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Optimization of Process Parameters with Minimum Surface Roughness in the Pocket Machining of AA5083 Aluminum Alloy via Taguchi Method

Ahmet Murat Pinar

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Abstract This paper aims at determining the effects of process parameters (cutting speed, feed rate, tool path pattern and depth of cut) on surface roughness and the factor levels with minimum surface roughness in pocket machining. The experiments conducted based on Taguchi's L27 orthogonal array are assessed with analysis of variance and signal-to-noise ratio. According to this, it is observed that surface roughness correlates negatively with cutting speed and positively with feed rate and cutting depth. Minimum surface roughness is predicted as 0.5413 μm with the cutting speed of 300 m/min, feed rate of 150 mm/min, spiral tool path pattern and 1 mm depth of cut. Finally, confirmation tests verify that Taguchi method achieves the optimization of the system with sufficient accuracy at 95 % confidence level.

Keywords Pocket machining · Optimization · Milling · Taguchi method · Surface roughness

الخلاصة

تهدف هذه الورقة العلمية إلى تحديد الآثار المترتبة على عوامل العملية (سرعة القطع ومعدل التغذية ونمط أداة المسار وعمق القطع) على خشونة السطح ومستويات العامل مع حد أدنى لخشونة السطح في تشكيل التجويف. وقد أجريت التجارب على أساس تجمع L27 تاجوشى متعامد (OA) ويتم تقييم وتحليل التباين (ANOVA)، ونسبة الإشارة إلى الضوضاء (N/S). وقد لوحظ وفقا لذلك أن خشونة السطح ترتبط سلبا مع خفض السرعة وبشكل إيجابي مع معدل التغذية وعمق القطع. وتم توقع الحد الأدنى لخشونة السطح بقيمة 0.5413 ميكرون مع سرعة قطع ب 300 م / دقيقة، ومعدل تغذية 150ملم/دقيقة، ونسق مسار أداة لولبي وعمق قطع 1 مم. وأخيرا أثبتت اختبارات التأكيد أن أسلوب تاجوشى يحقق الاستفادة المثلى من النظام بدقة كافية وعلى مستوى ثقة 95 ٪.

A. M. Pinar (✉)
Department of Machinery, Vocational High School,
Celal Bayar University, 45400 Turgutlu Manisa, Turkey
e-mail: ahmet.pinar@bayar.edu.tr

1 Introduction

Aluminum alloys, with the advantages of good corrosion and fatigue resistance, high strength to weight ratio and ease of fabrication, are increasing their popularity in automotive, marine and aircraft industries. Thus, the welding and machinability studies are becoming increasingly important. The flexibility in milling operations brought by CAD/CAM software, the innovations in high-speed CNC machine tools and the high metal removal rates of these materials cause the studies in this area to focus especially on $2^1/_2$D and 3D pocket machining. Surface roughness, one of the most important quality characteristics in machinability tests, constitutes a major part of the studies in this area. The experimental studies in which the surface roughness is evaluated in the milling of aluminum alloys are summarized below.

Kim and Kang [1] investigated the machining of AA2024 alloy with polycrystalline diamond end mill using the criteria of surface roughness, built-up edges at the cutting edge and burrs at the edge of the machined surface. As a result of the experiments conducted at different values of cutting speed, axial and radial depth of the cut, and feed per tooth parameters, it was obtained that, axial depth of cut is the most significant factor affecting surface roughness while radial depth of cut has a low effect.

Melkote and Thangaraj [2] studied the effects of radial rake and relief angles on the surface generated by end cutting edges in the machining of AA6061 aluminum alloy. It was concluded that the radial rake angle and primary and tooth relief angle have a tendency to increase surface roughness.

Rao and Shin [3] investigated the face milling of AA7075-T6 with a single insert fly-cutter analytically and experimentally. The specimens machined with carbide and diamond inserts were evaluated according to the criteria of cutting force, chip morphology and surface integrity (residual stress and surface roughness). As a result of the experiments conducted at different combinations of different tool materials, feed rate, cutting speed and depth of the cut process parameters, while a constant improvement in surface quality is obtained till 1,524 m/min, some degenerations occur above this level. In addition, a small deterioration in the surface is observed with an increase in depth of cut.

Lou et al. [4] modeled the surface roughness in the machining of AA 6061 aluminum alloy with HSS (high speed steel) flat end mill. They predicted the effects of spindle speed, feed rate and depth of cut factors on surface roughness with multiple regressions at the correlation coefficient of 0.93 using full factorial experimental design method. As a result, it was determined that feed rate is the most significant parameter affecting surface roughness.

Compared to the traditional full factorial experimental design, RSM makes the second order regression equations that can also obtain the quadratic effects of factors possible as well as permitting the optimization of the system with less number of trials. Fuht and Wu [5] obtained predictive models using Takushi method and RSM in order to examine the effects of tool nose radius and flank width and cutting conditions on residual stress and surface roughness. ANOVA was carried out to test the adequacy of the model and to determine the significant parameters in the model. It was observed that tool nose radius has a significant effect on the surface roughness. Whang and Chang [6] modeled the effects of different cutting parameters and tool geometry in the slot end milling on surface roughness via RSM. Cutting speed, feed rate and depth of cut were chosen as a cutting parameter and concavity and axial relief angles of the end cutting edge of the end mill were chosen as the tool geometry. Experiments conducted were divided into two groups as dry and wet cutting conditions. In the experiments carried out in wet conditions, it was observed that surface roughness decreases. While in dry model the significant factors are cutting speed, feed rate, concavity and axial relief angles, in the other, it is feed rate and concavity angle. Routara et al. [7] investigated the machining of AA6061-T4, AISI 1040 steel and medium leaded brass UNS C34000 with CVD-coated carbide flat end mill through RSM. They modeled the effects of depth of cut, spindle speed and feed rate parameters for five surface roughness measurement criteria as second order regression equation and optimized the surface roughness within specified factor levels. Öktem et al. [8] optimized the surface roughness of AA 7075-T6 mold surfaces combining RSM with genetic algorithm. To achieve this aim, the effects of feed per tooth, cutting speed, axial and radial depth of cut, and machining tolerance factors on surface roughness were modeled via RSM. The experiments based on third level full factorial experimental design were carried out to collect the surface roughness values. The GA algorithm was applied to optimize the cutting conditions for the desired surface roughness. As a result, it was observed that GA improved the mold surface by about 10 %. Erzurumlu and Öktem [9] studied the surface roughness in the milling of AA7075 alloy with the same process parameters by comparing the RSM with artificial neural network (ANN). As a result, maximum test errors in RSM model were obtained as 2.05 % while in ANN it was 1.48 %.

Taguchi method is widely used by many researchers as the effects of many process parameters on the quality characteristic and their optimal levels can be obtained with a few trials easily. Yang and Chen [10] studied the effects of depth of cut, spindle speed, feed rate and tool diameter factors on surface roughness in the milling of AA6061 via Taguchi method. The experiments based on L18 orthogonal array were evaluated with ANOVA and *S/N* ratio analysis and it was seen that all the factors except tool diameter were significant. In addition, optimal factor levels with lowest surface roughness were determined and predicted. Lo et al. [11] investigated the high speed milling of AA6061 in two parts. In the first part, an experimental model was developed for the quick measurement of surface roughness using laser speckle method and digital image processing. In the second part, the effects of feed rate, spindle speed, depth of cut and tool material process parameters on surface roughness were evaluated via Taguchi technique. The tests based on L9 OA were analyzed with *S/N* ratio and ANOVA. According to this, it was seen that depth of cut has the most dominant effect (40 %) followed by tool material (30 %) and spindle speed (21 %) in terms of order of significance. In contrast, feed rate does not have a significance effect. Öktem et al. [12] studied the surface roughness of the mold obtained by machining AA7075-T6 material with AlTiN-coated solid carbide end mill. The effects of cutting speed, feed per tooth, radial/axial depth of cut and machining tolerance were evaluated with Taguchi and full factorial methods. The surface roughness was modeled by regression analysis with a correlation coefficient of 0.96. The effects of factors and optimal surface roughness were determined by assessing the experiments based on L18 OA with *S/N* ratio and ANOVA. Finally, it was observed that the machining tolerance is the most dominant factor (96 %) followed by radial depth of cut (2.5 %), axial depth of cut (1.5 %), feed per tooth (0.177 %) and cutting speed (0.09 %).

Recently, the addition of vibration and cutting forces during machining as well as cutting geometry and parameters to the model has enabled it to be more realistic and has increased its accuracy. Lou and Chen [13] studied the effects of spindle speed, feed rate, depth of cut and vibration on surface roughness during the end milling of AA6061. The analysis of data and modeling was achieved via neural fuzzy method. They predicted the surface roughness with 96 % accuracy by the use of the proposed system. Chen and Savage [14] predicted the effects of feed rate, spindle speed, tool material, type and diameter, and vibration factors on surface roughness in the milling of AA6061 and AISI 1018 steel materials during cutting. The proposed neural fuzzy approach modeled the surface roughness during milling operation with 90 % accuracy. Yang et al. [15] proposed an adaptive system that can modify the table feed during machining to obtain the desired surface roughness in the face milling of AA6061. The system was constructed by combining two subsystems as fuzzy-nets in-process surface roughness recognition and fuzzy-nets adaptive feed rate control. As a result of the 25 test experiments, the desired surface roughness was obtained by modifying the feed rate of the CNC machine tool instantaneously by the use of the proposed system. Brezocnik et al. [16] predicted the effects of spindle speed, feed rate, depth of cut and vibrations on surface roughness via genetic programming method. The specimens were obtained by machining AA6061 aluminum with four-flute high speed steel. They observed that high vibration increases the prediction accuracy and feed rate has the most influence on surface roughness. Zhang and Chen [17] developed an in process surface roughness adaptive control system in the end milling of AA6061 alloy. They conducted experiments in all combinations of spindle speed, feed rate and depth of cut factor levels by the use of full factorial experimental design method. The surface roughness was predicted with 91.5 % accuracy with the system that can recognize cutting force signals collected during machining and the feed rate was modified in terms of desired surface roughness.

While AA5083 aluminum alloy is widely preferred in welding applications, AA6061, AA7075 and AA2024 materials are employed in the milling studies. In this paper, the effects of cutting speed, feed rate, depth of cut and tool path pattern (firstly tested in the milling of aluminum alloys) cutting parameters on surface roughness in milling of AA 5083 were assessed through Taguchi technique.

Fig. 1 Machine tool employed in the experiment

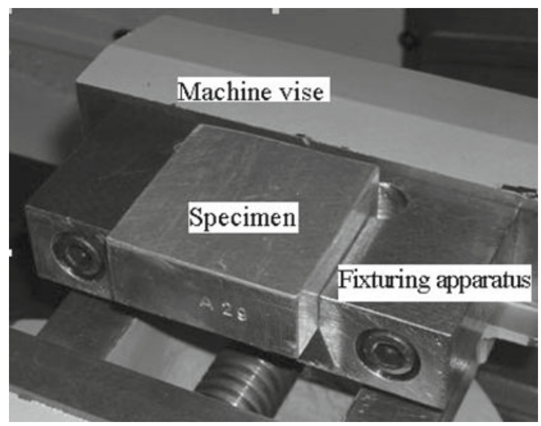

Fig. 2 Clamping of the specimen with the fixturing apparatus

2 Experimental Details

Pocket machining tests are performed on a 3-axis CNC Vertical Machining Center (First MCV 300) equipped with a maximum spindle speed of 8,000 rpm, feed rate of 10 m/min, 7.5 kW drive motor and a Fanuc CNC controller. Figure 1 depicts the machine tool employed in the experiment.

AA 5083-H36 aluminum alloy specimens with a dimension of 60 × 60 × 30 mm are clamped using a fixturing apparatus which is mounted to the standard machine vise by dismantling the fixed jaw (Fig. 2). Chemical composition and mechanical properties of the specimens are given in Table 1.

The cutting tools employed for the machining tests in wet conditions are single insert cemented carbide endmills with a diameter of 14 mm, lead angle of 90°, and nose radius of 0.8 mm. The details of insert and tool holder are given in Fig. 3. In the machining tests, ECOCOOL 2030 MB water soluble coolant is used at a concentration of 5 %.

Much CAD/CAM software makes different tool path patterns possible for pocket features and these patterns have their own advantages and disadvantages. As seen in Fig. 4, three different tool path patterns, viz. one way, parallel and spiral are employed under climb milling condition in the experiment using MasterCAM version 10. The levels of other cutting parameters (cutting speed, feed rate and depth of cut) are determined by taking the machine tool capacity and the product catalogue of cutting tool into consideration.

The average surface roughness (R_a, μm) of machined specimens is measured using a stylus type Mitutoyo Surftest SJ-301 within the sampling length of 5 mm. As shown in Fig. 5, measurements are carried out in the traverse direction for three times and mean values of these are used in the statistical analyses

Table 1 (a) Chemical composition (wt %) and (b) mechanical properties of the specimens

(a) Si	Cu	Mn	Mg	Cr	Zn	Pb	Al
0.4	0.1	0.6	4.4	0.1	0.2	–	bal.

(b) Yield stress (Mpa)	Tensile strength (Mpa)	Elongation (%)	Hardness (HB)
282.4	358.9	8	92

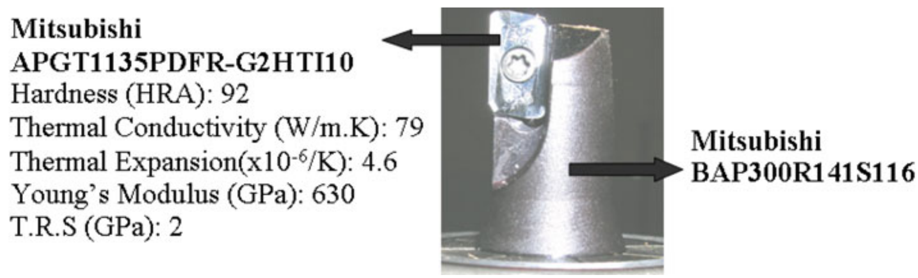

Fig. 3 The details of insert and tool holder

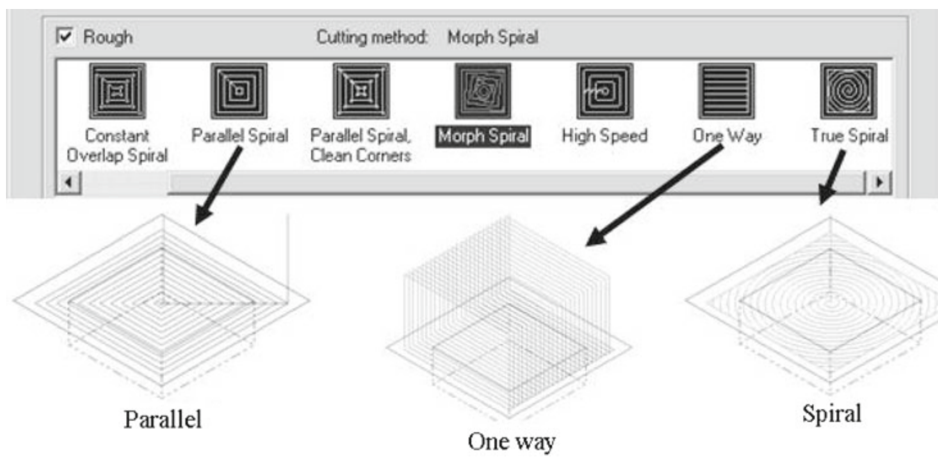

Fig. 4 Tool path patterns employed in the experiment

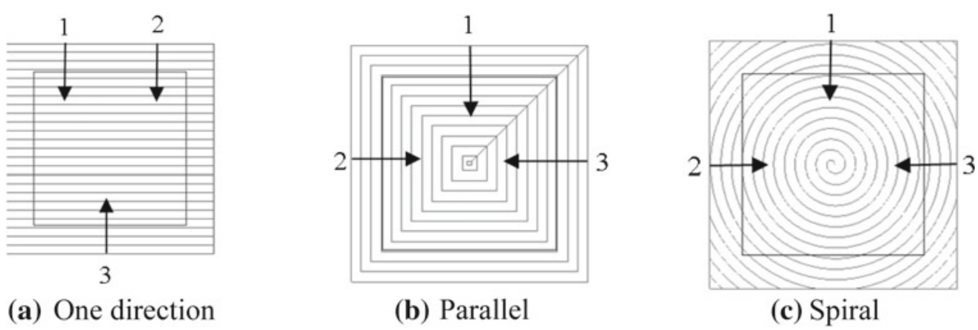

Fig. 5 Surface roughness measurements in terms of tool path pattern

3 Taguchi Method

The method proposed by Dr. Taguchi in 1960s is widely used in industrial and scientific studies, since it does not require complex mathematical calculations and can easily determine the optimum levels of process parameters. The method is applied in three main parts as system, parameter and tolerance design (Fig. 6).

System design is the part where the factors affecting the quality characteristic and their levels are determined and it requires technical knowledge regarding science and engineering. Parameter design is the most important and detailed part of the Taguchi method. It is the part in which the optimum levels of the factors are determined, the response in these levels is predicted and confirmation experiments are conducted. Finally, confidence interval that determines the

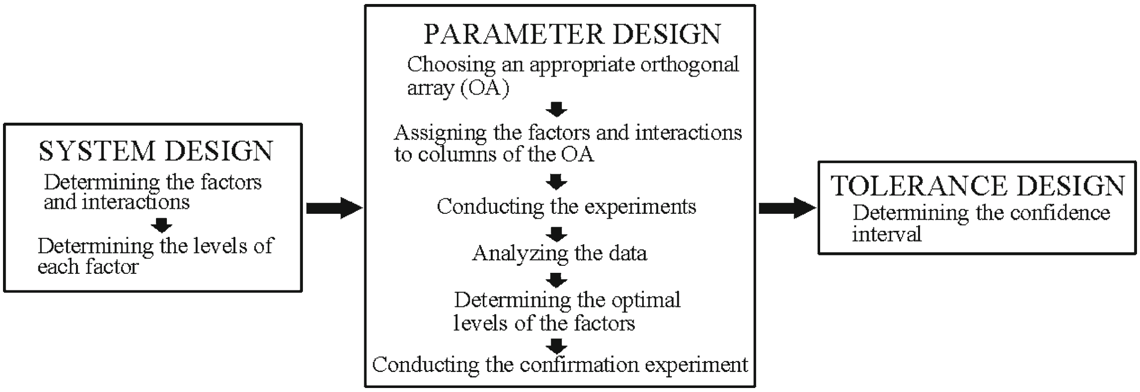

Fig. 6 Application steps of Taguchi technique in three main parts

lower and upper limits of the response predicted in the parameter design is calculated in the tolerance design. If the mean of the confirmation tests is within this range, it is accepted that the method achieves the optimization with sufficient accuracy.

4 Application of Taguchi Method

In this paper, the effects of control factors, such as cutting speed, feed rate, tool path pattern and depth of cut on surface roughness are determined and optimum factor levels are obtained by applying the steps given above. The chosen factors and their levels are given in Table 2.

The first step of the parameter design is to choose the appropriate orthogonal array that affects the experiment plan, accuracy of the statistical analysis and time/cost. As per Taguchi's method, the total DF (Degree of freedom) of the selected OA must be greater than or equal to the total DF required for the experiment [18]. The DF of experiment is calculated by adding the DFs of the factors and interactions used in the system. The DF of the related factor is calculated by extracting "1" from its level number and the DF of the interaction is obtained by multiplying the DFs of its factors. According to this, the DF of the experiment is 20. In other words, the DF for the experimental system that includes factors with equal number of levels is calculated as below:

$$T_{DF} = (n_l - 1) \times n_f + (n_l - 1) \times (n_l - 1) \times n_i \tag{1}$$

Table 2 Chosen factors and their levels

Factors	Units	Levels		
		1	2	3
Cutting speed (A)	m/min	100	200	300
Feed rate (B)	mm/min	150	675	1200
Tool path pattern (C)	–	One way	Parallel	Spiral
Depth of cut (D)	mm	1	1.75	2.5

where n_l is the number of the factor levels, n_f the number of factors and n_i the number of the interactions. In this experiment, these values are 3, 4 and 3, respectively. The L27 OA (DF = 26) which has 27 rows and 13 columns is thus selected for the experiment. The experimental design consists of 27 trials (each row in the L27 OA), and the columns of the OA are assigned to factors and their interactions via linear graph method (Fig. 7).

Based on the linear graph in Fig. 7, the first column is assigned to the cutting speed (A), the second column to the feed rate (B), the fifth column to the tool path pattern (C), the ninth column to the depth of cut (D) and the remaining columns are assigned to the interactions (A×B, A×C and B×C) in the orthogonal array (Table 3).

4.1 Experimental Results, Statistical Analyses and Discussion

Table 4 illustrates the experimental results based on the experimental plan. All statistical analyses are carried out for a significance level of 0.05, i.e., for a confidence level of 95 % via Minitab software.

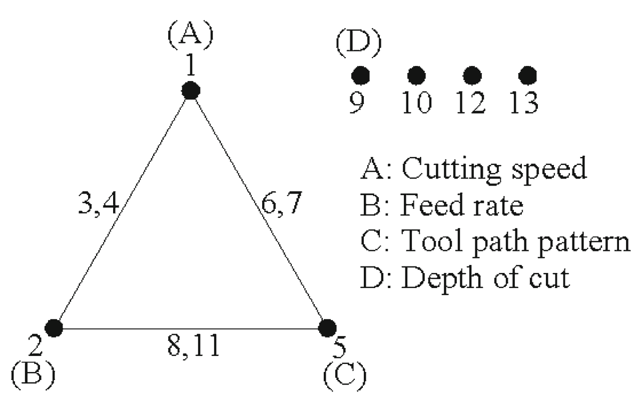

Fig. 7 A linear graph application of L27 OA

Table 3 L27 orthogonal array with factors and interactions assigned to columns

Trial no	Column no												
	1	2	3	4	5	6	7	8	9	10	11	12	13
	A	B	A×B	A×B	C	A×C	A×C	B×C	D	–	B×C	–	–
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

4.1.1 S/N Ratio Analysis

Taguchi method uses a statistical measure of performance called signal to-noise (*S/N*) ratio taken from electrical control theory in order to analyze the results [19,20]. In this technique, the term 'signal' refers to the desirable value (mean) for the output characteristic and the term 'noise' refers to the undesirable value (standard deviation). The determination of *S/N* ratio differs according to objective function, i.e., a characteristic value. There are three characteristic values as "Nominal is Best (NB)", "Smaller is Better (SB)" and "Larger is Better (LB)". As the goal of the study is to obtain minimum surface roughness, SB is chosen and can be calculated as below:

$$S/N = -10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \qquad (2)$$

where n is the number of measurements, and y_{i} the measured characteristic value. The unit of *S/N* ratio is decibel. Table 4 depicts the experimental results, mean and the corresponding *S/N* ratios.

4.1.2 ANOVA

The purpose of ANOVA in this study is to determine the significant process parameters and to measure their effects on the surface roughness. The pooled ANOVA results of the raw data and *S/N* ratios are given in Tables 5 and 6, respectively. In ANOVA, the ratio between the variance of the process parameter and of the error called as *F* test determines whether the parameter has a significant effect on the quality characteristic. This process is carried out by comparing the *F* test value of the parameter with the standard *F* table value ($F_{0.05}$) at the 5 % significance level. If the *F* test value is greater than $F_{0.05}$, the process parameter is considered significant or else it is considered pooled. In the ANOVA results for raw data, significant parameters affect the mean value while in the one for *S/N* ratio data, they affect the variation around the mean value. In the light of these data, it is clear that cutting speed and feed rate are significant in both ANOVAs while all interactions are insignificant. As for depth of cut process parameter, it is only significant in ANOVA for *S/N* ratio and affects the variation around the mean value of the surface roughness.

Table 4 Experimental results, mean and the corresponding *S/N* ratios for surface roughness

Trial no.	Cutting speed (A)	Feed rate (*B*)	Tool path pattern (*C*)	Depth of cut (*D*)	Ra_1	Ra_2	Ra_3	R_{mean}	*S/N*
1	100	150	One way	1	0.63	0.7	0.67	0.667	3.514
2	100	150	Parallel	1.75	0.66	0.69	0.63	0.660	3.603
3	100	150	Spiral	2.5	0.73	0.66	0.66	0.683	3.297
4	100	675	One way	1.75	1	0.86	1.04	0.967	0.267
5	100	675	Parallel	2.5	1.36	1.24	1.26	1.287	−2.197
6	100	675	Spiral	1	0.75	0.89	0.86	0.833	1.561
7	100	1,200	One way	2.5	2.06	1.6	1.74	1.800	−5.155
8	100	1,200	Parallel	1	0.95	1.02	0.97	0.980	0.172
9	100	1,200	Spiral	1.75	1.15	1.14	1.16	1.150	−1.214
10	200	150	One way	1.75	0.66	0.69	0.63	0.660	3.603
11	200	150	Parallel	2.5	0.67	0.67	0.67	0.670	3.479
12	200	150	Spiral	1	0.63	0.64	0.64	0.637	3.922
13	200	675	One way	2.5	0.81	0.79	0.75	0.783	2.117
14	200	675	Parallel	1	0.66	0.69	0.71	0.687	3.261
15	200	675	Spiral	1.75	0.72	0.68	0.67	0.690	3.219
16	200	1,200	One way	1	0.67	0.72	0.7	0.697	3.136
17	200	1,200	Parallel	1.75	0.83	0.91	0.87	0.870	1.203
18	200	1,200	Spiral	2.5	1.1	1.01	1.08	1.063	−0.539
19	300	150	One way	2.5	0.62	0.65	0.63	0.633	3.966
20	300	150	Parallel	1	0.71	0.60	0.55	0.620	4.149
21	300	150	Spiral	1.75	0.62	0.62	0.65	0.630	4.011
22	300	675	One way	1	0.7	0.65	0.71	0.687	3.259
23	300	675	Parallel	1.75	0.68	0.63	0.65	0.653	3.693
24	300	675	Spiral	2.5	0.76	0.76	0.71	0.743	2.572
25	300	1,200	One way	1.75	0.69	0.66	0.7	0.683	3.305
26	300	1,200	Parallel	2.5	0.9	0.79	1.07	0.920	0.657
27	300	1,200	Spiral	1	0.99	0.83	0.7	0.840	1.429

Table 5 ANOVA results of the raw data

Source	DF	SS	*V*	*F* test	SS'	*P*
Cutting speed (*A*)	2	0.44889	0.224445	6.25	0.37711	21.09
Feed rate (*B*)	2	0.54968	0.274842	7.66	0.4779	26.73
Tool path pattern (*C*)	(2)	(0.00566)	–	Pooled	Pooled	–
Depth of cut (*D*)	(2)	(0.23983)	–	Pooled	Pooled	–
$A\times B$	(4)	(0.19902)	–	Pooled	Pooled	–
$A\times C$	(4)	(0.11538)	–	Pooled	Pooled	–
$B\times C$	(4)	(0.04536)	–	Pooled	Pooled	–
Error	22	0.78959	0.035890	–	0.93315	52.18
Total	26	1.78816		–	1.78816	100

DF degree of freedom, *SS* sum of squares, *V* variance, *SS'* pure sum of squares, *P* percent of contribution, $F_{0.05,2,22} = 3.44$, $F_{0.05,4,22} = 2.82$

Table 6 ANOVA results of the *S/N* ratios

Source	DF	SS	*V*	*F* test	SS'	*P*
Cutting speed (*A*)	2	34.4756	17.2378	11.42	31.45554	23.64
Feed rate (*B*)	2	51.7097	25.8549	17.12	48.68964	36.59
Tool path pattern (*C*)	(2)	(0.0053)	–	Pooled	Pooled	–
Depth of cut (*D*)	2	16.6763	8.3381	5.52	13.65624	10.26
$A\times B$	(4)	(12.2042)	–	Pooled	Pooled	–
$A\times C$	(4)	(6.2980)	–	Pooled	Pooled	–
$B\times C$	(4)	(2.1247)	–	Pooled	Pooled	–
Error	20	30.2006	1.51003		39.26078	29.51
Total	26	133.0622			133.0622	100

DF degree of freedom, *SS* sum of squares, *V* variance, *SS'* pure sum of squares, *P* percent of contribution, $F_{0.05,2,20} = 3.49$, $F_{0.05,4,20} = 2.87$

4.1.3 Prediction of Optimal Surface Roughness

Optimum factor levels are determined considering ANOVAs and main effects plot (Fig. 8). Thus, it is observed that cutting speed correlates negatively with surface roughness and positively with feed rate and depth of cut.

As clearly seen in Fig. 8, the minimum surface roughness can be obtained in the third level of cutting speed and

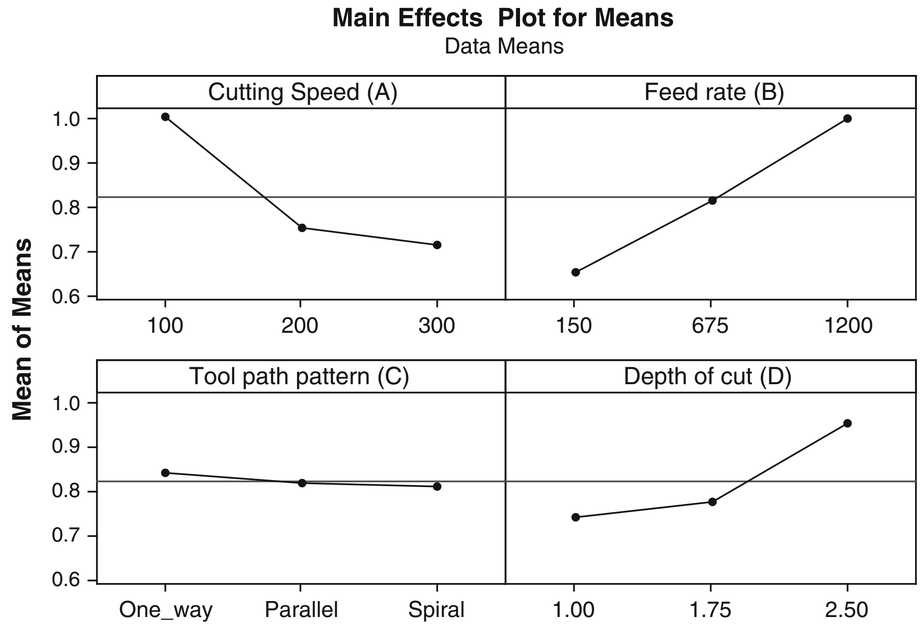

Fig. 8 Main effects plot of factors

tool path pattern, and the first level of feed rate and depth of cut. As tool path pattern and depth of cut are not significant according to both ANOVAs, they are ignored in the calculation of the optimum surface roughness. Accordingly, optimum condition is $A = 300$ m/min, $B = 150$ mm/min, $C =$ Spiral and $D = 1$ mm.

Based on these data, optimum surface roughness according to Taguchi is obtained in the equation below:

$$R_{OPT} = M_{A3} + M_{B1} - R_{MEAN} \tag{3}$$

where M_{A3} is the mean of the experiments in the third level of factor A, M_{B1} is the one in the first level of factor B, and R_{MEAN} is overall mean of surface roughness. Table 7 shows the response table where the average R_a values of factor levels are given.

Based on these data, the optimum surface roughness is predicted as $R_{\mathrm{OPT}} = 0.7122+0.6511-0.822 = 0.5413\mu$m.

A confidence interval, the last step of Taguchi, for the predicted mean on a confirmation run can be calculated using the Eq. 4 [21]:

$$\mathrm{CI} = \left(F_{0.05}(1, DF_{\mathrm{e}}) \times V_{\mathrm{e}}\left[\frac{1}{n_{\mathrm{eff}}} + \frac{1}{R}\right]\right)^{1/2} \tag{4}$$

where $F_{0.05}(1, \mathrm{DF_e})$ is the F value (4.30) taken from standard tables for a significance level of 0.05 and according to DF of 1 and the error. While $V_{\mathrm{e}}(0.035890)$ refers to the variance value of the error, R (3) is the number of repetitions for confirmation experiments. n_{eff} is the effective number of replications and can be calculated as below:

$$n_{\mathrm{eff}} = \frac{N}{1 + V_{\mathrm{t}}} \tag{5}$$

where N (27) is the total number of trials and V_{t} (4) is the total DF associated in the estimate of the mean. Accordingly, n_{eff} is calculated as 5.4. In the light of these data, the confidence interval is obtained as $\pm 0.28\,\mu$m. Thus, mean of surface roughness measurements in the confirmation tests must be within $R_{\mathrm{OPT}}-\mathrm{CI} < \mathrm{Ra} < R_{\mathrm{OPT}}+\mathrm{CI}$. In the three confirmation tests conducted under optimum condition (A = 300 m/min, B = 150 mm/min, C = Spiral and D = 1 mm), mean surface roughness of 0.55 µm is obtained and Taguchi method achieves the optimization for a confidence level of 95 % with sufficient accuracy.

In almost all machinability studies, depth of cut, cutting speed and feed rate are used as process parameters and they are the factors that can be taken as reference. In this paper,

Table 7 Response table for surface roughness

Level	Cutting speed (A)	Feed rate (B)	Tool path pattern (C)	Depth of cut (D)
1	1.0030	0.6511	0.8419	0.7385
2	0.7507	0.8144	0.8163	0.7737
3	0.7122	1.0004	0.8078	0.9537
Delta	0.2907	0.3493	0.0341	0.2152
Rank	2	1	4	3
$R_{\mathrm{mean}} = 0.822$				

the correlation between these parameters and surface roughness is parallel to other modeling and optimization studies. Different from other studies, in this paper, tool path pattern parameter was investigated in terms of surface roughness in milling of aluminum for the first time and was observed that it does not have a significant effect. The most important reason for this is that the hardness of the aluminum alloy is lower when compared to steel and as a result of this, low cutting forces are obtained. It is considered that this case prevents the mechanisms which deteriorate the surface quality such as vibration, tool deflection and tool wear which occur in different tool path patterns and high cutting forces. Parallel to this view, Kaymakci and Lazoglu [22] investigated the effects of different tool path patterns on cutting forces, tool deflection and machining time in 3D complex sculptured surface machining both theoretically and experimentally. Based on this, they determined that different tool path patterns have different cutting force, machining time and tool deflection characteristics. Gologlu and Sakarya [23] studied the effects of cutting speed, feed rate and axial/ radial depth of cut parameters on surface quality for three different tool path patterns (one-direction, zig-zag and spiral) in the pocketing of DIN 1.2738 mould steel with HSS flat endmill. They determined the factor levels that provide the minimum surface roughness and predicted the roughness at these levels. Significance comparison cannot be done between the two studies as tool path pattern is not considered as a factor in their study; however, the fact that lower roughness is obtained in spiral machining compared to others shows that similar results have been obtained.

5 Conclusions

The effects of cutting speed, feed rate, tool path pattern and depth of cut process parameters on surface roughness in the pocket machining of AA5083 aluminum alloy material were assessed via Taguchi experimental design method. The conclusions drawn from the statistical analysis were as follows:

1. Based on F test results carried out in both ANOVAs, it was observed that cutting speed and feed rate are significant in both ANOVAs while all interactions are not. As for depth of cut process parameter, it is only significant in ANOVA for S/N ratio and affects the variation around the mean value of the surface roughness.
2. Surface roughness correlated positively with feed rate and depth of cut but negatively with cutting speed. Although tool path pattern factor is not significant, spiral tool path pattern was proposed since lower average of surface roughness was obtained in the experiments conducted at this level.
3. Taking ANOVAs and main effects plot into consideration, the cutting condition that achieves minimum surface roughness was obtained at the third level of cutting speed ($A = 300$ m/min), first level of feed rate ($B = 150$ mm/min), third level of tool path pattern (C = spiral) and first level of depth of cut ($D = 1$ mm). Taguchi method predicted the optimum surface roughness as 0.5413μ m under this condition.
4. The average result ($0.55\,\mu$m) of the tree confirmation tests under optimum condition was within the confidence interval of the predicted result. Thus, the proposed method achieved the optimization of the system for a confidence level of 95 % with sufficient accuracy.
5. In the experimental plan, minimum surface roughness was obtained in the 20th trial ($A = 300$ m/min, $B =$ 150 mm/min, C = parallel, $D = 1$ mm) as 0.62 μm. In the confirmation experiments conducted in the optimum levels of the factors determined via Taguchi method, this value was improved by 11.29 %

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