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Modeling of Surface Roughness in Vibration Cutting by Artificial Neural Network

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Abstract—Development of artificial neural network (ANN) for prediction of aluminum workpieces' surface roughness in ultrasonic-vibration assisted turning (UAT) has been the subject of the present study. Tool wear as the main cause of surface roughness was also investigated. ANN was trained through experimental data obtained on the basis of full factorial design of experiments. Various influential machining parameters were taken into consideration. It was illustrated that a multilayer perceptron neural network could efficiently model the surface roughness as the response of the network, with an error less than ten percent. The performance of the trained network was verified by further experiments. The results of UAT were compared with the results of conventional turning experiments carried out with similar machining parameters except for the vibration amplitude whence considerable reduction was observed in the built-up edge and the surface roughness.

Keywords—Aluminum, Artificial Neural Network (ANN), Built-up Edge, Surface Roughness, Tool Wear, Ultrasonic Vibration Assisted Turning (UAT).

I. INTRODUCTION

IN ultrasonic vibration-assisted turning (UAT), the vibration produced by a generator at an ultrasonic frequency is transmitted to the cutting tool through an appropriately designed horn [1]. The ultrasonic vibration parameters commonly used in the vibration machining processes are in the ranges of few micrometers up to about thirty micrometers for the amplitude and about twenty to fifty kH for the frequency. The advantages and various applications of the intermittent engagement between the cutting tool and the workpiece in vibration cutting have already been subject to considerable research effort. In this regard, [2]-[4] may be consulted as some examples.

Artificial neural networks (ANN) have already been applied to various aspects of machining processes, such as optimization of machining parameters [5]-[6], prediction of cutting load [7]-[8], surface roughness modeling[8]- [14], tool-wear detection [15]-[16] and estimation of cutting tool stress [17]. Finesa and Agah [18], and El-Sonbaty et al [19] used neural network for positioning error compensation. Hao et al [20] used ANN and genetic algorithm for modeling the thermal error in turning. Kuljanic et al [21] and Cardi et al [22] applied ANN for detection of chatter vibration in milling and turning. Jamali et al [23] and Nalbant et al [24] modeled explosive cutting process by ANN. Kim et al [25] used neural network for performance evaluation of chip breaker.

This literature survey indicates that responses in cutting operations are well apt to be modeled by neural networks.

To the knowledge of the authors, no work can be mentioned to have been done on the application of neural networks to vibration cutting where far more complicated situation governs compared with the conventional turning (CT). The authors have recently developed an ANN model for prediction of machining force and surface roughness in UAT of steel components [12]. This work has been extended to include aluminum parts in the present study. A multi layer perceptron neural network was developed for predicting surface roughness of AL7075 parts in UAT. Creation of built-up edge in machining of aluminum parts is a serious problem. Built-up edge leads to high tool wear rate and unacceptable surface roughness. This adds to the scrap parts and machining cost. It is illustrated in this paper that UAT is an effective machining technique to alleviate this problem.

Modeling of surface roughness of aluminum parts has been done on the basis full factorial design of experiments. Separate experimental data were used for training and testing the network. The influence of UAT parameters including vibration amplitude, depth of cut, feed rate and cutting speed on the surface roughness were also investigated.

II. ANN FOR PREDICTING SURFACE ROUGHNESS OF ALUMINUM PART IN UAT

A. Experiments

The experiments were carried out with an ultrasonic vibration generator with 2 kW power and frequency range of 20±0.5 kHz. An aluminum horn was especially designed and manufactured for this purpose [1]. A special fixture was used for installing the assembly of horn and cutting tool on the saddle. Tool insert was DCGT11. The surface roughness was measured with Mahr surface roughness measuring device. The experiments setup is shown in Fig. 1. The workpiece of Al7075 shown in this figure was recessed at intervals of 17 mm long to separate the successive UAT and CT regions during the experiments. The CT experiments were simply

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carried out by switching the generator off. The cutting tool insert was replaced with a new one after each machining pass. This was done for properly distinguishing the influence of machining conditions. Other parameters were kept constant in each machining pass **.**

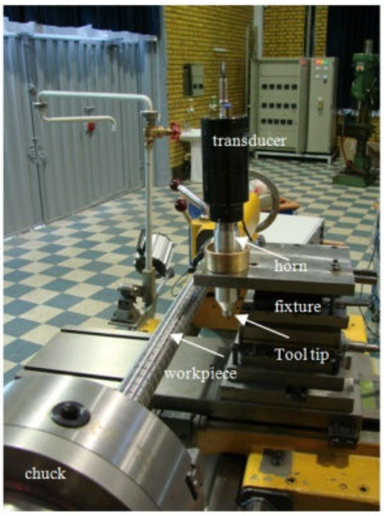


Fig. 1 Experiments setup

The values of machining parameters including vibration amplitude (a), depth of cut (d), feed rate (f_r) and cutting velocity (v_c) were adjusted at three levels as presented in Table I.

TABLE I UAT PARAMETERS

Factor	Level 1	Level 2	Level 3
$a(\mu m)$	6	12	0
$d(mm)$	0.4	0.8	1.4
$f_r(mm/rev)$	0.11	0.2	0.4
$v_c(m/\min)$	13.56	37.68	75.36

The results of fifty four tests carried out in UAT of aluminum parts are given Table II.

As it was noted earlier, CT experiments were also carried out in order to compare with the UAT results. CT parameters were the same as UAT given in Table I except for the vibration amplitude, a, which vanished in CT. The results of UAT and CT are compared in Fig. 2. As is evident from this figure, the surface roughness is much lower in UAT compared with CT.

In order to further investigate the causes of surface roughness of the machined aluminum parts, the cutting tool edge was analyzed by using a SEM of model XL30, as shown in Fig. 3.

TABLE II EXPERIMENTAL RESULTS

No	a	v_c	f_r	d	Ra	No	a	v_c	f_r	d	Ra
1	12	13.56	0.4	1.4	13.24	28	12	37.68	0.11	0.4	0.995
2	12	37.68	0.2	0.4	2.805	29	6	75.36	0.2	0.4	3.453
3	6	13.56	0.11	0.4	1.37	30	12	37.68	0.4	0.4	14.7
4	12	37.68	0.4	0.8	13.07	31	6	13.56	0.2	0.8	5.5
5	6	37.68	0.2	0.4	3.583	32	6	75.36	0.2	1.4	3.317
6	12	75.36	0.2	0.8	3.145	33	12	37.68	0.11	1.4	0.984
7	6	37.68	0.11	0.8	0.946	34	12	13.56	0.2	0.4	3.049
8	6	75.36	0.11	0.4	0.838	35	12	75.36	0.2	0.4	2.754
9	6	13.56	0.2	1.4	3.218	36	12	13.56	0.2	1.4	3.182
10	12	75.36	0.11	0.8	0.934	37	6	37.68	0.11	1.4	0.929
11	12	75.36	0.2	1.4	3.019	38	12	13.56	0.4	0.8	13.56
12	12	75.36	0.4	0.4	14.26	39	12	37.68	0.4	1.4	12.57
13	6	37.68	0.2	0.8	5.155	40	12	75.36	0.11	1.4	1.07
14	6	13.56	0.4	1.4	12.96	41	12	75.36	0.4	0.8	12.96
15	12	37.68	0.2	0.8	3.106	42	6	13.56	0.2	0.4	4.069
16	6	37.68	0.11	0.4	1.17	43	6	37.68	0.4	1.4	12.44
17	6	75.36	0.4	0.4	13.72	44	6	37.68	0.2	1.4	3.427
18	12	13.56	0.2	0.8	3.013	**45**	**6**	**75.36**	**0.4**	**0.8**	**12.68**
19	6	37.68	0.4	0.4	12.8	**46**	**6**	**37.68**	**0.4**	**0.8**	**12.8**
20	6	13.56	0.4	0.8	12.8	**47**	**12**	**13.56**	**0.11**	**0.8**	**0.86**
21	12	37.68	0.2	1.4	3.173	**48**	**12**	**37.68**	**0.11**	**0.8**	**1.076**
22	12	75.36	0.4	1.4	13.44	**49**	**12**	**13.56**	**0.4**	**0.4**	**14.28**
23	6	13.56	0.11	0.8	1.006	**50**	**6**	**75.36**	**0.2**	**0.8**	**3.27**
24	12	13.56	0.11	1.4	0.995	**51**	**12**	**75.36**	**0.11**	**0.4**	**0.849**
25	6	75.36	0.11	1.4	1.057	**52**	**6**	**13.56**	**0.11**	**1.4**	**1.295**
26	6	75.36	0.11	0.8	1.158	**53**	**6**	**75.36**	**0.4**	**1.4**	**14.06**
27	12	13.56	0.11	0.4	1.551	**54**	**6**	**13.56**	**0.4**	**0.4**	**13.59**

B. Development of ANN

A multilayer perceptron network was developed comprising three layers including the input, hidden and output layers with backward propagation training strategy. The input to the model consists of vibration amplitude, cutting speed, feed rate and depth of cut. Surface roughness is the output. The model is depicted in Fig. 4.

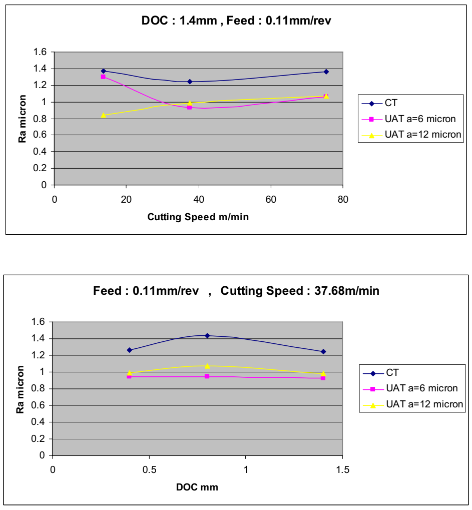


Fig. 2 Surface roughness in UAT and CT for different values of machining parameters

Fig. 3 SEM for studying built-up edge

For development of the model, 81% data were used for the training and the 19% data for the testing. The boldfaced values of parameters in Table II were not used for developing the model but were reserved for verification of the model.

The processing units or neurons in each layer pass the processed data to the neurons of the next layer. The network is trained to correlate the input to the output by assigning appropriate weights, $W = (W_{1l},...,W_{nl})$, where n is the number of input and l is the number of output. The input vector is denoted here by $X_j = (X_{1j},...,X_{nj})$ and the real output vector by $B_j = (B_{1j},...,B_{lj})$, where $1 \le j \le N$ and N is the number of training exemplifiers. The input layer receives the data embodied in the input vector. The weights are randomly selected at the first iteration and changed accordingly at each subsequent epoch. The output vector is generated on the basis of the calculated weights. The predicted output is denoted by $Q_j = (Q_{1j},...,Q_{lj})$. An error function is then defined as follows:

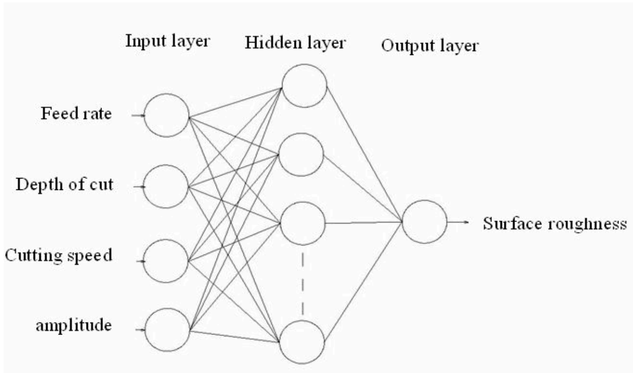


Fig. 4 Neural network for predicting surface roughness

$$E = \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{N}(B_{ij} - Q_{ij})^2 \tag{1}$$

The error is then propagated backward from the output layer to the hidden layer and new weights are generated based on the delta learning rule as follows:

$$\Delta W_{nl} = -\frac{\partial E}{\partial W_{nl}}\eta \tag{2}$$

$$W_{ij}^{new} = W_{ij}^{old} + \Delta W_{ij} \tag{3}$$

where 0< η < 1 is an indication of the convergence rate of the network. This procedure is repeated until the error diminishes to a value less than an acceptable limit.

The activation or transfer functions were selected to be hyperbolic tangent function. The parameters are scaled or normalized in order to avoid highly skewed results. The scaling is done by mapping the values to a range between 1 and -1.

The number of the hidden layers and the number of neurons in the hidden layer have an important impact on the accuracy of the model. Several networks have been tried and the parameter values presented in Table III have been found to yield sufficiently accurate results.

As mentioned earlier, the bold face data of Table II were then employed to verify the trained networks. The results of the network are compared with the experimental data. Fig. 5 illustrates the result of comparison. As mentioned earlier different experimental data have been used for training and testing the networks.

TABLE III THE OPTIMUM VALUES OF NETWORK PARAMETERS

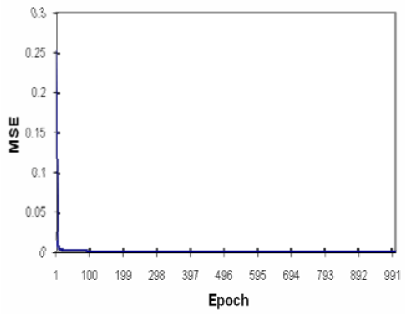
Number of hidden layer	1
Learning factor	0.1
Transfer function used	Tanh
Number of hidden neurons	4
Number of epochs	1000
Momentum factor	0.7

It is clear from Fig. 5 that a good agreement exists between the networks prediction and the experimental data. The linear correlation factor is 0.9974 and the average error is %12. The mean squared error (MSE) value of 0.0013 practically means that the model can recall the training data with minimal error.

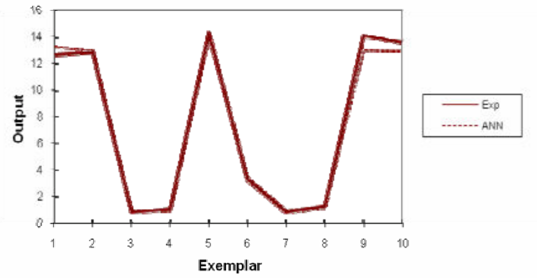
The improved weights of the neural network are presented in Tables IV and V. Table 4 gives the weights of the correlation between the input and the hidden layers. Table 5 presents the weighs of the correlation between the hidden and the output layers.

III. BUILT-UP EDGE IN UAT AND CT

Analysis of the material attached to the cutting tool indicated that this material was aluminum different from the tool material. A SEM picture of the tool tip is shown in Fig. 6.



(a)



(b)

Fig. 5 The results of validation test, a) MSE versus Epoch during training step, b) comparison of the output of the trained networks and the experimental data

TABLE IV WEIGHT FOR HIDDEN LAYER

input / neuron	vibration amplitude	depth of cut	feed rate	cutting velocity
1	-0.083071951511	0.282042974603	1.343516573344	-0.229600335712
2	-0.292414245649	-0.084818820484	-1.208477233325	-0.133840598362
3	0.52524681860	-0.154870234712	0.711218757181	0.165644870122
4	-0.698330133163	-0.354968062479	1.394806436282	-0.105274784408

TABLE V WEIGHT FOR OUTPUT LAYER

Neuron / output	1	2	3	4
surface roughness	0.427247982318	-0.348182974359	0.386548995916	0.519607771529

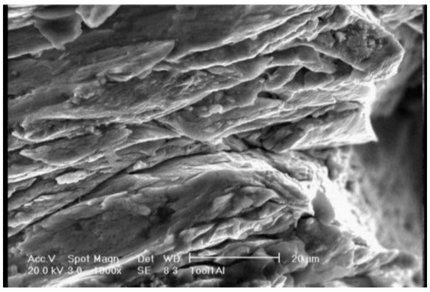
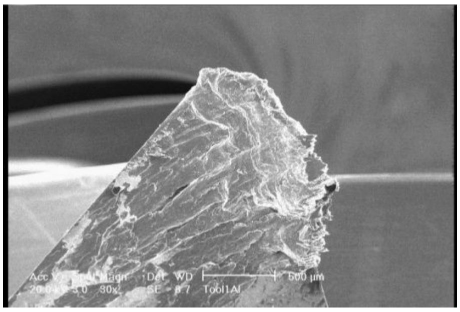
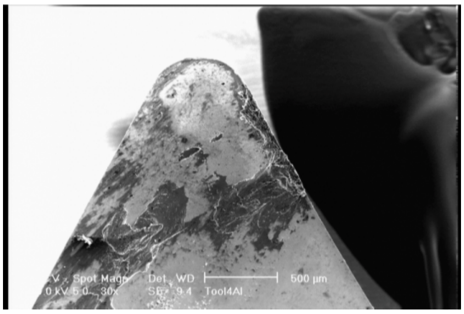


Fig. 6 SEM photo of the built-up edge

Considerable reduction was observed in the built up edge in vibration turning compare with CT. This is easily evident from Fig. 7 which depicts the magnified picture of the tool tips after machining operations in UAT and CT. The rationale behind this phenomenon is the intermittent engagement between the cutting tool and the workpiece in UAT against the continuous engagement in CT. This causes reduction in frictional effect. The mechanism of the reduction is both less period of engagement time and change of static friction to dynamic. Friction This reduced frictional effect in turn results in lower tool wear rate. Additionally, less engagement occurring in UAT does not leave sufficient time for the thermo chemical causes of the tool wear to take effect.



(a)



(b)

Fig. 7 Tool tip wear (d=1.4 mm, fr=0.4 mm/rev, v_c=13.56 m/min and was a in UAT =12 μm, a) CT, b) UAT

The machining parameters for this experiment in both UAT and CT were d=1.4 mm, fr=0.4 mm/rev, v_c=13.56 m/min and in the vibration amplitude in UAT was a=12 μm.

IV. CONCLUSION

The surface roughness of aluminum parts in ultrasonic-vibration assisted turning was modeled by artificial neural network, in the present study. The following characteristics of the network and training data could yield sufficiently accurate results: Multilayer perceptron was used for this purpose. The network was trained with experimental data carried out on the basis of full factorial design of experiments. The trained network was verified with separate experimental data. Totally, fifty four experiments were carried out for training and testing the network. Three different levels of UAT parameters consisting of vibration amplitude, cutting speed, feed rate and depth of were used for the experiments.

Three-layered back propagation network was proposed for modeling the surface roughness. Hyperbolic- tangent transfer function and one hidden layer accommodating four neurons could converge to acceptable output accuracy after 991 epochs.

The test of the trained networks showed good agreement existing between their predictions and the experimental results. The average error was %12.

Superimposition of ultrasonic vibration on the normal motion of the cutting tool led to considerable decrease in the tool tip's built up edge compared with the conventional turning, when machining aluminum parts. This is responsible for improved surface quality of workpieces in vibration cutting.

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