Using Artificial Neural Network(ANN) Machinability Investigation Of Yttria Based Zirconia Toughness Alumina (Y-ZTA) Ceramic Insert

Ishani Bishnu, Jyoti Vimal, Neha Kumari

Abstract- A back propagation neural network model has been developed for the machinability evaluation i.e flank wear, cutting force and surface roughness prediction of Zirconia Toughness Alumina(ZTA) inserting in turning process. Numerous experiments have been performed on AISI 4340 steel using developed yttria based ZTA inserts. These inserts are constructed through wet chemical co-precipitation route followed by powder metallurgy process. Process parametric conditions such as cutting speed, feed rate and depth of cut are nominated as input to the neural network model and flank wear, surface roughness and cutting force of the inserts corresponding to these conditions has been selected separately as the output of the network. The experimentally calculated values are used to train the feed forward back propagation artificial neural network(ANN) for forecasting. The mean square error both in training and testing results positively. The performance of the trained neural network has been confirmed with experimental data. The results reveal that the machining model is acceptable and the optimization technique satisfies practical prospects.

Keywords: Zirconia Toughness Alumina(ZTA), Artificial Neural Network(ANN), Flank Wear, Cutting Force, Surface Roughness, Back Propagation.

I. INTRODUCTION

Today manufacturing industries aim to produce high quality product in least time and minimum cost. Thus, prediction of cutting force, flank wear and surface roughness of machined component has been important. These are mainly influenced by cutting speed, depth of cut and feed rate. We have tried to find a correlation between cutting parameters and cutting force, flank wear and surface roughness of machined product.

II. LITERATURE SURVEY

Modeling of tool-chip interface temperature prediction with trained RA model and with trained ANN model using LM algorithm with Fermi transfer function have been studied by IHSAN KORKUT[1], in 2007 during the metal cutting process presented. This concluded that RA model according to ANN model has a slightly high accuracy for predicting the tool-chip interface temperature. Modeling the correlation between cutting and process parameters in high speed machining of Inconel 718 alloy have been studied by E.O.EZUGNU[2] at all using an artificial neural network.

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The input parameters of the ANN model are the cutting parameters: speed, feed rate, depth of cut, cutting time and coolant pressure. The output parameters of the model are seven process parameters measured during the machining trials, namely tangential force(cutting force, Fz), axial force(feed force, Fx) spindle motor power consumption, machined surface roughness, average flank wear(VB), maximum flank wear(VBmax) and nose wear(VC).The multilayer network with two hidden layers having 10'tangent sigmoid' neurons trained with Levenberg Marquardt algorithm combined with Bayesian regularization was found to be the optimum network for model developed in this study. This concluded that prolonged machining results in steady increase in component forces, power consumption, average and maximum flank wear and nose wear. Modelling of cutting forces in the 3axes(fx,fy,fz) have been studied by AYKUT[3] at all using feed forward propagation artificial neural network. They used cutting speed(Vc),m/min, feed rate(F mm/min) and depth of cut(Ap,mm) and the input parameters and cutting forces as output parameters. They concluded that ANN can be used for predicting the effect of machinability on chip removal cutting forces as output parameter or face milling of satellite in asymmetric meaning process. S.MITRA[4] has studied laser micro machining (LMM) of tungsten molybdenum general purpose high speed steel (Rex M2).A feed forward back-propagation neural network has been developed to model the machining process. The model, after proper training is capable of predicting the response parameters as a function of four different control parameters. A laser beam machining (LBM) of Rex M2 high speed has carried out, and an advanced optimization strategy has been used to determine the optimal combination of control parameters. It has been found that among several neural configurations, a cascade forward back-propagation ANN of type 4-25-2, one hidden layer with 25 neurons can provide a best prediction. SURJYA K.PAL[5] has used back propagation neural network model has been developed for the prediction of surface roughness in turning operation. Number of experiments have been conducted on mild steel work-piece using HSS as the cutting tool material. The optimum network architecture has been found out based on the mean square error and the convergence rate. J.PAULO DAVIM[6] have used artificial neural network (ANN) to investigate the effects of cutting conditions during turning of free machining steel. The investigation mainly focused on surface roughness prediction and analysis during turning of free machining steel using cemented carbide inserts. A multilayer feed forward ANN was employed for this purpose, which was trained by error back-propagation algorithm. The surface roughness parameters are highly sensitive to both cutting speed and feed rate. Depth of cut has the least effect. It has a tendency to reduce with the increase in cutting speed and reduce in feed rate. ULAS ETAL[7] used artificial neural network and regression analysis method to study surface roughness in abrasive water jet. They used a feed forward neural network based on back propagation with 13 input neuron, 22 hidden layer and 1 output neuron. They concluded that regression model showed better performance compared to ANN. MUAMMER ETAL[8] used ANN for surface roughness prediction with cutting parameter in CNC turning and compared it with Regression in year 2007 and concluded that predictive NN model give better prediction than regression model and also that both methods can be used for same purpose because of difference in RxR is very small.

III. SURFACE ROUGHNESS

A measure of the texture and geometry of a surface can be termed as surface roughness mainly depends on the machining process. Roughness is difficult to determine through analytical equation and expensive to control in manufacturing.
It is characterized by a parameter known as arithmetic mean roughness or roughness average (Ra). Ra is defined as the arithmetic value between the roughness profile and its center line i.e. It can be expressed by the following equation :

$$Ra = 1/L \int_0^L |y(x)|\, dx$$

Within L=0.8mm. Where the terms and defined as:
L: sampling length, y: profile curve, x: profile direction

IV.FLANK WEAR

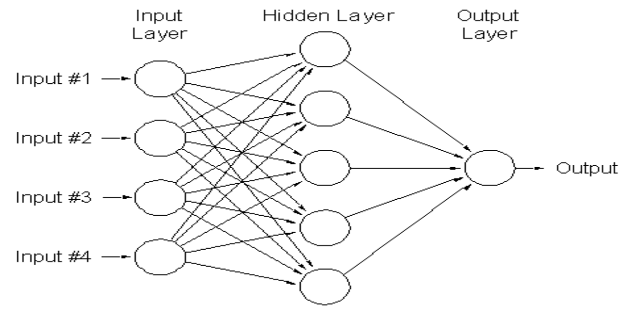
Due to fraction among machine surface of workplace and tool flank which leads to adverse effect on the surface of a cutting tool. Cutting force is directly proportional to flank wear. Value increases from its critical values, tool failure occurs. Thus flank wear help in estimation of tool life.

V. CUTTING FORCE

The high compression and frictional contact stresses on the tool face result in substantial cutting force F which is in direction of primary motion. It can be essential for proper design of cutting force or calculation of the machine tool power. It can also be used in selection of the cutting condition to avoid an excessive distortion of the work piece.

VI.ARTIFICIAL NEURAL NETWORK

ANN is an information processing paradigm which consists of neurons divided into input layer, output layer and hidden layers. Functioning of ANN basically depends on its physical structure and its configuration for specific application, such as pattern recognition or data classification through a learning process. Advantage of ANN mainly includes adaptive learning, self-organization, real time operation and fault tolerance ANN is a hierarchical set of neurons (processing elements) producing output for a certain input.



A. ANN TRAINING

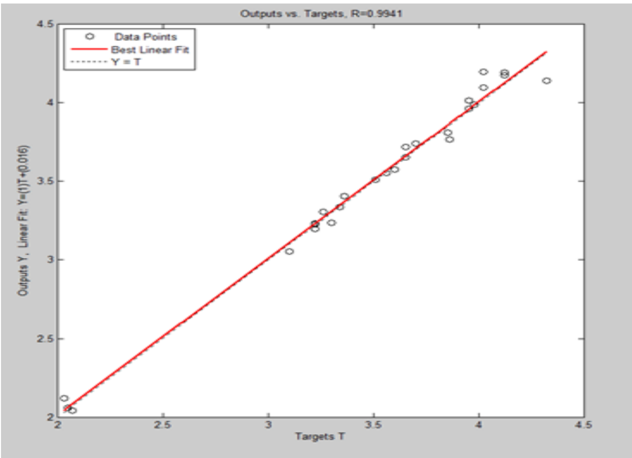
The training of ANN for given 25 input output patterns in which (1-20) training, (21-23) testing, (24-25) for validation. This training was achieved using fickle learning rate. Back propagation algorithm has been used for training and testing of network of MATLAB. In first step of training learning algorithm is made number of hidden nodes are determined, two start the training. This training condition either till iteration ends or target level of error is reached.

B. ANN TESTING

Each trained input pattern is tested and predicted value of Ra and Rt are compared with the respective measured value and absolute error is computed.

%absolute error=|(Yi,exp-Yi,pred)/Yi,exp|*100

Where, Yi,exp is experimental value and Yi,pred is predicted value of ANN for ith trial. It is found that approximated value and experimental value are similar.



VII. BACK PROPAGATION

Feed forward, time delay, cascade forward are type of Back propagation algorithm. It is most popular algorithm with different variance and not so complex structure and operation. It is mostly used for feed forward network. The basic structure of back propagation neural network include input layer, hidden layer and output layers information from external source is received by input layer. This information is passed to hidden layer where it undergoes through processing. This processed information is then passed to output layer which sends the result to external receptor. At the time of training the neural network the output calculated. If the mean square is more than the limiting value given, it is back propagated and interconnection weights are again modified. This process is contained till mean square error(mse) calculated is less the given limit mse, E where,

E = target output-calculated output

VIII. EXPERIMENTAL PLAN

The turing operation were conducted in a lathe machine(Hindustan Machine tool LTD, India) powered by an 11kw motor and 47-1600 rpm of speed range. AISI steel was machined by newly introduced co-precipitated process derived Y-ZTA composite as cutting tool inserts at different cutting conditions. Initially the diameter of steel bar was 140mm and length was 450mm. CSBNR 2525 N43(NTK) was used as tool holder and -6degree, -6 degree, 6degree,6 degree, 15 degree,15 degree and 0.8mm are tool angles.

IX. RESULT AND DISCUSSION

The aim of any training algorithm is to minimise the errors. For this model main parameters are cutting speed(m/min), depth of cut(mm), feed-rate(mm/rev). From the 27 data sets obtained from experiment, 20 have being selected for random training the network, 21 to 24 are used for testing and 25 to 27 are used as validation. The number of hidden layer, learning rate and momentum coefficient are decided by trial and error.

Table 1. Operating parameters with their levels

Operating parameters	Unit	Value
Cutting speed	m/min	420, 280, 140
Feed rate	mm/rev	0.12, 0.18, 0.24
Depth of cut	mm	0.5, 1.0, 1.5
Environment		Dry

Table 2. Data for neural network model measuring flank wear.

Exp No.	Cutting speed	Feed rate	Depth of cut	Flank wear
1	420	0.12	0.5	0.22
2	420	0.12	1	0.25
3	420	0.12	1.5	0.28
4	420	0.18	0.5	0.25
5	420	0.18	1	0.27
6	420	0.18	1.5	0.29
7	420	0.24	0.5	0.25
8	420	0.24	1	0.29
9	420	0.24	1.5	0.32
10	280	0.12	0.5	0.18
11	280	0.12	1	0.20
12	280	0.12	1.5	0.23
13	280	0.18	0.5	0.19
14	280	0.18	1	0.23
15	280	0.18	1.5	0.25
16	280	0.24	0.5	0.24
17	280	0.24	1	0.25
18	280	0.24	1.5	0.27
19	140	0.12	0.5	0.13
20	140	0.12	1	0.15
21	140	0.12	1.5	0.18
22	140	0.18	0.5	0.14
23	140	0.18	1	0.16
24	140	0.18	1.5	0.18
25	140	0.24	0.5	0.16
26	140	0.24	1	0.18
27	140	0.24	1.5	0.20

Table 3.Training and testing error for different neural network architectures

	Architecture	LR	MC	Mse training	Mse testing	Iteration
1	3-2-1	0.1	0.3	0.0069	0.0168	4542
2	3-2-1	0.5	0.7	0.0074	0.0183	4765
3	3-2-1	0.3	0.5	0.0082	0.0180	5245
4	3-3-1	0.7	0.9	0.0039	0.0090	3642
5	3-3-1	0.9	0.9	0.0039	0.0090	6231
6	3-3-1	0.02	0.9	0.0057	0.0097	6734
7	3-4-1	0.1	0.3	0.0067	0.0089	5845
8	3-4-1	0.3	0.5	0.0068	0.0083	7398
9	3-4-1	0.5	0.7	0.0078	0.0089	7965
10	3-5-1	0.7	0.9	0.0048	0.0076	8596

Table 4.Data for neural network model measuring roughness

Exp No.	Cutting speed	Feed rate	Depth of cut	Surface roughness
1	420	0.12	0.5	2.03
2	420	0.12	1	3.56
3	420	0.12	1.5	3.36
4	420	0.18	0.5	2.05
5	420	0.18	1	3.22
6	420	0.18	1.5	3.36
7	420	0.24	0.5	2.07
8	420	0.24	1	3.01
9	420	0.24	1.5	3.34
10	280	0.12	0.5	3.85
11	280	0.12	1	3.95
12	280	0.12	1.5	4.32
13	280	0.18	0.5	3.65
14	280	0.18	1	3.95
15	280	0.18	1.5	4.02
16	280	0.24	0.5	3.51
17	280	0.24	1	3.86
18	280	0.24	1.5	3.98
19	140	0.12	0.5	3.22
20	140	0.12	1	3.6
21	140	0.12	1.5	4.02
22	140	0.18	0.5	3.22
23	140	0.18	1	3.65
24	140	0.18	1.5	4.12
25	140	0.24	0.5	3.3
26	140	0.24	1	3.7
27	140	0.24	1.5	4.12

Table 5.Training and testing error for different neural network architectures

	Architectue	LR	MC	Mse training	Mse testing	Iteration
1	3-2-1	0.1	0.3	0.0374	0.0450	4978
2	3-3-1	0.7	0.9	0.0246	0.025	3742
3	3-3-1	0.9	0.8	0.0162	0.0264	6200
4	3-3-1	0.5	0.7	0.0141	0.0165	
5	3-4-1	0.02	0.7	0.0273	0.0302	8234
6	3-4-1	0.3	0.5	0.0028	0.0071	6000
7	3-4-1	0.9	0.9	0.0229	0.0384	7845
8	3-5-1	0.1	0.3	0.0333	0.0384	9256
9	3-5-1	0.5	0.7	0.0080	0.0175	12987
10	3-5-1	0.3	0.5	0.0081	0.0159	9900

Table 6.Data for neural network model measuring cutting force

Exp No.	Cutting speed	Feed rate	Depth of cut	Cutting force
1	420	0.12	0.5	325
2	420	0.12	1	342
3	420	0.12	1.5	365
4	420	0.18	0.5	373
5	420	0.18	1	384
6	420	0.18	1.5	396
7	420	0.24	0.5	423
8	420	0.24	1	435
9	420	0.24	1.5	453
10	280	0.12	0.5	340
11	280	0.12	1	360
12	280	0.12	1.5	383
13	280	0.18	0.5	390
14	280	0.18	1	405
15	280	0.18	1.5	417
16	280	0.24	0.5	422
17	280	0.24	1	435
18	280	0.24	1.5	455
19	140	0.12	0.5	390
20	140	0.12	1	410
21	140	0.12	1.5	435
22	140	0.18	0.5	435
23	140	0.18	1	450
24	140	0.18	1.5	465
25	140	0.24	0.5	498
26	140	0.24	1	502
27	140	0.24	1.5	510

Table 7.Training and testing error for different neural network architectures

	Arch	LR	MC	Mse training	Mse testing	Iteration
1	3-2-1	0.1	0.3	0.0082	0.0128	3124
2	3-2-1	0.5	0.7	0.0078	0.0165	5245
3	3-3-1	0.7	0.9	0.0046	0.0107	5987
4	3-3-1	0.02	0.9	0.0043	0.0133	6820
5	3-4-1	0.1	0.3	0.007	0.0164	7220
6	3-4-1	0.3	0.5	0.005	0.0129	8520
7	3-5-1	0.7	0.9	0.0096	0.0127	9987
8	3-5-1	0.9	0.9	0.0073	0.0102	12349
9	3-5-1	0.1	0.3	0.0051	0.0091	15245
10	3-5-1	0.5	0.7	0.0052	0.0098	18265

Where, MC- momentum coefficient
LR- learning rate
Different combination of learning rate and momentum coefficient and number of hidden layer have been tried. Depending on the mean square error the optimum networks:
For flank wear:
3-4-1, learning rate: 0.3, momentum coefficient:0.5

For surface roughness:
3-4-1, learning rate: 0.3, momentum coefficient: 0.5

For cutting force
3-5-1, learning rate : 0.1, momentum coefficient : 0.3
Next figure shows the variation of training and testing error with the number of iteration for the network used in present case.

MSE is calculated by

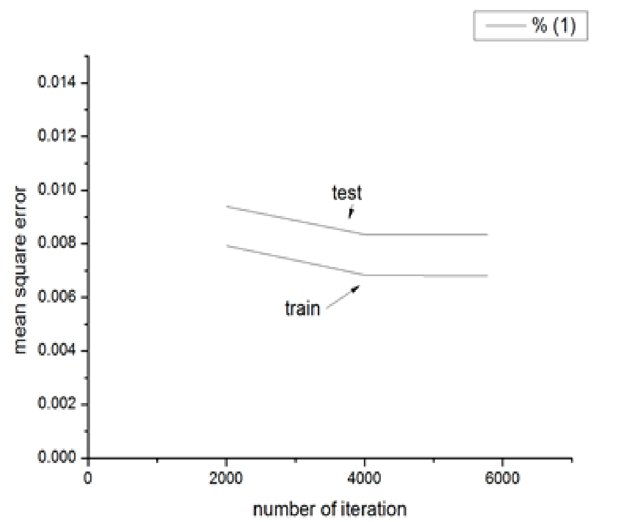
```
etest=Test.T-EstNormTest;
 perftest=mse(etest)
 etrain=TrainDataOutput-EstNormTrain;
 perftrain=mse(etrain)
```

Where,
Test.T = stores target value of testing.
EstNormTest = stores estimated value of testing part.

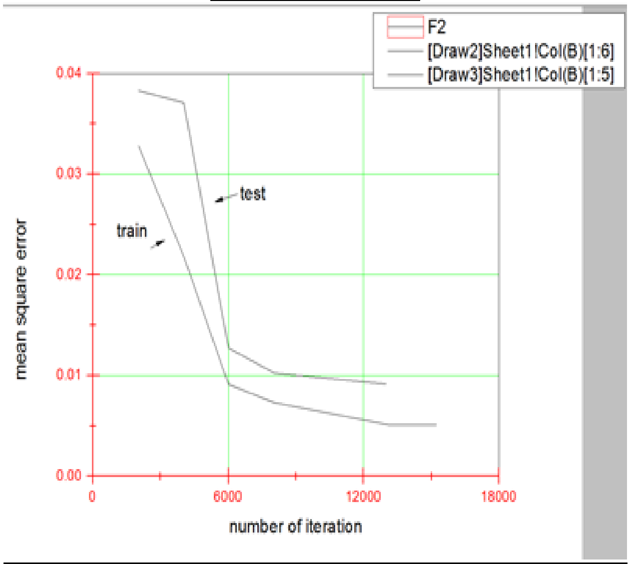
TrainDataOutput = stores target value of training.
EstNormTrain = stores estimated value of training part by neural network.
The data are normalized by using :
inputnorm(:) and outputnorm(:) functions.

Graph:

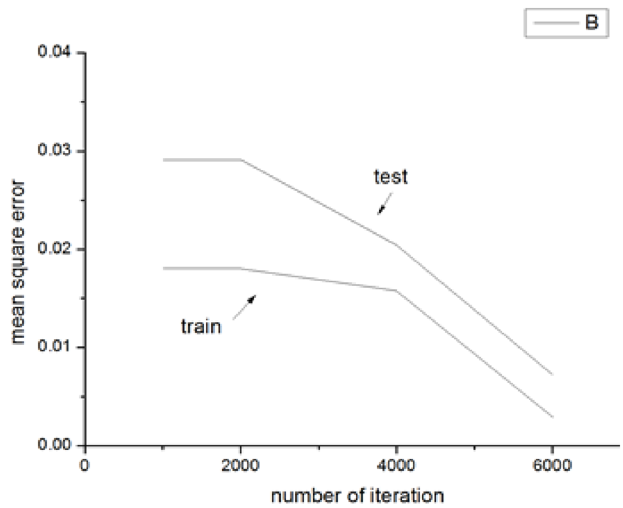
FLANK WEAR



CUTTING FORCE



ROUGHNESS



X. CONCLUSION

A methodology for prediction of flank wear, surface roughness and cutting force using back propagation neural network has been developed. The predicted value of all three is very close to the value that of measured experimentally.

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