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ORIGINAL ARTICLE

Applications of Taguchi and design of experiments methods in optimization of chemical mechanical polishing process parameters

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Abstract This investigation applied the Taguchi method and designs of experiments (DOE) approach to optimize parameters for chemical mechanical polishing (CMP) processes in wafer manufacturing. Planning of experiments was based on a Taguchi orthogonal array table to determine an optimal setting. In this study, the material removal rate and non-uniformity of surface profiles were selected as the quality targets. This partial factorial experimental planning provided an efficient and systematic approach of determining an optimal parameter condition. Mathematical prediction models for the material removal rate and the non-uniformity of surface profiles were derived in terms of platen speeds, carrier speeds, back side pressure, slurry flow rates and head down forces by regression analysis. These parameters are found to be significant to both the removal rate and the non-uniformity of surface profiles for CMP processes.

Keywords CMP · Taguchi method · DOE · Optimization

1 Introduction

Chemical mechanical polishing (CMP) is a smoothing process aided by chemical etching and mechanical grinding forces. CMP is achieved by bringing the wavy wafer surface into contact with a rotating polishing pad as tiny particles contained in the slurry are applied to the wafer/pad interface. This technique originated from glass polishing and brought into the semiconductor industry by IBM [1, 2]. As semiconductor chips are highly integrated, more precise planarization of each layer on chips is needed. One of the great challenges in developing very large scale integrated circuits (VLSI) fabrication techniques is the multilevel interconnected process and its relative wafer planarisation problem. CMP processes combine chemical reactions and mechanical grindings to smooth the desired surfaces; however, its action fundamentals and models are still not quite clear.

There are many factors [1] such as the rotating speed of the wafer carrier, the pressure of the wafer, the flow rate of the slurry, the pH value of slurry, etc., having great impact on polishing quality. How to precisely control the processes and get appropriate removal rates in polishing to avoid excessive or insufficient removal is an important research subject of CMP processes.

How the CMP process parameters impact the wafer material removal rate (MRR) and the non-uniformity (NU) of the surface profiles has been studied intensively. Lin and Ho [3] applied analysis of variance (ANOVA) and grey relation analysis to verify the relative importance of CMP parameters such as down force pressure, platen speeds, carrier speeds, oscillation and flow rates to MRR. Park et al. [4] investigated high MRR and low NU versus various process parameters like table and head speeds, slurry flow rates and down forces. Forsberg [5] studied process parameters on MRR in silicon substrates. The removal rate of silicon substrates with a lattice structure of Si(1 0 0) increases sub-linearly with applied pressure, plate speeds, and slurry silica contents. Wang and Chou [6] applied a neural-Taguchi method as a cost-effective quasi time-optimization technique for CMP processes. Process parameters of solid contents, down forces, back pressure, platen speeds, and polishing time were chosen to study how they influenced MRR and NU. Zhong et al. [7] investigated the

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CMP of polycarbonate (PC) and poly-methyl-methacrylate (PMMA) substrates. The experimental results showed key CMP process parameters on MRR and surface finish for PC and PMMA substrates. As head loads or table speeds were raised, surface roughness heights and MRR would also increase. Zhong et al. [8] further examined the CMP of PC and PMMA materials for MEMS applications. Through ANOVA, they found that the interaction of head loads and table speeds had a significant (with 95% confidence level) effect on surface finish of polished PMMA. Similarly, table speeds had significant (with 99% confidence level) influence on surface finish of polished PC. In addition, Kim et al. [9] inspected the interactions of process parameters such as turn table speeds, head speeds, down forces and back pressure to the optimization of copper chemical mechanical polishing (CMP) process.

Based on prior research results and experience from process engineers, five controlled factors including platen speeds, carrier speeds, back side pressure, slurry flow rates and head down forces are selected. This arrangement of experiments complies with an L_{18} ($2^1 \times 3^7$) orthogonal array table. Both the material removal rate and the non-uniformity of surface profiles are selected as the quality targets of the CMP process. Furthermore, an optimal parameter setting was identified from regression equations that relate the desired outputs to the significant factors.

2 Taguchi method and design of experiments approach

2.1 Taguchi method

Various industries have employed the Taguchi method [10, 11] over the years to improve products or manufacturing processes. It is a powerful and effective method to solve challenging quality problems. Actually, the Taguchi method has been used quite successfully in several industrial applications like in optimizing manufacturing processes or designing electrical/mechanical components [12–15].

Depending on objectives, the Taguchi method defines three different forms of mean square deviations (i.e., signal-to-noise ratios) including the nominal-the-better, the larger-the-better and the smaller-the-better. The signal-to-noise ratios can be considered as an average performance characteristic value for each experiment. The three different signal-to-noise ratios, corresponding to n experiments, are presented as follows:

– Nominal-the-better cases:

$$\begin{aligned} Signal-to-noise\,ratio &= -10\log\left[\frac{1}{n}\sum_{i=1}^{n}(y_i-m)^2\right] \\ &= -10\log\left[(\bar{y}-m)^2+S^2\right] \end{aligned} \quad (1)$$

– Larger-the-better cases:

$$Signal-to-noise\,ratio = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \quad (2)$$

– Smaller-the-better cases:

$$\begin{aligned} Signal-to-noise\,ratio &= -10\log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right) \\ &= -10\log\left(\bar{y}^2\right) \end{aligned} \quad (3)$$

where m is a target value for nominal-the-better cases; $\bar{y}$ is the mean value of the collected data; S denotes the standard deviation; y_i is the collected data through experiments and n represents the number of experimental runs (54 runs in this study). Since the objective is to find an optimal setting that targets a desirable amount of material removal rates and minimizes the non-uniformity of surface profiles, a nominal-the-better signal-to-noise ratio formula is chosen for the material removal rate and a smaller-the-better equation for the non-uniformity of surface profiles.

2.2 Design of experiments approach

The objective of this study is to identify an optimal setting that targets a specific amount of material removal rates and minimizes the non-uniformity simultaneously. To resolve this type of multi-output parameter design problems, an objective function, $F(x)$, is defined as follows [16]:

$$\begin{aligned} DF &= \left(\prod_{i=1}^{2} d_i^{w_i}\right)^{\frac{1}{\sum_{j=1}^{2} w_i}} \\ F(x) &= -DF \end{aligned} \quad (4)$$

where the d_i is the desirability defined for the ith targeted output and the w_i is the weighting of the d_i. For various goals of each targeted output, the desirability, d_i, is defined in different forms. If a goal is to reach a specific value of T_i, the desirability

$$\begin{aligned} d_i &= 0 && \text{if} \quad Y_i \leqq Low_i \\ d_i &= \left[\frac{Y_i-Low_i}{T_i-Low_i}\right] && \text{if} \quad Low_i < Y_i < T_i \\ d_i &= \left[\frac{Y_i-High_i}{T_i-High_i}\right] && \text{if} \quad T_i < Y_i < High_i \\ d_i &= 0 && \text{if} \quad Y_i \geqq High_i \end{aligned} \quad (5)$$

For a goal is to find a maximum, the desirability is shown as follows:

$$\begin{aligned} d_i &= 0 && \text{if} \quad Y_i \leqq Low_i \\ d_i &= \left[\frac{Y_i-Low_i}{High_i-Low_i}\right] && \text{if} \quad Low_i < Y_i < High_i \\ d_i &= 1 && \text{if} \quad Y_i \geqq High_i \end{aligned} \quad (6)$$

For a goal to search for a minimum, the desirability can be defined by the following formulas:

$$\begin{array}{lll} d_i = 1 & \text{if} & Y_i \leqq Low_i \\ d_i = \left[\frac{High_i - Y_i}{High_i - Low_i}\right] & \text{if} & Low_i < Y_i < High_i \\ d_i = 0 & \text{if} & Y_i \geqq High_i \end{array} \quad (7)$$

where the Y_i is the found value of the ith output during optimization processes; the Low_i and the $High_i$ are the minimum and the maximum values of the experimental data for the ith output. In the Eq. (4), the w_i is set to one since the d_i is equally important in this study. The DF is a combined desirability function [16], and the objective is to choose an optimal setting that maximizes a combined desirability function DF, i.e., minimizes $F(x)$.

2.3 Steps for process parameter optimizations

The following steps are followed for process optimization:

1. Plan and conduct experiments based on an appropriate orthogonal array table.
2. For the Taguchi method, implement signal-to-noise ratio analysis and identify an optimal parameter setting by selecting a factor combination that yields a maximized normalized signal-to-noise ratio.
3. For the DOE approach, identify significant factors through ANOVA and then apply regression analysis to model the relationship between the CMP process parameters and two targeted outputs, MRR and NU. Validate the adequacy of regression equations through residual analysis. Search for an optimal solution based on a desirability function defined in the Eq. (4).
4. Verify the Taguchi and DOE results by additional experimental runs.

3 Experimental procedures and results

3.1 CMP apparatus

Figure 1 schematically illustrates a Model-300 CMP machine from EBARA Company. The system consists of a CMP polisher, a slurry flow rate controller, a main control panel, a carrier head and a pad table. The material removal rate and the non-uniformity were measured by an Omni-Map RS-100 analyzer from the KLA-Tencor Co.; slurry with serial number of W2585 from Cobat Co. was selected.

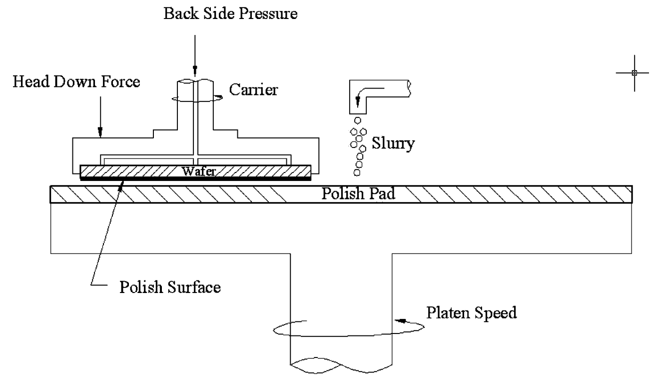

Fig. 1 A schematic diagram of CMP process and equipment

3.2 Experimental design

Usually, how to properly select the controlled parameters for CMP processes is determined mostly based on the handbooks of the equipment manufacturers. In practical applications, the process engineers need to select appropriate parameters and controlling ranges in order to adapt to the conditions of machines. Table 1 lists five controlled factors including platen speeds (i.e., factor "A" in rpm), carrier speeds (i.e., factor "B" in rpm), back side pressure (i.e., factor "C" in hpa), slurry flow rates (i.e., factor "D" in ml/min) and head down forces (i.e., factor "E" in hpa) with two levels for factor "A" and three levels for the rest of factors. Namely, the plan of experiments in this study follows an orthogonal array L_{18} ($2^1 \times 3^7$) table. The experimental results are presented in Table 2. The response variables are the material removal rate (in Å/min) and the non-uniformity (in %) of surface profiles after CMP process. Each combination of parameter sets is replicated three times. Therefore, there are totally fifty-four experimental runs.

Table 1 Experimental factors and factor levels

Levels	Experimental control factors				
	A/Platen speed (rpm)	B/Carrier speed (rpm)	C/BSP (hpa)	D/Slurry flow rate (ml/min)	E/Head down force (hpa)
1	85	80	80	120	250
2	90	90	90	150	275
3		100	100	180	300

Table 2 Orthogonal array L_{18} ($2^1 \times 3^7$) of the experimental runs and results

Run no.	A	B	C	D	E	MRR (Å/min)				NU (%)			
						no.1	no.2	no.3	Avg.	no.1	no.2	no.3	Avg.
1	1	1	1	1	1	1626	1666	1602	1631.33	20.6	22.1	18.5	20.40
2	1	1	2	2	2	2100	2150	2170	2140.00	21.6	22.9	24.0	22.83
3	1	1	3	3	3	1790	1750	1760	1766.67	12.4	11.2	13.4	12.33
4	1	2	1	2	1	2164	2216	2140	2173.33	24.3	26.1	23.5	24.63
5	1	2	2	3	2	1868	1902	1940	1903.33	16.3	18.0	18.5	17.60
6	1	2	3	1	3	2242	2300	2282	2274.67	21.3	24.6	23.1	23.00
7	1	3	2	1	1	1886	1924	1898	1902.67	16.9	18.6	17.2	17.57
8	1	3	3	2	2	2514	2482	2540	2512.00	24.7	22.1	25.9	24.23
9	1	3	1	3	3	1992	1956	2062	2003.33	21.6	19.9	23.0	21.50
10	2	1	3	3	1	2528	2462	2560	2516.67	27.6	25.1	28.4	27.03
11	2	1	1	1	2	2090	2110	2148	2116.00	26.3	27.5	29.0	27.60
12	2	1	2	2	3	2780	2830	2700	2770.00	23.7	23.9	21.8	23.13
13	2	2	2	3	1	2142	2198	2252	2197.33	18.2	19.1	21.0	19.43
14	2	2	3	1	2	2666	2602	2770	2679.33	22.2	21.5	24.2	22.63
15	2	2	1	2	3	2170	2242	2178	2196.67	25.1	27.7	25.7	26.17
16	2	3	3	2	1	2822	2922	2782	2842.00	17.9	17.1	16.2	17.07
17	2	3	1	3	2	2262	2304	2238	2268.00	19.6	20.9	18.1	19.53
18	2	3	2	1	3	3286	3362	3238	3295.33	25.2	27.9	22.9	25.33

4 Results and discussion

4.1 Taguchi method results

A material removal rate of 2000 (in Å/min) is recommended by process engineers and required to be properly controlled in order to avoid damage of the metal connection in wafers. This selection strikes the balances between the productivity and the process quality. Hence, a nominal-the-better quality characteristic (Eq. (1)) is chosen for this quality target. Similarly, a smaller-the-better (Eq. (3)) is selected for the non-uniformity.

The Taguchi method, which applies a signal-to-noise ratio to represent the quality characteristic, obtains an

Table 3 S/N ratios of Taguchi experimental results

Exp Run	Signal to noise ratio		Normalized		
	MRR (Å/min)	NU (%)	MRR η	NU η	Total (dB)
1	−51.35	−26.19	0.3713	0.3753	0.7465
2	−43.11	−27.17	0.6521	0.2354	0.8874
3	−47.38	−21.82	0.5066	1.0000	1.5066
4	−44.92	−27.83	0.5904	0.1412	0.7316
5	−40.09	−24.91	0.7550	0.5585	1.3135
6	−48.81	−27.23	0.4579	0.2263	0.6843
7	−39.88	−24.89	0.7621	0.5609	1.3230
8	−54.19	−27.69	0.2745	0.1615	0.4360
9	−32.90	−26.65	1.0000	0.3101	1.3101
10	−54.29	−28.64	0.2712	0.0258	0.2970
11	−41.47	−28.82	0.7079	0.0000	0.7079
12	−57.75	−27.28	0.1534	0.2192	0.3726
13	−46.12	−25.77	0.5495	0.4355	0.9850
14	−56.69	−27.09	0.1897	0.2463	0.4359
15	−45.99	−28.35	0.5540	0.0662	0.6202
16	−58.53	−24.64	0.1269	0.5968	0.7237
17	−48.61	−25.82	0.4648	0.4292	0.8940
18	−62.25	−28.07	0.0000	0.1064	0.1064
Avg.					0.7823

Table 4 A response tables for signal to noise ratios

Factor	A	B	C	D	E
Level 1	0.9932	0.7530	0.8350	0.6673	0.8011
Level 2	0.5714	0.7951	0.8313	0.6286	0.7791
Level 3		0.7989	0.6806	1.0510	0.7667
Effect	0.4218	0.0459	0.1545	0.4224	0.0345

optimal process parameter combination through finding the largest possible normalized signal-to-noise ratio. Table 3 shows the signal-to-noise ratios using the Taguchi method; Table 4 lists the responses of signal-to-noise ratios for different levels of factors. From Table 4, $A_1B_3C_1D_3E_1$ is an optimal combination for CMP processes since this selection gives the largest sum of signal-to-noise ratios. Namely, the optimal setting is with a platen speed of 85 rpm, a carrier speed of 100 rpm, back side pressure of 80 hpa, a slurry flow rate is 180 ml/min and a head down force of 250 hpa.

4.2 ANOVA results

Analysis of variance (ANOVA) was conducted to identify significant factors in CMP processes and the results are shown in Table 5(a) and (b). A "Model F value" is calculated from a model mean square divided by a residual mean square. It is a test of comparing a model variance with a residual variance. If the variances are close to the same, the ratio will be close to one and it is less likely that any of the factors have a significant effect on the response. If the "Model P value" is very small (less than 0.05) then the terms in the model have a significant effect on the response [17]. Similarly, an "F value" on any individual

Table 5 (a). ANOVA results for MRR, (b). ANOVA results for NU

Source	Sum of squares	Degree of freedom	Mean square	F value	P value
(a)					
Model	8283072.12	12	690256.01	39.70	<0.0001
A: platen speed (rpm)	203841.00	1	203841.00	11.72	0.0014
B: carrier speed (rpm)	803119.39	1	803119.39	46.19	<0.0001
C: back side pressure (hpa)	606591.86	1	606591.86	34.89	<0.0001
D: slurry flow rate (ml/min)	54030.68	1	54030.68	3.11	0.0854
E: head down force (hpa)	1117261.82	1	117261.82	64.25	<0.0001
AC	965301.36	1	965301.36	55.51	<0.0001
AE	530574.69	1	530574.69	30.51	<0.0001
BC	92434.82	1	92434.82	5.32	0.0263
BD	241667.75	1	241667.75	13.90	0.0006
BE	208785.45	1	208785.45	12.01	0.0013
CD	299666.01	1	299666.01	17.23	0.0002
DE	793543.51	1	793543.51	45.64	<0.0001
Residual	712920.25	41	17388.30	–	–
Total	8995992.37	53	–	–	–
(b)					
Model	703.58	12	58.63	12.56	<0.0001
A: platen speed (rpm)	41.04	1	41.04	8.79	0.0050
B: carrier speed (rpm)	0.01	1	0.01	0.00	0.9654
C: back side pressure (hpa)	4.99	1	4.99	1.07	0.3071
D: slurry flow rate (ml/min)	85.05	1	85.05	18.21	0.0001
E: head down force (hpa)	3.96	1	3.96	0.85	0.3627
AB	44.28	1	44.28	9.48	0.0037
AE	50.29	1	50.29	10.75	0.0021
BC	38.85	1	38.85	8.32	0.0062
BD	55.99	1	55.99	11.99	0.0013
CD	34.52	1	34.52	7.39	0.0096
CE	82.55	1	82.55	17.68	0.0001
DE	284.76	1	284.76	60.98	<0.0001
Residual	191.47	41	4.67	–	–
Total	895.05	53	–	–	–

Table 6 Residual results of MRR and NU

Run no.	RR (Å/min)			NU (%)		
	Actual	Pred.	Residual	Actual	Pred.	Residual
1	1626	1752	−126	20.6	21.60	−1.00
2	1666	1752	−86	22.1	21.60	0.50
3	1602	1752	−150	18.5	21.60	−3.10
4	2100	1838	262	21.6	21.97	−0.37
5	2150	1838	312	22.9	21.97	0.93
6	2170	1838	332	24.0	21.97	2.03
7	1790	1772	18	12.4	11.53	0.87
8	1750	1772	−22	11.2	11.53	−0.33
9	1760	1772	−12	13.4	11.53	1.87
10	2164	2116	48	24.3	21.39	2.91
11	2216	2116	100	26.1	21.39	4.71
12	2140	2116	24	23.5	21.39	2.11
13	1868	2116	−248	16.3	20.58	−4.28
14	1902	2116	−214	18.0	20.58	−2.58
15	1940	2116	−176	18.5	20.58	−2.08
16	2242	2410	−168	21.3	24.20	−2.90
17	2300	2410	−110	24.6	24.20	0.40
18	2282	2410	−128	23.1	24.20	−1.10
19	1886	1942	−56	16.9	19.52	−2.62
20	1924	1942	−18	18.6	19.52	−0.92
21	1898	1942	−44	17.2	19.52	−2.32
22	2514	2397	117	24.7	22.32	2.38
23	2482	2397	85	22.1	22.32	−0.22
24	2540	2397	143	25.9	22.32	3.58
25	1992	1965	27	21.6	21.00	0.60
26	1956	1965	−9	19.9	21.00	−1.10
27	2062	1965	97	23.0	21.00	2.00
28	2528	2523	5	27.6	26.78	0.82
29	2462	2523	−61	25.1	26.78	−1.68
30	2560	2523	37	28.4	26.78	1.62
31	2090	2060	30	26.3	27.33	−1.03
32	2110	2060	50	27.5	27.33	0.17
33	2148	2060	88	29.0	27.33	1.67
34	2780	2767	13	23.7	24.49	−0.79
35	2830	2767	63	23.9	24.49	−0.59
36	2700	2767	−67	21.8	24.49	−2.69
37	2142	2244	−102	18.2	20.17	−1.97
38	2198	2244	−46	19.1	20.17	−1.07
39	2252	2244	8	21.0	20.17	0.83
40	2666	2696	−30	22.2	21.18	1.02
41	2602	2696	−94	21.5	21.18	0.32
42	2770	2696	74	24.2	21.18	3.02
43	2170	2299	−129	25.1	25.20	−0.10
44	2242	2299	−57	27.7	25.20	2.50
45	2178	2299	−121	25.7	25.20	0.50
46	2822	2828	−6	17.9	17.13	0.77
47	2922	2828	94	17.1	17.13	−0.03
48	2782	2828	−46	16.2	17.13	−0.93
49	2262	2230	32	19.6	20.15	−0.55
50	2304	2230	74	20.9	20.15	0.75
51	2238	2230	8	18.1	20.15	−2.05
52	3286	3234	52	25.2	25.49	−0.29
53	3362	3234	128	27.9	25.49	2.41
54	3238	3234	4	22.9	25.49	−2.59

factor terms is calculated from a term mean square divided by residual a mean square. It is a test that compares a term variance with a residual variance. If the variances are close to the same, the ratio will be close to one and it is less likely that the term has a significant effect on the response. Correspondingly, if a “P value” of any model terms is very small (less than 0.05), the individual terms in the model have a significant effect on the response.

In Table 5(a), a “Model F value” of 39.70 with a “Model P value” smaller than 0.0001 implies that the selected model is significant and there is less than a 0.01% chance that the “Model F value” could occur due to noise. The “P values” for the model terms “A”, “B”, “C” and “E” are less than 0.05 indicating that these model terms are significant. There are seven interaction terms, “AC”, “AE”, “BC”, “BD”, “BE”, “CD” and “DE”, having significant impact to the material removal rate. The model term “D” is selected in order to comply with the hierarchy principle in model-building [17] even it’s “P value” is larger than 0.05.

Similarly, in Table 5(b), a “Model F value” of 12.56 with a “Model P value” less than 0.0001 implies that the selected model is significant and there is less than 0.01% chance that the “Model F value” could occur due to noise. The model terms “A” and “D” are significant since the “P value” is less than 0.05. Seven interactions, “AB”, “AE”, “BC”, “BD”, “CD”, “CE” and “DE”, have significant influence on the non-uniformity. Additional terms, “B’, “C” and “E”, are added due to the hierarchy principle.

4.3 DOE results

4.4 Regression models for the material removal rate and the non-uniformity

Based on the identified significant factors from Table 5(a) and (b), regression equations can be developed. Mathematical models for the MRR and the NU are shown as followed:

$$\begin{aligned} MRR = {} & 152825.13 - 2119.51 \times A + 234.77 \times B \\ & - 985.64 \times C - 62.91 \times D - 185.38 \times E \\ & + 11.44 \times AC + 4.11 \times AE - 1.95 \times BC \\ & + 1.27 \times BD - 0.78 \times BE + 1.29 \times CD \\ & - 0.62 \times DE \end{aligned} \tag{8}$$

$$\begin{aligned} NU = {} & 131.38 - 7.02 \times A + 4.87 \times B + 4.67 \times C \\ & - 0.29 \times D - 1.35 \times E - 0.05 \times AB + 0.04 \\ & \times AE - 0.03 \times BC + 0.01 \times BD + 0.009 \\ & \times CD - 0.01 \times CE - 0.007 \times DE \end{aligned} \tag{9}$$

and the proportion of total variability in the *MRR* deviation that can be explained by Eq. (8) is

$$R^2 = \frac{SS_{Model}}{SS_{Total}} = \frac{8283072.12}{8995992.37} = 92.08\% \tag{10}$$

where *SS* is the abbreviation of “sum of squares”.

Additionally, the proportion of total variability in the *NU* deviation that can be explained by Eq. (9) is

$$R^2 = \frac{SS_{Model}}{SS_{Total}} = \frac{703.58}{895.05} = 78.61\% \tag{11}$$

Before any conclusion from the ANOVA and regression equations are adopted, the adequacy of the derived models should be investigated. The primary diagnostic tool is residual analysis [17]. The residual is defined as the differences between the actual and predicted values for

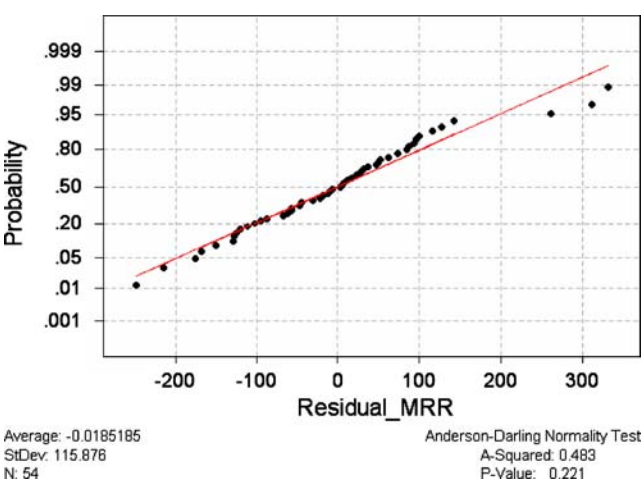

Fig. 2 A normal probability plot for the residual of MRR

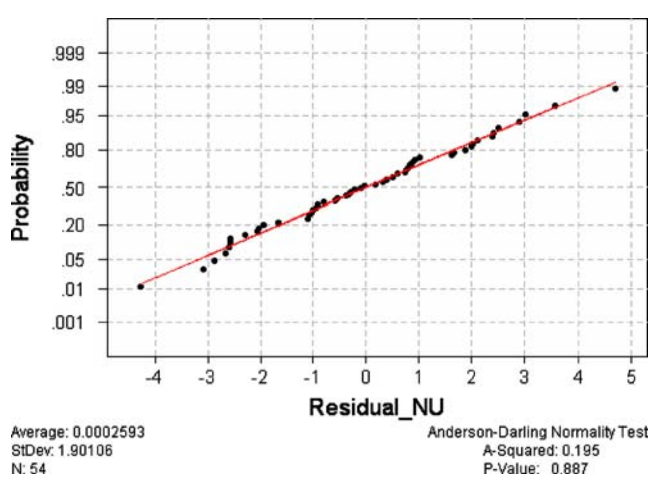

Fig. 3 A normal probability plot for the residual of NU

Table 7 Confirmation runs and an optimal setting showing results for the MRR and the NU

Run no.	A (rpm)	B (rpm)	C (hpa)	D (ml/min)	E (hpa)	Predicted/Experimental MRR	Predicted/Experimental NU
1	90	99	97	126	254	1970/1980	11.23/11.80
2	90	100	94	128	254	2000/2018	11.58/12.40
3	89	100	98	120	262	1967/1985	12.11/12.90
4	87	80	97	180	300	2026/ 2045	12.23/12.80
5	85	100	80	180	250	N.A./2037	N.A./14.25

each point in the design. The residual results for the MRR and the NU are shown in Table 6. If a model is adequate, the distribution of residuals should be normally distributed. Minitab® program [18] is utilized to perform a normality test. For the normality test, the hypotheses are,

$$\begin{cases} \text{Null hypothesis : residual data follow a normal distribution} \\ \text{Alternative hypothesis : residual data do not follow a normal distribution} \end{cases}$$

The vertical axis on Figs. 2 and 3 has a probability scale and the horizontal axis with a data scale. A least-squares line is then fit to the plotted points. The line forms an estimate of the cumulative distribution function for the population from which data are drawn.

As a “P-Value” is smaller than 0.05, it can be classified as “significant”, and then null hypothesis has to be rejected [17]. Since the “P-value” shown on the lower-right-hand side of Figs. 2 and 3 is larger than 0.05; there is not enough evidence to reject the null hypothesis. Therefore, both the residual data of the MRR and the NU do follow a normal distribution and the derived regression models have extracted all available information from the experimental data. The rests of information defined as residuals can be considered as errors from performing the experiments.

4.5 Confirmation tests

After identifying the most influential parameters and the regression equations, conducting confirmation experiments and comparing these validation runs with respect to the model predicted values are required.

According to Table 7, the first confirmation run with a combined desirability function value of 0.96, which is also an optimal setting identified by the DOE approach, is conducted under a platen speed of 90 rpm, a carrier speed of 99 rpm, back side pressure of 97 hpa, a slurry flow rate of 126 ml/min and a head down force of 254 hpa. The parameters for the second run are with a platen speed of 90 rpm, a carrier speed of 100 rpm, back side pressure of 94 hpa, a slurry flow rate of 128 ml/min and a head down force of 254 hpa. Similarly, the third confirmation run has the parameters of a platen speed of 89 rpm, a carrier speed of 100 rpm, back side pressure of 98 hpa, a slurry flow rate of 120 ml/min and a head down force of 262 hpa. A parameter setting with a platen speed of 87 rpm, a carrier speed of 80 rpm, back side pressure of 97 hpa, a slurry flow rate of 180 ml/min and a head down force of 300 hpa is the fourth confirmation run. According to the data from Table 7, an average error between the predicted and the experimental data for the MRR is 0.82% (i.e., $(0.51\% + 0.94\% + 0.91\% + 0.93\%)/4$) and 5.5% for the NU. The average error from the NU is higher than that from the MRR is due to the fact that the proportion of total variability in the NU deviation that can be explained by the Eq. (9) is 78.61%, which is much smaller than the Eq. (8) for the MRR.

The fifth confirmation rum is an optimal setting found by the Taguchi method with a platen speed of 85 rpm, a carrier speed of 100 rpm, back side pressure of 80 hpa, a slurry flow rate of 180 ml/min and a head down force of 250 hpa. Since the Taguchi method is only capable of searching for an optimal solution within the pre-defined level of factors, the MRR and the NU are 2037 Å/min and 14.25%, respectively, which is slightly inferior to the results found by DOE but better than those in Table 2.

5 Conclusions

This study investigated the parameter optimization of the CMP process with both the Taguchi method and the DOE approach. Fifty-four experimental runs based on an orthogonal array table were performed. The material removal rate and the non-uniformity of surface profiles were selected as the targets of product quality. Based on experiments, the results are summarized as follows.

1. The optimal parameter combination for the CMP process is with a platen speed of 85 rpm, a carrier speed of 100 rpm, a back side pressure of 80 hpa, a slurry flow rate is 180 ml/min and a head down force of 250 hpa via the Taguchi method; a platen speed of 90 rpm, a carrier speed of 99 rpm, back side pressure of 97 hpa, a slurry flow rate of 126 ml/min and a head down force of 254 hpa if the DOE approach is applied.
2. The regression equation for the MRR yields 0.82% average prediction error and 5.5% average error for the NU prediction model. Hence, these equations can be utilized to predict the MRR and the NU in CMP processes accurately.

3. The Taguchi method is only capable of searching for an optimal solution within the pre-defined level of factors; on the other hand, the DOE approach can find an optimal solution within the completed response surface. Therefore, DOE yields a better result than that from the Taguchi method in this study.
4. Normality analysis on residuals of the regression equations ensures that the models have extracted all applicable information from the experimental data.

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