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Research Article

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Optimization of Process Parameters in Machining of AA-6262 by Implementing Grey Relational Analysis

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Abstract

In research employing computed numerical control (CNC) machining of AA-6262 and tungsten carbide tools, the impacts of three cutting parameters—the effects of three outcomes—material removal rate (MRR), surface roughness (SR), and tool wear rate (TWR)—of cutting speed, feed rate, and depth of cut (DoC)—were examined. In order to obtain as many responses as feasible, the study employed Taguchi's design of Experiment approach and Grey relational analysis (GRA). The investigation's findings showed that the answers were strongly impacted by the cutting settings. 2000 rpm, 400 rev/min for the feed rate, and 0.5 mm for the DoC were found to be the parameters' ideal values. The validation test showed that the ideal settings produced the maximum rates of MRR, SR, and TWR. The work is important because it provides informative data on how the cutting settings impact how AA-6262 responds to CNC turning. The study's conclusions may be used to improve turning performance and efficiency.

Keywords

Grey Taguchi, Analysis of variance, AA-6262, CNC Turning, Multi-response optimization, Tungsten carbide

Introduction

The method of machining is adaptable and may be utilised to make a variety of items. The ease with which a material may be machined is what determines its machinability. Alloys made of aluminium are easily machinable under various circumstances. Designers can make high-quality components and optimise machining by carefully taking these parameters into account.

The machining characteristics of various steel grades have recently been the subject of several research. Xavior and Adithan [1] looked at how the various cutting fluids affected responses like TWR and SR throughout the turning process. It's critical to consider productivity (MRR), SR, and cutting force (Fc) while optimising the machining parameters. The traditional machining of a mild steel round bar was examined by Dagwa [2] in order to optimize the cutting parameters of speed, DoC, and feed rate. The Taguchi approach was utilized by Asiltürk and Akkuş [3] to reduce SR during a CNC turning process. Their research revealed that the feed rate had the greatest influence on SR. Shukla and Singh [4] optimized the process variables. They found that modifying the machining parameters might change the cutting force for grey iron. The Taguchi approach was utilized by Abdullah et al. [5] to reduce workpiece surface temperature and increase SR.

On multi-objective optimization, recent research on the machining of aluminum and related alloys has been concentrated. This suggests that researchers

are attempting to concurrently optimize a variety of responses, such as cutting power, TWR, SR, machining time, surface temperature, and MRR [6-8]. Various cutting fluids using nanoparticles were used by numerous researchers to remove the heat during machining [6]. The performance of the lubricant will be improved much by the addition of nanoparticles into the base fluid [7]. Recently, polymer nanocomposites have gained much interest due to their advanced applications [8].

The Taguchi approach is a statistical technique that employs design of experiments to pinpoint the key variables influencing a process' output. It is a strong tool that may be utilized to raise the caliber and effectiveness of machining operations. Numerous machining processes, including turning, milling, drilling, and grinding, have all been employed the Taguchi approach. It has been demonstrated to be beneficial in raising productivity, decreasing manufacturing costs, and enhancing the quality of machined components [9, 10]. The Taguchi approach offers certain benefits over other process optimization techniques. It is a methodical strategy that may be used to improve a variety of processes. It additionally represents a rigorous statistical approach that can produce accurate findings. It is also rather simple to use and apply [11].

Each potential answer is given a grey relational grade, with the best option receiving the highest Grey relational rating [12]. Based on the discrepancy between the real and ideal values of the replies, the Grey relational grade (GRG) is determined [13, 14]. Numerous research on machining operations have employed GRA to optimize the associated processes. It has been demonstrated to be beneficial in raising productivity, lowering manufacturing costs, and improving the quality of machined products. To get the best machining performance, the cutting parameters were optimized using GRA. The study's findings demonstrated that Vc had a significant impact on the responses.

Materials and Method

Workpiece components

The investigation made use of cylinders with a diameter of around 35 mm produced of the AA-6262. Table 1 and table 2 display AA-6262's chemical composition and physical characteristics, respectively.

Designing experiments with the Taguchi technique

The levels of each parameter are three. Based on a three-level design with three parameters, the L9 orthogonal array was employed. OA, fractional factorial test designs, are used in the Taguchi design approach to cut down on the number of trials required to determine how the key factors affect output [15]. The number of control factors and their values determine which OA is appropriate. The design should be orthogonal and balanced in order to assess the primary parameter impacts. For various numbers of parameter-level combinations, Taguchi has set up certain OA that satisfy the aforementioned two characteristics. Due to financial constraints and other test-related constraints, a nine-run partial factorial strategy was chosen from the complete factorial design, which had $3^3 = 27$ runs. Table 3 lists the mix of components and their corresponding levels.

Table 1: Composition of AA-6262

Element	% Present
Manganese (Mn)	0.15
Iron (Fe)	0.7
Magnesium (Mg)	0.85 - 1.2
Silicon (Si)	0.45 - 0.8
Zinc (Zn)	0.25
Titanium (Ti)	0.15
Chromium (Cr)	0.045 - 0.14
Copper (Cu)	0.16 - 1.4
Bismuth (Bi)	0.4 - 0.7
Lead (Pb)	0.4 - 0.75
Other (Each)	0.05
Others (Total)	0.15
Aluminum (Al)	Balance

Table 2: Properties of AA-6262.

Property	Value
Brinell hardness	72
Ultimate tensile strength	225 MPa
Yield strength	192 MPa
Young's modulus	69.0 GPa
Poisson's ratio	0.33

Table 3: Cutting parameters with its levels considered in the work.

S. No.	Process parameters	Level 1	Level 2	Level 3
1	Spindle speed (rpm)	2000	3000	3500
2	Feed rate (mm/min)	200	300	400
3	DoC (mm)	0.2	0.3	0.4



Figure 1: Workpiece before and after machining.

Experimental setup

On a CNC lathe, which was used to perform the turning operation, the trials were conducted. A PTGNR 2020 K16 tool holder held a tungsten carbide tool in place. The workpiece for the experiment was 30 mm long and held in a universal chuck. Figure 1 presents workpiece before and after machining. In figure 2, the experimental setup is displayed.



Figure 2: Experimental setup used for the present study.



Figure 3: Machining operation.

Results and Discussion

As shown in figure 3, SR was measured using SR testers. Figure 4 provides a visual representation of the procedure for measuring SR. SR was assessed over the machined specimen at five different locations, and the mean of these readings was recorded. The weights of the tool and workpieces were determined using a weighing scale with a two-digit precision. Table 4 contains a list of the experimental run parameters and their results.

$$MRR = \frac{\text{initial sample weight} - \text{final sample weight}}{\text{time of machining x sample density}} \quad (1)$$

$$TWR = \frac{\text{initial tool weight} - \text{final tool weight}}{\text{time of maching x tool density}} \quad (2)$$

Grey relational technique

GRA is a method that can combine two or more output parameters into one output parameter, depending on the desired outcome. Computing the grey relation grade that was discovered through the GRA is how to do this. The subsections [16, 17] provide descriptions of the GRA technique. Figure 5 displays the flow chart for GRA.

Normalization of experimental results

The larger, superior response type's normalized value is:

$$Z_i(P) = \frac{Y_i(P) - \min Y_i(P)}{\max Y_i(P) - \min Y_i(P)} \quad (3)$$

The smaller response type's normalized value is:

$$Z_i(P) = \frac{\max Y_i(P) - Y_i(P)}{\max Y_i(P) - \min Y_i(P)} \quad (4)$$

Where, $Z_i(P)$ is the value produced by the grey relation and normalizing data. The lowest value of $Y_i(P)$ for a P^{th} answer is min $Y_i(P)$. The highest value of $Y_i(P)$ for the P^{th} answer is called max $Y_i(P)$. Table 5 displays the replies' normalized values.

Grey relationship coefficients analysis

Equation 5 may be used to compute the values of the grey relationship coefficients (GRC).



Figure 4: SR measurement instrument.

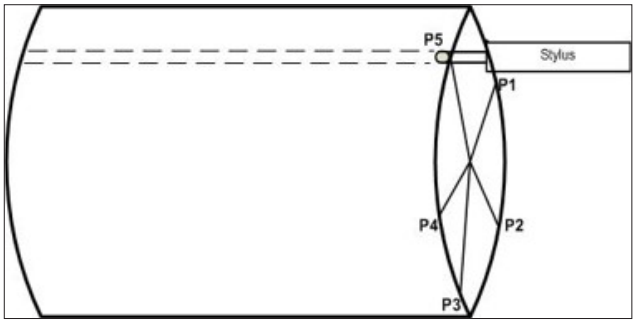


Figure 5: Graphical illustration of SR measured path criteria.

$$\varepsilon_i(P) = \frac{\Delta_{min} + \varphi\Delta_{max}}{\Delta_{oi}(M) + \varphi\Delta_{max}} \quad (5)$$

The number of φ must be between 0 and 1 and if this case it is considered as 0.5. Table 6 contains the derived and tabular GRCs.

Grade and order of Grey relations

Brownian motion coefficients are averaged to determine the GRGs. The GRG is calculated by combining several responses using equation 6.

$$GRG(\gamma_i) = \frac{1}{n}\sum_{P=1}^{n}\varepsilon_i(P) \quad (6)$$

Table 4: Experimental design and output responses.

Speed	Feed	DoC	SR	MRR	TWR
2000	200	0.2	1.09	3500	0.15
2000	300	0.3	1.15	4000	0.12
2000	400	0.4	1.24	4500	0.11
3000	200	0.3	1.91	3900	0.19
3000	300	0.4	2.21	4500	0.15
3000	400	0.2	2.56	4600	0.13
3500	200	0.4	2.84	4300	0.21
3500	300	0.2	2.94	4100	0.19
3500	400	0.3	2.87	4800	0.17

Table 5: Normalized values of the outputs.

Experimental run No.	Normalized values		
	MRR	SR	TWR
1	0.000	1.000	0.600
2	0.385	0.968	0.900
3	0.769	0.919	1.000
4	0.308	0.557	0.200
5	0.769	0.395	0.600
6	0.846	0.205	0.800
7	0.615	0.054	0.000
8	0.462	0.000	0.200
9	1.000	0.038	0.400

Table 6: GRC of the outputs.

Experimental run No.	GRC		
	MRR	SR	TWR
1	0.333	1.000	0.556
2	0.448	0.939	0.833
3	0.684	0.860	1.000
4	0.419	0.530	0.385
5	0.684	0.452	0.556
6	0.765	0.386	0.714
7	0.565	0.346	0.333
8	0.481	0.333	0.385
9	1.000	0.342	0.455

Table 7: GRG and their rank.

Experimental run No.	GRG	Rank
1	0.630	3
2	0.740	2
3	0.848	1
4	0.445	7
5	0.564	6
6	0.622	4
7	0.415	8
8	0.400	9
9	0.599	5

Where, i(P) is the Grey connection coefficient and n is the number of responses. The GRGs and their ranks are shown in table 7 (biggest GRG is at the top). Table 8 presents a response table for GRG.

Table 8: Response table for GRG.

Level	Speed	Feed	DoC
1	0.7393	0.4967	0.5507
2	0.5437	0.5680	0.5947
3	0.4713	0.6897	0.6090
Delta	0.2680	0.1930	0.0583
Rank	1	2	3

Table 9: ANOVA of GRG.

Source	DF	Adj SS	Adj MS	F-value	p-value
Speed	2	0.115342	0.057671	59.96	0.016
Feed	2	0.057140	0.028570	29.71	0.033
DoC	2	0.005544	0.002772	2.88	0.258
Error	2	0.001924	0.000962		
Total	8	0.179950			

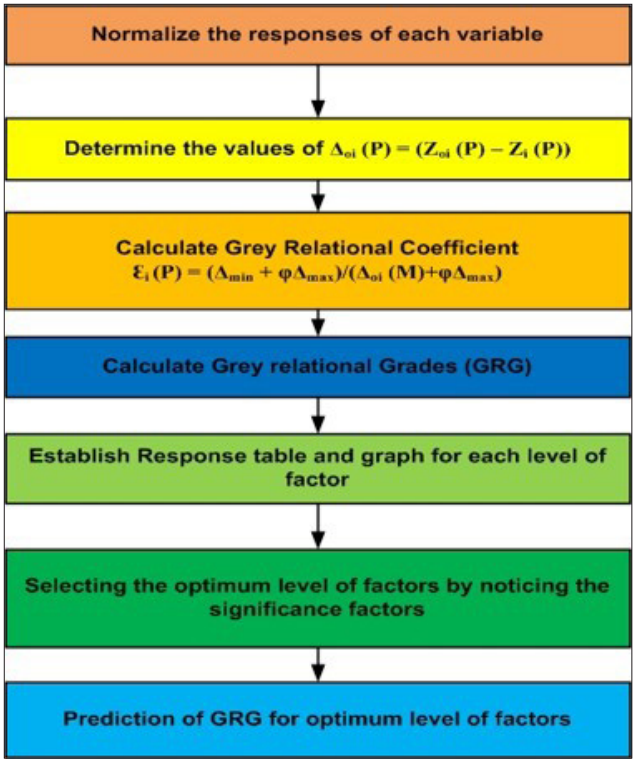


Figure 6: Flow chart of GRA.

Taguchi analysis

The chart in figure 6 may be used to estimate the ideal level of input parameters. The best results are obtained at 2000 rpm, 400 rev/min, and 0.4 mm, respectively, for feed rate, speed, and DoC.

ANOVA of GRG

The outcomes of the GRGs are shown in table 9. (GRG) ANOVA. Speed has the biggest proportion of contribution, according to the data, whereas DoC has the lowest percentage. Figure 7 presents main effect plot for GRG.

Confirmation test

The response table for mean GRGs was used to determine the ideal parameter values. The experimental GRG was dis-

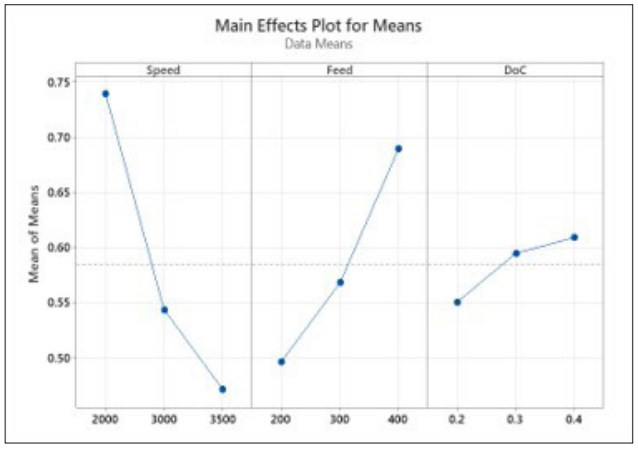


Figure 7: Main effect plot for GRG.

covered to be 0.914 at the parameter settings that gave the best results. According to Minitab 17, GRG was predicted to be estimated at 0.912 at the same ideal levels for the parameters. The mistake rate is minimal at less than 1%. As a result, the experimental findings are reliable.

Conclusions

The purpose of the study was to find out whether it was possible to concurrently improve TWR, SR, and MRR. When turning the material AA-6262 in a CNC machine using a Taguchi-based GRA. We evaluate the L9 OA. The variables that could be controlled were speed, feed rate, and DoC. Following analysis of the experimental findings, the following conclusions were made:

- The three responses were combined through normalization to provide GRGs for a single answer to be used.
- The amount that each parameter contributed to the result response was calculated using an ANOVA.
- For CNC turning of the component AA-6262, the ideal combination of multi-response cutting settings is 2000 rpm speed, 400 rev/min feed rate, and 0.4 mm DoC.
- The confirmation test was used to validate the GRG's best prediction.

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None.

Conflict of Interest

None.

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