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## Performance Evaluation of Grey Relational Analysis Method in the Optimization of Machining Operation Performed on Cylindrical Mild Steel Bar

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**ABSTRACT:** Machining operation is a core aspect of the manufacturing industry as it involves a process of material removal using cutting and machine tools to accurately obtain the required product dimensions with good surface finish. The objective of this paper was to investigate the performance evaluation in the optimization of machining operations performed on a 30 mm cylindrical mild steel bar, with cutting speed, feed rate and depth of cut as cutting parameters and metal removal rate and surface roughness as responses using a lathe machine to obtained the responses, afterwhich the results were analysed by Grey Relational Analysis (GRA) technique. Data obtained show that the nineteenth experimental run with the following combined parameters; cutting speed 120rev/min, feed rate 0.1rev/mm, and depth of cut 0.5mm gave the optimal responses.

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Machining operations have been the core of the manufacturing industry since the industrial revolution. It involves a process of material removal using cutting tools and machine tools to accurately obtain the required product dimensions with good surface finish (Rahman et al., 2009). Machining processes are used when higher dimensional accuracy and higher quality surface finish are required than obtainable from casting, forming, or shaping processes alone (Aboloje et al., 2024). Moreover, the flexible nature of machining processes enables the cost-effective, fast manufacture of products in small batch sizes (Sada, 2018). There are various machining operations, each of which is capable of generating a certain part geometry and surface texture. Irrespective of the type of machining process, the machining operation requires a relative motion

\*Corresponding Author Email: affeejovi@gmail.com \*Tel: +2348109110733 between a cutting tool, and a work piece. Depending on the machining operation, a specialized tool is employed (Dhar *et al.*, 2006).

The machining process is influenced by a number of input and output variables. These machining processes include large number of input parameters which may affect the cost and quality of the products. Selection of optimum machining parameters in such machining processes is very important to satisfy all the conflicting objectives of the process. There different options to choose the optimal cutting parameters for a given economic objective (Saravanakumar *et al.*, 2014; Sada 2020). One of such is concerned with the need of a machine expert that manually selects the machining parameters on the basis of its own experience and by means of a proper machining handbook. This despite its possibility generates many uncertainties and drawbacks in terms of efficiency of solutions and time/cost requirements (Kalita *et al.*, 2012). Another is the the application of mathematical techniques in determining the optimal combination of process parameters. One of such widely used applications, is the Grey relational analysis, which is useful for the multi response optimization (Balasubramanian and Ganapathy 2011).

The Grey relational analysis (GRA) proposed by Deng is a method of measuring the degree of approximation among sequences according to the grey relational grade. GRA analyzes uncertain relations between one main factor and all the other factors in a given system between the sequences with less data. The process provides an efficient solution to the uncertainty, multi-input and discrete data problem (Balasubramanian, and Ganapathy 2011).

The relation between machining parameters and machining performance can be found out by using the Grey relational analysis. The objective of this paper was to investigate the performance evaluation in the optimization of machining operations performed on a 30 mm cylindrical mild steel bar, with cutting speed, feed rate and depth of cut as cutting parameters and metal removal rate and surface roughness as responses using a lathe machine to obtained the responses, afterwhich the results were analysed by Grey Relational Analysis (GRA) technique.

#### **MATERIALS AND METHOD**

The materials selected for the experiment, are as follows; 10 mm mild steel bar, Cutting tool (Tungsten carbide tool), the Lathe Machine. The lathe machine as shown in Figure 1, with a set up for cylindrical turning with the high speed steel tool clamped to the tool post and the mild steel work piece of 30mm diameters by 200mm lengths were fixed and held by the 3 jaw chuck was employed in carrying this experiment.

With soluble oil as the cutting fluids, the machining was performed at every 120 seconds, thereby repeating the machining procedure for 240, 360, 480, 600, 720, 840, 960, 1080 and 1200 seconds respectively using either of the cutting tools. The corresponding metal removal rate were determined and recorded. The Process parameters and their levels as tabulated in Table 1, were selected along with a selected range of values from literature (Sada, 2020).



Fig 1: Pictorial view of a standard engine lathe.

Table 1: Process para	meters and their levels
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Factor	Unit	Level 1	Level 2	Level 3
Cutting Speed	m/min	120	170	220
Feed	mm/rev	0.10	0.17	0.24
Depth of cut	Mm	1.0	1.25	2.5

*Material removal rate:* The selected response material removal rate (MRR), measures the volume of material/metal removed per unit time in m3/min. This is calculated using Equation (1) for each experimental run and recorded.

$$MRR = \frac{\pi x (D_{o} - D_{i}) x N x f x d}{1000} \left(\frac{m3}{min}\right) (1)$$

Where, D0 initial diameter in mm, Di final diameter in mm, f - feed rate in mm/rev, and N spindle speed in rpm, d depth of cut in mm.

Surface Roughness ( $\mu m$ ): The surface roughness is a widely accepted product quality index, and of great importance while considering the functional behavior of a part (Benardos, and Vosniakos 2002). The measurement is performed using a portal stylus-type profilometer.

*Gray Relational Analysis:* The Grey relational analysis (GRA) method, measures the degree of approximation among sequences based on the grey relational grade. GRA analyzes uncertain relations between one main factor and all the other factors in a given system between the sequences with less data (Tosun and Pihtili 2010). The processing steps are listed below (Rahman *et al.*, 2009).

Normalize the response matrix from zero to one by using Equation (2) and (3).

Lower-the-better (LB) is the criterion:

$$x_i(k) = \frac{maxy_i(k) - y_i(k)}{maxy_i(k) - miny_i(k)}$$
(2)  
Higher-the-better (HB) is the criterion:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$
(3)

where,  $x_i(k)$  is the normalised value of  $k^{th}$  response, min $y_i(k)$  is the smallest value of  $y_i(k)$  for  $k^{th}$  response and max  $y_i(k)$  is the largest value of  $y_i(k)$  for  $k^{th}$  response. x is the normalised array.

Calculation of grey relational coefficient from the normalised matrix.

$$\xi_i(k) = \frac{\Delta_{min} + \varsigma_{max}}{\Delta_{oi}(k) + \varsigma \Delta_{max}}$$
(4)

Where,  $\Delta_{oi} = ||x_o(k) - x_i(k)||$ : is the is the deviation of absolute value  $x_o(k)$  and  $x_i(k)$ .  $\varsigma$  is the distinguishing coefficient  $0 \le \psi \le 1.1$ .

$$\Delta_{\min} = \frac{\min\min}{\forall j \in i} \frac{\min}{\forall k} \| x_o(k) - x_j(k) \|$$
(5)

$$\Delta_{max} = \frac{\max}{\forall j \in i} \frac{\max}{\forall k} \| x_o(k) - x_j(k) \|$$
(6)

Determination of overall grey relational grade: The overall gray relational grade represents as the overall performance characteristic of multiple responses of the process. This is calculated as the average of individual gray relational grades of the responses at  $i^{th}$  experimental run.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \tag{7}$$

It means, the overall gray relational grade converts the multi-response (multi-gray relational grades) optimization problem into a single response (overall gray relational grade) optimization problem, with the objective function as maximization of overall grey relational grade. Hence, the overall grey relational grades rank the experimental runs as; the experimental run having higher grey relational grade refers as that corresponding combination of variables is closer to the optimal values. The optimal parametric combination is then evaluated by maximizing the overall grey relational grade (Abhang and Hameedullah, 2012). After the calculation of normalized values, the GRC (grey relational coefficient) is calculated. The GRC expresses the relationship between the ideal and the actual normalized experimental results. The results of the Grey Relational Coefficient,  $\xi ij$  is presented as shown in Table 4

### **RESULTS AND DISCUSSION**

Based on the experimental run generated, two sets of experiment were performed, and the responses were recorded as tabulated in Table 2. The normalized or data preprocessing results for the response parameters; metal removal rate and surface roughness is presented in Table 3

 Table 2: Experimental Result Based on the Machining Operation

ExP.	Cutting	Feed	Depth of	Metal	Surface
Run	Speed rpm	Rate mm/rev	Cut (mm)	Removal Rate (m³/min)	Roughness (µm)
1	120	0.1	2.5	0.267	4.57
2	170	0.1	1.25	0.357	3.74
3	220	0.1	1	0.258	3.8
4	120	0.17	2.5	0.345	5.72
5	170	0.17	1.25	0.284	4.45
6	220	0.17	1	0.292	4.84
7	120	0.24	2.5	0.445	4.03
8	170	0.24	1.25	0.321	4.68
9	220	0.24	1	0.275	3.82
10	120	0.1	2.5	0.443	7.59
11	170	0.1	1.25	0.320	4.42
12	220	0.1	1	0.231	3.56
13	120	0.17	2.5	0.267	4.34
14	170	0.17	1.25	0.370	5.59
15	220	0.17	1	0.238	4.74
16	120	0.24	2.5	0.325	3.93
17	170	0.24	1.25	0.231	6.49
18	220	0.24	1	0.272	4.7
19	120	0.1	2.5	0.375	3.09
20	170	0.1	1.25	0.238	6.42

 Table 3: Normalized values (Data Preprocessing of experimental results)

	lesuits)		
Normalizing			
	Higher the better	Smaller the better	
Expt.No.	Metal Removal	etal Removal Surface	
-	Rate(m <sup>3</sup> /min)	Roughness (µm)	
1	0.24137931	0.671111111	
2	0.629310345	0.855555556	
3	0.202586207	0.842222222	
4	0.577586207	0.415555556	
5	0.314655172	0.697777778	
6	0.349137931	0.611111111	
7	1.00862069	0.791111111	
8	0.474137931	0.646666667	
9	1	0.837777778	
10	0.275862069	0	
11	0.469827586	0.704444444	
12	0.086206897	0.895555556	
13	0.24137931	0.722222222	
14	0.685344828	0.44444444	
15	0.11637931	0.633333333	
16	0.49137931	0.813333333	
17	0	0.244444444	
18	0.262931034	0.642222222	
19	0.706896552	1	
20	0.11637931	0.26	

Derivation Sequence			Grey Relational Coefficient		
Expt.No.	Thrust Force	Surface Roughness	Thrust Force	Surface Roughness	
1	0.75862069	0.328888889	0.397260274	0.603217158	
2	0.370689655	0.14444444	0.574257426	0.775862069	
3	0.797413793	0.157777778	0.38538206	0.760135135	
4	0.422413793	0.58444444	0.542056075	0.461065574	
5	0.685344828	0.302222222	0.421818182	0.623268698	
6	0.650862069	0.388888889	0.434456929	0.5625	
7	-0.00862069	0.208888889	1.01754386	0.705329154	
8	0.525862069	0.353333333	0.487394958	0.5859375	
9	0	0.162222222	1	0.755033557	
10	0.724137931	1	0.408450704	0.333333333	
11	0.530172414	0.295555556	0.485355649	0.62849162	
12	0.913793103	0.104444444	0.353658537	0.827205882	
13	0.75862069	0.277777778	0.397260274	0.642857143	
14	0.314655172	0.55555556	0.613756614	0.473684211	
15	0.88362069	0.366666667	0.361370717	0.576923077	
16	0.50862069	0.186666667	0.495726496	0.72815534	
17	1	0.755555556	0.333333333	0.398230088	
18	0.737068966	0.357777778	0.404181185	0.582901554	
19	0.293103448	0	0.630434783	1	
20	0.88362069	0.74	0.361370717	0.403225806	

The GRC values of various response parameters entered in Table 4 is further reduced to a single value known as Grey Relational Grade (GRG) as presented in Table 5.

Table 5: Grade Relational Grade			
Grey Relational Grade			
Expt.No.	Grey Relational Grade		
1	0.500239		
2	0.67506		
3	0.572759		
4	0.501561		
5	0.522543		
6	0.498478		
7	0.861437		
8	0.536666		
9	0.877517		
10	0.370892		
11	0.556924		
12	0.590432		
13	0.520059		
14	0.54372		
15	0.469147		
16	0.611941		
17	0.365782		
18	0.493541		
19	0.815217		
20	0.382298		

The Grey Relational Grade (GRG) is the average value of GRC"s of the various response parameters. The highest grey relational grade obtained gives the optimal combination of various process parameters. from Table 5, experimental no 19 is te optimal.

*Conclusion:* The study on the performance evaluation of Grey Relational Analysis (gra) method in the optimization of machining parameters was successfully performed on a cylindrical mild steel bar, with cutting speed, feed rate and depth of cut as cutting parameters and metal removal rate and surface roughness as responses. The experiment was performed using a lathe amchine to obtained the responses, afterwhich the results were analysed using the GRA technique. From the result obtained, the nineteenth experimental run gave the optimal responses.

*Declaration of Conflict of Interest:* The authors declare no conflict of interest (if none).

*Data Availability Statement:* Data are available upon request from the first author or corresponding author or any of the other authors.

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