Optimizing the process parameters of ELID grinding using neuro-fuzzy network

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Summary
Composite materials have been used in many industrial applications due to their light weight and high tensile strength. However, the machining costs of these materials may be high and the grinding of these materials is much more susceptible to surface damage as compared to metals. Electrolytic In- Process Dressing (ELID) grinding can be used to machine hard and brittle materials to achieve high surface quality and high material removal rate. In the present work, to conduct experiments, the Design of Experiments (DOE) technique is developed for five factors at three levels. Experiments have been conducted for measuring surface roughness, hardness and metal removal rate based on the DOE technique in an ELID grinding machine using a carbon boron nitride wheel. The experimentally measured values are also used to train the feed forward back propagation neuro-fuzzy for prediction of surface roughness. The predictive neuro fuzzy model was found to be capable of better prediction of surface roughness, hardness and metal removal rate within the trained range
Key words:
ELID grinding process, Optimization, ANN, Fuzzy Logic.

1. Introduction

The metal grinding process is one of the vital manufacturing processes in industries. The present scenario enlighten that application of composite materials has increased significantly due to their light weight ratio and better mechanical properties [1]. Grinding composite materials using conventional surface grinding process shows poor surface finish and accuracy [2].
To obtain better surface finish, ELID grinding technique has been adopted. A good understanding of the relationship between the work materials and cutting tool materials, cutting conditions and the process parameter are the essential requirements for the optimization of the grinding process [3-5]. More work has been carried out to determine the effect of ELID grinding in ductile mode on brittle materials that decreases the surface fracture and fragmentation and enables higher material removal rate [6].
Neuro-fuzzy is one of the most powerful computer modeling technique, based on statistical approach, currently being used in many fields of engineering for modeling complex relationships which are difficult to describe with physical models. Neuro-fuzzy has been extensively applied in modeling many metal cutting operations [7]. Process optimization has also been studied extensively for various manufacturing processes including grinding [8,9]. Optimization of ELID grinding on ceramics by using the process models built with Neuro-fuzzy theory, an optimization algorithm is constructed for multiple objectives function [10].
This research aims at the problems in surface finish in grinding composite materials. It is shown that the proposed method can greatly reduce the effort of the optimization procedure. Furthermore, the results of the confirmation experiments reveal that the obtained optimal combination of the grinding parameters can effectively improve surface finish and metal removal rate.

2. ELID Grinding Mechanism

The mechanism of ELID grinding for a metal bonded diamond wheel is shown in Fig. 1. After truing, the grains and bonding material of the wheel surface are flattened.

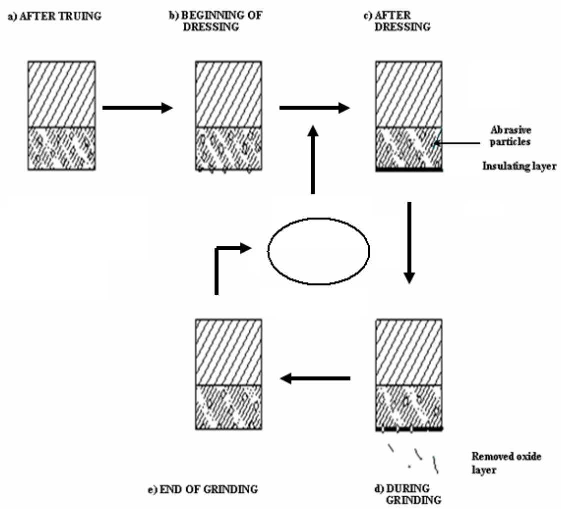

Fig. 1 ELID grinding process.

Manuscript received November 5, 2010
Manuscript revised November 20, 2010

It is necessary for the trued wheel to be electrically pre dressed to protrude the grains on the wheel surface. When pre-dressing starts [Fig. 1(a)], the bonding material flows out from the grinding wheel and an insulating layer composed of oxidized bonding material is formed on the wheel surface [Fig. 1(b)]. This insulating layer reduces the electrical conductivity of the wheel surface and excessive flow-out of the bonding material from the wheel. As grinding begins [Fig. 1(c)], diamond grains wear out and the layer also becomes worn out [Fig. 1(d)], as a result of which the electrical conductivity of the wheel surface increases and the electrolytic dressing starts with the flow-out of bonding material from the grinding wheel. The protrusion of diamond grains from the grinding wheel therefore remains constant. This cycle is repeated during the grinding process to achieve stable grinding.

3. Experimental Procedure

3.1. ELID grinding process

The experimental set up is shown in Fig. 2. The experiment was carried out on a precision surface grinding machine. An electrode made of copper, covering 1/6 of the perimeter of the grinding wheel, was used. The metal bonded cubic boron nitride wheel was mounted on a horizontal spindle and the gap between the grinding wheel and the copper electrode was adjusted to 0.2 mm. The carbon brush was made in such a way to have smooth contact with the grinding wheel shaft. The dynamometer, vice and the work piece assembly were fixed on the machine table. An electric current in the form of a square pulse wave was supplied from the ELID power supply to the positive and negative poles. A standard coolant namely CG-7 was prepared with ordinary tap water in a ratio of 1:50 and used as electrolyte and coolant for the experiment. Electrolyte was applied in between the grinding wheel and the electrode to start the electrolysis.

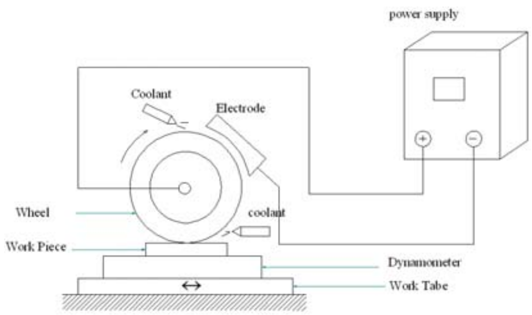

Fig. 2 Schematic illustration of ELID grinding

The experiment was performed on Al–10%SiCP composites, to study the metal removal rate, surface roughness and hardness. The normal force and tangential force were observed using a digital dynamometer. The surface roughness was measured with a Mitutoyo surftest. The micro hardness was measured using a Vickers micro hardness tester.

3.2. Design of experiment

In this experiment with five factors at two levels each, the fractional factorial design used is a standard L18 orthogonal array [11]. This orthogonal array is chosen due to its capability to check the interactions among factors. Each row of the matrix represents one trial. However, the sequence in which these trials are carried out is randomized. The factors and levels are assigned as in Table 1. The L18 orthogonal array is adopted for experimental layout of the machining parameters is shown in Table 2.

Table. 1 Machining parameters and their levels

Sl. No	Symbols	Factors	Level I	Level II	Level III
1.	N	No of Pass	50	100	150
2.	W	Work Speed (mm/min)	200	300	400
3.	D	Depth of Cut (μm)	2	4	6
4.	C	Current Duty Ratio (%)	30	40	50
5.	V	Voltage (V)	70	80	90

Table 2 L18 orthogonal array for experimental layout

Exp. No	No of Pass	Work Speed	Depth of Cut	Current Duty Ratio	Voltage
1.	1	1	1	1	1
2.	1	1	2	2	2
3.	1	1	3	3	3
4.	1	2	1	1	2
5.	1	2	2	2	3
6.	1	2	3	3	1
7.	2	3	1	2	1
8.	2	3	2	3	2
9.	2	3	3	1	3
10.	2	1	1	3	3
11.	2	1	2	1	1
12.	2	1	3	2	2
13.	3	2	1	2	3
14.	3	2	2	3	1
15.	3	2	3	1	2
16.	3	3	1	3	2
17.	3	3	2	1	3
18.	3	3	3	2	1

4. Artificial Neural Network Model

Predicting accurately the quality of the machining parts and finding the optimal process parameters is very vital; this is needed to build a model of the complete grinding process. The ANN approach ensures efficient and fast selection of the optimal process parameter of a process [12]. The approach which is dealt with here is having the following aims [13].

i) Maximizing the rate of production.
ii) Reducing the cost of production.
iii) Improving the quality of the product.

For prediction and to obtain optimal process parameter, back propagation neural network algorithm is used. Input parameters are number of pars, work speed, depth of cut, current duty ratio and voltage. These are needed to train neural network.

Table 3 Experimental and Trained data using neural network

Sl. No	**Roughness**			**Hardness**			**Metal Removal Rate**			**Normal Force**			**Tangential Force**		
	measured	Trained	% Error	Measured	Trained	% Error	Measured	Trained	% Error	Measured	Trained	% Error	Measured	Trained	% Error
1	1.965	1.949	0.783	120.33	122.509	1.811	2.786	2.760	0.897	6.69	6.536	6.09	0.99	0.957	3.303
2	1.424	1.452	2.029	131.62	131.985	0.277	2.581	2.501	3.099	5.78	5.785	0.096	0.82	0.805	1.780
3	1.45	1.452	0.001	131.51	131.985	0.361	2.43	2.420	0.411	5.28	5.303	0.482	0.74	0.736	0.486
4	1.98	1.961	0.924	120.68	129.061	0.069	3.62	3.662	1.160	4.8	4.580	4.583	0.78	0.773	0.782
5	1.46	1.472	0.863	139.38	138.538	0.603	2.65	2.630	0.754	6.28	5.864	6.622	0.88	0.897	1.988
6	1.82	1.819	0.820	132.68	132.083	0.449	2.62	2.612	0.305	7.12	7.144	0.342	1.12	1.129	0.848
7	1.92	1.918	0.083	135.16	129.061	4.511	3.98	3.662	7.899	5.98	5.761	3.655	0.86	0.840	2.325
8	1.78	1.773	0.365	128.22	129.061	0.656	2.79	2,789	0.035	6.37	6.040	5.179	0.84	0.845	0.617
9	1.33	1.338	0.654	139.13	129.061	7.236	3.386	3.662	8.151	8.24	8.373	1.617	1.08	1.077	0.231
10	1.35	1.339	0.814	125.53	122.509	2.406	2.81	2.798	0.427	4.98	5.186	4.148	0.86	0.845	1.744
11	1.95	1.961	2.182	131.22	129.061	1.644	2.91	2.817	0.429	8.86	8.753	1.197	1.14	1.128	1.008
12	1.62	1.619	0.055	138.22	129.061	6.625	2.92	2.892	0.941	9.25	8.926	3.496	1.21	1.115	7.851
13	1.56	1.447	7.243	119.33	129.061	8.155	3.059	3.285	0.997	7.92	7.672	3.127	0.91	0.895	1.648
14	1.36	1.433	5.389	113.67	120.061	5.623	2.864	2.844	0.680	7.29	7.962	9.222	0.82	0.815	0.609
15	1.68	1.674	0.339	123.34	129.061	4.639	2.947	2.932	0.458	10.02	9.736	2.827	1.25	1.248	0.152
16	1.37	1.369	0.072	131.63	129.061	1.951	3.232	3.208	0.734	7.82	7.703	1.494	0.79	0.805	1.898
17	1.42	1.426	1.426	130.12	129.061	0.813	3.52	3.501	0.508	7.51	8.181	8.976	0.77	0.755	1.948
18	1.31	1.290	1.290	137.18	129.061	5.917	3.12	3.040	2.5	10.8	10.942	1.322	1.34	1.359	1.455

The output parameters are surface roughness, hardness, metal removal rate normal force and tangential force (via fig 3). To train the network, the TRAINLM function of MATLAB was used. For generating the training data in neural network 18 experiments were used. Table 3 shows the training data. The TRAINLM function of MATLAB works on back propagation Algorithm [14]. Fig. 4 shows trained value of surface roughness with measured value, the training continued for ten thousand epochs with a performance of 0.038 out of 0.001 goal.

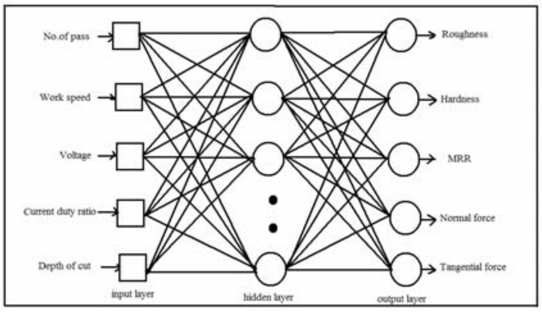

Fig. 3 Configuration of the neural network

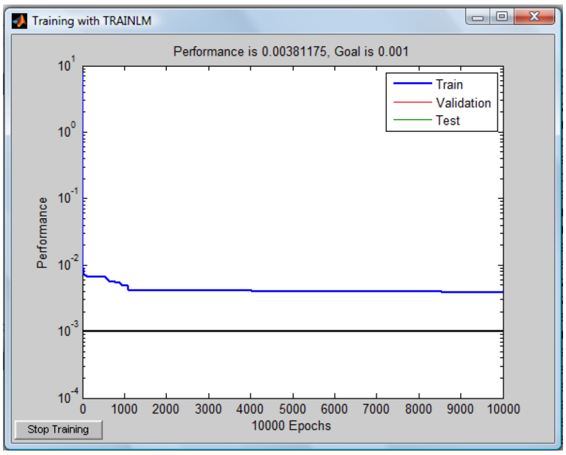

Fig.4 Trained value of surface roughness

The prediction error has been defined as follows:

Prediction error %=[(Experimental result – Predicted result)/(Experimental result)]*100 (1)

When the neural network gets trained if can provide the result for any arbitrary value of input data set. It is observed that the prediction based on an ANN model is quite close to the experimental observation. To predict the response parameters like number of pass, work speed, depth of cut, current duty ratio and voltage for all possible combinations of the input parameters the ANN model was used. For attaining better parameter level the optimal combinations were found out. The each of five input parameters has been considered into three levels and this helps in generating more predictions (3^5=243) more combinations were analyzed to get a better optimization process. Since surface roughness is vital when compared with other outputs, the output hardness, metal removal rate, normal force and tangential fore are excluded.

5. Fuzzy Logic Model

A fuzzy logic unit comprise of a fuzzifier, membership functions, a fuzzy rule base, an inference engine and a defuzzifier. In the fuzzy logic analysis, the tested values of neural network are fuzzified by the membership functions of fuzzifier. Then inference engine performs a fuzzy reasoning using fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts the fuzzy value into single grade. The structure built for this study is a five input-one-output fuzzy logic unit. The function of the fuzzifier is to convert outside crisp sets of input data into proper linguistic fuzzy sets of information. The input variables of the fuzzy logic system in this study are surface roughness, hardness, metal removal rate, normal force and tangential force. They are converted into linguistic fuzzy subsets using membership functions of a triangle form, that are shown in Fig. 5 (a), (b), (c), (d) & (e) are uniformly assigned into three fuzzy subsets—Low, Medium and High grade.

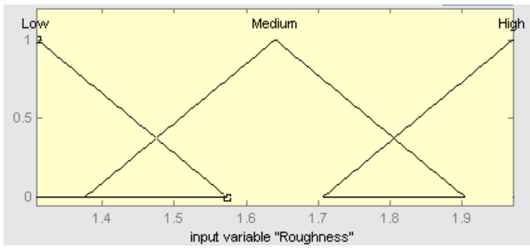

Fig 5 (a) Membership function for surface roughness

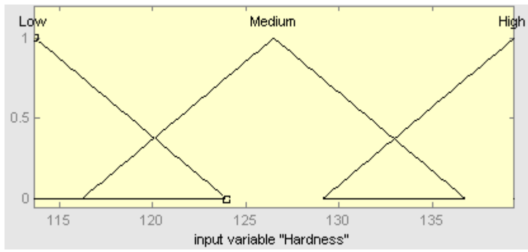

Fig 5 (b) Membership functions for hardness

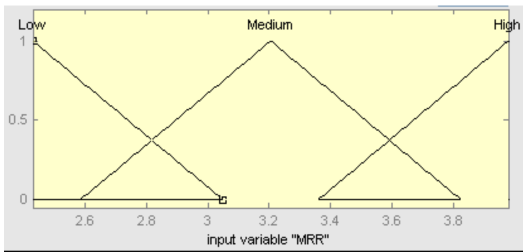

Fig 5 (c) Membership function for MRR

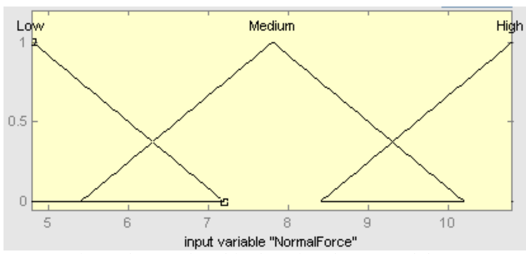

Fig 5 (d) Membership function for normal force

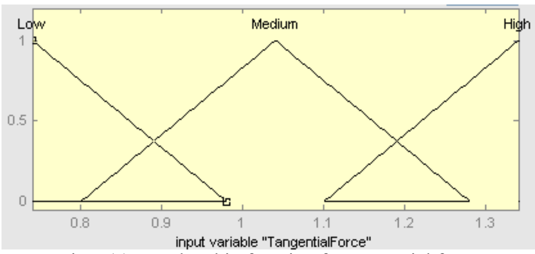

Fig 5 (e) Membership function for tangential force

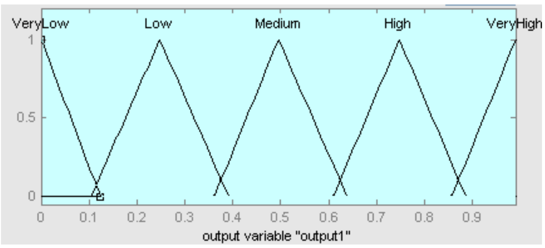

Fig.6 Membership function for output

The fuzzy rule base consists of a group of if-then control rules to express the inference relationship between input and output. A typical linguistic fuzzy rule called Mamdani is described as

Rule 1: if x_1 is A_1 and x_2 is B_1 then y is C_1 else
Rule 2: if x_1 is A_2 and x_2 is B_2 then y is C_2 else
Rule n: if $x_1$is An and x_2 is Bn then y is Cn else

Ai, Bi, and Ci are fuzzy subsets defined by the corresponding membership functions ie ,μ_{Ai}, μ_{Bi} and μ_{Ci}.
The fig.6 shows output grade, which was converted into linguistic fuzzy subsets using membership functions of a triangle form. The output grade are assigned into five subsets i.e., Very Low, Low, Medium, High, Very High grade.
Thirty two fuzzy rules are derived to achieve better process response. A fuzzy multi response out put is obtained from these rules by using max-min inference operation

$$\mu D0(y) = (\mu A1(x1) \Lambda \mu B1(x2) \Lambda \mu C1(x2) \Lambda \mu D1(y)) \cdots V (\mu An(x1) \Lambda \mu Bn(x2) \Lambda \mu Cn(x3) \Lambda \mu Dn(y)) \quad (2)$$

where Λ is the minimum operation and V is the maximum operation.
Finally, a centroid defuzzification method is adopted to transform the fuzzy multi-response output μD0(y) into a nonfuzzy value y_0, that is:

$$y0 = \Sigma y \mu D0(y) / \mu D0(y) \quad (3)$$

In this paper, the non-fuzzy value *y*0 is called a fuzzy reasoning grade. Based on the study, higher fuzzy reasoning grade produce better process response. Table 5 shows the predicted data and fuzzy reasoning grade using the trained neural data.

6. Conclusion

In this paper an attempt is made to present the use of Neuro - Fuzzy method for the optimization of the ELID grinding process. Machining data is closer to measured values. Neural network is used to train and predict machining data. In order to find out the optimum combination from these 243 predictions a program has been developed. Ten optimum parametric combinations were sorted out among these 243 combinations.

The fuzzy logic unit in fact, performs a fuzzy reasoning of the multi performance characteristics. The end result of the optimization methodology developed in this investigation is its essential used in improving the multi performance characteristic of the ELID grinding process.

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