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MODELLING AND MULTI-RESPONSE OPTIMIZATION OF FACE MILLING PROCESS BASED ON GRA APPROACH

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Abstract : This research involves milling investigations on Magnesium Calcium Alloy with DLC coated carbide cutting inserts. The experiment was originally planned using the Central Composite method, which took into account the machining variables of depth of cut, feed, and spindle speed. Surface roughness and cutting forces were measured for each experimental run. Using the ANOVA method, the 95 percent confidence interval was used to test the models' adequacy. Because the influence of machining settings on surface roughness and cutting forces is conflicting, the topic is characterized as a multi-objective optimization problem. As a consequence, Gray relational analysis (GRA) was used to fit the values and identify the optimal solution. The ANOVA results showed that the feed rate has the greatest impact on surface roughness. For the principal cutting force, speed is a most significant influencing factor

***Index Terms* – Face Milling, ANOVA, GRA. RSM.**

I. INTRODUCTION

Magnesium alloys have been widely employed in the automobile, electronics, and aerospace industries for their exceptional features such as low density, high strength-to-weight ratio, and high stiffness, and are considered one type of green metallic structural materials for the twenty-first century (Mordike Bl 2001). Magnesium alloy is the lightest of the metallic materials, with a density of 1.7 g/cm3 and is 35 percent lighter than aluminium alloy and 77 percent lighter than steel.(Polmear 1994) Thin and light chips are created during dry high-speed cutting of magnesium alloy. Because of their poor heat capacity and high thermal expansion, these chips are prone to igniting(Hou 2015). Additionally, when the cutting speed exceeds a threshold number, a buildup edge can form, causing substantial damage to the machined surface (Anon 2016). Only a few research have looked into how cutting parameters affect surface quality while milling magnesium alloy. P. Muthuraman et al.(Muthuraman and Karunakaran 2020) used the GRA technique to investigate cryogenic-based machining of Face milling process parameters. Under the same operating conditions, the cryogenically treated industrial carbide tool outperformed the traditional non-cryogenic treated tool in terms of wear resistance on cutting edges and tool surface hardness. Ch Vasu et al.(Vasu, Andhare, and Dumpala 2021) conducted an experimental investigation on turning of AZ91 Mg alloy in dry conditions using uncoated carbide tools. The best conditions were discovered using the GRA method. In end milling Magnesium (Mg) Metal Matrix Composite (MMC) using a carbide tool, P.M. Gopal et al.(Gopal and Prakash 2017) evaluated the influence of material and machining settings on cutting force, surface roughness, and temperature. GRA and TOPSIS were used to perform multioptimisation.

Under cryogenic conditions, Pu et al.(Pu et al. 2012)found that increasing the cutting edge radius could result in a deeper distribution of compressive residual stress and improved surface integrity on the AZ31B Mg alloy. Denkena and Lucas(Denkena and Lucas 2007) discovered that using the right set of process parameters, they could improve the surface quality of the Mg-Ca3.0 alloy and improve its corrosion resistance. However, only Guo and Salahshoor (Guo and Salahshoor 2010)have shown that improved surface integrity was achieved in the presence of a particular amount of FBU during high-speed dry milling of Mg-Ca0.8 alloy.Process parameters, such as cutting speed, feed rate, and depth of cut greatly influence surface integrity (Jin and Liu 2012; Umbrello 2013)

The assessment and adjustment of performance characteristics in turning MG alloy under dry and MQL conditions was studied by Viswanathan R et al(Viswanathan, Ramesh, and Subburam 2018). The feed rate is the most relevant aspect for the multi-objective function, followed by the cutting condition, depth of cut, and cutting speed, according to the analysis. Using Taguchi design of experiments with Grey Relational Analysis, Vikas Marakini et al(Marakini et al. 2021) investigated the best machining parameters for improving the surface roughness and hardness of the AZ91 alloy. Girish Kant et. al.(Kant and Sangwan 2014) investigated a multi-objective prediction model for reducing power consumption and surface roughness while cutting AISI 1045 steel.

Kaining Shi et al (Shi, Zhang, and Ren 2015)studied the effect of speed, feed, and cut depth on surface roughness and microhardness while milling Magnesium alloy in dry conditions. In the milling of magnesium alloy, the feed rate was found to be the most important factor determining surface integrity. Suresh Nipanikar et al(Nipanikar et al. 2018). studied the effect of cutting parameters on surface roughness and flank wear during machining of titanium alloy TI-6Al-4V ELI in MQL conditions and used GRA, TOPSIS, and RSA models to find the optimal parameter.

II. MATERIALS AND EXPERIMENTAL DETAILS

Experimental setup to conduct milling experiments is shown in Figure1. Work material, Mg-Ca 1.0 alloy in the form of plates 80 mm x 60 mm x 10 mm is used in dry face milling. CNC milling center Hardinge VMC 600 II) with a max spindle speed of 3800 rpm has been used to carry out experiments. DLC coated carbide cutting inserts (Make- HITACHI) were used and the cutting diameter is 50 mm.

Figure 1 Experimental Setup

Table 1: Face milling parameter

Cutting speed Vc (m/min)	**Feed *f* (mm/rev)**	**Depth of cut a_p (mm)**
350	0.15	0.15
450	0.20	0.20
550	0.30	0.25

In this study, cutting experiments have been planned using Response surface methodology design using MINITAB 18. This design is created considering three milling parameters namely milling speed, feed and depth of cut. 20 experiments have been carried out with the parameters given in Table 1. After machining surface roughness is measured using Mitutoyo surface roughness tester (model- SJ-201, make- Mitutoyo). A sampling length of 2.5 mm has been considered, while measuring the surface roughness parameter R_a.

In the current study, the experiments were organized following a central composite matrix, according to the response surface methodology (RSM). Statistical analysis (ANOVA) was used to assess the effects of the input parameters upon the outcomes of the process. The responses taken into consideration for analysis in this paper are surface roughness (Ra) and Cutting forces. In a central composite design (CCD), the design points consist of three groups: two level factorial points, which are all the combinations of the +1 and -1 levels of the factors; the central points corresponding to the average value of the factors, which are repeated four times for a better estimation of the error; the axial (star) points resulted by multiplying the factorial levels with +/-α (alpha), which is calculated in order to assure the rotatability of the design.(Chirita et al. 2019) The levels of each experimental factor are presented in Table 2.

Table 2 Experimental factors and levels.

Expt No.	**Speed (m/min)**	**Feed (mm/rev)**	**Depth of cut (mm)**	**Roughness in (µm)**	**Cutting force (N)**
1	450.00	0.225	0.200	0.208	10.822
2	550.00	0.300	0.250	0.224	10.308
3	450.00	0.225	0.115	0.202	10.213
4	350.00	0.300	0.250	0.274	12.936
5	550.00	0.150	0.150	0.142	8.441
6	450.00	0.225	0.200	0.202	10.478
7	450.00	0.225	0.200	0.210	10.601
8	450.00	0.098	0.200	0.143	8.491
9	618.17	0.225	0.200	0.166	8.479
10	550.00	0.300	0.150	0.218	9.813

Expt No.	**Speed (m/min)**	**Feed (mm/rev)**	**Depth of cut (mm)**	**Roughness in (µm)**	**Cutting force (N)**
11	450.00	0.225	0.200	0.206	10.470
12	350.00	0.150	0.250	0.198	11.564
13	350.00	0.150	0.150	0.192	11.069
14	281.82	0.225	0.200	0.250	12.898
15	450.00	0.225	0.200	0.207	10.678
16	450.00	0.225	0.284	0.213	10.976
17	450.00	0.351	0.200	0.272	12.007
18	450.00	0.225	0.200	0.208	10.608
19	550.00	0.150	0.250	0.148	8.940
20	350.00	0.300	0.150	0.268	12.441

III. GREY RELATIONAL ANALYSIS

Grey relational analysis (GRA) proposed by Deng is a method of measuring the degree of approximation among sequences according to the grey relational grade [10]. GRA analyzes uncertain relations between one main factor and all the other factors in a given system between the sequences with less data [11]. The processing steps are listed below [13].

1. Normalise the response matrix from zero to 1 by using equation (1) and (2)
   Lower the better is the criterion

$$x_i(k) = \frac{maxy_i(k) - y_i(k)}{maxy_i(k) - miny_i(k)} \quad (1)$$

Higher the Better is the criterion

$$x_i(k) = \frac{y_i(k) - miny_i(k)}{maxy_i(k) - miny_i(k)} \quad (2)$$

Where $x_i(k)$ is the normalized 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 normalized array.

2. Calculation of grey relational coefficient from the normalized matrix.

$$\xi_i(k) = \frac{\Delta_{min}+\zeta\Delta_{max}}{\Delta_{oi}(k)-\zeta\Delta_{max}} \quad (3)$$

Where, $\Delta_{oi} = \| x_o(k) - x_i(k) \|$: is the deviation of the absolute value $x_o(k)$ *and* $x_i(k)$. ζ is the distinguishing coefficient $0 \leq \psi \leq 1$.

3. 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.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad ---------------- 4$$

IV. RESULTS AND DISCUSSION

Analysis of variance (ANOVA) is a statistical tool used in DOE to establish the significance of the factors or their interactions. As a general rule, total variance of a model is attributed to the factors and to the random error, respectively. The significance of a factor is assessed by performing statistical (F-tests) under a null hypothesis: large values of *F*-ratios imply a high influence of the factor on the response. Significance is determined according to a confidence interval, which is established for a certain *p*-value. The *p*-value represents the probability that the results of the tests could have occurred by random chance. This study uses (corresponding to a 95% confidence interval), which means that a factor is considered significant only if *p* value is less than 0.05(Chirita et al. 2019).

4.1 Surface Roughness Analysis

The goal of the research is to reduce the surface roughness parameters Ra while taking into account the input parameters cutting speed, feed, and cut depth. The analyses' findings are presented in Table 3. Feed rate is the most important component (with 69.63 percent contribution). Speed was also shown to be considerable (with a contribution of 29.88 percent)/Depth of cut had a lesser impact on Surface roughness. When the feed values rise, the surface roughness rises with them. As demonstrated in Figure 2, the roughness values increase from 0.143 m to 0.272 m.

4.2 Cutting force Analysis

Table IV displays the results of an ANOVA on the principal cutting force. The model is quite important. In this the most important component is Speed, which contributes 69.21 percent, followed by Feed, which contributes 27.92 percent. Although there are additional important aspects, their influence is minor. Figure 3 shows that as the cutting force reduces from 12.90 N to 8.47 N as the speed increases from 281 m/min to 618 m/min. This is because when the speed of the machine increases, the material softens, reducing the amount of cutting force required for machining.

Table 3 Analysis of Variance for Roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% of Contribution
Speed	1	0.008528	0.008528	2259.45	0	29.88
Feed	1	0.019872	0.019872	5265.02	0	69.63
Depth of cut	1	0.000132	0.000132	35.04	0	0.46
Speed*Speed	1	0.000003	0.000003	0.85	0.378	0.01
Feed*Feed	1	0.000001	0.000001	0.33	0.577	0.00
Depth of cut*Depth of cut	1	0.000001	0.000001	0.33	0.577	0.00
Speed*Feed	1	0	0	0	1	0.00
Speed*Depth of cut	1	0	0	0	1	0.00
Feed*Depth of cut	1	0	0	0	1	0.00
Error	10	0.000038	0.000004			
Total	19	0.028575				

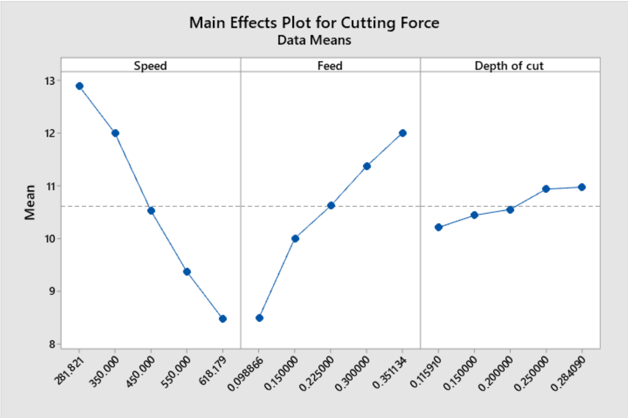

Fig. 2 Main Effects plot for Roughness

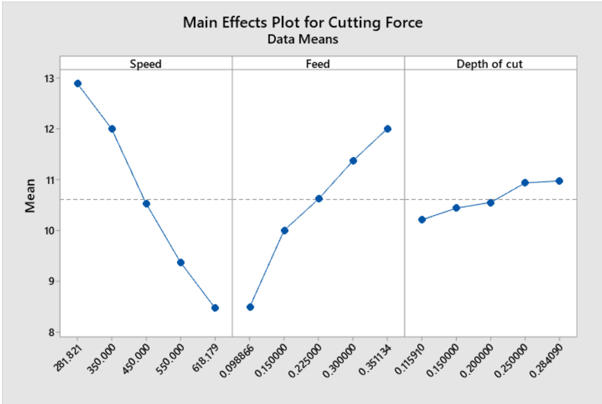

Fig. 3 Main Effects plot for Cutting force

Table 4 Analysis of Variance for Cutting Force

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% of Contribution
Speed	1	23.571	23.571	376.86	0	69.21
Feed	1	9.5089	9.5089	152.03	0	27.92
Depth of cut	1	0.7814	0.7814	12.49	0.005	2.29
Speed*Speed	1	0.0644	0.0644	1.03	0.334	0.19
Feed*Feed	1	0.1129	0.1129	1.81	0.209	0.33
Depth of cut*Depth of cut	1	0.0162	0.0162	0.26	0.622	0.05
Speed*Feed	1	0	0	0	0.996	0.00
Speed*Depth of cut	1	0	0	0	0.996	0.00
Feed*Depth of cut	1	0	0	0	0.996	0.00
Error	10	0.6255	0.0625			
Total	19	34.7015				

V. IMPLEMENTATION OF GRA

As the first stage in the GRA technique, the results are normalised using equation 1 as indicated in Table 5. The quality loss estimates for each individual have been produced and listed in Table 5 as part of the computation of grey relationship coefficients. The individual grey relational grades as well as the overall grey relational grade were determined using Eqs. 3 and the results are displayed in Table 5. The value of the distinguishing coefficient is assumed to be 0.5 in this case. The quality index of the process's various answers is represented by the overall grey relational grade; hence, the multi-objective optimization issue has been reduced to a single-objective optimization problem.

Table 5 Normalized values and grey relational coefficient and Ranks

	Normalised values		Δ_{oi}		$\xi_i(k)$	
Expt No.	**Roughness in (µm)**	**Cutting force (N)**	**Roughness in (µm)**	**Cutting force (N)**	γ_i	Rank
1	0.5	0.470430588	0.5	0.485639913	0.49282	14
2	0.378788	0.584728832	0.445946	0.546286191	0.496116	13
3	0.545455	0.605892767	0.52381	0.55921704	0.541513	6
4	0	0	0.333333	0.333333333	0.333333	20
5	1	1	1	1	1	1
6	0.545455	0.546770185	0.52381	0.524532481	0.524171	7
7	0.484848	0.51948284	0.492537	0.509934982	0.501236	12
8	0.992424	0.988890152	0.985075	0.978263288	0.981669	2
9	0.818182	0.991696379	0.733333	0.983664052	0.858499	4
10	0.424242	0.694820277	0.464789	0.620979374	0.542884	5
11	0.515152	0.548719281	0.507692	0.525607205	0.51665	8
12	0.575758	0.305179723	0.540984	0.418472978	0.479728	15
13	0.621212	0.415271168	0.568966	0.460944694	0.514955	9
14	0.181818	0.008303621	0.37931	0.335188854	0.35725	18
15	0.507576	0.502265824	0.503817	0.501135485	0.502476	11
16	0.462121	0.435996557	0.481752	0.469923291	0.475838	16
17	0.015152	0.206652915	0.336735	0.386593828	0.361664	17
18	0.5	0.517858593	0.5	0.509091661	0.504546	10
19	0.954545	0.889161401	0.916667	0.818546832	0.867607	3
20	0.045455	0.110091445	0.34375	0.359735896	0.351743	19

Therefore, 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 as listed in the Table 6. The optimal set of input parameters is Depth of cut =0.15 mm, Feed 0.15 mm/rev and Speed 550 m/min and the optimal values of the out response obtained are Surface roughness 0.142 µm and Cutting force 8.441N.

VI. CONCLUSION

The RSM approach was utilized to explore the high-speed milling of a magnesium calcium alloy in this work (MgCa1.0). The goal of the research was to see how machining factors such as cutting speed, feed, and depth of cut affect surface quality and the main cutting force. The following are the study's most important findings:
The feed (represented in this study as the feed mm/rev) has the greatest impact on surface roughness. Under the conditions studied, a combination of high cutting speed, small feed, and depth of cut is the most beneficial for good surface quality.
For the principal cutting force, speed is a significant influencing factor. Feed, on the other hand, has a significant impact on cutting force, with a contribution of 27.92 %. To a much lesser extent, the cutting force is influenced by their interaction.
The above various quality criteria were converted to a single-objective problem in grey relational analysis, which was graded using grey relational grade. Thus, the optimum of process parameters, such as cutting speed of 550 m/min, feed rate of 0.15 mm/rev, and depth of cut of 0.15 mm in this study, may be combined to achieve decreased surface roughness and lower cutting forces.

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