Intelligent Modeling of Surface Roughness during Diamond Grinding of Advanced Ceramics

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Abstract- Advanced structural ceramics such as Silicon Carbide and Silicon Nitride have high demand in technologically advanced industries due to their improved properties such as high strength at elevated temperature, resistance to chemical degradation, wear resistance and low density. Since these ceramics are used in various engineering applications, it is desired that the components made of ceramics must have good surface finish and low surface damage. Diamond grinding is the only conventional method to Achieve the above keeping in view of the material removal rate. This paper presents experimental study of diamond grinding of Sintered Silicon Carbide (SiSiC). In the paper two different approaches, multiple regression analysis (MRA) and artificial neural network (ANN) have been used to predict the surface roughness values. The results show that ANN model has better accuracy as compared with MRA model.

Nomenclature

d	Depth of cut (μm).
f	Feed (m/min).
g	Grit size
Ra	Surface roughness (μm).
ϕ	Constant in the MRA model
α	Depth of cut exponent in MRA model
ψ	Feed exponent in MRA model
γ	Grit size exponent in MRA model
w_{ij}	weight of the connection in ANN

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I. 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 high strength at elevated temperatures, can be machined to closer tolerance, more precise geometry, are more chemically stable than metal and they are more wear resistant.

Because of these special qualities advanced ceramics are used in wide varity of applications such as turbine blades, valves and valves seats, bearings for the normal engineering application, heat exchanger parts etc[1]. But the widespread utilization of high strength ceramic material has been limited by high cost of machining these materials.

The high degree of hardness of advanced ceramics make it difficult for the cutting tool to penetrate into the work piece, hence cutting tool deteriorate rapidly, moreover if we use large depth of cut so there will be sudden breaking of work piece in case of conventional tool so grinding with diamond abrasive, has been only the method for machining of ceramics. Another problem with grinding of ceramic is surface damage that may be in form of residual stress, micro cracking and poor surface quality [2]. One of the passing needs is to obtain information on how to optimize the grinding process for achieving good surface quality, minimum subsurface damage and maximum removal rate. Grinding of ceramic involves a large number of interdependent parameters such as depth of cut, feed, cutting speed, machine tool characteristics and wheel type [3]. The type of surface quality obtained greatly depends on these parameters. So the modeling of output parameters in grinding of ceramics is required to predict the surface quality, subsurface damage etc.

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II. DESIGN OF EXPERIMENTS & EXPERIMENTAL SET-UP

The mathematical modeling of surface roughness involves lots of factors but to facilitate the experimental data collection, only three dominant factors were considered in the planning of experiments. 3^k factorial design has been used to plan 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. Based on this setting, a total of 27 experiments, each having a combination of different levels of factors as shown in Table I, were carried out. The response measured was surface roughness. Experiments were performed on Hydraulic Surface grinding Machine, shown in fig 1. Special vice had been procured for holding of ceramic work piece. The work piece selected for the experimentation was Silicon carbide. The dimension of the work-piece was 100x40x25 mm. The properties of the selected silicon carbide are given in Table II. Total 9 numbers of work-pieces were taken. Before performing actual experiments, all the three sides of work-piece were flattened. For this purpose initially, nearly 800 mm^3 materials were removed by giving very low depth of cut like 1-2 μm. Diamond grinding wheels were selected for the present work. Three different girt sizes of wheels selected were 120,240 and 500. The specification of diamond grinding wheel is given in Table III.

A TAYLOR HOBSON TALYSURF at 0.8 mm cutoff value was applied to measure the average surface roughness (ASR) of each machined specimen.

III .MODELING

A. MRA Model

A model establishes a relation between input and output quantities in order to describe the dynamic as well as the static performance of each individual process. The simplified formulation of process condition is referred to as modeling [4].

Surface roughness model developed in this study is as follows:

$$R_a = \Phi d^{\alpha} f^{\Psi} g^{\gamma} \qquad (1)$$

Parameters Φ, α, Ψ and γ can be solved by using multiple regression analysis.

B. Artificial neural network model:

Neural network: It is information processing paradigm inspired by biological nervous systems like our brain. In neural network a large number of highly interconnected processing elements (neurons) are working together. Like people, they learn from experience. Neural networks are configured for a specific application, such as pattern recognition or data classification, through a learning process. In a biological system, learning involves adjustments to the synaptic connections between neurons, same for artificial neural networks (ANNs) [5]. In the network, each neuron receives total input from all of the neurons in the preceding layer as

$$net_j = \sum_{j=0}^{N} w_{ij} x_i \qquad (2)$$

where netj is the total or net input and N the number of inputs to the jth neuron in the hidden layer. wij the weight of the connection from the ith neuron in the forward layer to the jth neuron in the hidden layer and xi the input from the ith neuron in the preceding layer. A neuron in the network produces its output (outj) by processing the net input through an activation function f, such as sigmoid function chosen in this study as below:

$$out_j = f(net_j) = \frac{1}{1 - e^{net_j}} \qquad (3)$$

the ANN architecture used in this study is shown in fig 2 [6-8]

In calculation of connection weights, often known as network training, the weights are given quasi-random initial values. They are then iteratively updated until converges to the certain value using the gradient descent method. Gradient descent method updates weights so as to minimize

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the mean square error between the network output and the training data set.

IV. EXPERIMENTAL RESULT & ANALYSIS

The experimental results are shown in Table IV. The variations of machining response with the input parameters are shown graphically in fig 3. It is clear that the It is clear that the surface finish improves through the smaller depth of cut, lower feed and high grit number (or lower grit size). With the increase in depth of cut and feed, the normal and tangential force increases so surface roughness increases while with increase in grit size, the fineness of abrasive increases which results in the improvement of surface finish. The result obtained is accordance with the literature [9].

A. Surface roughness model:

In this work, a commercially available software package MATLAB was used for the computation of regression parameters [10].

After doing the regression analysis, the values of constant Φ and exponents' α, β and γ are as follows,

$\Phi = 0.242$, $\alpha = 0.2133$, $\Psi = 0.415$ and $\gamma = -0.2123$, so

Surface roughness model,

$Ra = .242d^{0.2133}f^{0.415}g^{-0.2123}$

The results predicted from the MRA model are compared with the experimental results in the table V

B. ANN model :

The results predicted from the ANN model are compared with the experimental result in table VI. It is seen from table VI that ANN prediction presents a good agreement with the experimental measurements.

V CONCLUSION

The effects of process parameters like depth of cut, feed and grit size on the surface finish have been studied. The result presented in this work shows that surface roughness can be estimated under the knowledge of machining condition.

In this study, MRA model and ANN model were developed by using surface roughness data. By comparing Ra values predicted from MRA model with those predicted from ANN (Table VII), it is found that the maximum test errors were 14.28% and 3.77 %. From this, it can be inferred that ANN model give better prediction than MRA model and the models created for surface roughness can be applied for predicting manufacturing problems such as surface roughness.

Table I values of Test Variables

Designation	Description	Low (-)	Medium (0)	High (+)
d	Depth of cut (µm)	5.0	15	30
f	Feed (m/min)	8.6	10.9	13.4
g	Grit Size	120	240	500

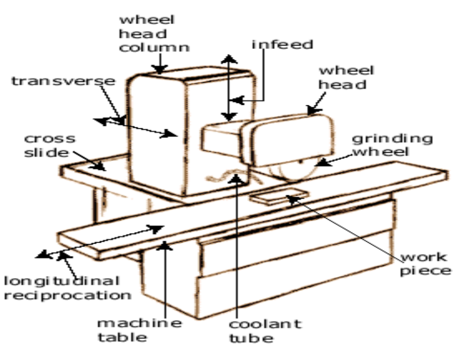

Fig 1 Experimental Set up

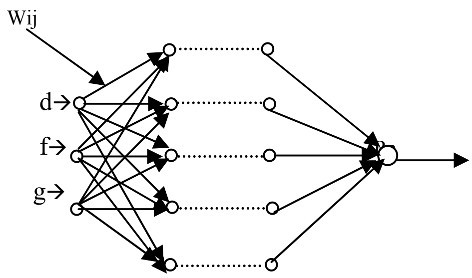

Fig 2 ANN Architecture

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Table II Mechanical properties of Silicon carbide

Material	Specific Density	Fracture toughness K^{lc} [$Mpam^{1/2}$]	Thermal conductivity [$Wm^{-1}K^{-1}$]	Thermal expansion coefficient $10^{-6}K^{-1}$	Hardness HV1 [GPa]
Sic	5.8	8	60-150	8-10	10

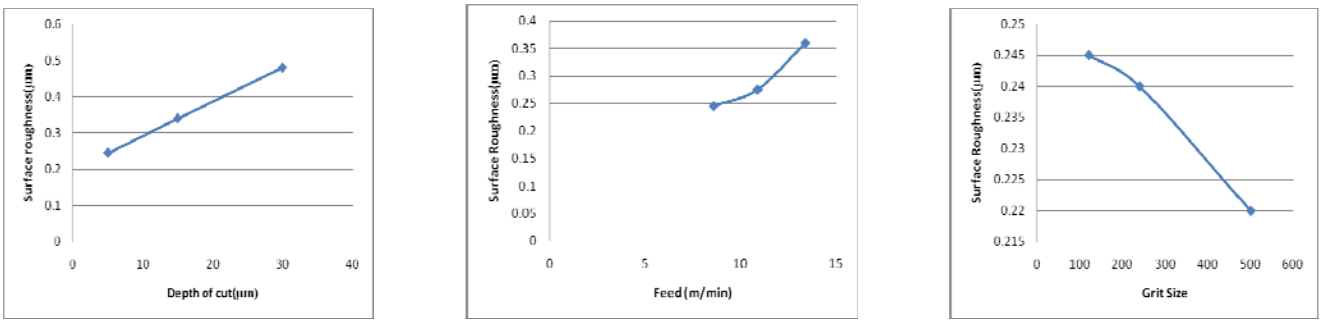
Table III Specification of Diamond Grinding Wheels

Size of the Wheel → 250-19-4-76.2 mm.

Wheel 1	ASD 120 R 50 B2
Wheel 2	ASD 240 R 50 B2
Wheel 3	ASD 500 R 50 B2

Table IV Test Result

S.N.	**d**	**f**	**g**	**Ra**
1	5	8.6	120	0.25
2	15	8.6	120	0.34
3	30	8.6	120	0.48
4	5	10.9	120	0.28
5	15	10.9	120	0.39
6	30	10.9	120	0.41
7	5	13.4	120	0.36
8	15	13.4	120	0.48
9	30	13.4	120	0.58
10	5	8.6	240	0.24
11	15	8.6	240	0.38
12	30	8.6	240	0.42
13	5	10.9	240	0.27
14	15	10.9	240	0.39
15	30	10.9	240	0.41
16	5	13.4	240	0.27
17	15	13.4	240	0.42
18	30	13.4	240	0.46
19	5	8.6	500	0.22
20	15	8.6	500	0.34
21	30	8.6	500	0.39
22	5	10.9	500	0.23
23	15	10.9	500	0.24
24	30	10.9	500	0.26
25	5	13.4	500	0.27
26	15	13.4	500	0.38
27	30	13.4	500	0.4



(a) (b) (c)

Fig 3 Effect of input parameters on surface roughness

(a) Depth of cut Vs surface roughness

(b) Feed Vs surface roughness

(c) Grit size Vs surface roughness

Table V Comparison of measurement result with MRA Model

	Input Parameters			Surface Roughness		
	d	f	g	Experimental Result	MRA Model	Error
1	5	8.6	120	0.245	0.28	Minimum- 0%
2	30	8.6	120	0.48	0.44	
3	15	10.9	120	0.39	0.42	
4	5	10.9	240	0.265	0.287	
5	30	13.4	240	0.46	0.457	
6	5	8.6	500	0.22	0.22	
7	15	13.4	500	0.38	0.336	Maximum-14.28%

Table VI Comparison of measurement result with ANN Model

S.N.	Input Parameters			Surface Roughness		
	d	f	g	Experimental Result	ANN Model	Error
1	5	8.6	120	0.245	0.2451	Minimum-0.009%
2	30	8.6	120	0.48	0.4799	
3	15	10.9	120	0.39	0.3900	
4	5	10.9	240	0.265	0.255	
5	30	13.4	240	0.46	0.469	
6	5	8.6	500	0.22	0.2199	
7	15	13.4	500	0.38	0.375	Maximum-3.77%

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Table VII Comparison of MRA Model & ANN Model

S.N.	Surface Roughness(μm)		
	Experimental Result	MRA Model	ANN Model
1	0.245	0.28	0.2451
2	0.48	0.44	0.4799
3	0.39	0.42	0.3900
4	0.265	0.287	0.255
5	0.46	0.457	0.469
6	0.22	0.22	0.2199
7	0.38	0.336	0.375

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