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# Optimization of CNC Turning Operations with Multiple Performance Characteristics using Taguchi based Grey Relational Analysis

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**ABSTRACT:**

*This study investigates the optimization of CNC turning operation parameters for Al6061 nickel coated graphite (NCG) metal matrix composite using the Taguchi based grey relational analysis method. The turning operations are carried out with carbide cutting tool inserts. According to the Taguchi quality concept, 3-level orthogonal array was chosen for the experiments. The experiments are conducted at three different cutting speeds (125, 175, 225m/min) with feed rates (0.1, 0.15, 0.2mm/rev) and depth of cut (0.5, 1, 1.5mm) and different % of reinforcement (2.5%, 5%, 7.5%), signal to noise ratio and the analysis of variance are used to optimize cutting parameters. The effects of cutting speed, feed rate and depth of cut on surface roughness and MRR are analyzed. Mathematical models are developed by using the response surface method to formulate the cutting parameters experimental results shown that machining performance can be improved effectively by using this approach, the analysis of variance (ANOVA) is applied to identify the most significant factor for the turning operations according to the weighted sum grade of the GRG. The predict responses shows the models have more than 95% of confident level of R2 value, from the obtained confirmation experiment result, it is observed, there is a good agreement between the estimated value and the experimental value of the grey relational grade. This experimental study reveals that the grey-Taguchi and RSM can be applied successfully for multi response characteristic performances.*

**KEYWORDS:**

*Al6061; Nickel coated graphite (NCG); Metal matrix composite; CNC turning; Taguchi; Grey relation analysis*

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## 1. Introduction

In recent, the industry goal is to manufacture high quality products within minimal time and at low cost. Automated and FMS employ for that purpose along with computerized numerical control (CNC) machines that are capable of attaining high accuracy with very low processing time. Turning is the most commonly used method in metal cutting process and especially for the finishing machined parts. Furthermore, in order to produce any product with desired quality by machining, cutting parameters should be selected properly. In turning process parameters such as cutting tool materials and geometry, cutting speeds, the depth of cut, feed rates, and the use of cutting fluids will impact the material removal rates and the machining qualities like the surface roughness, the roundness of circular and dimensional deviations of the product [1]. In order to find the optimized set of input parameters and also to identify the effect of each towards a particular output, researchers have been trying for years together. Meng [2] tried to calculate optimum cutting condition for turning operation using a machining theory.

Researchers [2-5] have tried to optimize the machining parameters using various methods like genetic algorithm, simulated annealing method, multi-objective evolutionary algorithm, Taughi method, grey relation analysis etc. in the globalized market, manufacturing companies have to counter the challenges in producing high quality products while simultaneously improving the processes with a significant slash in time and cost. One of the most efficient tools to counter the challenge is Taguchi method, an off line quality control concept. The main theme of Taguchi method is stated as, quality variation is the main enemy and that every effort should be made to reduce the variations in quality characteristic. There are three types of quality characteristics in the Taguchi methodology, namely smaller the better, larger-the-better and nominal-the best. For instance, smaller the better is considered in surface roughness and larger the better is for surface roughness for machining condition [5].

Hence, in this study the smaller the better characteristic is implemented for surface roughness and maximum the better characteristic is implemented for metal removal rate. Lin [6] employed the Taguchi method and the grey relational analysis to optimize the turning operations with multiple performance characteristics. Chiang and Chang [7] used the grey relational analysis to optimize of the wire electric discharge machining process of particle-reinforced material with multiple performance characteristics. Yang et al [8] also used to optimize the dry machining parameters for high-purity graphite in end milling process, etc., by Taguchi method and grey relational analysis. In recent era, aluminium based metal matrix composite (MMC) materials are unique and widely recognized composites which originate significant applications in aerospace, automotive and electronic industries because of their improved strength, stiffness, corrosion resistance and increased wear resistance over unreinforced alloys [9].

Technical problems encountered in making aluminium alloy-graphite fibre composites had hindered the progress and thus commercialization of such MMCs. One of the major drawbacks in making graphite reinforced MMCs are that metals generally do not wet graphite. As a result, it is difficult to impregnate the fibre or particulate with the molten metal. Poor wettability also results in inadequate bonding between the metal and the graphite. In spite of the difficulties, Stephenson et al [10] and Bell et al [11] reported that, by coating graphite particles with nickel and incorporating them into molten aluminium, they produced wear resistant aluminium MMC. This composite, commercially known as aluminium nickel coated graphite MMC, has been successfully cast and tested as automobile engine cylinder liner and brake rotor. The graphite particles provided lubrication against wear while the aluminium-nickel intermetallic formed to improve the strength of the aluminium matrix. This research work attempts to develop Al6061-NCG composite with different weight fraction of NCG particles say (2.5, 5 and 7.5) %.

Also, machining operations are performed on this composite to analyze the performance characteristics. Using an appropriate design of experiments, the turning experiments are conducted on Al6061-NCG composite specimens with different levels of input parameters and the corresponding responses are determined. The process parameters include cutting speed, feed rate, depth of cut and weight fraction of NCG. The influence of these process parameters and their level of significance on the performance characteristics of surface roughness (Ra), material removal rate (MMR) has been evaluated. The optimal parameters setting for CNC turning are found out for individual and multi-performance characteristics using response table and grey relational approach.

## 2. Experimental details

The Al6061-NCG composite material used for the present investigation is produced by stir pellet casting method. The Al6061 alloy is heated to melt at 750°C, and then the reinforcement pellets are added as per the required mixture of the composite to be prepared. The pellets disintegrate and disperse inside the molten alloy [10]. After this, the molten mixture is stirred at 450 RPM for 10 minutes to ensure good distribution of reinforcement within the matrix. The stirred molten mixture is poured into moulds and the mixture is allowed to solidify to get the composite specimens. By adopting the above said procedure, composite specimens containing 2.5%, 5%, 7.5% by weight of reinforcement are prepared. The composition of specimens is varied by varying the number of pellets added to the molten Al6061 alloy. The prepared specimen is shown in Fig. 1.

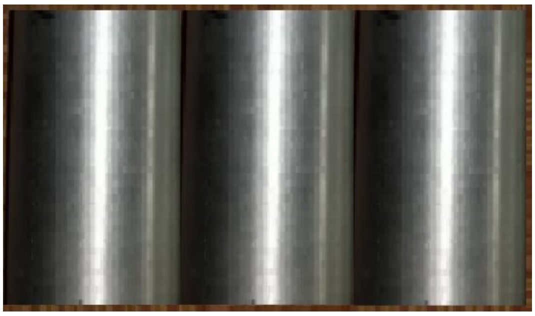

**Fig. 1: Prepared specimen**

The experiments are performed on CNC lathe selected (CNC-GGEDEE WEILER UNITURN 300) using Taguchi's orthogonal array in the design of experiments (DoE), which helps in reducing the number of experiments. The experiments are conducted according to a 3-level L9 orthogonal array. The machining parameters considered for the present investigations are: (1). % weight fraction of NCG, (2). cutting speed, (3). Feed, (4). depth of cut and out of which % weight fraction of NCG is specially applied to MMC composites. The interactions in the composite machining process may also play some role in deciding the surface roughness. The tool material selected were carbide CCGX 12 04 08 AL-H10. The process parameters are shown in Table 1. Taguchi's L9 orthogonal array (OA) was employed to obtain from Minitab -17 and it is shown in Table 2. It has sixteen rows and four columns. Rows correspond to test runs; column corresponds to the process parameter level.

**Table 1: Process parameters**

| Parameters | Level-1 | Level-2 | Level-3 |
|---|---|---|---|
| % of reinforcement | 2.5 | 5 | 7.5 |
| Cutting speed (m/min) | 125 | 175 | 225 |
| Feed (mm/rev) | 0.10 | 0.15 | 0.20 |
| Depth of cut (mm) | 0.5 | 1 | 1.5 |

**Table 2: Experimental results for L9 orthogonal array**

| % of reinforcement | Speed (m/min) | Feed (mm/rev) | Depth of cut (mm) |
|---|---|---|---|
| 2.5 | 125 | 0.1 | 1 |
| 2.5 | 175 | 0.15 | 2 |
| 2.5 | 225 | 0.2 | 1.5 |
| 5 | 125 | 0.15 | 1.5 |
| 5 | 175 | 0.2 | 1 |
| 5 | 225 | 0.1 | 2 |
| 7.5 | 125 | 0.2 | 2 |
| 7.5 | 175 | 0.1 | 1.5 |
| 7.5 | 225 | 0.15 | 1 |

## 3. Results and discussion

After each experiment, measurements were carried out on the work piece. In each test run, the measurement of surface roughness using a surface roughness tester was carried out at different locations of workpiece to minimize the measurement error and then a mean value of the surface roughness value was calculated. Similarly, the metal removal rate was calculated using the ratio of the difference in weight of the specimen (converted to volume) taken before and after machining to the time taken for machining. The actual values of investigation parameter and output response are tabulated in Table 3.

**Table 3: Response table for test run**

| Process parameters | | | | Response | |
|---|---|---|---|---|---|
| % of reinf. | Cutting speed (m/min) | Feed rate (mm/rev) | Depth of cut (mm) | MRR ($mm^3$/sec) | SR (μm) |
| 2.5 | 125 | 0.1 | 1 | 389.23 | 1.05 |
| 2.5 | 175 | 0.15 | 2 | 206.810 | 1.01 |
| 2.5 | 225 | 0.2 | 1.5 | 240.32 | 0.86 |
| 5 | 125 | 0.15 | 1.5 | 286.951 | 0.86 |
| 5 | 175 | 0.2 | 1 | 335.920 | 0.54 |
| 5 | 225 | 0.1 | 2 | 348.320 | 0.75 |
| 7.5 | 125 | 0.2 | 2 | 281.517 | 0.9 |
| 7.5 | 175 | 0.1 | 1.5 | 273.823 | 0.83 |
| 7.5 | 225 | 0.15 | 1 | 372.650 | 0.68 |

## *3.1. Multi-response optimization using grey relational analysis*

Grey relational grade is employed to convert multi objective problem into a single objective. The scope of this study was to identify the optimal combination of process parameters that concurrently minimize the surface roughness (Ra) and maximize the material removal rate (MRR). In order to accomplish this, grey relational analysis was employed.

**3.1.1. Generation of grey level**

Grey level is generated by normalizing the quality characteristics in between levels of 0-1. In the grey level generation smaller the better criteria to be used and which can be calculated by the following Eqn.

$$Xi(k) = \frac{\max yi(k) - yi(k)}{\max yi(k) - \min yi(k)} \tag{1}$$

Larger the better criteria to be used and which can be calculated by the following Eqn.

$$Xi(k) = \frac{yi(k) - \min yi(k)}{\max yi(k) - \min yi(k)} \tag{2}$$

Xi(k) - value of grey relational generation, max yi(k) is the biggest value of yi(k) at the $k^{th}$ responses and min yi(k) is the smallest value of yi(k) at the $k^{th}$ responses. Initially pre-processing has been calculated for normalizing the raw data for analysis, the normalizing table is shown in Table 4.

**Table 4: Normalization table**

| Pre-processing | | Deviation sequence | |
|---|---|---|---|
| MRR | SR | MRR | SR |
| 1.00 | 1.00 | 0.00 | 0.00 |
| 0.00 | 0.94 | 1.00 | 0.06 |
| 0.24 | 0.70 | 0.76 | 0.30 |
| 0.52 | 0.70 | 0.48 | 0.30 |
| 0.77 | 0.00 | 0.23 | 1.00 |
| 0.82 | 0.49 | 0.18 | 0.51 |
| 0.49 | 0.77 | 0.51 | 0.23 |
| 0.44 | 0.65 | 0.56 | 0.35 |
| 0.93 | 0.35 | 0.07 | 0.65 |

**3.1.2. Grey relational coefficient**

The grey relational coefficient (GRC) is calculated from the normalized values and it denotes the correlation between actual and desired experimental values.

$$\xi i(k) = \frac{\Delta \min - \Psi \Delta \max}{\Delta oi(k) + \Psi \Delta \max} \tag{3}$$

Where Δoi(k) is the deviation sequence in between the absolute value of Xo(k) and Xi(k) and Ψ is the value of distinguishing coefficient and it be $0 \leq \Psi \geq 1$. For that take the value of distinguishing coefficient was 0.5 Δmax X and Δmin are the maximum and minimum value of the corresponding $k^{th}$ response.

**3.1.3. Grey relational grade**

Grey relational grade calculated by the following Eqn.

$$\gamma i = \frac{1}{n} \sum_{k=1}^{n} \xi i(k) \tag{4}$$

From the grey grade γi, it indicates the level between comparability sequences and references. Here n is the number of responses. Optimization of the complicated multi process responses is changed into a single grey relational grade. The maximum value of grey grade indicates a stronger degree of relation between the given xi(k) and reference xo(k) sequences.

**3.1.4. Grey relational ordering**

An order of 1 is allotted to greatest grey relational grade. Grey relational grades are calculated using Eqn. (4) and grey relational order was figured out in Table 3. The control parameter's setting of 1 (experiment 1) have the greatest grey relational grade indicates the experiment 1 is the optimal turning factors setting for minimum surface roughness and maximization of MRR, simultaneously among the chosen 9 experiments. The larger better S/N quality characteristics were considered for grey relational grade, since higher multiple performance characteristics was our target.

**Table 5: Grade relational grade**

| Grey relational coefficient | | Grey relational grade | Rank |
|---|---|---|---|
| MRR | SR | | |
| 0.999999 | 0.999926 | 1.0000 | 1 |
| 0.333333 | 0.895345 | 0.6143 | 3 |
| 0.39603 | 0.624834 | 0.5104 | 8 |
| 0.50912 | 0.624834 | 0.5670 | 6 |
| 0.682196 | 0.333329 | 0.5078 | 9 |
| 0.740073 | 0.497008 | 0.6185 | 4 |
| 0.493913 | 0.683203 | 0.5886 | 5 |
| 0.47342 | 0.585749 | 0.5296 | 7 |
| 0.87899 | 0.433515 | 0.6563 | 2 |

## *3.2. Response table for GRA*

Taguchi used the signal-to-noise (S/N) ratio as the quality characteristic of choice. S/N ratio is used as deviation also decreases and vice versa. Larger the grey relational grade, the better is the multiple performance characteristics. However, the relative importance among the machining parameters for the multiple performance characteristics still need to be known, so that the optimal combinations of the machining parameter levels can be determined more accurately with the help of the response table at level of larger is better i.e., the optimal parameter combination is A1 (% of reinforcement - 0%), B4 (cutting speed - 125m/min), C1 (feed - 0.10mm/rev), D3 (depth of cut - 1.5mm).

**Table 6: Response table for GRG**

| Level | % of rein. | Cutting speed | Feed rate | Depth of cut |
|---|---|---|---|---|
| 1 | -3.182 | -3.358 | -3.178 | -3.231 |
| 2 | -4.336 | -4.996 | -5.213 | -4.273 |
| 3 | -5.430 | -4.595 | -4.557 | -5.444 |
| Delta | 2.248 | 1.638 | 2.035 | 2.213 |
| Rank | 1 | 4 | 3 | 2 |

### *3.3. Plot for means of S/N ratio*

The level of a parameter with the highest S/N ratio gives the optimal level. So the optimal process parameter setting for the multiple performance characteristic is A1-B1-C1-D1. The main effects plot for mean for GRG is shown in Fig. 2 and the main effects plot for S/N ratio for GRG.

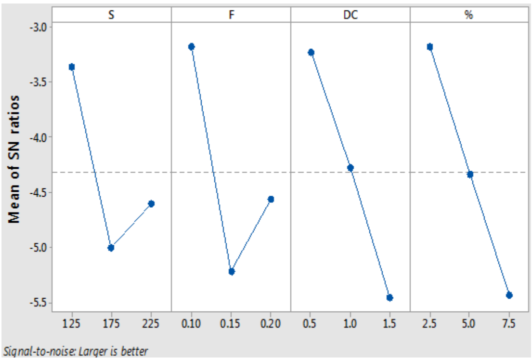


**Fig. 2: Plot for means of SN ratio for GRG**

### *3.4. ANOVA analysis for GRG*

ANOVA is a statistical method used to detect the individual interactions of all the control factors in the experimental results. The significant machining parameters were identified with the help of the analysis of variance (ANOVA). ANOVA analysis was performed with a 95% confidence level and 5% significance level. F values of the control factors indicated the significance of control factors with ANOVA analysis. The percentage contribution of each parameter is shown in the last column of the ANOVA table.

**Table 7: ANOVA analysis for GRG**

| Source | DF | Sum square | Mean square | F-value | P-value |
|---|---|---|---|---|---|
| Model | 7 | 0.18202 | 0.02600 | 101.10 | 0.076 |
| Linear | 4 | 0.03267 | 0.00817 | 31.76 | 0.132 |
| 2-way interaction | 3 | 0.03817 | 0.01272 | 49.47 | 0.104 |
| Error | 1 | 0.00025 | 0.00025 | $R^2$ = 98.87% | |
| Total | 8 | 0.18227 | | | |

### *3.5. Response surface regression based modelling*

Response surface methodology was conducted to model and analyze several variables, which have a relation between an output parameter and one or more input parameters. The test results were utilized to create the mathematical models with the help of the response surface methodology (RSM). In the present work, Minitab17 was utilized to compute the regression model. In order to investigate the effect of the tuning parameters on the responses (i) material removal rate (MRR) and (ii) surface roughness (SR) R-Sq values. Mathematical models are established between output responses and the turning process parameters by machining Al6061 NCG composite using Eqns. (5) and (6). The predicted MRR with $R^2$ = 99.96% is as follows,

$$\begin{aligned} MRR &= 32.575 - 3.1761\%R - 0.11518N - 271.26s \\ &+ 10.147d + 0.000887\%R*N + 21.234\%R*s \\ &+ 0.8233N*s \end{aligned} \tag{5}$$

Where $R$ is rein, $N$ is cutting speed, $s$ is feed rate and $d$ is depth of cut. The predicted SR with $R^2$ = 97.38% is as follows,

$$\begin{aligned} MRR &= -42.51 + 1.862\%R + 0.2691N + 341.5s \\ &- 62.38d - 0.00443\%R*N - 10.36\%R*s \\ &- 1.613N*s \end{aligned} \tag{6}$$

The adequacy of the model is further analyzed by using the values of R-Sq represent the regression confidence. The larger value of R-Sq is always desirable. In the present case, the R-Sq value is more than 95%, which shows the high correlation that exists between the experimental values and predicted values.

The experimental data and the predicted data by using the aforesaid model is plotted as shown in Figs. 3 and 4, which indicates a good correlation between the model and experimental values, and hence the developed model can be effectively used to predict the metal removal rate and surface roughness in machining Al6061 NCG MMC composites quadratic response surface models are fitted.

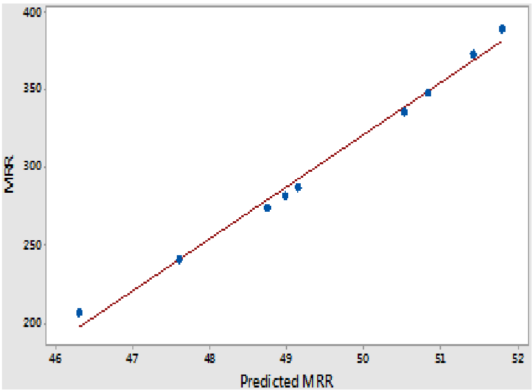


**Fig. 3: Comparison between predicted MRR and actual MRR**

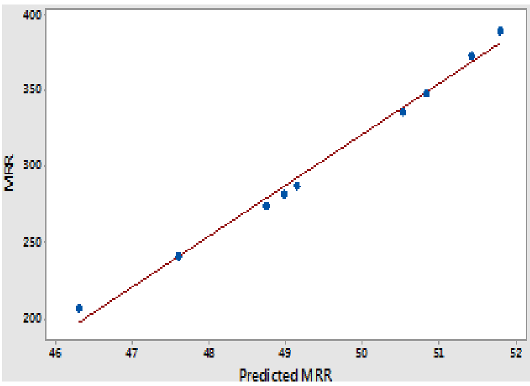


**Fig. 4: Comparison between predicted SR and actual SR**

## 4. Validation

In the final step of Taguchi based GRA, confirmation experiment of the control factors at optimal levels are conducted to verify the accuracy of optimization. It was clear that the optimum condition of process parameters is A1-B1-C1-D1 for the best multi objective output characteristics and result obtained from the confirmation Table 8. The experimental values are less than predicted value. Hence, the RSM is very useful for predicting the MRR and SR on the machining of Al6061-NCG composites within the chosen parameter settings:

Predicted response = Average of A1 + Average of B1 + Average of C1 + Average of D1 – 2 x Mean

**Table 8: Confirmation table**

| Response | Predicted | Experimental |
|---|---|---|
| Optimum set | A1(1) - B4(1) - C1(1) - D(1) | A1(1) - B4(1) - C1(1) - D(1) |
| MRR($mm^3$/sec) | 414.48 | 412.12 |
| SR(μm) | 1.88 | 1.82 |
| GRG | 1.622 | 1.582 |

## 5. Conclusion

Grey relational analysis is a very effective technique for optimization of machining processes which involves multiple responses, the optimal cutting parameters determined for parameters taken for investigation is A1-B1-C1-D1 i.e., 2.5% of reinforcement, cutting speed at 125m/min, feed rate at 0.10mm/rev and depth of cut at 1mm. The predicted results are validated with experimental results and found to have good agreement. Mathematical models were developed by using the response surface method to formulate the cutting input parameters like % of reinforcement, cutting speed, feed and depth of cut to the output parameters like metal removal rate and surface roughness. It is found out that response surface models could be used to predict responses due to more than 95% of confident level of $R^2$ result. It shows a good relationship between the test results and predicted results. Further, the normal probability plot of residual for responses shows that the residuals fall on a straight line implying that the errors are distributed normally. It is evident that the developed models are very reliable.

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