Int J Adv Manuf Technol (2017) 93:727–746
DOI 10.1007/s00170-017-0460-5

ORIGINAL ARTICLE

To characterize and optimize the surface quality attributes in slot milling operation

Seyed Ali Niknam [1] · **Marek Balazinski** [2] · **Victor Songmene** [3]

Received: 11 January 2017 / Accepted: 25 April 2017 / Published online: 26 May 2017

Abstract Burr formation and surface roughness are crucial surface quality attributes that vary widely according to machining conditions used. Inappropriate selection of cutting parameters may lead to tremendous non-desirable expenses and poor product quality. This becomes more apparent in slot milling operation that has a complex burr formation mechanism, and it is associated with multiple burrs with non-uniform dimensions appearing in the machined part edges. Therefore, as the first objective of this study, experimental characterization of governing cutting parameters on surface quality attributes, including exit burr size as well average surface roughness (R_a), is presented. Based on experimental observations, each aforementioned surface quality attribute is affected by different cutting parameters, and in fact, no systematic relationship can be formulated between them and the cutting parameters used. Therefore, advanced strategies are demanded for adequate selection of cutting parameters and reduction in the needs of deburring and surface treatment operations. Except the works reported by the authors, very limited studies are available on advanced optimization approaches for simultaneous minimization of surface quality attributes in slot milling operations. This can be considered as the second objective of this work. To that end, desirability function, D_i (x), was used as the proposed approach to evaluate the possibility of simultaneous minimization of aforementioned surface quality attributes, despite the low control ability of each response. Using this approach, the optimum and near to optimum setting levels of cutting parameters were defined by means of surface quality improvement and the adequacy of the proposed optimum cutting conditions was reconfirmed through verification tests. The presented results in principle can be very useful in practice by local and international automotive industries dealing with similar family of materials.

Keywords Slot milling · Aluminum alloy · Burr · Surface quality · Desirability function

✉ Seyed Ali Niknam
saniknam@iust.ac.ir

Marek Balazinski
marek.balazinski@polymtl.ca

Victor Songmene
victor.songmene@etsmtl.ca

[1] Sustainable Manufacturing systems research Laboratory, School of Mechanical Engineering, Iran University of Science and Technology, Tehran, Iran

[2] School of Mechanical Engineering, Polytechnique Montréal, Montréal, QC, Canada

[3] School of Mechanical Engineering, École de Technologie Supérieure, Montréal, QC, Canada

1 Introduction

Surface finish and burr formation are known as important surface quality attributes. Although fundamental aspects of burr formation in milling operations have been studied comprehensively [1–5], among milling operations, slot milling has a very complex burr formation mechanism which may require further attention [6, 7]. Among various types of slot milling burrs, exit burrs have a very complex formation mechanism and morphology which are directly affected by cutting conditions, lubrication modes, materials, etc. [8]. The three modes of slot milling burrs are presented in Fig. 1. As shown in Fig. 2, the exit up milling side burr (B_1) is commonly considered as the largest burr. Although experimental characterization of milling was studied comprehensively [9–16], surprisingly, except limited studies by Niknam et al. [17–23] and

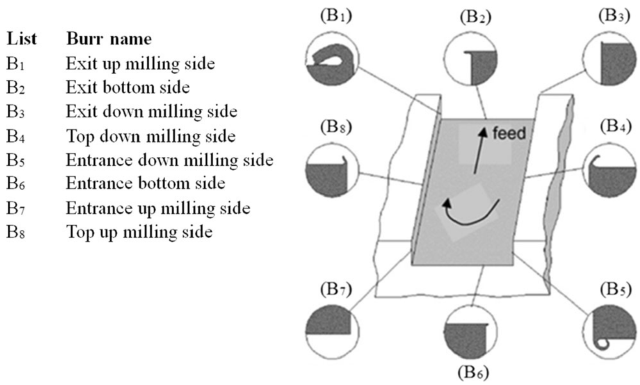


Fig. 1 Slot milling burrs [8]

other distinguished researchers in open literature [24–27], limited studies were conducted on comprehensive characterization and optimization of the slot milling burrs of ductile materials such as wrought aluminum alloys which have received limited attention and dominant process parameters. In addition, in order to conduct a precise determination of the dominant process parameters on the burr size, only few studies have used statistical analysis [19, 28–31]. This therefore recalls further investigations on experimental characterization of the cutting factors governing slot milling exit burr formation and size.

As well as the burr size, optimum or near to optimum surface roughness is the subject of interest in almost all manufactured parts in various industrial sectors. Surface roughness can be defined as the irregular deviation on a scale smaller than the scale of waviness. There are several solutions to describe surface roughness. As noted earlier in ISO468: 1982, the average value of surface roughness, often denoted as R_a, is the most widely used surface roughness parameter (Eq. 1).

$$R_a = \frac{1}{l}\int_0^l |y(x)|dx \tag{1}$$

or

$$R_a = \frac{1}{n}\sum_{i=1}^{n} |y_i| \tag{2}$$

where l is the sampling length and y is the ordinate of the profile curve.

Furthermore, the R_a in milling can be predicted by the following [32]:

$$R_a = 318\frac{f_z}{\tan(l_a) + \cot(C_a)} \tag{3}$$

where l_a is the lead (corner) angle and C_a is the clearance angle.

Although conventionally the cutting conditions were entirely selected by machinists, even for a professional machinist, it is a very challenging task to accomplish the optimum values each time [33]. In fact, the non-adequate selection of cutting parameters affects not only R_a but also several functional characteristics, including friction, resisting fatigue, tool insert coating, and heat transmission. This reveals that to remain competitive in the industrial market through maintaining the high level of product quality, the use of optimization methods by means of adequate selection cutting process parameters is highly demanded. Knowing that the proposed cutting parameters for one response may not be compatible for other responses, adequate manipulation of the simultaneous multiple response optimization methods is therefore recommended. As per the authors' knowledge, due to the complex mechanism of burr formation as well as severe interaction effects between cutting process parameters, limited works were reported yet on simultaneous improvement of the surface roughness and exit burrs, in particular exit up milling side burr size (thickness and height). Moreover, machining aluminum alloys is associated with certain amount of difficulties, such as built up edge (BUE) [34] and the material's tendency to adhere to the tool surface which might yield to catastrophic burr formation at the work part edges [35]. The presence of the abovementioned concerns may pose major difficulties on proper development of the process simulations and optimization models. This therefore recalls the use of optimization methods. The proper optimization of process parameters needs an organized methodology and an adequate use of

Fig. 2 The main slot milling exit burrs. **a** Exit up milling side (B_1). **b** Exit bottom side burr (B_2)

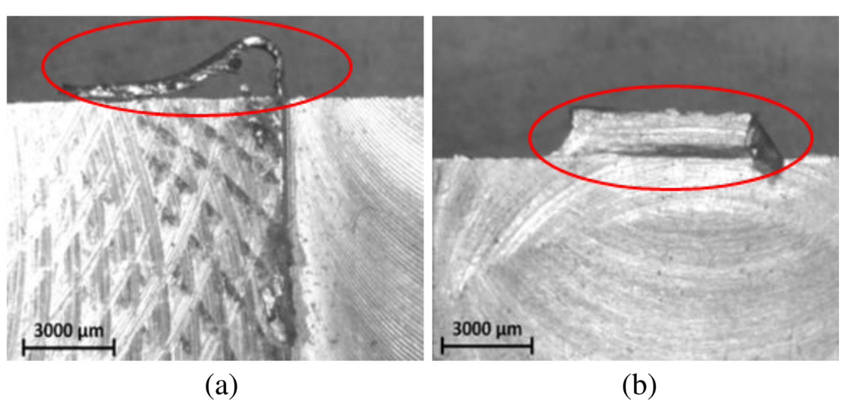


Table 1 Experimental parameters used

Experimental parameters		Level		
		1	2	3
A: Material		6061-T6	–	2024-T351
B: Tool	*Insert Ref*	IC 328	IC 908	IC 4050
	Coating	TiCN	TiAlN	TiCN + Al_2O_3 + TiN
	Insert nose radius Rε. (mm)	0.5	0.83	0.5
C: Depth of cut, a_p (mm)		1	–	2
D: Feed per tooth, f_Z (mm)		0.01	0.055	0.1
E: Cutting speed, v_c (m/min)		300	750	1200
● Dry condition				
● Tool diameter (D) 19.05 mm				

combined experimental methods and mathematical/statistical models [36]. For that to be accomplished, several optimization techniques including fuzzy logic (FL), genetic algorithm (GA), neural network (NN), Taguchi method, response surface methodology (RSM), and desirability function are among the proposed approaches [37–39]. The wide applications and advantages of the RSM-based models in machining operations are presented in [40–43]. However, it should be underlined that the RSM models are only accurate for limited input parameters and higher-order models need a large number of experiments [39]. According to review of literature and the acute need for evaluating the possibility of simultaneous minimization of R_a and exit burr thickness and height in slot milling operation, a desirability function, D_i (x), was used as the proposed approach. The combination of statistical tools and experimental studies was then used to firstly characterize the factors governing surface quality parameters during slot milling of AAs 2024-T351 and 6061-T6 work parts.

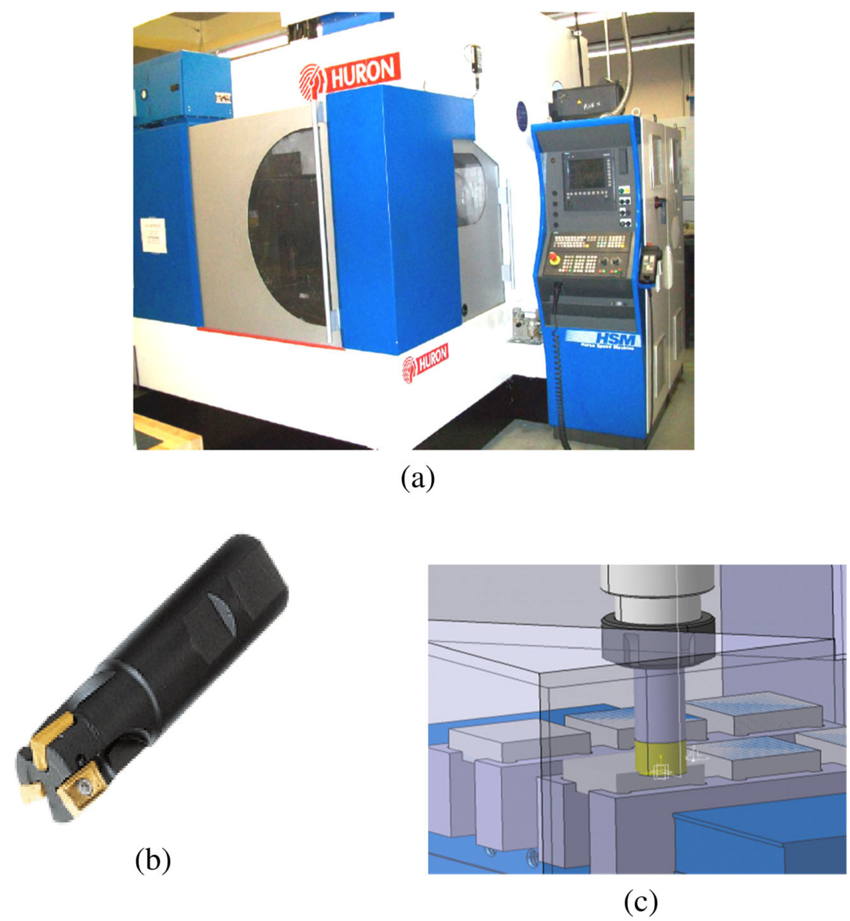


Fig. 3 Experimental devices. **a** Three-axis CNC machine. **b** Cutting tool used. **c** Work part configuration

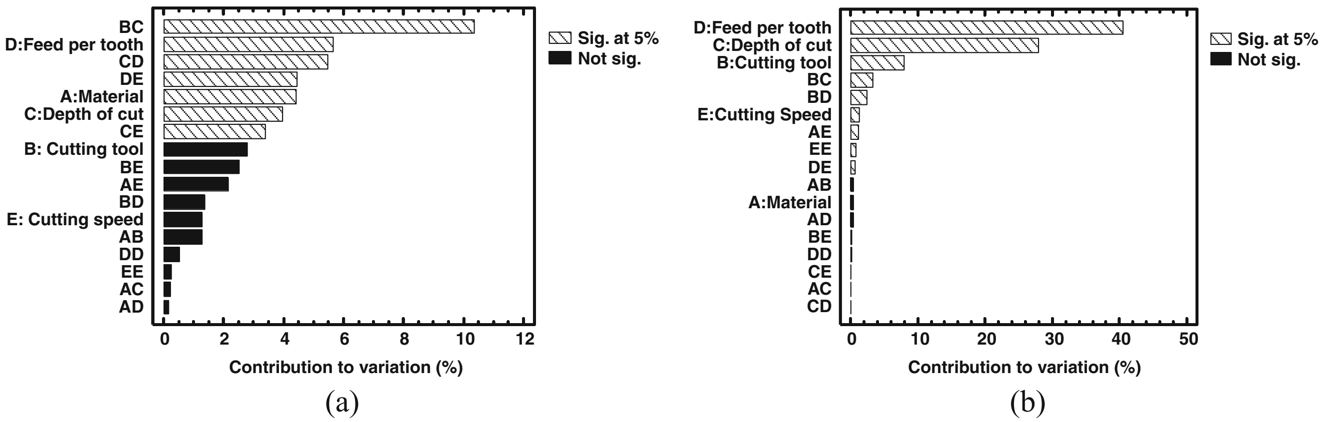


Fig. 4 Pareto chart of **a** B_1 height and **b** B_1 thickness

Secondly, the desirability function D_i (x) was used to define the direct and interaction effects between cutting process parameters that influence the mechanism and morphology of the abovementioned responses.

2 Experimental procedure

2.1 Experimental plan and method of analysis

The experimental study consisted of five controllable cutting parameters, including cutting speed, feed per tooth, cutting tool, material, and depth of cut (see Table 1). In total, 108 milling tests were necessary to complete the study. A three-axis CNC machine tool (power 50 kW, maximum speed 28,000 rpm, torque 50 Nm) was used in milling tests (Fig. 3a). A slot milling tool with three flutes $Z = 3$ and tool diameter D 19.05 mm (Table 1) was used (Fig. 3b). Experimental parameters used on both tested materials (Table 1) are denoted as finishing conditions. Therefore, excellent surface and edge finishing quality is expected. This implies adequate experimental characterization of the surface quality attributes as well as the use of advanced optimization strategies for simultaneous multiple response optimization. The milling tests were repeated once, and the mean values of recorded responses were used for statistical and optimization works. The effect of process parameters (Table 1) on the machining responses is identified using statistical approaches including analysis of variance (ANOVA) and the Pareto chart. A detailed description of the method of analysis is presented in Appendix 1. A proper determination of the controllable cutting factors that generate optimum or near to optimum setting levels of cutting parameters was conducted by the desirability function D_i (x).

2.2 Experimental observations

Burr size measurement was conducted on a high-resolution optical microscope (×1000). The same tools and measurement

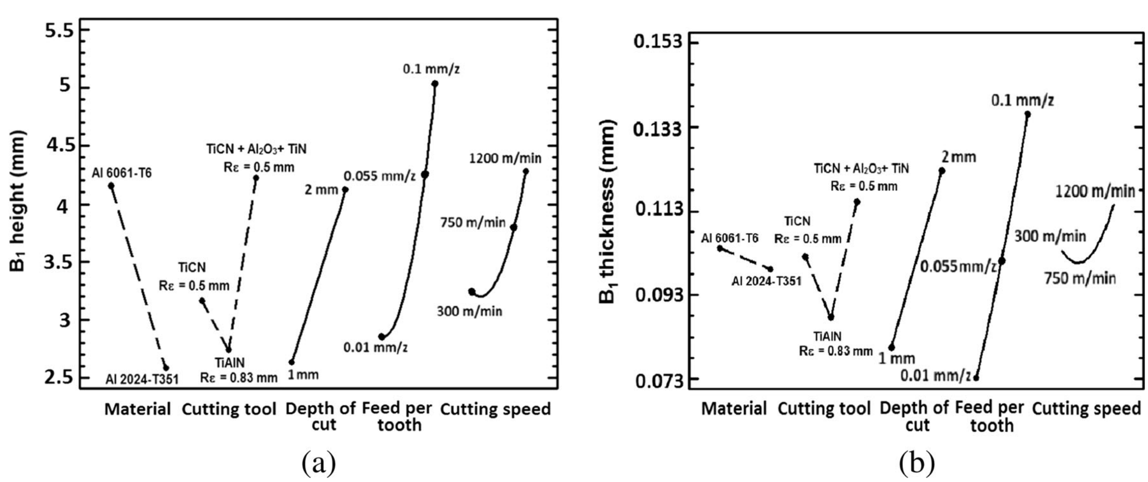


Fig. 5 Direct effect plot of **a** B_1 height and **b** B_1 thickness (*adapted from* [18])

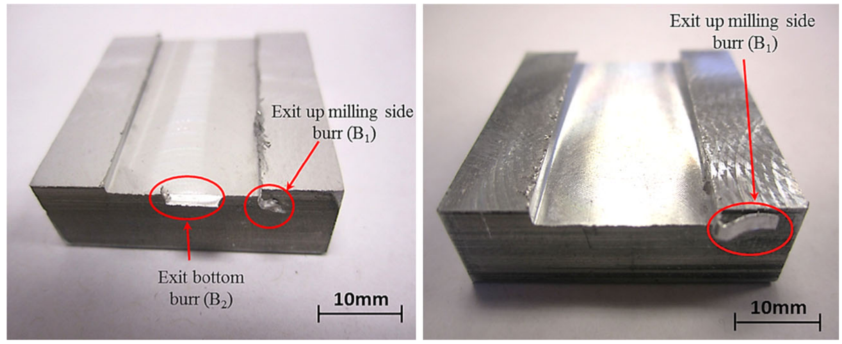


Fig. 6 Slot milling exit burrs (*adapted from* [8])

methods as described in [19, 44] were used in this work to measure the burr height and thickness and surface roughness attributes. As noted earlier, the average surface roughness R_a was used as the measure of the surface quality in this work. As previously remarked, the burr formation and work material adhesion are the most commonly observed in machining AAs [35]. To reduce the effects of abovementioned issues on experimental results, the following assumptions were made:

- The vibrations and deflections in the machine and cutting tools were evaluated through preliminary tests. No chatter vibration was found, and the operated system was assumed stable through the entire duration of milling tests.
- Potential sources of deviations in experimental results were avoided by using a new insert in each test.

3 Results and discussion

The results of this work will be presented in certain categories, including experimental characterization of the governing parameters on surface quality attributes (Sect. 3.1) followed by simultaneous multiple response optimization (Sect. 2) and experimental validations (Sect. 3.2.3).

3.1 Governing parameters on surface quality attributes

3.1.1 Exit burr size

Figures 4 and 5 present standardized Pareto charts of exit up milling side burr B_1 thickness and height. As can be seen in Fig. 4, both responses are highly affected by feed rate (D). As shown in Fig. 4a, B_1 height is affected by interaction effects between cutting parameters, including CD, BC, DE, and CE, followed by direct effects of feed rate (D), workpiece material (A), and depth of cut (C). It is believed that normal yield strength (σ_e) and tensile strength (σ) are the main mechanical properties with substantial influence on burr formation mechanism [29].

According to Fig. 4b, B_1 thickness is highly affected by several direct and interaction effects between cutting parameters. Among them, direct effects of feed rate (D), depth of cut (C), and tool (B) are the most dominant factors. As illustrated in Fig. 5, those tests with higher levels of depth of cut and feed rate and smaller R_ε led to longer and thicker B_1. This is not favorable in high-precision machining. Referring to literature, primary and secondary burrs were introduced in [45]. As noted in [5], a secondary burr is attributed to residual material at the machined parts following the deburring process, while secondary burrs that are in general smaller than the depth of cut refer to breakage of the primary burrs [45]. Exit up milling side burr (B_1) and exit bottom burr (B_2) are considered as

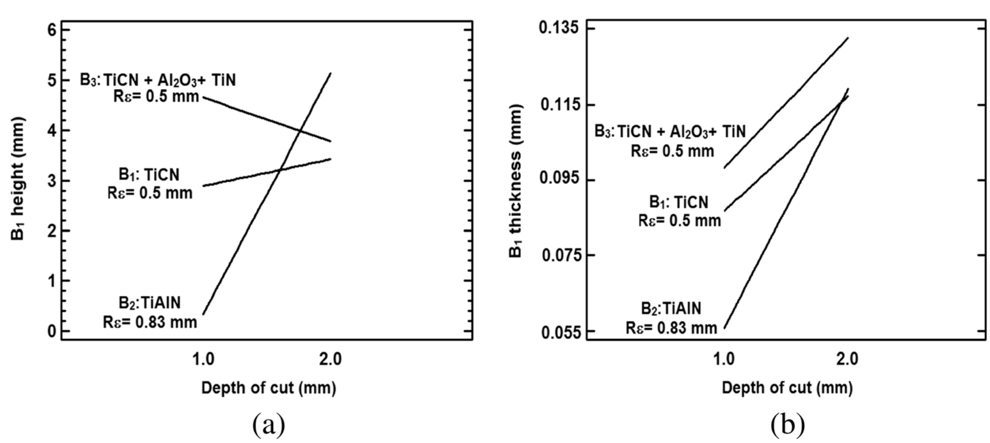
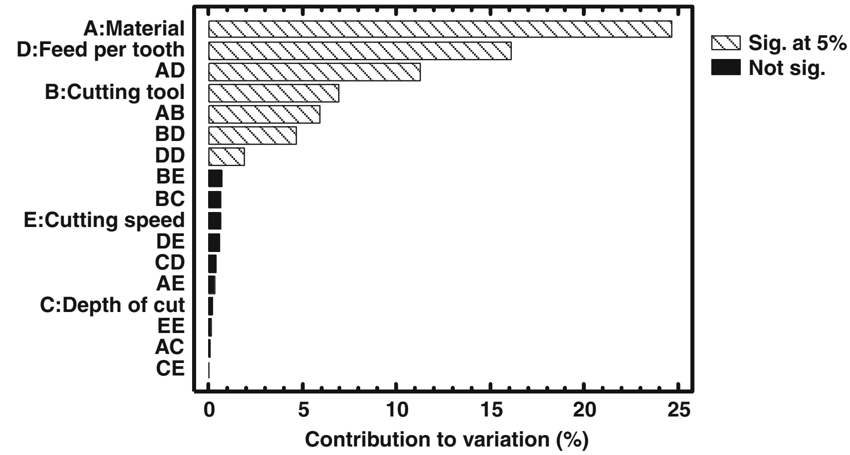


Fig. 7 **a** Interaction effect of tool-depth of cut (BC) on B_1 height and **b** on B_1 thickness (*adapted from* [18])

Fig. 8 Pareto chart of R_a



primary and secondary slot milling burrs. As noted in [46], B_2 is formed by a loss of material from B_1. It is agreed upon that exit side burrs along up/down milling sides appeared due to transition from primary to secondary burr formation [18]. In fact, the deburring process can be simplified when primary burrs appeared as secondary burrs. This may lead to side burr formation, rather than exit bottom (B_2) or entrance burr formation (see Fig. 1).

When transition from primary to secondary burr formation is not conducted properly, primary B_2 appears on the exit side when the tool leaves the machined part. Longer B_1 and smaller B_2 occurred when burr smoothly leans towards the transition material and breaks off from the machined surface (Fig. 6). This is not however demanded in high precision machining. In fact, based on the slot milling burr formation mechanism, those cutting parameters that reduce the B_2 size may increase the B_1 height (Fig. 1). Knowing that B_1 is the largest slot milling burr (Fig. 1), it is therefore intended to define setting levels of process parameters which minimize the incidence of exit up milling side burr (B_1) or, in other words, primary burrs with big size. According to Figs. 3 and 4, the cutting speed has a negligible effect on the slot milling exit burrs. Under similar cutting conditions, smaller and thinner B_1 was recorded for AA 6061-T6. This could be attributed to higher yield strength of AA 2024-T351 than AA 6061-T6 [21].

It is agreed upon that the presence of interaction effects between cutting process parameters has significant intense effects on burr formation morphology and size. The phenomenon may cause severe difficulties when burr formation modeling and size reduction are demanded. The interaction effects of the cutting parameters on B_1 height and thickness are presented in Fig. 7. According to Fig. 7a, the longest and shortest B_1 resulted when using tool 3 and tool 2 at lower levels of depth of cut (see Table 1), respectively. This may lead to a substantial difference between B_1 height when using different cutting tools. When using cutting tool 2 at higher level of depth of cut (2 mm), the longest B_1 was recorded. As depicted in Fig. 7, the insignificant variation of B_1 height under various insert nose radiuses R_ε and cutting tool may be attributed to the strong interaction effects between cutting tool and depth of cut (BC). A strong interaction effect is also visible in Fig. 7b. Generally, it can be stated that BC has significant effects on B_1 size. Furthermore, considering the same R_ε in cutting tools 1–2 (Table 1), although insignificant, the effects of cutting tool coating on burr morphology and size can be observed. This is in conflict with the conclusion made by Olvera and Barrow [33]. A coated tool constitutes higher wear resistance and lower coefficient of friction than an uncoated one. The increased wear resistance affects the burr dimension. Also, due to the larger cutting edge radius of coated tools, plowing effects and reduced friction and deformation may occur which in fact resulted in catastrophic changes in the burr size. It is to underline that unworn tools were used in all machining tests to avoid deflections in machine tools and deviations on machining results.

Due to lack of space in this article and great importance of B_1, only the effects of cutting parameters on B_1 thickness and

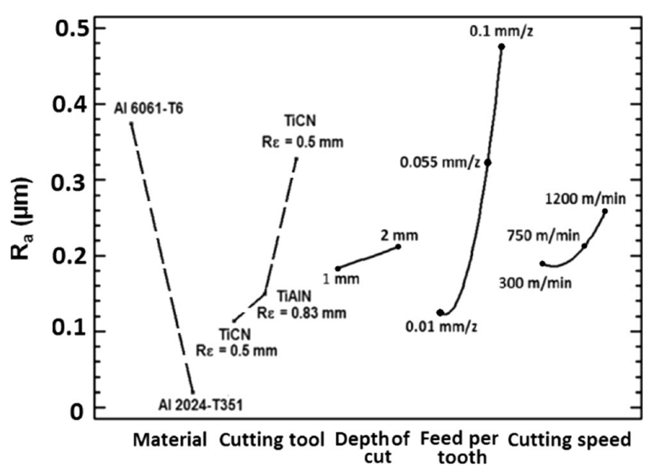


Fig. 9 Main effect plot of R_a (*adapted from* [18])

Table 2 Statistical results of surface quality attributes

Responses	R^2	R^2_{adj}	*P* value	*F* ratio	Dominant process parameters	Optimum setting levels
B_1 thickness (mm)	0.925	0.899	0	27.53	Feed rate (D), tool (B), depth of cut (C), AB, DD	$A_2B_2C_1D_2E_2$
B_1 height (mm)	0.578	0.396	0.0019	3.17	Depth of cut (C), AB, CD	$A_2B_2C_1D_1E_1$
B_2 thickness (mm)	0.377	0.216	0.0029	2.4	Depth of cut (C), tool (B), CE	$A_2B_3C_2D_1E_2$
B_2 height (mm)	0.511	0.385	0	4.4	Tool (B), depth of cut (C), speed (E)	$A_1B_1C_2D_2E_2$
R_a (μm)	0.769	0.67	0	7.73	Feed rate (D), tool (B), AC, BD, DD	$A_2B_1C_1D_1E_2$

height are comprehensively evaluated in this work and other burrs depicted in Fig. 1 are not studied in detail. As well as B_1, only optimum setting levels of process parameters and factors governing exit burr B_2 along with corresponding statistical results are presented in Tables 10 and 11.

3.1.2 Average surface roughness (R_a)

The surface integrity parameters of AAs are largely affected during machining operation. Among the abovementioned surface alterations in the last section, the effects of cutting parameters (Table 1) on recorded values of R_a will be studied in this work. Generally, innovative strategies to reduce the surface roughness when machining AAs have been always welcomed [47, 48], because post-processing methods including laser shock peening and ball burnishing processes are demanded to improve the machine's surface [49]. These methods however increase the non-desirable expenses and production time. It has been found that the surface roughness in aluminum work parts is widely affected by various phenomena, including cutting parameters (e.g., cutting speed and depth of cut), built up edge (BUE) formation, tool operating conditions (shape, coating, geometry, wear mode), and temperature [8]. As noted in [50], the main factors leading to generation of these phenomena are thermal and mechanical cycling, microstructural transformations, and mechanical and thermal deformations generated in machining processes. As shown in Fig. 8, material (A), feed per tooth (D), tool material, and coating (B) are the most effecting parameters on R_a. Based on Fig. 9, higher levels of feed per tooth (D), depth of cut (C), and speed (A) led to increased R_a and, certainly, more deteriorated surface quality is expected. The level of importance of the aforementioned individual cutting parameters may vary subject to individual material and machining methods used.

3.1.3 Statistical analysis of results

According to presented results (Figs. 4, 5, 6, 7, 8, and 9), the governing factors on each individual machining parameter studied as well as optimum process parameter setting levels that minimize each individual machining output are different and no systematic relationship can be formulated between exit burr size attributes (height and thickness) and R_a in both tested materials (Table 2). This may pose severe difficulties on burr formation modeling as well as surface quality improvement and optimization. This therefore recalls the use of optimization methods for proper selection of cutting parameters, which implies simultaneous optimization of machining responses for each individual material. This is the subject of investigation in the upcoming sections. Referring to presented results, it can be inferred that milling tests with AA 6061-T6 led to higher resulting values of R_a and burr size. In the next section, the results of milling tests on AA 6061-T6 will be discussed and corresponding results as well as optimum setting levels of process parameters for each machining attribute in AA 6061-T6 and AA 2024-T321 will be presented in Tables 3 and 4.

3.1.4 Individual analysis on studied work materials

Results of aluminum alloy 6061-T6 As noted earlier, the effects of cutting parameters (Table 1) on R_a and exit up milling side burr (B_1) thickness and height will be discussed in the course of this study.

Table 3 Statistical results of responses in AA 6061-T6

Responses	R^2	R^2_{adj}	*P* value	*F* ratio	Dominant process parameters	Optimum setting levels
B_1 thickness (mm)	0.922	0.889	0	27.5	Feed per tooth (C), tool (A), depth of cut (B), AB, DD	$A_2B_1C_1D_2$
B_1 height (mm)	0.578	0.396	0.0019	3.17	Depth of cut, AB, CD	$A_2B_2C_2D_3$
B_2 thickness (mm)	0.461	0.228	0.043	1.98	Tool (A), AC	$A_3B_2C_1D_2$
B_2 height (mm)	0.581	0.40	0.0017	3.21	Tool (A), depth of cut (B), AB	$A_1B_2C_2D_1$
R_a (μm)	0.769	0.67	0	7.73	Feed per tooth (C), tool (A), AC, CC	$A_1B_1C_1D_1$

Table 4 Statistical results of responses in AA 2024-T351

Responses	R^2	R^2_{adj}	P value	F ratio	Dominant process parameters	Optimum setting levels
B_1 thickness (mm)	0.871	0.81	0	15.4	Feed per tooth (C), tool (A), depth of cut (B), AB, DD	$A_2B_1C_1D_1$
B_1 height (mm)	0.584	0.404	0.0016	3.24	BC, BD	$A_1B_1C_2D_2$
B_2 thickness (mm)	0.481	0.257	0.02	2.15	AB, BD	$A_3B_2C_1D_1$
B_2 height (mm)	0.564	0.375	0.003	2.99	Tool (A), depth of cut (B)	$A_3B_2C_2D_1$
R_a (μm)	0.891	0.844	0	18.9	Tool (A), feed per tooth (C), AC, AB, depth of cut (B)	$A_2B_2C_1D_2$

- ***Exit up milling side burr (B_1) thickness***

The relative Pareto chart and main effect plot of B_1 thickness in the multiplicative design model are presented in Figs. 10 and 11. According to Fig. 10, feed per tooth (C), depth of cut (B), tool (A), and interaction effect between cutting speeds (DD) and the tool and depth of cut (AB) are the governing direct and interactive factors on variation of B_1 thickness. As noted in [23] and based on Fig. 11, increased feed per tooth and depth of cut led to larger chip thickness and undeformed chip thickness, and eventually larger burr size. According to Fig. 11, minimum burr thickness was obtained when using the middle level of cutting speed (750 m/min). Considering the negligible effects of cutting speed on variation of the burr size (see Figs. 8 and 9), the effects of various cutting speed on B_1 thickness will therefore not be studied in further details.

As noted in [5, 6], the deburring time and methods are usually assessed based on the burr thickness. This therefore implies adequate understanding of the factors governing burr thickness. Referring to the insignificant effect of cutting speed on B_1 thickness (Fig. 10), 3D surface plots of B_1 thickness at cutting speed 1200 m/min and cutting tool 3 with the highest B_1 thickness are presented) Fig. 12 (to explore the relationship between the B_1 thickness and the cutting parameters. According to Fig. 12, the burr thickness increases at higher values of feed per tooth and depth of cut. Moreover, thin burrs were also found when lowest levels of feed per tooth and depth of cut were used. This is in agreement with observations made in Figs. 10 and 11.

Interaction effects between tool and depth of cut (AB) are considered as a statistically significant factor on variation of B_1 thickness when using cutting the tools 1–2 (Fig. 13). The difference in resulting values of B_1 thickness when using cutting tools 1 and 3 (Table 1) can be attributed to significant effects of tool coating on B_1 thickness. Referring to Table 3 and Fig. 11, the minimum B_1 thickness can be achieved when the optimum setting level of cutting parameters is $A_2B_1C_1D_2$. From Table 3, the high values of correlation of determination ($R^2 = 0.0925$; $R^2_{adj} = 0.889$) denote that B_1 seems to be highly controlled with variation of cutting process parameters when similar setting levels of cutting parameters as listed in Table 1 are used. It can be therefore classified as a statistically significant machining attribute.

- ***Exit up milling side burr (B_1) height***

According to Fig. 14, the interaction effect between cutting tool and depth of cut (AB) and depth of cut and feed per tooth (BC) as well as direct effects of depth of cut (B) are the main affecting parameters on B_1 height. As shown in Fig. 15, the shortest B_1 height was obtained when using cutting tool 2, higher value of depth of cut (2 mm), middle level of feed per tooth (0.055 mm), and higher level of cutting speed

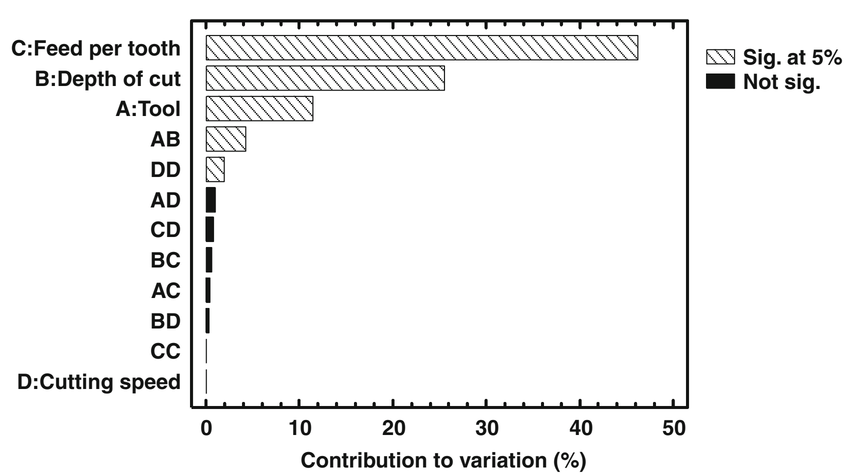


Fig. 10 Pareto chart of B_1 thickness

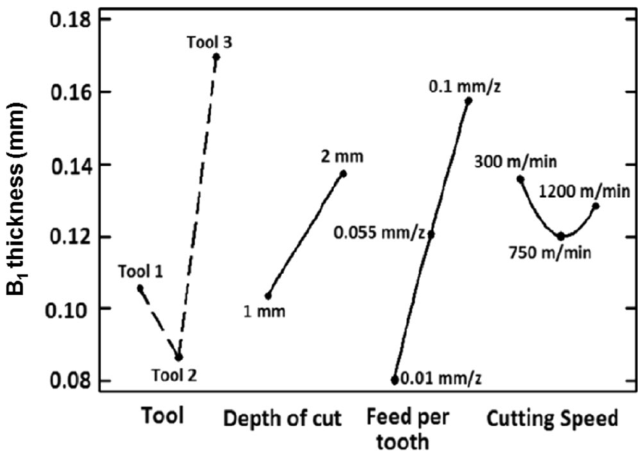


Fig. 11 Main effect plot of B_1 thickness (*adapted from* [19])

(1200 m/min), quoted as $A_2B_2C_2D_3$. Referring to Fig. 16, the longest and shortest burrs were obtained when using cutting tools 3 and 2 at the fixed depth of cut at 1 mm. This reveals the significant influence of interaction effects between tool and depth of cut (AB), which mainly controls the variation of B_1 height.

As similar as B_1 thickness, the lower level of depth of cut when using cutting tool 2 with larger insert nose R_ε (0.83 mm) led to shorter B_1 height. Based on Fig. 16, a similar value of B_1 height resulted when using tools 1–3 at a depth of cut very close to 2 mm. However, at a higher level of depth of cut (2 mm), shortest and longest burrs were obtained when using tools 1 and 3, respectively. This can be attributed to effects of tool coating on burr formation morphology when depth of cut varies. From Table 3, R^2 and R^2_{adj} indicate that the model as fitted explains 57.81 and 39.57% of the variability in B_1 height. It can be inferred that due to strong interaction effects between process parameters, controlling the variation of B_1 height by means of employing advanced modeling approaches for process control is a complex task. Knowing that B_1 height is considered as an insignificant response, the use of

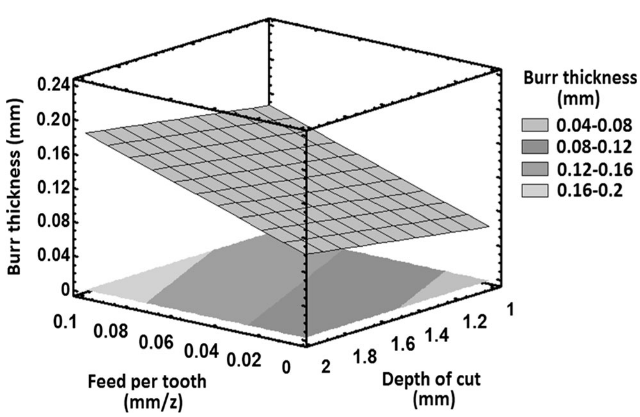


Fig. 12 3D plot of B_1 thickness where using cutting tool 3 and cutting speed 1200 m/min (*adapted from* [44])

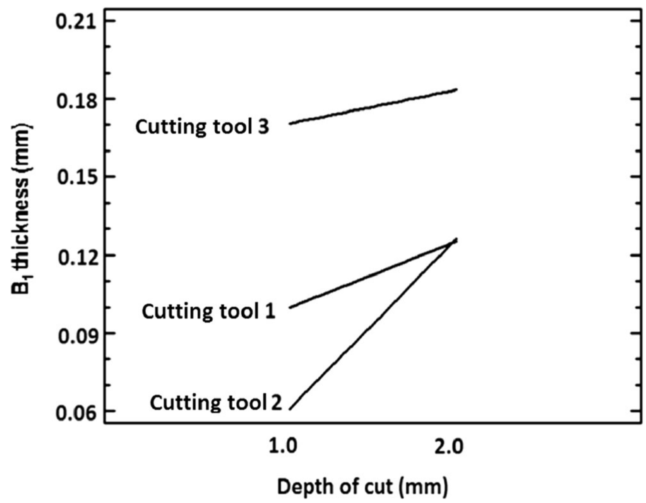


Fig. 13 The interaction effect of AB (cutting tool and depth of cut) on B_1 thickness (*adapted from* [44])

advanced optimization strategies for adequate selection of setting levels of cutting process parameters is demanded.

- ***Average surface roughness (R_a)***

According to Fig. 17, it is evident that feed per tooth (C), tool (A), the interaction effects between tool and feed per tooth (AC), and feed per tooth (CC) are the main governing factors on R_a. According to Fig. 18, higher levels of feed per tooth and depth of cut led to higher resulting values of R_a. In addition, lower R_a was obtained at the middle level of cutting speed (750 m/min).

As similar as B_1 height and thickness, R_a is not widely affected by cutting speed (see Fig. 17). As shown in Fig. 18, the use of cutting tools 1 and 3 led to maximum and minimum R_a values, respectively. Referring to Table 1, based on similar R_ε in both tools, it can be stated that R_a is mainly controlled by changing the cutting tool coating, not R_ε.

From Fig. 19, the maximum value of R_a was obtained at the highest level of feed per tooth and the lowest level of depth of cut. Changing the cutting tools 1 to 2, the lower R_a was obtained. The maximum R_a was obtained at the highest feed per tooth and the lowest depth of cut. Based on Fig. 18, the maximum R_a was obtained at the highest feed per tooth and depth of cut, when cutting tool 3 was in operation. From Fig. 19, it is evident that when feed per tooth varies from 0.01 to 0.1 mm, the highest and lowest R_a values were obtained when using cutting tools 3 and 1, respectively. As clearly shown in Fig. 19, despite of the cutting tools used at the feed per tooth at 0.01 mm, very similar values of R_a with a slight difference resulted. However, an enormous difference appeared between R_a results, when cutting tools 1 and 3 were used at feed per tooth of 0.1 mm. This observation reconfirms the significant effects of feed per tooth (C) on R_a which is also shown in Figs. 17 and 18.

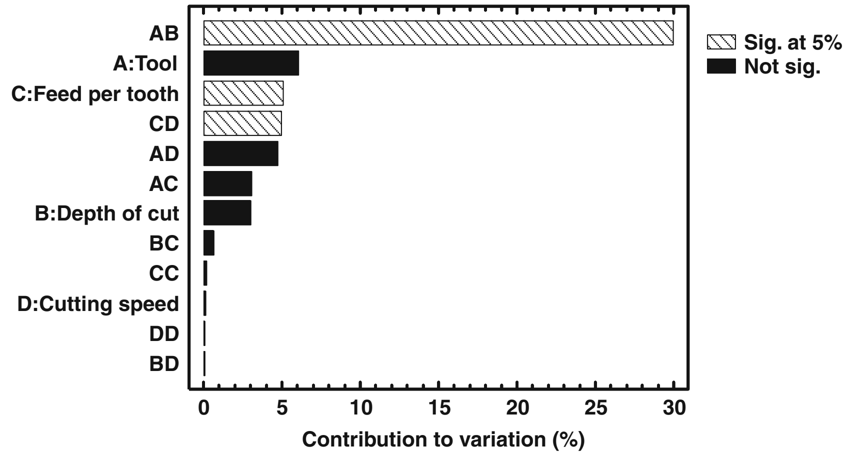


Fig. 14 Pareto chart of B_1 height

According to Table 3, R^2 and $R^2{}_{adj}$ show that the model as fitted explains 76.88 and 67.03% of the variability in R_a. Due to high interaction effects between tool and feed rate (AC), R_a is considered as a middle significant response. It is exhibited that manipulation of an in-process and/or out-process control of R_a seems to be difficult. As similar as the burr size attributes, the use of advanced optimization approaches for adequate selection of setting levels of process parameters is required to achieve an acceptable level of surface quality.

Results of aluminum alloy 2024-T351 Using the same method of analysis, the governing factors on AA 2024 are found in Table 4. The statistically dominant process parameters as well as optimum setting levels of cutting parameters which led to minimized values of responses are listed in Table 4. Comparing the presented results in Tables 2 and 4 reveals that the optimum setting levels of cutting parameters for each surface quality attribute are different in each material. This may recall the use of optimization methods to define the optimum or at least near to optimum setting levels of cutting parameters. This will be studied in the next section.

3.2 Optimization

3.2.1 Optimization methodology

When several response variables $y_1, y_2, \ldots \ldots y_m$ are presented by fitted equations $y_1, y_2, \ldots\ldots y_m$ (see Eq. A1), according to input process parameters $x_1, x_2, \ldots \ldots x_m$, the main inquiry refers to the following: in the x space, the best set of responses can be obtained. The proposed methodology by Derringer and Suich [51], which introduces an overall criterion of desirability of the proposed input setting parameters, is considered as an interesting approach to overcome this problem. Using this method, the optimization of multiple responses becomes simpler. A complete overview of the

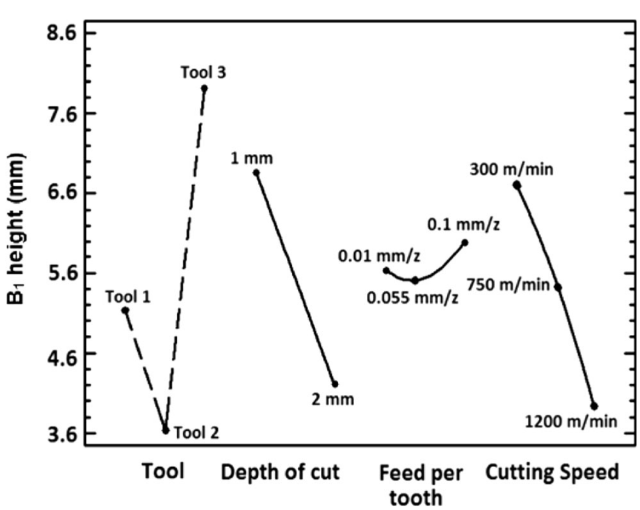


Fig. 15 Main effect plot of B_1 height (*adapted from* [44])

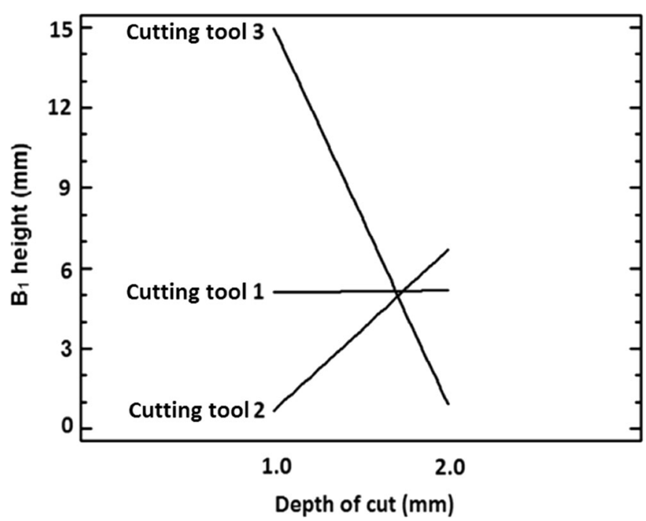


Fig. 16 The interaction effect of AB (cutting tool and depth of cut) on B_1 height (*adapted from* [44])

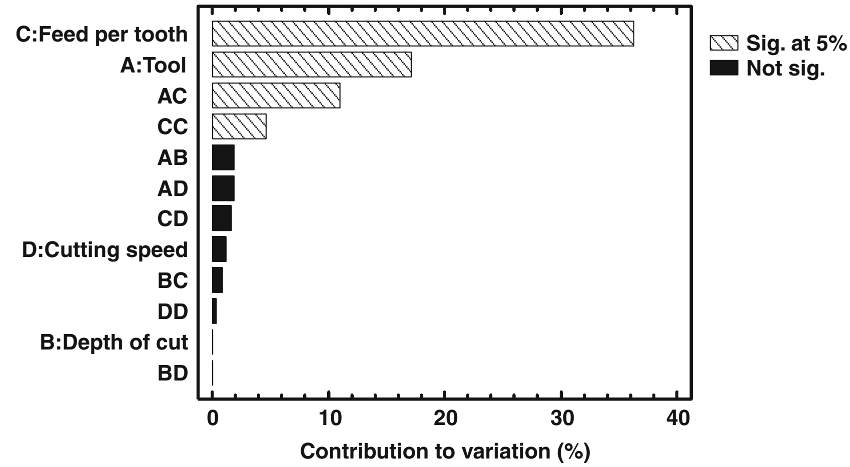


Fig. 17 Pareto chart of R_a

optimization methodology and formulations are presented in Appendix 2.

3.2.2 Multiple response optimization

In general, when all responses are optimized with similar weightage value t, the geometric mean of overall desirability (D_i) with five optimized responses is expressed as follows:

$$D_i = \left(d\left(B_{1,H}\right) \times d\left(B_{2,H}\right) \times d\left(B_{1,T}\right) \times d\left(B_{2,T}\right) \times d(Ra)\right)^{0.2} \quad (4)$$

where

- $B_{1,H}$ is exit up milling side burr (B_1) height
- $B_{2,H}$ is exit bottom side burr (B_2) height
- $B_{1,T}$ is exit up milling side burr (B_1) thickness
- $B_{1,T}$ is exit bottom side burr (B_2) thickness
- R_a is average surface roughness

Based on experimental results and by knowing that the main size attributes of exit up milling side burr (B_1) (thickness and height) as well as R_a are the most critical surface quality parameters, two other optimization conditions based on various weightage value t are also proposed in Table 6, containing the calculated geometric mean of overall desirability (D_i). This may allow easier interpretation of optimization results and definition of the setting levels of cutting process parameters. The optimization strategy as aforementioned was applied individually for each tested material using Eqs. A1–A3 and 4. The optimization results in all three tested conditions (Table 6) are presented in Tables 7 and 8. The factor setting levels with the maximum value of D_i are considered as the optimal level of cutting parameters. The following sections present the optimization results of AA 6061-T6 and AA 2024-T351.

As shown in Table 6, with respect to the operating conditions used, $(D_i)_{max}$ is calculated for each optimization condition. When all surface quality attributes with equal weightage value t are considered (Table 6), the optimum setting levels of

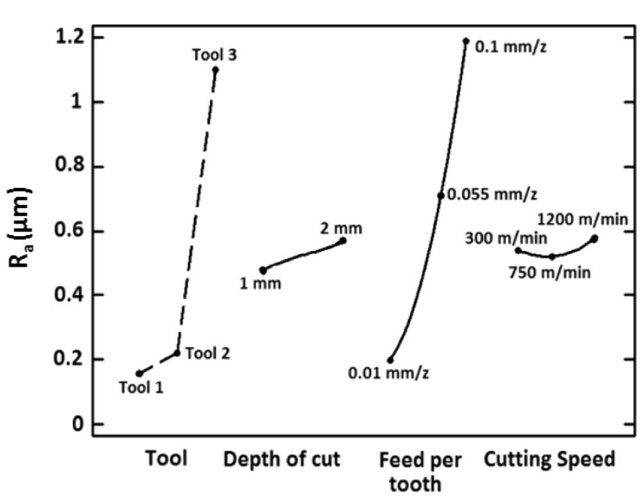


Fig. 18 Main effect plot of R_a (*adapted from* [44])

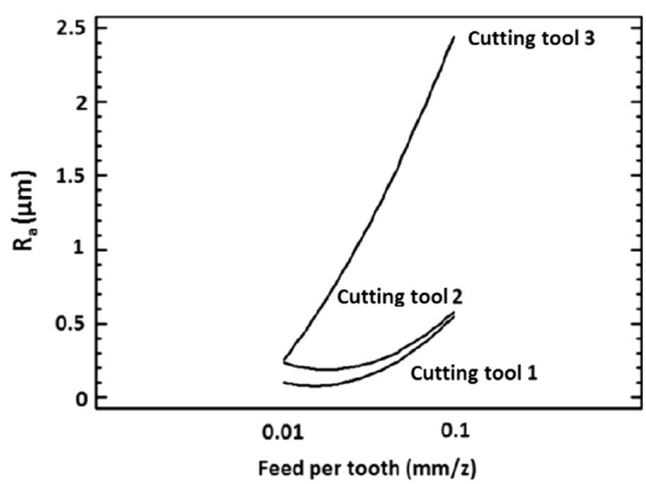


Fig. 19 The interaction effect of AC (cutting tool and feed per tooth) on R_a (*adapted from* [44])

Table 5 Optimization conditions

Conditions	Optimized responses	Weight value t	Geometric mean of overall desirability (D_i)
1	$B_{1,H}$, $B_{1,T}$, R_a, $B_{2,H}$, $B_{2,T}$	1, 1, 1, 1, 1	$D_i = \left(d\left(B_{1,H}\right) \times d\left(B_{2,H}\right) \times d\left(B_{1,T}\right) \times d\left(B_{2,T}\right) \times d(Ra)\right)^{0.2}$
2	$B_{1,H}$, $B_{1,T}$, R_a	1, 1, 1	$D_i = \left(d\left(B_{1,H}\right) \times d\left(B_{2,H}\right) \times d(Ra)\right)^{0.33}$
3	$B_{1,H}$, $B_{1,T}$, R_a, $B_{2,H}$, $B_{2,T}$	2, 2, 2, 1, 1	$D_i = \left(d\left(B_{1,H}\right) \times d\left(B_{2,H}\right) \times d\left(B_{1,T}\right) \times d\left(B_{2,T}\right) \times d(Ra)\right)^{0.14}$

process parameters for AA 6061-T6 and AA 2024-T351 are denoted as $A_1B_1C_1D_3$ (test no. 1) and $A_1B_1C_1D_1$ (test no. 3) which are as follows:

Optimum conditions for AA 6061-T6	Optimum conditions for AA 2024-T321
• Cutting tool (A): tool 1	• Cutting tool (A): tool 1
• Depth of cut a_p (B): 1 mm	• Depth of cut a_p (B): 1 mm
• Feed per tooth f_z (C): 0.01 mm	• Feed per tooth f_z (C): 0.01 mm
• Cutting speed v_c (D): 1200 m/min	• Cutting speed v_c (D): 300 m/min

Despite of the tested material used, the dissimilar weightage value t of surface quality attributes yields similar setting level $A_2B_1C_1D_1$ as the optimum cutting condition (Table 5). In fact, based on Tables 5 and 6, optimum conditions are observed when the cutting tool 2 with a bigger R_ε (0.81 mm) is used. As noted earlier, B_1 and B_2 burrs are considered as primary and secondary burrs, respectively. Assuming that the face milling burr formation mechanism appears on the exit side of slot milling parts, transition from primary to secondary burr formation is observed on the exit side burrs along up/down milling sides [18]. When burr smoothly leans towards the transition material and breaks off from the machined surface, then longer B_1 and shorter B_2 resulted (Fig. 6). This generally occurred when using cutting tools with smaller R_ε on materials with poor machinability. As shown in this work, larger resulting values of B_2 size (height and thickness) and smaller and thinner B_1 were obtained for AA 6061-T6, as compared with that observed in AA 2024-T351 (Fig. 5). In fact, as shown in Table 6, despite of the material used, the use of a cutting tool with bigger R_ε leads to thinner and smaller B_1 and a relatively optimum value of R_a. The proposed optimized setting levels of process parameters need to be validated through verification tests.

3.2.3 Experimental validation

The proposed setting levels of cutting parameters for each individual optimization condition and material as listed in Fig. 6 were tested through three repeated verification tests. The average of recorded responses was then calculated, and accordingly, the corresponding D_i for each optimization condition was calculated (Table 7). It is inferred that relatively similar values of D_i were obtained in each verification condition (Table 7) as compared with those observed in experimental studies (Fig. 6).

In the course of optimization, it is always intended to obtain the absolute optimum responses or near to optimum responses that are much smaller than the average values of experimental responses. This would require adequate proposal of the optimum setting levels of process parameters. To evaluate the adequacy of each optimized responses, a new term so-called optimization rate (k_i) was used to measure the closeness of the proposed optimized responses to the mean value experimentally measured. The optimization rate (k_i) is calculated as shown in Eq. 5:

$$k_i = \frac{y_{\text{mean}} - y_{\text{opt}}}{y_{\text{mean}}} \times 100\% \tag{5}$$

where

k_i is the optimization rate
y_{mean} is the mean value of experimental responses
y_{opt} is the optimal response

Table 6 Optimization results

Optimization conditions	AA 6061-T6		AA 2024-T321	
	$(D_i)_{\max}$	Optimized setting level	$(D_i)_{\max}$	Optimized setting level
1	0.921	$A_1B_1C_1D_3$	0.94	$A_1B_1C_1D_1$
2	0.986	$A_2B_1C_1D_1$	0.98	$A_2B_1C_1D_1$
3	0.941	$A_1B_1C_1D_3$	0.95	$A_1B_1C_1D_1$

Table 7 Experimental verification of the optimized setting levels

Optimization conditions	AA 6061-T6		AA 2024-T321	
	D_i	Optimized setting level	D_i	Optimized setting level
1	0.916	$A_1B_1C_1D_3$	0.931	$A_1B_1C_1D_1$
2	0.944	$A_2B_1C_1D_1$	0.958	$A_2B_1C_1D_1$
3	0.932	$A_1B_1C_1D_3$	0.925	$A_1B_1C_1D_1$

Table 8 Optimization rate of each individual response under different optimization conditions when milling AA 6061-T6

Responses		y_{mean}	Optimization condition 1 $A_1B_1C_1D_3$		Optimization condition 2 $A_2B_1C_1D_1$		Optimization condition 3 $A_1B_1C_1D_3$	
			$y_{i,1}$	$k_{i,1}$ (%)	$y_{i,2}$	$k_{i,2}$ (%)	$y_{i,3}$	$k_{i,3}$ (%)
1	$B_{1,H}$ (mm)	4.80	0.15	3100	0.59	713.6	0.15	3100
2	$B_{1,T}$ (mm)	0.12	0.03	300	0.03	300	0.03	300
3	$B_{2,H}$ (mm)	0.93	0.38	144.7	1.41	−34	0.38	144.7
4	$B_{2,T}$ (mm)	0.09	0.09	0	0.05	80	0.09	0
5	R_a (μm)	0.45	0.15	200	0.1	350	0.15	200
Desirability $(D_i)_{max}$	$D_i = 0.921$	$D_i = 0.986$	$D_i = 0.941$					

According to optimization results and optimum setting levels of process parameters (Table 6), the optimization rate of each individual response under each proposed optimization condition is presented in Tables 8 and 9. It is inferred that despite of the material tested, under optimization condition 2, both $B_{1,H}$ and $B_{1,T}$ as well as R_a were improved as compared to the mean values of the responses. On the other side, larger $B_{2,H}$ values as compared to the recorded mean values were obtained in both tested materials. This reconfirms that a larger resulting value of $B_{2,H}$ (mm) resulted when it is intended to achieve smaller and thinner B_1. Moreover, as the weightage value t of each response varies in optimization conditions 1 and 3 (Table 5), similarly, both $B_{1,H}$ and $B_{1,T}$ as well as R_a were improved with less resulting influence on $B_{2,H}$ and $B_{2,T}$, although both responses are still smaller than the recorded mean values. It can be underlined that according to tested conditions and proposed optimum setting levels of cutting conditions, relatively optimum $B_{1,H}$, $B_{1,T}$, and R_a are obtained for both materials under optimization conditions, while in respect to proposed optimization conditions and weightage value t of each response (Table 5), relatively near to optimum and near to average $B_{2,H}$ and $B_{2,T}$ resulted.

4 Conclusion

As noted earlier, several studies have employed experimental studies to identify the cutting factors governing machining responses. This is considered as a serious industrial demand. However, due to complex mechanisms of burr formation and direct and interaction effects between process parameters, numerous experimental tests are needed to assess the factors governing burr formation and size [29]. As well as considerable amount of expenses, the main factors governing burr formation during oblique and orthogonal milling operations are still unclear. The main governing factors seem to be temperature effects, machine tool conditions, stability of cutting process, material properties, etc. Limited information in this regards may lead to inconsistency on experimental results. Moreover, although dry machining of aluminum alloys is a widely used approach, limited information is available for adequate selection of cutting parameters in dry cutting condition. Proper selection of cutting parameters by means of burr size minimization is even more complicated in slot milling operation, particularly when various levels of machining parameters such as cutting tools with various insert nose radiuses and coatings are used. Therefore, to remedy the lack of knowledge noted, the combination of statistical and experimental

Table 9 Optimization rate of each individual response under different optimization conditions when milling AA 2024-T351

Responses		y_{mean}	Optimization condition 1 $A_1B_1C_1D_1$		Optimization condition 2 $A_1B_1C_1D_1$		Optimization condition 3 $A_1B_1C_1D_1$	
			$y_{i,1}$	$k_{i,1}$ (%)	$y_{i,2}$	$k_{i,2}$ (%)	$y_{i,3}$	$k_{i,3}$ (%)
1	$B_{1,H}$ (mm)	3.17	0.68	366	2.15	47.5	0.68	366
2	$B_{1,T}$ (mm)	0.11	0.04	175	0.04	175	0.04	175
3	$B_{2,H}$ (mm)	1.01	0.91	11	1.33	−24	0.91	11
4	$B_{2,T}$ (mm)	0.08	0.04	100	0.03	166.7	0.04	100
5	R_a (μm)	0.11	0.04	175	0.04	175	0.04	175
Desirability $(D_i)_{max}$			$D_i = 0.94$		$D_i = 0.98$		$D_i = 0.95$	

approaches was used in this work for experimental characterization of the factors governing exit burr size attributes (height, thickness) which are very difficult to model explicitly. Therefore, acute information on factors governing burr formation mechanism and size is strongly demanded. As well as edge quality, surface quality needs to be improved. Knowing that single response optimization (e.g., burr size) may lead to non-acceptable or non-optimum surface quality, the use of optimization strategies to assess the possibility of simultaneous multiple response optimization is necessary.

Based on experimental observations, statistical analysis, and the employed optimization strategy, the following conclusions are drawn:

- Regardless of the material used, B_1 thickness is a statistically significant response which can be highly controlled by feed per tooth, tool (geometry and coating), depth of cut, and interaction effects between cutting parameters, including AB and DD. Moreover, the minimum B_1 thickness in both materials resulted when using low levels of depth of cut and feed per tooth as well as a tool with bigger R_ε. It was found that the changes in R_ε and tool coating led to significant effect on B_1 thickness.
- Despite of the tested material, B_1 height is considered as a non-statistically significant response that cannot be accurately controlled by cutting parameters. The only effective cutting process parameter on B_1 height is depth of cut.
- As similar as B_1 thickness, R_a can highly vary by cutting parameters, including feed per tooth, tool geometry and coating, depth of cut, and interaction effects (AB). The effect of cutting tool coating on R_a is significant. Lower levels of depth of cut, feed per tooth, middle level of cutting speed, and cutting tool with smaller R_ε led to a minimum value of R_a.
- It was observed that the optimal parameters to minimize each machining response studied are different. Among studied responses, both B_2 height and thickness are considered as non-significant responses. Except B_1 thickness, B_1 height and R_a are also considered as statistically non-significant responses to variation of cutting process parameters which cannot be precisely controlled by cutting parameters used.
- As noted earlier, except B_1 thickness, the controllability of other surface quality attributes is difficult. To remedy this lack, desirability function $D_i\ (x)$ was implemented to ascertain the adequate setting levels of cutting process parameters. To better investigate the optimum cutting parameters, desirability function $D_i\ (x)$ was calculated under three conditions on the basis of defined levels of weightage value t as shown in Table 6. The optimum conditions in all three conditions were defined. This reveals that despite of the conditions used (Table 6), relatively optimum and near to optimum results were obtained for each individual response. This confirms the possibility of simultaneous optimization of multiple surface quality attributes, despite of their insignificant sensitivity to cutting parameters. According to experimental results, it is inferred that under finishing conditions when milling aluminum alloys from relatively similar family of materials, feed per tooth and tool (geometry and coating) have the most substantial influence on simultaneous minimization of exit burr size attributes (thickness and height) and R_a, but cutting speed and depth of cut have relatively less contribution on $D_i\ (x)$.
- Regardless of the tested materials and weightage value t, multiple response optimization of slot milling responses can be achieved at low levels of feed per tooth and depth of cut as well as high levels of cutting speed and cutting tool with relatively bigger R_a. The proposed optimum setting levels of cutting process parameters for each individual optimization condition and material (Table 6) were confirmed through verification tests.
- As a final remark, it can be underlined that due to limited amount of investigations on simultaneous optimization of the surface quality attributes, the results of this work could be used as an operational window for adequate selection of process parameters.
- Although optimum or near to optimum parameters and cutting conditions could be proposed to optimize the machining responses, this method is not a practical approach on non-statistically significant responses such as burr height. Therefore, to remedy this lack, it is proposed to define the best setting levels of process parameters and evaluate their desirability with respect to existing or proposed optimum responses using predefined scale values. The process parameter adjustment and optimization based on real-time approaches can also be conducted using intelligent approaches such as advanced artificial intelligence methods (e.g., NN, fuzzy logic, ANFIS).

Acknowledgments The authors would like to acknowledge the financial support received by the Fonds Québécois de la Recherche sur - la Nature et les Technologies (FQRNT) and Aluminum Research Centre Canada - REGAL.

Appendix 1

The following terms and techniques are used in this work for statistical analysis:

1. *ANOVA:* The analysis of variance (ANOVA) allows an examination of the main effects of independent variables and their interaction effects to determine their combined effects on the responses at 95% confidence interval (CI).

The following statistical terms are used for results analysis:

- *P value*: The probability (ranging from 0 to 1) that the results observed in a study (or results more extreme) could have occurred by chance

– If P value >0.10, the parameter is insignificant.
– If $0.05 \leq P$ value ≤ 0.10, the parameter is mildly significant.
– If P value <0.05, the parameter is significant.
– The coefficient of determination (R^2) provides a measure of variability in the observed response values and can be explained by the controllable factors and their interactions. If R^2 is greater than 0.75, the predicted model is thought to be *sensitive* to variation of process variables. If not, the model is considered as *insignificant*.
– R^2_{adj} is more suitable for comparing models with different numbers of independent variables. Unlike R^2, R^2_{adj} increases only if the new term improves the model more than would be expected. R^2_{adj} can be negative and is always smaller than or equal to R^2.

2. *Pareto analysis*: A Pareto chart compares the relative importance and statistical significance of the main and interaction effects between process parameters. This chart identifies influential factors in order of decreasing contribution.
3. *Main effect plot*: The analysis of means (ANOM) is used to determine the optimal cutting conditions by estimating the effect of each parameter on response, which is presented in the main effect plot diagram [52].
4. *Interaction effects analysis:* Presents the interaction effects between process parameters.

Appendix 2

When there are many input process parameters, it becomes more complex to find the appropriate input setting levels.

$$\hat{Y}_i = a_0 + \sum_{i=1}^{4} a_i X_i + \sum_{i=1}^{4} a_{ii} X_i^2 + \sum_{i=1}^{4} \sum_{j=1}^{4} a_{i_j} X_i X_j \tag{A1}$$

Let

Y_i Response system
X_i Coded variable
$X_i X_j$ Interaction between parameter
a_i Effect of each process parameter
a_{ii} Effect of each process parameter
a_{ij} Interaction effect between i and j

An interesting approach to overcome this difficulty is to use a methodology proposed by Derringer and Suich [51], which introduces an overall criterion of desirability of the proposed input setting parameters. Using this method, the optimization of multiple responses becomes simpler. This method uses an objective function as D_i (x), called desirability function, and transforms the estimated response into a scale-free value (d_i), called desirability which ranges from 0 to 1 (see Eq. A2).

Suppose Y_i is within the range of (B, C), where B and C are minimum and maximum measured/expected response values. Therefore, the desired range is as following $B \leq Y \leq C$. In this case, the desirability of each response (d_i) can be defined as below:

$$d_i = \left(\frac{\hat{Y} - C}{B - C} \right)^t \tag{A2}$$

where t is a weightage value.

Assuming that the significance value of all responses is similar, t is considered 1. From Eq. A2, it is clear that if any response y_i is completely undesirable, then $d_i = 0$ (Eq. A2). Therefore, the objective function is a geometric mean of all transformed responses as shown in Eq. A3:

$$D_i = (d_1 \times d_2 \times d_3 \times \ldots\ldots d_n)^{1/m} = \left(\prod_{i=1}^{n} d_i \right)^{1/m} \tag{A3}$$

where m is the number of responses.

Table 10 Experimental measured and optimization responses of AA 6061-T6

Test no.	Experimental parameters				Responses					Desirability (D_i)		
	A Tool	B a_p (mm)	C f_z (mm)	D V_c(m/min)	$B_{1,H}$ (mm)	$B_{1,T}$ (mm)	$B_{2,H}$ (mm)	$B_{2,T}$ (mm)	R_a (μm)	Condition 1	Condition 2	Condition 3
1	1	1	0.01	300	4.88	0.04	0.25	0.11	0.11	0.836	0.872	0.829
2	1	1	0.01	750	5.72	0.06	0.75	0.11	0.14	0.783	0.827	0.774
3	*1*	*1*	*0.01*	*1200*	*0.15*	*0.03*	*0.38*	*0.09*	*0.15*	*0.921*	*0.984*	*0.931*
4	1	1	0.055	300	5.00	0.10	0.38	0.10	0.16	0.795	0.786	0.765
5	1	1	0.055	750	7.45	0.08	0.64	0.08	0.23	0.766	0.736	0.724
6	1	1	0.055	1200	6.10	0.13	0.29	0.08	0.12	0.766	0.715	0.715
7	1	1	0.1	300	2.31	0.13	0.23	0.08	0.30	0.797	0.759	0.755

Table 10 (continued)

Test no.	Experimental parameters				Responses					Desirability (D_i)		
	A Tool	B a_p (mm)	C f_z (mm)	D v_c(m/min)	$B_{1,H}$ (mm)	$B_{1,T}$ (mm)	$B_{2,H}$ (mm)	$B_{2,T}$ (mm)	R_a (μm)	Condition 1	Condition 2	Condition 3
8	1	1	0.1	750	6.61	0.15	0.30	0.10	0.34	0.704	0.64	0.641
9	1	1	0.1	1200	7.66	0.15	0.88	0.07	1.51	0.565	0.442	0.467
10	1	2	0.01	300	6.44	0.09	0.36	0.08	0.11	0.802	0.764	0.76
11	1	2	0.01	750	5.12	0.08	0.40	0.08	0.11	0.834	0.817	0.805
12	1	2	0.01	1200	4.72	0.09	0.36	0.08	0.13	0.832	0.811	0.801
13	1	2	0.055	300	3.98	0.23	0.42	0.13	0.18	0.553	0.492	0.482
14	1	2	0.055	750	0.96	0.12	0.66	0.09	0.13	0.817	0.826	0.797
15	1	2	0.055	1200	6.73	0.19	0.38	0.06	0.34	0.675	0.555	0.585
16	1	2	0.1	300	4.73	0.27	0.52	0.06	0.36	0	0	0
17	1	2	0.1	750	7.60	0.24	0.35	0.04	0.32	0.558	0.387	0.437
18	1	2	0.1	1200	6.31	0.24	0.33	0.06	0.59	0.562	0.403	0.447
19	*2*	*1*	*0.01*	*300*	*0.59*	*0.03*	*1.41*	*0.05*	*0.10*	*0.912*	*0.986*	*0.941*
20	*2*	*1*	*0.01*	*750*	*0.96*	*0.03*	*1.31*	*0.05*	*0.13*	*0.918*	*0.974*	*0.931*
21	*2*	*1*	*0.01*	*1200*	*0.14*	*0.05*	*1.24*	*0.06*	*0.17*	*0.898*	*0.951*	*0.906*
22	2	1	0.055	300	0.90	0.08	1.71	0.22	0.34	0	0.871	0
23	2	1	0.055	750	0.21	0.05	1.64	0.13	0.70	0.725	0.864	0.746
24	2	1	0.055	1200	1.25	0.07	4.46	0.20	0.28	0	0.883	0
25	2	1	0.1	300	0.63	0.07	1.33	0.05	0.49	0.847	0.861	0.832
26	2	1	0.1	750	0.31	0.09	1.32	0.10	0.47	0.776	0.846	0.776
27	2	1	0.1	1200	1.16	0.09	2.28	0.18	0.44	0.583	0.842	0.632
28	2	2	0.01	300	6.04	0.06	0.62	0.05	0.08	0.855	0.82	0.821
29	2	2	0.01	750	5.81	0.08	0.80	0.04	0.09	0.85	0.802	0.809
30	2	2	0.01	1200	0.29	0.07	0.85	0.09	0.12	0.865	0.934	0.876
31	2	2	0.055	300	5.81	0.08	0.60	0.12	0.52	0.721	0.741	0.695
32	2	2	0.055	750	0.28	0.11	1.06	0.08	0.20	0.826	0.849	0.813
33	2	2	0.055	1200	7.90	0.07	0.52	0.11	0.32	0.726	0.723	0.691
34	2	2	0.1	300	6.11	0.17	0.59	0.10	0.69	0.641	0.57	0.571
35	2	2	0.1	750	11.71	0.15	0.73	0.11	0.71	0.553	0.464	0.47
36	2	2	0.1	1200	16.21	0.15	0.63	0.10	0.43	0	0	0
37	3	1	0.01	300	6.69	0.04	0.60	0.06	0.34	0.827	0.794	0.79
38	3	1	0.01	750	6.80	0.05	4.06	0.10	0.30	0.493	0.785	0.543
39	3	1	0.01	1200	5.16	0.08	2.26	0.11	0.26	0.69	0.798	0.695
40	3	1	0.055	300	5.56	0.09	0.79	0.07	0.43	0.787	0.746	0.742
41	3	1	0.055	750	8.07	0.10	1.37	0.07	0.21	0.725	0.693	0.678
42	3	1	0.055	1200	7.06	0.09	0.36	0.04	0.51	0.798	0.703	0.731
43	3	1	0.1	300	11.91	0.10	0.38	0.06	1.33	0.574	0.427	0.465
44	3	1	0.1	750	5.77	0.11	1.76	0.10	0.92	0.634	0.636	0.594
45	3	1	0.1	1200	5.19	0.11	3.14	0.12	1.31	0.503	0.576	0.482
46	3	2	0.01	300	6.51	0.09	0.42	0.05	0.29	0.81	0.735	0.753
47	3	2	0.01	750	5.44	0.16	0.97	0.04	0.33	0.737	0.649	0.667
48	3	2	0.01	1200	0.34	0.15	0.40	0.05	0.27	0.824	0.756	0.772
49	3	2	0.055	300	4.59	0.15	0.37	0.06	0.48	0.754	0.658	0.682
50	3	2	0.055	750	5.52	0.17	0.91	0.06	0.26	0.703	0.623	0.633
51	3	2	0.055	1200	5.71	0.18	0.34	0.05	0.48	0.708	0.585	0.619
52	3	2	0.1	300	5.24	0.23	0.32	0.08	1.25	0.516	0.37	0.405
53	3	2	0.1	750	4.54	0.23	0.33	0.07	1.65	0.476	0.315	0.357
54	3	2	0.1	1200	0.45	0.21	0.42	0.09	2.21	0	0	0
Minimum					*0.14*	*0.03*	*0.23*	*0.04*	*0.08*	*0.00*	*0.00*	*0.00*
Maximum					*16.21*	*0.27*	*4.46*	*0.22*	*2.21*	*0.92*	*0.99*	*0.94*
Mean					*4.80*	*0.12*	*0.93*	*0.09*	*0.45*	*0.66*	*0.68*	*0.63*

Appendix 3

Table 11 Experimental measured values of response characteristics in AA 2024-T351

Test no.	Experimental parameters				Responses					Desirability (D_i)		
	A Tool	B	C f_z (mm)	D v_c (m/min)	$B_{1,H}$ (mm)	$B_{1,T}$ (mm)	$B_{2,H}$ (mm)	$B_{2,T}$ (mm)	R_a (μm)	Condition 1	Condition 2	Condition 3
1	*1*	*1*	*0.01*	*300*	*0.68*	*0.04*	*0.91*	*0.04*	*0.04*	*0.94*	*0.95*	*0.95*
2	1	1	0.01	750	2.37	0.07	1.21	0.04	0.07	0.83	0.81	0.80
3	1	1	0.01	1200	0.25	0.08	1.42	0.08	0.08	0.78	0.80	0.76
4	1	1	0.055	300	0.12	0.08	0.15	0.05	0.08	0.88	0.84	0.85
5	1	1	0.055	750	0.08	0.08	0.37	0.08	0.08	0.84	0.84	0.82
6	1	1	0.055	1200	3.52	0.10	2.18	0.25	0.10	0.00	0.67	0.00
7	1	1	0.1	300	0.16	0.12	0.19	0.08	0.12	0.71	0.63	0.64
8	1	1	0.1	750	8.22	0.11	0.19	0.05	0.11	0.65	0.51	0.55
9	1	1	0.1	1200	2.31	0.11	2.04	0.07	0.11	0.64	0.62	0.59
10	1	2	0.01	300	0.15	0.13	0.34	0.08	0.13	0.67	0.56	0.58
11	1	2	0.01	750	0.14	0.10	0.23	0.05	0.10	0.79	0.70	0.72
12	1	2	0.01	1200	6.10	0.13	0.18	0.04	0.13	0.63	0.47	0.52
13	1	2	0.055	300	0.10	0.10	0.23	0.07	0.10	0.78	0.73	0.73
14	1	2	0.055	750	0.27	0.09	0.38	0.05	0.09	0.83	0.78	0.79
15	1	2	0.055	1200	5.94	0.13	0.21	0.04	0.13	0.64	0.49	0.54
16	1	2	0.1	300	0.07	0.12	0.24	0.07	0.12	0.70	0.60	0.62
17	1	2	0.1	750	1.10	0.15	0.34	0.07	0.15	0.56	0.42	0.45
18	1	2	0.1	1200	12.82	0.15	0.34	0.08	0.15	0.39	0.24	0.28
19	*2*	*1*	*0.01*	*300*	*2.15*	*0.04*	*1.33*	*0.03*	*0.04*	*0.91*	*0.98*	*0.91*
20	2	1	0.01	750	1.14	0.06	1.63	0.10	0.06	0.79	0.90	0.81
21	2	1	0.01	1200	0.82	0.07	1.21	0.11	0.07	0.78	0.85	0.78
22	2	1	0.055	300	0.57	0.06	1.20	0.07	0.06	0.85	0.89	0.85
23	2	1	0.055	750	0.76	0.04	1.31	0.17	0.04	0.75	0.96	0.80
24	2	1	0.055	1200	1.17	0.07	1.38	0.08	0.07	0.79	0.83	0.78
25	2	1	0.1	300	0.61	0.07	1.24	0.10	0.07	0.80	0.87	0.80
26	2	1	0.1	750	0.27	0.08	4.46	0.19	0.08	0.00	0.80	0.00
27	2	1	0.1	1200	0.79	0.09	1.25	0.18	0.09	0.65	0.79	0.66
28	2	2	0.01	300	0.14	0.06	0.57	0.05	0.06	0.90	0.90	0.89
29	2	2	0.01	750	0.23	0.12	3.92	0.12	0.12	0.44	0.62	0.46
30	2	2	0.01	1200	0.17	0.11	2.97	0.06	0.11	0.63	0.70	0.61
31	2	2	0.055	300	0.15	0.09	0.69	0.06	0.09	0.80	0.76	0.76
32	2	2	0.055	750	7.79	0.11	0.99	0.04	0.11	0.64	0.53	0.55
33	2	2	0.055	1200	8.43	0.15	1.19	0.03	0.15	0.49	0.34	0.38
34	2	2	0.1	300	13.06	0.19	0.91	0.05	0.19	0.17	0.06	0.09
35	2	2	0.1	750	0.16	0.14	1.01	0.03	0.14	0.65	0.53	0.55
36	2	2	0.1	1200	13.85	0.17	0.60	0.03	0.17	0.29	0.14	0.18
37	3	1	0.01	300	9.46	0.05	0.34	0.07	0.05	0.75	0.67	0.68
38	3	1	0.01	750	3.78	0.06	1.90	0.08	0.06	0.75	0.82	0.75
39	3	1	0.01	1200	3.90	0.06	1.55	0.09	0.06	0.77	0.83	0.76
40	3	1	0.055	300	5.50	0.10	0.26	0.07	0.10	0.72	0.63	0.65
41	3	1	0.055	750	5.03	0.09	1.59	0.08	0.09	0.68	0.66	0.64
42	3	1	0.055	1200	0.13	0.13	2.55	0.13	0.13	0.55	0.59	0.52
43	3	1	0.1	300	0.04	0.12	0.59	0.08	0.12	0.69	0.60	0.61

Table 11 (continued)

Test no.	Experimental parameters				Responses					Desirability (D_i)		
	A Tool	B	C f_z (mm)	D V_c (m/min)	$B_{1,H}$ (mm)	$B_{1,T}$ (mm)	$B_{2,H}$ (mm)	$B_{2,T}$ (mm)	R_a (µm)	Condition 1	Condition 2	Condition 3
44	3	1	0.1	750	3.02	0.14	2.03	0.08	0.14	0.53	0.47	0.46
45	3	1	0.1	1200	2.32	0.14	1.62	0.09	0.14	0.54	0.46	0.46
46	3	2	0.01	300	0.07	0.06	0.24	0.07	0.06	0.89	0.89	0.88
47	3	2	0.01	750	5.35	0.09	0.48	0.06	0.09	0.74	0.65	0.67
48	3	2	0.01	1200	0.32	0.09	0.50	0.06	0.09	0.82	0.77	0.78
49	3	2	0.055	300	0.18	0.12	0.27	0.09	0.12	0.70	0.62	0.63
50	3	2	0.055	750	0.11	0.13	0.50	0.07	0.13	0.67	0.57	0.59
51	3	2	0.055	1200	7.88	0.15	0.22	0.05	0.15	0.52	0.35	0.40
52	3	2	0.1	300	6.29	0.17	0.29	0.07	0.17	0.45	0.29	0.33
53	3	2	0.1	750	6.52	0.20	0.20	0.06	0.20	0.00	0.00	0.00
54	3	2	0.1	1200	14.72	0.19	0.27	0.08	0.19	0.00	0.00	0.00
Minimum					*0.04*	*0.04*	*0.15*	*0.03*	*0.04*	*0.00*	*0.00*	*0.00*
Maximum					*14.72*	*0.20*	*4.46*	*0.25*	*0.20*	*0.94*	*0.98*	*0.95*
Mean					*3.17*	*0.11*	*1.01*	*0.08*	*0.11*	*0.64*	*0.63*	*0.59*

Appendix 4

Table 12 The average value of recorded responses in verification tests

Responses		AA 6061-T6			AA 2024-T351		
		Optimization condition 1 $A_1B_1C_1D_3$	Optimization condition 2 $A_2B_1C_1D_1$	Optimization condition 3 $A_1B_1C_1D_3$	Optimization condition 1 $A_1B_1C_1D_1$	Optimization condition 2 $A_2B_1C_1D_1$	Optimization condition 3 $A_1B_1C_1D_1$
1	$B_{1,H}$ (mm)	0.2	0.21	0.2	0.19	0.21	0.19
2	$B_{1,T}$ (mm)	0.04	0.035	0.04	0.04	0.05	0.04
3	$B_{2,H}$ (mm)	0.39	0.42	0.39	0.41	0.42	0.41
4	$B_{2,T}$ (mm)	0.08	0.067	0.08	0.05	0.06	0.05
5	R_a (µm)	0.39	0.42	0.39	0.12	0.1	0.12
D_i		*0.931*	*0.968*	*0.942*	*0.963*	*0.972*	*0.961*

References

1. Olvera O, Barrow G (1998) Influence of exit angle and tool nose geometry on burr formation in face milling operations. Proc Inst Mech Eng B J Eng Manuf 212(1):59–72
2. Lin TR (2000) Experimental study of burr formation and tool chipping in the face milling of stainless steel. J Mater Process Technol 108(1):12–20
3. Biermann D, Heilmann M (2010) Burr minimization strategies in machining operations. Burrs-Anal Control Removal (Part 1):13–20
4. Chern GL (2006) Experimental observation and analysis of burr formation mechanisms in face milling of aluminum alloys. Int J Mach Tools Manuf 46(12–13):1517–1525
5. Aurich JC, Dornfeld D, Arrazola PJ, Franke V, Leitz L, Min S (2009) Burrs analysis, control and removal. CIRP Ann Manuf Technol 58(2):519–542
6. Niknam SA, Zedan Y, Songmene V (2014) Machining burrs formation & deburring of aluminium alloys light metal alloys applications. p 99–122
7. Niknam SA, Songmene V (2014) Analytical modelling of slot milling exit burr size. Int J Adv Manuf Technol 73(1–4):421–432
8. Niknam SA. Burrs understanding, modeling and optimization during slot milling of aluminium alloys Ph.D. Thesis, École de Technologie Superieure, Universite du Quebec, 2013.

9. San-Juan M, Martín Ó, Santos F (2010) Experimental study of friction from cutting forces in orthogonal milling. Int J Mach Tools Manuf 50(7):591–600
10. Tripathi S, Dornfeld DA (2006) Review of geometric solutions for milling burr prediction and minimization. Proc Inst Mech Eng B J Eng Manuf 220(4):459–466
11. Sharan R, Onwubolu G. Comparison of manual and image processing methods of end-milling burr measurement. Innovations and advances in computing, informatics, systems sciences, networking and engineering: Springer; 2015. p. 133–7.
12. Sun SF, Yin AC, Wang PP, Zhang QD, editors. Experimental study of micro milling burr control based on process parameters optimization. Applied mechanics and materials; 2014: Trans Tech Publ.
13. Tripathi S, Dornfeld DA (2006) Review of geometric solutions for milling burr prediction and minimization. Proc Inst Mech Eng B J Eng Manuf 220(4):459
14. Matuszak J, Zaleski K. Effect of milling parameters upon burr formation during AZ91 HP magnesium alloy face milling. New materials and it technologies in production engineering 2011:31–42.
15. Kobayashi R, Xu S, Shimada K, Mizutani M, Kuriyagawa T (2017) Defining the effects of cutting parameters on burr formation and minimization in ultra-precision grooving of amorphous alloy. Precis Eng
16. Tsann-Rong L (2000) Experimental study of burr formation and tool chipping in the face milling of stainless steel. J Mater Process Technol 108(1):12–20
17. Niknam SA, Tiabi A, Kamguem R, Zaghbani I, Songmene V. Milling burr size estimation using acoustic emission and cutting forces. Proceedings of the ASME 2011 International Mechanical Engineering Congress & Exposition IMECE2011; 11–17 November 2011; Denver, Col, USA 2011.
18. Niknam SA, Songmene V (2013) Factors governing burr formation during high-speed slot milling of wrought aluminium alloys. Proc Inst Mech Eng B J Eng Manuf 227(8):1165–1179
19. Niknam SA, Songmene V (2013) Simultaneous optimization of burrs size and surface finish when milling 6061-T6 aluminium alloy. Int J Precis Eng Manuf 14(8):1311–1320
20. Niknam SA, Songmene V (2017) Burr formation and correlation with cutting force and acoustic emission signals. Proc Inst Mech Eng B J Eng Manuf 231(3):399–414
21. Niknam SA (2016) Modeling and experimental characterization of the friction effects on orthogonal milling exit burrs. Int J Adv Manuf Technol:1–11
22. Niknam SA, Kouam J, Songmene V (2016) Experimental investigation on part quality and metallic particle emission when milling 6061-T6 aluminium alloy. Int J Mach Mach Mater 18(1–2):120–137
23. Niknam SA, Songmene V (2013) Modeling of burr thickness in milling of ductile materials. Int J Adv Manuf Technol 66(9):2029–2039
24. Chen M, Liu G, Shen Z, editors. Study on active process control of burr formation in al-alloy milling process: Proceeding of the IEEE, International Conference on Automation Science and Engineering, Shanghai, China, October 7–10, 2006.
25. Luo M, Liu G, Chen M (2008) Mechanism of burr formation in slot milling Al-alloy. Int J Mater Prod Technol 31(1):63–71
26. Kiswanto G, Zariatin D, Ko T (2014) The effect of spindle speed, feed-rate and machining time to the surface roughness and burr formation of aluminum alloy 1100 in micro-milling operation. J Manuf Process 16(4):435–450
27. Chen N, Chen MJ, Ni HB, He N, Liu ZQ (eds) (2014) Research on the modeling and experimenting of burr formation process in double-edged micro-plat end milling operation. In: Materials Science Forum. Trans Tech Publ
28. Lekkala R, Bajpai V, Singh RK, Joshi SS (2011) Characterization and modeling of burr formation in micro-end milling. Precis Eng 35(4):625–637
29. Lauderbaugh L (2009) Analysis of the effects of process parameters on exit burrs in drilling using a combined simulation and experimental approach. J Mater Process Technol 209(4):1909–1919
30. Niknam SA, Songmene V (eds) (2013) Experimental investigation and modeling of milling burrs. ASME 2013 International Manufacturing Science and Engineering Conference collocated with the 41st North American Manufacturing Research Conference, Madison
31. Niknam SA, Wygowski W, Balazinski M, Songmene V (2014) Milling burr formation and avoidance. In: Davim JP (ed) Machinability of advanced materials. ISTE Wiley, London, pp 57–94
32. Razfar M, Farshbaf Zinati R, Haghshenas M (2011) Optimum surface roughness prediction in face milling by using neural network and harmony search algorithm. Int J Adv Manuf Technol 52(5):487–495
33. Olvera O, Barrow G (1996) An experimental study of burr formation in square shoulder face milling. Int J Mach Tools Manuf 36(9):1005–1020
34. Wain N, Thomas N, Hickman S, Wallbank J, Teer D (2005) Performance of low-friction coatings in the dry drilling of automotive Al-Si alloys. Surf Coat Technol 200(5–6):1885–1892
35. Songmene V, Khettabi R, Kouam J (2012) High speed machining: a cost effective & green process. Int J Manuf Res (IJMR) 7(3):229–256
36. Gaitonde VN, Karnik SR, Davim J (2009) Multiperformance optimization in turning of free-machining steel using Taguchi method and utility concept. J Mater Eng Perform 18(3):231–236
37. Vafaeesefat A (2009) Optimum creep feed grinding process conditions for Rene 80 supper alloy using neural network. Int J Precis Eng Manuf 10(3):5–11
38. Tong K, Kwong C, Yu K (2004) Process optimisation of transfer moulding for electronic packages using artificial neural networks and multiobjective optimisation techniques. Int J Adv Manuf Technol 24(9):675–685
39. Karnik S, Gaitonde V, Davim J (2008) A comparative study of the ANN and RSM modeling approaches for predicting burr size in drilling. Int J Adv Manuf Technol 38(9):868–883
40. Lee P, Chung H, Lee S (2011) Optimization of micro-grinding process with compressed air using response surface methodology. Proc Inst Mech Eng B J Eng Manuf 225(11):2040–2050
41. Mandal N, Doloi B, Mondal B (2012) Force prediction model of Zirconia Toughened Alumina (ZTA) inserts in hard turning of AISI 4340 steel using response surface methodology. Int J Precis Eng Manuf 13(9):1589–1599
42. Yang RT, Liao HT, Yang YK, Lin SS (2012) Modeling and optimization in precise boring processes for aluminum alloy 6061T6 components. Int J Precis Eng Manuf 13(1):11–16
43. Moola MR, Gorin A, Hossein KA (2012) Optimization of various cutting parameters on the surface roughness of the machinable glass ceramic with two flute square end mills of micro grain solid carbide. Int J Precis Eng Manuf 13(9):1549–1554
44. Niknam SA, Kamguem R, Songmene V. Analysis and optimization of exit burr size and surface roughness in milling using desirability function ASME 2012 International Mechanical Engineering Congress & Exposition IMECE2012; 9–15 November 2012; November 9–15, Houston, TX, USA.
45. Kishimoto W, Miyake T, Yamamoto A, Yamanaka K, Takano K (1981) Study of burr formation in face milling. Conditions for the secondary burr formation. Bull Jpn Soc Precis Eng 15(1):51–52

46. De Souza AM, Sales WF, Ezugwu EO, Bonney J, Machado AR (2003) Burr formation in face milling of cast iron with different milling cutter systems. Inst Mech Eng B J Eng Manuf 217(11): 1589–1596
47. Zhang JZ, Chen JC, Kirby ED (2007) Surface roughness optimization in an end-milling operation using the Taguchi design method. J Mater Process Technol 184(1):233–239
48. Nalbant M, Gökkaya H, Sur G (2007) Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning. Mater Des 28(4):1379–1385
49. Ulutan D, Ozel T (2011) Machining induced surface integrity in titanium and nickel alloys: a review. Int J Mach Tools Manuf 51(3): 250–280
50. Axinte D, Dewes R (2002) Surface integrity of hot work tool steel after high speed milling—experimental data and empirical models. J Mater Process Technol 127(3):325–335
51. Derringer G, Suich R (1980) Simultaneous-optimization of several response variables. J Qual Technol 12(4):214–219
52. Phadke MS (1989) Quality engineering using robust design. Prentice Hall Englewood Cliffs, NJ