first level is chosen as optimal since a large r is desired (see Fig. 8). Since *gas 1 flow* has a significant effect on both quantities, its optimal level for $\left(-10\log\widehat{c^2}\right)$ might be different from that for $\left(10\log\widehat{r}^2\right)$ (i.e., a conflict might exist). However, for the current problem, no conflict exists and the third level of *gas 1 flow* is best for both $\left(-10\log\widehat{c^2}\right)$ and $\left(10\log\widehat{r}^2\right)$.

In summary, optimal levels of *pressure*, *RF power*, *gas 1 flow*, *gas 2 flow* are 1, 1, 3, and 1, respectively. Levels of *temperature* and *gas 3 flow* may be selected based on the ease and cost of processing. Notice that a direct comparison of the present and Hsia and Hwan [13] results is not possible since the former is based on the new (unconditional) performance measure while the latter is on the Taguchi SNR which is conditional on the signal parameter values (i.e., deposition times) included in the parameter design experiment.

At the selected optimal condition, $\left(-10\log\widehat{c^2}\right)$ and $\left(10\log\widehat{r}^2\right)$ are respectively estimated as follows.

$$\begin{aligned}\left(-10\log\widehat{c^2}\right)_{estimated} &= \overline{T} + \left[\overline{(\text{gas 1 flow})}_3 - \overline{T}\right]\\ &= 28.41 + (29.71 - 28.41) = 29.71\end{aligned}$$

Table 1 Analysis of variance for $\left(-10\log\widehat{c^2}\right)$

Source	Degree of freedom	Sum of squares	Mean square	*F*	*P*
Temperature	1	0.0280	0.0280	0.01	0.928
Pressure	2	0.6029	0.3015	0.10	0.911
RF power	2	1.4474	0.7237	0.23	0.802
Gas 1 flow	2	25.9548	12.9774	4.10	0.076
Gas 2 flow	2	1.1823	0.5912	0.19	0.834
Gas 3 flow	2	13.1275	6.5637	2.07	0.207
Error	6	19.0083	3.1680		
Total	17	61.3512			

Table 2 Analysis of variance for $10\log\widehat{r}^2$

Source	Degree of freedom	Sum of squares	Mean square	F	P
Temperature	1	0.0058	0.0058	0.04	0.853
Pressure	2	4.2994	2.1497	13.86	0.006
RF Power	2	1.0777	0.5388	3.48	0.099
Gas 1 Flow	2	64.0687	32.0343	206.61	0.000
Gas 2 Flow	2	1.8049	0.9025	5.82	0.039
Gas 3 Flow	2	0.9922	0.4961	3.20	0.113
Error	6	0.9303	0.1551		
Total	17	73.1791			

$$\begin{aligned}\left(10\log\widehat{r}^2\right)_{estimated} &= \overline{T} + \left[\left(\overline{pressure}\right)_1 - \overline{T}\right] + \left[\left(\overline{RFpower}\right)_1 - \overline{T}\right] \\ &\quad + \left[\left(\overline{gas\,1\,flow}\right)_3 - \overline{T}\right] + \left[\left(\overline{gas2flow}\right)_1 - \overline{T}\right] \\ &= 36.98 + (37.48 - 36.98) + (37.25 - 36.98) \\ &\quad + (39.08 - 36.98) + (37.31 - 36.98) = 40.18\end{aligned}$$

where $\overline{T}$ is the overall mean and $(\overline{\bullet})_i$ represents the ith level mean of design parameter (•). The above-estimated values respectively correspond to $\widehat{c} \approx 0.033$ and $\widehat{r} \approx 102.1$. As mentioned earlier, the magnitude of the estimate of r depends on the assumed deposition times. In addition, 100(1-α)% prediction interval for a characteristic W can be constructed as follows [14].

$$W_{observed} \in W_{estimated} \pm t_{v,1-\alpha/2}\sqrt{(k+1)MSE}$$

where $t_{v,1-\alpha/2}$ is the (1-α/2)th quantile of a t distribution with v being equal to error degrees of freedom, MSE is the error mean square, and k is defined as:

$$k = \frac{\text{sum of degrees of freedom involved in calculating}\,W_{estimated}}{\text{total number of characteristics in the experiment}}.$$

For instance, 90% prediction interval for $\left(-10\log\widehat{c^2}\right)_{observed}$ is given by

$$\begin{aligned}\left(-10\log\widehat{c^2}\right)_{observed} &\in 29.71 \pm 1.943\sqrt{\left(\tfrac{3}{18}+1\right)3.1680} \\ &= (25.97,\ 33.45)\end{aligned} \quad (15)$$

Similarly, 90% prediction interval for $\left(10\log\widehat{r^2}\right)_{observed}$ is obtained as (39.24, 41.12).

Finally, it is desirable to check whether or not the expected results are actually obtained at the optimal condition. A confirmation experiment serves this purpose, but cannot be conducted in the present study due to the obvious reason. On the other hand, the L_{18} parameter

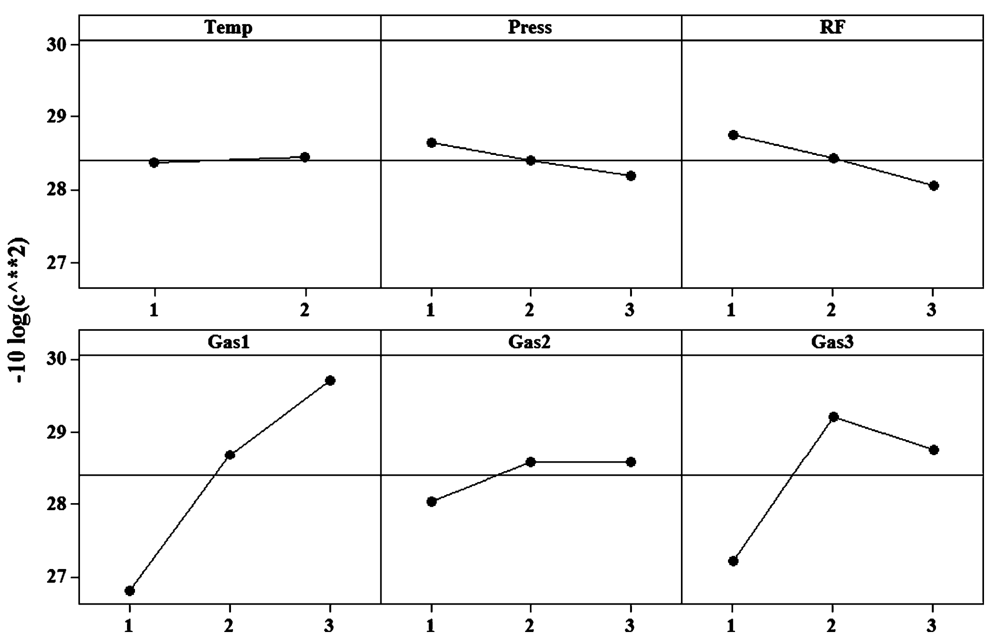

Fig. 7 Effect plots for $\left(-10\log\widehat{c^2}\right)$

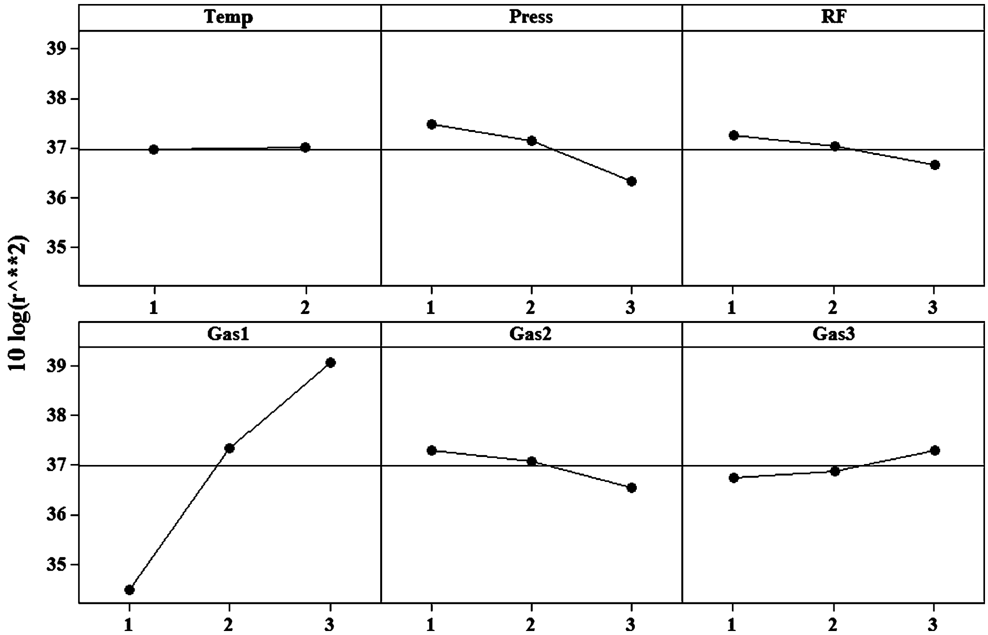

Fig. 8 Effect plots for $10\log\widehat{r}^2$

design experiment includes six runs for which gas 1 flow is at the third level which is the optimal condition for $\left(-10\log\widehat{c^2}\right)$. The values of $\left(-10\log\widehat{c^2}\right)$ for the six runs are 31.75, 26.70, 28.05, 29.79, 32.10, and 29.88, respectively. Notice that these values are well within the 90% prediction interval in Eq. 15. If there exist strong interaction effects between *Gas 1 Flow* and other design parameters, it is very likely that some of the above six values lie outside the prediction interval. A similar analysis for $\left(10\log\widehat{r}^2\right)$ is not possible since the corresponding optimal condition was not included in the L_{18} parameter design experiment.

5 Discussions

The uniformity measure has long been used in semiconductor manufacturing (e.g., see Ref. [15]), even before the Taguchi SNR was introduced for robust design. In this paper, the relationship between the two measures was investigated for both static and dynamic parameter design of deposition processes. For the static case, it can be easily shown that the uniformity measure is directly related to the Taguchi SNR for an NB characteristic (e.g., deposition thickness). As such, the uniformity measure is also directly related to the expected loss after the mean thickness is adjusted to the target. For the dynamic case, however, the Taguchi SNR is conditional on the signal parameter values (e.g., deposition times) included in the experiment. In this paper, a general distribution of the target thickness is assumed, which in turn determines the distribution of the deposition time. Then, the expected loss after the deposition rate is adjusted to a certain value is derived, and it is shown that the uniformity measure is also directly related to the expected loss for the dynamic case. In summary, it is shown that the uniformity measure can be used as a valid performance measure not only for the static but also for the dynamic parameter design of a deposition process.

Based on the above findings, static and dynamic parameter design procedures for a deposition process are developed considering not only U but also the deposition rate, and the proposed dynamic procedure is illustrated with an example case study.

Some tactical issues, not fully covered in this paper, but important to the parameter design of a system in general, include type of experimental designs to use, multi-characteristic optimization, and response modeling as a function of design and signal parameters and optimization. For these and other related issues, the reader is referred to Refs. [16–19].

Other manufacturing processes, such as an etching and chemical–mechanical polishing (CMP), have similar as well as dissimilar nature with the deposition process. The deposition thickness and deposition rate respectively correspond to the etched depth and etch rate for an etching process, and to the amount removed and removal rate for a CMP process. The difference between deposition and etching or CMP is that in the former the thickness has no upper bound, while in the latter the etched depth or amount removed has. It is desired to investigate whether the proposed approach for a deposition process is still valid for an etching or CMP process or should be modified based on the above difference.

Conflicts of interest The authors declare that they have no conflict of interest.

References

1. Guo RS, Sachs E (1993) Modeling, optimization and control of spatial uniformity in manufacturing processes. IEEE Trans Semicond Manuf 6(1):41–57
2. Buie MJ, Pender JTP, Dahimene M (1998) Characterization of the etch rate non-uniformity in a magnetically enhanced reactive ion etcher. J Vac Sci Technol A16(3):1464–1468
3. Wang GJ, Chen JL, Hwang JY (2001) New optimization strategy for chemical mechanical polishing process. JSME Int J Ser C44 (2):534–543
4. Taguchi G, Phadke MS (1984) Quality engineering through design optimization. In: Proceedings of GLOBECOM 84 Meeting, Atlanta, Georgia. pp. 1106–1113
5. Taguchi G, Yokoyama Y (1993) Taguchi methods: design of experiments, Quality engineering 4. ASI, Dearborn
6. Smith T, Boning D, Fang S, Shinn G, Stefani J (1990) A study of within-wafer non-uniformity metrics. In: Proceedings of the 4th International Workshop on Statistical Metrology, Kyoto, Japan. pp. 46–49
7. Olson JM (2002) Analysis of LPCVD process conditions for the deposition of low stress silicon nitride. part I: preliminary LPCVD experiments. Mater Sci Semicond Process 5(1):51–60
8. Takeuchi J, Mizuno T (2005) Development of scan coating by using parameter design of the Taguchi method. IEEE Trans Semicond Manuf 18(4):554–560
9. Hong CC, Yen YR, Su JL, Hwu JG (2002) Improvement in ultrathin rapid thermal oxide uniformity by the control of gas flow. IEEE Trans Semicond Manuf 15(1):102–107
10. Shie JR, Yang YK (2008) Optimizations of a photoresist coating process for photolithography in wafer manufacture via a radial basis neural network: a case study. Microelectron Eng 85 (7):1664–1670
11. Murphy TE, Tsui KL, Allen JK (2005) A review of robust design methods for multiple responses. Res Eng Des 16(3):201–215
12. Dharmadhikari VS, Lynch RO, Brennan W, Cronin W, Rastogi R (1990) Physical vapor deposition equipment evaluation and characterization using statistical methods. J Vac Sci Technol A 8 (3):1603–1607
13. Hsia WJ, Hwan M (1993) Parameter design of a PECVD oxide process using dynamic characteristic. In: Proceedings of the 11th Symposium on Taguchi Methods, Dearborn, Michigan. pp. 87–102
14. Taguchi G (1987) System of experimental design, vol 2. UNIPUB/Karus International Publication and ASI, White Plains, New York
15. Kohler WA (1970) Structural properties of vapor deposited silicon nitride. Metall Mater Trans B 1(3):735–740
16. Hsieh KL, Tong LI, Chiu HP, Yeh HY (2005) Optimization of a multi-response problem in Taguchi's dynamic system. Comput Ind Eng 49(4):556–571
17. Wu FC, Yeh CH (2005) Robust design of multiple dynamic quality characteristics. Int J Adv Manuf Technol 25(5–6):579–588
18. Robinson TJ, Borror CM, Myers RH (2004) Robust parameter design: a review. Qual Reliab Eng Int 20(1):81–101
19. Tsui KL (1999) Modeling and analysis of dynamic robust design experiments. IIE Trans 31(12):1113–1122