Modeling of Surface Roughness and MRR in MQL aided Turning of SiC Reinforced Al Alloy Composite Using an integrated RSM-PCA approach

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***Abstract* — This paper focuses on the effect of different machining parameter on surface roughness and material removal rate in turning SiC reinforced Al alloy composite through experimental analysis and response surface methodology (RSM) based predictive modeling which has been further optimized using principal component analysis (PCA). Experimental study has been carried out under minimum quality lubricant (MQL) condition. Palm oil has been used as lubricant where pressure and flow rate were kept at 8 bar and 120 ml/hr. The study has been planned using central composite design approach where cutting speed, feed rate and depth of cut has been taken as input parameters to check the desired resultant responses. Response model for surface roughness and material removal rate (MRR) has been developed using quadratic model. Correlation coefficient values of 0.99872 and 0.99974 implies the adequacy of the model. Main effect plot and 3D surface plot have been used to assess the effects and interaction of the input parameter. Afterwards, machining parameters were optimized using PCA technique. To obtain favorable responses, depth of cut, cutting speed and feed rate need to be at 0.5 mm, 131 m/min and 0.10 mm/rev respectively. By implementing the model, surface roughness of 0.989 µm and MRR of 21111.488 mm^3/min can be attained.**

Keywords— SiC reinforced Al alloy composite, Turing, Minimum Quality Lubricant, Surface Roughness, MRR, Response surface methodology, Principal component analysis

I. INTRODUCTION

Composite materials produce some combinational properties of two or more materials that cannot be achieved by either fiber or matrix when they are acting alone. Fiber-reinforced composites were successfully used for many decades for all engineering applications [1]. Metal matrix composites (MMC) are the new class of materials and are rapidly replacing conventional materials in various engineering applications such as the aerospace and automobile industries. Some of the typical applications are bearings, automobile pistons, cylinder liners, piston rings, connecting rods, sliding electrical contacts, turbo charger impellers, space structures etc. The most popular reinforcements are silicon carbide (SiC) and alumina (Al_2O_3). Aluminium, titanium, and magnesium alloys are commonly used as the matrix phase. The density of most of the MMCs is approximately one third that of steel, resulting in high specific strength and stiffness. It is possible to produce high-quality MMC components to near net shape through various manufacturing techniques, but additional machining is unavoidable to achieve the desired surface quality and dimensional tolerance for efficient assembly [2].

Clearly, the applications will also vary widely to reflect the balance between cost and properties offered by each type of MMCs. Metal matrix composites (MMCs) belong to a group of high-performance engineering materials, which combine tough metallic matrix with a hard ceramic or soft reinforcement to produce composite materials. Among modern composites materials, particle reinforced MMCs are finding increased application due to their favorable mechanical properties and good wear resistance. SiC reinforced is considered widely and other compositions for the matrix are available commercially [3,4].

The surface finish is an important parameter in the machining process. Surface roughness has received serious attention for many years. In addition to tolerances, surface roughness imposes one of the most critical constraints for selection of machines and cutting parameters in process planning. In the view of above machining problems, the main objective of the present work is to investigate the influence of different cutting parameters on the surface roughness. To the best of the authors' knowledge, little research has been carried out to determine the effects of cutting parameters on machining of hard ceramic composite and hybrid composite Al/SiC/Graphite particulate metal matrix composite. Response surface methodology (RSM) is utilized and for experimental planning and analysis during turning of SiC/Al alloy composite. The results are analyzed to achieve optimal surface. In order to know surface quality and dimensional properties, it is necessary to employ theoretical models for prediction purpose. For prediction, the response surface method (RSM) is practical, economical and relatively easy to use. The relationships between response and process parameters are commonly found using multiple linear regression analysis techniques (RA), response surface methods (RSM) and artificial neural networks (ANN) [5,6].

Various machining processes such as turning, drilling and milling have been used to machine composite materials for different product requirements. Despite the existing experience in machining traditional materials such as metals, it has been a challenge to maintain consistent results in terms of machining quality for composite materials [7]. Li and Seah investigated machining properties of 5% SiC-Al-MMC material using coated carbide cutting tool in turning operation. They applied various cutting speed (maximum was 88 m/min) and concluded that increasing cutting speed raised tool wear. They also noticed abrasion wear on the flank face of the tool [8]. Al/SiC-MMC was manufactured through stir casting process and turning operation was performed by Arokiadass et al. to study the effects on surface roughness. Feed rate found to be the most dominant parameter on the surface roughness followed by spindle speed and weight percentage of SiC [9].

An investigation focuses on the influence of machining parameters on the surface finish obtained in turning of Al-SiC particulate composites. In this work, the effect of machining parameters on the surface roughness is evaluated and optimum machining conditions for maximizing the metal removal rate and minimizing the surface roughness are determined using response surface methodology. A second-order response surface model for the surface roughness is developed to predict the surface roughness. The predicted values and measured values are fairly close to each other, which indicates that the developed model can be effectively used to predict the surface roughness on the machining of Al-SiC MMC composites with 95% confidence intervals within the ranges of parameters studied [10].

An application of response surface methodology (RSM) and central composite design (CCD) for modeling, optimization, and an analysis of the influences of dominant machining parameters on thrust force, surface roughness and burr height in the drilling of hybrid metal matrix composites produced through stir casting route. Experiments are carried out using Al 356-aluminum alloy reinforced with silicon carbide of size 25 µm and Mica of size 45 µm. Drilling operation is carried out using carbide drill of 6 mm diameter. The multiple regression analysis using RSM is used to establish the input-output relationships of the process. The optimized drilling process parameters have been obtained by numerical optimization using RSM by ensuring the minimum thrust force of 84 N, surface roughness of 1.67 µm, and the burr height of 0.16 mm [11]. 3D surface plots of Response Surface Methodology (RSM) for AA7075-15 wt % SiC composite revealed that cutting speed is the most significant factor followed by depth of cut, feed and nose radius [12].

Abhang and Hameedullah developed a predictive model using RSM for turning of EN-31 steel with tungsten carbide tool. The results showed that feed rate has the most significant effect on power consumption, followed by the depth of cut, tool nose radius and cutting speed. It was shown that the second order model is more precise than the first order model in predicting the power consumption during machining [13]. RSM and Taguchi's technique was also used by Aggarwal et al. to investigate the effect of cutting speed, feed, depth of cut, nose radius, and cutting environment during turning of AISI P20 tool steel on the power consumption. Results show that the cutting speed is the most significant factor followed by depth of cut and feed rate [14].

To investigate the influences of machining parameters, the application of RSM on the hard turning of Hadfield steel with Al_2O_3/TiC mixed ceramic tool had carried out the mathematical models of the flank wear (V_{bmax}) and the surface roughness (R_a). For finding optimum value of machining parameters, the quadratic model of RSM associated with SAO method was utilized. Using the SAO method of RSM, the optimal setting of machining parameters is found to be cutting speed of 209.29 m/min, feed rate of 0.08 mm/rev., cutting depth of 0.25 mm and nose radius of 0.88 mm. For machining Hadfield steel in the hard-turning process, the optimal values of the flank wear (V_{bmax}) and surface roughness (R_a) represent the reduction of 9.25% and 8.74%, which is compared to the results of initial machining parameters, using this optimal process [15].

Debaprasanna Puhan, Siba Sankar Mahapatra have investigated the multi-response optimization of non-conventional machining on Al-SiC/p MMC. In order to simultaneously optimize multiple responses, a hybrid approach combining principal component analysis (PCA) and fuzzy inference system is coupled with Taguchi method. In this experimental study, it is found that the influence of each parameter on the responses is established using analysis of variances (ANOVA) at 5% level of significance & the hardness of MMC is increasing with increasing weight% of SiC in the composite and mesh size. The conductivity of MMC is decreasing with increasing weight percentage of SiC. The optimal values of responses such as MRR, TWR, surface roughness and circularity are found as 14.376 mm^3/min, 0.018 mm^3/min, 3.043 µm and 0.970 respectively [16].

Optimization design and the effects of cutting speed, feed rate, depth of cut, and nose radius in computer numerical control (CNC) turning operation of a turning process performed on red mud-based aluminum metal matrix composites have investigated by S. Rajesh, D. Devaraj, R. Sudhakara Pandian & S. Rajakarunakaran. The taguchi-based grey analysis is specifically adapted to determine the optimal combination of turning parameters. The principal component analysis (PCA) is applied to evaluate the weighting values corresponding to various performance characteristics. The outcome of confirmation experiments reveals that grey relational analysis coupled with PCA can be effectively used to obtain the optimal combination of turning parameters &

useful tool to improve the turning performance of red mud-based aluminum metal matrix composites in CNC turning process [17].

However, not a lot of effort has been put on by the researchers to analyze the impact of different parameter under MQL cutting condition. An integrated RSM-PCA approach has also been rarely used by researchers to develop a predictive model. This existing study discloses the effect of different machining parameter in turning SiC reinforced Al alloy composite under Minimum Quality Lubricant (MQL) assisted cutting environment. In order to obtain examined data, coated carbide is employed after taking different range of cutting speed, feed rate and depth of cut into consideration. Main effect plot and 3D surface plot are used to analyze the impact of various parameters. An RSM based quadratic model has been developed while parameters are optimized using PCA. This presented study avails the necessity of incorporating RSM-PCA method to establish an effective predictive modeling of surface roughness and material removal rate.

II. MATERIALS AND METHODS

A. *MATERIALS AND EXPERIMENTAL DETAILS*

Metal matrix composite was developed using SiC as reinforcement material whereas Al alloy was used as matrix material. Composition of Al 6061 and developed MMC were as follows:

Developed MMC composition		
Al 6061-90%	SiC-10%	
Al 6061 Composition		
Al - 98 %	Mg - 0.8 %	Fe - 0.50 %
Zn - 0.25 %	Cr - 0.25 %	Cu - 0.2 %

The composite was fabricated using stir casting process as portrayed in Fig.1.

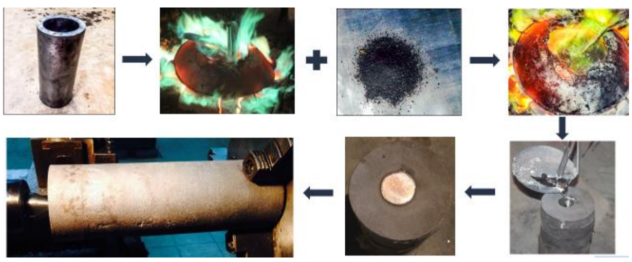
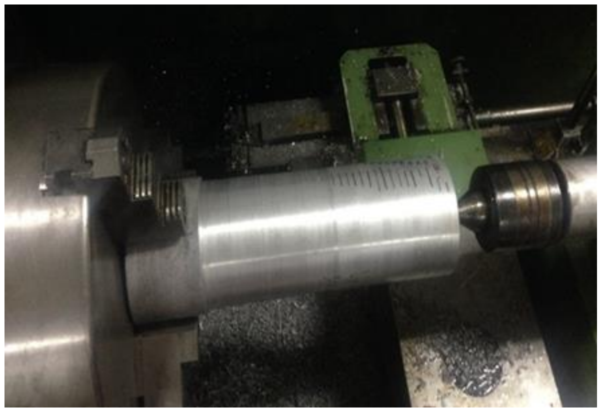


Fig.1: Development process of SiC reinforced Al Alloy composite

Final length and diameter of the material was 300mm and 105mm respectively. MQL assisted turning operation was carried out using a center lathe machine by using SNMG coated carbide insert. Experimental setup is shown in Fig. 2. During MQL condition, Pressure was set at 8 bar, Flow rate was at 120 ml/hr.



(a)

(b)

Fig.2: Experimental Setup (a & b) under MQL cutting condition

In this work machining was initiated with different levels of depth of cut, cutting speed and feed rate. The measurements were carried out by varying three machining parameters: cutting speed (V_c), feed rate (S_o) and depth of cut (t) which was considered as input variables and assigned to different levels as shown in Table 1. The combinations of machining parameter that was designed by response surface methodology and observed resultant outputs (surface roughness, material removal rate) are shown in Table 2.

TABLE 1: ASSIGNMENTS OF FACTORS TO DIFFERENT LEVEL

Variables	**Units**	**Low**	**High**	**-alpha**	**+alpha**
t	mm	0.25	0.75	0.25	0.75
V_c	m/min	131	329	131	329
S_o	mm/rev	0.1	0.14	0.1	0.14

TABLE 2: EXPERIMENTAL INPUT VARIABLES AND MEASURED RESPONSES FOR MQL CUTTING CONDITION

Factors			Responses	
t (mm)	**V_c** (m/min)	**S_o** (mm/rev)	**R_a** (µm)	**MRR** (mm^3/min)
0.25	131	0.1	0.96	3298.65
0.75	131	0.13	0.98	6234.48
0.25	329	0.1	1.37	9236.25
0.25	329	0.13	1.30	13194.68
0.75	230	0.16	1.00	4618.11
0.5	131	0.16	1.14	8728.27
0.25	230	0.1	1.20	12930.75
0.75	329	0.1	1.29	18472.55
0.75	131	0.13	0.98	5277.84
0.25	329	0.1	1.25	9975.16
0.5	329	0.1	1.42	14778.00
0.5	131	0.1	0.98	21111.48
0.75	131	0.13	1.03	7257.03
0.25	131	0.16	1.17	13715.85
0.5	329	0.16	1.22	20319.76
0.5	230	0.1	1.32	29028.29
0.75	131	0.13	1.07	8576.49
0.25	131	0.16	0.95	16209.64
0.5	329	0.1	1.24	24014.26
0.75	230	0.1	1.55	34306.16

B. Response Surface Methodology

Response surface methodology establishes the relationships between several explanatory variables and one or more responses or outcomes. RSM is an empirical modeling approach for determining the relationship between various process parameters and responses for establishing the significance of these process parameters on the coupled responses. It is a combination of design of experiments, regression analysis and statistical inferences. RSM model can be utilized to state the degree of co-relation between one or more response and some selected control variables, to determine through goodness of fit-statistical significance of the factors connected with a particular response and to determine the optimum settings within the higher or lower level of control variables to minimize or maximize the response of interest [18,19].

Commonly used mathematical model for the response y and independent variables ξ1, ξ2… ξk can be represented as:

$$y = f(\xi_1, \xi_2, \ldots, \xi_k) + \varepsilon \qquad (1)$$

where, ε is termed as a statistical error, which is normally distributed by response y with mean zero and variance σ^2. Then,

$$E(y) = \eta = E[f(\xi_1, \xi_2, \ldots, \xi_k)] + E(\varepsilon) = f(\xi_1, \xi_2, \ldots, \xi_k) \qquad (2)$$

The variables ξ1, ξ2…., ξk in Eq. (2) are called as natural variables, as they are expressed in the natural units of measurement. However, it is more convenient to use coded variables (x_1, x_2, x_3...) which are dimensionless. The response function (η) can be written as

$$\eta = f(x_1, x_2, \ldots, x_k) \qquad (3)$$

It is evident from the literature that second orders mathematical model is mostly used due to flexibility, wide variety of functional forms and use of significant least square method. Second order quadratic model can be expressed as

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i<j=2}^{k} \sum \beta_{ij} x_i x_j \qquad (4)$$

where, β_{js} are regression coefficient and X_{js} are coded form of independent variables

In present work, central composite design (CCD) concept of RSM was adopted to design the experimental run. CCD design is frequently used together with response models of the second order. Statistical analysis of variance (ANOVA) is also connected with RSM.

C. Principal Component Analysis

Principal component analysis is a multivariate statistical method, which allows the original initial variables to transform into another dimensional set of uncorrelated variables called principal components (PCs). The principal components are transformed by calculating the Eigen-vectors of the covariance matrix of the original inputs. To keep some observations or variables from discriminating the calculations, the data are normalized prior to finding the principal components. Such data preprocessing can avoid the influences of the units and the relative spread of the data used for evaluating the multiple performance characteristics. The original data are converted into a range 0–1 with 1 counting the best performance and 0 the worst. The transformed variables are ranked according to their variance reflecting a decreasing importance in order to capture the whole information content of the original dataset. The PCs, which are expressed as linear combinations of the original variables, are orthogonal to each other and can be used for the effective representation of the system under investigation [16].

The principal components are calculated as

$$\boldsymbol{P_j} = \sum_{i=1}^{r} (\boldsymbol{a_{ji} Y_i}) \quad \text{for } j = 1\ldots\ldots k \qquad (5)$$

Where, Y_i is the normalized value of i^{th} response (i=1,2,…r). The coefficient a_{ji} termed as eigen vector.

As each principal component has its own variance which might not be same, in this work, variance of every principal component is used as weight to compute multi response performance index (MPI). MPI can be measured as

$$\boldsymbol{MPI} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{k}} (\boldsymbol{W_j P_j}) \quad (6)$$

Where, W_j is regarded as weight of the corresponding principal component. MPI value defines the response and it is regarded as the quality index. Hereafter, larger the MPI value insures more quality.

III. RESULTS

A. *Analysis of Variance*

Analysis of variance for the response surface models were conducted in this study. Sum of squares (SS), degree of freedom (df), Mean Square (MS), F-value and P-value for all the input variables along with their interaction terms are shown in Table 3 for MQL assisted cutting environment.

B. *Analysis of Variance for Surface Roughness*

ANOVA model was developed under MQL assisted condition The Model F-value of 18.38 implies the model is significant. There is only 0.01% chance that an F-value this large could occur due to noise. P-values less than 0.05 indicate model terms are significant. Moreover, Fit summary response for surface roughness is shown in Table 6 where R^2 value is 0.9430, which suggests a very reasonable goodness of fit of the model. The adjusted R^2 value of 0.8917 is in reasonable agreement with predicted R^2 value.

TABLE 3: ANOVA MODEL FOR SURFACE ROUGHNESS

Source	**SS**	**df**	**MS**	**F-value**	**p- value**
Model *	0.546	9	0.0607	18.38	<0.0001
t	0.360	1	0.3604	109.09	<0.0001
V_c	0.202	1	0.2027	61.35	<0.0001
S_o	0.053	1	0.0538	16.29	0.0024
$t * V_c$	0.171	1	0.1718	51.99	<0.0001
$t * S_o$	0.206	1	0.2062	62.43	<0.0001
$V_c * S_o$	0.217	1	0.2177	65.90	<0.0001
t^2	0.148	1	0.1487	45.01	<0.0001
V_c^2	0.146	1	0.1466	44.37	<0.0001
S_o^2	0.081	1	0.0811	24.54	0.0006
Residual	0.0330	10	0.0033		
* Lack of fit	0.003	3	0.0010	0.235	0.8690
Pure Error	0.0300	7	0.0043		
Cor. Total	0.5796	19			
** Model is significant; Lack of fit is not significant*					

TABLE 4: FIT SUMMARY RESPONSE FOR SURFACE ROUGHNESS

Source	Sequential p- value	Lack of fit p-value	Adjusted R^2	Predicted R^2
Linear	0.185	0.002	0.1134	0.1677
2FI	0.020	0.011	0.4733	0.1949
Quadratic*	0.0002	0.869	0.8917	0.8333
Quadratic (suggested)*				

C. *Analysis of Variance for MRR*

Using a similar approach mentioned above, ANOVA analysis has been performed for Material removal rate (MRR) where model is found to be significant after incorporating linear and quadratic interaction effect of the input parameters. ANOVA analysis and fit summary response for MRR has are shown in Table 5 and 6 respectively.

TABLE 5: ANOVA MODEL FOR MRR

Source	**SS**	**df**	**MS**	**F-value**	**p-value**
Model *	1.2E+09	9	1.4E+08	23.90	<0.0001
t	3.2E+07	1	3.2E+07	5.47	0.0415
V_c	2.8E+07	1	2.8E+07	4.73	0.0546
S_o	8.2E+07	1	8.2E+07	13.95	0.0039
$t * V_c$	6.0E+07	1	6.0E+07	10.23	0.0095
$t * S_o$	5.8E+08	1	5.8E+08	98.30	<0.0001
$V_c * S_o$	6.7E+07	1	6.7E+07	11.32	0.0072
t^2	4.9E+07	1	4.9E+07	8.35	0.0161
V_c^2	1.3E+08	1	1.3E+08	22.06	0.0008
S_o^2	4.3E+07	1	4.3E+07	7.34	0.0220
Residual	5.9E+07	10	5.9E+06		
* Lack of fit	7.3E+06	4	1.8E+06	0.2119	0.9225
Pure Error	5.2E+07	6	8.6E+06		
Cor. Total	1.3E+09	19			
**Model is significant ; Lack of fit not significant*					

TABLE 6: FIT SUMMARY RESPONSE FOR MRR

Source	Sequential p- value	Lack of fit p-value	Adj R^2	Predicted R^2
Linear	0.3949	0.0031	0.0089	0.3040
2FI	0.0091	0.0155	0.4827	0.0996
Quadratic*	< 0.0001	0.9225	0.9156	0.8719
Quadratic (suggested)*				

D. *Main Effect Plot Surface Roughness and MRR*

With respect to input parameters, measure of mean for surface response and MRR are studied here where depth of cut, cutting speed and feed rate are used as input parameters. Surface roughness and MRR have been used as resultant output can be observed in Fig. 3 and 4. Higher depth of cut and lower cutting speed is recommended to obtain minimum value of surface roughness. However, lower feed rate and moderate depth of cut-cutting speed combination is appreciable to induce higher material removal rate.

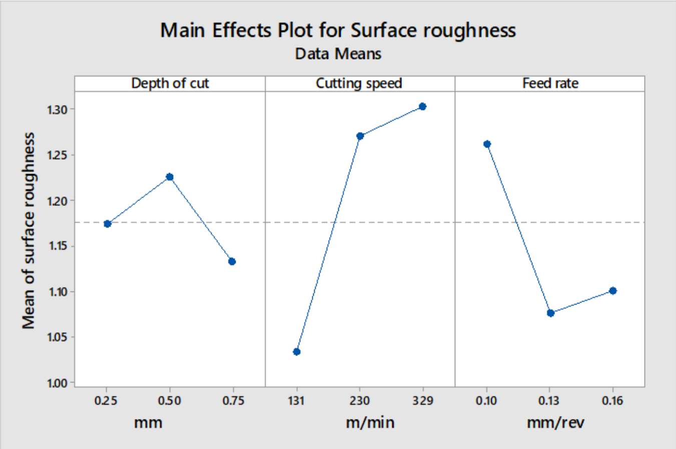


Fig. 3: main effect plot for surface roughness

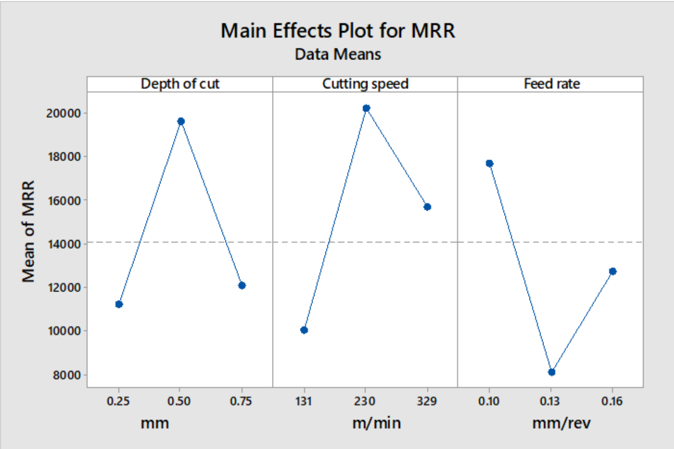
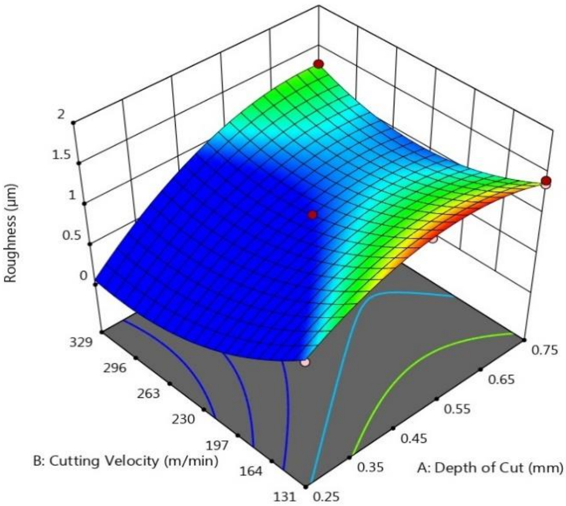


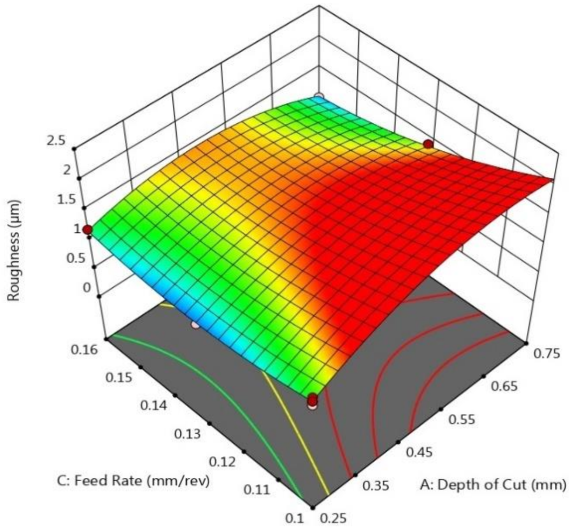
Fig. 4: main effect plot for material removal rate

E. 3D Response Surface Plot

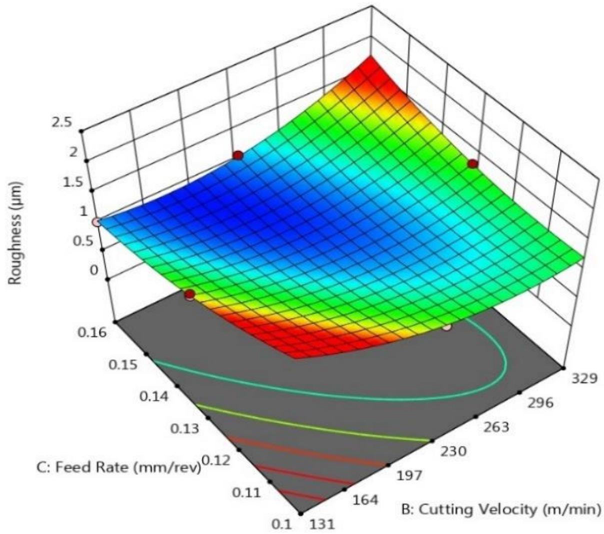
A 3D surface plot is a three-dimensional graph that is useful for investigating desirable response values and operating conditions. It is used to see how a response variable relates to two predictor variables. Effect of the resultant outputs with respect to different interaction combination are shown in Fig. 5 and 6.



(a)

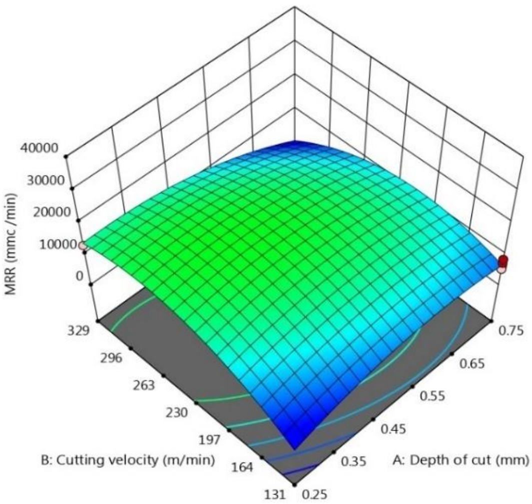


(b)

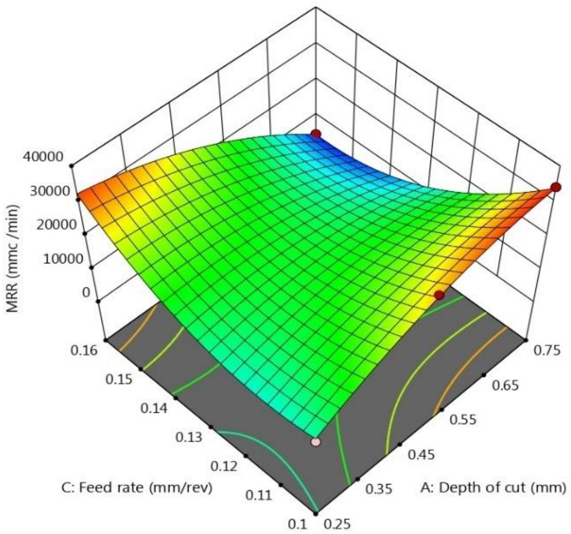


(c)

Fig. 5: 3D surface plot of surface roughness (a) with respect to cutting speed and depth of cut; (b) with respect to feed rate and depth of cut and; (c) with respect to feed rate and cutting speed



(a)



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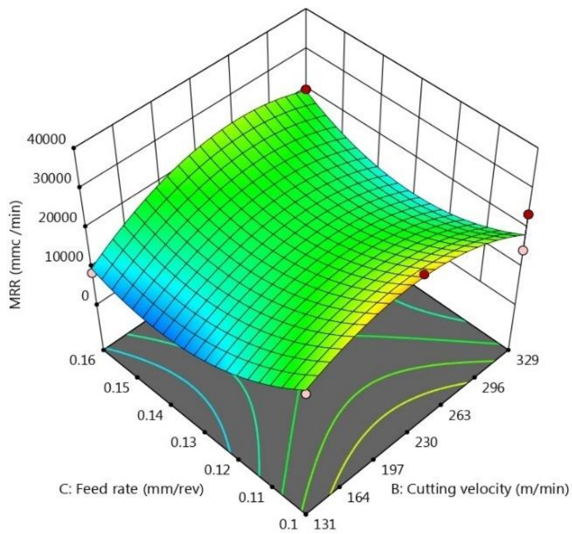


(c)

Fig. 6: 3D surface plot of surface roughness (a) with respect to cutting speed and depth of cut; (b) with respect to feed rate and depth of cut and; (c) with respect to feed rate and cutting speed

F. Quadratic Model by RSM

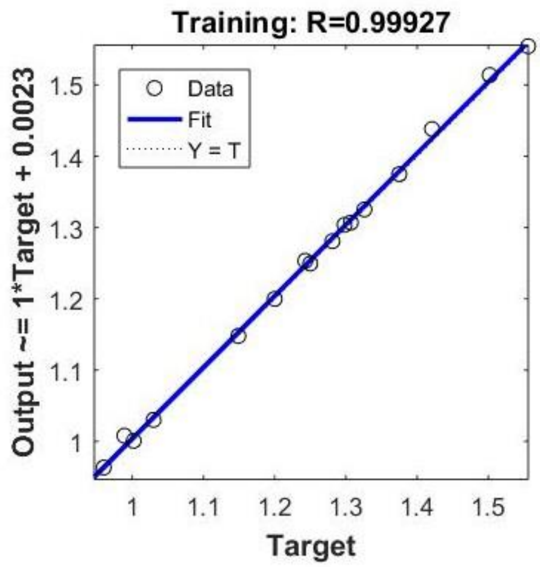
Quadratic model equations developed for surface roughness and material removal rate by using response surface methodology are shown in eqn. (7) and (8). Correlation co-efficient (R^2) value is found to be 94.30% for response surface and 95.56% for material removal rate which indicate that articulated RSM value can be used to predict the surface roughness value. In this case, t (Depth of Cut), V_c (Cutting Velocity), S_o (Feed rate) are significant model terms.

$$R_a = 7.053 + 9.411 * t - 0.039 * V_c - 64.325 * S_o + 0.008 * t * V_c - 32.608 * t * S_o + 0.130 * V_c * S_o - 5.604 * t^2 + 3.469e\text{-}05 * V_c^2 + 208.526 * S_o^2 \quad (7)$$

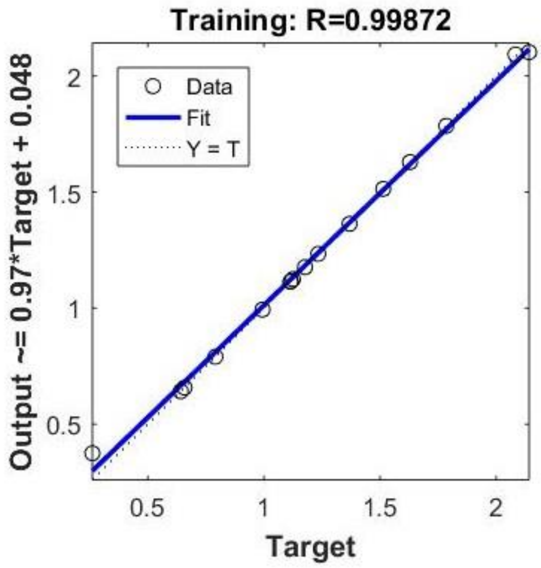
$$MRR = 26970.279 + 315977.770 * t + 342.941 * V_c - 1876087.473 * S_o - 201.642 * t * V_c - 1599587.367 * t * S_o + 1116.887 * V_c * S_o - 69451.099 * t^2 - 0.804 * V_c^2 + 8951917.435 * S_o^2 \quad (8)$$

G. Comparison of Experimental Values with RSM Model

Linear regression for the both experimental and RSM predicted values of surface roughness for MQL cutting condition & for material removal rate are shown respectively in Figure (7) & (8). The value of correlation coefficient is very close to 1 which implies that the experimental values are fairly accurate.

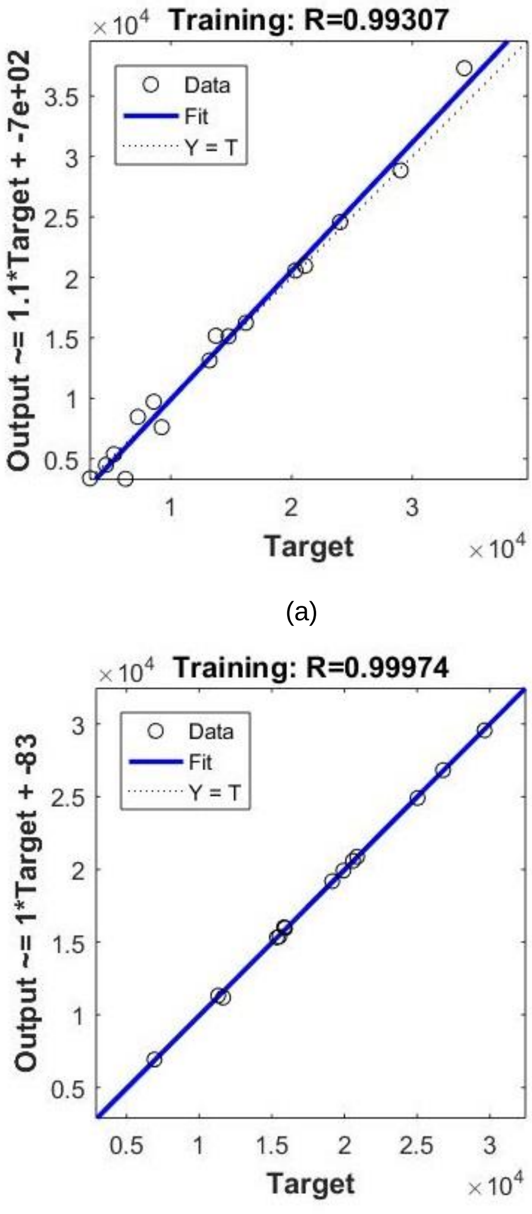


(a)



(b)

Fig. 7: Linear Regression plot for MQL cutting condition (a) Experimental value of surface roughness (R = 0.99927) and (b) RSM Predicted value of surface roughness (R= 0.99872)



(a)

(b)

Fig. 8: Linear Regression plot for MRR (a) Experimental value of MRR (R = 0.99307) and (b) RSM Predicted value of MRR (R= 0.99974)

H. Principal Component Analysis

Firstly, Experimental data of surface roughness and material removal rate are normalized as shown in Table 7. The normalized responses range is kept in between 0 to 1. Pearson's correlation coefficient for the response is shown in Table 8. The non-zero value of the co-efficient indicates that the responses are corelated. Using MINITAB, PCA has been applied to eliminate the correlation between the responses. Details of PCA (Eigen value, eigen vector, accountability proportion and cumulative accountability proportion) are shown in Table 9. From the corelated responses using eqn. 5, principal components are obtained. To calculate MPI, accountability proportion has been used as individual weight of the principal components. Measured values from eqn. 6 are shown in Table 10. Higher MPI value gives better result. The factorial combination that maximizes MPI can be considered as most optimum combination to ensure low surface roughness and high MRR. From Table 10, it is observed that highest MPI value is 0.101683. Highest MPI value having the combination of depth of cut 0.75 mm, cutting speed 230 m/min and feed rate 0.10 mm/rev and surface roughness value of 1.556 µm and MRR value of 34306.168 mm^3/min are shown in Table 11.

Table 7: Normalized response for surface roughness and material removal rate

Run	R_a	MRR
1	0.9896	0.0962
2	0.9606	0.1817
3	0.6909	0.2692
4	0.7269	0.3846
5	0.9478	0.1346
6	0.8272	0.2544
7	0.7919	0.3769
8	0.7317	0.5385
9	0.9664	0.1538
10	0.7600	0.2908
11	0.6685	0.4308
12	0.9606	0.6154
13	0.9220	0.2115
14	0.8075	0.3998
15	0.7738	0.5923
16	0.7162	0.8462
17	0.8854	0.2500
18	1.0000	0.4725
19	0.7643	0.7000
20	0.6105	1.0000

Table 8: Co-relation test

Co-relation between Responses	Pearson Correlation coefficient	P-Value	Comment
R_a and MRR	0.62	0.004	Co-related

Table: 9 Principal component analysis

	PC_1	PC_2
Eigen value	1.6204	0.3796
Eigen vector	0.707 0.707	-0.707 0.707
AP	0.810	0.190
CAP	0.810	1.000

TABLE 10: PRINCIPAL COMPONENTS AND MPI

Run	Individual Principal components		MPI
	P1	*P2*	
1	0.767616	0.631655	0.741783
2	0.807604	0.550637	0.75878
3	0.678818	0.298127	0.606487
4	0.78581	0.241964	0.682479
5	0.765254	0.57491	0.729089
6	0.764673	0.404919	0.69632
7	0.826338	0.293368	0.725073
8	0.897999	0.136614	0.753336
9	0.792034	0.574497	0.750702
10	0.742893	0.331747	0.664776
11	0.777213	0.168107	0.661483
12	1.114197	0.244044	0.948868
13	0.801429	0.502316	0.744597
14	0.853543	0.288214	0.74613
15	0.965845	0.128323	0.806716
16	1.104616	-0.09184	0.877289
17	0.802704	0.449207	0.735539
18	1.041056	0.372944	0.914115
19	1.035245	0.045447	0.847183
20	1.138652	-0.27535	0.869992

TABLE 11 OPTIMUM MACHINING PARAMETERS BY PCA

t, V_c and S_o	R_a	MRR	MPI value
0.5 mm; 131 m/min; 0.1 mm/rev	0.989 µm	21111.488 mm^3/min	0.948868

IV. DISCUSSION

This research work focuses on the potentials of accomplishing machining operation in hard to machine metal matrix composite under MQL condition. An integrated RSM and PCA technique has been used to develop a predictive modeling to obtain good surface roughness and maximum material removal rate where predictive modeling was done using RSM and machining parameters were optimized by Principal component analysis. The outcomes of the summaries can be listed as follows:

- From ANOVA analysis for surface roughness and MRR, P-value is found to be at 0.001 which implies that the model is significant. In case of surface roughness, Depth of cut and cutting velocity are touted to play the most prominent role whereas, the interaction between depth of cut and feed rate is the most prominent factor to achieve desired MRR.
- 3D surface plot indicates that a certain amount of interaction effect exists among the parameters. Combination effect of depth of cut and feed rate
- From the main effect plot it is appreciable that to generate minimum surface roughness value, higher depth of cut and moderate feed rate is favorable. However, lower feed rate and medium to higher range of cutting speed can induce maximum amount of material removal rate under certain condition.
- Linear regression plot of experimental values of surface roughness and MRR shows that correlation coefficient values are 0.99927 and 0.99307 respectively
- RSM generated mathematical model can be successfully used to predict the resultants responses. Correlation coefficient value is 0.99872 for surface roughness and 0.99974 for MRR which is very close to the experimental results that clearly pinpoints the validity of the developed quadratic model.
- Principal component analysis is an attempt to improve the results found from main effect plot due to its acceptance of optimizing the parameters as it considers individual weights of the principal components.
- Considering the largest MPI value as an index, it is suggested that to ensure optimum conditions for both the responses depth of cut need to be at 0.5 mm followed by cutting speed of 131 m/min and feed rate of 0.10 mm/rev.
- PCA recommended that by ensuring mentioned cutting parameters surface roughness of 0.989 µm and maximum MRR of 21111.488 mm^3/min can be achieved

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