

# Experimental Investigation and Optimization of Material Removal Rate and Surface Roughness in Centerless Grinding of Magnesium Alloy Using Grey Relational Analysis

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**ABSTRACT:** Modern enterprises concentrate on higher production rates with reduced time and admired quality. The surface integrity defines the quality of the product. Several processes like grinding, polishing and buffing have been used to improve the surface texture of the machined products. The most prominent challenge that is faced by an engineer is to manufacture a component with better surface integrity at reduced time, leading to increased production rate and improved profit. It is important to select proper combination of the machining parameters for obtaining the best results. The process called through feed centerless grinding helps in obtaining better surface texture. The main aim of this work is to examine the influence of various machining parameters such as regulating wheel angle, regulating wheel speed and depth of cut over surface roughness and machining time in machining magnesium alloy using silicon carbide grinding wheel. Grey relational analysis method is used for investigating the results. The optimal machining parameters were found with regulating wheel speed, regulating wheel angle and depth of cut being 46 rpm, 2 degree and 0.2 mm.

**KEYWORDS:** MRR; Surface roughness; Magnesium alloy; silicon carbide grinding wheel; Grey relational analysis.

## I. INTRODUCTION

Phan Bui Khoi et al [1] carried out the experimentation on centerless grinding with center height angle, longitudinal grinding wheel dressing feed rate, plunge feed rate and control wheel velocity as input parameters on 20 X- infiltration carbon steel. Genetic algorithm (GA) and Response surface methodology (RSM) was adopted to optimize the machining parameters which revealed that GA produced the best optimized result with a minimized roundness error of 0.0001. Kaifei Zhang et al [2] conducted an experimental study on internal cylindrical grinding of bearing steel with electrolytic in-process dressing grinding which revealed that optimal results were as follows: depth of cut 1–2  $\mu\text{m}$ , current duty ratio 50 % (5  $\mu\text{s}$ /5  $\mu\text{s}$ ), and open circuit voltage 90 V for minimum surface roughness and coarser grit size wheel is often used to achieve high grinding efficiency while the finer one needs to realize fine surface quality. Dapeng Dong et al [3] investigated on the effect of different heat treatment processes on grinding machinability and surface integrity of 9Mn2V which revealed superior grinding integrity with the occurrence of grinding burn and grinding

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cracks reduced by using this process. Cryogenic and tempering treatment improved the grinding machinability of 9Mn2V greatly, grindability would be further enhanced if the material could be cryogenic and tempering treated in twice.

Hairong Wang et al [4] investigate the influence of main grinding parameters on the micro cracks of subsurface damage, relationships among the average abrasive size, grinding force, wheel speed, and grinding depth and characterization parameters of micro cracks are established. The influences of average abrasive size, grinding force, wheel speed, grinding depth, and other grinding process parameters on the length of subsurface micro cracks are consistent with those on the surface roughness of samples, so the information of the micro crack length can be used to estimate the degree of SSD caused during the machining process. Jorge Alvarez et al [5] proposed a simulation method to improve the infeed grinding process by continuously varying the feed rate (CVFR) which studied the influence of variation parameters in process forces, workpiece roughness, roundness and size tolerance, or dynamic behaviour. The analysis proved that CVFR lead to more efficient cycles without the difficulty of defining feed rate and stock removal values. This work concluded that grinding processes can be improved with this method regarding productivity and workpiece geometrical and surface tolerances. W. Brian Rowe [6] suggested a new method of optimization considering the effect of positive grain boundaries and negative up boundaries in dynamic stability charts which helped in understanding the dynamic behaviour of the centerless grinding process and roundness of the workpiece. This helped in selection of grinding parameters such a work speed, set-up and number of lobes. Do Duc Trung et al [7] focused on determining the optimum centerless grinding parameters which included center height angle of the workpiece , longitudinal dressing feed-rate, plunge feed-rate and control wheel velocity over the responses surface roughness (SR) and roundness error. The analysis revealed that all the four parameters had a significant effect on the responses. The minimized average surface roughness of 0.3090  $\mu\text{m}$  and roundness error of 1.3493  $\mu\text{m}$  was obtained. Mondal and mandal [8] proposed an empirical model using Artificial Neural Network (ANN) in terms of wheel speed, depth of cut and coolant flow rate for predicting the surface roughness in centerless grinding process. This model was trained and when tested with the experimental data, it proved to be efficient and depth of cut was the most significant factor.

David Barrenetxea et al [9] introduced a new algorithm for analysis of stability and optimization of infeed centerless grinding process which involved transforming the high level grinding models into a web based simulation to reduce the cycle time. The model was created based on dressing speed, regulating wheel speed, dressing stock and work piece height to analyse cycle time and roundness error. The simulation resulted in 70 % reduction in cycle time and improved the roundness by 6%. Jorge Alvarez et al [10] proposed a semi-discretization method for dynamic stability analysis of the in-feed cylindrical grinding process. The residual flexibility has been included in this method since it has much influence on grinding processes due to the deformations of the grinding wheel and the workpiece at the contact point. A higher residual flexibility leads to a more stable process. A special care has to be taken analysing dynamic instability when grinding at different positions along their length because both equivalent stiffness of the process and dynamic stiffness of workpiece vibration modes change. Contrary to expected, in some cases, chatter frequencies and their amplitudes decrease at positions with higher process equivalent stiffness, as seen in the paper theoretical and experimentally. Garitaonandia et al [11] established an efficient modelling procedure to optimize an active chatter control system and developed a finite element model center height angle and angular velocity of workpiece to study the effect on the roundness. The model developed helped in improved in chatter stability.

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## II. EXPERIMENTAL SETUP

Star make model centerless grinding machine is used for the experimental work.



Figure 1 – Centerless Grinding Machine

The above machine shown in figure 1, has a maximum regulating wheel speed of 50 rpm, grinding pressure that can be developed is 0.148 amp/cm (0.375 amp/inch), abrasive speed of 1219 surface m/min (4000 surface ft/min) , Through – feed rate of 3.05 m/min t/min) and collant used is water based.

### 2.1. Work piece material – Magnesium alloy

Magnesium bars of 20 mm diameter and 75 mm length were used for the experimentation processes.

### 2.2. Process variables and their limits

In the present experimental study, spindle regulating wheel speed, regulating wheel angle and depth of cut have been considered as process variables. The working range of each parameter with their units is listed in table 1.

Table 1 - Process Variables and their Limits

Parameters	Levels		
	1	2	3
Regulating wheel speed(rpm)	12	25	46
Regulating wheel angle (degree)	2	3	4
Depth of cut: D (mm)	0.1	0.16	0.2

### 2.3. Measuring Device

The time was measured using stopwatch; however the machining time is the sum of tool travel time from approach point, machining time and tool relieving.

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Figure 2 – Surface Roughness Tester

The surface roughness is measured by using MITUTOYO make surface roughness tester. The length and diameter of work piece is measured using Vernier caliper. The surface roughness tester is shown in fig 2. The device sophisticates measurement of surface roughness interms of microns for three different travel lengths.

## 2.4. Selection of experimental design

Table 2 - Process Variables and their Limits

Experiment no.	Regulating Wheel Speed (rpm)	Regulating Wheel Angle (degrees)	Depth of Cut (mm)
1	12	3	0.04
2	12	3	0.08
3	12	3	0.12
4	12	2	0.04
5	12	2	0.08
6	12	2	0.12
7	12	1	0.04
8	12	1	0.08
9	12	1	0.12
10	25	1	0.04
11	25	1	0.08
12	25	1	0.12
13	25	2	0.04
14	25	2	0.08
15	25	2	0.12
16	25	3	0.04
17	25	3	0.08
18	25	3	0.12
19	46	3	0.04

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20	46	3	0.08
21	46	3	0.12
22	46	2	0.04
23	46	2	0.08
24	46	2	0.12
25	46	1	0.04
26	46	1	0.08
27	46	1	0.12

Based on full factorial design, the L27array have been selected. The machining for various combinations had to carried. The combinations are specified in the table 2.

### 2.4. Material Removal Rate

The material removal rate is a function of weight and machining time that are measured using weighing pan and stopwatch. Following equation is used to calculate the response Material Removal Rate (MRR).

$$MRR = \frac{\text{Initial weight of workpiece} - \text{Final weight of workpiece}}{\text{Density} \times \text{Machining time}}$$

### III. EXPERIMENTAL RESULTS

Table 3 - Response values from experimental work

Experiment no.	Material removal rate (g/sec)	Surface Roughness $R_a$ ( $\mu\text{m}$ )
1	0.0880	1.53
2	0.0980	1.31
3	0.0381	1.72
4	0.1041	3.62
5	0.0471	1.45
6	0.0483	5.32
7	0.2395	1.83
8	0.3333	3.15
9	0.0689	5.45
10	0.1333	1.80
11	0.2500	1.43
12	0.1639	2.81
13	0.3225	2.96
14	0.1190	5.24
15	0.1886	2.46
16	0.1298	3.80
17	0.1818	4.15
18	0.1851	3.22
19	0.1613	2.03
20	0.1369	4.14
21	0.1123	4.36
22	0.2127	3.13
23	0.1960	3.18

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24	0.2500	2.63
25	0.2500	2.05
26	0.5710	2.55
27	0.7890	3.40

The experiments were conducted to study the effect of process parameters over the output response as designed in the table. The experimental results of Surface Roughness and Material Removal Rate are given in the table 3. The material removal rate was calculated by recording the weight of the specimen before machining, after machining and the machining time.

### 3.1. Grey Relational Analysis

Grey relational analysis is a method that is used to predict the approximate sequence among a cluster of sequences using the entity called Grey Relational Grade (GRG). The responses that are measured is normalized between the range of 0 to 1. Thereafter the optimization of multiple characteristics is converted into single optimization of Grey relational grade. The data must be pre-processed to a group of sequence called 'grey relational generation'. Normalization is done for converting the raw data into comparable data. This process of transferring is called data processing.

The following formulae's are used in normalization.

If the expectation is "larger the better".

$$xi(k) = \frac{x_i(k) - \min(x_i^0(k))}{\max(x_i^0(k)) - \min(x_i^0(k))}$$

If the expectation is "smaller the better".

$$xi(k) = \frac{\max(x_i(k)) - (x_i(k))}{\max(x_i^0(k)) - \min(x_i^0(k))}$$

Where

$i = 1, \dots, m; k = 1, \dots, n.$

$m$  is number of experimental data items,

$n$  is the number of parameters;

$x_i^0(k)$  is the original sequence,

$x_i^*(k)$  is the sequences after data preprocessing,

$\min x_i^0(k)$  and  $\max x_i^0(k)$  are the smallest and the largest value of  $x_i^0(k)$ .

The relationship between the model and actual normalized experimental values is expressed in terms of grey relational coefficient following data pre-processing. The grey relational coefficient is calculated with the following formulae.

$$\xi_i(k) = \frac{\Delta \min - \zeta \Delta \max}{\Delta_{i,0}(k) + \zeta \Delta \max}$$

Where

$\xi_i(k)$  is the grey relational coefficient ranging from 0 to 1.

$\zeta$  is the identification coefficient which is 0.5 because it offers moderate distinguishing factor.

$\Delta \min$  and  $\Delta \max$  are the minimum and maximum of the series which is 0 and 1.

$x_i^0(k)$  is the original sequence,

$x_i^*(k)$  is the sequences after data preprocessing

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Table 4 – Grey relational grades for the responses

S.NO	NOR MRR	NOR SR	DEL MRR	DEL SR	GRC 1	GRC 2	TOTAL GRC
1	0.09135	0.68182	0.90865	0.31818	0.35495	0.61111	0.96606
2	0.19231	0.72727	0.80769	0.27273	0.38235	0.64706	1.02941
3	0.19231	0.00000	0.80769	1.00000	0.38235	0.33333	0.71569
4	0.03571	0.84091	0.96429	0.15909	0.34146	0.75862	1.10008
5	0.10989	0.70455	0.89011	0.29545	0.35968	0.62857	0.98826
6	0.22115	0.79545	0.77885	0.20455	0.39098	0.70968	1.10065
7	0.00148	0.56818	0.99852	0.43182	0.33366	0.53659	0.87025
8	0.00000	0.34091	1.00000	0.65909	0.33333	0.43137	0.76471
9	0.03846	0.79545	0.96154	0.20455	0.34211	0.70968	1.05178
10	0.12130	0.61364	0.87870	0.38636	0.36266	0.56410	0.92676
11	0.04808	0.45455	0.95192	0.54545	0.34437	0.47826	0.82263
12	0.04808	1.00000	0.95192	0.00000	0.34437	1.00000	1.34437
13	0.09135	0.79545	0.90865	0.20455	0.35495	0.70968	1.06463
14	0.13462	0.56818	0.86538	0.43182	0.36620	0.53659	0.90278
15	0.10989	0.38636	0.89011	0.61364	0.35968	0.44898	0.80866
16	0.48077	0.22727	0.51923	0.77273	0.49057	0.39286	0.88342
17	0.16923	0.34091	0.83077	0.65909	0.37572	0.43137	0.80710
18	0.37692	0.56818	0.62308	0.43182	0.44521	0.53659	0.98179
19	0.30769	0.22727	0.69231	0.77273	0.41935	0.39286	0.81221
20	1.00000	0.79545	0.00000	0.20455	1.00000	0.70968	1.70968
21	0.48077	0.20455	0.51923	0.79545	0.49057	0.38596	0.87653
22	0.22115	0.34091	0.77885	0.65909	0.39098	0.43137	0.82235
23	0.65385	0.29545	0.34615	0.70455	0.59091	0.41509	1.00600
24	0.65385	0.22727	0.34615	0.77273	0.59091	0.39286	0.98377
25	0.48077	0.27273	0.51923	0.72727	0.49057	0.40741	0.89797
26	0.10989	0.56818	0.89011	0.43182	0.35968	0.53659	0.89627
27	0.25824	0.79545	0.74176	0.20455	0.40265	0.70968	1.11233

The grey relational codes for the corresponding experiments are tabulated below in table 4. After obtaining the grey relational coefficient, the grey relational coefficient is obtained by taking the average of the grey relational codes. The ranking is done of maximum to minimum value of GRG, as it depicts the order of desirability. The final average GRG value for the individual level of the input parameters is given in table 5.

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Table 5 – Selected machining parameters based on GRG

	Regulating Wheel speed	Regulating wheel angle	Depth of cut
<b>Level 1</b>	4.29344	4.34354	4.17187
<b>Level 2</b>	4.27107	<b>4.38859</b>	4.46342
<b>Level 3</b>	<b>4.55856</b>	3.95268	<b>4.48779</b>

The above table 5 shows the GRG of various levels for the input input parameters. The level that shows the maximum GRG of the input parameters are considered as the optimized level of the corresponding input. Hence, level 3 of regulating wheel speed, level 2 of regulating wheel angle and level 3 of depth of cut is considered to be the optimized input parameters.

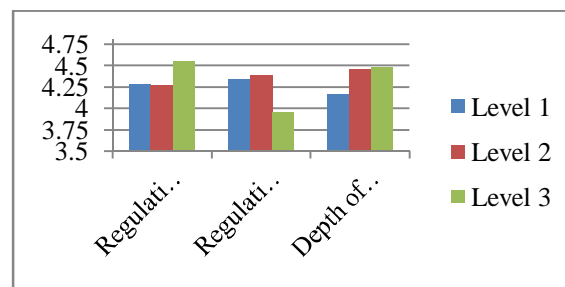


Fig 3 – Optimized machining parameters based on GRG

The figure 3 depicts the selected level of each input for attaining best machining characteristics based on the average Grey Relation Grade value. The optimal machining parameter was found to have the regulating wheel speed of 46 rpm, regulating wheel angle of 2 degree and depth of cut of 0.2 mm.

## IV. CONCLUSION

The previous works discovered the domination of various parameters for different process which involved the study of MRR, surface roughness and roundness of machined component. In our work, the experimental examination involves centerless grinding of magnesium alloy using silicon carbide grinding wheel. The main aim of the work is to extend an empirical model using Grey relational analysis. Thus, an empirical model for predicting the values of surface roughness and Material Removal Rate was developed successfully to select the optimal machining parameters.

## REFERENCES

- [1] Phan Bui Khoi, Do Duc Trung,, Ngo Cuong, Nguyen Dinh Man (2015), 'Research on Optimization of Plunge Centerless Grinding Process using Genetic Algorithm and Response Surface Method', International Journal of Scientific Engineering and Technology (ISSN : 2277-1581), Volume No.4 Issue No.3, pp : 207-211.
- [2] Kaifei Zhang, Yongchang Yu, Wanzhang Wang & He Li (2015), 'Experimental study on internal cylindrical grinding of bearing steel with electrolytic in-process dressing grinding', International Journal of Advanced Manufacturing Technology, pp. 1175–1185.
- [3] Dapeng Dong, Guoqiang Guo, Dedong Yu, Qinglong An & Ming Chen (2015), 'Experimental investigation on the effects of different heat treatment processes on grinding machinability and surface integrity of 9Mn2V', International Journal of Advanced Manufacturing Technology, pp. 1165–1174.
- [4] Hairong Wang, Hongfeng Chen, Guanglong Fu & Huapan Xia (2015), 'Relationship between grinding process and the parameters of subsurface damage based on the image processing', International Journal of Advanced Manufacturing Technology, pp. 1–9.
- [5] Jorge Alvarez, David Barrenetxea, Jose Ignacio Marquinez, Iñigo Bediaga & Ivan Gallego (2014), 'Continuous variable feed rate: a novel method for improving infeed grinding processes', International Journal of Advanced Manufacturing Technology, pp. 53–61.



## International Journal of Innovative Research in Science, Engineering and Technology

*(An ISO 3297: 2007 Certified Organization)*

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- [6] W.Brian Rowe (2014), 'Rounding and stability in centerless grinding', International Journal of Machine Tools & Manufacture pp. 1–10.
- [7] Phan Bui Khoi, Do Duc Trung, & Ngo Cuong (2014), 'A study on multiobjective optimization of Plunge centerless grinding process', International Journal of Mechanical Engineering and Technology (IJMET), ISSN 0976 – 6340(Print), ISSN 0976 – 6359(Online), Volume 5, Issue 11. 31
- [8] Mondal S.C & Mandal P(2014),' Application of Artificial Neural Network for Modeling Surface Roughness in Centerless Grinding Operation', All India Manufacturing Technology, Design and Research.
- [9] David Barrenetxea, Jorge Alvarez , Jose IgnacioMarquinez , IvanGallego , Ignacio Muguera Perello & Peter Krajnik (2014) , 'Stability analysis and optimization algorithms for the set-up of infeed centerless grinding', International Journal of Machine Tools & Manufacture, pp 17–32.
- [10] Jorge Alvarez, Mikel Zatarain, David Barrenetxea & Naiara Ortega & Ivan Gallego (2013),'Semi-discretization for stability analysis of in-feed cylindrical grinding with continuous workpiece speed variation', International Journal of Advanced Manufacturing Technology, pp. 113–120.
- [11] Garitaonandia, J. Albizuri, J.M. Hernandez-Vazquez, M.H. Fernandes, I. Olabarrieta & D. Barrenetxea. (2013),'Redesign of an active system of vibration control in a centerless grinding machine: Numerical simulation and practical implementation', Precision Engineering, pp 562–571
- [12] B Kumaragurubaran1, P Gopal, T Senthil Kumar, M Prasanna Mugunthan & N H Mohamed Ibrahim (2013), 'Optimization of turning parameters of EN-9 steel using Design Of Experiments concepts', International Journal of Mechanical Engineering and Robotics Research, ISSN 2278 – 0149, Vol 2, No. 3, July 2013..