Optimizing the Turning Operation via Using the Grey Relational Grade

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***Abstract*—The turning process is considered to be one of the most important machining processes. The various combinations of the input parameters can indeed determine the fate of the quality of the produced parts. This study aims to investigate the effect of various combinations of the input parameters on the surface roughness and the force required in order to elicit the optimal set. An L18 orthogonal array has been constructed using the JMP software for four input variables (i.e. the use of lubricant, cutting speed, depth of cut, and feed rate). Grey relational analysis has been utilized to identify the optimal set of the investigated inputs, which leads to the optimal machining characteristics (i.e. surface roughness and cutting force).**

***Index Terms*—grey relational analysis, Taguchi, turning process, surface roughness, cutting force**

I. Introduction

Turning operation is the most common machining process, which is implemented using a lathe machine to produce cylindrical or conical part [1] by using a single point or multi points cutting tool. The overall efficiency of turning operations can be evaluated based on different characteristics such as tool life, cutting force, surface roughness, production cost, production time, and dimensional accuracy [1], [2]. Cutting speed, feed rate, depth of cut, and tool geometry are considered to be the most important parameters that affect not only the overall efficiency of such a process but also the quality of the produced product [3]. It is very crucial to select optimal levels of the machining parameters that can improve the performance and effectiveness in addition to minimizing the production costs. In this study, we used grey relational analysis to optimize the turning operations with multiple performance characteristics, including cutting force and surface roughness.

The research in this study builds on existing literature that uses an optimization approach to manage machining by turning to achieve optimal machining characteristics. The turning optimization problem has been extensively studied by researchers considering multiple performance characteristics such as surface roughness, material removal rate, cutting force, and tool life. The importance of using optimal cutting parameters was first identified by Taylor [4] in his book entitled "On the art of cutting metals". His study aimed to improve the performance and productivity of the Midvale steel company in the state of Philadelphia. Different optimization techniques have been implemented in the related literature to optimize the machining processes. These techniques were primarily focused on determining the optimal quality characteristics. According to Lakshmanan *et al*. [5], the optimization problems can be classified into single or multi-objective based on the solution being provided. A single objective optimization problem usually defines an optimal solution. On the other hand, a multi-objective optimization identifies a set of optimal solutions from which one solution needs to be elicited. This is due to the number of objectives that need to be considered in each problem. Many studies propose optimization models that aim to optimize single performance characteristics, including production cost [2],[6]-[9] and surface roughness [10]-[12]. In general, machining optimization problems aim to optimize more than one quality characteristics, in other words, it takes into account more than one objective. Therefore, it is considered to be a multi-objective problem. Other models also account for optimizing multiple performance characteristics, such as surface roughness and residual stress [3], power consumption and surface roughness [13], surface roughness and material removal rate [14], and surface roughness and cutting force [15].Surface roughness is one of the most important performance characteristics for the turning operation .It has considerable influence on other properties such as fatigue strength, wear resistance, and aesthetic appeal [16]-[18]. Mahapatra *et al*. [17] study was focused on investigating the factors that affect the surface roughness of parts produced using the turning operation. Their results showed that surface roughness is affected by many factors such as: feed rate, work material characteristics, work hardness, cutting speed, unstable built-up edge, cutting time, depth of cut, tool cutting edge angle and nose radius, and the stability of machine tool and workpiece. Likewise, Sonowal *et al*. [19] reported that there are four factors that significantly affect surface roughness, namely; cutting speed, spindle speed, feed rate, and depth of cut.

The Taguchi method has been widely adopted in the experimental design of the turning operation. It is a powerful tool that serves as a basis for the optimization of a large variety of machining processes.

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The traditional Taguchi method has been employed to solve a single objective optimization problem in various applications. However, most of the machining optimization problems are multi-objective. Kacal and Yildirim [20] used Grey Rational Analysis (GRA) to optimize the turning parameters of AISI D6 tool steel for better surface finish and lower tool wear. According to their results, the preferred cutting parameters of the work material included 250 m/min cutting speed, 0.05 mm feed rate, and 0.2 mm depth of cut for better machining performance.

GRA, is usually utilized to convert a multi-objective problem into a single objective one [21], [22]. Note that GRA is derived based on the Taguchi method. Therefore, it is suitable for solving problems with complicated input/output interrelationships [23]. Several research studies have been implemented using the well-known Taguchi method, or the Taguchi based GRA technique to find the optimal parameters for different machining processes. For instance, Shunmugesh and Paratheesh applied the GRA to find the optimal parameters for the drilling operation [24]. Thorat and Thakur used it to optimize the parameters of burnishing operation [25]. Using the Grey-Based Taguchi method, Franko Puh *et al*. [26] studied the multi-criteria optimization of turning process parameters to obtain maximum Material Removal Rate (MRR) while achieving low surface roughness (Ra). In Eskandari *et al*. [27] Taguchi-based GRA was applied in optimizing turning parameters for multiple response variables, including surface finish, tool life, and material removal rate of a super alloy based on iron-nickel.

Table I summarizes some of the research studies that utilize Taguchi method and the GRA, also, it provides the type of materials and the investigated inputs and outputs. The majority of work presented in the related literature were focused on optimizing the quality attributes of the machined specimen individually, or improving the process effectiveness or efficiency. However, both the quality attributes of the machined specimens and the process performance need to be considered simultaneously in any optimization attempt. Therefore, in this research work, the grey based relational approach based on multi objective is employed to define the process parameters' levels that can optimize both the quality attribute of the machined specimen represented by the surface roughness and the machine performance represented by the cutting force required. The rest of the paper is organized as follows: The experimental work is summarized in Section II. The theoretical background of the grey relation-based optimization technique is provided in Section III. The results obtained from this study are presented and discussed in Section IV. Finally, Section V provides conclusions and some recommendations for future work.

II. Experimental Work

There are many parameters that can affect the required cutting force and the surface roughness of a specimen machined using the turning process. Such parameters have different effects (i.e. direct or inverse, and considerable or negligible). Among the various parameters, rotational cutting speed, depth of cut, feed rate and the use of lubricant are investigated in this research work primarily because of their considerable effects. Cylindrical AISI D2 steel specimens with a diameter of 20mm and length of 110mm were processed by a lathe machine (Colchester Master 2500, UK) under different combination of the cutting parameters, Fig. 1. Such a machine is equipped with a Carbide tipped insert coated with TiN cutting tool. Each specimen has a chemical composition of 1.5% Carbon, 0.3% Silicon, 12% Chromium, 0.8% Molybdenum and 0.9% Vanadium. In order to machine the specimens, each one was placed with its longitudinal axis aligned with the feed direction. It is worth mentioning that at this stage the levels of the parameters were determined based on trial experiments. Table II. presents the values used in this experiment, these values were tied to the machine limits and are based on expert's knowledge.

Figure 1.Thelathe machine

TABLE I. Summary of Some Publications on Optimizing the Turning Operation via Taguchi Method and GRA

References	Material type	Input parameter	Output
Prakash *et al*. [21]	AlSi7Mg	feed rate, cutting speed, and depth of cut	surface roughness, material removal rate
Lakshmanan *et al*. [5]	Al7075	feed rate, cutting speed, and depth of cut	surface roughness, material removal rate
Palanisamya & Selvarajb[28]	Incoloy 800H	feed rate, cutting speed, and depth of cut	surface roughness, material removal rate
Sreejith *et al*. [3]	---	feed rate, cutting speed, depth of cut, tool edge geometry, and the work piece hardness.	surface roughness, residual stresses.
Ranganath*el al*. [29]	Aluminium 6061	feed rate, cutting speed, and depth of cut	surface roughness
Nalbant*et al*.[30]	AISI 1030 steel	insert radius, feed rate and depth of cut	surface roughness
Hasçalık and Çaydaş [31]	Ti-6Al-4V	feed rate, cutting speed, and depth of cut	surface roughness and tool life
Kishore *et al*.[32]	Al6061-TiC	feed rate, cutting speed, and depth of cut	surface roughness and cutting force

Kosaraju and Chandraker [33]	MDN350 steel	feed rate, cutting speed, and depth of cut	surface roughness and cutting force
Ramesh *etal* [34]	Mg Alloy (AZ91D)	feed rate , cutting speed	surface roughness, tool flank wear
Viswanathan *et al* [35]	Mg Alloy (AZ91D)	cutting condition, cutting speed, feed rate, depth of cut	tool flank wear, surface roughness, cutting force, cutting temperature
Viswanathan *et al* [36]	Mg Alloy (AZ91D)	cutting speed, feed rate, depth of cut	cutting force, material removal rate, tool flank wear, surface roughness

In this research work, a partial factorial design of experiments based on L18 orthogonal array was employed using the JMP software. It is worth emphasizing that each experiment was repeated three times to ensure good precision of analysis. Once the specimens were machined, the cutting force (KGF) and the surface roughness represented by the Ra value (μm) were measured. The cutting force and the surface roughness value were measured using two Dial Gauges Type 60/0.002mm and a Portable Stylus-Type Profilometer with LCD display, respectively. The well-known linear correlation analysis was employed to investigate the relationships between the input parameters (Table II).

TABLE II. THE LEVEL OF THE INPUTS PARAMETER

Inputs	Inputs' level
Use of lubricant	Dry and Cutting fluid (Zinol, UAE)
Cutting speed	175, 235 and 320 (rpm)
Feed rate	0.05, 0.1 and 0.16 (mm/rpm)
Depth of cut	0.1, 0.15 and 0.2 (mm)

TABLE III. THE LINEAR CORRELATION ANALYSIS OF THE INVESTIGATED INPUT PARAMETERS

Outputs	Dry		Cutting fluid	
Inputs	Cutting Force	Surface roughness*	Cutting Force	Surface roughness*
Cutting speed	0.07	-0.29	0.67	-0.09
Depth of cut	0.65	0.15	-0.1	0.62
Feed rate	0.75	0.14	0.48	-0.08

Both the cutting force and the surface Ra values are presented in Table III. Various correlation coefficients were obtained for the numerical input parameters (i.e. cutting speed, depth of cut and feed rate) with and without the use of lubricant. The correlation coefficients were in the range of -0.29 to 0.75 for experiments without the use of lubricant. On the other hand, the correlation coefficients were in the range were in the range of -0.10 to 0.67 for experiments that were performed with the use of lubricant. Note that the impact of using lubricant-as a classical input parameter- was evaluated through the test of hypothesis. It was evident that such a parameter has a significant impact on both the cutting force and the surface roughness as the P-values were less than 0.05.

III. GREY RELATIONAL GRADE

The GRA is usually used to determine a correlation between sequences. The sequences can be ranked according to their favorability using the resulting correlation values. Since it is a simple technique that uses the original data, the GRA has been employed in various areas such as academia and manufacturing. The main steps of the GRA are summarized as follows:

Generate grey relational: the main objective of this step is to transfer the original data to compatibility sequences. Thus, experimental results for the cutting force and the surface roughness are first normalized to be in the range of 0 to 1. For the kth response in the ith orthogonal array experiment, the normalized value $x_i^*(k)$ can be calculated according to the following equations:

For the larger the better:

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{1}$$

For the smaller the better:

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

For the desired the value $x^*(k)$ the better:

$$x_i^*(k) = \frac{x_i(k) - x^*(k)}{\max\{\max x_i(k) - x^*(k), x^*(k) - \min x_i(k)\}} \tag{3}$$

where the use of specific equation depends mainly on the nature of the output/response. For instance, in some applications, users prefer a very smooth surface (i.e. very low surface roughness represented by the Ra value). Therefore, the Ra value in such a case needs to be as small as possible, and accordingly, Equation (2) should be used.

Define a reference sequence: the second step in the GRA is to define a reference sequence. After generating the grey relational according to the previous step, the values of $x_i^*(k)$ will be in the range of 0 to 1.A value of 1 means that the value of the k'th response in i'th experiment is the best among all experiments. Therefore, the reference sequence is represented by x_0 and has a value of 1 for all responses.

Define the deviation sequence: the deviation sequence (Δ_{oi}) is calculated from the reference sequence and the comparability sequence as follows:

$$\Delta_{oi}(k) = |x_o^*(k) - x_i^*(k)| \tag{4}$$

Calculate the relational coefficient: The grey relational coefficient is calculated from the normalized data using Equation (5). Note that this equation expresses the relationship between the desired and actual values:

$$\xi_i(k) = \frac{\Delta_{min} + \delta\Delta_{max}}{\Delta_{oi}(k) + \delta\Delta_{max}} \tag{5}$$

Δ_{min} and Δ_{max} are the largest and smallest value of the deviation sequence (Δ_{oi}), respectively. In this study, δ is the distinguishing or identification coefficient which is in the range of 0 to 1. In this research work, the value of δ was 0.5.

Calculate the grey relational grade: the grey relational grade (γ_i) is a performance index that is used to determine the optimal combination of the cutting parameters. It converts the grey relational coefficient values into single grey relational grade. The grey relational grade is calculated by determining the average of the grey relational coefficients for each output/response as follows:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \tag{6}$$

IV. Results and Discussion

In this study, Taguchi's method and grey relational analysis are used to optimize turning operations with multiple performance characteristics. Most of the work presented in the related research centered around improving either the quality attributes of the machined specimen or the efficiency or effectiveness of the process itself. However, regardless of optimization attempts, it is necessary to consider both the quality attributes of the machined specimens as well as the process itself. In this study, a grey based relational approach is applied and a multi objective approach is employed to identify the process parameters' levels compatible with maximizing the quality of the machined specimen, which is represented by the surface roughness, as well as the machine performance, depicted by the cutting force. In grey relational analysis, cutting force and surface roughness obtained from Taguchi method may be converted into a single performance characteristic, grey relational grade, to optimize multiple performance characteristics at once. Using this method, it is possible to optimize multiple performance characteristics that are complicated in many ways. The study shows that the performance characteristics of turning operations such as cutting force and surface roughness can be improved simultaneously with this proposed method.

An L18 orthogonal array was constructed using the JMP software. The cutting force (F) and the surface roughness were measured as explained in Section II. Table IV summarizes the results obtained through our experiments.

TABLE IV. The L18 Orthogonal Array and the Experimental Results Obtained

Exp.	Lubricant	Rotational speed	Feed rate	Depth of cut	Force		Ra	
					Average	Std	Average	Std
1	1	1	3	3	14.3133	2.5990	34.2923	4.1569
2	1	2	3	3	22.7948	4.1565	27.4307	4.3343
3	2	3	1	3	14.5646	3.0251	15.13	5.6902
4	2	1	1	3	10.3174	6.4722	10.7977	3.3991
5	1	2	1	1	11.0558	6.7929	39.2583	22.2166
6	2	3	2	3	19.4257	8.0025	15.3057	4.70334
7	2	1	2	2	11.6473	4.377	13.1437	4.8361
8	2	2	1	1	12.5305	1.5394	11.1597	6.8925
9	1	3	2	1	10.8025	8.9244	17.382	4.7628
10	2	1	3	1	10.0393	4.9002	20.1397	9.2483
11	2	2	2	2	15.3466	3.4296	14.9527	5.1538
12	1	3	1	2	13.9578	5.4084	19.6247	3.2699
13	1	1	1	2	11.7055	3.4432	15.0383	2.0562
14	1	2	2	3	17.2986	11.7992	23.7783	13.3391
15	2	3	3	1	11.9882	1.3439	11.915	3.9577
16	1	1	2	1	12.3435	2.7549	20.8193	13.016
17	2	2	3	2	14.0119	3.6750	20.5857	1.2822
18	1	3	3	2	16.6982	3.8927	19.815	4.3697

In this research work, the cutting force and the surface roughness were preferred to be as small as possible. Therefore, Equation 2 was applied for the two outputs/responses to calculate $x_i^*(1)$ and $x_i^*(2)$ (which are the grey relational for the cutting force and the surface roughness for the ’'th experiment, respectively).

The grey relational converted the values for each response in all experiments into a value in the range of 0 and 1 (a value of 1 means that the response of a given experiment is the best among all other values). The resulting grey relational values from all experiments are shown in Table V.

TABLE V. THE GREY RELATIONAL AND DEVIATION SEQUENCE VALUES FOR THE 18 EXPERIMENTS

Run	$x_i^*(1)$	$x_i^*(2)$	$\Delta_{oi}(1)$	$\Delta_{oi}(2)$
1	0.664	0.174	0.335	0.825
2	0	0.415	1	0.584
3	0.645	0.847	0.354	0.152
4	0.978	1	0.021	0
5	0.920	0	0.079	1
6	0.264	0.841	0.735	0.158
7	0.873	0.917	0.126	0.082
8	0.804	0.987	0.195	0.012
9	0.940	0.768	0.059	0.231
10	1	0.671	0	0.328
11	0.583	0.854	0.416	0.145
12	0.692	0.689	0.307	0.310
13	0.869	0.851	0.130	0.148
14	0.430	0.543	0.569	0.456
15	0.847	0.960	0.152	0.039
16	0.819	0.647	0.180	0.352
17	0.688	0.656	0.311	0.343
18	0.477	0.683	0.522	0.316

TABLE VI. THE GREY RELATIONAL COEFFICIENTS AND GREY RELATIONAL GRADES

Exp.	$\xi_i(1)$	$\xi_i(2)$	γ_i	Rank
1	0.59	0.37	0.48	17
2	0.33	0.46	0.39	18
3	0.58	0.76	0.67	8
4	0.95	1	0.97	1
5	0.86	0.33	0.59	13
6	0.40	0.75	0.58	14
7	0.79	0.85	0.82	4
8	0.71	0.97	0.84	2
9	0.89	0.68	0.78	6
10	1	0.60	0.80	5
11	0.54	0.77	0.65	10
12	0.61	0.61	0.61	11
13	0.79	0.77	0.78	7
14	0.46	0.52	0.49	16
15	0.76	0.92	0.84	3
16	0.73	0.58	0.66	9
17	0.61	0.59	0.60	12
18	0.48	0.61	0.55	15

After calculating the grey relational for the two responses, the deviation sequence was calculated as shown in Equation 4, ($\Delta_{oi}(1)$ and $\Delta_{oi}(2)$ are the deviation sequence for the cutting force and the surface roughness, respectively). The deviation sequence values are also listed in Table V. The grey relational coefficient for the cutting force $\xi_i(1)$ and for the surface roughness $\xi_i(2)$ were calculated as described in Equation 5 and are presented in Table VI. Note that the higher the value of the grey relational coefficient indicates a better response value for the experiment.

As can be seen in this table, the best values of the grey relational coefficient for the cutting force and the surface roughness were the ones achieved in the 10'th and 4'th experiments, respectively. In order to identify the experiment that has the best performance considering the two responses at the same time, the grey relational grade was calculated to obtain a single numerical value for each experiment.

Based on the grey relational grade, the experiments were ranked, higher grey relational grade means that the experiment is better according to the quality of the two responses. The grey relational grades for the 18 experiments are listed in Table VI.

In order to define the best level for each input parameter, the average values of the parameters were calculated and presented in Table VII.

TABLE VII. THE AVERAGE VALUES OF THE GREY RELATIONAL GRADES FOR EACH INPUT PARAMETER

Level	Lubricant	Rotational speed	Feed rate	Depth of cut
1	0.597	0.756	0.749	0.757
2	0.758	0.600	0.669	0.673
3		0.676	0.614	0.602

This step enables the user to choose the best level for each parameter. In order to select the optimal combination of the levels of the input parameters, the levels with the maximum grey relational grade values need to be selected.

Based on the results obtained, the experiment that was conducted using the cutting fluid, speed value of 175rpm, feed rate of 0.05 mm/rpm and depth of cut of 0.1mm provided a compromised solution for the two investigated outputs (i.e. the surface finish and the cutting force).

The effect of each parameter level on the grey relational grade is shown in Fig. 2.

Confirmation test: As a final step, and after identifying the most influential parameters, the confirmation experiments are conducted to verify surface roughness and the cutting force. To check the model, we have repeated the experiment at different values of input parameter. We included the proposed values by this paper as one of the four experiments each experiment was repeated three times. The average values for the cutting force and the surface roughness were calculated as in Table VIII. It is clear from the table that the proposed values for the input parameters gave the optimal values for both the surface roughness and the cutting force

TABLE VIII. VALIDATION OF THE MODEL

exp	Lubricant	Rotational speed	Feed rate	Depth of cut	Force	Ra
1	1	1	1	1	15.867	21.005
2	**2**	**1**	**1**	**1**	**10.752**	**10.136**
3	2	1	2	3	20.935	18.942
4	2	3	3	2	19.708	28.537

V. CONCLUSION

This research work was focused on investigating the impact of input parameters on output parameters in turning operation. Four input and two output parameters of the turning process were analyzed. Namely; cutting fluid, feed rate, depth and speed. And surface roughness and the cutting force. The goal was to define the best combination that lead to the minimum surface roughness and cutting force. Since such a case is considered as a multi-objective optimization problem, the Gray Relational Analysis (GRA) was used to determine the optimal combination of the input parameters. Among the various levels of the input parameters, it was found that the best surfaces roughness and cutting force can be obtained by using a cutting fluid, cutting speed of 175 rpm, depth of cut of 0.1 mm, and feed rate of 0.05 rpm/mm. Future work should focus on investigating the advantages of combining the fuzzy logic with the GRA. This approach will enable further analysis that account for uncertainties (e.g., measurement uncertainties).

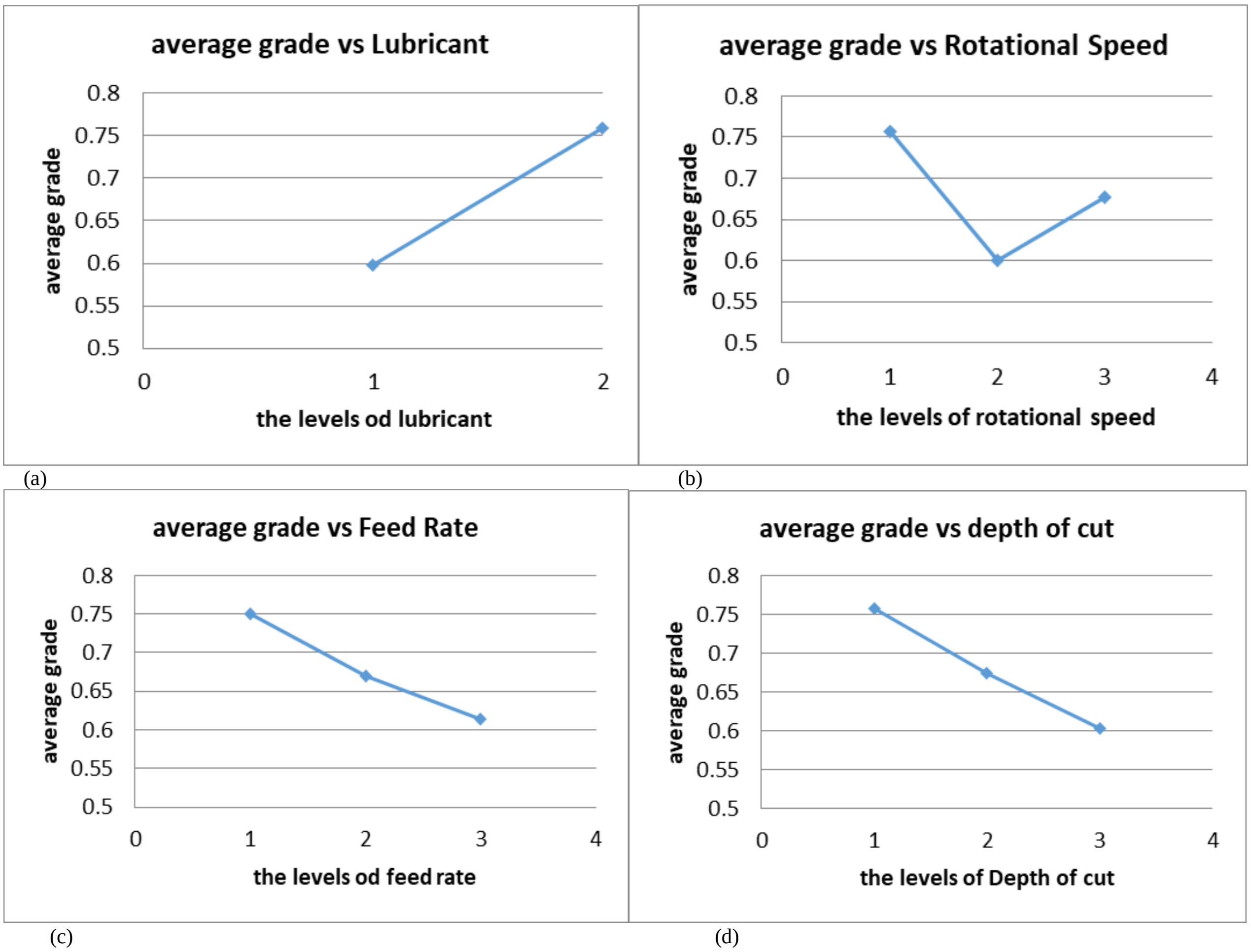

Figure 2. The grey relational grade for (a) Use of lubricant; (b) Rotational speed; (c) The feed rate; (d) The depth of cut

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript equally, all authors had approved the final version.

REFERENCES

[1] C. L.Lin, "Use of the taguchi method and grey relational analysis to optimize turning operations with multiple performance characteristics," *Materials and Manufacturing Processes*, vol. 19, no. 2, pp. 209-220, 2004.

[2] A. Jabri, A. E. Barkany, and A. El Khalf, "Multipass turning operation process optimization using hybrid genetic simulated annealing algorithm," *Model. Simul. Eng.*, p. 10, 2017.

[3] S. Sreejith, A. Priyadarshini, and P. K.Chaganti, "Multi-objective optimization of surface roughness and residual stress in turning using grey relation analysis," *Materials Today: Proceedings*, vol. 26, pp. 2862–2868, 2020.

[4] F. W. Taylor, "On the art of cutting metals," *American Society of Mechanical Engineers*, vol. 23, 1906.

[5] M. Lakshmanan, J. S. Rajadurai, and S. Rajakarunakaran, "Machining studies of Al7075 in CNC turning using grey relational analysis," *Materials Today: Proceedings*, July 2020. (in press)

[6] M. A. Mellal and E. J. Williams, "Cuckoo optimization algorithm for unit production cost in multi-pass turning operations," *International Journal of Advanced Manufacturing Technology*, vol. 76, no. 1-4, pp. 647-656, 2015.
[7] A. Aryanfar and M. Solimanpur, "Optimization of multi-pass turning operations using genetic algorithms," in *Proc. International Conference on Industrial Engineering and Operations Management*, Istanbul, Turkey, 2012.
[8] S. Xie and Y. Guo, "Optimisation of machining parameters in multi-pass turnings using ant colony optimisations," *International Journal of Machining and Machinability of Materials*, vol. 11, no. 2, pp. 204-220, 2012.
[9] M. C. Chen and D. M. Tsai, "A simulated annealing approach for optimization of multi-pass turning operations," *International Journal of Production Research*, vol. 34, no. 10, pp. 2803-2825, 1996
[10] K. S. Sangwan, S. Saxena, and G. Kant, "Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach," *Procedia Cirp*. 2015.
[11] G. Kant and K. S. Sangwan, "Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm," *Procedia CIRP*, vol. 31, pp. 453–458, 2015.
[12] R. Davis, "Optimization of surface roughness in wet turning operation of En24 steel," *International Journal of Mechanical and Production Engineering Research and Development*, vol. 2, no. 3, pp. 28-35, 2012
[13] G. Kant and K. S. Sangwan, "Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining," *Journal of Clean Production*, vol. 83, pp. 151-164, 2014.
[14] L. Bouzid, S. Boutabba, M. A. Yallese, S. Belhadi, and F.Girardin, "Simultaneous optimization of surface roughness and material removal rate for turning of X20Cr13 stainless steel," *The International Journal of Advanced Manufacturing Technology*, vol. 74, no. 5-8, pp. 879-891, 2014.
[15] A. Chabbi, M. A. Yallese, I. Meddour, M. Nouioua, T. Mabrouki, and F. Girardin, "Predictive modeling and multi-response optimization of technological parameters in turning of Polyoxymethylene polymer (POM C) using RSM and desirability function," *Measurement*, vol. 95, pp. 99-115, 2017.
[16] G. C. Onwubolu, "A Note on 'Surface roughness prediction model in machining of carbon steel by PVD coated cutting tools'," *American Journal of Applied Sciences*, vol. 2, no. 6, pp. 1109-1112, 2005
[17] S. S. Mahapatra, A. Patnaik, and P. K. Patnaik, "Parametric analysis and optimization of cutting parameters for turning operations based on Taguchi method," in *Proc. International Conference on Global Manufacturing and Innovation*, 2006, pp. 1-7.
[18] W. AlAlaween, A. AlAlawin, L. Al-Durgham, and N. Albashabsheh, "A new integrated modelling architecture based on the concept of the fuzzy logic for the turning process," *Journal of Intelligent & Fuzzy Systems*, vol. 41, pp. 655–667, 2021.
[19] D. Sonowal, D. Sarma,P. B. Barue, and T. Nath, "Taguchioptimization of cutting parameters in turning AISI 1020 MS with M2 HSS tool," in *Proc. IOP Conf. Series: Materials Science and Engineering*, 2017.
[20] A. Kacal and F. Yıldırım, "Application of grey relational analysis in high-speed machining of hardened AISI D6 steel," in *Proc. Inst Mech Eng. Part C J. Mech Eng. Sci*., vol. 227, no. 7, pp. 1566–1576, 2013.
[21] P. B. Prakash, K. B. Raju, K. V. Subbaiah, P. C. Krishnamachary, N. ManiKandan, and V. Ramya, "Application oftaguchi based grey method for multi aspects optimization on CNC turning of AlSi7 Mg," *Materials Today: Proceedings*, vol. 5, pp. 14292–14301, 2018.
[22] S. K. Nayak, J. K. Patro, S. Dewangan, and S. Gangopadhyay, "Multi-objective optimization of machining parameters during dry turning of AISI 304 Austenitic stainless steel using grey relational analysis," *Procedia Mater. Sci.*, vol. 6, pp. 701–708, 2014.
[23] Y. Kuo, T. Yang, and G. W. Huang, "The use of grey relational analysis in solving multiple attribute decision-making problems," *Computers & Industrial Engineering*, vol. 55, pp. 80-93, 2008.
[24] K. Shunmugesh and A. Pratheesh, "Taguchi grey relational analysis based optimization of micro-drilling parameters on carbon fiber reinforced plastics," *Materials Today: Proceedings*, vol. 24, pp. 1994–2003, 2020.
[25] S. R. Thorat and A. G. Thakur, "Optimization of burnishing parameters by taguchi based GRA method of AA 6061 aluminum alloy," *Materials Today: Proceedings*, vol. 5, pp. 7394–7403, 2018.
[26] F. Puh, Z. Jurkovic, M. Perinic, M. Brezocnik, and S. Buljan, "Optimization of machining parameters for turning operation with multiple quality characteristics using grey relational analysis," *Tech. Gazette*., vol. 23, no. 2, pp. 377-382, 2016.
[27] B Eskandari, B. Davoodi, and H. Ghorbani, "Multi-objective optimization of parameters in turning of N-155 iron-nickel-base superalloy using gray relational analysis," *J Braz. Soc Mech Sci*., vol. 40, no. 4, p. 233, 2018.
[28] A. Palanisamya, and T. Selvarajb, "Optimization of machining parameters for dry turning of incoloy 800H using taguchi - based grey relational analysis," *Materials Today: Proceedings*, vol. 5, pp. 7708–7715, 2018.
[29] M. S. Ranganath, R. S. Vipin, and S. Mishra, "Optimization of process parameters in turning operation of aluminium (6061) with cemented carbide inserts using taguchi method and ANOVA," *International Journal*, vol. 1, no. 1, pp. 13-21, 2013.
[30] M. Nalbant, H. Go ̈kkaya, and G. Sur, "Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning," *Materials and Design*, vol. 28, pp. 1379–1385, 2007.
[31] A. Hasçalık and U. Çaydaş, "Optimization of turning parameters for surface roughness and tool life based on the Taguchi method," *Int. J Adv Manuf. Technol.*, vol. 38, pp. 896–903, 2008.
[32] D. S. Kishore, K. P. Rao, and A. Ramesh, "Optimization of machining parameters for improving cutting force and surface roughness in turning of Al6061-TiC in-situ metal matrix composites by using Taguchi method," *Materials Today: Proceedings*, vol. 2, pp. 3075–3083, 2015.
[33] S. Kosaraju and S. Chandraker, "Taguchi analysis on cutting force and surface roughness in turning MDN350 steel," *Materials Today: Proceedings*, vol. 2, pp. 3388–3393, 2015.
[34] S. Ramesh, R. Viswanathan, and S. Ambika, "Measurement and optimization of surface roughness and tool wear via grey relational analysis, TOPSIS and RSA techniques," *Measurement*, vol. 78, pp. 63–72, 2016.
[35] R. Viswanathan, S. Ramesh, and V. Subburam, "Measurement and optimization of performance characteristics in turning of Mg alloy under dry and MQL conditions," *Measurement*, vol. 120, pp. 107-113, 2018.
[36] R. Viswanathan, S. Ramesh, S. Maniraj, and V. Subburam, "Measurement and multi-response optimization of turning parameters for magnesium alloy using hybrid combination of Taguchi- GRA- PCA technique," *Measurement*, vol. 159, 2020.

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