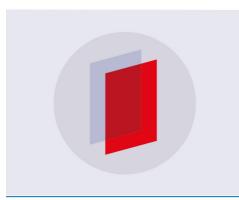
PAPER • OPEN ACCESS

Predictive modelling and analysis of surface roughness in CNC milling of green alumina using response surface method and genetic algorithm

To cite this article: Raja Das et al 2018 IOP Conf. Ser.: Mater. Sci. Eng. 410 012022

View the article online for updates and enhancements.



IOP ebooks[™]

Bringing you innovative digital publishing with leading voices to create your essential collection of books in STEM research.

Start exploring the collection - download the first chapter of every title for free.

Predictive modelling and analysis of surface roughness in CNC milling of green alumina using response surface method and genetic algorithm

Raja Das¹, Sushree Swati Mohanty², Muktikanta Panigrahi³, Saralasrita Mohanty^{4,5}

² School of Advanced Sciences, VIT University, Vellore, TN-632014, India ² Schools of Life Science, Ravenshaw University, Cuttack-753003 ³ Metallurgical Engineering Department, Gandhi Institute of Engineering and Technology (GIET), Gunupur, Rayagada, Odisha, PIN-765022, India

School of Physical Sciences, National Institute of Science Education and Research, HBNI, Jatni - 752050, India

ABSTRACT

Modelling and optimization of machining parameters are essential in Computer Numerical Control (CNC) milling process. The objective of current study is to develop a functional relationship between various factors and responses of CNC machined alumina green ceramic compact. As, ceramic material is notch sensitive in nature, the measurement of average surface roughness (Ra) is vital as it influences the quality and performance of the finished product. In this context, optimization of surface roughness is of maximum importance in manufacturing sectors. To accomplish the required optimal levels of surface quality, the proper selection of machining parameters in CNC milling is highly needed. In this study, four significant machining parameters including spindle speed, XY speed, Z speed and depth of cut in CNC milling process have been selected and along with various combination experiments were conducted. A mathematical regression model was developed to predict the average surface roughness in CNC milling machined surface of alumina based green ceramic compact. The developed model was validated with the new experimental data. Further, the model was coupled with Genetic Algorithm (GA) technique, to predict the optimum possible surface roughness. The results demonstrate the potential to improve the efficacy of production and quality of the finished product as well.

Keywords: CNC Milling, Surface Roughness, Response Surface Method, Genetic Algorithm

Corresponding author -e-mail: saralasrita@niser.ac.in

1. INTRODUCTION

Advanced ceramics is increasingly popular in several engineering applications ranging from automotive and electronics to aerospace fields due to their superior properties including high corrosion resistance, wear resistance, chemical stability, compressive strength and stiffness at high-temperature [1, 2, 3]. Different new technologies such as Computer Numerical Control (CNC) machine tool, lithography, ultrasonic, beam etching and laser machining are adapted for mould-free fabrication of advanced ceramics for various applications [4, 5, 6, 7]. However, sintered state ceramic machining create barrier for economically and efficiently productions due to its brittle and high hardness value and thus imposing high machining of ceramics is considered as a potential alternative for manufacturing of high quality products due to high material removal rates, consumption of lower energy and lesser tool wear [9, 10, 11]. CNC machining of green ceramics is one of the machining methods for fabrication of miniaturized components using diamond embedded pointed tool [12, 13].

Apart from material speciation and dimensions tolerance, the quality of the machined ceramic surface is greatly influences the performance, longevity, reliability, surface texture and manufacturing cost of the finished ceramic part either directly or indirectly. The finer irregularities of the machined surface texture leads to affect other functional features of the final product such as work piece rejection, friction, fracture etc. In CNC machining of green ceramics operations, several factors such as uncontrollable factors (cutting tools material properties and geometry) and controllable factors (cutting speed, depth of cut, spindle speed and feed rate) significantly influence the final surface finish of the ceramic part [14]. Generally, different machining parameters are chosen based upon the prior experience of the person who performed the cutting operation followed by optimization of the process parameters for obtaining better surface finish.

However, this conventional trial and error method is not only a tedious task but also time consuming and ultimately provide high cost. To avoid time and money consuming experiments, different statistical techniques are employed to evaluate the surface finish parameters and optimizing the controllable factors in order to obtain desired level of surface roughness of the final ceramic components. Among different surface finish parameters, average surface roughness (Ra) is widely used as surface parameters in industry. Several studies have been performed in the past few years in order to predict the surface roughness value using statistical tool [15, 16, 17]. Previously, Suresh et al. developed a mathematical model for surface roughness (Ra) prediction through response surface method (RSM) while machining mild steel using carbide-coated tool [18]. In this study, a genetic algorithm (GA) was used and results were compared with RSM to validate the objective function. Further, in order to obtain maximum material removal rate at minimum surface roughness and cutting forces, Prajina implemented RSM in CNC end milling operation [19].

Routara et al. predicted surface quality through optimizing the different machining parameters including depth of cut, spindle speed and cutting speed of CNC end milling by using Taguchi method [20]. Oktem et al. combined RSM along with GA and neural network to analyze the optimum cutting conditions for obtaining minimum average roughness in aluminium and plastic mold parts using CNC milling machine [21].

However, from the literature survey it can be realized that no one reported the result for prediction the surface roughness of machinable green alumina through CNC milling using diamond embedded tool [12]. The main objective in this work is to investigate the best combination of machining parameters of CNC milling of green alumina compacts using diamond-embedded tool to achieve desired level of surface roughness. In this context, RSM has been employed as a mathematical model using different combinations of cutting parameters from the experimental data (Table 1) and developed model is tested with the experimental data for reliable predictions of surface roughness and optimize machining performances.

Та	Fable 1. Experimental Values					
	Levels					
Variables	1	2	3	4		
XY speed(mm/s)	4	6	8	10		
Z speed(mm/s)	1	3	5	7		
Spindle						
speed(rpm)	8000	10000	11000	12000		
Depth of cut(mm)	0.1	0.3	0.5	0.7		

2. METHODOLOGY

2.1. FABRICATION OF GREEN ALUMINA COMPACTS

The process for fabrication of green alumina compacts with reasonable strength has been reported by Mohanty et al [22]. In brief, the aqueous slurry consists of highly loaded alumina powder (RG 4000, Almatis (Germany), alongwith polymaleic acid (PMA, Aquapharm, India) used as dispersant. The volumetric % of aqueous alumina slurry was 55% in which PMA of 3.8 mg per gram of alumina powder (optimized) was used. Further, in the mixture, sucrose and ovalbumin were used as binders and the binder amount was optimized by rheological studies. Finally, according to the optimized data, 10 volume % ovalbumin, 3 wt% sucrose were added to the aqueous solution. Zirconia balls (3mm diameter, Jyoti Ceramics, India) which functions as milling media were added to prepare the constituents of 55% volume alumina loaded slurry. The homogenous slurry with good owability was produced after 24hrs of ball milling. And through sieving, the milling media has been removed from slurry. After this process, an anti-foaming agent 1-octanol (1ml/100ml of slurry, Merck, India) was added to the slurry. The function of anti-foaming agent is to remove the air bubbles. Distinctive rectangular silicon elastic molds were utilized for slurry casting. The slurry dried at 40C to avoid warpage connected with drying under controlled humid conditions. From the mold, the dried alumina were removed and the rectangular green alumina compacts was ready for CNC machining.

2.2. MACHINING OPERATION

For CNC machining of green alumina rectangular compacts, a bench-top CNC milling machine (MDX 540, Roland DG Ltd., Japan) was used. Further, a conically pointed end diamond embedded tool with mesh size of 625 was used to assess surface roughness of the green alumina compacts. Before machining operation, the CNC machine table is mounted with vacuum dried green alumina. The green alumina samples were machined by CNC milling machine using diamond embedded tools. Preceding machining "stl" configuration of 3D pictures of rectangular block was prepared using solidworks to machine alumina compacts through CNC machining. The conically pointed end diamond embedded tool was mounted at the tool post of the CNC machine. The green alumina compact was machined by raster pattern on the top surface of the green alumina compacts using different machining parameters [12, 23].

2.3. MEASUREMENT OF SURFACE ROUGHNESS

The surface roughness of the machined green alumina compacts was measured using surface profilometry (Talysurf i60/i120/i200-Inductive Systems, Taylor Hobson Limited, Leicester, England). The mean Arithmetic roughness (Ra) was measured by surface profilometer at 1 mm interval of each sample along and perpendicular direction of machining using contact type stylus profilometer with a 1mm tip radius.

3. REGRESSION MODEL DEVELOPMENT USING RESPONSE SURFACE METHOD (RSM)

In the recent paradigm, RSM method is very often employed to establish the relationship between different input parameters with output one. The rationale of the present work is to predict the average surface roughness (Ra) of CNC milled green alumina compacts by making a relationship between the different input process parameters of CNC milling with the output surface finish through RSM. In this aspect, a second order polynomial response surface mathematical model was undertaken as shown in the Equation (1) to study the influence of input machining parameters of CNC milling of green alumina compact on its surface finish.

$$Ra = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_1^2 + a_6x_2^2 + a_7x_3^2 + a_8x_4^2 + a_9x_1x_2 + a_{10}x_1x_3 + a_{11}x_1x_4 + a_{12}x_2x_3 + a_{13}x_2x_4 + a_{14}x_3x_4$$
(1)

where,

 $x_1 = XY$ speed(mm/s), $x_2 = Z$ speed(mm/s), $x_3 = Spindle$ speed(rpm) and $x_4 = Depth$ of cut(mm).

The coefficient a_0 is the constant term; the coefficients a_1,a_2 , a_3 and a_4 are the linear terms; the coefficients a_5,a_6 , a_7 and a_8 are the quadratic terms; the coefficients $a_9,a_{10},a_{11},a_{12},a_{13}$ and a_{14} are the interaction terms. The coefficients of regression model were estimated from the experimental results and the model is developed.

4. GENETIC ALGORITHM (GA)

Genetic algorithm was employed to acquire the optimum machining parameters for output surface roughness by using the numerous combinations of the input parameters. In the present study MATLAB code was used to perform the computational algorithm. The simplest Genetic algorithms (GAs) consist of different operators including reproduction, crossover, and mutation. The reproduction is characterized by copying the best individuals from one generation to the next. In this context, the best solution is monotonically improving from one generation to the next. For the crossover operator, the chosen parents are submitted for generating one or two children. The crossover is performed with an allotted probability, which is usually rather high. It is noteworthy that the crossover is carried out when a number, sampled at random, is inferior to the probability. The genetic mutation establishes diversity in the population through an occasional random replacement of the individuals. Using an assigned probability, the mutation is carried out. A random number is employed to determine if a new individual will be produced to substitute the one generated by crossover. The mutation procedure involves substituting one of the decision variable values of an individual, without affecting the remaining variables. The changed variable is randomly chosen, and its new value is taken by randomly sampling within its specific range. The regular genetic algorithm is stated as given below.

BEGIN

INITIALIZE population with a random candidate solution EVALUATE each candidate;

REPEAT UNTIL (terminate conditions) is satisfied DO

- 1. **SELECT** parents;
- 2. **RECOMBINE** pairs of parents;
- 3. **MUTATE** the resulting o spring;
- 4. SELECT individuals or the next generation;

END

5. OPTIMIZATION OF CNC MILLING PARAMETERS

In view of the above, GA was employed as an optimization technique to address a boundconstrained optimization problem. The regression model developed by response surface methodology was employed as an objective function and the upper and lower bound parameters are identified by conducting experiments. The problem can be formulated as given below.

Minimize

$$Ra = f(x_1, x_2, x_3, x_4)$$

Where,

$$1 \le x_1 \le 4$$

 $4 \le x_2 \le 10$
 $8000 \le x_3 \le 1200$
 $0.1 \le x_4 \le 0.7$

6. RESULTS AND DISCUSSION

RSM was developed by using the average surface roughness (Ra) of green alumina compacts obtained from the experimental results. For Ra in perpendicular and parallel tool movement path directions, ANOVA was used to confirm the value of the regression model and model coefficients. Moreover, it was employed for analyzing the null hypothesis of the experimental data with a confidence level of 95%. It is to be noted that if the p-value 0.05 for the F -statistic, H_0 is true and treatments have statistically no effect. However, If the p-value 0.05, it is to be concluded that H is true and the treatments have a statistically significant effect. The average surface roughness value (Ra) that acquired from the experimental data was compared with the predicted value obtained from the model. Table 2 and Table 4 are ANOVA outline tables of the terms in the model, to decide whether to eliminate or fail null hypothesis for average surface roughness in the perpendicular and parallel tool motion directions, respectively. Further, to design the regression model, the

Minitab software was employed.

It was observed that p-value of six terms are less than 0.05 for both the directions, hence they are significant in the regression models. Table 3 and Table 5 demonstrates the ANOVA analysis of the models, and the column illustrating the degrees of freedom (DF), the sequential sums of squares (Seq:SS), the adjusted sums of squares (AdjSS), the adjusted mean squares (AdjMS), the F -statistics from the adjusted mean squares, and its p-value. The sequential sum of squares is the added sums of squares given that prior terms are in the model, which depends on the model order.

Term	Coeff.	SE Coeff.	Т	Р
constant	0.544944	0.02675	20.375	0
\mathbf{x}_1	0.063875	0.02057	3.105	0.005
x ₂	0.016525	0.02057	0.803	0.43
X ₃	0.199292	0.01534	12.996	0
X ₄	-0.01275	0.02057	-0.62	0.541
x_1^2	0.072131	0.0308	2.342	0.028
x_{3}^{2}	-0.015208	0.02656	-0.573	0.572
x_1x_2	-0.049802	0.02155	-2.31	0.03
x_1x_3	0.025838	0.0252	1.025	0.315
x_1x_4	-0.080341	0.02155	-3.727	0.001
x_2x_3	0.00465	0.0252	0.185	0.855
x ₃ x ₄	-0.030488	0.0252	-1.21	0.238

Table 2. ANOVA summary of surface roughness in perpendicular direction

The adjusted sums of squares are the sums of squares given that all other terms are in the model that does not depend upon the model order. It can be observed in this table, the p-value of regression model is less than 0.05, hence, the Ra fitting the regression model with the linear, and square terms are significant at the level of 95%. The terms x_{2}^{2} , x_{4}^{2} , and $x_{2}x_{4}$ are not included in the 0.05 for both the perpendicular and parallel directions. This way the simplified truncated models is shown in the following equations (2) and (3).

Table	3. Varia	ance analysis	s of surface	roughness ir	n perpendi	icular direction
Source	DF	Seq. SS	Adj. SS	Adj. MS	F	Р
Regression	11	1.1541	1.1541	0.104918	18.59	0
Linear	4	1.04955	1.04955	0.262387	46.49	0
Square	2	0.00773	0.03281	0.016404	2.91	0.074
Interaction	5	0.09682	0.09682	0.019365	3.43	0.018
Residual error	24	0.13546	0.13546	0.005644		
Total	35	1.28956				

7

(2)

IOP Conf. Series: Materials Science and Engineering **410** (2018) 012022 doi:10.1088/1757-899X/410/1/012022

Term	Coeff.	SE Coeff.	T	Р
constant	0.210528	0.014601	14.418	0
\mathbf{X}_1	0.01715	0.011233	1.527	0.14
X2	0.03695	0.011233	3.29	0.003
X ₃	0.082792	0.008372	9.889	0
\mathbf{X}_4	0.0143	0.011233	1.273	0.215
x_1^2	0.020579	0.016815	1.224	0.233
x_{3}^{2}	0.046958	0.014501	3.238	0.004
x_1x_2	-0.007152	0.011768	-0.608	0.549
x_1x_3	-0.024825	0.013757	-1.805	0.084
x_1x_4	-0.024585	0.011768	-2.089	0.047
X ₂ X ₃	0.035625	0.013757	2.59	0.016
x_3x_4	0.011025	0.013757	0.801	0.431

Table 4. ANOVA summary of surface roughness in parallel direction

Table 5. Variance analysis of surface roughness in parallel direction

Source	DF	Seq. SS	Adj SS	Adj. MS	F	Р
Regression	11	0.245556	0.245556	0.022323	13.27	0
Linear	4	0.206459	0.206459	0.051615	30.68	0
Square	2	0.018352	0.020161	0.01008	5.99	0.008
Interaction	5	0.020745	0.020745	0.004149	2.47	0.061
Residual error	24	0.040374	0.040374	0.001682		
Total	35	0.285931				

 $Ra = 0.544944 \qquad 0.063875x_1 + 0.199292x_3$

 $+ 0:072131x_{1}^{2} \quad 0:049802x_{1}x_{2} \quad 0:080341x_{1}x_{4}$

 $Ra = 0:210528 + 0:03695x_2 + 0:082792x_3 + 0:0:0469589x_3^2 - 0:024585x_1x_4 - 0:035625x_2x_3$ (3)

Using MATLAB environment, the GA optimization is carried out. By varying GA parameters, the different optimized process parameters were obtained and the resulted parameters further used for optimization in the following manner:

Population type: Double vector; Population size: 100; Number of generations: 200; Number of stall generation: 50; Fitness function: Rank scaling; Selection function: Roulette wheel, Crossover function: Two point; Crossover fraction: 0.8; Mutation function: adaptive feasible; Migration: Forward, Migration fraction: 0.2.

The condition of optimal material removal, offering least surface roughness is shown in Table.4. An experiment was performed based upon the optimal parameter settings for surface roughness to achieve the targeted surface finish. Table.4 demonstrated the average surface roughness (Ra) by regression model and the experimental Ra with the setting of optimal parametric setting as acquired from the GA. The result revealed, a reliable prediction with reasonable accuracy as the percentage error of the predicted average surface roughness value is in close correlation with the experimentally observed value.

Response	XY speed (mm/s)	Z speed (mm/s)	Spindle speed (rpm)	Depth of cut (mm)	Predicted Value	Exp. Value	% error
Ra in perpen- dicular direc- tion	4	7	8000	0.1	0.2048	0.314	34.777
Ra in parallel direction	4	7	8000	0.1	0.1339	0.138	2.971

7. CONCLUSIONS

In the present study, the roughness (experimental results) obtained from the extensive machining conducted on the surface of green alumina compact with diverse input parameters of CNC machine using diamond embedded tool are compared and validated with the predictions. A hybrid GA based RSM approach was successfully projected to obtain optimum CNC machining parameters for the prediction of optimum surface roughness of CNC machined green alumina surface in both the directions of tool movements (along and perpendicular direction of tool path movement). Initially, the RSM model was employed to build up the mapping between input process parameters of CNC milling machine and surface roughness. Further, the developed regression models were combined with the projected GA to acquire optimum material removal parameters that leading to the minimum surface roughness value. It was observed that prediction accuracy of hybrid GA based RSM were fairly close correlation with the experimental values with maximum percentage absolute error of 34.777 and 2.971, in perpendicular and parallel direction of tool movement, respectively. Thus, the obtained hybrid model can be an ideal approach to level the input parameters of CNC Milling of ceramic compacts with reasonable accuracy for prediction of surface finish, and hence a significant saving of cost and time.

ACKNOWLEDGEMENTS

The author acknowledges BMTE Lab, School of Medical Science and Technology, IIT Kharagpur-721302 for assistance with the development, CNC machining and characterization of ceramic compacts.

REFERENCES

- [1] L.M. Sheppard, 1991, Ceramic Bulletin, Vol. 70, pp. 692.
- [2] R.W. Rice, 1990, Advances in Chemical Engineering Journal, Vol. 36, pp. 481.
- [3] M. Savitz, 1999, American Ceramic Society Bulletin, Vol. 78, pp. 53.
- [4] J. Yang, J. Yu, Y. Cui, and Y. Huang, 2012, Ceramics International, Vol. 38, pp. 3643.
- [5] P. Dadhish, P.K. Srivas, S. Mohanty, S. Dhara, 2015, Journal of European Ceramic Society, Vol.35, pp. 3909.
- [6] S. Baskaran, G.D. Maupin, G.L. Gordon, 1998, American Ceramic Society Bulletin, Vol. 77 pp 53
- [7] J.D. Cawley, 1999, Current Opinion in Solid State and Materials Science, Vol. 4, pp. 483.
- [8] G.P Birkby, P Dranseld, J.H McColgan, J.R.G. Evans, 1994, British Ceramic Transection, Vol. 93, pp. 183.
- [9] S. Dhara and B. Su, 2005, International Journal of Applied Ceramic Technology, Vol. 2, pp. 262.
- [10] B. Su, S. Dhara, and L. Wang, 2008, Journal of the European Ceramic Society, Vol. 28, pp. 2109.
- [11] R.K. Kamboj, S. Dhara, and P. Bhargava, 2003, Journal of the European Ceramic Society, Vol. 23, pp. 1005.
- [12] S. Mohanty, A.P. Rameshbabu, and S. Dhara, 2013, Ceramic International, Vol. 39, pp. 8985.
- [13] M.S, Lou. J.C Chen., C.M Li., 1998, Industrial Technology, Vol.15, pp. 1.
- [14] P.G. Bernados and G.C. Vosniakos, 2003, International Journal of Machine Tools and Manufacture, Vol. 43. No.8, pp. 833.
- [15] J.L, Yang. J.C, Chen, 2001, Industrial Technology, Vol. 17, pp. 1.

- [16] Pradhan, Das R, Biswas, 2009 International Journal on Design and Manufacturing Technologies, Vol. 2, pp. 20.
- [17] S. Zainal, K. Z. Nadzirah*, A. Noriham, I. Normah, 2013, Agricultural Sciences, Vol. 5B, pp. 65.
- [18] P. V. S. Suresh, P. V. Rao, and S. G. Deshmukh, 2002, International Journal of Machine Tools and Manufacture, Vol. 6, pp. 675.
- [19] N. V. Prajina, 2013, International Journal of Engineering Research and Technology, Vol. 6, pp. 739.
- [20] B. C. Routara, A. Bandyopadhyay, and P. Sahoo, 2009, International Journal of Advanced Manufacturing Technology, Vol. 11, pp. 1166.
- [21] H. Oktem, T. Erzurumlu F. Erzincanli, 2006, Materials Design, Vol. 9, pp. 735.
- [22] S Mohanty, B Das, S Dhara, 2013, Journal of Asian Ceramic Societies, Vol. 2, pp. 184.
- [23] S Mohanty, A Rameshbabu, S Mandal, B Su, S Dhara 2013, Journal of Asian Ceramic Societies, Vol. 1, pp. 274.