International Journal of Advanced Engineering: Artificial Intelligence, Robotics and Automation
ISSN XXXX-XXXX
Vol.:1 Issue: 1
Published online on: Dec 2024
PP.47-58

Machining Process Parameters Optimization of Aluminium Alloy AA6463 for CNC Turning Using Grey Relational Analysis

Suneel Kumar[1], Nishant Singh Kushwah[2] , Elammaran Jayamani[3]
[1, 2] Vikrant University, Gwalior, India
[3]Swinburne University of Technology Sarawak Campus, Malaysia

Abstract

Most of the present-days machining is accomplished by computer numerical control (CNC), in which computers are used to controlled,the operations of multiple machines like drilling,milling, lathes, and other cutting machines. The CNC lathe machine was selected due to its wide availability and versatility, allowing it to handle multiple operations with minimal changes in setup. Turning was specifically chosen for this study because of its numerous benefits. This experiment focuses on optimizing the CNC turning process for machining AA 6463. The input parameters considered in this investigation include spindle speed (SS), feed rate (FR), depth of cut (DOC), and the use of coolant under both dry and wet conditions, where the output parameters are surface roughness i.e. arithmetic average (Ra).The designed experimental results are used in GRA. A 16 run Full Factorial design is chosen for ultimate tentative design considering two levels for the selected four parameters. The results of the confirmation trials reveal that grey relational analysis identifies the optimal combination of turning parameters. Performance metrics, such as surface roughness and material removal rate, are evaluated by calculating the grey relational grade. Ultimately, confirmation tests conducted under optimal conditions demonstrate improved surface finish, and the experimental values for surface roughness and material removal rate are compared with the predicted values.

Keywords: **CNC turning; Surface Roughness; Gray Relation analysis (GRA); Taguchi; Optimization.**

Nomenclature

SS	Spindle Speed in rpm
FR	Feed Rate in mm/min.
Doc	Depth of cut in mm.
SR	Surface Roughness in µm.
GRD	Grey Relational Deviation
GRC	Grey Relational Coefficient
GRG	Grey Relational Grade
GRA	Grey relational analysis
MS	Mean square

1. Introduction

Industrial production continually strives to achieve higher productivity and superior-quality products to maintain a competitive edge. Desired profiles, dimensions, and finished ferrous and non-ferrous materials are typically manufactured through turning, where pre-shaped blanks are machined using cutting tools that move relative to the workpiece in a machine tool. Turning is a vital and widely used machining procedure in manufacturing industries

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

(P.G.Benardos et al., 2007).It is one of the significant and broadly used machining processes in engineering productions. In turning, the cutting conditions such as Spindle Speed, feed rate and depth of cut, features of tools, coolant and work piece materials etc. affect the procedure efficiency and Features (Boothroyd and Knight et al., 1898). Performance estimation of CNC turning is established on the response parameter like tool wear, surface roughness, tool life, material removal rate (MRR), and power consumption etc. (Chinchanikar et al., 2014) represents a comprehensive literature review on machining of hardened steels using coated tools, studies related to hard turning, different cooling methods and attempts made so far to model machining performances, so as to give proper attention to the various researcher works. The high investment price of CNC machine tool demands its effective usage for fast profit of investment (Davim et al., 2003).A three dimensional system approach by(Yuan, et al., 2014) raised sustainability concerning issues of manufacturing from pollution prevention point of respect. (Liu et al., 2014) an attempt has been made to investigate the effect of operating parameters on depth of penetration and surface roughness in turning of alumina ceramics using abrasive water jet.

Surface roughness is a critical quality indicator for machined surfaces (I.P. Arbizu et al., 2003). Achieving a high-quality turned surface can enhance various properties, including thermal resistance, aesthetics, cleanability, friction coefficient, fatigue strength, wear resistance, assembly precision, and corrosion resistance. However, an increase in process parameters often leads to higher cutting temperatures, which negatively impact both the product and the tool. Elevated temperatures can cause dimensional inaccuracies due to thermal distortion, degrade the machined surface by inducing thermal effects and built-up edge formation, and compromise tool sharpness while increasing vibrations. Therefore, selecting the appropriate process parameters is crucial for ensuring efficiency, effectiveness, and the overall economic performance of machining processes to achieve goals such as higher material removal rates (MRR), lower surface roughness, and superior product quality. In turning operations, parameters like cutting speed, feed rate, and depth of cut significantly influence the surface finish. Typically, cutting parameters are determined based on experience or reference handbooks, which may not guarantee optimal performance (M.P. Groover, 1966). (Kaladhar M et al., 2010) have taken AISI 202 austenitic stainless for present investigation, full factorial experiment has been employed to determine the best combination of the machining parameters such as cutting speed, feed rate, depth of cut and nose radius to attain the minimum surface roughness also predictive models obtained for surface roughness.

Numerous processes and their associated factors have been optimized using various statistical techniques, including the response surface methodology, Taguchi method, and grey relational analysis. These methods were employed depending on the desired final response objective. Multi-objective optimization techniques are preferred for response variables with diverse objectives. For instance, (Sefika Kasman et al., 2013) used a Taguchi-based grey relational analysis to maximize the tensile strength and elongation of FS-welded butt joints.(W.K. Kim et al., 2010) used the response surface method to optimize the tensile strength by controlling the welding process parameters and tool design specifications.(Alagarsamy et al., 2016) perform multi-objective optimization of surface roughness(SR) and MRR in turning of AA 1040 steel have used grey relational analysis and resolute that cutting speed is the most manipulating parameter affecting joint grey relational grade followed by depth of cut and feed rate.(Chorng-Jyh Tzeng et al., 2009) have used Grey relational analysis to achieve optimization of turning processes with multiple performance characteristics such as roughness maximum, roughness average, and roundness. The depth of cut was recognized to be the most manipulating parameter affecting the grey relational grade followed by feed rate and cutting speed. For synchronized optimization of multi-responses, Taguchi normalized quality loss function (C.Y. Nian et al.,1999) and grey based Taguchi method have been generally used in turning (C.L. Lin et al., 2004) and drilling(A. Noorul Haq et al., 2008) significantly upgraded through this method. The GRA based on grey system theory can be used for resolving the complicate interrelationships among the several responses (R. Jeyapaul et al., 2005). Grey analysis effectively utilizes a grey relational grade (GRG) as a measure to evaluate multiple

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

performance characteristics. In recent years, grey relational analysis (GRA) has emerged as a prominent method for analyzing processes with diverse performance attributes.

2. Literature Review

Several researchers have explored machining processes and their effects on material properties under varying conditions. For instance, Shazzad Hossain et al. (2024) investigated the machining of Ti-6Al-4V alloy, analyzing the influence of cutting speeds (88–120 m/min), feed rates (0.08–0.15 mm/min), and depths of cut (0.10–0.20 mm) on cutting temperature and surface roughness. Similarly, N.H. Mohamad Nor et al. (2024) studied titanium alloys (Ti-6Al-4V) using parameters such as feed rates (0.20–0.30 mm/rev), cutting speeds (250–1000 rpm), depths of cut (0.5–2.0 mm), cutting angles (50°–100°), and mist inlet pressures (1–3 bar). They evaluated surface roughness and tool flank wear as the primary outcomes.

Adnan Ahmad et al. (2024) focused on Titanium Grade 3 alloy, emphasizing the impact of cutting speeds (75–125 m/min), feed rates (0.16–0.24 mm/min), and depths of cut (0.80–1.60 mm) on surface roughness and material removal rates. For Aluminum Alloy AA6262, Rahul Sharma et al. (2020) studied feeds (0.05–0.11 mm/min), speeds (700–1100 m/min), and depths of cut (0.8–1.6 mm) while analyzing surface finish and material removal rate.

Mehdi Heidari et al. (2017) examined porous carbon, focusing on feed rates (25–100 mm/min), cutting speeds (30–120 m/min), and depths of cut (0.2–0.8 mm) to assess surface roughness. For AISI 4140 steel, Aydin Salimiasl et al. (2016) investigated cutting speeds (110–160 m/min), feed rates (0.17–0.27 mm/rev), and depths of cut (0.75–1.75 mm), measuring cutting forces as the main parameter.

Wilson Luis Guesser et al. (2016) explored machining of grey cast iron, employing speeds (400–1400 m/min), a feed rate of 0.2 mm/rev, and a fixed depth of cut (2 mm) to evaluate surface roughness (Ra, Ry, and Rz). Sanghamitra Das et al. (2016) analyzed AISI H13 steel under cutting speeds (120–240 m/min), feed rates (0.1–0.32 mm/rev), and depths of cut (0.3–0.7 mm), with a focus on tool wear, surface finish, and material removal rate.

N. Senthilkumar et al. (2016) studied AISI D2 steel using cutting speeds (253–338 m/min), feed rates (0.203–0.432 mm/rev), and depths of cut (0.3–0.6 mm). They also examined the effect of various tool coatings (TiAlN, TiCN, TiN, uncoated) on tool wear, surface roughness, and material removal rate. V.K. Chaurasia et al. (2016) analyzed the machining of AA 6061 T6 alloy using cutting speeds (120–240 m/min), feed rates (0.1–0.32 mm/rev), and depths of cut (0.3–0.7 mm), focusing on material removal rate.

Ranganath M.S. et al. (2015) explored aluminum 6061 alloy under spindle speeds (500–600 rpm), depths of cut (0.10–0.30 mm), and feed rates (0.20–0.28 mm/rev) to study surface roughness. Lastly, S.J. Raykar et al. (2015) investigated aluminum 7075, considering cutting conditions (wet/dry), insert types (coated/uncoated), cutting speeds (200–370 m/min), feed rates (0.1–0.3 mm/rev), and depths of cut (0.1–1.5 mm). They measured roughness parameters (Ra and Rt), power consumption, cycle time, and material removal rate.

3. Experimental Work

3.1 Plan of experiment

ISSN XXXX-XXXX
Vol.:1 Issue: 1
Published online on: Dec 2024
PP.47-58

It includes a technique to produce the desired product from raw materials to the final product. Each experiment is conducted based on prescribed operational values and fixed experiment levels. The machining process involves several parameters such as speed, feed, and depth of cut to obtain the final product. These process parameters depend on various factors, including the shape, size, and geometry of the product. Grey relational analysis is employed as an optimization method in this context.

3.2 Machine Tool

The experimental work was conducted using a UNITURN 500 HD CNC Lathe machine, which has a maximum spindle speed of 4000 rpm. Half of the trials were carried out under dry conditions, while the remaining trials utilized coolant.

The surface roughness of the workpiece profile was measured using a Surface Roughness Measuring instrument. The Time@3100 (V20150210) is a portable, all-in-one device designed for measuring surface smoothness, suitable for both workshop and research laboratory environments. It uses SR for surface texture estimation, with microprocessor-based functions for constraint estimation and other operations. The results are shown on an LCD screen, and an optional printer or computer can be used to obtain printed results or further analysis.

Fig. 1 CNC turning machine

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

International Journal of Advanced Engineering: Artificial Intelligence, Robotics and Automation
ISSN XXXX-XXXX
Vol.:1 Issue: 1
Published online on: Dec 2024
PP.47-58

Fig. 2 Surface Roughness Tester

3.3 Work piece material

For the current experiment on optimizing surface roughness, we have selected AA 6463 as the material. This alloy is widely used in modern industries, particularly in applications such as window, patio door, curtain wall, storefront, and skylight architectural projects, as well as in the automotive, aircraft, boating, and sporting goods sectors. AA 6463 is found in various forms including tubing, pipes, rods, bars, extrusions, and structural shapes. A 185 mm long rod with a diameter of 50 mm made of AA 6463 was used in this experiment. The cutting tool employed is a CNMG 120408 PS CA6525 insert with a corner radius of 0.8 mm.

Fig. 3 Workpiece Post Machining

The chemical composition of the materials used for the workpiece is presented. in table 2.

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

Table 1: Chemical Composition of AA 6463

Elements	**Si**	**Fe**	**Cu**	**Mn**	**Mg**	**Al**
Chemical Composition Wt. (%)	0.870	0.168	0.027	0.510	0.438	Balance

3.4 Experimental Plan

An experiment was carried out to analyze the influence of machining parameters, including spindle speed (rpm), feed rate (mm/min), depth of cut (mm), and coolant type (dry/wet), on the machining of an AA 6463 workpiece using a CNC lathe. The experimental design was created using Design Expert 6 software. For each trial, an optimized combination of input parameters was selected. This study utilized the full factorial experimental method with two levels, resulting in a total of 16 runs, with the actual parameter values provided. in Table 3.

Table 2: Machining parameters and their levels

Factors	unit	Levels (Coded Value)	
		(-1)	(+1)
Spindle Speed(SS)	rpm	850	1150
Feed Rate(FR)	mm/min.	44	56
Depth of Cut(Doc)	mm	0.36	0.54
Coolant	-	Dry	Wet

4. Grey Relational Analysis (GRA)

The Grey Relational Analysis (GRA) method, rooted in grey system theory, was originally proposed by Deng JL in 1989. In grey system philosophy, "black" represents a system with insufficient information, while "white" signifies one with complete information. The grey relation, however, describes a scenario with partial information and is used to assess the degree of association between two categories, allowing the distance between two factors to be evaluated independently. When trials are uncertain or if the trial technique cannot be carried out precisely, grey analysis supports to reimburse for the absence in statistical regression. Grey relational analysis is an adequate way to evaluate the relationship between sequences with smaller amount data and can analyses many factors that can overcome the disadvantages of a statistical method (Changc et al., 2003). Further, it is essential to identify the best significant prominent constraints for CNC Turning. For such systems, GRA, as one of the best authoritative contents of grey theory, has been applied extensively. The principle of GRA is to evaluate the similarity and degree of the compactness among factors based on the geometric shape of the dissimilar sequences (Chang c et al., 2003).

***Step 1*:** Grey Relation Generation

The initial step involves calculating the normalized values for the experiment show in table 4.

Table 3: Practical value for L16 Array

International Journal of Advanced Engineering: Artificial Intelligence, Robotics and Automation
ISSN XXXX-XXXX
Vol.:1 Issue: 1
Published online on: Dec 2024
PP.47-58

Exp. No.	Speed(S)	Feed (F)	DOC(D)	Coolant(C)	MRR	SR
1	850	44	0.36	Dry	984.03	1.550
2	1150	44	0.36	Dry	1061.01	1.150
3	850	56	0.36	Dry	1383.6	1.860
4	1150	56	0.36	Dry	1470.03	0.260
5	850	44	0.54	Dry	1579.75	1.550
6	1150	44	0.54	Dry	1565.25	1.150
7	850	56	0.54	Dry	2022.8	1.860
8	1150	56	0.54	Dry	2095.04	0.260
9	850	44	0.36	Wet	1244.47	0.280
10	1150	44	0.36	Wet	1231.18	0.780
11	850	56	0.36	Wet	1634.63	1.250
12	1150	56	0.36	Wet	1749.34	0.530
13	850	44	0.54	Wet	1825.55	0.280
14	1150	44	0.54	Wet	1612.17	0.780
15	850	56	0.54	Wet	1640.06	1.250
16	1150	56	0.54	Wet	1376.84	0.530

For Higher-the-better (HB),

$$Z_i^*(k) = \frac{Z_i(k) - \min Z_i(k)}{maxZ_i(k) - minZ_i(k)} \quad (1)$$

The normalized values are calculated to maximize the material removal rate and minimize the surface roughness.

$$Z_i^*(k) = \frac{maxZ_i(k) - Z_i(k)}{maxZ_i(k) - minZ_i(k)} \quad (2)$$

Conversely, if a specific target value is to be achieved, then the original sequence will be normalised by the following equation of NB:

$$Z_i^*(k) = 1 - \frac{|Z_i(k) - Z_{op}(k)}{maxZ_i(k) - minZ_i(k)} \quad (3)$$

Here i = 1, 2…n; k = 1, 2, y, p; Z^*_i (k) represents the normalized value of the k-th element in the i-th sequence;Z_{0p}(k) denotes the target value of the k-th quality characteristic; max Z^*_i(k) is the maximum value of Z_i(k); min Z^*_i(k) is the minimum value of Z_i(k); n refers to the total number of experiments; and p indicates the total number of quality characteristics.

Step 2: For each experiment deviation sequence is calculated show in table 4.

Table 4: Grey relational normalization and deviation sequence $\Delta_{0,i}$

Exp.	Normalization Data		Deviation sequence ($\Delta_{0,i}$)	
	MRR	***SR***	***MRR***	***SR***
1	0	0.19375	1	0.80625
2	0.069288	0.44375	0.9307117	0.55625
3	0.359646	0	0.6403543	1
4	0.43744	1	0.5625602	0
5	0.536197	0.19375	0.4638032	0.80625
6	0.523146	0.44375	0.4768544	0.55625
7	0.934978	0	0.0650219	1
8	1	1	0	0
9	0.234417	0.9875	0.7655827	0.0125
10	0.222455	0.675	0.7775448	0.325
11	0.585593	0.38125	0.4144067	0.61875
12	0.688842	0.83125	0.3111583	0.16875
13	0.757437	0.9875	0.2425631	0.0125
14	0.565377	0.675	0.4346226	0.325
15	0.590481	0.38125	0.4095193	0.61875
16	0.353561	0.83125	0.6464388	0.16875

Step 3: Grey relational coefficient and grey relational grade

Subsequently as we normalizing the data, usually grey relational coefficient is calculated to show the relationship between the optimal and actual normalized experimental results. The grey relational coefficient can be expressed as

$$\beta_i^k = \beta\big(Z_0(k) - Z_i(k)\big) = \frac{\Delta min + \Delta max}{\Delta_{0,i}(k) + \in \Delta max} \tag{4}$$

$$i = 1\ldots n\ ;\ k = 1, \ldots, p,$$

here $\Delta_{0,i}(k) = |Z_0(k) - Z_i(k)|$ represents the absolute difference, referred to as the deviation sequence, between the reference sequence $Z_0(k)$ and comparability $Zi(k)$. The distinguishing coefficient $\in$, also known as the identification coefficient, ranges from $0 \leq \in \leq 1$. Typically, it is set to 0.5; which has also been adopted in this study, as recommended by Deng [20 The purpose of the grey relational coefficient is to quantify the relationship between the reference sequence $Z_0(k)$ and the comparability sequences Z_i (k), where i = 1, 2, ...,m and k = 1, 2, ..., n with m = 16 and n = 4 in this case. The grey relational grade (GRG) is defined as the weighted sum of the grey relational coefficients.

$$\beta\big(Z_{0,} Z_i\big) = \frac{1}{n}\sum_{k=1}^{n} \varepsilon_k\, \beta_{i,} \sum_{k=1}^{n} \varepsilon_k = 1 \tag{5}$$

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

International Journal of Advanced Engineering: Artificial Intelligence, Robotics and Automation
ISSN XXXX-XXXX
Vol.:1 Issue: 1
Published online on: Dec 2024
PP.47-58

here ε_k represent the weight assigned to the k^{th} performance characteristic.

Table 5: Experimental value of gray Relation coefficient and Overall GRG

Exp.	**Grey relation Coefficient (GRC)**		**Gray Relational Grade (GRG)**	**Rank for GRG values**
	MRR	***SR***		
1	0.333333	0.382775	0.358054	15
2	0.349476	0.473373	0.429007	13
3	0.43846	0.333333	0.360617	15
4	0.470562	1	0.752173	6
5	0.518778	0.382775	0.445609	12
6	0.511847	0.473373	0.596596	10
7	0.884921	0.333333	0.407896	14
8	1	1	0.851611	2
9	0.395075	0.97561	0.808511	4
10	0.391376	0.606061	0.634644	8
11	0.546803	0.446927	0.651495	7
12	0.616402	0.747664	0.873832	1
13	0.673343	0.97561	0.828929	3
14	0.534975	0.606061	0.629906	9
15	0.549741	0.446927	0.567747	11
16	0.436133	0.747664	0.755694	5

Step 4: Calculate for Overall GRG., Table 6 present the GRG values for the experimental results.

Experiment No. 12 demonstrates the highest values of the GRG.

The highest GRG value corresponds to rank 1. The grey relational grades are computed using Equation 5. Table 6 shows that Experiment No. 12 yields the highest grey relational grade. The optimal parameters are identified by examining the highest value on the S/N curve. Based on the calculations, the optimized parameters are S2F2D1C2.

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

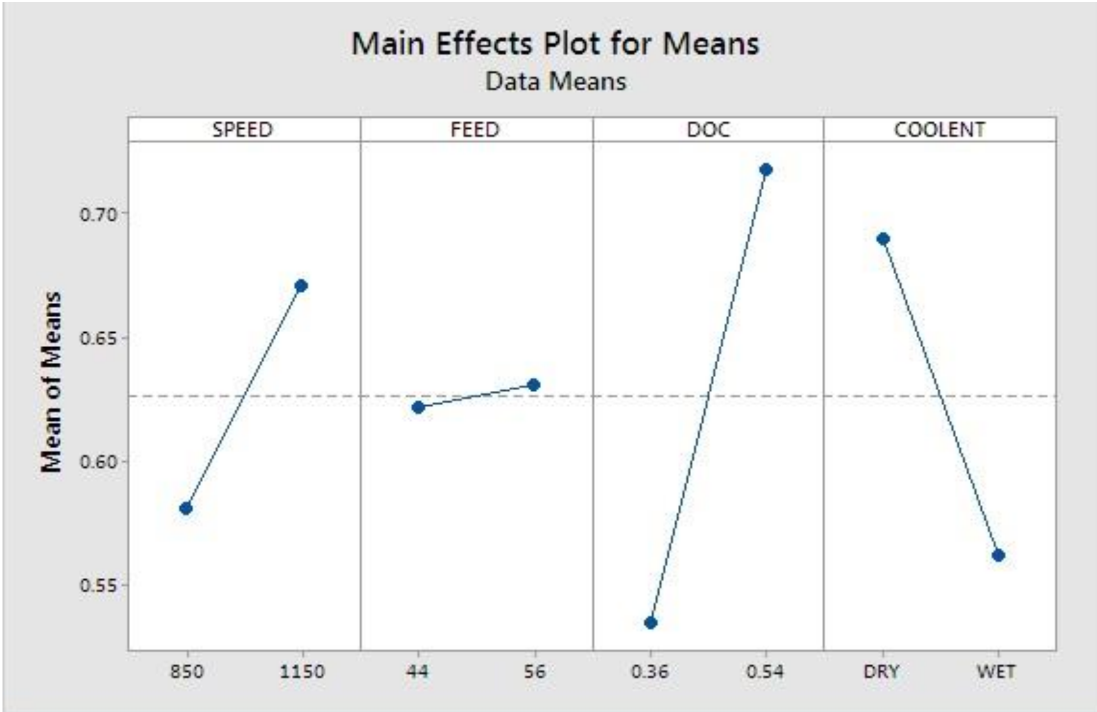

Fig. 4 Main effect plot for Mean of Grey relation grade.

Table 6: Response table for the grey relational grade

Symbol	CNC Turning Parameter	Level 1	Level 2	Max – Min	Rank
A	Speed	0.5815	0.6714	0.0899	3
B	Feed	0.6220	0.6309	0.0088	4
C	DOC	0.5347	0.7182	0.1834	1
D	Coolant	0.6904	0.5625	0.1280	2

5. Results and Discussions

The significance of parameters is determined by the difference between the highest and lowest GRG values. A larger difference indicates greater significance. As shown in Table 7, the Depth of Cut (DOC) has the most significant impact on the machining process, followed by Coolant, Speed, and Feed, respectively. A greater difference corresponds to a higher level of significance. Figure 4 illustrates the mean of the GRG, which shows that:

- The optimum process parameters are S1F1D2C2, meaning Speed = 850 RPM, Feed = 0.44 mm/rev, DOC = 0.54 mm, and Wet Condition.
- The optimized surface roughness is 0.280 µm.
- The optimized material removal rate (MRR) is 1825.54 mm^3/sec.

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

Table 7: Result of confirmation experiment for GRG.

Experiments	Variables	SR	MRR
Earliest Prediction	S2F2D1C2	0.530	1749.53
Experimental	S1F1D2C2	0.280	1825.55

6. Conclusions

Grey Relational Analysis (GRA) is utilized to optimize the process parameters. Through this study, the author determines the optimal values for the experimental parameters—feed, speed, depth of cut, and coolant—using the Grey Relational Grade (GRG). The focus of this research is to minimize surface roughness (SR) and maximize material removal rate (MRR). GRG serves as an essential method for calculating the optimal values in the least amount of time.

The conclusions drawn from the experimental results are as follows:

- Increasing the depth of cut (DOC) leads to maximum MRR and minimum surface roughness.
- A combination of speed at level 2, feed at level 2, DOC at level 1, and coolant at level 2 results in maximum MRR and optimal surface finish.
- DOC is the most influential factor, ranking first in terms of optimization.
- Coolent (C) had the 2nd Rank.
- Speed had a 3rd Rank.
- Feed had a 3rd Rank.

References

[1] Benardos P. G. and Vosniakos., G.Predicting surface roughness in machining : a review, International Journal of Machine Tools & Manufacture,Vol 43, 2003, pp. 833-844.

[2] Chaurasia V. K., Kasdekar D. K., Shivhare V.,Development of Artificial Intelligence Model for the Prediction of MRR in Turning',Vol.9,No.2, 2016, pp.75-82.

[3] Chaurasia V. K., Kasdekar D. K., Parashar V., Analysis of the Influence and Artificial Intelligence Model to Predict MRR in CNC Turning,Vol.7, 2015, pp.24-31.

[4] Doley R.,Kashyap S., Das Sanghamitra.,Pathak Hrishikesh. Cutting process optimisation and modelling in dry turning of AISI H13 tool steel with brazed carbide tip, *Int. J. Precision Technology,*Vol. 6, No.1, 2016, pp.42-60.

[5] Guesser W.L., Pereira F. S., Boehs L., Surface changes during turning of grey cast iron, *Int. J. Machining and Machinability of Materials*,Vol. 18,No. 3, 2016, pp.313-323.

[6] Haq A. N., Marimuthu P.,Jeyapaul R., Multi response optimization of machining parameters of drilling Al / SiC metal matrix composite using grey relational analysis in the Taguchi method,*Int J Adv Manuf Technol*,Vol.37, 2008, pp. 250-255.

[7] Jayaraman P., Mahesh. L., Multi-response Optimization of Machining Parameters of Turning AA6063 T6 Aluminium Alloy using Grey Relational Analysis in Taguchi Method, *Procedia Engineering* 97, 2014, p.197- 204 97.

[8] Kaladhar M., Subbaiah K.V., Rao K. N., Rao Ch. Srinivasa.,Optimization of process parameters in turning of AISI 202 Stainless Steel,*ARPN Journal of Engineering and Applied Sciences*,Vol.5, No. 9, 2010, pp.79-87.

[9] Kasdekar D K.,Parashar V., Principal Component Analysis to Optimize the ECM Parameters of Aluminium Alloy,*7th International Conference on Materials Processing and*

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in

Characterization,ICMPC,India, 2017.

[10] Kim W. K., Goo B. C., Won Si-t., Optimal design of friction stir welding process to improve tensile force of the joint of AA 6005 Extrusion, *Materials and Manufacturing Processes,*Vol. 25, 2010, pp.637-643.

[11] Krishnaiah K., Jeyapaul R., Shahabudeen P.,Quality management research by considering multi-response problems in the Taguchi method– a review, *Int J Adv Manuf Technol*, Vol. 26, 2005, pp.1331-1337.

[12] Liu D., Huang C., Wang J., Zhu H., Yao P., Liu Z., Modeling and optimization of operating parameters for abrasive waterjet turning alumina ceramics using response surface methodology combined with Box – Behnken design, *Ceramics Inter-national. Elsevier*, Vol.40(6), 2014, pp. 7899-7908.

[13] Lu H.S.,Chung C.K.,Hwang N.C.,Chung C.T., Grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high speed end milling,*Journal Of Materials Processing Technology*,Vol.209, 2009, pp. 3808-3817.

[14] Mukherjee S., Kamal A and Kumar K., Optimization of Material Removal Rate During Turning of SAE 1020 Material in CNC Lathe using Taguchi Technique,*Procedia Engineering,*Vol.97, 2014, pp.29-35.

[15] Nian C. Y., Yang W. H. and Tarng Y. S., Optimization of turning operations with multiple performance characteristics, *Journal of Materials Processing Technology* ,Vol.95, 1999, pp. 90-96.

[16] Özdemir A., and Salimiasl A., Modelling of the cutting forces in turning process for a new tool, *Int. J.Mechatronics and Manufacturing Systems,*Vol. 9, No. 2, 2016, pp.160-172.

[17] Ranganath M. S. and Mishra R. S., Optimization of Surface Roughness in CNC Turning of Aluminium 6061Using Taguchi Techniques,*International Journal Of Modern Engineering Research,*Vol.5, 2015, pp.42-50.

[18] Raykar S. J., Addona D. M. D and Mane A. M., Multi-objective optimization of high speed turning of Al 7075 using grey relational analysis,*Procedia CIRP,*Vol. 33, 2015, pp. 293-298.

[19] Routara B. C. and Mohanty S. D., Combined quality loss (CQL) concept in WPCA-based Taguchi philosophy for optimization of multiple surface quality characteristics of UNS C34000 brass in cylindrical grinding grinding,*Int J Adv Manuf Technol*,Vol. 51, 2010, pp. 135-143.

[20] Siddiquee A.N., Khan Z.A., Mallick Z., Grey relational analysis coupled with principal component analysis for optimization design of the process parameters in in-feed ceterless cylindrical grinding, *Int. J. Adv. Manuf. Technology,*Vol.46, 2010, pp. 983-992.

[21] Singh Bikram Jit.,Sodhi Harsimran Singh., Parametric optimisation of CNC turning for Al-7020 with RSM,*Int.J. Operational Research*, Vol. 20, No. 2, 2014, pp.180-206.

[22] Saini S.K., S., Pradhan S.K., Optimization of Multi-Objective Response during CNC Turning using Taguchi-Fuzzy Applicat-ion,*Procedia Engineering*, Vol.97, 2014, pp.141-149.

[23] Suneel kumar Rathore, Jyoti Vimal, Multi Objective Optimization in Turning Parameters of AI 6463 using Principal Component Analysis, Journal of Material & Metallurgical Engineering, Vol. 7, No. 2, 2016, pp. 6-15.

[24] Ankita Kar, Nishant Singh Kushwah, Optimizing of cutting parameter on Aluminium alloy 6063 for maximum MRR and minimum SR using Taguchi approach, International Journal For Research In Applied Science & Engineering Technology, Vol. 8, No. 03, 2020, pp.211-215.

Corresponding Author's E-mail ID: me_suneel@vikrantuniversity.ac.in