MODELING AND OPTIMIZATION OF GRINDING OF CERAMICS USING HYBRID ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM APPROACH

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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. Artificial neural network is used to develop the model for grinding force. Further, optimization has been done to achieve minimum grinding force using genetic algorithm.

Keywords - Artificial Neural Network, Ceramic grinding, Genetic Algorithm, Surface roughness, Grinding force.

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 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. Artificial neural network (ANN) model for one of the important parameter, that is F_T, has been developed. Further, single objective optimization using hybrid approach of ANN and genetic algorithm has been done.

II. METHODOLOGY

2.1 Artificial Neural Network

The ANN is a boon to the science. In the recent years, the application of artificial intelligence is tremendous in virtually all field of engineering. The typical ANN architecture is shown in Fig. 1.

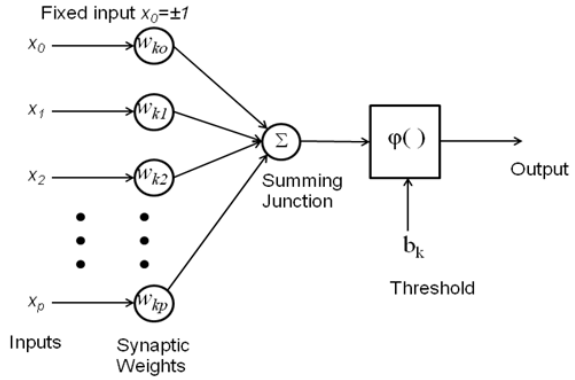


Fig. 1 Architecture of artificial neural network

The network architecture consists of: (i) Input layer (ii) hidden layer and (iii) output layer. The inputs are multiplied by their respective weighting factor and then these inputs are fed into the summing function, which usually just sums these products. The output of the summing function is then sent into an activation function, which maps the net input of neurons to its output. The number of neurons in the input and output layer are fixed. The number of hidden layer and number of neurons in each hidden layer are determined by network training. Many different ANN algorithms have been proposed by researchers for the modeling purpose such as Cascade-forward back propagation, Elman back propagation, Time-delay back propagation, Feed forward back propagation, Radial basis and Self-organizing map.

The past research elucidates that, due to its simplicity and accuracy, the feedforward backpropagation algorithm is mostly applied by researchers for predicting the process performance in manufacturing science. The feedforward network based on back propagation is a multilayered architecture made up of one or more hidden layers placed between the input and output layers. In back-propagation algorithm, a training input pattern is presented to the input layer. The network propagates the input pattern from layer to layer until the output pattern is generated by the output layer. If this pattern is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated.

In the network, each neuron receives total input from all of the neurons in the preceding layer as:

$$net_r = \sum_{r=1}^{N} w_{qr} X_r + b_q \quad (1)$$

where net_r is the total or net input and N are the number of inputs to the r_{th} neuron in the forward layer. w_{qr} is the weight of the connection to the q_{th} neuron in the forward layer from the r_{th} neuron in the preceding layer , X_r is the input from the r_{th} neuron in the preceding layer to the forward layer and b_q the bias to q_{th} neuron . A neuron in the network produces its output (out_r) by processing the net input through an activation function. The most widely used activation functions with their characteristics have been shown in the Fig. 2.

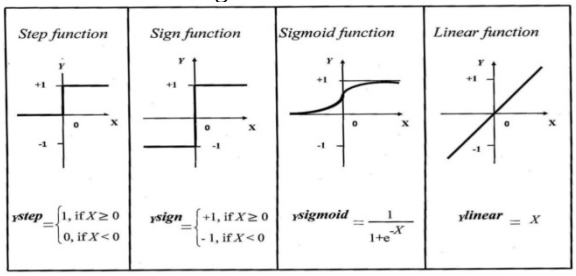


Figure 2 Different types of activation functions

The selection of activation functions is done by trial and error. The different activation functions and their different combinations for hidden and output layer are tried and the combination which gives minimum mean square error (MSE) is selected. The MSE measures the average of squares of error between the experimental values and model predicted values. The mean square error between the experimental values and ANN predicted value is given by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(out_r - out_e)^2 \quad (2)$$

Where the out_e is the experimental values of quality characteristics.

In calculation of connection weights, often referred to as network training, the weights are given quasi random, intelligently chosen initial values. They are then iteratively updated until convergence to the certain values using the gradient descent method. Gradient descent method updates weights so as to minimize the MSE between the network prediction and training data set as below:

$$w_{qr}^{new} = w_{qr}^{old} + \Delta w_{qr} \quad (3)$$

$$w_{qr} = -\delta \frac{\partial E}{\partial w_{qr}} out_r \quad (4)$$

Where E is the MSE and out_r is the r^{th} neuron output. δ is the learning rate parameter controlling stability and rate of convergence of network.

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].

III. 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 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 mm^3 materials were removed by giving very low depth of cut like 1-2 µm.
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.

Size of the Wheel: 250-19-4-76.2 mm	
Wheel	Specification
Wheel 1	CBN 120 R 50 B2
Wheel 2	CBN 240 R 50 B2
Wheel 3	CBN 500 R 50 B2

Table 1 Wheel Specification

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.

Factors	Depth of cut (µm)	Feed (m/min)	Grit No
Symbol	x_1	x_2	x_3
Level 1	6.0	10.5	120
Level 2	12.0	12.5	240
Level 3	18.0	14.5	500

Table 2 Control factors and their levels

IV. 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 ANN 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.

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

Table 3 Experimental Result

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.

Table 4 Analysis of variance for grinding force

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

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

Fig. 3 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.

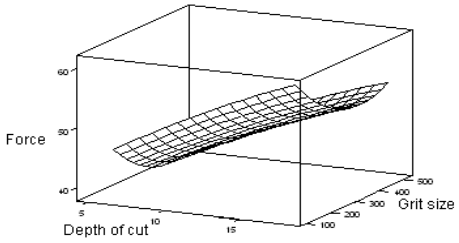


Figure 3 Effect of depth of cut and grit number on F_T

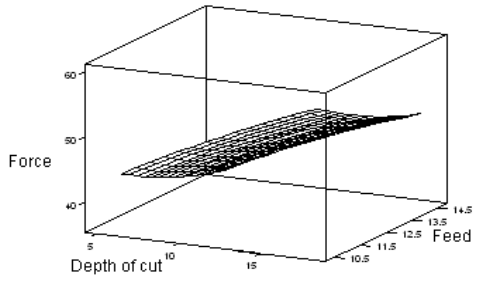


Figure 4 Effect of depth of cut and feed on F_T

The Fig. 4 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

In this research, after trying different activation functions and their combinations, it has been found that log sigmoid and pure linear activation function, for hidden layer and output layer, respectively, are best for all the quality characteristics. So, the log sigmoid and pure linear activation function has been utilized to develop ANN models. The values of weights and biases, after network getting trained, have been used to develop the ANN model for grinding force in mathematical form. The model with 3 neurons in the hidden layer has been found appropriate for F_T model. The ANN model in mathematical form can be expressed as:

$$F_T = 0.66574 * y_1 - 0.9091 * y_2 - 0.65311 * y_3 + 0.16693 \quad (5)$$

Where,

$$y_1 = \frac{1}{[1 + e^{-(6.855*x_1+6.33*x_2-6.5923*x_3-12.83)}]}$$

$$y_2 = \frac{1}{[1 + e^{-(-0.84686*x_1+2.45*x_2+0.8163*x_3-2.8444)}]}$$

$$y_3 = \frac{1}{[1 + e^{-(-3.33*x_1-4.2696*x_2+7.4723*x_3-10.5828)}]}$$

Fig. 5 compares the ANN predicted values with the experimental values. Its evident that ANN model gives good prediction of grinding force.

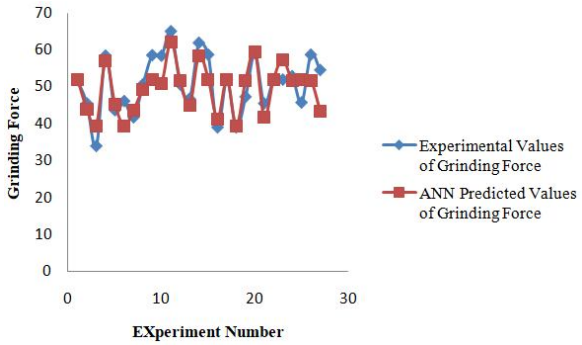


Fig. 5 Comparison of ANN predicted result with experimental values

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

$$F_T = 0.66574 * y_1 - 0.9091 * y_2 - 0.65311 * y_3 + 0.1669 \quad (6)$$

With range of process input parameters:
$6 \leq x_1 \leq 18$
$10.5 \leq x_2 \leq 14.5$
$120 \leq x_3 \leq 500$

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. (6) has been solved without any constraint. In Fig. 6, 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 µm, 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.

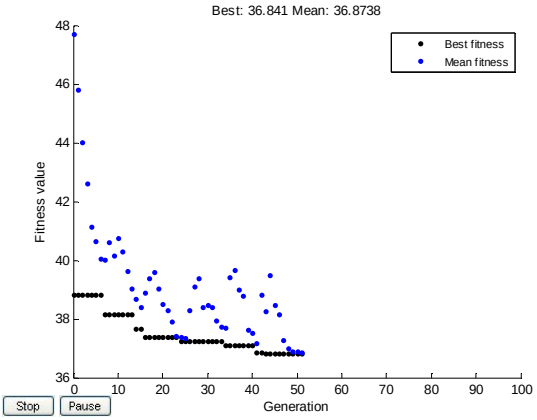


Fig. 6 Generation-fitness graphics for F_T

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 ANN 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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