Tuijin Jishu/Journal of Propulsion Technology
ISSN : 1001-4055
Vol. 44 No. 5 (2023)

Modeling and Optimization of Face Milling Operation of Magnesium Calcium Alloy Based on Response Surface Methodology

Niket Malvade[1], Dr. R.S. Pawade[2]
[1]Research Scholar, [2]Associate Professor
Department of Mechanical Engineering, Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, India

Abstract

Various aspects such as work material, cutting environment, machining parameters influence the surface finish, microstructure, and subsurface properties of the machined surface while machining Physical and mechanical qualities, as well as the surface condition, are critical parameters in the machining of biomedical implants since they have a direct impact on the implant's performance Surface finish, microhardness, microstructure, and residual stress also have a lot of attention in recent years as they have a direct impact on the implant's strength and degrading behavior The current study focuses on the Mg-Ca1 0 biomedical alloy, which is commonly used in bone support plates, bone support rods, and bone fixation screws In light of the aforementioned, a study is being prepared with the aim of enhancing the cutting circumstances in order to enhance the quality of magnesium implants To assess the effects of cutting speed, feed, and depth of cut on process parameters.

Keywords: Face Milling, Optimization, Modelling, Response Surface Methodology, Cutting forces.

Introduction

The current study focuses on the Mg-Ca1.0 biomedical alloy, which is commonly used in bone support plates, bone support rods, and bone fixation screws during orthopedic surgery due to its biocompatibility and biodegradability. These orthopedic implant from MgCA1.0 alloy are having better compatibility with the human fluid and hence neeeds wider attraction for the manufacturing at lower cost with intended surface quality. Additionally the characteristics being identical to those of human bone, magnesium-based alloys are promising application with biomeical field. Although polymers such as poly-L-Lactic acid are used to make biodegradable implants. However, these polymer-based implants typically lack mechanical strength, resulting in a low load-bearing capability.[1].

In vivo experiments have shown that the magnesium-calcium alloys are suitable as a biodegradable biomaterial for use in medical implants. Because the young's modulus of magnesium (40 GPa) and cancellous bones (young's modulus 10 – 30 GPa) are so close, the stress shielding effect is diminished. Magnesium is an essential component of the human body's metabolic functions; the average daily magnesium requirement for the human body is 300–400 mg. In the deterioration of a 9-cm magnesium implant, a weight loss rate of 19–44 mg/cm2/day was reported [3]. Magnesium alloys provide a number of advantages as temporary biomaterials, including strong mechanical characteristics and biocompatibility. Table 1 indicated the different properties of biomaterials.

MgCa1.0 alloys show comparable values of the properties like tensile strength, density and elastic modulus as that of natural bone, see Table 1.

Magnesium is lighter than aluminium and stronger than steel in terms of tensile strength. As a result of its lightness, durability, and long life, use of magnesium in industry is increased.[3]. Portable microelectronics, telephony, automotive, material handling, and aerospace industries all employ them [4]. It is also primarily used for applications such as bone supporting plates, rods, and bone fixing screws as indicated in Figure 1 due to its biocompatibility and biodegradability.

The RSM is a dynamic and crucial Design of Experiment (DOE) technique that maps the link between process outputs and their input decision variables to achieve the goal of maximisation or minimization of output attributes. RSM has been successfully used to forecast and optimise cutting parameters.[5], [6] Using a genetic algorithm, Shunmugam et al explored the selection of optimal conditions in multi-pass face-milling.[5] Using a surface roughness model, Baek et al examined feed rate optimization in a face milling operation.[7] Benardos et al.[5] studied the use of neural networks and Taguchi's design of experiments to predict surface roughness in CNC face milling. For geometric inaccuracy in the surface grinding process, Jae-Seob Kwak used Taguchi and RSM [8].Korkut et al.[9] studied the effects of feed rate and cutting speed on cutting forces, surface roughness, and tool–chip contact length during face milling. Genetic algorithms were used by Libao An et al[10]. to design a multi-objective optimization of machining parameters for face-milling operations with the goal of minimising unit production cost, unit machining time, and unit profit rate. Abhijith et.al [12] Optimised machining parameters such as cutting speed, feed rate, and depth of cut using optimization techniques such as the firefly algorithm , particle swarm optimization , and artificial bee colony algorithm in order to achieve the lowest possible surface roughness of AZ31 magnesium alloy in face milling. The mathematical predictive models for surface roughness parameters and micro-hardness of the turned AZ31 magnesium alloy samples were developed by Danish et al [13].. Using the RSM technique, Puneet Kumar et al.[14] investigated the influence of several variables on surface roughness and material removal rate. For the response parameters they have created a second order model. Selvan[11] studied the effect of parameters on surface roughness in end milling and developed a quadratic polynomial regression model based on RSM and the Box-Behnken design. Solemani[12] conducted end milling experiments and constructed the model using RSM and ANN approaches. Kannan[13] investigated the effect of face milling on aluminium using RSM and GA technique. For simulating surface roughness in face milling, Kovac[14] studied the use of fuzzy logic and regression analysis. Rashmi[15] used response surface approach and the PSO technique to explore the influence of machining parameters on AA6061 material.

Response surface design was used in this study to construct the models for cutting forces (Fz) and Surface roughness (Ra) based on experimental data from the face milling process optimised cutting parameters were explored by using, response surface approach. The accuracy of the optmised results was confirmed again by the additional experiments.

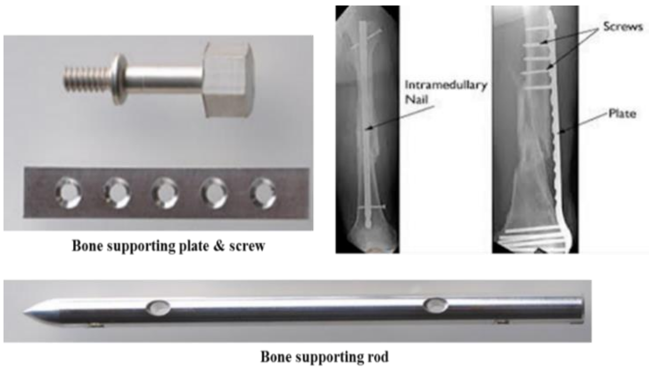


Figure 1 Biomedical applications of magnesium alloy [3], [4]

Table 1 Mechanical Properties Of Different Biomaterials [1][2]

Tissue/ Material	Density (g/cm^3)	Compressive Strength (MPa)	Tensile Strength (MPa)	Elastic Modulus (GPa)	Fracture Toughness ($MPam^{1/2}$)
Natural Bone	1.8 - 2.1	130 - 180	35 - 283	3 - 23	3 - 6
Titanium Alloys	4.4	758 - 117	550 - 985	100 - 125	55 - 155
Stainless Steel	7.9	170 - 310	480 - 620	193 - 200	50 - 200
Cobalt-Chrome alloy	7.8	450 - 1000	450 - 960	195 - 230	-
PMMA Polymer	1.12-1.20	45 - 107	38 - 80	1.8 - 3.3	-
Mg-Cast	1.74	65 - 100	83 - 95	41	-
Hot Rolled MgCa	1.74	-	180 - 220	-	15 - 40

Materials and Methods

To investigate how the process parameters affects the surface topography the several experiments were conducted. The experimental setup for the face milling of MgCa1.0 alloy is shown in Figure 2. Mg-Ca 1.0 alloy plates of dimension 80 mm x 60 mm x 10 mm are clamped on the cutting force dynamometer [9257A]as shown in Figure 2. Experiments were carried out on a CNC milling center (Hardinge VMC 600 II) with a maximum speed of 3800 rpm.. DLC coated carbide cutting inserts having 50 mm diameter (Make- HITACHI) as shown in Figure 3 were used and the cutting diameter is 50 mm.

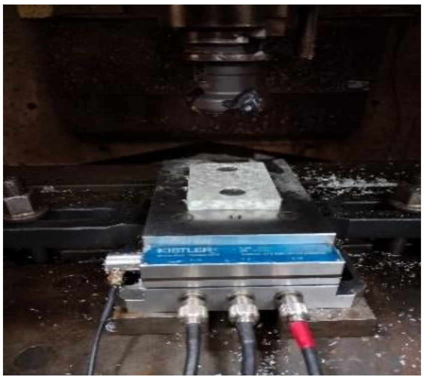


Figure 2 Expérimental Setup

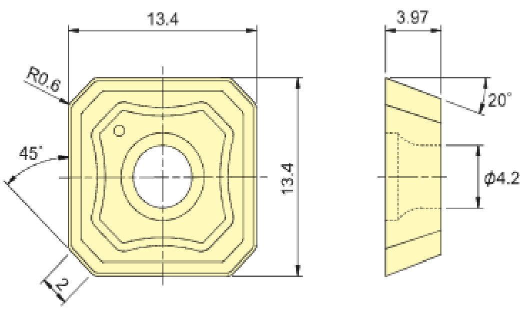


Figure 3 Coated carbide face milling inserts

The experimental trials in this investigation were carried out utilising a central composite design with three levels of each variable as shown in Table 2. With the parameters listed in Table 3, a total # 20 experiments were conducted.

Tuijin Jishu/Journal of Propulsion Technology
ISSN : 1001-4055
Vol. 44 No. 5 (2023)

Table 2 Process Variable and Experimental Levels

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**

Surface roughness was measured with a surface roughness tester after machining (model- SJ-201, make- Mitutoyo). When measuring the surface roughness parameter Ra, a sampling length of 2.5 mm was used. Kistler dynamometer Type 9257 was used to measure the cutting forces.

Table 3 Expérimental factors and their levels

Expt No.	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Surface 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
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

Results and discussion

Response surface methodology (RSM) is a set of mathematical and statistical techniques for analysing problems in which a large number of independent factors influence a single dependent variable or response, with the goal of optimising the response[19]. To forecast the extraction efficiency of different sets of combinations of three process variables, a mathematical model was built by fitting a second-order polynomial equation with interaction factors to the experimental results.

Tuijin Jishu/Journal of Propulsion Technology
ISSN : 1001-4055
Vol. 44 No. 5 (2023)

This study produced results for forecasting cutting force and surface roughness. The resulting regression equations are shown in Table 4. A regression fitted model's relevance is measured using the R-sq coefficient correlation. Surface roughness and Cutting force models show R-sq values of 99.67 and 98.2, respectively while shows the fit is adequate. Table 5 illustrates the experimental vs. expected values.

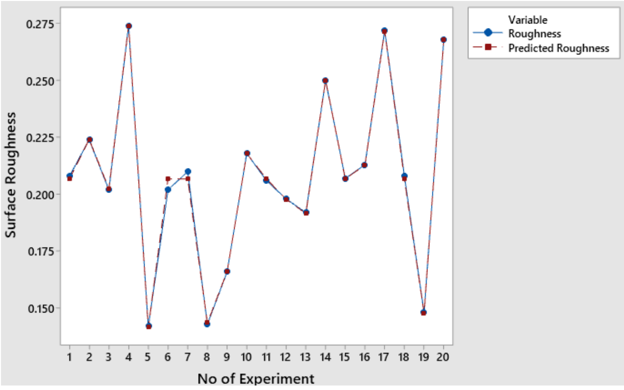
Table 4 Equations of Regression Model

Sr. No.	Responses	Equations
1	Surface Roughness	0.2093- 0.000292 Cutting Speed+ 0.4850 Feed+ 0.015 Depth of cut+ 0.000000 Cutting Speed* Cutting Speed +0.0525 Feed*Feed + 0.118 Depth of cut*Depth of cut- 0.000000 Cutting Speed*Feed- 0.000000 Cutting Speed*Depth of cut - 0.000 Feed*Depth of cut
2	Cutting Force	14.15- 0.01916 Cutting Speed+ 18.26 Feed- 0.6 Depth of cut+ 0.000007 Cutting Speed* Cutting Speed- 15.7 Feed*Feed + 13.4 Depth of cut*Depth of cut - 0.0001 Cutting Speed*Feed + 0.0001 Cutting Speed*Depth of cut - 0.1 Feed*Depth of cut

Table 5 Experimental v/s RSM predicted results

Expt No.	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Experimental		RSM Prediction		Error (%)	
				Surface Roughness (µm)	Cutting force (N)	Surface Roughness (µm)	Cutting force (N)	Surface Roughness	Cutting force
1	450.00	0.225	0.200	0.208	10.822	0.20682	10.604	0.567	2.014
2	550.00	0.300	0.250	0.224	10.308	0.22416	10.375	-0.071	-0.650
3	450.00	0.225	0.115	0.202	10.213	0.20243	10.296	-0.213	-0.813
4	350.00	0.300	0.250	0.274	12.936	0.27413	13.002	-0.047	-0.510
5	550.00	0.150	0.150	0.142	8.441	0.14164	8.228	0.254	2.523
6	450.00	0.225	0.200	0.202	10.478	0.20682	10.604	-2.386	-1.203
7	450.00	0.225	0.200	0.210	10.601	0.20682	10.604	1.514	-0.028
8	450.00	0.098	0.200	0.143	8.491	0.14351	8.95	-0.357	-5.406
9	618.17	0.225	0.200	0.166	8.479	0.16613	8.583	-0.078	-1.227
10	550.00	0.300	0.150	0.218	9.813	0.21793	9.897	0.032	-0.856
11	450.00	0.225	0.200	0.206	10.470	0.20682	10.604	-0.398	-1.280
12	350.00	0.150	0.250	0.198	11.564	0.19784	11.334	0.081	1.989
13	350.00	0.150	0.150	0.192	11.069	0.19162	10.855	0.198	1.933
14	281.82	0.225	0.200	0.250	12.898	0.25019	13.002	-0.076	-0.806
15	450.00	0.225	0.200	0.207	10.678	0.20682	10.604	0.087	0.693
16	450.00	0.225	0.284	0.213	10.976	0.21289	11.101	0.052	-1.139

17	450.00	0.351	0.200	0.272	12.007	0.27181	11.757	0.070	2.082
18	450.00	0.225	0.200	0.208	10.608	0.20682	10.604	0.567	0.038
19	550.00	0.150	0.250	0.148	8.940	0.14786	8.708	0.095	2.595
20	350.00	0.300	0.150	0.268	12.441	0.26791	12.526	0.034	-0.683
Overall Percentage of Error								**0.359**	**1.423**



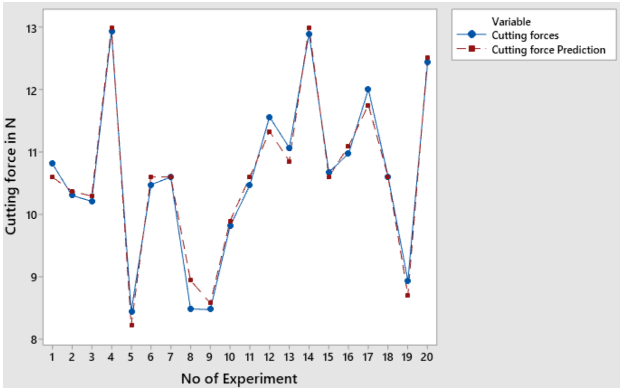


Figure 4 Actual v/s Expected Roughness **Figure 5 Actual v/s Expected Cutting forces**

The Actual and expected comparison plots for Surface roughness and Cutting forces, respectively, are shown in Figures 4 and 5. The actual numbers are extremely close to those expected. Roughness has a very low percentage of error of 0.359 percent and Cutting forces has a percentage of error of 1.423 percent. As a result, the optimization model established can be expanded. An ANOVA includes the sum of squares, the degree of freedom (DF), the mean square, the F-value, and the P-value. The use of ANOVA (Analysis of Variance) is required to determine the parameters that have an impact on the responses. ANOVA was used to validate the model's performance. Central composite design has build up the quadratic model which is used to optimized the parameters. Statistics (F-tests) under the null hypothesis are used to determine the importance of a factor: large F-ratios suggest that the factor has a significant impact on the response. For each p-value, a confidence interval is calculated and used to assess significance. The p-value reflects how likely it is that the results of the tests happened by coincidence. The p value in this study is less than 0.05, which indicates that a factor is only considered significant if the p value is less than 0.05.

Table 6 ANOVA for Surface Roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% of Contribution
Cutting 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

Cutting Speed* Cutting 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
Cutting Speed*Feed	1	0	0	0	1	0.00
Cutting 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				

The research's purpose is to lower the surface roughness value Ra while accounting for the input parameters cutting speed, feed, and depth of cut. The analysis findings are presented in Table 6. Feed rate is the most important component (with 69.63 percent contribution). Cutting speed was also shown to be considerable (with a contribution of 29.88 percent) depth of cut shows lesser impact on surface roughness. The response surface contour plots and surface plots for the influence of machining parameters cutting speed and feed on the surface roughness are shown in figure 6 and figure 7. The figure shows that when the cutting speed is higher and feed rate is lower at the experimented range, lower surface roughness is obtained at any given depth of cut.

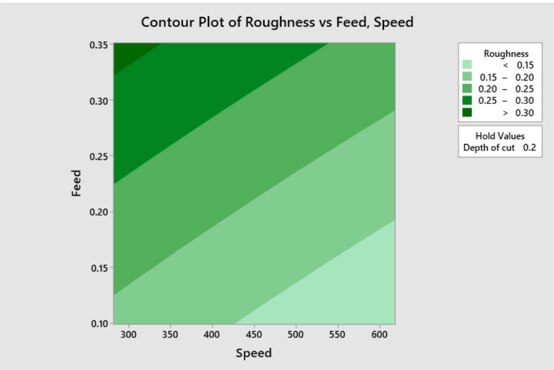


Figure 6 Contour plot of Surface Roughness

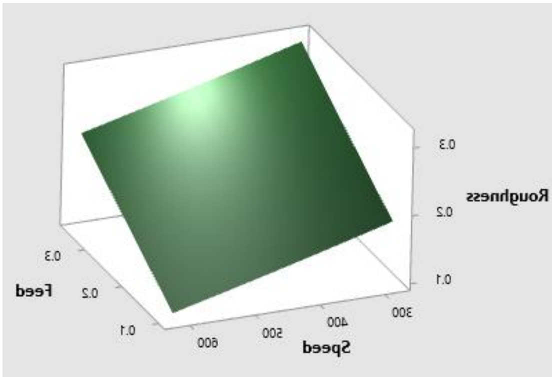


Figure 7 Surface plot of Surface Roughness

Table 7 shows the results of an ANOVA on the principal cutting force. The most significant factor is the cutting speed, which accounts for 69.21 percent of the total, followed by feed, accounting 27.92 percent. Although there are other crucial factors, having minimal impact.

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% of Contribution
Cutting 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
Cutting Speed* Cutting 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
Cutting Speed*Feed	1	0	0	0	0.996	0.00
Cutting 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				

The response surface contour plots and surface plots for influence of machining parameters Speed and Feed on the cutting forces are shown in figure 8 and figure 9. The figure shows that when speed is higher and feed rate is lower at the experimented range, the smallest cutting forces are obtained at any given depth of cut..

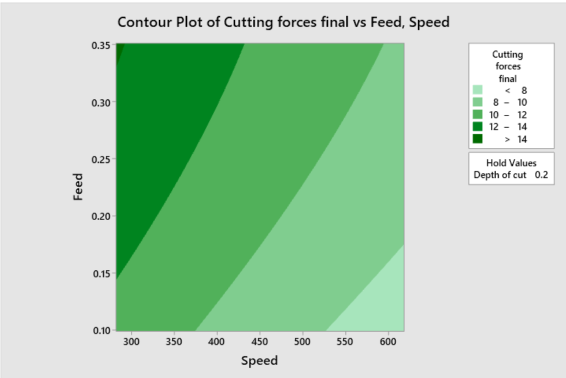


Figure 8 Cutting force Contour plot.

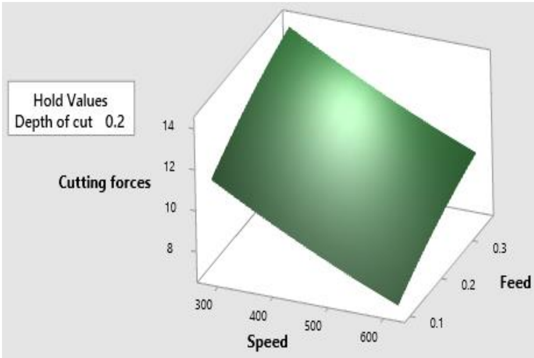


Figure 9 Cutting force Surface plot

Conclusion

The challenge of machining parameter optimization is approached as a multi-objective optimization problem. An RSM approach was designed to address such a multi-objective optimization problem in face milling to improve the machining parameters. Using the calculated second order equation, the expected and experimental values demonstrate a strong correlation.

- The results of the ANOVA revealed that the effect of Feed rate on surface roughness is much stronger than the effects of Speed and depth of cut.
- The results of the ANOVA revealed that the influence of Speed on cutting force is significantly greater than the effects of Feed rate and cut depth.
- CCD evaluates the interaction of parameters by formulating a polynomial model. The 2nd order model predicted surface roughness and cutting forces values for the machining process with 0.35 percent and 1.42 percent error, respectively, at a 95 percent confidence level for adequacy.
- The optimum surface roughness and cutting forces produced by the RSM model were 6.62 N and 0.098 m, respectively, at a cutting speed of 618.719 m/min, a feed rate of 0.098 mm/rev, and a depth of cut of 0.098 mm.

References

[1] M. P. Staiger, A. M. Pietak, J. Huadmai, and G. Dias, “Magnesium and its alloys as orthopedic biomaterials: A review,” *Biomaterials*, vol. 27, no. 9, pp. 1728–1734, 2006, doi: 10.1016/j.biomaterials.2005.10.003.

[2] G. Eddy Jai Poinern, S. Brundavanam, and D. Fawcett, “Biomedical Magnesium Alloys: A Review of Material Properties, Surface Modifications and Potential as a Biodegradable Orthopaedic Implant,” *Am. J. Biomed. Eng.*, vol. 2, no. 6, pp. 218–240, 2013, doi: 10.5923/j.ajbe.20120206.02.

[3] M. Salahshoor and Y. Guo, “Biodegradable orthopedic magnesium-calcium (MgCa) alloys, processing, and corrosion performance,” *Materials (Basel).*, vol. 5, no. 1, pp. 135–155, 2012, doi: 10.3390/ma5010135.

[4] berat baris, “Investigation of Magnesium Alloys Machinability,” *Int. J. Electron. Mech. Mechatronics Eng.*, vol. 2, no. 3, pp. 261–268, 2013.

[5] P. G. Benardos and G. C. Vosniakos, “Predicting surface roughness in machining: A review,” *Int. J. Mach. Tools Manuf.*, vol. 43, no. 8, pp. 833–844, 2003, doi: 10.1016/S0890-6955(03)00059-2.

[6] I. Mukherjee and P. K. Ray, “A review of optimization techniques in metal cutting processes,” *Comput. Ind. Eng.*, vol. 50, no. 1–2, pp. 15–34, 2006, doi: 10.1016/j.cie.2005.10.001.

[7] D. K. Baek, T. J. Ko, and H. S. Kim, “Optimization of feedrate in a face milling operation using a surface roughness model,” *Int. J. Mach. Tools Manuf.*, vol. 41, no. 3, pp. 451–462, 2001, doi: 10.1016/S0890-6955(00)00039-0.

[8] J. S. Kwak, “Application of Taguchi and response surface methodologies for geometric error in surface grinding process,” *Int. J. Mach. Tools Manuf.*, vol. 45, no. 3, pp. 327–334, 2005, doi: 10.1016/j.ijmachtools.2004.08.007.

[9] I. Korkut and M. A. Donertas, “The influence of feed rate and cutting speed on the cutting forces, surface roughness and tool-chip contact length during face milling,” *Mater. Des.*, vol. 28, no. 1, pp. 308–312, 2007, doi: 10.1016/j.matdes.2005.06.002.

[10] L. An, “Multi-Objective Optimization for Milling Operations using Genetic Algorithms under Various Constraints,” vol. 2, no. 2, pp. 108–114, 2014.

[11] V. Sathyamoorthy, S. Deepan, S. P. Sathya Prasanth, and L. Prabhu, “Optimization of Machining Parameters for Surface Roughness in End Milling of Magnesium AM60 Alloy,” *Indian J. Sci. Technol.*, vol. 10, no. 32, pp. 1–7, 2017, doi: 10.17485/ijst/2017/v10i32/104651.

[12] M. R. SOLEYMANI YAZDI and A. KHORRAM, “Modeling and Optimization of Milling Process by using RSM and ANN Methods,” *Int. J. Eng. Technol.*, vol. 2, no. 5, pp. 474–480, 2010, doi: 10.7763/ijet.2010.v2.167.

[13] S. Kannan and N. Baskar, “Modeling and optimization of face milling operation based on response surface methodology and genetic algorithm,” *Int. J. Eng. Technol.*, vol. 5, no. 5, pp. 4164–4175, 2013.

[14] P. Kovac, D. Rodic, V. Pucovsky, B. Savkovic, and M. Gostimirovic, “Application of fuzzy logic and regression analysis for modeling surface roughness in face milliing,” *J. Intell. Manuf.*, vol. 24, no. 4, pp. 755–762, 2013, doi: 10.1007/s10845-012-0623-z.

[15] R. Lmalghan, K. Rao, S. ArunKumar, S. S. Rao, and M. A. Herbert, “Machining Parameters Optimization of AA6061 Using Response Surface Methodology and Particle Swarm Optimization,” *Int. J. Precis. Eng. Manuf.*, vol. 19, no. 5, pp. 695–704, 2018, doi: 10.1007/s12541-018-0083-2.