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Prediction of the surface roughness and wheel wear of modern ceramic material (Al_2O_3) during grinding using multiple regression analysis model

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Grinding process is used widely for producing industrial parts with high precision and high surface quality for modern ceramics. But only a few machining tests were carried out on grinding by using silicon carbide (SiC) grinding wheel with various parameters. In this paper, an analytical model is developed to determine the surface roughness (R_a) and wheel wear (W_w) of modern ceramic material (Al_2O_3) during grinding. The model is developed to fitting the relationships R_a, W_w versus three process parameters (depth of cut, feed and grain size) using multiple regression analysis method. The main objective of this paper is to develop a model for optimizing the R_a and W_w values of modern Al_2O_3 ceramic material and SiC grinding wheels during grinding. Besides, experimental results are used to establish the multiple regression analysis equations for R_a and Ww. The predicted values of R_a and W_w show linear relationships versus three parameters and have a good agreement with experiment results.

Keywords: Multiple regression analysis, Al_2O_3, SiC, Surface roughness, Wheel wear

In recent years, modern ceramics are utilized widely in various fields, such as medical, aerospace, marine, nuclear power plant, chemical industry and automobile etc. They are generally used to produce clay, stone elements, powders, water and preferred forms. It will be sintered at high temperature when the modern ceramics have been shaped, and the shrinkage phenomenon will occur. Therefore, machining of sintered ceramics is necessary to obtain the final parts with shape and accuracy requirement. However, the hardness and brittleness nature of modern ceramic materials make machining difficult. In machining, surface quality (i.e., surface roughness (R_a)) is one of the most important qualities for machined components that customers require. Hence, grinding process is used widely for machining surface finishing in modern ceramic industry. The performance of machining is measured in terms of R_a and grinding wheel wear (W_w). The R_a and W_w values are influenced by various process parameters, such as depth of cut, feed and grain size. Recently, a number of researches have been focused on the tool wear mechanism and material surface roughness of advanced ceramic materials.

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Xhou and Xi[1] proposed a new model for R_a prediction in ceramic during grinding by calculating random distribution of the grain protrusion heights through Gaussian distribution model. Agarwal and Rao[2] developed an analytical model for R_a prediction of ground ceramics based on analysis of the grooves left by the grains that intersect with the work-piece. Therefore,

The described experimental design was used to develop a R_a prediction model for a turning operation. A single cutting parameter and vibration subsequently to three axes were used to construct a multiple regression model for an in-process R_a prediction system. A physically effective linear correlation amid the parameters (feed rate and vibration measured in three axes) and the response like R_a were found using multiple regressions and ANOVA analysis by Daniel Kirby *et al*.[3] Gopalsamy *et al*.[4] reported that Taguchi method was applied to find optimum process parameters for end milling during hard machining of hardened steel. AL18 array, signal-to-noise ratio and ANOVA had been implemented to apprehend the performance characteristics of machining parameters (cutting speed, feed, depth of cut and width of cut) by considering surface finish and tool life. However, Hsu *et al.*[5] suggested that Taguchi approach was a powerful design tool for expert systems. The research group also investigated the wire saw machining aluminum oxide (Al_2O_3) material by using ultrasonic vibration. In addition, material removal rate, wafer surface roughness, steel wire wear, kerf width and flatness during machining were identified as quality character factors to optimize the machining parameters for better machining characteristics by using Taguchi method. Bakharev *et al.*[6]established a generalized algorithm based on systematic analysis for estimating the efficiency of diamond machined ceramic materials.

Liao[7] studied that the acoustic emission signals were first collected during grinding process to develop autoregressive modeling or discrete wavelet decomposition for feature extraction. The best subsets were found by three different feature selection methods, including two proposed ant colony optimization based method and the famous sequential forward floating selection method. Ji *et al.*[8] investigated machining of silicon carbide (SiC) ceramic material through the combined process of electrical discharge milling and mechanical grinding process. This process effectively machined a large surface area on SiC material with high quality surface finish. The effects of peak current, peak voltage, pulse on-time and pulse off-time on the material removal rate, electrode wear ratio and R_a were studied through Taguchi experimental design. Kumar *et al.*[9] adopted Taugchi's method to lessen the surface roughness and to achieve the maximum material removal rate while machining unidirectional glass fiber reinforced plastics composite with a polycrystalline diamond tool.

Singh *et al.*[10] had developed empirical models and proposed an optimum R_a by using CNC lathe for 316L stainless steel pipe. This approach was based on multiple regression analysis and artificial neural networks method. Kulekc *et al.*[11]focused on multiple regression models to predict the R_a of dievar hot-work tool steel during the wire-EDM process. Kromanis and Krizbergs[12] explored the new quality standards for manufactured components. According to the technologicalparameters a technique was developed by the manufacturer to facilitate the control of R_a in production and provides possibility to control the R_a. Feng *et al.*[13] examined the numerical modeling of surface generation by using joined trajectory and finite element analysis in micro-grinding of ceramic materials. Das *et al.*[14]analyzed the effect of cutting parameters (cutting speed, depth of cut and feed) in dry turning of AlSl D2 steel to achieve minimum tool wear and low work-piece surface temperature. The experimental ideas were designed to identify the effect of cutting parameters on the response variables based on the performance of Taugchi's L9 orthogonal array technique and ANOVA. In addition, few resplendent works had been carried out by the author on grinding operation using acoustic emission (AE) testing technique. Kanakarajan *et al.*[15] investigated the machining of WR 90% alumina ceramics through applied two specific grinding wheels preferred of Al_2O_3 and SiC under varying depth of cut. The AE parameters were observed to be higher and comparisons of softer material (Al_2O_3) less wear have been showed in harder grinding wheel (SiC) material. The development in amplitude and energy of each grinding wheels were obtained with increase in depth of cut, wheel wear and R_a of work-piece material. As a result, good machining quality during grinding operation was achieved using SiC wheel.

This research work mainly focuses on optimizing the process parameters of modern ceramic material (Al_2O_3) when machining with SiC grinding wheels. Hence, an attempt is made to develop an analytical model for the prediction of R_a and $W_w$over a wide range of operating conditions is achieved during the grinding of Al_2O_3 with SiC grinding wheels. The developed model is experimentally validated and finally R_a and W_w is optimized by considering machining parameters like depth of cut, feed and grain size.

Experimental Procedure

The experimental studies were performed on a RAMANA horizontal surface grinding machine, as shown in Fig. 1. The modern ceramic $Al_2O_3$with the dimension of 150 mm × 150 mm × 20 mm was used as a preferred work material for experimental tests. The standard basic parameters of material and the specification of grinding wheels are given in Tables 1 and 2. The various machining parameters for different levels were given in Table 3. Three dominant factorial (depth of cut, feed and grain size) were considered for Al_2O_3 ceramic material during grinding with SiC grinding wheels. The experiments were repeated for several times (approx. nine times) whereas, their corresponding R_a, grinding W_w were measured using surfcorder and digital vernier height gauge. The experimental results of R_a and W_w values are given in Table 4.

Results and Discussion

Experimental validation of the model

First order regression model were constructed to study the variation of R_a and W_w with various grinding parameters (depth of cut, feed and grain size). The multiple linear regression equation for these experiments can be written as:

$$R_a = \beta_0 + \beta_1 D + \beta_2 F + \beta_3 G \quad \dots (1)$$

$$Ww = \beta_0 + \beta_1 D + \beta_2 F + \beta_3 G \quad \dots (2)$$

Where, R_a is surface roughness (µm), W_w is wheel wear (mm), D is depth of cut (mm), F is feed (m/min), G is grain size (µm) and β_0, β_1, β_2 and β_3 are regression coefficients.

The regression coefficients were obtained by inputting the experimental data in MINITAB 16 software package. The multiple linear regression equation with regression coefficients for R_a and grinding $W_w$obtained in real factor forms can be written as:

$$R_a = 0.20633 + 11.167D + 0.039274F - 0.002049G \quad \dots (3)$$

$$W_w = -0.07940 + 2.9000D + 0.016568F + 0.000547G \quad \dots (4)$$

Table 5 shows the comparison between measured and predicted results of R_a and W_w. It is clearly evident that the R_a and W_w values predicted using first order regressive model are very close to the experimental values. The average errors are 0.26% and 0.54% respectively which are less than the reported values when compared with published research work and hence the model was used for further analysis.

The increase of depth of cut and feed rate during the process shows the enhancement of R_a and W_w values, as shown in Figs 2 and 3. In addition, the increase of grain size shows the improvement of W_w and reduction of R_a values. The higher depth of cut (0.025 mm) depicts the maximum R_a and W_w are 0.93 µm and 0.264 mm respectively when the depth of cut is 0.025 mm. Concurrently, the minimum R_a and W_w are 0.32 µm and 0.035 mm respectively when the depth of cut is 0.005 mm. However, the analytical model obtained through a full factorial multiple regression analysis fits well the experimental results, and they show reasonable correlations with minimum errors.

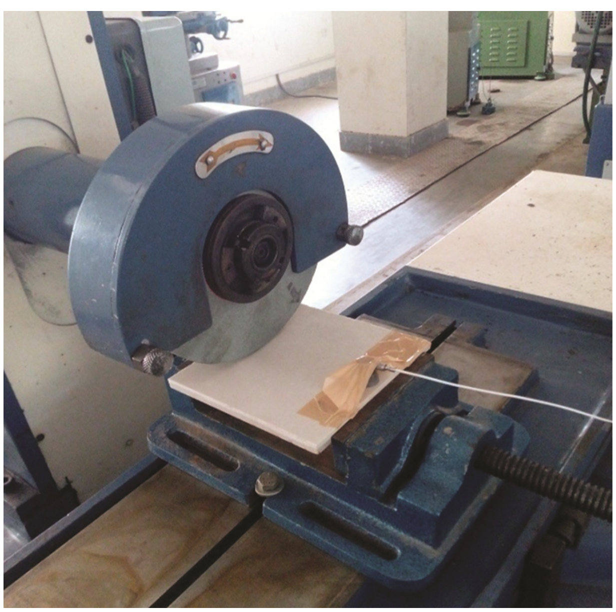

Fig. 1 — Experimental setup of horizontal surface grinding machine

Table 2 — Specification of grinding wheels

S. No.	Size of the wheel (mm)	Grinding wheel designation
1.		GC 54 JV
2.	150 × 19 × 31.75	GC 60 JV
3.		GC 100 JV

Table 3 — Values of test variables

Symbols	Machining parameters	Levels		
		1	2	3
D	Depth of cut (mm)	0.005	0.015	0.025
F	Feed (m/min)	4.3	9.4	14.4
G	Grain size (µm)	54	60	100

Table 1 — Basic parameters of material

Material designation	Color	Mechanical properties			
		Density (g/cm^3)	Compressive strength @ 25 °C (MPa)	Hardness R45N	Tensile strength @ 25°C (MPa)
90% Al_2O_3	White	3.60	2482	75	221

Table 4 — Experimental results based on process parameters

S. No.	Depth of cut [D] (mm)	Feed [F] (m/min)	Grain Size [G] (μm)	Surface roughness [R_a] (μm)	Wheel wear [W_w] (mm)
1.	0.005	4.3	54	0.3200	0.0350
2.	0.005	9.4	60	0.5100	0.1240
3.	0.005	14.4	100	0.6200	0.2280
4.	0.015	4.3	60	0.4200	0.0690
5.	0.015	9.4	100	0.5400	0.1750
6.	0.015	14.4	54	0.8300	0.2330
7.	0.025	4.3	100	0.4500	0.1190
8.	0.025	9.4	54	0.7400	0.1780
9.	0.025	14.4	60	0.9300	0.2640

Table 5 — Comparison between measured and predicted results of R_a and W_w

No. of Exp.	Measured R_a(μm)	Predicted R_a(μm)	% of Error	Measured W_w (mm)	Predicted W_w (mm)	% of Error
1.	0.3200	0.3204	-0.1250	0.0350	0.0358	-2.2857
2.	0.5100	0.5084	0.3137	0.1240	0.1236	0.3226
3.	0.6200	0.6228	-0.4516	0.2280	0.2283	-0.1316
4.	0.4200	0.4198	0.0476	0.0690	0.0682	1.1594
5.	0.5400	0.5381	0.3519	0.1750	0.1745	0.2857
6.	0.8300	0.8287	0.1566	0.2330	0.2322	0.3433
7.	0.4500	0.4495	0.1111	0.1190	0.1190	0.0000
8.	0.7400	0.7440	-0.5405	0.1780	0.1783	-0.1685
9.	0.9300	0.9281	0.2043	0.2640	0.2644	-0.1515
	Average Error:		0.26%	Average Error:		0.54%

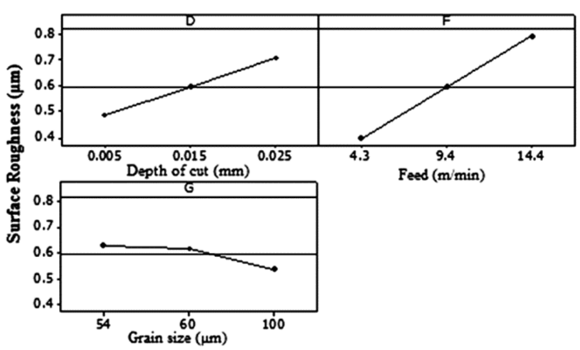

Fig. 2 — Effect of input parameters on surface roughness

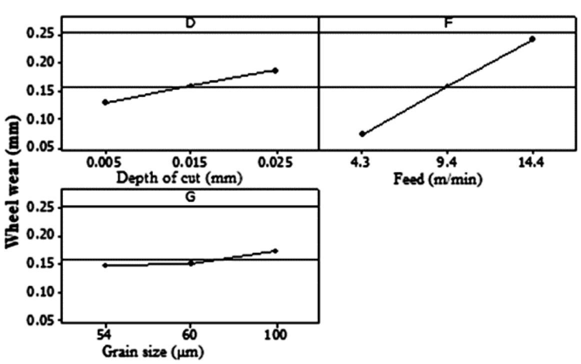

Fig. 3 — Effect of input parameters on wheel wear

Conclusions

Based on the experimental and analytical results, we concluded that a full factorial regression analysis is a powerful tool for predicting the response variables using a small number of experiments. The proposed analytical model predicts the R_a and W_w values with an average error of 0.26% and 0.54%. The analytical results showed minimum R_a (0.3204 μm) and W_w (0.0358 mm) values were obtained when the smaller values of feed (4.3 m/min), depth of cut (0.005 mm) and grain size (54 μm) were designed. Concurrently, the maximum R_a (0.9281 μm) and W_w (0.2644 mm) values were obtained when the higher values of feed (14.4 m / min), depth of cut (0.025 mm) and grain size (60 μm) were designed during the process.

References

1 Zhou X & Xi F, *Int J Mach Tools Manuf*, 42 (2002) 969-977.
2 Agarwal S & Rao P V, *Int J Mach Tools Manuf*, 50 (2010) 1065-1076.
3 Daniel Kirby E, Zhe Zhang & Joseph C. Chen, *J Ind Technol*, 20(4) (2004).
4 Gopalsamy Bala Murugan, Mondal Biswanath & Ghosh Sukamal, *J Sci Ind Res*, 68 (2009) 686-695.

5 Hsu C Y, Chen C S & Tsao C C, *Int J Adv Manuf Technol*, 40 (2009) 503-511.
6 Bakharev V P, Yu M Kulikov, Nechaev D A & Yakovchik E V,*Russ Eng Res*, 28 (2008) 1183-1187.
7 Warren Liao T, *Eng Appl Artif Intell*, 23 (2010) 74-84.
8 Ji Renjie, Liu Yonghong, Zhang Yanzhen, Cai Baoping, Li Hang & Ma Jianmin, *Int J Adv Manuf Technol*, 16 (2010) 1061-1072.
9 Kumar Surinder, Gupta Meenu, Satsangi P S & Sardana H K, *Int J Eng Sci Technol*, 3 (2012) 248-270
10 Singh Rajendra, Gupta Rahul Kumar & Tripathi Jitendra Kumar, *Int J Eng Sci*, 3 (2014) 58-71.
11 Kulekci Mustafa Kemal, Akkurt Adnan, Esme Ugur & Ozkul Iskender, *Mater Technol*, 48 (2014) 9-14.
12 Kromanis Artis & Krizbergs Juris, *Transport Eng Prod Technol*, 35 (2013) 130-137.
13 Feng Jie, Chen Peng & Ni Jun, *Finite Elem Anal Des*, 57 (2012) 67-80.
14 Das S R, Nayak R P & Dbupal D, Int J Eng Res & Technol, 1 (2012) 1-10.
15 Kanakarajan Periyasamy, Sundaram Sengottuvelu, Kumaravel Arumugam, Rajasekar Rathanasamy & Sathish Kumar Palaniappan, *Mater Test*, 57 (2015) 337-342.