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Multi-response Optimization of End Milling Parameters for Al-Zn-Mg/SiC Co-continuous Composite Using Response Surface Methodology

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A co-continuous ceramic composite (C4) was manufactured by gravity infiltration. The effect of varying machining parameters namely, speed, feed and depth of cut during end milling of C4, on the multi-responses of surface roughness, tool wear and depth of cut was investigated using response surface methodology. Non-linear regression models were generated and optimal machining parameters were determined using desirability analysis. Confirmation experiments performed, validated the models with a ± 5 % error in prediction.

Keywords: Co-continuous composite, response surface methodology (RSM), machinability, optimization.

1. INTRODUCTION

The term 'co-continuous' refers to a class of composites in which the two phases namely, metal and ceramic are topologically interconnected resulting in a three-dimensionally interpenetrating structure which possesses near to isotropic properties [1]. Co-continuous ceramic composites (referred to as C4) possess the advantages of higher wear resistance, enhanced thermal and electrical conductivity, high stiffness and hardness over discontinuous phase composites [2]. C4 with Al and SiC as the metal and ceramic phases have been widely researched. These composites have potential for applications involving high temperature, superior wear characteristics, high strength and specific modulus [3]. Specifically, the Al 7xxx series alloys with composition Al-Zn-Mg-Cu in varying proportions are lightweight, corrosion resistant and possess high specific strength. In the 1990s, Al 7068 was specially developed by Kaiser Aluminium. It was designed as an alternative to Al 7075, which is typically used in aerospace and valve components. Al 7068 retains its mechanical properties even at elevated temperatures and has a higher strength to weight ratio compared to Al 7075 [4]. This strongest commercially available alloy is widely used as alternative material for connecting rods, valve bodies and prosthetic limbs [5]. With increasing applications for Al-SiC C4 composites in industry, machinability studies are required to analyze how the characteristics like tool wear, surface roughness and material removal rate vary with cutting speed, feed and depth of cut. Machinability studies were performed on Al reinforced with 5, 10 and 15 % SiC particles using a TiN coated hard carbide tool [6]. It was found that cutting speed and feed had a major effect on tool wear. Also, there was an improvement in the surface quality when cutting speeds were decreased. A Taguchi and Response Surface Methodology (RSM) based analysis for determining the optimal machining conditions has been discussed by Sarikaya and Gullu [7]. S/N ratio, surface graphs and desirability analysis were utilized to determine the optimal operating parameters. Results indicated that feed rate significantly affected the surface roughness of the workpiece. Box Behnken Designs in RSM have been deployed to develop mathematical models during machining of Ti-6242S alloy using cemented carbide end mill [8]. This study, reported a deviation of the RSM predicted values from the measured response by 0.53 % indicating the robustness of the developed mathematical models. Multi-response parameter optimization using RSM has been performed on thermal insulation coatings [9]. Here, optimization of unique multi-WATIC thermal insulation was conducted using single factor experiments by RSM. A good fit between experimental and test data with 0.4 °C deviation was reported.

A review of previous literature reveals that RSM in conjunction with Taguchi design has been extensively used to optimize machining parameters. However, very few studies have investigated the machinability of co-continuous composites. The present study focuses on ascertaining the optimal process parameters to achieve desirable response values of machining characteristics during end milling of a C4. Fig. 1 illustrates the methodology followed for optimizing the machining process parameters.

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2. EXPERIMENTAL METHODS

2.1. Design of experiments (DOE)

Statistical DOE has been extensively used in machinability studies to determine the most significant factors affecting the output of the machining process. Experimental analyses involving one-factor at a time consume time and are expensive. On the other hand, analyzing a limited set of statistically fitting data can yield reliable results. Therefore, DOE techniques such as Taguchi methods, response surface design and factorial design are widely applied in order to overcome the limitations of one-factor approach [10, 11]. To determine the most effective machining conditions, literature indicates that an extensive study of machining parameters and their responses is essential. Consequently, the present study investigates the effect of three machining parameters namely, speed, feed and depth of cut on the responses particularly, surface roughness, tool wear and material removal rate.

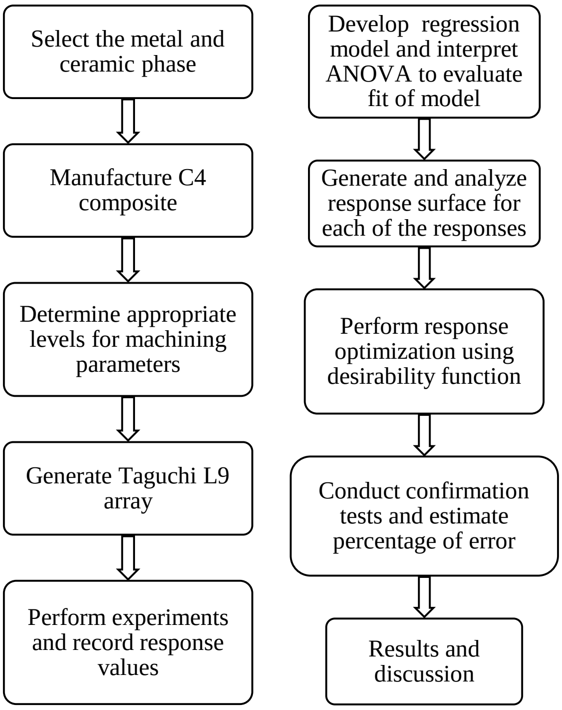

Fig. 1. Flow chart of the methodology

2.2. Response surface methodology (RSM)

RSM is an empirical modeling approach, typically employed to model and analyze problems in which multiple, controllable factors affect a response. By simultaneously varying the input parameters and the interactions of these independent variables, their effect on the response value can be precisely studied using RSM. In RSM, it is possible to achieve the exact value in addition to determining the levels for optimal design of a factor [12]. Central composite design (CCD) and Box-Behnken designs (BBD) are the two most widely used response surface designs. Typically, a BBD entails fewer experiments and does not examine extreme factor combinations [13]. Hence, BBD is chosen to model the experimental design in this study. In RSM, the relationship between the independent input variables and response can be represented by Eq. 1.

$$y = \phi\ (v, f, d), \tag{1}$$

where y and ϕ denote the desired response and response function (surface) respectively. Essentially, Eq. 1 depicts the response as a function of speed (v), feed (f) and depth of cut (d). The response y, can be approximated using the two factor interaction model shown in Eq. 2.

$$y = \beta_0 + \sum_{i=1}^{3} \beta_i\, x_i + \sum_{i<j}^{3} \beta_{ij}\, x_i x_j, \tag{2}$$

where β_0 is a constant, and β_i, β_{ij} represent the coefficients of linear and cross-product terms respectively. The values of the coded variable x_i (i = 1,2,3) can be obtained from the transformation equations shown in Eq. 3 – Eq. 5.

$$x_1 = \frac{v - v_0}{\delta v}\ ; \tag{3}$$

$$x_2 = \frac{f - f}{\delta f}\ ; \tag{4}$$

$$x_1 = \frac{d - d_0}{\delta d}\ , \tag{5}$$

where x_1, x_2 and x_3 denote the coded values of the input parameters v, f and d. The zero levels of the input parameters are represented by v_0, f_0, d_0 and the intervals of the variations in the input parameters are indicated by δv, δf and δd. In this study, RSM is combined with Taguchi method to find optimal values of machining parameters.

3. EXPERIMENTAL PROCEDURE

3.1. Test specimen

In order to fabricate the C4, Al 7068 alloy and commercially available SiC foam of size 10 ppi were chosen as the metal and ceramic phase respectively. Spectroscopy was performed for compositional evaluation of Al 7068. From the composition listed in Table 1, it can be inferred that the alloy confirms to ASM specifications. This Al alloy was then infiltrated to the SiC foam using gravity infiltration technique [14] without application of pressure.

Table 1. Composition of Al 7068

Element	Al	Zn	Mg	Cu	Zr	Fe
Composition %	87.1	7.75	2.74	2.05	0.114	0.107

As evident from the machined composite in Fig. 2, the Al and ceramic phase form an interpenetrating structure and are yet, clearly distinguishable.

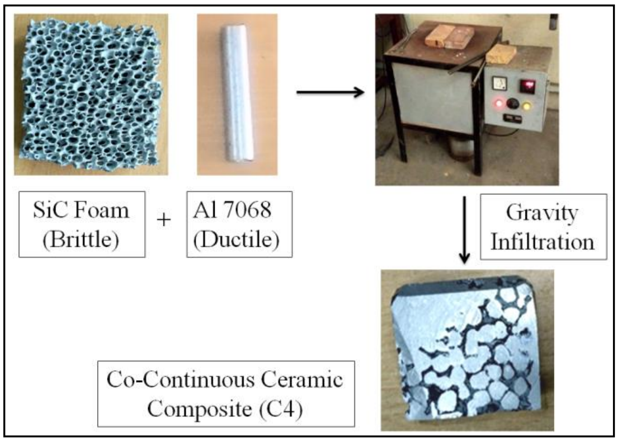

Fig. 2. Manufacturing process of C4

3.2. Machinability studies

A 5 mm solid carbide tool in uncoated condition was used to conduct machinability studies on the C4 composite thus manufactured. Three control factors, namely, speed (v), feed (f) and depth of cut (d) at three levels as shown in Table 2, were selected for experimental study.

Table 2. Control factors and levels

Factors	Unit	Code	Level 1	Level 2	Level 3
speed (v)	rpm	A	3000	5000	7000
feed (f)	mm/min	B	450	600	750
depth of cut (d)	mm	C	0.2	0.4	0.6

In order to study the effect of the control factors v, f and d on the multi-responses of surface roughness (SR), tool wear (TW) and material removal rate (MRR), a Taguchi L9 array shown in Table 3 was formulated.

End milling of slots was then performed on the C4 using a Makino VMC-S33 machine as shown in Fig. 3.

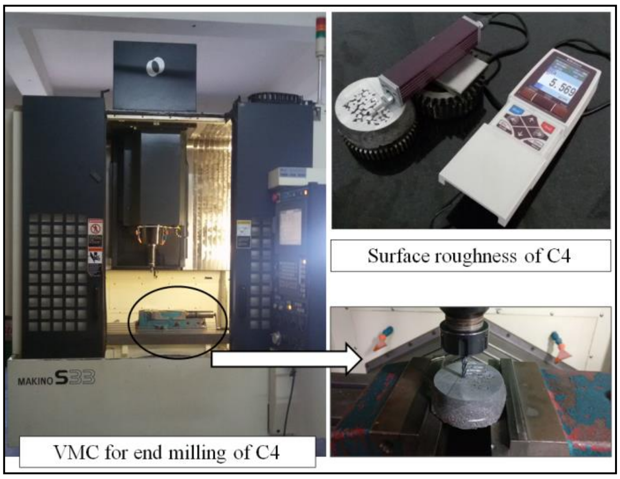

Fig. 3. End milling of C4

Surface roughness was measured using a Mitutoyo Surftest SJ-210 surface roughness tester. Tool wear as depicted in Fig. 4, was evaluated using a Dino-Lite AM7013MZT digital microscope. MRR, as shown in Eq. 6, was calculated from the weight difference of the C4 during machining.

$$MRR = \frac{w_b - w_a}{\rho_a t} , \tag{6}$$

where w_b and w_a represent weight of C4 before and after machining, ρ_a is the density of Al 7068 (2.7×10^{-3} g/mm^3) and t is the machining time. The values of the responses are tabulated in Table 3.

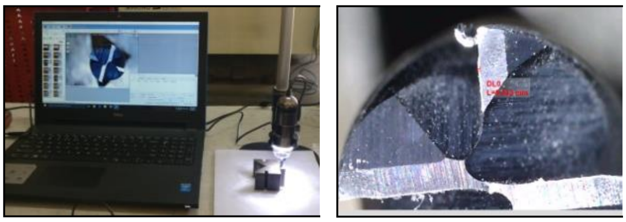

Fig. 4. Tool wear during machining of C4

Table 3. Taguchi L9 orthogonal array for machining of C4

Exp No	Levels of control factors			Values of response		
	A	B	C	SR, µm	TW, mm	MRR, mm^3/min
1	1	1	1	2.572	0.032	535
2	1	2	2	3.545	0.031	1202
3	1	3	3	5.569	0.029	1970
4	2	1	2	2.742	0.028	1075
5	2	2	3	3.731	0.027	1866
6	2	3	1	4.180	0.027	767
7	3	1	3	2.967	0.026	1559
8	3	2	1	3.362	0.025	675
9	3	3	2	5.014	0.023	1462

4. RESULTS AND DISCUSSION

4.1. ANOVA and RSM

A non-linear regression analysis was performed on the responses using statistical analysis software by defining a custom BBD - response surface design for Taguchi L9 array. Certain insignificant terms were discarded through the backward elimination process to arrive at the fitted regression models with interaction effects. The response equations for SR, TW and MRR in terms of coded factors are shown in Eq. 7 – Eq. 9.

$$SR = 3.55 + 0.11\times A + 1.08\times B + 0.36\times C + 0.33\times B\times C + 0.29\times B^2; \tag{7}$$

$$TW = 0.028 - 0.003\times A - 0.001167\times B - 0.00053\times C - 0.0004\times A\times B; \tag{8}$$

$$MRR = 1234.56 + 11.67\times A + 155.24\times B + 606.24\times C + 73.14\times A\times B - 32.86\times A\times C + 27\times B\times C. \tag{9}$$

An ANOVA was performed to evaluate the significance of the fitted models of SR, TW and MRR as shown in Table 4. A model can be considered to be statistically fit when the P value is less than 0.05 at 95 % confidence level. It is evident from Table 4 that the P values for the regression models of SR, TW and MRR are less than 0.05 and hence, significant. The coefficient of determination R^2, is a measure of the closeness of the response data to the fitted regression model. The closer the value of R^2 is to unity, the better the response equations fit the observed data [15]. In particular, R^2_{pred} denotes the ability of the fitted regression model to predict responses for new observations. It can be observed from Table 4 that, the values of R^2, R^2_{pred}, and R^2_{adj} for all the three responses, approach unity. Additionally, the value of R^2_{pred} lies in close proximity to R^2_{adj} indicating the ability of the regression model to predict new observations. The normal probability plots revealed that the residuals are normally distributed. The plots of residuals versus predicted response displayed no obvious pattern implying that the three proposed models are adequate and no violation of the constant variance assumption exists [16].

4.2. Effect of machining parameters on SR

Since the regression models are adequate, 3D surface plots of all the three responses can be utilized to predict new observations for a given combination of machining parameters.

Table 4. ANOVA table for the fitted models

	Sum of squares (Seq SS)	Degrees of freedom	Mean square (Adj MS)	F value	P value
For surface roughness (SR)		PRESS = 0.78			
Model	8.23916	5	1.65	80.44	0.0021
Residual Error	0.061	3	0.020		
Total	8.30	8			
$R^2 = 99.26$ %		$R^2_{pred} = 90.60$ %		$R^2_{adj} = 98.03$ %	
For tool wear (TW)		PRESS = 4.51E-06			
Model	0.000063	4	0.000015	63.94	0.0007
Residual Error	0.000001	4	0.0000002		
Total	0.000064	8			
$R^2 = 98.46$ %		$R^2_{pred} = 92.98$ %		$R^2_{adj} = 96.92$ %	
For material removal rate (MRR)		PRESS = 88749.3			
Model	0.000002	6	0.000035	499.1	0.002
Residual Error	1431	2	715.54		
Total	0.000002	8			
$R^2 = 99.93$ %		$R^2_{pred} = 95.86$ %		$R^2_{adj} = 99.73$ %	

The estimated response surface in Fig. 5 a shows a non-linear variation of SR. The interactions in Fig. 5 a show that, when speed is constant, SR increases moderately at high DoC and rapidly with higher feed rate. Significantly, the value of SR peaks at high feed and DoC. Therefore, better surface quality can be obtained at lower feed rate and DoC. The contour lines in Fig. 5 a, signify a curvilinear surface. This indicates the existence of a second order regression model in which the maximum power of the terms in the model is two. The response equation for SR in Eq. 7 contains a second order term for feed. This confirms the inference from the contour plot.

4.3. Effect of machining parameters on TW

The 3D surface plot of tool wear is depicted in Fig. 5 b. The plot reveals that, at constant DoC, the interaction between speed and feed is significant. In particular, higher tool wear occurs at lower cutting speed and lower feed values. This can be attributed to high cutting forces and built-up edge formation during end milling at low speeds and feeds [17]. The contour lines of TW for the interaction between speed and feed in Fig. 5 b reveal a linear relationship between speed and feed. The slopes of the graphs reveal that, variation in speed has a higher influence on the TW.

4.4. Effect of machining parameters on MRR

The three dimensional surface plots of the effect of machining parameters on MRR are displayed in Fig. 5 c, d and e. It can be seen from the surface plots that, invariably, a high MRR is attained at higher values of speed, feed and DoC. It can also be deciphered from the contour plot in Fig. 5 c that, the interaction between speed and DoC significantly affects MRR.

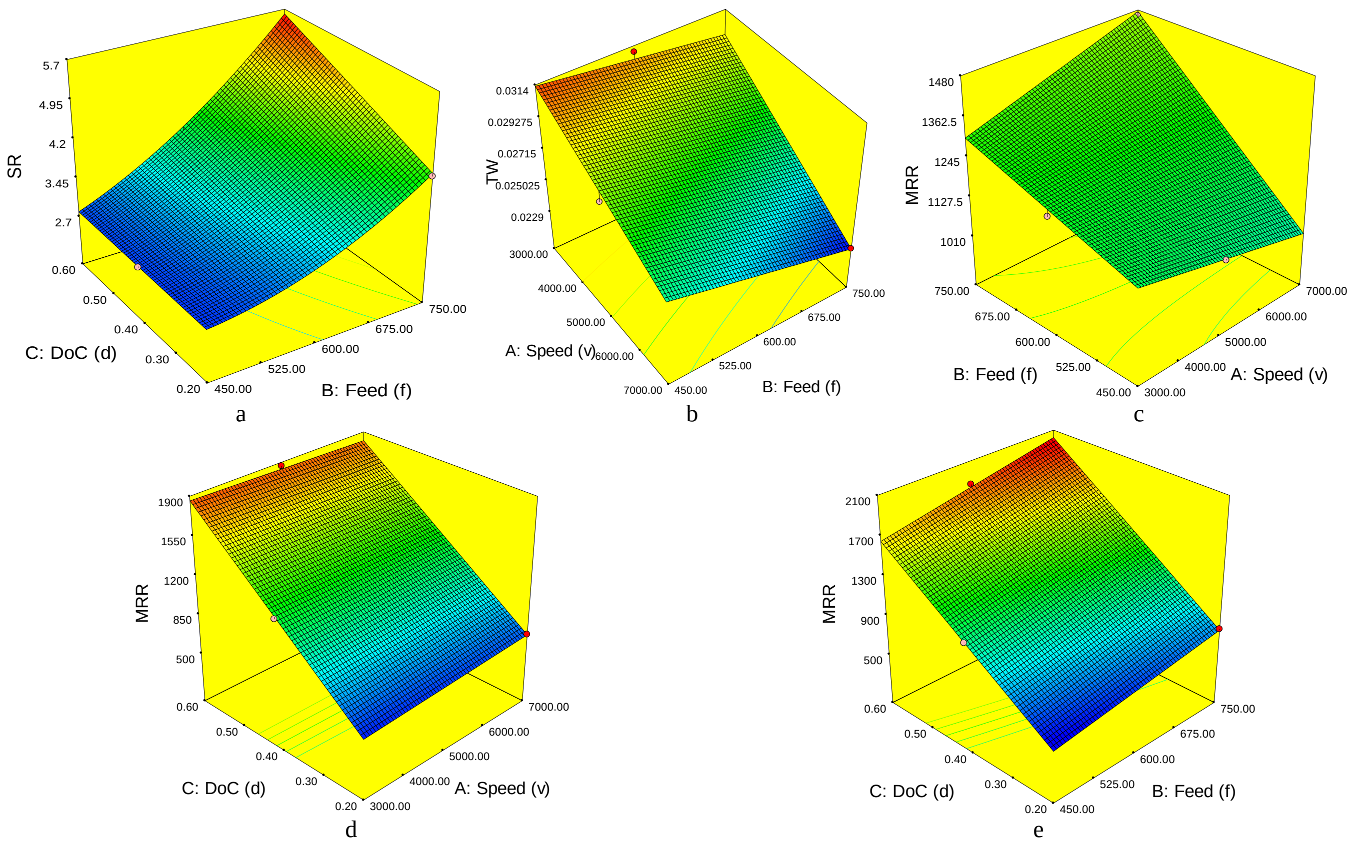

Fig. 5. The response surfaces of the regression models: a – the effect of interaction of BC on surface roughness; b – the effect of interaction of AB on toll wear; c – the effect of interaction of AB on MRR; d – the effect of interaction of AC on MRR; e – the effect of interaction of BC on MRR

The contour lines in Fig. 5 d and e lie close together, indicating a steep slope of the 3D surface.

4.5. Response optimization using desirability function

In addition to understanding the effect of varying machining parameters on the response values, one of the principal objectives of applying RSM technique is to determine the optimal values of machining parameters. Response surface optimization is performed using desirability function approach outlined by Derringer and Suich [18]. In this approach, a dimensionless value of desirability 'd_i' is calculated by transforming the values of each predicted response on a scale from 0 to 1 where, $d_i = 0$ indicates an unacceptable value of response and $d_i = 1$ denotes response achieving the target value. Desirability functions are of three types (i) smaller the better (ii) nominal the better and (iii) larger the better. For a response y_i to be minimized, the desirability is defined by Eq. 10.

$$d_i = \begin{cases} 0 & \text{if } y_i < L_i \\ \left(\frac{U_i - y_i}{U_i - L_i}\right)^r & \text{if } L_i < y_i < U_i \text{ ; weight } r \geq 0. \\ 1 & \text{if } y_i > U_i \end{cases} \quad (10)$$

The desirability function to maximize a response y_i is described by Eq. 11.

$$d_i = \begin{cases} 0 & \text{if } y_i < L_i \\ \left(\frac{y_i - L_i}{U_i - L_i}\right)^r & \text{if } L_i < y_i < U_i \text{ ; weight } s \geq 0. \\ 1 & \text{if } y_i > U_i \end{cases} \quad (11)$$

In Eq. 10 and Eq. 11, U_i and L_i refer to the acceptable range of upper and lower values of the response. The values of the weights r and s influence the closeness of the response y_i to minimum or maximum, depending on the optimization problem. Subsequently, the individual desirability functions of all the responses can be combined to form a unique function termed as composite desirability (D) [7], defined by Eq. 12

$$D = \left(d_1^{w_1} x\, d_2^{w_2} x\, d_3^{w_3} \ldots\ldots\ldots x\, d_i^{w_i}\right)^{\frac{1}{\sum w_i}}, \quad (12)$$

where w_i refers to the weight of each response relative to the other. Factor settings leading to higher values of composite desirability represent optimal machining conditions. The optimization goals set for each of the responses are tabulated in Table 5.

Table 5. RSM optimization results

Response	Goal	Individual desirability, d_i	Predicted value, y	Optimal machining parameters
SR	Min	0.98130	2.6828	v = 3000 rpm f = 450 mm/min d = 0.6 mm
TW	Min	0.86335	0.0308	
MRR	Max	0.92284	1752.89	
Optimal composite desirability (D) = 0.92124				

SR and TW are to be minimized whereas MRR is to be maximized. The results of the desirability analysis from statistical software are shown in Fig. 6. The individual desirabilities for SR, TW and MRR have been estimated as 0.9813, 0.86335 and 0.92284 respectively. Further, the composite desirability for the combination of all the goals is 0.92124, close to the highest attainable desirability of 1.

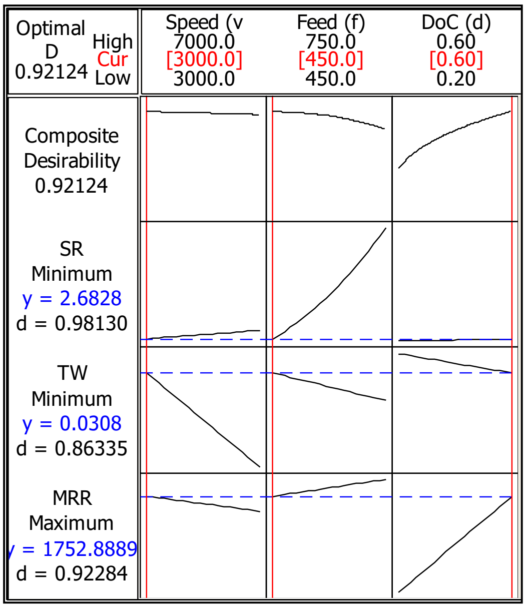

Fig. 6. Composite desirability of responses

4.6. Confirmation Experiment

In order to validate the model developed using RSM, three confirmation experiments were conducted. The test conditions were selected within the range of the experimental values. The predicted values were compared with the experimental values. The deviations as quantified by the error percentages in Table 6 reveal that, the measured values are close to predicted values.

Table 6. Results of confirmation experiments

S. No	v, rpm	f, mm/min	d, mm	Experimental result		RSM predicted	Error, %
1	3000	600	0.6	SR	3.921	3.7975	3.15
				TW	0.029	0.030	–3.44
				MRR	1838	1861.9841	–1.30
2	5000	750	0.4	SR	4.776	4.9210	–3.04
				TW	0.027	0.0264	2.22
				MRR	1335	1389.7937	–4.11
3	7000	450	0.4	SR	2.952	2.8677	2.86
				TW	0.025	0.0261	–4.40
				MRR	1062	1017.8413	4.16

This affirms that, the response equations obtained through RSM can reliably predict the values of SR, TW and MRR for a given combination of speed, feed and DoC within the range of the experiments performed.

5. CONCLUSIONS

In the present work, end milling of a co-continuous ceramic composite was performed using Taguchi method. Regression models were developed using response surface methodology and experimental results were evaluated using ANOVA, surface and contour plots. The optimal operating parameters were then identified by desirability analysis. The following conclusions are established based on this work:

1. The P values in the ANOVA indicate that the fitted regression equations are statistically significant.
2. The surfaces, contours and equations reveal that feed rate and depth of cut have a major influence on surface roughness followed by cutting speed. The interaction between feed rate and depth of cut also influences the smoothness of the surface.
3. Tool wear depends primarily on feed rate and depth of cut. The interaction of speed and feed also influences the life of the tool.
4. MRR was particularly affected by the depth of cut, interactions between all factors being significant.
5. The confirmation experiments exhibit that the developed models can reliably predict experimental results as, the deviations between predicted and measured values vary within a narrow range of ± 5 %.
6. Applying composite desirability in RSM, the optimal machining parameters were established as: speed (*v*) at 3000 rpm, feed (*f*) at 450 mm/min, depth of cut (*d*) at 0.6 mm. At these levels, the values of surface roughness, tool wear and material removal rate were 2.6828 µm, 0.0308 mm, 1752.89 mm^3/min respectively.
7. The composite desirability of the three responses was 0.92124, close to 1, indicating the ability of the model to reliably predict with 95 % confidence.

Therefore, this work presented experimental results to develop a statistical prediction model which can be employed to ascertain the favorable combination of cutting conditions to achieve the desired surface roughness, tool wear and material removal rate in a C4.

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