MODELLING AND OPTIMIZATION OF GRINDING OF CERAMICS USING HYBRID APPROACH OF RSM AND GA

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ABSTRACT

In modern age, the technology is continually becoming more advance rapidly. The new materials are required in many technological fields. In manufacturing many engineering components, there is requirement of materials which has high strength at high temperature, good resistance to chemical degradation, good resistance to wear and having low density. Advance structural ceramics such as silicon carbide, silicon nitride etc. fulfill these requirements. These materials are used in many engineering applications to make various components. There are certain other parameters which are essentially required such as good surface finish and low surface damage. Grinding with superabrasive is one of the method to acquire good surface finish considering the factors such as grinding forces and material removal rate.

In the present work ceramic is chosen to perform various experiments and variables were grit size, depth of cut and feed using CBN grinding wheel to study the effect of control factors on grinding forces. Multiple regression method has been used to develop the model for grinding force. Further, optimization has been done to achieve minimum grinding forces.

Keywords: Ceramic Grinding, Optimization, Surface Roughness, Grinding Force

1. INTRODUCTION

The application of hard and brittle materials, typically represented by advanced ceramics, for a number of high-performance components have recently generated high interest because they have superior mechanical, thermal and physical properties. Because of these special qualities, advanced ceramics are used in wide verity of applications such as turbine blades, valves and valve seats, bearing, heat exchanger and many more engineering components. However, grinding of ceramics poses problems by conventional machining techniques.

Literature survey revealed that ample of research work has been done on the grinding of ceramic. Horvath et al. [1] discussed the problems with conventional grinding while machining advanced ceramics. They demonstrated the application of advanced precision grinding based on the electrochemical principle. They concluded that there is considerable improvement in the performances in terms of material removal rate and surface roughness. Zhang et al. [2] performed surface grinding on the silicon nitride ceramics using diamond grinding wheel. They analyzed normal grinding force (F_T), actual depth of cut of a grinding wheel, stock removal rate and residual strength of ground workpieces theoretically and then they validated the results with experimentation. Shen et al. [3] concluded that effects of grinding pressure and the rotational speed of the spindle in the machining of ceramic materials are very significant on the quality of the grinding process. Also, to achieve stable grinding conditions, they developed new grinding control scheme in which the grinding pressure

was maintained constant. Huang et al. [4] discussed the high speed grinding characteristics of engineering ceramics. They compared the grinding characteristics of ceramics under high speed and conventional speed. For that purpose, F_T and acoustic emission energy were taken as parameters. They concluded that vibration and coolant are important factor for achieving good grinding performance. Shen et al. [5] performed the face grinding on two different ceramics to study thermal aspects at the wheel-workpiece contact zone. The temperature characteristics and mechanism of energy partition were discussed. Mayer et al. [6] conducted experiments on the hot pressed silicon-nitride using diamond grinding wheel. The aim of this work was to study the effect of grit size on surface damage, rupture strength, surface roughness and microcrack. They concluded that with increasing mean grit size from 5.1µm to 249µm the percent damaged area increases from 2.8% to 24.91% and surface roughness increases from 0.0508µm to 0.409µm. In case of rupture strength, there was no change in the strength in the longitudinal direction but in transverse direction the rupture strength decreases as the grit size increases. The trend was towards less damage and more ductile mode appearance as the grit size becomes smaller.

In the present research, the surface grinding has been performed on the ceramic workpiece using grinding wheel with CBN superabrasive. Regression model for one of the important parameter, that is F_T, has been developed. Further, single objective optimization using hybrid approach of regression model and genetic algorithm has been done.

2. METHODOLOGY

2.1. **Regression Model**

Response surface methodology or RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. Mathematically it can be expressed as:

$$y = f(x_1, x_2) + \epsilon$$
 (1)
Where ϵ represents the noise or error observed in the response y. If we denote the expected response by $E(y) = f(x_1, x_2) = \eta$, then the surface represented by

$$\eta = f(x_1, x_2)$$

is called a response surface [7].

Where ¢

2.2. Genetic Algorithm

Genetic algorithms (GA) are computerized search and optimization algorithms based on mechanics of natural genetics and natural selection. GAs are fundamentally different than classical optimization algorithms. The GA is quite suitable to solve the problems that are highly complex and nonlinear. The working principle of GA has been discussed elsewhere [8].

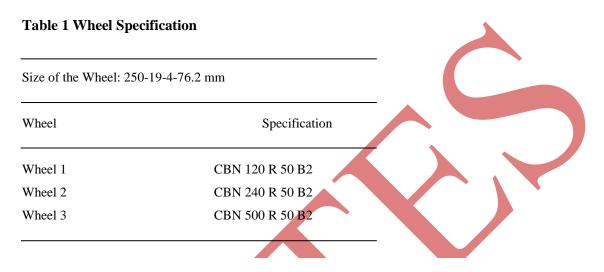
3. EXPERIMENTATION

The objective of the present section is to furnish experimental details. Experiments were performed on hydraulic surface grinding machine. The special vice has been procured for holding the workpiece. The

(2)

workpiece selected is ceramic with dimension 120 X 50 X 25 mm. Total 9 number of workpiece were taken. Before performing the experiments, all the three sides were flattened. For this purpose initially, nearly 8 mm³ materials were removed by giving very low depth of cut like 1-2 μ m.

CBN grinding wheels was selected for the present work. Three different grit sizes of wheels selected were 120, 240 and 500. The specification of CBN grinding wheel is given in Table 1.



The design of experiments is a systematic and scientific procedure to perform the experiments in order to analyze the effect of various control factors on different quality characteristics. 3^k factorial design has been used to plan and perform the experiments. The three factors are depth of cut, feed and grit size. The range of value of each factor has been set at three levels namely low, medium and high as shown in Table 2.

Table 2 Con	trol factors and their	levels	
Factors	Depth of cut (µm)	Feed (m/min)	Grit No
Symbol	X ₁	X2	x ₃
Level 1	6.0	10.5	120
Level 2	12.0	12.5	240
Level 3	18.0	14.5	500

4. RESULTS AND DISCUSSIONS

The experimental results are shown in Table 3. This section discusses the effect of various control factors on one of the important quality characteristic F_T . The regression model has been developed for grinding force using MINITAB software. The single objective optimization for the quality characteristic has been done by using hybrid approach of regression models and genetic algorithm.

Table 3 Experimental Result

S.N.	Depth of Cut(µm)	Feed (m/min)	Grit Size	Grinding Force (N)
1	6	10.5	120	51.87
2	18	14.5	500	45.5
3	6	14.5	500	33.93
4	18	10.5	500	58.5
5	6	12.5	240	43.68
6	6	14.5	500	46.15
7	6	14.5	120	41.73
8	12	12.5	500	50.7
9	12	10.5	120	58.63
10	18	12.5	500	58.5
11	18	10.5	120	65.13
12	12	12.5	120	50.7
13	12	14.5	240	46.8
14	18	12.5	120	62.01
15	18	10.5	240	58.76
16	6	12.5	500	39
17	18	12.5	240	52
18	6	14.5	500	39
19	12	12.5	120	47.32
20	18	14.5	120	59.15
21	6	10.5	500	45.5
22	12	10.5	240	52
23	18	14.5	240	52
24	12	14.5	120	52.91
25	6	10.5	240	45.76
26	12	12.5	120	58.76
27	12	10.5	500	54.6

4.1. Parametric analysis

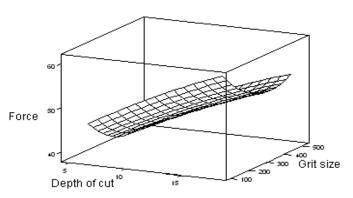
ANOVA [7] of F_T (Table 4) identifies feed as most significant factor affecting F_T followed by depth of cut and grit number.

Source (%)	Degree of freedom	Sum of square	Mean square	F	Contribution
Depth of cut 37.31	2	0.08589	0.04294	8.27	
Feed 44.22	2	0.10188	0.05094	9.8	
Grit No 18.45	2	0.04248	0.02124	4.09	
Error	20	0.10391	0.0052		
Total	26	0.33568			

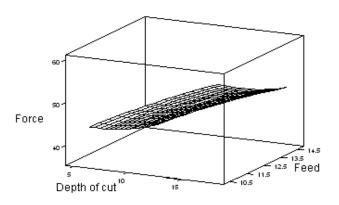
Table 4 Analysis of variance for grinding force

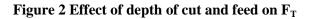
F value at 95% confidence level: $F_{0.05,2,18}$ = 3.55

Fig. 1 shows the response surface plots for the grinding force with respect to depth of cut and grit size. It is clear from the response surface plot that with increase in depth of cut, the grinding force increases for all values of grit size. The increase in depth of cut results in increase in contact area of the grit and hence results in higher forces. Similarly, with the increase in the grit size, the grinding force reduces. Since with the increase in grit size, the coarseness of the grain decrease and a fine grain takes less depth of cut as compared to coarse grain and hence forces decreases.









The Fig 2 shows the variation of force with the feed and depth of cut. It can be concluded from the response surface plot that with increase in the feed, the grinding force decreases.

4.2. Modeling

Eq. (3) shows the second order regression model for grinding force. It has been developed by using data of all 27 runs as given in Table 3. The results of ANOVA for model F_T is shown in Table 5. The model F-value 7.30 implies that quadratic model is statically significant. There is negligible chances that a model F-value of this much magnitude could occur due to noise. The value of coefficient of determination \mathbb{R}^2 and adjusted \mathbb{R}^2 are 84.0 and 76.9, respectively which means a very high percent of the variation in the response variable can be explained by the explanatory variable. The negligible variation can be explained by unknown or inherent variability. The S value of the regression analysis is 3.725, which is smaller. The associated p-value for the model as well as linear and square term is lower than 0.05 (i.e. α =0.05, or 95% confidence) which indicates that the model is considered to be statistically significant.

The final regression model for F_T (N), after removing the non-significant terms is given as follows:

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 \begin{array}{c} {F_{\rm T}} \\ = \\ {96.7 + 2.03 x_1 - 6.69 x_2 - 0.0811 x_2 - 0.0206 x_1^2 + \ 0.203 x_2^2 + 0.0000118 x_3^2 - 0.0228 x_1 x_2 - 0.000511 x_1 x_3 \end{array}
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(3)
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Table 5 Analysis of variance for developed model of F_T

Residual Error 18 249.69 13.87 Total 26 1559.04 S=3.725 R-Sq = 84.0% R-Sq (adj) = 76.9% 4.3. Optimization In the present case, the objective function of optimization problem can be stated as below: Find: $x_1, x_2, and x_3$ Minimizes $F_T = 96.7 + 2.03x_1 - 6.69x_2 - 0.0811x_3 - 0.0206x_1^2 + 0.203x_2^2 + 0.000118x_3^2 - 0.0228x_1x_2 - 0.000511x_1x_3$ (4) With range of process input parameters: $6 \le x_1 \le 18$ $10.5 \le x_2 \le 14.5$	Source	Degree of freedom	Seq SS	Adj SS	Adj MS	F	Р
In the present case, the objective function of optimization problem can be stated as below: Find: x_1, x_2 , and x_3 Minimizes $F_{T}=$ $96.7 + 2.03x_1 - 6.69x_2 - 0.0811x_3 - 0.0206x_1^2 + 0.203x_2^2 + 0.000118x_3^2 - 0.0228x_1x_2 - 0.000511x_1x_3$ With range of process input parameters: $6 \le x_1 \le 18$ $10.5 \le x_2 \le 14.5$	Regression Residual Erro Total S=3.725	r 18 26	249.69 1559.04		163.67	11.80	0.000
Find: x_1, x_2 , and x_2 Minimizes $F_T = 96.7 + 2.03x_1 - 6.69x_2 - 0.0811x_3 - 0.0206x_1^2 + 0.203x_2^2 + 0.000118x_3^2 - 0.0228x_1x_2 - 0.000511x_1x_3$ With range of process input parameters: $6 \le x_1 \le 18$ $10.5 \le x_2 \le 14.5$							
Minimizes $F_{T}= \begin{array}{c} 96.7 + 2.03x_{1} - 6.69x_{2} - 0.0811x_{3} - 0.0206x_{1}^{2} + 0.203x_{2}^{2} + 0.000118x_{3}^{2} - 0.0228x_{1}x_{2} - 0.000511x_{1}x_{3}x_{3} - 0.000511x_{1}x_{3}x_{3} - 0.0228x_{1}x_{2} - 0.000511x_{1}x_{3}x_{3} - 0.000511x_{3}x_{3}x_{3} - 0.000511x_{3}x_{3} - 0.000511x_{3} - 0.000511x_{3} - 0.000511x_{3} - 0.000511x_{3} - 0.00051x_{3} - 0.0005x_{3} - 0.0005x_{3} - 0.0005x_{3} - 0.0005x_{3} - 0.000$	In the present	case, the objective function	on of optimization p	roblem can be s	tated as below:		
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$0.000511 x_1 x_2 $ (4) With range of process input parameters: $6 \le x_1 \le 18$ $10.5 \le x_2 \le 14.5$	F _T =						
$6 \le \mathbf{x_1} \le 18$ $10.5 \le \mathbf{x_2} \le 14.5$			-	-	0118x ₃ * - 0.0228x	t ₁ x ₂ -	
$10.5 \le x_2 \le 14.5$	With range of	process input parameters					
-	6≤ x ₁ ≤ 18						
120≤x ₃ ≤500	10.5≤ x₂ ≤14.5						
	120≤ x ₃≤500						

The critical parameters of GA are the size of the population, mutation rate, cross-over rate and number of generations. After trying different combinations of GA parameters, the population size 40, cross-over rate 1.0, mutation rate 0.01 and number of generation 60 have been taken for F_T . The objective function in Eq. (4) has been solved without any constraint. In Fig. 3, the best and mean fitness curves are illustrated in the search space. The fitness function is optimized when the mean curve converges to the best curve after 25 generation. The corresponding values of control factors depth of cut, feed, and grit number have been found as 6.0 μ m, 14.83 m/min, 383. Hence these are the optimum values of control factors. Using these values, the value of F_T has been obtained as 36.84 N.

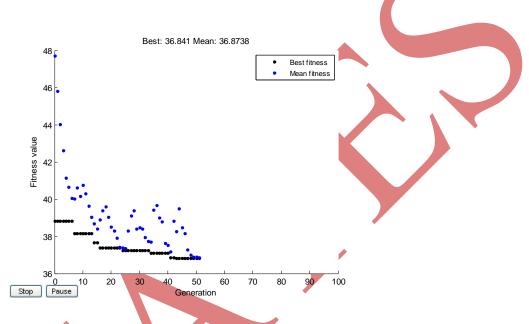


Fig. 3 Generation-fitness graphics for F_T

5. CONCLUSIONS

Following conclusions can be drawn from the present paper:

- 1. Feed has been identified and most significant control factor affecting grinding force followed by depth of cut.
- 2. The developed regression model for grinding force has been found reliable and adequate with negligible prediction error.
- 3. The grinding force has been found to increase with the increase of depth of cut or decrease of grit number.
- 4. The grinding force has found to decrease with the increase in feed.
- 5. Single objective optimization results show improvements of 29% in the grinding force.

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