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Full Paper

Machinability study on discontinuously reinforced aluminium composites (DRACs) using response surface methodology and Taguchi's design of experiments under dry cutting condition

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Abstract: The development of metal matrix composites with discontinuous reinforcement represents a well-established method for improving the strength and stiffness of a material. This paper discusses the use of Taguchi's design of experiments and response surface methodology (RSM) for minimising the surface roughness in turning of discontinuously reinforced aluminium composites (DRACs) having aluminum alloy 6061 as the matrix and containing 15 vol. % of silicon carbide particles with a mean diameter of 25μm under dry cutting condition. The measured results are then collected and analysed with the help of a commercial software package MINITAB15. The experiments are conducted using Taguchi's experimental design technique. The matrices of test conditions include cutting speed, feed rates and depth of cut. The effect of cutting parameters on surface roughness is evaluated and the optimum cutting condition for minimising the surface roughness is determined. A second-order model is established between the cutting parameters and the surface roughness using RSM. The experimental results reveal that the most significant machining parameter for surface roughness is feed, followed by cutting speed. The predicted values and measured values are fairly close, which indicates that the developed model can be effectively used to predict the surface roughness in the machining of DRACs.

Keywords: discontinuously reinforced aluminium composites (DRACs), metal matrix composites (MMCs), surface roughness, Taguchi's design of experiments, response surface methodology

Abbreviations:

DRACs	: discontinuously reinforced aluminium composites	DF	: degrees of freedom
MMCs	: metal matrix composites	Seq SS	: sequential sum of squares
ANOVA	: analysis of variance	Adj SS	: adjusted sum of squares
BUE	: built-up edges	Adj MS	: adjusted mean of squares
BHN	: Brinells hardness number	F	: Fishers Test
SEM	: scanning electron microscope	P	: probability statistic
CBN	: cubic boron nitride		
RSM	: response surface methodology		

Introduction

Machining of discontinuously reinforced aluminium composites (DRACs) presents a significant challenge to the industry since a number of reinforcement materials are significantly harder than the commonly used high speed steel tools and carbide tools [1]. The reinforcement phase causes rapid abrasive tool wear; thus the widespread usage of DRACs is considerably impeded by their poor machinability and high machining costs. Based on the available literature on DRACs it is clear that the morphology, distribution and volume fraction of the reinforcement phase, as well as the matrix properties are all factors that affect the overall cutting process [1-2], but as yet relatively few published reports are related to the optimisation of the cutting process.

From some early conventional turning tests on Al/SiC metal matrix composites (MMCs) [3-4] it is found that the tool wear is excessive and surface finish is very poor when carbide tip tools are used for machining. The hard SiC particles of Al/SiC MMCs, which intermittently come into contact with the hard surface, act as small cutting edges like those of a grinding wheel on the cutting tool edge which in due course gets worn out by abrasion and resulting in the formation of poor surface finish during turning . When Al/SiC MMCs job slides over a hard cutting tool edge during turning, it always presents a newly formed surface to the same proportion as the cutting edge and consequently, due to friction, high temperature and pressure the particles of the Al/SiC MMCs adhere to the cutting tool edge, as shown in our case for a cubic boron nitride (CBN) tool (Figure 1). In this way more particles will join up with those already adhering and the so-called built-up edge (BUE) is formed and if this process is continued for some time, it appears to nibble away on the turned surface and produces a very poor surface finish during turning [5].

Due to the high cost of these tools, it is still desirable to optimise the cutting conditions. Moreover to get good surface quality and dimensional properties, it is necessary to employ optimisation techniques to find the optimal cutting parameters and also to employ theoretical models to do predictions. Taguchi's design of experiments (DOE) and response surface methodology (RSM) can be conveniently used for these purposes. Suresh et al. [6] used the response surface method and genetic algorithm for predicting the surface roughness and optimising the process parameters. Kwak [7] has applied Taguchi's DOE and RSM for optimising geometric errors in the surface grinding process. According to Sahin and Motoreu [8], RSM is more practical, economical and relatively easy to use. In the present study, the effect of cutting parameters on the surface roughness of DRACs upon machining under dry cutting is evaluated and a second-order model is developed for predicting the surface roughness.

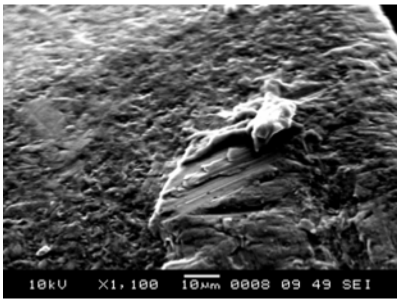

Figure 1. Typical wear pattern and material sediments observed on a CBN tool

Materials and Methods

General

The work piece specimens used were Al/SiC MMCs popularly known as DRACs. They consisted of aluminum alloy 6061 as the matrix and containing 15 vol. % of silicon carbide particles (mean diameter 25µm) in the form of cylindrical bars of length 120 mm and 40 mm in diameter manufactured in Vikram Sarabhai Space Centre (VSSC) Trivandrum. This was prepared by stir casting process (pouring temperature 700-710°C, stirring rate 195 rpm, extrusion at 457°C, extrusion ratio 30:1, direct extrusion speed 6.1m/min) to produce Ø40mm cylindrical bars. The specimens were solution-treated for 2h at a temperature of 540^{o}C in a muffle furnace (temperatures were accurate to within ±2^{o}C and quench delays in all cases were within 20 s). After solutionising, the samples were water-quenched to room temperature, and subsequently aged for six different times to obtain samples with different Brinell hardness numbers (BHN), out of which one sample was selected: one with 94 BHN obtained at peak condition, i.e. 2h at 220^{o}C. The sample selected was kept in a refrigerator right after the heat treatment. Figure 2 shows the SEM image of DRACs containing 6061 Al and 15 vol.% SiC particles of 25 µm. The chemical composition of the specimen is shown in Table 1.

The turning method as a machining process was selected. The experimental study was carried out using a PSG A141 lathe (2.2 KW) with variable cutting speed, feed and depth of cut. The selected cutting tool was cubic boron nitride insert KB-90 (ISO code) for machining of DRAC material. The ISO codes of the cutting tool insert and tool holders are shown in Table 2. The surface condition of the machined work-piece was observed using a JEOL JSM-6380LA analytical scanning electron microscope. Surface roughness was measured using a Taylor/Hobson surtronoic 3+ surface roughness measuring instrument (Figure 3).

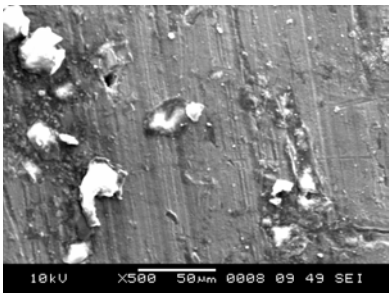

Figure 2. SEM image of DRACs (6061 Al/ 15% SiC, 25 µm)

Table 1. Nominal chemical composition of base metal (6061 Al alloy)

Element	Cu	Mg	Si	Cr	Al
Weight percentage	0.25	1.0	0.6	0.25	Balance

Table 2. Details of cutting tool and tooling system used for experimentation

Tool holder ISO code	STGCR 2020 K-16
Tool geometry specification	Approach angle:91^o Tool nose radius:0.4 mm Rake angle: 0^o Clearance angle: 7^o
Tool insert CBN (KB-90) ISO code	TPGN160304-LS

Figure 3. Layout of equipment for roughness measurement

Response surface methodology

The surface finish of machined DRACs is important in manufacturing engineering applications. It has a considerable effect on some properties such as wear resistance, light reflection, heat transmission, coating and resisting fatigue. While machining, the good quality of the parts can be achieved only through proper cutting conditions. In order to know the surface quality and dimensional properties in advance, it is necessary to employ theoretical models making it feasible to predict the function of operation conditions [9]. Response surface methodology (RSM) is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimise this response [10].

In many engineering fields, there is a relationship between an output variable of interest 'y' and a set of controllable variables $\{x_1, x_2 . . . .x_n\}$. In some systems, the nature of the relationship between 'y' and 'x' values might be known. Then, a model can be written in the form:

$$y = f(x_1, x_2, ..., x_n) + \varepsilon \tag{1}$$

where 'ε' represents the noise or error observed in the response 'y'. If we denote the expected response as:

$$E(y) = f(x_1, x_2, ..., x_n) = \hat{y} \tag{2}$$

then the surface is represented by:

$$\hat{y} = f(x_1, x_2, ..., x_n) \tag{3}$$

This is called the response surface. In most of the RSM problems, the form of relationship between the response and the independent variable is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between 'y' and the set of independent variables employed. Usually a second-order model is utilised in response surface methodology [10]:

$$\hat{y} = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i} \sum_{j} \beta_{ij} x_i x_j + \varepsilon \tag{4}$$

The β coefficients used in the above model can be calculated by means of using the least square method. The second-order model is normally used when the response function is not known or nonlinear.

Taguchi's DOE method

Taguchi's DOE method has been used widely in engineering designs [11-12]. The main trust of the Taguchi's DOE technique is the use of parameter design, which is an engineering method for product or process design that focuses on determining the parameter (factor) settings producing the best level of a quality characteristic (performance measure) with minimum variation. Taguchi design provides a powerful and efficient method for designing processes that operate consistently and optimally over a variety of conditions. To determine the best design requires the use of a strategically designed experiment which exposes the process to various levels of design parameters.

Experimental design methods were developed in the early years of the 20th century and have been extensively studied by statisticians since then, but they were not easy to use by practitioners [12]. Taguchi's approach to the design of experiments is easy to adopt and apply for users with limited knowledge of statistics; hence it has gained a wide popularity in the engineering and scientific communities. There have been plenty of recent applications of Taguchi technique to material processing for process optimisation; some of the previous works are listed [13-16]. In particular, it is recommended for analysing metal cutting problems to find the optimal combination of parameters [16]. Further, depending on the number of factors, interactions and their levels, an orthogonal array is selected by the user. Taguchi's DOE uses signal–noise [S/N] ratio as the quality characteristic of choice. The S/N ratio is used as the measurable value instead of the standard deviation due to the fact that as the mean decreases, the standard deviation also decreases and vice versa. In other words, the standard deviation cannot be minimised first and the mean brought to the target. In practice, the target mean value may change during the process development. Two of the applications in which the concept of the S/N ratio is useful are the improvement of quality through variability reduction and improvement of measurement. The S/N ratio characteristics can be divided into three categories given by equations (5-7), when the characteristic is continuous:

Category 1, nominal is the best characteristic,

$$\frac{S}{N} = 10\log\frac{\bar{y}}{s_y^2} \tag{5}$$

Category 2, smaller is the best characteristic,

$$\frac{S}{N} = -10\log\frac{1}{n}\left(\sum y^2\right) \tag{6}$$

Category 3, larger is the best characteristic,

$$\frac{S}{N} = -\log\frac{1}{n}\left(\sum\frac{1}{y^2}\right) \tag{7}$$

where '$\bar{y}$' is the average of observed data, 's_y^2' the variation of 'y', 'n' the number of observations, and 'y' the observed data. For each type of characteristics, with the above S/N ratio transformation, the smaller the S/N ratio the better is the result.

Experimental details

The orthogonal array for two factors at three levels was used for the elaboration of the plan of experiments. The array L_{27} was selected, which has 27 rows corresponding to the number of tests (26 degrees of freedom) with 13 columns at three levels. The factors and the interactions were assigned to the columns. The first column (A) was assigned to the cutting speed (m/min), the second column (B) to feed (mm/rev), the fifth column (C) to the depth of cut (mm), and the remaining were assigned to interactions. The output to be studied was the surface roughness, for which an analysis of variance (ANOVA) was carried out. The steps of our study of optimisation are presented in Figure 4. The selected levels and factors in machining of DRACs are shown in Table 3.

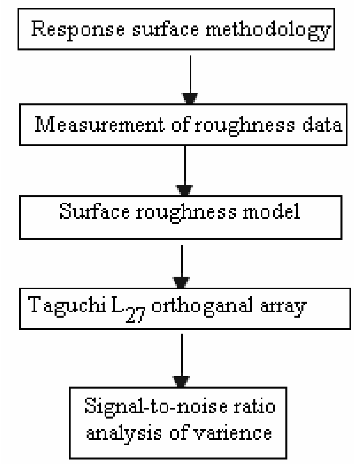

Figure 4. Steps of the optimisation process

Table 3. Levels and factors in machining of DRACs

Level	(A) Cutting speed (m/min)	(B) Feed (mm/rev)	(C) Depth of cut(mm)
1	45	0.11	0.25
2	73	0.18	0.50
3	101	0.25	0.75

Results and Discussion

Effect of control parameters on surface roughness

In Taguchi's DOE method, the term "signal" represents the desirable value and "noise" represents the undesirable value. The objective of using S/N ratio is to obtain a measure of performance to develop products and processes insensitive to noise factors. The S/N ratio indicates the degree of predictable performance of a product or process in the presence of noise factors. Process parameter settings with the highest S/N ratio always yield the optimum quality with minimum variance. The S/N ratio for each parameter level is calculated by averaging the S/N ratios obtained when the parameter is maintained at that level. Table 4 shows the S/N ratios obtained for different parameter levels.

Table 4. Response table for S/N ratios for the condition: smaller is better (surface roughness)

Level	(A) Cutting speed (m/min)	(B) Feed (mm/rev)	(C) Depth of cut (mm)
1	-10.629	-8.680	-10.386
2	-10.421	-9.967	-10.351
3	-10.162	-12.565	-10.476
Delta	0.466	3.885	0.124
Rank	2	1	3

The calculated S/N ratio for three factors on the surface roughness in machining of DRACs for each level is shown in Figure 5. As also shown in Table 4, feed is a dominant parameter on the surface roughness followed by cutting speed. The depth of cut had a much lower effect on the surface roughness. Lower surface roughness is always preferred. The quality characteristic considered in the investigation is "the smaller the better". In the present investigation, when the feed is at 0.11mm/rev the surface roughness was minimum. Contrary to the feed, low cutting speed had the maximum effect. The reason is that the increase in feed increases the heat generation and hence, tool wear, which results in higher surface roughness. The increase in feed also increases shatters and produces incomplete machining of the work piece, which leads to higher surface roughness. Figure 6 shows the interaction plot for S/N ratios (dB) at different feeds.

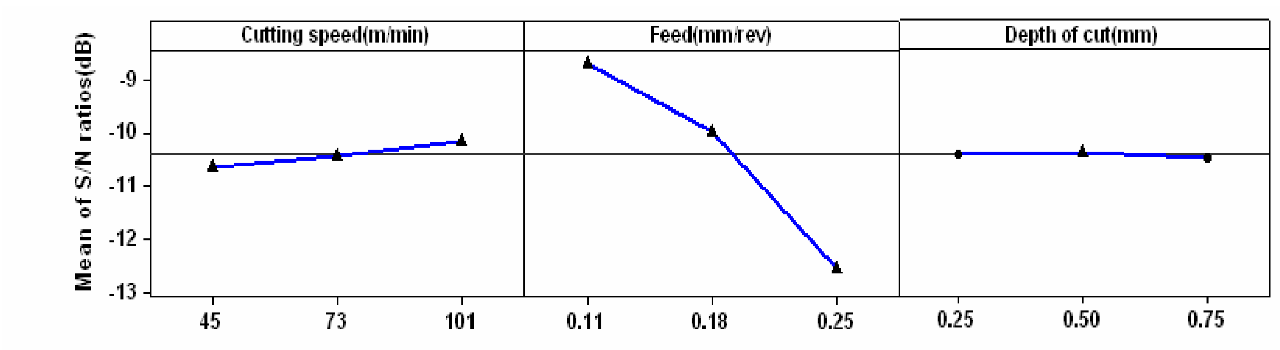

Figure 5. Mean S/N graphs for surface roughness under different parameters

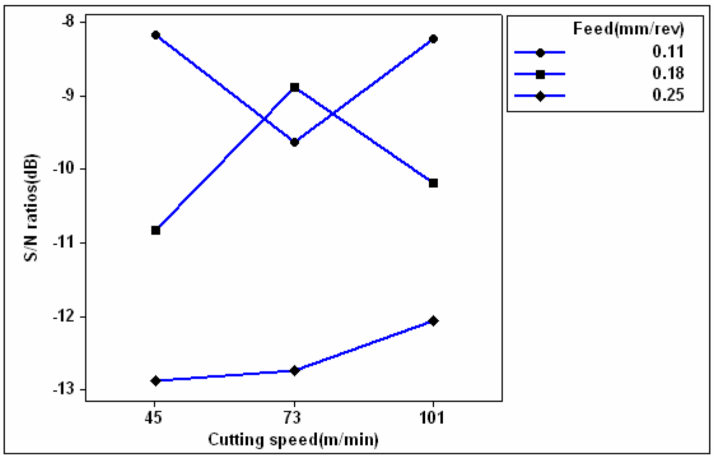

Figure 6. Interaction plot for S/N ratios (dB) at different feeds and cutting speeds

On the examination of the percentage of contribution (P %) of the different factors (Table 5) for surface roughness it can be seen that feed has the highest contribution of about 85.85%. Thus feed is an important factor to be taken into consideration while machining DRACs. Interactions (AxC), cutting speed (m/min), depth of cut (mm) does not present a statistical significance or a percentage of physical significance of contribution to the surface roughness.

Table 5. Analysis of variance for S/N ratios for surface roughness

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Percent P (%)
(A) Cutting speed (m/min)	2	0.9829	0.9829	0.4914	0.89	0.447	1.20
(B) Feed (mm/rev)	2	70.4764	70.4764	35.2382	63.92	0.000	85.85
(C)Depth of cut(mm)	2	0.0742	0.0742	0.0371	0.07	0.935	0.09
AxB	4	10.1851	10.1851	2.5463	4.62	0.032	6.20
AxC	4	0.9231	0.9231	0.2308	0.42	0.791	0.56
BxC	4	10.0143	10.0143	2.5036	4.54	0.033	6.10
Residual Error	8	4.4102	4.4102	0.5513			
Total	26	97.0662					100

Note: DF = degree of freedom; Seq SS = sequential sum of squares;
Adj MS = adjusted mean of squares; F = Fishers Test; P = probability statistic

Response surface analysis

The second-order response surface representing the surface roughness (Ra) can be expressed as a function of cutting parameters such as cutting speed (A), feed (B), and depth of cut (C). The relationship between the surface roughness and machining parameters has been expressed as follows:

$$R_a = \beta_0 + \beta_1(A) + \beta_2(B) + \beta_3(C) + \beta_4(A^2) + \beta_5(B^2) + \beta_6(C^2) + \beta_7(AB) + \beta_8(AC) + \beta_9(BC) \tag{8}$$

From the observed data for surface roughness, the response function has been determined in uncoded units as:

$$R_a = 8.17546 - 0.0596633A - 42.2636B - 0.863964C + 0.000394133A^2 + 118.878B^2 - 4.55200C^2 - 0.0331633AB + 0.0105357AC + 26.0714BC$$

The result of ANOVA for the response function of surface roughness is presented in Table 6. This analysis is carried out for a level of significance of 5%, i.e. for a level of confidence of 95%. From the analysis in Table 6, it is apparent that the F (calculated value) is greater than the F (table value) ($F_{0.05}$, 9, 10 = 3.02) and hence the second-order response function developed is quite adequate.

Table 6. ANOVA table for response function of surface roughness

Source	DF	Seq SS	Adj MS	F	P
Regression	9	10.0318	10.0318	23.53	0.000
Residual Error	10	0.4737	0.47365		
Total	19	10.5055			

Note: DF = degree of freedom; Seq SS = sequential sum of squares;
Adj MS = adjusted mean of squares; F = Fishers Test; P = probability statistic

From equation (8) contours for each of the response surfaces at different feeds are plotted. Surface plots of surface roughness at cutting speed - feed planes are shown in Figure 7. These plots can help in the prediction of the surface roughness at any zone of the experimental domain. It is clear from these figures that the surface roughness increases with the increase of feed; Figure 8 shows the SEM images of the machined surface under different feeds. Contour plots of surface roughness at cutting speed - feed planes are shown in Figure 9.

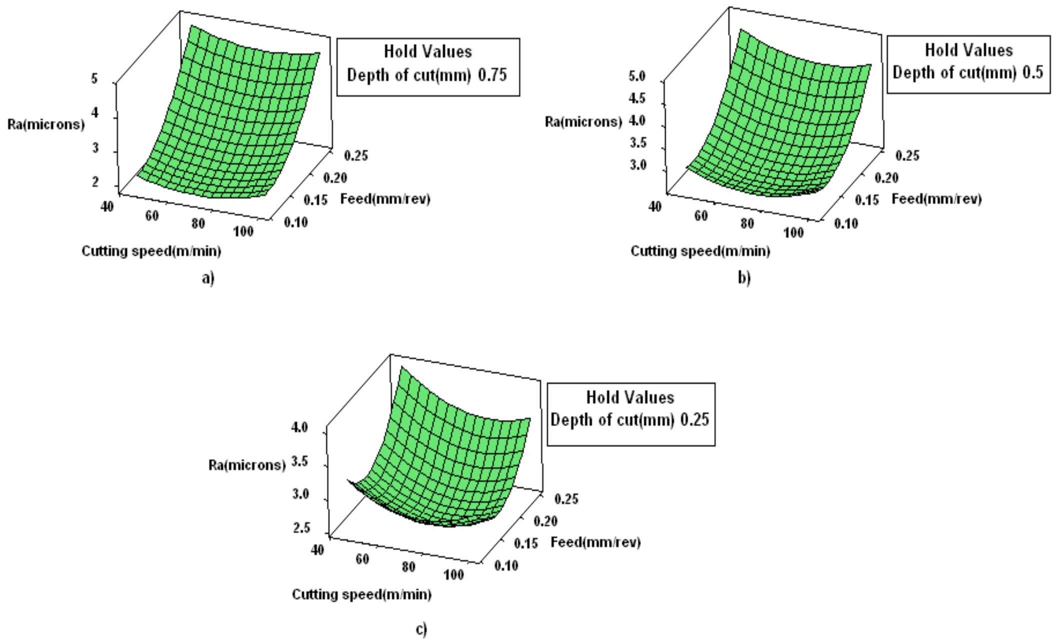

Figure 7. Surface plots of surface roughness at cutting speed - feed planes for different depths of cut: a) 0.75mm, b) 0.5mm, c) 0.25mm

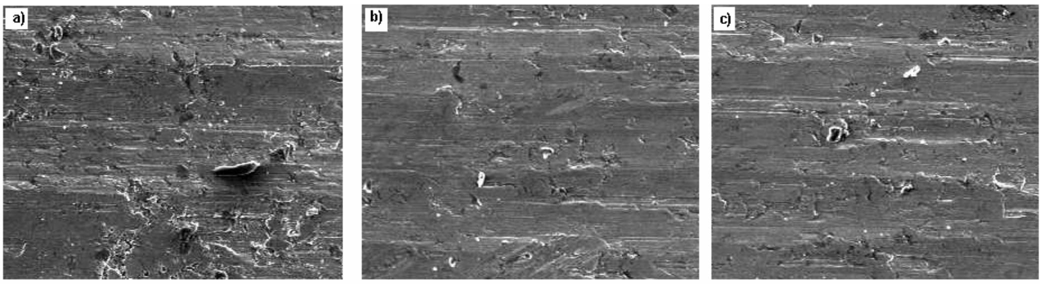

Figure 8. SEM images of machined surface at different feeds: (a) 0.25mm/rev, (b) 0.18mm/rev, (c) 0.11mm/rev

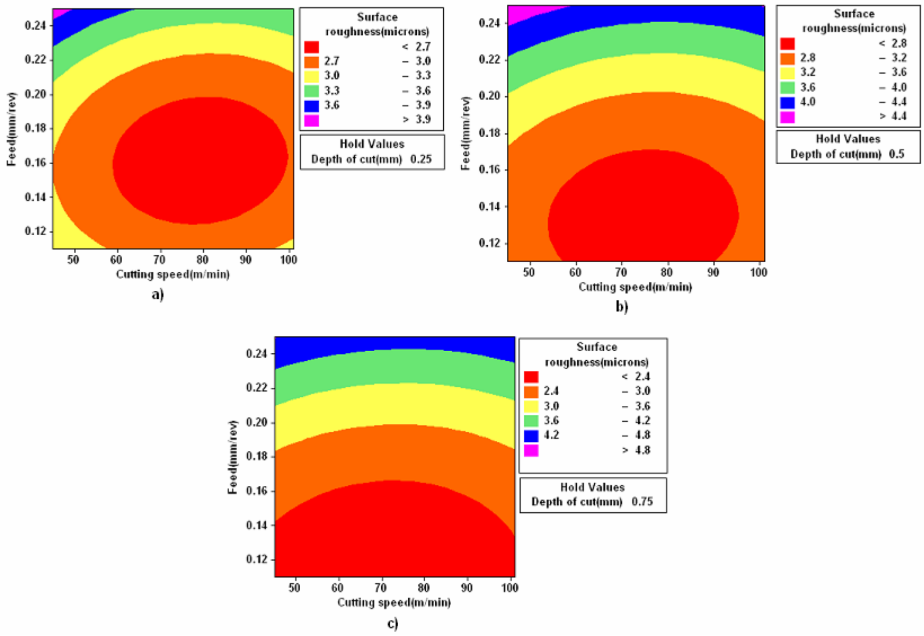

Figure 9. Contour plots of surface roughness at cutting speed - feed planes for different depths of cut: a) 0.25mm, b) 0.5mm, c) 0.75mm

Confirmation experiment

In this study, a confirmation experiment was conducted with the 3 levels of optimal process parameters (A, B, C– Table 3). Resulting from the optimisation process, three R_a values (3.249µm, 2.889 µm and 4.674 µm) were obtained from the response function derived from equation 8 for levels 1, 2 and 3, respectively. These R_a values were compared against the experimentally determined values (3.220µm, 2.720 µm and 4.600 µm). The predicted values and the measured ones are fairly close, which indicates that the developed model can be effectively used to predict the surface roughness in the machining of DRACs. A comparison between predicted and measured values is shown in Figure 10.

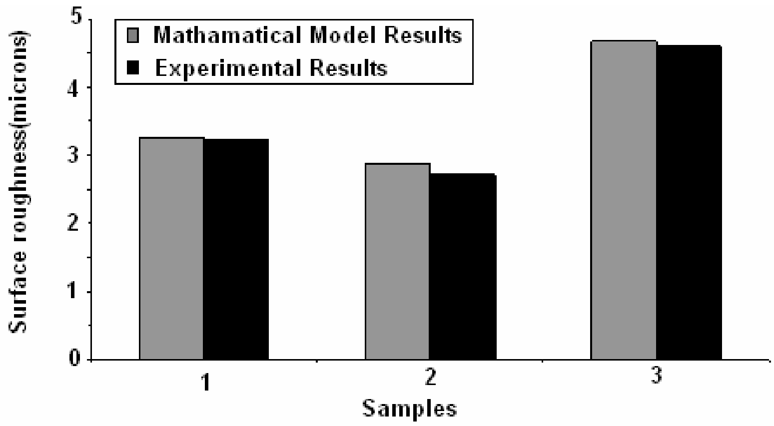

Figure 10. Comparison of surface roughness obtained by mathematical modeling and experiment for three different conditions: (1) cutting speed 45m/min, feed 0.11mm/rev, depth of cut 0.25mm; (2) cutting speed 73m/min, feed 0.18mm/rev, depth of cut 0.5mm; (3) cutting speed 101m/min, feed 0.25mm/rev, depth of cut 0.75mm

Conclusions

The effects of different cutting conditions under dry cutting on the surface roughness resulting from the turning process in machining of DRACs have been evaluated with the help of Taguchi's technique and response surface methodology, and optimal machining conditions to minimise the surface roughness have been determined. It was found that feed is the dominant parameter affecting surface roughness, followed by cutting speed while depth of cut shows minimal effect on surface roughness compared to other parameters. To achieve a good surface finish of the DRACs work piece a slower feed is preferred.

Response surface methodology provides a large amount of information with a small amount of experimentation. A second-order response surface model for surface roughness has been developed from the observed data. The predicted and measured values are fairly close, which indicates that the developed model can be effectively used to predict the surface roughness resulting from the machining of DRACs with 95% confidence intervals. Using such model, one can obtain a remarkable savings in time and cost.

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