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PREDICTION OF FRACTAL DIMENSION IN ALUMINIUM MILLING USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT
In this paper, artificial neural network methodology is applied in CNC milling of aluminium surfaces to predict fractal dimension, which is used to describe surface roughness. For the study, spindle speed, depth of cut and feed rate are chosen as the process parameters. To develop multi-layer back propagation neural network model, these three cutting parameters are used as the input neurons and corresponding fractal dimension as the output neuron. For the developed model, mean absolute percentage error for training data is 0.76% only which implies that the ANN predicted and experimental fractal dimensions are close to each other. The network is also tested with a testing set. Mean absolute percentage error is 0.84 for testing pattern which implies that the experimental and ANN predicted values lie very close to each other. From the results it can be concluded that the network has a good prediction capability in CNC milling.

Keywords: Fractal Dimension (D), CNC Milling, ANN, Aluminium.

1. INTRODUCTION
Surface roughness is an important parameter in manufacturing science. It has large impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life etc. It also affects other functional attributes of machine components like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity etc. Surface roughness may depend on various factors like machining parameters, work-piece materials, cutting tool properties, cutting phenomenon etc.

Generally, the surface roughness is expressed by conventional roughness parameters such as centre line average value (R_a), root mean square value (R_q), mean line peak spacing (R_{sm}) etc. As the surface topography is a non-stationary random process, the variances of slope and curvature depend strongly on the resolution of the roughness-measuring instrument or any other form of filter and these conventional roughness parameters are strongly depend on the resolution and filter processing of the instrument. In this context to express surface roughness the concept of fractal is applied. The concept is based on the self-affinity and self-similarity of surfaces at different scales. Roughness measurements on a variety of surfaces show that the power spectra of the surface profiles follow power laws. This suggests that when a surface is magnified appropriately, the magnified image looks very similar to the original surface. Fractals may retain all the structural information and are characterized by single descriptor, the fractal dimension, *D*.

There are many researchers who have tried to model the surface roughness in milling. Literature survey on milling shows that most of the literatures deal with conventional roughness parameters to describe surface roughness [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]. To modeling surface roughness, different tools are used viz. response surface methodology, Taguchi analysis, artificial neural network (ANN) etc. Now-a-days, artificial neural networks are successfully used to develop models to predict surface roughness more accurately [3, 11, 12, 13, 14, 15].

In the present study, using artificial neural network, models are developed to predict fractal dimension accurately, reliably in CNC end milling of aluminium material. Three machining parameters viz. spindle speed, feed rate and depth of cut are used as the inputs of the neural network and corresponding fractal dimension is as the output of the neural network.

2. FRACTAL CHARACTERIZATION
Multi-scale property of the rough surfaces including machining surfaces is characterized as self similarity and self affinity in fractal geometry implying that when the surface or the profile is magnified more and more details emerge and the magnified image is statistically similar to the original topography. Statistical self-similarity means that the probability distribution of a small part of a profile will be congruent with the probability distribution of the whole profile if the small part is magnified equally in all directions. On the other hand, self-affinity implies unequal scaling in different directions. The qualitative description of statistical self-affinity for a surface profile is shown in Fig. 1.

The property of self-affinity can be characterized by the profile fractal dimension *D* ($1< D <2$). Isotropic and homogeneous rough engineering surface of dimension

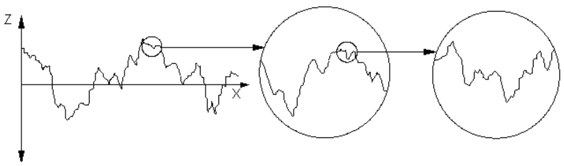

Fig 1. Qualitative description of self-affinity of a surface profile

Ds (2 < Ds < 3) is considered in this study. The property of isotropy means that the probability distribution of heights is invariant when the coordinate axes are rotated and the surface is reflected on any plane. The property of homogeneity of a surface indicates that the probability distribution of the height is independent of the location on the surface. Therefore, the profile, z(x), of such a surface along a straight line and in any arbitrary direction is of dimension D = Ds -1 and is a statistically valid representation of the surface. Thus the profile fractal dimension D is adopted to characterize the fractal nature of the surface in this paper. The profile z(x) in Fig. 1 has the mathematical properties of being continuous everywhere but non-differentiable and is self-affine in roughness structure. These properties are satisfied by the Weierstrass–Mandelbrot (W-M) fractal function, which can be used to characterize the roughness of surface profile and is given as

$$z(x) = G^{(D-1)} \sum_{n=n_1}^{\infty} \frac{\cos 2\pi\gamma^{n} x}{\gamma^{(2-D)n}} \; ; \; 1 < D < 2; \; \gamma > 1 \tag{1}$$

where G is a characteristic length scale, γ where L is the sampling length. $\gamma^{n} = \omega$, where frequency ω is the reciprocal of wave length and n is called wave number. To provide both the phase randomization and high spectral density γ is selected to be 1.5. The parameters G and D form the set to characterize profile z(x). The methods for calculating profile fractal dimension mainly include the yard-stick, the box counting, the variation, the structure function and the power spectrum methods. Out of these, the power spectrum and structure function methods are most popular. Sahoo et al. [16] have presented the procedure to calculate fractal dimension using power spectrum and structure function methods.

3. EXPERIMENTAL DETAILS

Milling operation on aluminium is carried out on 'DYNA V4.5' CNC end milling machine having the control system SINUMERIK 802 D with a vertical milling head and equipped with maximum spindle speed of 9000 rpm, feed rate 10 m/min and 10kW driver motor. For generating the milled surfaces, CNC part programs for tool paths are created with specific commands. Commercially available CVD coated carbide tools are used in this investigation. The tools used are flat end mill cutters (8 mm diameter, 300 helix angle, TiAlN coated solid carbide, parallel shank, 4 flutes) produced by WIDIA (EM-TiAlN). The tools are coated with TiAlN coating having hardness, density and transverse rupture strength as 1570 HV, 14.5 g/cc and 3800 N/mm^2. The compressed coolant servo-cut is used as cutting environment. All the specimens are in the form of 100 mm x 75 mm x 25 mm blocks. For the experimentation, a full factorial design of experiment is used with five levels of each of the three design factors viz. depth of cut (d, mm), spindle speed (N, rpm) and feed rate (f, mm/min). Thus the design chosen is five level-three factor (5^3) full factorial design consisting of 125 sets of coded combinations. Three cutting parameters are selected as design factors while other parameters have been assumed to be constant over the experimental domain. The upper and lower limits of a factor are coded as +1 and -1 respectively. The process variables with their values on different levels are listed in Table 1. The response variable used to accomplish the present study on surface topography characterization is the profile fractal dimension, D. Roughness profile measurement is done using a portable stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+).The measured profile is digitized and processed through the dedicated advanced surface finish analysis software Talyprofile.

Table 1: Variable levels used in the experimentation

Levels	**d** (mm)	**N** (RPM)	**f** (mm/min)
-1	0.10	4500	900
-0.5	0.15	4750	950
0	0.20	5000	1000
0.5	0.25	5250	1050
1	0.30	5500	1100

4. ARTIFICIAL NEURAL NETWORK

A neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use [17]. In this study, to construct the neural network models, three cutting parameters viz., spindle speed, feed rate and depth of cut are used as the input neurons and corresponding fractal dimension as the output neuron. To construct the models, the hyperbolic tangent sigmoid function in the hidden layer and linear activation function in the output layer is considered. Determination of hidden layer(s) and numbers of neurons in the hidden layer(s) is a considerable task. But, generally, one hidden layer network is selected first. If it does not perform well then two or more hidden layers are used. Optimum number of neurons in the hidden layer is decided by trail with increasing the number of neurons. In this study, to train the network, Levenberg-Marquardt algorithm is selected for training. The best network is selected based on the minimum mean square error (MSE) which is expressed as follow.

$$MSE = \frac{1}{N} \sum_{p=1}^{N} \sum_{k=1}^{n} (d_{k,p} - o_{k,p})^2 \tag{2}$$

where, N is the number of pattern, n is the number of node in the output layer, $d_{k,p}$ is the desired/experimental output for k^{th} node of the p^{th} pattern and $o_{k,p}$ is the calculated/predicted output of k^{th} node of p^{th} pattern.

Nguyen-Widrow weight initialization algorithm has been applied which generates initial weight and bias values for a layer so that the active regions of the layer's neurons will be distributed roughly evenly over the input space [18]. The main target of a properly trained neural network is to give reasonable answers when presented with inputs that they have never seen which is called the generalization capability. In the current study, “early stopping” technique is implemented. For this, out of 125 datasets, randomly 75 sets are used for training, 25 datasets for testing and rest 25 datasets for validation purpose. The validation set determines when the training should stop by monitoring the error. Testing set does not participate in the training of the network but is used to test the generalization of the trained network.

5. RESULTS AND DISCUSSION

According to the full factorial design of experiments, total 125 experiments are carried out. These datasets are randomized and 60% of data are chosen for training, 20% for testing and rest 20% for validation purpose. Three cutting parameters viz., spindle speed, feed rate and depth of cut are used as the input neurons and corresponding fractal dimension as the output neuron. For training with Levenberg-Marquardt (L-M) algorithm is applied, initial learning rate for the network is kept at 0.001 with learning rate decrease factor as 0.10 and learning rate increase factor as 10. The maximum learning rate is 10^{10}. Number of neurons in the hidden layer is decided by trail with increasing number of neurons. The neurons in the hidden layers are varied from 5 to 20 to find out the best neural network model. Minimum mean squared error (MSE) is used as the selection parameter. Besides this parameter, for the network, correlation coefficient (R) and maximum absolute percentage error for the training data set and testing data set are calculated. MATLAB 6.5 is used to develop the neural network, train and test the network.

Table 2: Performance comparison of different models for aluminium

Model	MSE	Correlation Coefficient (R)	Max. Training Error (%)	Max. Testing Error (%)
3-5-1	0.00036419	0.621	4.59	8.24
3-6-1	0.00059051	0.619	8.14	3.38
3-7-1	0.00037458	0.684	6.47	4.22
3-8-1	0.00030738	0.766	4.79	2.99
3-9-1	0.00023574	0.721	3.94	7.19
3-10-1	0.00030109	0.741	5.10	3.18
3-11-1	0.00038570	0.741	6.41	5.71
3-12-1	0.00040127	0.728	5.46	2.94
3-13-1	0.00026732	0.735	3.37	8.12
3-14-1	0.00022923	0.825	3.79	3.62
3-15-1	**0.00021834**	**0.862**	**5.16**	**2.24**
3-16-1	0.00038897	0.829	5.49	2.99
3-17-1	0.00050077	0.753	7.68	4.67
3-18-1	0.00023998	0.824	5.00	4.79
3-19-1	0.00036579	0.704	7.29	5.86
3-20-1	0.00022096	0.853	2.94	11.95

The performances of different developed networks are presents in Table 2. It is seen from the table that the architecture 3-15-1 gives the minimum mean squared error and is selected for further study. It is seen that the maximum absolute percentage error is 5.16% for training data set. However, mean absolute percentage error for training data is 0.76% which is very low. It implies that the ANN predicted and experimental fractal dimensions are close to each other. The performance of the neural network is tested by carrying out regression analysis and it is seen that correlation coefficient (R) is 0.862 (Fig. 2) which is a good indication of correlation of predicted and experimental fractal dimensions. The network is also tested with 25 new testing sets. Table 3 presents the comparative study of the experimental fractal dimension (*D*) and ANN predicted fractal dimension (*D*) for testing pattern. Maximum absolute percentage error and mean absolute percentage error are 2.24 and 0.84 respectively for testing pattern (Table 3). It implies that the experimental value and ANN predicted values lie very close to each other. Regression analysis is conducted for testing pattern also and it is observed from the regression analysis that correlation coefficient (R) is 0.817 (Fig. 3)

Table 3: Comparative study of experimental and ANN predicted fractal dimension, *D* for testing set (aluminium)

Cutting Parameters			Experimental *D*	Neural Network Predicted *D*	Absolute Percentage Error for NN
d	N	f			
-1	-0.5	1	1.36	1.3612	0.09
-1	0	-1	1.35	1.3266	1.73
-1	0	-0.5	1.34	1.3467	0.50
-1	0	0.5	1.34	1.3445	0.34
-1	1	1	1.38	1.3589	1.53
-0.5	0	-1	1.35	1.3197	2.24
-0.5	0	0	1.34	1.3393	0.05
-0.5	0	0.5	1.34	1.3365	0.26
-0.5	0.5	-1	1.33	1.3343	0.32
-0.5	1	1	1.38	1.3505	2.14
0	-1	-1	1.41	1.408	0.14
0	-1	-0.5	1.35	1.3435	0.48
0	-0.5	0	1.35	1.3384	0.86
0	-0.5	1	1.31	1.3376	2.11
0	0	1	1.31	1.2997	0.79
0	0.5	0	1.34	1.3571	1.28
0	1	-1	1.36	1.3517	0.61
0	1	-0.5	1.35	1.3663	1.21
0.5	0	-1	1.33	1.3277	0.17
1	-1	-0.5	1.32	1.3082	0.89
1	0	-0.5	1.34	1.3283	0.87
1	0.5	0	1.32	1.3238	0.29
1	0.5	0.5	1.35	1.3357	1.06
1	1	0.5	1.3	1.3088	0.68
1	1	1	1.32	1.3248	0.36
Mean absolute error for ANN predicted *D* = 0.84%					

which implies moderate correlation between experimental and predicted responses. From the results, it is obvious that the network gives a good prediction of fractal dimension in milling of aluminium material.

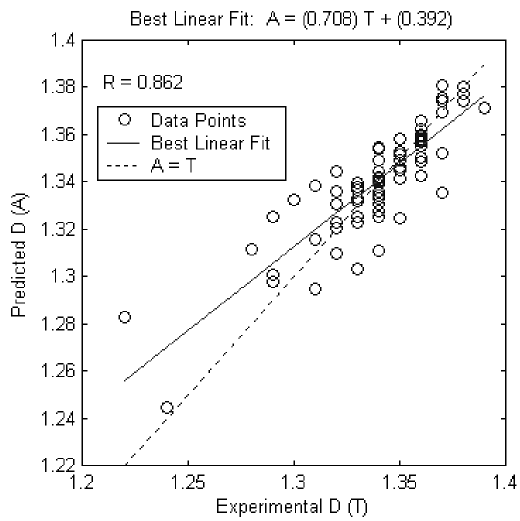

Fig 2. Performance of ANN model using regression analysis for training pattern (aluminium)

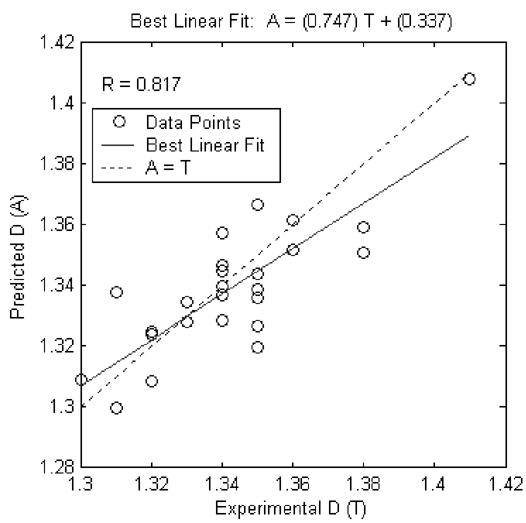

Fig 3. Performance of ANN model using regression analysis for testing pattern (aluminium)

6. CONCLUSION

Using back-propagation algorithm, artificial neural networks are developed for predicting fractal dimension (*D*) in CNC end milling of aluminium work-pieces. Levenberg-Marquardt training algorithm is used to train the network. Considering minimum mean squared error, architecture with 15 neurons in the hidden layer is selected as the best network. The mean absolute errors for training and testing patterns are 0.76% and 0.84% respectively. The results imply that the developed network predicts fractal dimension accurately. From the regression analyses, it is also clear that the experimental and predicted fractal dimensions are in good agreement. It can be concluded that the developed neural network model can reliably, successfully and accurately predict fractal dimension (*D*). The network also has a good generalization capability.

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