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# Multi objective Optimization of CNC Turning Parameters for AA2024/SiC MMC's using Grey Relational Analysis

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***Abstract*— In the present investigation, optimization of turning parameters on Aluminium hybrid metal matrix composites were studied using grey integrated fuzzy. AA2024/SiC MMC were prepared using liquid metallurgy route, and CNC turning was employed for machining the composites. L9 array was used as DOE, and a linguistic relationship was established between process parameter levels and the outcomes. The key objectives of this investigation is to analyze the effect of process variables i.e., cutting speed, feed, and depth of cut on minimizing surface roughness and maximizing material removal rate. Grey Relational Analysis (GRA) was used for multi-objective optimization.**

***Keywords — Metal Matrix composites; AA2024; Silicon carbide; CNC Turning; Multi-objective optimization; Grey Relational Analysis.***

## I. INTRODUCTION

Past two decades, composite materials were designed and developed as an alternative to the conventional/regular metals, due to its superior characteristics such as improved strength with low density [1]. Still today polymer, metal, and ceramic matrix composites are not intensifying in the market due to the manufacturing limitations such as expensive equipment, skilled labor, and sophisticated facilities. Among composites, Metal matrix composites exhibits superior properties i.e., higher strength, stiffness, high wear resistance, low density, high modulus, high thermal conductivity and low thermal expansion. Aluminium based metal matrix composites are of much interest at present, because of ease of production, availability of metals and enhancement in the properties with the addition of ceramic fillers such as zirconia, alumina, silicon carbide (SiC) compared to unreinforced alloys [2]. These features attracts its usage in the automobile, aerospace, electronics, structural and medical industries, but the abiding problem is that that they are very difficult to machine [3]. The difficulties are mainly due to abrasive nature of the ceramic reinforcement causes tool wear and machining defects, which intern decreases the quality and lifetime of product. These limitations can be minimized/avoided only by the skilled labor or advanced equipment, but in industrial scenario it is not suitable to have skilled labor in front of each machine which increases the production cost with less profits.

From the literature, it is observed that optimization techniques meets the demands of industries i.e., quality product with lesser production time and costs. It is also observed that optimization of single response is not suitable and beneficial to the present manufacturing firms which consists of multi objectives. Therefore multiple objective techniques yields the best solutions compared to single objective [4]. A Brief summary of optimization of process parameters of CNC turning on aluminium alloys and Al based metal matrix composites are discussed here. Kathirvel et al. [5] investigated the effect of material and process parameters on machining Al6061/SiC composites using neural networks and observed vol.% of reinforcement, speed, feed and depth of cut affects the quality. Uday et al. [6] conducted their studies on turning of Al/Sic composites for the optimal parameter combination using Grey Relational Analysis, and observed size and volume fraction of reinforcement in composites also affects along with the process variables. Jayaraman et al. [7] investigated the effect of effect of machining parameters on surface roughness for AA6063 using Taguchi integrated Grey relational analysis, and found that the feed rate provides primary contribution and influences most significantly on the surface roughness. The increase of feed rate increases the surface roughness. Suresh et al. [8] studied the effect of turning parameters on Al/ SiC/Gr hybrid composites using Grey Fuzzy and noticed two key observations i.e., Al−10%(SiC−Gr) provides better machinability compared with AMCs with 5% and 7.5% of SiC−Gr and Fuzzy logic improved the performance index. Mishra et al. [9] investigated on AA 7075/SiC metal matrix composites using GRA and concludes that observed feed was the most significant factor on machining of composite. Ravinder et al. [10] studied the effect of process parameters on MRR and surface roughness in turning operation on AA 7075 Hybrid MMC's using Response surface methodology and artificial neural networks and learned that presence of graphite particle into Al 7075 MMCs improves the surface roughness. Hybrid composite reinforced with graphite is easier to machine and provided smooth surface.

Kumaran et al. [11] investigated their studies on effect of cutting parameters on average surface roughness and material removal rate during turning of AA6351/SiC/ B4C metal matrix composite using GRA and observed that cutting speed is the most important and influential machining parameter that affect the average surface roughness. The depth

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of cut has significant for both the average surface roughness and metal removal rate for the MMC. Bansal et al. [12] studied the optimization of cutting parameters in turning operation of aluminium 2024 alloy with Al2O3 reinforcement and observed that feed observed that tool wear increases with the process variables whether it is coated or uncoated tool, however tool wear is less in coated tool as compared to uncoated due to the coating. Vamsi Krishna [13] studied the mechanical behavior of AlMg1SiCu MMC using Taguchi integrated Fuzzy and and observed improved mechanical properties. Approach Surface Roughness increase with the process variables except the speed, speed made adverse effect on surface roughness. MRR increases with the process parameters except the concentration of reinforced particles due the presence of hard ceramic particles. It is clear that speed, feed, depth of cut has significance on machining various alloys with various reinforcements.

It is evident that no literature available in turning of AA2024/SiC metal matrix composites and this motivates us to investigate the effect of process parameters on surface roughness and material removal rate. AA6082 was chosen because it possesses good formability, weldability, machinability and corrosion resistance, with good strength compared to other grades of aluminium alloys.

## II. MATERIALS AND METHODS

AA2024 and Silicon carbide was selected as the matrix and reinforcement respectively as shown in Fig. 1. The chemical composition of AA2024 is presented in Table 1.

TABLE I: CHEMICAL COMPOSITION OF AA2024

| Element | Cu | Mn | Mg | Al |
|---|---|---|---|---|
| Composition | 4.4 | 0.6 | 1.5 | Bal |

### A. *Preparation of Composite*

At first, in this process, first the aluminium alloy was preheated at 450 – 800 °C for 2 hours in an electrical resistance furnace before melting. Reinforcing particulates (SiC) are preheated at 600 °C for a soaking period of 2 hours improve the wetness properties to remove the adsorbed hydroxide and other gases from the surface.

After preheat, the aluminium pieces was feed into the graphite crucible and then heated above 50 °C of the melting point for complete melting. Add the preheated SiC reinforcement to the melt along with minimal amount of magnesium for better wettability, and sodium hexachloroethane was used to remove the entrapped gases in the melt. Now the melt along with reinforcement was mechanically mixed with a phosphor coated stirrer at moderate speed for homogeneous distribution, and poured into the 300 °C preheated mold at pouring temperature, to obtain a defect free casting.

Fig. 1 Stir casting Setup

### B. *Microstructure*

To ensure the distribution of the reinforcement in the matrix, microstructure characterization was investigated experimentally by using inverted metallurgical microscope. First the specimens were cut from the central portion of the composites, and then polished on the belt grinding machine for 2 mins, and next polished on a disc polishing machine with different grades of emery papers for 2 min each rotating the specimen 900 for every time, and then finally on a velvet disc polishing machine with Alumina paste for 5 min, and then etched with Keller's reagent to remove the burrs and foreign particles. And then, the specimen was placed on the viewing stage of the inverted metallurgical microscope and then examined the microstructure with the monochromatic light source and photographs of microstructure was captured at magnification of 500 X. Fig. 2 depicts the microstructure of Al/SiC MMC, to ensure the distribution of SiC particles in the melt.

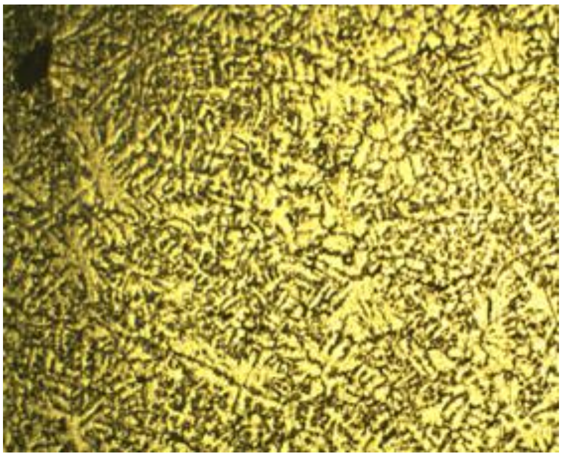

Fig. 2 Microstructure of AA2024/SiC MMC

## III. MACHINING AND MEASUREMENT

The experiments (machining) were performed employing MTAB - FLEXTURN CNC turning centre under dry conditions (room temperature) with three process parameters at three levels each as shown in Table II. High speed steel (HSS) tool was selected for machining of MMC.

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TABLE II. MACHINING PARAMETERS AND LEVELS

| S. No. | Process parameters | Levels | | | |
|---|---|---|---|---|---|
| | | *1* | *2* | *3* | *Units* |
| 1 | Speed | 1000 | 1200 | 1400 | RPM |
| 2 | Feed | 0.02 | 0.04 | 0.06 | mm/rev |
| 3 | Depth of Cut | 0.1 | 0.2 | 0.3 | mm |

Surface roughness is measured by using the mitutuyo handheld talysurf instrument, and the material removal rate is measured using the formula as shown in Eq. (1).

$$MRR = (W_i - W_f) / t \ldots\ldots (1)$$

Where $W_i$ = initial weight of the work piece, $W_f$ = final weight of the work piece, t = machining time (sec)

### A. *Design of Experiments (DOE)*

$L_9$ array DOE is chosen for conducting experiments in order to reduce the cost and time. DOE and the responses i.e., surface roughness, material removal rate are tabulated in Table III.

TABLE III. DOE AND RESPONSES.

| S.No | Speed (rpm) | FEED (mm/rev) | DEPTH OF CUT (mm) | MRR (gm/sec) | Ra (µ) |
|---|---|---|---|---|---|
| 1 | 1000 | 0.02 | 0.1 | 0.350 | 5.63 |
| 2 | 1000 | 0.04 | 0.2 | 1.770 | 10.39 |
| 3 | 1000 | 0.06 | 0.3 | 5.455 | 19.70 |
| 4 | 1200 | 0.02 | 0.2 | 0.521 | 5.18 |
| 5 | 1200 | 0.04 | 0.3 | 1.879 | 10.47 |
| 6 | 1200 | 0.06 | 0.1 | 5.677 | 19.07 |
| 7 | 1400 | 0.02 | 0.3 | 0.777 | 4.87 |
| 8 | 1400 | 0.04 | 0.1 | 1.914 | 10.20 |
| 9 | 1400 | 0.06 | 0.2 | 5.765 | 19.45 |

Fig. 3 Specimens after Machining

## IV. GREY RELATIONAL ANALYSIS

Deng (1989) proposed Grey Relational Analysis for solving complicated interrelationships between the multiple response characteristics problems. In GRA, the system has information in the form of black and white. If the system is grey, the some information is mixed i.e., known and unknown, i.e., relationships among factors in the system are uncertain. If the system is white, the relationships between factors are certain.

In the grey relational analysis, grey relational grade is used to optimize multi-response system. The use of GRA includes the following steps:

a. Conduct the experiments as per DOE.

b. Transform the experimental results into signal-to-noise ratio (S/N).

c. Normalize S/N.

d. Calculate grey relational coefficients of each response.

e. Calculate the grey relational grade by averaging the grey relational coefficients.

A. *Normalization:* **C**onvert the original sequences to a set of comparable sequences by normalizing the data. Depending upon the response characteristic, three main categories for normalizing the data is as follows:

*'Larger the better'*

$$a_i^{(*)}(k) = \frac{b_i^{(*)}(k) - \min b_i^{(*)}(k)}{\max b_i^{(*)}(k) - \min b_i^{(*)}(k)} \qquad (2)$$

'S*maller the better'*

$$a_i^{(*)}(k) = \frac{\max b_i^{(*)}(k) - b_i^{(*)}(k)}{\max b_i^{(*)}(k) - \min b_i^{(*)}(k)} \qquad (3)$$

'*Nominal the better*'

$$a_i^{(*)}(k) = 1 - \frac{b_i^{(*)}(k) - OV}{\max\{\max b_i^{(*)}(k) - OV, OV - \min b_i^{(*)}(k)\}} \qquad (4)$$

Where $b_i^{(*)}(k)$ is the experimental result in $i^{th}$, $a_i^{(*)}(k)$ is the normalized result in the $i^{th}$ experiment and OV is the optimum value. The original reference sequence $a_0^{(*)}(k) = 1$ and normalized data $a_i^{(*)}(k)$ (*comparability sequence*) where i = 1,2,….,m; k =1,2,.....,n respectively, where m is the number of experiments and n is the total number of observations of data.

### B. *Grey relational coefficient and grey relational grade:*

Grey relation coefficient ($\alpha_{ij}$) is calculated for each of the performance characteristics, which expresses the relationship between ideal and actual normalized experimental results, as shown in "Eq.(5)."

$$\alpha_{ij} = \frac{\Delta\min + \xi\Delta\max}{\Delta oi(k) + \xi\Delta\max} \qquad (5)$$

Where i =1,2,….,m; k =1,2,.....,n respectively, where m is the number of experiments and n is the total number of observations of data. Where $\Delta oi(k)$is the deviation sequence of the reference sequence $a_0^{(*)}(k)$ and comparability sequence $a_i^{(*)}(k)$.

i.e.; $\Delta oi(k) = |a_0^{(*)}(k) - a_i^{(*)}(k)|$, and

$\Delta min = min|a_0^{(*)}(k) - a_i^{(*)}(k)|$,

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$$\Delta max = max|a_0^{(*)}(k) - a_i^{(*)}(k)|$$

'$\xi$' is the distinguishing coefficient and the value lies between 0 and 1 i.e. $0 \leq \xi \geq 1$. The distinguishing coefficient $\xi$ value generally chosen to be 0.5. Grey relational grade can be calculated by taking the average of is the weighted grey relational coefficient and defined as follows:

$$\Sigma \beta_k \gamma(x_0^{(*)}(k), x_i^{(*)}(k)) = 1 \qquad (6)$$

where $\beta_k$ is the weighting factor of each response. In the present study, all process parameters influence the responses, so equal weights are assigned to parameters.

TABLE IV. S/N RATIOS, NORMALIZED AND GREY RELATIONAL COEFFICIENTS

| Expt No | S/N ratios | | Normalized values | | Grey Relational Coefficients | |
|---|---|---|---|---|---|---|
| | ***MRR*** | ***SR*** | ***MRR*** | ***SR*** | ***MRR*** | ***SR*** |
| 1. | -9.109 | -15.012 | 0.000 | 0.103 | 0.333 | 0.358 |
| 2. | 4.958 | -20.330 | 0.578 | 0.541 | 0.542 | 0.522 |
| 3. | 14.735 | -25.889 | 0.980 | 1.000 | 0.962 | 1.000 |
| 4. | -5.668 | -14.293 | 0.141 | 0.044 | 0.368 | 0.343 |
| 5. | 5.476 | -20.401 | 0.599 | 0.547 | 0.555 | 0.525 |
| 6. | 15.082 | -25.608 | 0.994 | 0.976 | 0.989 | 0.956 |
| 7. | -2.195 | -13.756 | 0.284 | 0.000 | 0.411 | 0.333 |
| 8. | 5.637 | -20.168 | 0.606 | 0.528 | 0.559 | 0.515 |
| 9. | 15.216 | -25.777 | 1.000 | 0.990 | 1.000 | 0.982 |

TABLE V GREY RELATIONAL GRADES

| Expt. No | Grey Relational Coefficients | | Grey Relational grade | Order |
|---|---|---|---|---|
| | ***MRR*** | ***SR*** | | |
| 1 | 0.333 | 0.358 | 0.346 | 9 |
| 2 | 0.542 | 0.522 | 0.532 | 6 |
| 3 | 0.962 | 1.000 | 0.981 | 2 |
| 4 | 0.368 | 0.343 | 0.356 | 8 |
| 5 | 0.555 | 0.525 | 0.540 | 4 |
| 6 | 0.989 | 0.956 | 0.972 | 3 |
| 7 | 0.411 | 0.333 | 0.372 | 7 |
| 8 | 0.559 | 0.515 | 0.537 | 5 |
| 9 | 1.000 | 0.982 | **0.991** | **1** |

Table VI RESPONSE TABLE FOR S/N RATIOS FOR GREY RELATIONAL GRADE

| LEVEL | Speed | Feed | DC |
|---|---|---|---|
| 1 | -4.9556 | -8.9262 | -4.9552 |
| 2 | -4.8566 | -5.4115 | -4.8438 |
| 3 | -4.6894 | -0.1639 | -4.7026 |
| DELTA | 0.2662 | **8.7623** | 0.2526 |
| RANK | 2 | 1 | 3 |

## V. ANALYSIS OF VARIANCE

ANOVA is performed to identify the contribution of process parameters of WEDM on MPCI's. This is accomplished by separating the total variability of the grey relational grades, which is measured by the sum of the squared deviations from the total mean of the grey fuzzy reasoning grade, into contributions by each machining process parameters and the error. An ANOVA table as shown in Table VII consists of degrees of freedom, sums of squares and the percentage of contribution.

TABLE VII. ANALYSIS OF VARIANCE

| Source | DF | Seq SS | Adj SS | F Value | P value | % Contribution |
|---|---|---|---|---|---|---|
| Speed | 2 | 0.0003 | 0.0001 | 199 | 0.005 | 0.05 |
| Feed | 2 | 0.6183 | 0.3091 | 397525 | 0 | 99.90 |
| DOC | 2 | 0.0002 | 0.0001 | 158.29 | 0.006 | 0.03 |
| Error | 2 | 0.0000 | 0.0000 | | | 0.02 |
| Total | 8 | 0.6189 | | | | 100.00 |

| S | R-sq | R-sq (adj) | R-sq (pred) |
|---|---|---|---|
| 0.000882 | 100% | 100% | 99.99% |

From Table VII it shows that the process parameter feed has the most influence on the Grey relational grade, which coincides with the results of Table V. It is observed that the feed (99.90%) is most significant factor followed by speed (0.05 %) and depth of cut (0.03 %).

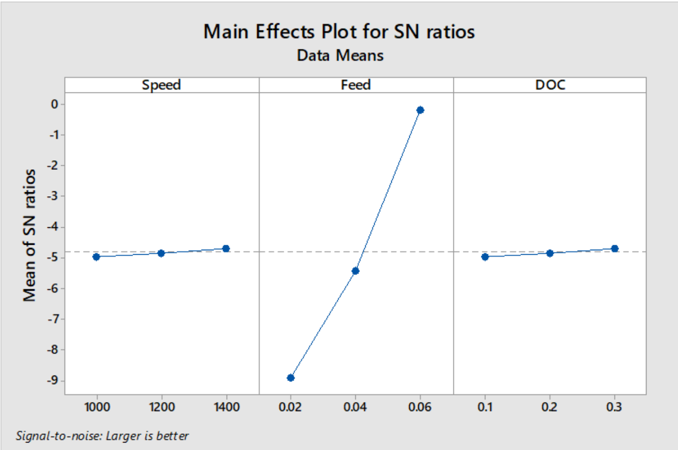


Fig. 4 Optimal process parameters

## VI. CONFIRMATION RUN

After determining the optimal combination of parameters, the last phase is to verify the MRR, surface roughness by conducting the confirmation experiment. The $A_3B_3C_3$, is an optimal parameter combination of the machining process by Grey Relational Analysis. The confirmation test is carried out with the optimal parameter combination $A_3B_3C_3$, and the results are tabulated in Table VIII, it is clear that the MRR and SR almost coincides with the optimal combination of parameters indicates the methodology is accurate.

TABLE VIII. CONFIRMATION TEST RESULTS

| Type | Optimal / Predicted | Optimal/Experimental |
|---|---|---|
| Level combination | $A_3B_3C_3$ | $A_3B_3C_3$ |
| MRR | 5.765 | 5.772 |
| SR | 19.45 | 19.23 |

## CONCLUSIONS

- Metal matrix composites were prepared with homogeneous distribution of reinforcement.
- Grey Relational Analysis methodology effectively optimizes the process parameters.
- The optimal combination of parameters obtained are of Speed – 1000 RPM, Feed – 0.03 mm/rev and Depth of cut – 0.3 mm.
- Feed found to be the most significant factors influencing all responses investigated for both the experiment sets.
- Grey relational grades increases the performance index and optimal combination of process parameters for best quality with short time.
- Confirmation test gave the least error and confirms the optimal parameter combination set.

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