engineering proceedings

Proceeding Paper

Optimization of Turning Parameters and Cooling Techniques for Enhanced Machining Performance of EN8 Steel Using L9 Orthogonal Array [†]

Barkur Shrinivasa Somayaji [1], Ritesh Bhat [2,*], Nithesh Naik [1,*] and Beedu Rajendra [1]

[1] Department of Mechanical and Industrial Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal 576104, Karnataka, India; shrinivasa.b@manipal.edu (B.S.S.); rajbeedu60@gmail.com (B.R.)
[2] Department of Mechatronics Engineering, Rajalakshmi Engineering College, Thandalam 602105, Tamil Nadu, India
* Correspondence: riteshbhat.rb@rajalakshmi.edu.in (R.B.); nithesh.naik@manipal.edu (N.N.)
† Presented at the International Conference on Recent Advances in Science and Engineering, Dubai, United Arab Emirates, 4–5 October 2023.

Abstract: This study presents a detailed analysis of the effects of machining parameters, including the cutting speed (v), feed (f), depth of cut (d), and type of coolant flow (CF), on two primary performance characteristics in a machining process, namely, surface roughness (Ra) and material removal rate (MRR). A series of experiments were conducted, and the resulting data were analyzed using regression models, analysis of variance (ANOVA), Taguchi's L9 orthogonal array analysis, and grey relational analysis. The initial findings from the raw experimental data revealed that, while Ra appeared to be influenced by a combination of parameters, an increasing trend in MRR was observed with higher values of feed rate and depth of cut. The regression models suggested the significant influence of the machining parameters on the Ra and MRR, with the type of coolant flow playing a critical baseline role. The ANOVA results statistically validated these models and ranked the significance of each parameter in affecting Ra and MRR. Furthermore, Taguchi's analysis supported the findings and highlighted the potential for process optimization. The grey relational analysis revealed that the combination with a speed of 130 m/min, a feed of 0.1 mm/rev, a depth of cut of 0.15 mm, and a minimum quantity lubrication type of coolant flow provided the optimal result, with a GRG of 0.704, ranking first among all other parameter combinations, providing valuable insights for improving machining processes. The results, thus, indicated that the best results were generally obtained with higher speeds, lower feed rates, and moderate depths of cut under minimal quantity lubrication conditions. These findings could greatly benefit industry professionals in optimizing their processes for efficiency and quality, though it is noted that results may vary with different materials and machining conditions, presenting potential areas for future research.

Keywords: EN8 steel; machining parameters; orthogonal array; surface roughness; material removal rate

Citation: Somayaji, B.S.; Bhat, R.; Naik, N.; Rajendra, B. Optimization of Turning Parameters and Cooling Techniques for Enhanced Machining Performance of EN8 Steel Using L9 Orthogonal Array. *Eng. Proc.* **2023**, *59*, 243. https://doi.org/10.3390/engproc2023059243

Academic Editors: Rajiv Selvam, Pavan Hiremath and Suhas Kowshik CS

Published: 20 March 2024

1. Introduction

The significance of understanding the interactions between various machining parameters and their effects on machining performance cannot be overstated [1–4]. As manufacturing industries continually endeavor to improve efficiency, performance, and product quality, it is crucial to comprehend the interrelationships between these variables. Due to the widespread use of metallic materials in industries, machining, particularly the efficacy of turning operations on metals, has been the subject of numerous studies [5,6]. Among these, EN8 steel holds a key position due to its extensive use in the automotive industry for studs, keys, axles, and shafts [7–9].

Thus, the present study seeks to examine EN8 steel machining performance under different coolant flows, filling a gap in the existing literature, as very few researchers have discussed this topic to date [10,11]. Surface roughness (Ra) and material removal rate (MRR) are two fundamental performance characteristics considered in any metal-cutting process [12]. The Ra influences the functional properties of machined components, such as wear resistance, fatigue strength, and frictional behavior [13–15]. In contrast, the MRR directly affects the productivity and effectiveness of the machining process [16,17]. Both of these characteristics are known to be influenced by machining parameters such as the cutting speed (v), feed rate (f), depth of cut (d), and coolant flow type (CF) [18–20]. Despite extensive prior research on these parameters, the specific impact of coolant flow on the Ra and MRR during the machining of EN8 steel has not been explored in detail. To decipher the intricate relationships between these variables, the present study employed a multifaceted analytic strategy, including regression models, analysis of variance (ANOVA), Taguchi's L9 orthogonal array analysis, and grey relational analysis (GRA).

2. Materials and Methods

2.1. Materials

EN8 (080M40), an unalloyed medium carbon steel [21], is the material utilized in this study. Thermo-mechanical rolling is responsible for EN8's superior strength compared to conventional bright mild steel. EN8 is suitable for various engineering applications where steel with greater strength may be required due to its superior strength [22]. Although EN8's tensile properties can differ, they are typically between 500 and 800 N/mm^2 [23]. EN8 is commonly available in various diameter bar forms. Considering the objectives of the present study, attempts were made to acquire three sets of nine workpieces, each sourced from a unique lot of material. In this study, we used EN8 steel, a grade of carbon steel known for its excellent tensile strength and toughness, making it a popular choice for various industrial applications. The EN8 steel used in our experiments has a specific chemical composition that confirms its grade according to standard specifications. It contains carbon (C) in a proportion of 0.36 to 0.44 %, manganese (Mn) from 0.60 to 1.00 %, and silicon (Si) from 0.10 to 0.40 %. Additionally, it has a maximum of 0.050 % sulfur (S) and 0.050 % phosphorus (P). This strategy was employed to accommodate and account for any minor differences in the properties of the workpiece materials. Bars with a diameter of 25 mm were cut into 70 mm long sections. Following the initial preparation, each of the twenty-seven sample workpieces was turned to have a diameter of 24 mm and a length of 20 mm, ensuring uniformity.

2.2. Experimental Setup

The investigations were conducted on an ACE Jobber Jr. machine. It is a CNC lathe with a 300 mm center-to-center distance, a 250 mm maximum turning diameter, and a 300 mm maximum turning length. The machine has a 450 mm swing over the platform, a 130 mm X-axis, and a 300 mm Z-axis stroke. The variable feed rate ranges from 0 to 10,000 mm/min, and the X and Z axes traverse at 20 m/min. The spindle motor has a power rating of 5.5 kW and can operate between 50 and 3000 RPM. A water-based Veedol Amulkut 4G was used as a coolant during the operation. CNMG 120408 TN 2000 cutting tool inserts were utilized for turning operations.

2.3. Measuring Techniques

The present work employed surface roughness measurement and material removal rate (MRR) calculation as key measuring techniques. The Ra is a common surface roughness parameter that measures the average surface roughness by comparing all peaks and valleys to the mean line and aggregating them over the entire cut-off length. This investigation measured the surface roughness with a Taylor Hobson surface roughness tester: a stylus-type surface roughness measuring instrument designed for shop floor use. The material removal rate (MRR) is another important metric measured in this investigation.

It was calculated by dividing the difference in weight before and after the turning operation by the machining time and is represented mathematically by the following equation:

$$\text{MRR} = \frac{\text{Initial weight} - \text{Final weight}}{\text{Machining time}} \quad (1)$$

2.4. Experimental Design

Four crucial turning parameters, namely, the cutting speed (v), feed (f), depth of cut (d), and coolant flow type (CF), were evaluated at three distinct levels in the present study. These parameters were chosen due to their well-established importance in machining processes, as these factors largely determine the product's overall quality. As discussed earlier, the investigation was centered on two response variables: the surface roughness (Ra, measured in µm) and the machined specimens' material removal rate (MRR). The experimental design was based on the Taguchi method, which aims to minimize process variation using a robust design [24]. The Taguchi method organizes process parameters and their corresponding levels using orthogonal arrays (OAs). Degrees of freedom (equal to the number of levels for a given parameter minus one) are associated with selecting an orthogonal array [25]. In this investigation, 27 experiments were conducted, with three sets of experiments for each of the nine parameter combinations. The effectiveness of various coolant flow types (dry, flood, and minimum quantity lubrication) was evaluated for each parameter combination. Table 1 outlines the parameters and corresponding levels utilized in this study.

Table 1. Parameters and levels used in the experiment.

S. No	Parameters	Symbol	Units	Levels
1	Cutting speed	v	mm/min	Low: 105, Med: 130, High: 155
2	Feed	f	mm/rev	Low: 0.10, Med: 0.15, High: 0.20
3	Depth of cut	d	mm	Low: 0.10, Med: 0.15, High: 0.20
4	Coolant flow type (categorical factor)	CF	-	Dry, Flood, MQL

3. Multiresponse Optimization Using Grey Relational Analysis

Grey relational analysis (GRA) has been demonstrated to be highly effective for optimizing situations involving multiple performance characteristics. By optimizing a single parameter known as the grey relational grade, GRA permits the transformation of a multiobjective optimization problem into a single-objective optimization problem [26]. The GRA analysis consists of three main steps: preprocessing the raw data, estimating the grey relational coefficients, and calculating the grey relational grade. The original data are normalized to dimensionless values between 0 and 1 during preprocessing. Normalization varies depending on the sort of quality attribute [27]. For the surface roughness (Ra), which follows the "smaller-the-better" criterion, normalization is performed utilizing the following equation:

$$x_i^*(k) = \frac{\max x_0(k) - x_i(k)}{\max x_0(k) - \min x_0(k)} \quad (2)$$

And for the material removal rate (MRR), which follows the "larger-the-better" criterion, normalization is performed utilizing the following equation:

$$x_i^*(k) = \frac{x_i(k) - \min x_0(k)}{\max x_i(k) - \min x_i(k)} \quad (3)$$

where $x_0(k)$ is the original sequence, $x_i^*(k)$ the sequence after the data preprocessing, $\max x_i(k)$ the largest value of $x_i(k)$, and $\min x_i(k)$ the smallest value of $x_i(k)$. The second step involves the calculation of the grey relational coefficient, which helps establish a relationship between the actual normalized sequence and the ideal or reference sequence [27]. This relationship can be expressed mathematically, as shown in the following equation:

$$\zeta_i(k) = \frac{\delta_{\min} + \zeta\delta_{\max}}{\delta_i(k) + \zeta\delta_{\max}} \tag{4}$$

where $\delta_{0i}(k)$ is the deviation sequence of the reference sequence, and ζ is the distinguishing or identification coefficient: $\zeta \in [0,1]$. However, a ζ of 0.5 is generally used. The final step involves the calculation of the weighted grey relational grade using the following equation:

$$\text{Weighted GRG} = (0.5 \times \zeta_i(k) \text{ for } Ra) + (0.5 \times \zeta_i(k) \text{ for } MRR) \tag{5}$$

The weighted grey relational grade is the weighted sum of the estimated grey relational coefficients. Due to their similar importance in the machining process, both response variables (MRR and Ra) were allotted equal weights of 50% each in this study. The GRA technique was chosen for its ability to handle multiple performance characteristics simultaneously. It transforms a multiobjective optimization problem into a single-objective optimization problem by optimizing a single parameter known as the grey relational grade. This makes it particularly suitable for our study, where we are dealing with multiple machining parameters and their effects on the surface roughness and material removal rate. The GRA technique allows us to evaluate the performance of different parameters and their levels in a comprehensive and efficient manner.

4. Results and Discussion

This study's experimental investigation aimed to determine the effect of machining parameters and coolant flow type on the surface roughness (*Ra*)) and material removal rate (*MRR*). The experimental data are presented in Table 2. From the preliminary analysis of the data, there does not seem to be an obvious trend that indicates which parameter has the greatest effect on the Ra, and it seems to be sensitive to a combination of parameters as opposed to a singular factor. For *MRR*, greater values of f and d correspond to an increase in *MRR*. This observation highlights the complexity of the manufacturing procedure, in which multiple variables interact to determine the ultimate results.

Table 2. Experimental data.

S. No.	Speed v (mm/min)	Feed f (mm/rev)	Depth of Cut d (mm)	Type of Coolant Flow CF	Surface Roughness Ra (µm)	Material Removal Rate MRR
Trial 1	1	1	1	1	1.78	6.64
Trial 2	1	2	2	2	3.21	12.27
Trial 3	1	3	3	3	3.13	18.66
Trial 4	2	1	2	3	1.52	10.04
Trial 5	2	2	3	1	3.02	19.10
Trial 6	2	3	1	2	3.49	11.61
Trial 7	3	1	3	2	2.41	16.03
Trial 8	3	2	1	3	1.55	10.08
Trial 9	3	3	2	1	2.97	17.73

The regression models for the surface roughness given by Equations (6)–(8) for $CF = 1$, 2, and 3 revealed the combined effect of v, f, d, and CF on the surface roughness. From the equations, it can be inferred that as v increases, the *Ra* decreases, as denoted by the negative sign preceding the coefficient of v. On the other hand, the positive sign for f, d, and CF suggests that an increase in these variables causes an increase in the *Ra*. In a regression model, the constant term (also known as the intercept) represents the average expected value of the response variable when all predictor variables are set to zero [28].

$$Ra = 1.113 - 0.1983v + 0.6467f + 0.2911d \tag{6}$$

$$Ra = 1.554 - 0.1983v + 0.6467f + 0.2911d \tag{7}$$

$$Ra = 0.588 - 0.1983v + 0.6467f + 0.2911d \tag{8}$$

It can be interpreted as the average surface roughness (*Ra*) for each form of CF when v, f, and d are set to zero. The fact that the constant varies with each form of CF indicates that the CF has a baseline effect on the surface roughness that is independent of the other factors (v, f, and d). Even before v, f, and d enter into play, the average *Ra* is highest when CF = 2 and lowest when CF = 3, for instance. Before contemplating the machining parameters, the constant terms for each CF level indicate that the choice of coolant flow can significantly impact the surface roughness. This understanding could influence the selection of coolant flow during the machining process to optimize the surface roughness. In addition, the ANOVA results in Table 3 statistically validate the regression models, revealing that the contribution of the feed to the total sum of squares is the highest, followed by the coolant flow type and depth of cut, emphasizing their importance in influencing the Ra. However, the cutting speed demonstrated the least influence.

Table 3. ANOVA results for surface roughness.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	*p*-Value
Regression	5	4.65879	98.69%	4.65879	0.93176	45.23	0.005
v	1	0.23602	5.00%	0.23602	0.23602	11.46	0.043
f	1	2.50907	53.15%	2.50907	2.50907	121.79	0.002
d	1	0.50847	10.77%	0.50847	0.50847	24.68	0.016
CF	2	1.40523	29.77%	1.40523	0.70262	34.10	0.009
Error	3	0.06181	1.31%	0.06181	0.02060		
Total	8	4.72060	100.00%				

The Taguchi analysis reconfirmed these results by identifying the feed as the most influential factor on the *Ra*, followed by the coolant flow type, depth of cut, and cutting speed. This validated the prior analysis and highlighted the significance of optimizing f and CF for an enhanced surface finish. Table 4 is the response table of means depicting the greatest delta value for f (1.293). Figure 1 depicts the obtained main effect plots, where the steep line for f was observed again.

Table 4. Response table of means for surface roughness.

Level	v	f	d	CF
1	2.706	1.903	2.271	2.592
2	2.678	2.592	2.568	3.033
3	2.309	3.197	2.853	2.067
Delta	0.397	1.293	0.582	0.967
Rank	4	1	3	2

The regression models for the MRR given by Equations (9)–(11) for $CF = 1, 2$, and 3 revealed that all four factors v, f, d, and CF play significant roles in determining the MRR, with the depth of cut being the most influential parameter. This result is consistent with the practical comprehension of machining processes, according to which deeper cuts remove material more rapidly, thereby increasing the MRR.

$$MRR = -1.186 + 1.044v + 2.547f + 4.246d \tag{9}$$

$$MRR = -2.372 + 1.044v + 2.547f + 4.246d \tag{10}$$

$$MRR = -2.748 + 1.044v + 2.547f + 4.246d \tag{11}$$

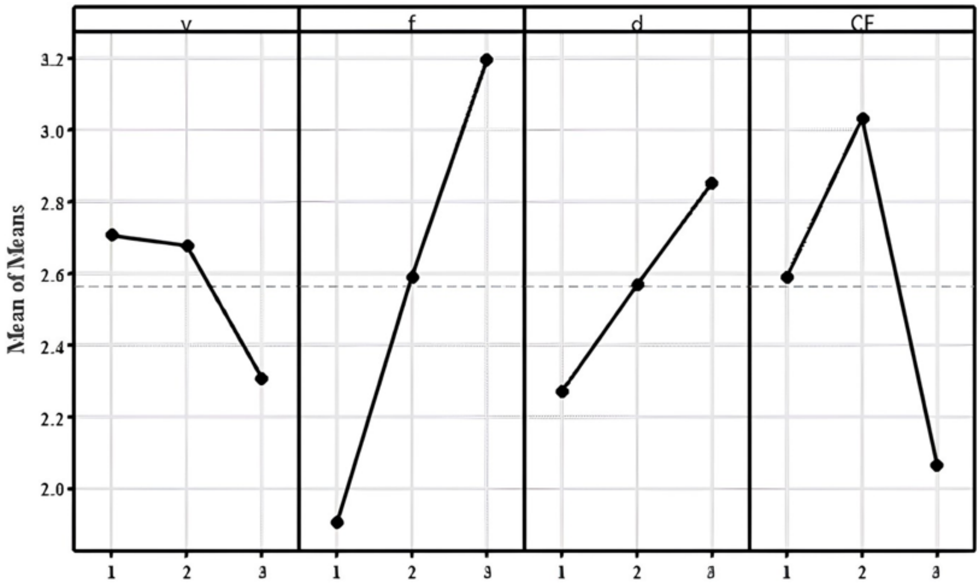

Figure 1. Mean effect plot for surface roughness.

Different intercepts in each model suggest that the type of coolant flow influences the basal MRR. Specifically, the models indicate that the *MRR* decreases as we transition from arid conditions to a flood-type coolant flow and decreases further as we switch to a minimal quantity lubrication flow type. As the *MRR* cannot be negative in practical situations, these values represent the intercept term in the regression model rather than a direct physical interpretation. The ANOVA results presented in Table 5 support the conclusion by disclosing that the greatest sum of squares was associated with the depth of cut, followed by the feed and cutting speed, indicating their significant contribution to the total variation in*MRR*. Despite having a lesser impact, the coolant flow type, nonetheless, performed a significant role.

Table 5. ANOVA results for material removal rate.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	*p*-Value
Regression	5	157.613	99.69%	157.613	31.523	189.95	0.001
v	1	6.545	4.14%	6.545	6.545	39.44	0.008
f	1	38.930	24.62%	38.930	38.930	234.58	0.001
d	1	108.148	68.40%	108.148	108.148	651.67	0.000
CF	2	3.990	2.52%	3.990	1.995	12.02	0.037
Error	3	0.498	0.31%	0.498	0.166		
Total	8	158.111	100.00%				

Taguchi's analysis confirmed these findings by identifying the depth of cut as the most influential factor for the MRR, followed by the feed, cutting speed, and coolant flow type. It revealed the possibility of optimizing machining parameters to increase the *MRR*. Table 6 represents the response table of means, in which the maximum delta value for the depth of cut (8.491) is found. Figure 2 depicts the obtained main effect plots, in which the steep line for the depth of cut is observed once again.

The conducted analyses provide valuable insights for process optimization in machining operations by highlighting the importance of the cutting speed, feed, depth of cut, and coolant flow type on the surface roughness and material removal rate. The obtained results can assist industry professionals in improving the efficacy and quality of their processes. However, it is important to note that these results may vary with various materials and machining conditions, highlighting areas for future research. Based on the experimental data, the GRA was utilized to comprehend the interrelationships between the machining parameters and their impacts on the *Ra* and *MRR*. Table 7 provides the results of this analysis.

Table 6. Response table of means for material removal rate.

Level	v	f	d	CF
1	12.523	10.904	9.441	14.489
2	13.582	13.814	13.344	13.302
3	14.612	15.999	17.932	12.927
Delta	2.089	5.094	8.491	1.562
Rank	3	2	1	4

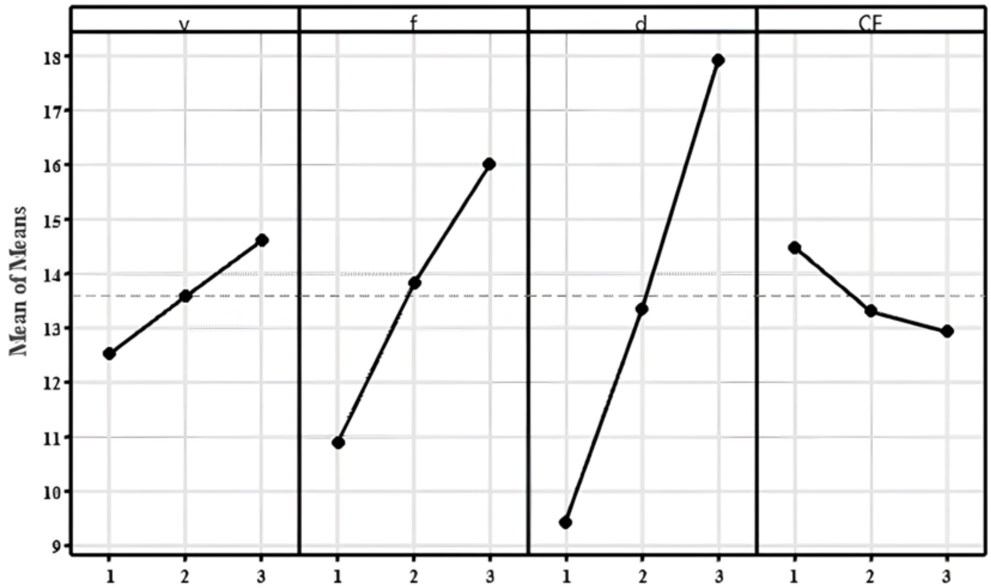

Figure 2. Mean effect plot for material removal rate.

Table 7. Results of grey relational analysis.

Trial	v	f	d	CF	Ra	MRR	GRG	Rank
1	1	1	1	1	0.158	0.802	0.653	7
2	1	2	2	2	0.313	0.245	0.437	8
3	1	3	3	3	0.313	0.033	0.337	9
4	2	1	2	3	0.125	0.350	0.525	5
5	2	2	3	1	0.313	0.010	0.497	6
6	2	3	1	2	0.438	0.247	0.479	8
7	3	1	3	2	0.188	0.388	0.642	2
8	3	2	1	3	0.125	0.350	0.525	5
9	3	3	2	1	0.313	0.123	0.420	9

According to the obtained grey relational grade (GRG), the combination with a speed of 130 mm/min, a feed of 0.1 mm/rev, a depth of cut 0.15 mm, and the third type of coolant flow (MQL) produced the best results with a GRG of 0.653, ranking first among all other parameter combinations. Intriguingly, the second-best combination in terms of GRG also operated at 130 mm/min but with a higher feed (0.15 mm/rev), a greater depth of cut (0.2 mm), and under dry cutting conditions (CF). This indicates that, despite the increased feed rate and depth of cut, the surface roughness was maintained at a lower level due to the high cutting speed and dry cutting conditions, while the *MRR* was maximized. On the opposite extreme of the spectrum, the parameter set with the lowest GRG consisted of a cutting speed of 130 mm/min, a high feed of 0.2 mm/rev, a shallow depth of cut (0.1 mm), and a coolant flow that was continuous (Flood). This led to an increase in the surface irregularity and a decrease in the material removal rate. Even with a reduced depth of cut, the increased feed rate appeared to have resulted in a poorer surface finish.

Despite the continuous flow of the coolant, the MRR was not maximized, indicating that other parameters, such as the cutting speed and depth of cut, were more influential. The GRA revealed the optimal machining parameters for harmonizing the surface roughness (Ra) and material removal rate (*MRR*). Under minimal quantity lubrication conditions (CF = 3), the greatest results were significantly obtained with higher feed rates, a slower speed, and moderate depths of cut. While the findings of this study provide valuable insights into the machining of EN8 steel under different coolant flows, it is important to note certain limitations. The results are specific to the material (EN8 steel) and the machining conditions tested in this study. Therefore, the generalizability of the findings to other materials and machining conditions may not be direct and would require further investigation. Future research could extend this work by exploring other materials and varying machining conditions. In addition to the academic contributions of this study, there are several practical implications worth noting. The findings of this study provide valuable insights for industry professionals seeking to optimize their machining processes. Specifically, the results indicate that the best results are generally obtained with higher speeds, lower feed rates, and moderate depths of cut under minimal quantity lubrication conditions. This information could be used to guide decision-making in real-world machining operations, potentially leading to improvements in efficiency and product quality. However, it is important to note that these results are specific to the machining of EN8 steel under the conditions tested in this study. Therefore, the direct applicability of these findings to other materials and machining conditions may require further investigation.

5. Conclusions

The present study examined how machining factors affect the surface roughness (*Ra*) and material removal rate (*MRR*). The cutting speed, feed, depth of cut, and coolant flow type (CF) were studied. Regression models, ANOVA, Taguchi's L9 orthogonal array, and GRA, were used to assess these parameters' effects on the Ra and MRR. The feed rate (f), coolant flow (CF), and depth of cut (d) have the greatest impact on the surface roughness (*Ra*). The Ra was least affected by the cutting speed. The study showed that the coolant flow type affects the Ra before machining settings. The material removal rate (*MRR*) was most affected by the depth of cut (d), feed (f), and cutting speed (v). The MRR was slightly affected by the coolant flow type (CF). As the coolant flow changed from dry to continuous to minimal quantity lubrication, the baseline MRR decreased. The GRA results revealed the optimum machining parameters and coolant flow type for the surface roughness and material removal rate. Higher speeds, lower feed rates, and moderate depths of cut under minimal quantity lubrication (CF = 3) produced the greatest results. This study will help industrial professionals optimize machining operations for efficiency and quality.

Author Contributions: Conceptualization R.B., B.R. and N.N.; methodology, B.S.S.; software, R.B. and B.S.S.; validation, B.S.S.; formal analysis, B.S.S.; investigation, B.S.S.; resources, B.S.S. and R.B.; data curation, B.S.S.; writing—original draft preparation, R.B.; writing—review and editing, R.B., N.N. and B.R.; visualization, B.S.S.; supervision, B.R.; project administration, B.R., N.N. and R.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data used have been presented in the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Nayak, B.B.; Abhishek, K.; Mahapatra, S.S.; Das, D. Application of WPCA based taguchi method for multiresponse optimization of abrasive jet machining process. *Mater. Today Proc.* **2018**, *5*, 5138–5144. [CrossRef]
2. Gaudêncio, J.H.D.; de Almeida, F.A.; Turrioni, J.B.; Quinino, R.d.C.; Balestrassi, P.P.; de Paiva, A.P. A multi-objective optimization model for machining quality in the AISI 12L14 steel turning process using fuzzy multivariate mean square error. *Precis. Eng.* **2019**, *56*, 303–320. [CrossRef]
3. Bhat, R.; Mohan, N.; Sharma, S.; Rao, S. Influence of Seawater Absorption on the Hardness of Glass Fiber/Polyester Composite. *J. Comput. Mech. Manag.* **2022**, *1*, 1–11. [CrossRef]
4. Singaravel, B.; Selvaraj, T. Multi criteria optimisation using analytic hierarchy process in turning operation. *Int. J. Mach. Mach. Mater.* **2017**, *19*, 218–229. [CrossRef]
5. Jakhar, V.; Nayak, M.; Sharma, N. A literature review on optimization of cutting parameters for surface roughness in turning process. *Int. J. Eng. Res. Dev.* **2017**, *4*, 2810–2815.
6. Kumar, M.; Singh, S. A Review on Lathe Machine Turning Process Parameter. *J. Inst. Eng. (India) Ser. C* **2022**, *3404*, 40–44.
7. Gugulothu, B.; Kalbessa Kumsa, D.; Bezabih Kassa, M. Effect of process parameters on centre lathe of EN8 steel in turning process. *Mater. Today Proc.* **2021**, *46*, 228–233. [CrossRef]
8. Akram, S.; Babutskyi, A.; Chrysanthou, A.; Montalvão, D.; Whiting, M.J.; Modi, O.P. Improvement of the wear resistance of EN8 steel by application of alternating magnetic field treatment. *Wear* **2021**, *484–485*, 203926. [CrossRef]
9. Moleejane, C.M.; Sanusi, K.O.; Ayodele, O.L.; Oliver, G.J. Microstructural features and mechanical behaviour of unalloyed medium carbon steel (EN8 steel) after subsequent heat treatment. *Lect. Notes Eng. Comput. Sci.* **2014**, *2*, 1034–1039.
10. Sultana, M.N.; Dhar, N.R.; Zaman, P.B. A Review on Different Cooling/Lubrication Techniques in Metal Cutting. *Am. J. Mech. Appl.* **2019**, *7*, 71. [CrossRef]
11. Sharma, A.K.; Tiwari, A.K.; Dixit, A.R. Effects of Minimum Quantity Lubrication (MQL) in machining processes using conventional and nanofluid based cutting fluids: A comprehensive review. *J. Clean. Prod.* **2016**, *127*, 1–18. [CrossRef]
12. Pimenov, D.Y.; Mia, M.; Gupta, M.K.; Machado, Á.R.; Pintaude, G.; Unune, D.R.; Khanna, N.; Khan, A.M.; Tomaz, Í.; Wojciechowski, S.; et al. Resource saving by optimization and machining environments for sustainable manufacturing: A review and future prospects. *Renew. Sustain. Energy Rev.* **2022**, *166*, 112660. [CrossRef]
13. Chen, Z.; Cao, S.; Wu, X.; Davies, C.H.J. Surface roughness and fatigue properties of selective laser melted Ti-6Al-4V alloy. In *Additive Manufacturing for the Aerospace Industry*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 283–299. [CrossRef]
14. Grzesik, W. Prediction of the Functional Performance of Machined Components Based on Surface Topography: State of the Art. *J. Mater. Eng. Perform.* **2016**, *25*, 4460–4468. [CrossRef]
15. Yue, C.; Gao, H.; Liu, X.; Liang, S.Y. Part functionality alterations induced by changes of surface integrity in metal milling process: A review. *Appl. Sci.* **2018**, *8*, 2550. [CrossRef]
16. Puh, F.; Jurkovic, Z.; Perinic, M.; Brezocnik, M.; Buljan, S. Optimization of machining parameters for turning operation with multiple quality characteristics using Grey relational analysis. *Teh. Vjesn.-Tech. Gaz.* **2016**, *23*, 377–382. [CrossRef]
17. Mia, M.; Gupta, M.K.; Lozano, J.A.; Carou, D.; Pimenov, D.Y.; Królczyk, G.; Khan, A.M.; Dhar, N.R. Multi-objective optimization and life cycle assessment of eco-friendly cryogenic N2 assisted turning of Ti-6Al-4V. *J. Clean. Prod.* **2019**, *210*, 121–133. [CrossRef]
18. Meher, J.; Nayak, B.B.; Panda, A.; Kumar, R.; Sahoo, A.K. Recent research development of CNC based milling machining conditions: A comprehensive review. *Mater. Today Proc.* **2022**, *62*, 3983–3989. [CrossRef]
19. Kumar, S.; Rao, P.S. Machining of EN31 Steel using CNC Vertical Milling Machine for different parameters: A Review. *J. Univ. Shanghai Sci. Technol.* **2022**, *24*, 283–287.
20. Patil, S.; Rao, P.S.; Prabhudev, M.S.; Khan, M.Y.; Anjaiah, G. Optimization of cutting parameters during CNC milling of EN24 steel with Tungsten carbide coated inserts: A critical review. *Mater. Today Proc.* **2022**, *62*, 3213–3220. [CrossRef]
21. Joshi, A.; Saraf, A.K.; Goyal, R.K. EDM machining of die steel EN8 and testing of surface roughness with varying parameters. *Mater. Today Proc.* **2020**, *28*, 2557–2560. [CrossRef]
22. Tindell, H. *Engineering Materials*; Crowood Press: Marlborough, UK, 2014.
23. Dave, H.K.; Patel, L.S.; Raval, H.K. Effect of machining conditions on MRR and surface roughness during CNC turning of different materials using TiN coated cutting tools—A taguchi approach. *Int. J. Ind. Eng. Comput.* **2012**, *3*, 925–930. [CrossRef]
24. Hamzaçebi, C. Taguchi Method as a Robust Design Tool. In *Quality Control—Intelligent Manufacturing, Robust Design and Charts*; BoD—Books on Demand: Norderstedt, Germany, 2021. [CrossRef]
25. Semioshkina, N.; Voigt, G. An overview on Taguchi Method. *J. Radiat. Res.* **2006**, *47* (Suppl. A), A95–A100. [CrossRef]
26. Kuo, Y.; Yang, T.; Huang, G.W. The use of grey relational analysis in solving multiple attribute decision-making problems. *Comput. Ind. Eng.* **2008**, *55*, 80–93. [CrossRef]

27. Senthilkumar, N.; Tamizharasan, T.; Anandakrishnan, V. Experimental investigation and performance analysis of cemented carbide inserts of different geometries using Taguchi based grey relational analysis. *Meas. J. Int. Meas. Confed.* **2014**, *58*, 520–536. [CrossRef]
28. Gelman, A. Struggles with survey weighting and regression modeling. *Stat. Sci.* **2007**, *22*, 153–164. [CrossRef]