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Optimization of Process Parameters for Multi-Objective Quality Characteristics in Turning of Al-MMCs

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Abstract: *The industrial sectors such as automotive, aerospace, aircraft and train companies realize a need to replace monolithic metals (steel and cast iron) with lighter high-strength alloys. A new class of material, the aluminium based metal matrix composites (Al-MMCs) have been identified. These composites possess better physical and mechanical properties with its low density. The uses of low weight, high strength mechanical components lead to a reduction in the fuel consumption and environment impact.*

The presence of ceramic particles in aluminium based metal matrix composites make it difficult to machine, and consequently they find limited applications in the aforesaid industries. While machining of metal matrix composites the ceramic particles are pulled out and rub over the machined surface and also increase the abrasion wear on tool surfaces. The MMCs reinforcement particles are very hard and produce a fast tool wear rate, which leads to the increase in the cutting forces, surface roughness and a reduction in the material removal rate. So for the economy of machining (turning, milling, drilling, threading) there exists a need to optimize the machining parameters for the attainment of the multi-objective function of high material removal along with better surface finish.

Present work focuses on application of principal component analysis, grey relation theory combined with Taguchi's robust design. This technique is used for optimization of process parameters for the achievement of multi-objectives simultaneously. Surface roughness, cutting force and material removal rate (MRR) are taken as output responses in straight turning of aluminium based metal matrix composite (MMC). The aims of this study is to evaluate the most favorable process parameter's combination for achieving a high surface finish, ensuring low cutting force and improvement in productivity. The multi-objective optimization problem in MMCs turning operation has been solved by using this new method.

1. INTRODUCTION

A few decades before, a new class of material named metal matrix composite (MMC) has been developed. This new class of material attains greater attention to the manufacturing of the various industrial components. The metal matrix composites are widely used in the industries like aerospace, automotive, aircraft, military, sports and medical. The properties like high strength to weight ratio, high wear resistance, high thermal conductivity, low thermal expansion, low density, high specific stiffness and high temperature resistance make it more desirable than monolithic material especially for designing components such as brake disc, piston and cylinder liners etc. of various industries.

The metal matrix composites are the special type of advanced materials in which the hard and stiff ceramic particles are reinforced. The ceramic particles generally used are SiC, Al_2O_3, TiB_2, B_4C and Zirconia. These ceramic particles are reinforced in the form of whickers or particulates, continuous or discontinuous fibers in the matrix metal. The matrix of metal can be prepared by any available suitable material, but aluminium, magnesium and titanium alloys are most popular. The aluminium based MMCs reinforced of SiC particle have been turned into useful materials because of their properties such as low weight, heat-resistant, wear-resistant and low cost [1]. The metal matrix composites are commonly manufactured by near net shape manufacturing methods and are machined by conventional machining [2]. The conventional machining (turning, drilling, milling, sawing, etc.) results in rapid tool wear due to the presence of hard and stiff ceramic particles. So while machining there is often involvement of frequent and expensive tool changes, resulting in additional job completion time. Consequently there is also an increase in machining cost. These reasons limit the application of metal matrix composites for the production of mechanical components.

2. LITERATURE REVIEW

Several studies have been done in order to study the machinability of metal matrix composites. A wide variety of tool materials have been tried to improve the machinability. While machining of MMCs the extensive tool wear was caused by the abrasion action of very hard and abrasive reinforcements [3]. Manna and Bhattacharya [4] investigated the machinability of Al/SiC MMC. They have found good surface finish at high speed with a low feed rate and depth of cut condition. Sahoo et al. [5] examined the effect of process parameters like cutting speed, feed and depth of cut on flank wear and surface roughness in turning of Al/SiC metal matrix composites. Srinivasan et al. [6] concluded that the surface roughness improves with an increase in the cutting speed. However, at the same time increasing feed adversely affects the surface roughness. Kannan et al. [7] studied the effect of tool wear, surface roughness, and chip formation during machining. Sikder and Kishawy [8] observed that the increase in feed tends to raise the forces, and also the value of forces increase when the percentage of alumina increased in the MMCs.

In machining, the product quality of workpiece is prime importance which can be directly influenced by the selection of cutting speed, depth of cut and feed rate. Through the optimization, the desired product quality with the available facilities can be achieved. Rajesh et al. [9] performed the machining of red mud aluminium based metal matrix composites by uncoated carbide tool. They have found that the Taguchi-based grey analysis was good for optimizing the machining parameters like cutting speed, feed, depth of cut, and nose radius for the desired multi responses. Lu et al. [10] have used the principle component analysis approach to simplify a large number of correlated variables into fewer correlated and independent principle components.

From the literature, it is clear that very few studies have been carried out related to optimization of surface roughness (Ra), cutting force (Fc) and material removal rate (MRR) while machining of particulate aluminium metal matrix composite. The main objective of the present work is to optimize, surface roughness, cutting force and material removal rate during the machining of Al-SiC metal matrix composite using the recently developed methods. The present study, applied a Taguchi (L9) orthogonal array to plan the experiments on turning operations. After that, through the principle component coupled with a Grey relational Taguchi method, the most influencing factors for individual desired quality of turning operations have been identified.

3. PROCEDURE ADAPTED FOR OPTIMIZATION

The proposed optimization methodology is as follows:

Assuming, the number of experimental runs in Taguchi's OA design is m, and the number of quality characteristics is n, the experimental results can be expressed by the following series: $X_1, X_2, X_3, ..., X_i, ..., X_m$

Here,

$$X_1 = \{X_1(1), X_1(2).........X_1(k).....X_1(n)\}$$

$$X_i = \{X_i(1), X_i(2).........X_i(k).....X_i(n)\}$$

$$X_m = \{X_m(1), X_m(2).........X_m(k).....X_m(n)\}$$

Here, X_i represents the $i\,th$ experimental results and is called the comparative sequence in grey relational analysis.

Let, X_0 be the reference sequence:

Let, $X_0 = \{X_0(1), X_0(2).........X_0(k).....X_0(n)\}$

The value of the elements in the reference sequence means the optimal value of the corresponding quality characteristic. X_0 and X_i both includes n elements, and $X_0(k)$ and $X_i(k)$ represent the numeric value of $k\,th$ element in the reference sequence and the comparative sequence, respectively, $k = 1, 2, ..., n$. The following illustrates the proposed parameter optimization steps in details:

Step 1: Normalization of the responses (quality characteristics) There are three different types of data normalization according to whether we require the LB (lower-the-better), the HB (higher-the-better) and NB (nominal-the-best). The normalization is done by the following equations.

(a) LB (lower-the-better)

$$X_i^*(k) = \frac{\min X_i(k)}{X_i(k)} \tag{1}$$

(b) HB (higher-the-better)

$$X_i^*(k) = \frac{X_i(k)}{\max X_i(k)} \tag{2}$$

(c) NB (nominal-the-best)

$$X_i^*(k) = \frac{\min\{X_i(k), X_{0b}(k)\}}{\max\{X_i(k), X_{0b}(k)\}} \quad \begin{matrix} i = 1, 2, ..., m; \\ k = 1, 2, ..., n \end{matrix} \tag{3}$$

Here, $X_i^*(k)$ is the normalized data of the $k\,th$ element in the $i\,th$ sequence $X_{0b}(k)$ is the desired value of the $k\,th$ quality characteristic. After data normalization, the value of $X_i(k)$ will be between 0 and 1. The series $X_i^*, i = 1, 2, 3, ..., m.$ can be viewed as the comparative sequence used in the grey relational analysis.

Step 2: Checking for correlation between two quality characteristics

Let, $Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i), ..., X_m^*(i)\},$
$where,\ i = 1, 2, ..., n.$

It is the normalized series of the $i\,th$ quality characteristic. The correlation coefficient between two quality characteristics is calculated by the following equation:

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}}, \quad \begin{array}{l} j = 1,2,3......,n. \\ k = 1,2,3,........,n., \\ j \neq k \end{array} \tag{4}$$

Here, ρ_{jk} is the correlation coefficient between quality characteristic j and quality characteristic k; $Cov(Q_j, Q_k)$ is the covariance of quality characteristic j and quality characteristic k; σ_{Q_j} *and* σ_{Q_k} are the standard deviation of quality characteristic j and quality characteristic k, respectively.

The correlation is checked by testing the following hypothesis:

$$\begin{cases} H_0 : \rho_{jk} = 0 & (There\,is\,no\,correlation) \\ H_1 : \rho_{jk} \neq 0 & (There\,is\,correlation) \end{cases}$$

Step 3: Calculation of the principal component score

- Calculate the Eigenvalue λ_k and the corresponding eigenvector $\beta_k\ (k = 1,2,......,n)$ from the correlation matrix formed by all quality characteristics.
- Calculate the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\beta_{kj}, \quad \begin{array}{l} i = 0,1,2,.......,m; \\ k = 1,2,........,n. \end{array} \tag{5}$$

Here, $Y_i(k)$ is the principal component score of the $k\,th$ element in the $i\,th$ series. $X_i^*(j)$ is the normalized value of the $j\,th$ element in the $i\,th$ sequence, and β_{kj} is the $j\,th$ element of eigenvector β_k.

Step 4: Calculation of the individual grey relational grades

(1) Calculation of the individual grey relational coefficients:

The following equation is used to calculate the grey relational coefficient between $X_0(k)$ and $X_i(k)$.

$$r_{0,i}(k) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{0,i}(k) + \xi\Delta_{\max}}, \quad \begin{array}{l} i = 1,\ 2,..........,m; \\ k = 1,\ 2,.....,n. \end{array} \tag{6}$$

Here, $r_{0,i}(k)$ is the relative difference of $k\,th$ element between sequence X_i and the comparative sequence X_0 (also called grey relational grade), and $r_{0,i}(k)$ is the absolute value of difference between $X_0(k)$ and $X_i(k)$.

$$\Delta_{0,i}(k) = \begin{cases} \left|X_0^*(k) - X_i^*(k)\right|, no\ significant\ correlation \\ \left|Y_0(k) - Y_i(k)\right|, significant\ correlation \end{cases} \tag{7}$$

$$\Delta_{\max} = \begin{cases} \max\limits_i \max\limits_k \left|X_0^*(k) - X_i^*(k)\right|, no\ significant\ correlation \\ \max\limits_i \max\limits_k \left|Y_0(k) - Y_i(k)\right|, significant\ correlation \end{cases} \tag{8}$$

$$\Delta_{\min} = \begin{cases} \min\limits_i \min\limits_k \left|X_0^*(k) - X_i^*(k)\right|, no\ significant\ correlation \\ \min\limits_i \min\limits_k \left|Y_0(k) - Y_i(k)\right|, significant\ correlation \end{cases} \tag{9}$$

Note that ξ is called the distinguishing coefficient, and its value is in between 0 to 1. In general, it is set to 0.5.

(2) Calculation of the overall grey relational grade:

After the calculation of the grey relational coefficient and the weight of each quality characteristic, the grey relational grade is determined by:

$$\Gamma_{0,i} = \sum_{k=1}^{n} w_k r_{0,i}(k), \ i = 1,2,...................,m. \tag{10}$$

4. EXPERIMENTS AND DATA ANALYSIS

The present study has been done through the following plan of the experiment:

a) Checking and preparing the CNC Lathe ready for performing the machining operation.
b) Performing initial turning operation in Lathe to get the desired dimension of the workpiece. .
c) Performing straight turning operation on specimen by TiAlN coated tungsten carbide with various cutting environments involving various combinations of process control parameters like: spindle speed, feed and depth of cut.
d) Determining the cutting forces while turning by using Kistler dynamometer has a dynoware software interface.
e) Measuring surface roughness and surface profile with the help of a portable stylus-type profilometer, Talysurf (Taylor Hobson).
f) Calculating the material removal rate (MRR=V.*f*.d).

The working ranges of the parameters for subsequent design of experiment, based on Taguchi's L9 Orthogonal Array (OA) design have been selected. Machining tests were carried out on CNC lathe (Lead Well 6). The setup is shown in Fig. 1 and Fig. 2. The coated (TiAlN) tungsten carbide inserts were clamped in a rigid tool holder. The process variables with their levels are listed in Table 1. The experimental data (Table 2) have been normalized using Equations (1) and (2). Normalized experimental data are shown in Table 3. For surface roughness and cutting force (Lower-the-Better) LB; and for material removal rate (Higher-the-Better) HB criteria have been selected. After data normalization, a check has been made to verify whether the responses are correlated or not. The coefficient of correlation, between two responses, has been calculated using Equation (4). Table 4 represents

Fig. 1 CNC lathe machine

Fig. 2 The enlarge view of workpiece and cutting insert setup

Pearson's correlation coefficients. It has been observed that, all responses are correlated to each other. In order to eliminate response correlations, Principal Component Analysis (PCA) has been applied to derive three independent quality indices to derive three independent quality indices (called principal components), Table 5 presents Eigen values, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP) computed for the all responses indicators. It has been found that first three principal components; PC1, PC2, PC3 can take care of 55.6%, 28.2% and 16.2% variation in data respectively. Correlated responses

Table 1: Process variables and their limits

	Process variables		
Values in coded form	**Cutting Speed, V (m/min)**	**Feed, f (mm/rev)**	**Depth of cut, d (mm)**
-1 (A)	50	0.08	0.25
0 (B)	100	0.12	0.5
+1 (C)	150	0.16	0.75

Table 2: Machining responses of MMCs

	Response variables		
Sl. No.	**Surface roughness Ra,** (μm)	**Cutting force Fc (N)**	**MRR** $\left(\frac{mm^3}{min}\right)$
1	2.24	75.4	320
2	3.87	116.2	720
3	2.54	231.0	1280
4	1.98	95.91	640
5	0.95	152.4	1440
6	2.21	67.59	2560
7	0.83	108.3	960
8	1.29	60.59	2160
9	1.18	115.8	3840

Table 3: Normalized values $X_i^*(k)$ **of responses**

S. No.	**Ra**	**Fc**	**MRR**
Ideal Value	1.0000	1.0000	1.0000
1	0.37054	0.80358	0.08333
2	0.21447	0.52143	0.18750
3	0.32677	0.26229	0.33333
4	0.41919	0.63174	0.16667
5	0.87368	0.39757	0.37500
6	0.37557	0.89643	0.66667
7	1.00000	0.55946	0.25000
8	0.64341	1.00000	0.56250
9	0.70339	0.52323	1.00000

Table 4: Correlation among responses

S. No.	**Correlation between responses**	**Pearson correlation coefficient**	**Comment**
1	R and Fc	0.158	Both are correlated
2	Ra and MRR	0.458	Both are correlated
3	Fc and MRR	0.364	Both are correlated

have been transformed into three independent quality indices (major principal components). These have been furnished in Table 6 using Equation (5). $\Delta_{0i}(k)$ (Quality loss estimates) for all three principal components have been calculated using Equations (7-9), and presented in Table 7. Grey relational coefficients of individual principal components have been calculated using Equation (6) and the overall grey relational grade has been calculated using Equation (10); their values are furnished in Table 8. Thus, the multi-criteria optimization problem has been transformed into a single objective optimization problem using the combination of Taguchi approach and grey relational analyses. The main effect plot [HB (higher-the-better)] for the overall grey relational grade is represented graphically in Fig. 3. With the help of the Fig. 3, optimal parametric combination has been determined. The optimal factor setting becomes $V_1 f_{-1} d_0$. The corresponding factor combination is said to be close to the optimal result has been verified through confirmatory experiment.

Table 5: Eigenvalues, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP)

	PC1		**PC2**	**PC3**
Eigenvector	Ra	0.568	-0.607	-0.556
	Fc	0.494	0.792	-0.360
	MRR	0.659	-0.070	0.749
Eigenvalue	1.6682		0.8465	0.4852
AP	0.556		0.282	0.162
CAP	0.556		0.838	1.000

Table 6: Principal components (PC) in all L9 OA experimental observations

S. No.	$Y_i(k)$	$Y_i(k)$	$Y_i(k)$
Ideal value	1.721	0.115	-0.167
1	0.6623	0.4057	-0.4329

2	0.5030	0.2697	-0.1665
3	0.5348	-0.0139	-0.0264
4	0.6600	0.2342	-0.3357
5	0.9398	-0.2417	-0.3480
6	1.0955	0.4353	-0.0322
7	1.0091	-0.1814	-0.5702
8	1.2301	0.3621	-0.2964
9	1.3170	-0.0826	0.1696

Table 7: Quality loss estimates Δ_{0i} (k) (for principal components)

S. No.	Δ0i (k)	Δ0i (k)	Δ0i (k)
1	1.0587	-0.2907	0.2659
2	1.2180	-0.1547	-0.0005
3	1.1862	0.1289	-0.1406
4	1.0610	-0.1192	0.1687
5	0.7812	0.3567	0.1810
6	0.6255	-0.3203	-0.1348
7	0.7119	0.2964	0.4032
8	0.4909	-0.2471	0.1294
9	0.4040	0.1976	-0.3366

Table 8: Individual grey relational coefficients and overall grey relational grade for the principal components

S. No.	$r_{0,i}(k)$	$r_{0,i}(k)$	$r_{0,i}(k)$	$\Gamma_{0,i}$
1	0.6074	-0.3195	-0.2888	-0.0003
2	0.5545	-0.7980	-0.6712	-0.3049
3	0.5643	-3.7559	-2.2115	-1.8010
4	0.6066	-0.4091	-0.3646	-0.0557
5	0.7287	-0.3950	-0.3528	-0.0064
6	0.8206	-3.2598	-2.0211	-1.4868
7	0.7669	-0.2441	-0.2232	0.0999
8	0.9210	-0.4612	-0.4078	0.0173
9	1.0000	0.8973	1.0004	0.9659

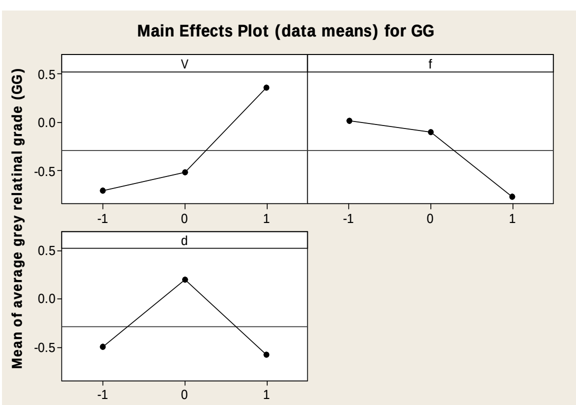

Fig. 3: Main effect plot of overall grey relational grade

5. RESULTS AND DISCUSSION

Fig. 4 shows the influence of cutting speed on the surface roughness and cutting forces during machining of MMC. Turning operations were performed considering a constant feed rate of 0.12 mm/rev and a depth of cut of 0.5 mm, and continuous length of turning of 8 mm.

The influence of feed rate on the surface roughness and cutting forces is examined by considering a constant speed of 100 m/min with a depth of cut of 0.5 mm, and a length of turning of 8 mm. as shown in the Fig. 5.

Fig. 6 shows the effect of the depth of cut on the surface roughness and cutting forces during turning of cast aluminium based metal matrix composite without the use of a coolant. Turning operations was performed considering a constant feed rate of 0.12 mm/ rev, a constant speed of 100 m/min, and a length of turning of 8 mm.

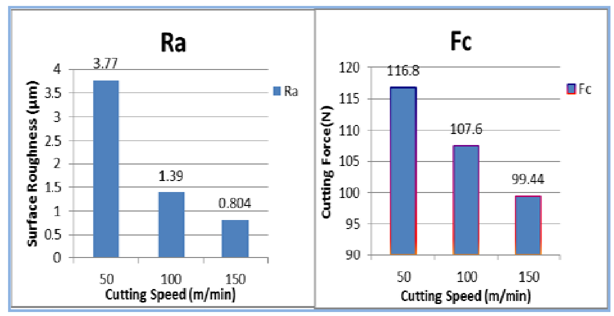

Fig. 4: Influence of cutting speed on surface roughness and cutting force

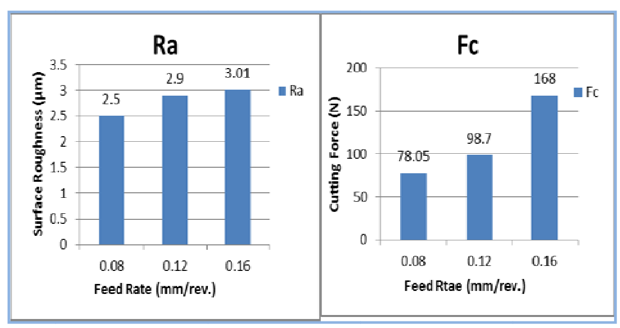

Fig. 5: Influence of feed on surface roughness and cutting force

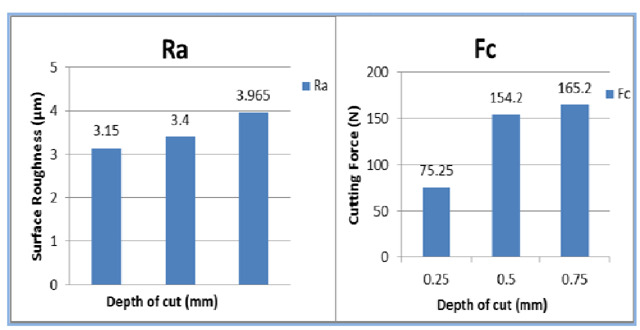

Fig. 6: Influence of depth of cut on surface roughness and cutting force

6. CONCLUSION

The followings are the major conclusions:

1. The optimized cutting condition that gives lower surface roughness, cutting force and improve MRR when machining Al-MMC have been identified: Cutting speed 'V'150 m min-1, Feed '*f*' 0.08 mm/rev and Depth of cut 'd' 0.5 mm.
2. The surface roughness improves with the increase of the cutting speed whereas increasing feed adversely affects the surface roughness.
3. The cutting force almost linearly varies with the feed and at low cutting speed the cutting force is higher.
4. The machining parameters for turning process are optimized using PCA coupled Taguchi's technique for minimizing the surface roughness and cutting force and maximizing material removal rate
5. The optimization technique has been validated experimentally and reveals low values of error.

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