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RESEARCH

Experimental and Statistical Study of Surface Roughness in CNC Slot Milling of AL 7075 Alloy Using Full and Fractional Factorial Design

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A B S T R A C T

This work deals with comparing the fractional and full factorial design of experiments on evaluating surface roughness characteristics during slot milling of Al 7075 alloy. Mean surface roughness (Ra) was selected as the response parameter. Cutting variables (cutting speed, feed rate, axial depth of cut) were the input parameters, each having three levels. The input parameters were assigned to an L27 orthogonal array to determine the experiments. Thereby, the L27 OA was split into three L9 sub-arrays where each held the "orthogonality property". Several statistical tools indicate that the fractional factorial approach is just as suitable as the full factorial design of experiments for analyzing machining (milling) results of aluminum alloys.

1. INTRODUCTION

Material removal by milling is probably one of the most often applied manufacturing processes. Currently, significant enhancements have been achieved in milling, especially in difficult-to-cut alloys machining, while requiring better surface finish and high precision [1,2]. Even though machinability spans many parameters characterizing it, such as cutting force, tool wear and surface roughness, the latter is the only indicator to be directly related to surface finish, precision machining and surface integrity. High surface finish is a fundamental requirement for products used in various industrial sectors, especially in mould/die, automobile, aerospace, and artificial implants manufacturing [3]. When it comes to milling, higher finishing quality is related to low surface roughness, which is also a surface texture indicator [4]. Low roughness values imply

that material properties like corrosion resistance, fatigue strength and aesthetic appeal are improved [5]. Therefore, controlling surface roughness in milling is a mandatory research topic [6]. In addition machinability performance of various alloys may vary significantly and this proves that knowledge of machining properties with emphasis to the resulting surface topography and roughness is essential [7].

Design of experiments (DOE) allows for efficient experimental identification of correlating independent variables affecting a process to its corresponding response or multiple responses [8]. DOE methodology is distinguished to the full factorial design (FD) and fractional FD [9]. Fractional FD aims at examining a rigorously selected subset, or equivalently, a fraction of a full FD, under the notion that some experimental runs found in a full FD may be redundant, thus offering few or no contribution at all, referring to experimental outputs. A very popular fractional FD is the "Taguchi's" design of experiments [10]. Taguchi's approach employs the so-called "orthogonal arrays-OA" for designing fractional FD experiments [11].

Numerous studies have applied both full and fractional DOE to conduct their experiments; hence it is mandatory to select the experimental design approach that best fits applied research to obtain trustworthy results [12]. Dahbi et al. [13] implemented a full FD to optimize surface roughness for turning of AISI 1042 Steel. They investigated the impact of four cutting parameters, i.e. cutting speed, feed rate, depth of cut and tool nose radius. Mahesh et al. [14] applied the Taguchi-fuzzy approach to optimize surface roughness and material removal rate for Al 7075-T6 end milling. The process parameters were speed, feed, depth of cut and nose radius. Taguchi's L27 OA was used as the design of experiments. It is found that depth of cut and nose radius had the most notable effect on the responses. Abbas et al. [15] studied the effect of three process parameters (spindle speed, depth of cut and table feed rate) on surface roughness of high strength steel face milling. They concluded that feed rate is the most effective parameter, followed by the depth of cut. Fratila et al. [16] examined the optimization of cutting parameters and cooling lubrication technique in surface roughness for AlMg3 face milling. Taguchi's L9 OA was used as DOE, while Analysis of Means (ANOM) and ANOVA were utilized as the main statistical tools. Feed rate is found to have the most important effect on surface roughness. Jebaraj et al. [17] investigated the influence of cooling environment, feed rate and cutting velocity on cutting temperature, feed force, normal force, axial force and average surface roughness for Al6082-T6 alloy milling. The results showed that surface roughness increases with an increase of feed rate while decreases when cutting velocity increases. Ribeiro et al. [18] studied the impact of feed per tooth, cutting speed and radial depth of cut on the surface finish of hardened steel block (steel 1.2738) end milling. It is found that radial depth of cut was the most influential parameter. Mia [19] utilized both Response Surface Methodology (RSM) and Taguchi's method to examine cutting energy and surface finish of AISI 4140 steel milling. Tlhabadira et al. [20] examined the surface roughness of AISI P20 steel in milling, using the Taguchi method. The process parameters were the depth of cut, spindle speed and cutting feed. Finite element analysis (FEA) was used to analyse the experimental data. In [21], the authors have investigated the impact of depth of cut, feed and cutting speed on flank wear of tungsten carbide and polycrystalline diamond (PCD) inserts in CNC turning of 7075 AL alloy with 10 wt% SiC composite using predictive Artificial Neural Networks (ANNs). Aslantas et al. [22] examined the effect of cutting conditions on burr width and surface finish of Ti-6Al-4V alloy during micro-milling. Chethan et al. [23] implemented a Taguchi L27 OA for selecting the optimal cutting conditions of Nimonic 75 superalloy accompanied by machine vision signals and acoustic emission.

Contributions dealing with comparative studies concerning full and fractional FD experiments involve examining process parameters' effects on their corresponding responses and the facilitation in applying experimental – statistical tools to actual industrial practices. You et al. [10] compared a full FD comprising 288 runs to 26-2 fractional FD along with an L16 Taguchi orthogonal design to examine the influence of cutting conditions on surface finish. In their work, the only statistical method adopted to analyse the experimental results was ANOVA. After analysing all data, it is finally observed that the effects resulting from the different experimental designs followed quite similar trends. Tay et al. [24] compared several experimental designs aiming at delivering a solution to the problem concerning the inability of practitioners to implement

experimental design techniques on actual production operations. In [25], Kechagias et al. studied the machinability of turning a Ti-6Al-4V ELI alloy in terms of main cutting force and surface roughness by adopting both full and fractional FDs to analyse the experimental results. A variety of statistical tools are used for comparing the results of full and fractional FDs. Both approaches resulted in almost identical outcomes in terms of turning parameters for cutting forces. In the case of surface roughness, full FD gave better results. From the above-mentioned reports, it is evident that a knowledge gap exists among researchers and industry concerning both the application of systematic experimental design methods and the analysis of their corresponding results. Statistical analysis is, in general, related to a non-formal, exploratory analysis of data. The process of extracting such data for further experimental characterization is known as exploratory data analysis (EDA). EDA ingredients involve model-formulation and description of the data [26]. Box plots and stem-and-leaf plots are among the most extensively applied EDA tools. Contributions such as those in [27-29] are cases where boxplots and other related outputs have been used for interpreting machinability performance.

Similar to the work presented in [25], this study compares the application of full and fractional FDs on surface roughness prediction of Al 7075 alloy in milling, based on different statistical analysis tools. As a major quality indicator for characterizing surface finish, the mean surface roughness $R\alpha$ was considered. A variety of statistical tools have been utilized, namely analysis of means (ANOM), analysis of variance (ANOVA), stem-and-leaf plots and box plots. This research aims to investigate further the usage of full and fractional FDs for examining machinability issues of various materials with great industrial interest.

2. MATERIALS AND METHODS

As a first step for designing a full FD experiment, cutting parameters, i.e., cutting speed V_c (mm/min), feed rate f (mm/rev) and axial depth of cut a_p (mm), were selected. For each of the three parameters, three levels were selected as is shown in Table 1. Cutting parameters and corresponding levels are selected based on the specifications of the tool's manufacturer along with other studies regarding slot milling [14-20]. Moreover, in this study,, the cutting forces are relatively small, i.e., smaller than 200N. According to number of the parameters and their levels, the combinations constituting the experimental design were generated and formulated an L_{27} array shown in Table 2. In the same table, the last two columns tabulate the experimental results of mean surface roughness, Ra.

Table 1. 3^3 (L_{27}) parameter design.

Process parameters	Levels		
	1	2	3
Depth of cut a_p (mm)	0.5	1	1.5
Cutting speed V_c (mm/min)	50	100	150
Feed rate f (mm/rev)	0.05	0.08	0.11

Table 2. Full factorial experimental array for mean surface roughness, R_a.

No.	a_p (mm)	V_c (mm/min)	f (mm/rev)	R_a (μm)
1	0.5	50	0.05	0.247
2	0.5	50	0.08	0.717
3	0.5	50	0.11	1.080
4	0.5	100	0.05	0.335
5	0.5	100	0.08	0.427
6	0.5	100	0.11	0.813
7	0.5	150	0.05	0.250
8	0.5	150	0.08	0.377
9	0.5	150	0.11	0.423
10	1	50	0.05	0.307
11	1	50	0.08	0.557
12	1	50	0.11	0.867
13	1	100	0.05	0.387
14	1	100	0.08	0.693
15	1	100	0.11	1.017
16	1	150	0.05	0.447
17	1	150	0.08	0.617
18	1	150	0.11	0.907
19	1.5	50	0.05	0.307
20	1.5	50	0.08	0.497
21	1.5	50	0.11	0.773
22	1.5	100	0.05	0.343
23	1.5	100	0.08	0.620
24	1.5	100	0.11	0.853
25	1.5	150	0.05	0.657
26	1.5	150	0.08	0.567
27	1.5	150	0.11	0.990

The test material was the Al 7075 (90% Al, 5.6% Zn, 2.5% Mg, 1.6% Cu, and 0.23% Cr) aluminium alloy. Al 7075 was used in three plates 12 mm thick, 150 mm in length, and 50 mm in width (Fig. 1).

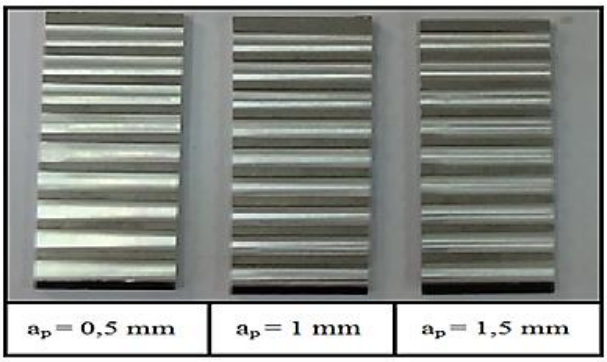

Fig. 1. Machined specimens of Al 7075 alloy.

A D8 mm two-flute Kennametal® flat end-mill with 30° helix angle (KC633M) was selected for conducting the 27 slots on the aluminium plates. The machining mode was climbing milling with multilayered PVD solid carbide tool (Fig. 2).

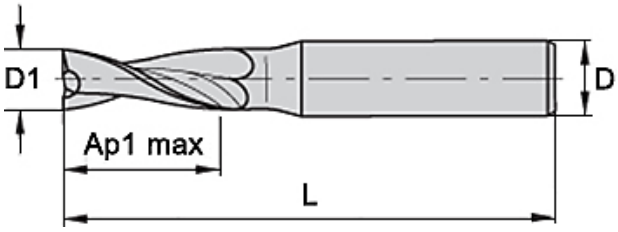

Fig. 2. Cutting tool dimensions (D1: 8mm, z: 2, 30°).

To obtain accurate roughness measurements, a set of 27 milling tools was used; that is one tool for each experiment. In this way, the tool wear was negligible and did not significantly affect the obtained measurements. The HAAS® VF1 4-axis vertical CNC machining centre with continuous controls for feeds and speeds was used for producing the 27 slots (Fig. 3). During slot milling operations, an appropriate coolant fluid (semisynthetic, oil-based) was used, namely KOOLrite™ 2270.

Fig. 3. HAAS® VF1 CNC machine center (max. 7500 rpm, 15 kW).

For the surface roughness measurements, the portable Mitutoyo® Surftest SJ-210 profilometer was used (Fig. 4). This instrument has a measuring range of -200 μm and +160 μm in the Z-axis measuring range, while it is equipped with a stylus tip of a 2 μm radius. This profilometer can measure various surface roughness parameters based on the standards, whereas a series of filters can be applied if required.

Fig. 4. A machined specimen and the surface profilometer. (Arrows indicate the direction and the position of surface roughness measurements).

Measurements followed ISO 4287 (1997) standard, whereas traversing length, total length and cut-off distance were 4.8 mm, 4 mm, and 0.8 mm, respectively. The ISO 4287 (1997) standard suggests that measuring parameters should have stable and robust definitions to reflect genuine surface properties. Note that the parameter definition is considered mathematically stable only if a small change in the profile implies a small change in the parameter value. The measuring speed was 0.5 mm/sec. Four measurements are taken in each slot and the average value was considered the final output for *Ra*.

3. EXPERIMENTAL RESULTS AND STATISTICAL ANALYSIS

The present study compares the full factorial experimental design approach with the fractional factorial experimental design by utilizing descriptive data analysis tools. Box plots and stem-and-leaf diagrams are

generated first to arrange the data corresponding to each experimental design. Both diagrams assist in visualizing the shape of the distribution of the *Rα* values. Further on, ANOM and ANOVA were performed for both full and fractional FD approaches to determine which factors exhibit the strongest effect on mean surface roughness *Rα* values. It should be mentioned that smaller *Rα* values indicate better surface finish, therefore "the-smaller-the-better" approach has been utilized in ANOVA. Statistical analysis outputs have been used to judge whether fractional FDs offer similar results to full FD. Therefore both methodologies are proper for designing experiments related to machinability investigations for difficult-to-cut materials like high-alloyed steels, titanium alloys and superalloys. The authors believe that surface quality prediction in different cutting conditions and cutting materials is an important challenge. At the same time, data descriptive analysis and other statistical tools (i.e., interaction charts) can be used to generate more reliable predictive models.

3.1 Full factorial experimental design

As reported earlier, Table 2 tabulates the complete 27-array combination with experimental data for *Ra*. First, the stem-and-leaf plot is created. It can be noticed that for *Ra* (Table 3), the groups with the largest number of data are: 0.3 - 0.4 μm (6 values), 0.4 - 0.5 μm and 0.6 - 0.7 μm (4 values). Fig. 5 illustrates the box plot for *Ra*, while Table 4 summarizes the corresponding results. Both indicate that the quartiles for mean surface roughness are 0.377 - 0.813 μm. The whiskers end at the values 0.247 μm – 1.080 μm for *Ra* whilst the median is 0.567 μm.

Table 3. Stem-and-leaf plot for mean surface roughness, R_a (data has been scaled to 10^{-1}).

2	47	50				
3	07	07	35	43	77	87
4	23	27	47	97		
5	57	67				
6	17	20	57	93		
7	17	73				
8	13	53	67			
9	07	90				
10	17	80				

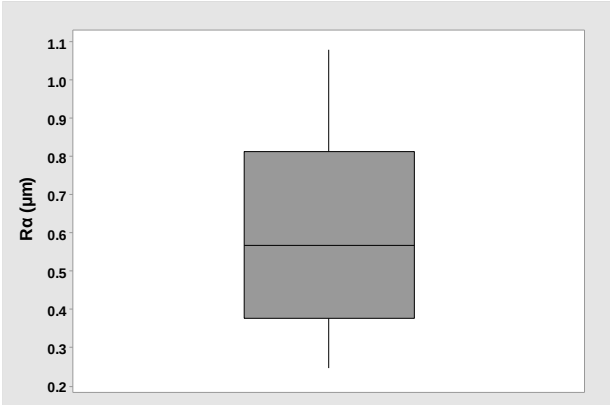

Fig. 5. Box plot for mean surface roughness, R_a.

Table 4. Values used for the box plot of mean surface roughness, R_a.

Magnitude	*Ra (μm)*
Min	0.247
Lower Quartile	0.377
Median	0.567
Upper Quartile	0.813
Max	1.080

For the ANOM, the derived mean values of *Ra* are summarized in Table 5 whilst the main effects plot for the mean values of *Ra* are depicted in Fig. 6. ANOVA is presented in Table 6. Both ANOM and ANOVA can be used for ranking the cutting parameters in terms of their impact on the quality response of *Ra*. In this study, the optimum parameter levels are considered to be the ones that minimize *Ra*. The best parameter values for *Rα* are: 1st level of a_p = 0.5 mm; 3rd level of V_c = 150 mm/min and 1st level of f = 0.05 mm/rev. When it comes to ANOVA, *F* and *P* values should be considered to decide which parameters strongly affect the response. Significance is implied by high *F*-values or equivalently, low *P*-values (P < 0.05). Consequently, feed rate, *f* is the dominant parameter affecting mean surface roughness (F = 25.23, P = 0.001), followed by depth of cut, a_p (F = 1.85, P = 0.184) and cutting speed, V_c which doesn't affect *Ra* that much as the other two parameters (F = 0.08, P = 0.923). Coefficient of Determination-*R* squared (R^2) is generally utilized as a statistical measure of how close the data is to the fitted regression line, while it has a range between 0-100 %. The higher the R^2, the better the model. Usually, R^2 values greater than 70% are considered good. In the case of full FD, the R^2 value is 73.08% for *Ra*.

Table 5. Response table for R_a.

Level	a_p (mm)	V_c (mm/min)	f (mm/rev)
1	0.5188	0.5947	0.3644
2	0.6443	0.6098	0.5636
3	0.6230	0.5817	0.8581
Delta	0.1256	0.0281	0.4937
Rank	2	3	1

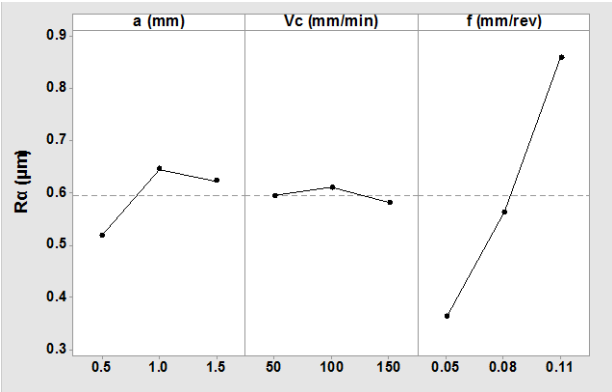

Fig. 6. Plot for means for mean surface roughness, R_a.

Table 6. ANOVA results for R_a.

Source	DF	F	P	Contribution (%)
a_p (mm)	2	1.85	0.184	4.97
V_c (mm/min)	2	0.08	0.923	0.22
f (mm/rev)	2	25.23	0.001	67.89
Error	20			26.92
Total	26			
R^2 (%)	73.08			

From the results presented in above in ANOVA, a noticeable unacceptable error is depicted. In general, surface roughness is hardly correlated to its independent parameters. The percentage of error contribution referring to *Ra* is 26.92%. Interactions involved should be considered to reduce the error in ANOVA analysis. Here, the primary objective is to compare full and fractional FDs using specific statistical tools and interactions could be examined in future studies.

3.2 Fractional factorial experimental designs

Three OAs of nine experiments were extracted from the original L_{27} OA according to [25]. The first L_9 OA for *Ra* is presented in Table 7, whilst Table 8 shows the stem-and-leaf plot for the 1st L_9 OA. The groups with the largest data number are 0.3 – 0.4 *µm* and 0.6 – 0.7 *µm* for *Ra*. In addition, boxplot (Fig. 7, Table 9) shows that the quartiles are 0.347 – 0.840 µm. The whiskers end at the values 0.250 – 0.990 *µm* while the median is 0.620 *µm*.

Table 7. 1st L_9 fractional factorial experimental OA.

No.	a_p (mm)	V_c (mm/min)	f (mm/rev)	Ra (µm)
1	0.5	50	0.08	0.717
2	0.5	100	0.11	0.813
3	0.5	150	0.05	0.250
4	1	50	0.11	0.867
5	1	100	0.05	0.387
6	1	150	0.08	0.617
7	1.5	150	0.11	0.990
8	1.5	50	0.05	0.307
9	1.5	100	0.08	0.620

Table 8. 1st L_9 OA stem and leaf plot for R_a (data has been scaled to 10^{-1}).

2	50	
3	07	87
4		
5		
6	17	20
7	17	
8	13	67
9	90	

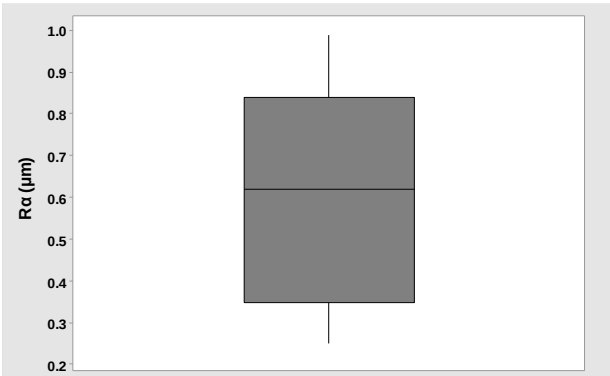

Fig. 7. 1st L_9 OA box plot for mean surface roughness, R_a.

Table 9. Results used for the 1st L_9 OA box plot for mean surface roughness, R_a.

Magnitude	*Ra (µm)*
Min	0.250
Lower Quartile	0.347
Median	0.620
Upper Quartile	0.840
Max	0.990

As it can be noticed in the ANOM (Table 10) and plot of means (Fig. 8), the parameter levels which minimize mean surface roughness are: the 1st level of a_p = 0.5 mm, 2nd level of V_c = 100 mm/min, and 1st level of f = 0.05 mm/rev. ANOVA (Table 11) shown that when it comes to *Ra*, feed rate is the most important parameter (F = 17.70, P = 0.053), followed by depth of cut (F = 0.11, P = 0.897) and cutting speed, (F = 0.03, P = 0.971). R^2 is 94.69%.

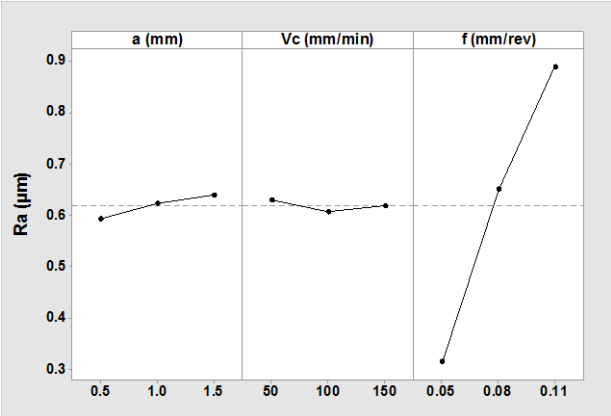

Fig. 8. Plot for means for mean surface roughness, R_a for the 1st L_9 OA.

Table 10. Response table for R_a (1st L_9 OA).

Level	a_p (mm)	V_c (mm/min)	f (mm/rev)
1	0.5933	0.6303	0.3147
2	0.6237	0.6067	0.6513
3	0.6390	0.6190	0.8900
Delta	0.0457	0.0237	0.5753
Rank	2	3	1

Table 11. ANOVA results for R_a (1st L_9 OA).

Source	DF	F	P	Contribution (%)
a_p (mm)	2	0.11	0.897	0.61
V_c (mm/min)	2	0.03	0.971	0.16
f (mm/rev)	2	17.70	0.053	93.93
Error	2			5.30
Total	8			
R^2 (%)	94.69			

The second L_9 OA for *Ra* is presented in Table 12. Stem-and-leaf plot (Table 13) shows that the groups of 0.3-0.4 µm and 0.6-0.7 µm have three and two *Ra* values, respectively. The box plot (Fig. 9, Table 14) indicates that *Ra* is between 0.356-0.880 μm. The whiskers end at the values 0.250 – 0.990 μm while the median is 0.657 μm.

Table 12. 2nd L_9 fractional factorial experimental OA.

No.	a_p (mm)	V_c (mm/min)	f (mm/rev)	Ra (µm)
1	0.5	50	0.11	1.080
2	0.5	100	0.05	0.335
3	0.5	150	0.08	0.377
4	1	50	0.05	0.307
5	1	100	0.08	0.693
6	1	150	0.11	0.907
7	1.5	50	0.08	0.497
8	1.5	100	0.11	0.853
9	1.5	150	0.05	0.657

Table 13. 2nd L_9 OA stem and leaf plot for R_a (data has been scaled to 10^{-1}).

2	50	
3	07	87
4		
5		
6	17	20
7	17	
8	13	67
9	90	

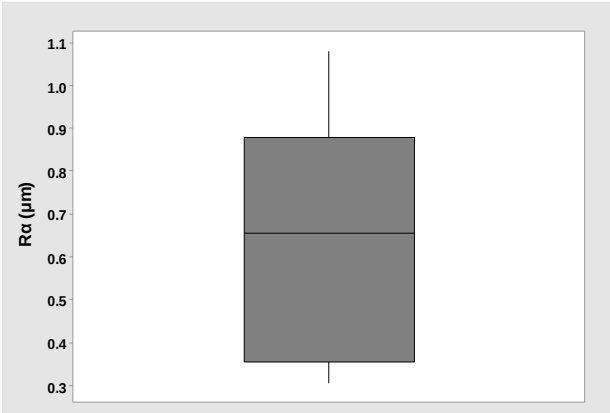

Fig. 9. 2nd L_9 OA box plot for mean surface roughness, R_a.

Table 14. Results used for the 2nd L_9 OA box plot for mean surface roughness, R_a.

Magnitude	*Ra (µm)*
Min	0.307
Lower Quartile	0.356
Median	0.657
Upper Quartile	0.880
Max	1.080

From the plot of means (Fig. 10) and ANOM (Table 15) it is shown that best parameter values for *Ra* are: 1st level of a_p = 0.5 mm; 1st level of V_c = 50 mm/min and 1st level of f = 0.05 mm/rev. ANOVA (Table 16) shows that for *Ra*, feed rate is the dominant parameter (F = 3.09, P = 0.244), followed by depth of cut (F = 0.05, P = 0.950) and cutting speed, (F = 0.01, P = 0.995). The most significant influence on *Ra* is exerted by feed rate (F = 5.68, P = 0.150), whilst the least significant influence is depth of cut (F = 0.62, P = 0.52). R^2 is equal to 75.9%.

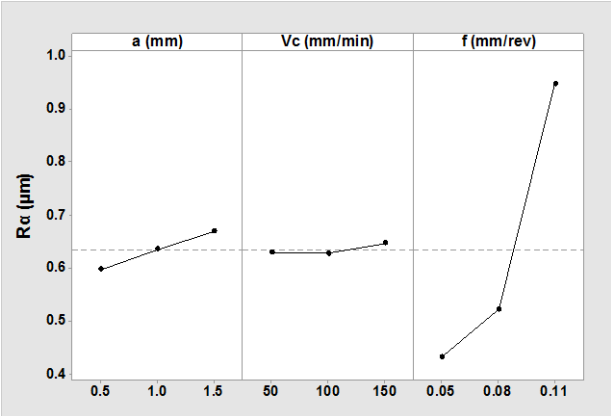

Fig. 10. Plot for means for mean surface roughness, R_a for the 2nd L_9 OA.

Table 15. Response table for R_a (2nd L_9 OA).

Level	a_p (mm)	V_c (mm/min)	f (mm/rev)
1	0.5973	0.6280	0.4330
2	0.6357	0.6270	0.5223
3	0.6690	0.6470	0.9467
Delta	0.0717	0.0200	0.5137
Rank	2	3	1

Table 16. ANOVA results for R_a (2nd L_9 OA).

Source	DF	F	P	Contribution (%)
a_p (mm)	2	0.05	0.950	1.27
V_c (mm/min)	2	0.01	0.995	0.13
f (mm/rev)	2	3.09	0.244	74.50
Error	2			24.10
Total	8			
R^2 (%)	75.90			

The third L_9 OA for *Ra* is presented in Table 17. Stem-and-leaf plot (Table 18) shows that the groups of 0.4-0.5 µm and 0.5-0.6 µm have two and three *Ra* values, respectively. The box plot (Fig. 11, Table 19) indicates that *Ra* is between 0.383-0.670 μm. The whiskers end at the values 0.247-1.017 μm for *Ra*. The median is found equal to 0.447 μm.

Table 17. 3rd L_9 fractional factorial experimental OA.

No.	a_p (mm)	V_c (mm/min)	f (mm/rev)	Ra (µm)
1	0.5	50	0.05	0.247
2	0.5	100	0.08	0.427
3	0.5	150	0.11	0.423
4	1	50	0.08	0.557
5	1	100	0.11	1.017
6	1	150	0.05	0.447
7	1.5	50	0.11	0.773
8	1.5	100	0.05	0.343
9	1.5	150	0.08	0.567

Table 18. 3rd L_9 OA stem and leaf plot for R_a (data has been scaled to 10^{-1}).

2	47		
3	43		
4	23	27	47
5	57	67	
6			
7	73		
8			
9			
10	17		

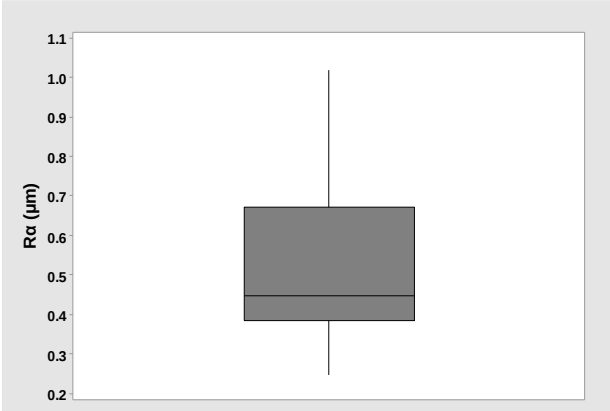

Fig. 11. 3rd L_9 OA box plot for mean surface roughness, R_a.

Table 19. Results used for the 3rd L_9 OA box plot for mean surface roughness, R_a.

Magnitude	Ra (µm)
Min	0.247
Lower Quartile	0.383
Median	0.447
Upper Quartile	0.670
Max	1.017

ANOM (Table 20) and the plot of means (Fig. 12) indicate that the parameter levels which minimize mean surface roughness are: 1st level of a_p = 0.5 mm; 3rd level of V_c = 150mm/min and 1st level of f=0.05 mm/rev. ANOVA (Table 21) shows that for *Ra*, f is the dominant parameter (F = 5.25, P = 0.160), followed by α_p (F = 3.30, P = 0.232) and V_c (F = 0.47, P = 0.681). R^2 is equal to 90.03%.

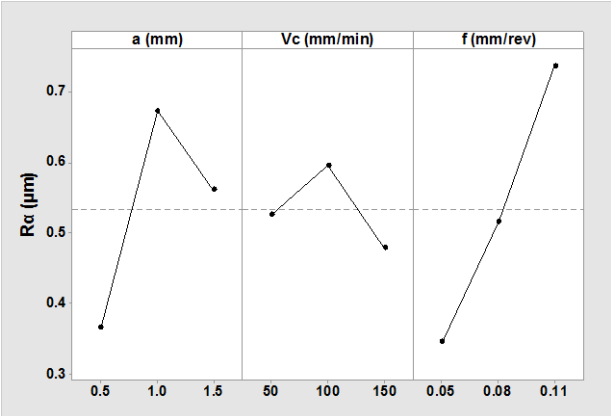

Fig. 12. Plot for means for mean surface roughness, R_a for the 3rd L_9 OA.

Table 20. Response table for R_a (3rd L_9 OA).

Level	a_p (mm)	V_c (mm/min)	f (mm/rev)
1	0.3657	0.5227	0.3457
2	0.6737	0.5957	0.5170
3	0.5610	0.4790	0.7377
Delta	0.3080	0.1167	0.3290
Rank	2	3	1

Table 21. ANOVA results for R_a (3rd L_9 OA).

Source	DF	F	P	Contribution (%)
a_p (mm)	2	3.30	0.232	32.95
V_c (mm/min)	2	0.47	0.681	4.68
f (mm/rev)	2	5.25	0.160	52.39
Error	2			9.98
Total	8			
R^2 (%)	90.03			

4. DISCUSSION

In the present study, the comparison between full and fractional designs of experiments for CNC slot-milling of Al 7075 is investigated. Cutting conditions for all designs were cutting speed (V_c), depth of cut (a_p) and feed rate (f). To evaluate machinability, mean surface roughness, Ra was selected. Cutting forces and tool wear have not been considered in this study; a new (unworn) cutting tool has been used for each experimental trial, while the appropriate cutting conditions are selected for slot milling. Under this concept, cutting forces were considered insignificant. Data analysis for results was performed employing different statistical tests. The entire analysis presented in the study is summarized as follows:

- Stem and leaf plots indicate that most data is between the range of 0.3-0.5 μm and 0.6-0.7 μm in the case of Ra with slight variations between full and fractional FDs.
- Box plots of Ra have almost the same size and shape for all FDs: min value is in the range of 0.25-0.3 μm, upper quartile is around 0.36 μm, the median is between 0.45-0.65 μm, upper quartile is around 0.85 μm, except for the 3rd fractional FD that is 0.67 μm and finally, the maximum value is between 0.25-0.3 μm.
- ANOM resulted in quite interesting findings regarding the comparative analysis between the full and fractional FDs. For Ra, the parameter levels which minimize it are not the same for all FDs. For the full and the 3rd fractional FDs are: a_p=0.5 mm, V_c=150 mm/min, f=0.05 mm/rev. For the 1st and 2nd fractional FDs are: a_p - 0.5 mm (level 1), V_c=100 mm/min, f=0.05 mm/rev. This finding is consistent with the relevant output for Ra in the study presented in [25], where ANOM gave the same results for the L_{27} array, 1st L_9 and 2nd L_9 arrays but not for the 3rd L_9 array.
- ANOVA reveals the same results referring to $R\alpha$, both full and fractional FDs. The process parameter that mainly affects Ra is the feed rate.
- F values for feed rate are larger than 4 for Ra (except 3.09 for Ra on 2nd L_9). This is a strong sign that in the experimental region, feed rate is the dominant parameter. P values for feed rate are lower than 0.05 for the L_{27} and the 1st L_9 OA, while for the 2nd and 3rd L_9 OAs are larger than 0.05. P-values larger than 0.05 indicate a significant probability of observing extreme results. This signifies that the linear model used for ANOVA analysis is not appropriate for the two cases, those of 2nd and 3rd L_9 OAs.
- Cutting speed is insignificant compared to the other two process parameters in almost all OAs. P values are all larger than 0.05.
- Depth of cut also seems to be insignificant. All F values are lower than 2.
- R^2 is found to be between 73-95% for Ra in all FDs. Especially in the case of the 2nd and 3rd fractional FDs is around 90%.

From the above analysis, it is evident that full and fractional FDs can lead to quite similar outcomes, but not the same. Both methodologies appear to have their advantages and disadvantages; for example, the application of fractional FDs can reduce cost and time, yet; it may not guarantee that the same results as those of the full FD will be obtained. Therefore, it is mandatory to choose between these two experimental designs, depending on the resources and targets.

5. CONCLUSIONS

Summarizing the results presented in the previous section, it is safe to conclude that both full and fractional FDs can be applied for the study of machinability indicators such as the surface roughness parameters of "difficult-to-cut" materials (such as milling of Al 7075); however, several reservations should be taken into account. It is useful to know the advantages and disadvantages of each methodology to choose the most suitable one for extracting reliable conclusions. Definitely, one may benefit from the application and the results' comparison between the two experimental designs.

Looking further ahead, the authors plan to examine more materials under the same experimental concept to analyse the adequacy of these methods by adopting responses related not only to surface quality but also to cutting forces and energy consumption. The same methods can also be applied for investigating other performance indicators such as tool wear and chip formation. The above descriptive data analysis of results combined with other statistical tools such as interaction charts should be beneficial for selecting the appropriate predictive mathematical models. This work is also proposed as a future study for different machining areas (i.e., roughing, semi-finishing and/or finishing conditions) and materials.

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