

SURFACE QUALITY INVESTIGATION IN MACHINING OF TITANIUM ALLOY WITH ROUND CVD COATED INSERTS BY NEURAL NETWORK APPROACH

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Abstract: Productivity and quality in the finish turning of titanium alloys can be improved by utilizing predicted performance of the work surface. This paper combines predictive machining approach with neural network modeling of surface roughness in order to estimate performance of chemical vapor deposition (CVD) coated (TiN-TiCN-Al₂O₃-TiN) round carbide inserts (Grade TT3500) for a variety of cutting conditions. Machining trials were conducted in lathe. The control parameters used were cutting speed, feed, and depth of cut. Machining trials were designed using the statistical design of experiment (DoE) techniques. Surface roughness have been measured for each operation and the associated data have been used to train an artificial neural network (multi-layer perceptron) using the back-propagation algorithm. The trained neural network has been used to predict the surface quality in terms of surface roughness. The developed prediction model was found to be capable of accurate surface roughness classification for the range it had been trained.

Key words: Turning Titanium alloy; CVD coated Round insert; Surface roughness; Artificial Neural networks (ANN)

1. INTRODUCTION

The quality of a machined surface is becoming more and more important to satisfy the increasing demands of sophisticated hardware performance, longevity, and reliability. Aerospace structures are being subjected to more severe conditions of stress, temperature, and hostile environments. In response to the above needs, there has been a continued development and use of heat resistant, corrosion resistant, and high strength alloys in a wide variety of structural applications.

Titanium alloys are generally used for structural applications, such as cases and impellers while nickel-based materials are used primarily in the hot section of the turbine. This arises due to their metallurgical and thermo-mechanical characteristics. For these particular alloys, machining productivity is limited by tool wear which indirectly represents a significant portion of the machining costs. However, properly selecting the tool material and cutting conditions provide an acceptable rate of tool wear and thus lowering the total machining cost. Machining of titanium alloys was the subject of interest for many years (Komanduri et al 1981, Hartung et al 1982, Kuljanic et al 1998, Dornfeld et al 1999, and Shivpuri et al 2002). Some researchers studied the mechanics of the chip formations and others investigated the wear mechanisms and surface quality. In all these studies the main objective was to increase the tool life while maintaining good surface quality and integrity (Kishawy et al 2004).

Major indication of surface quality on machined parts is surface roughness. In manufacturing systems, in order to

improve the quality of machining surface, it is necessary to select the most appropriate cutting conditions for any cutting tool and material with its own history of use (Che-Haron et al, 2005, Ezugwu et al 1997). At the time of making this selection, one of the most important tasks is to estimate as accurately as possible the surface roughness under specified cutting conditions.

The present study focuses on the surface roughness of titanium alloy (Gr 5) in turning by CVD coated (TiN-TiCN-Al₂O₃-TiN) round carbide inserts apart from regular cutting inserts (Ramesh et al 2006, Kevin Chou et al 2004). ANN model has been used for prediction of surface roughness in machining of titanium alloy.

2. METHODOLOGY ADOPTED

The methodology used in this paper is attempts to formalize and structure a procedure in which the conceptual design is done on paper based on experimental work and the later steps are an iterative cycle of modeling and simulation carried out on a computer using artificial Neural Network development tools and continued until the model behaves as desired. The methodologies involved in the simulation are given in the form of flow chart and shown in Fig. 1.

3. EXPERIMENTAL WORK

The experimental work was carried out on all geared high speed lathe. The turning operation was carried out on Titanium alloy (Ti64) having hardness from 305.2 to 307.3

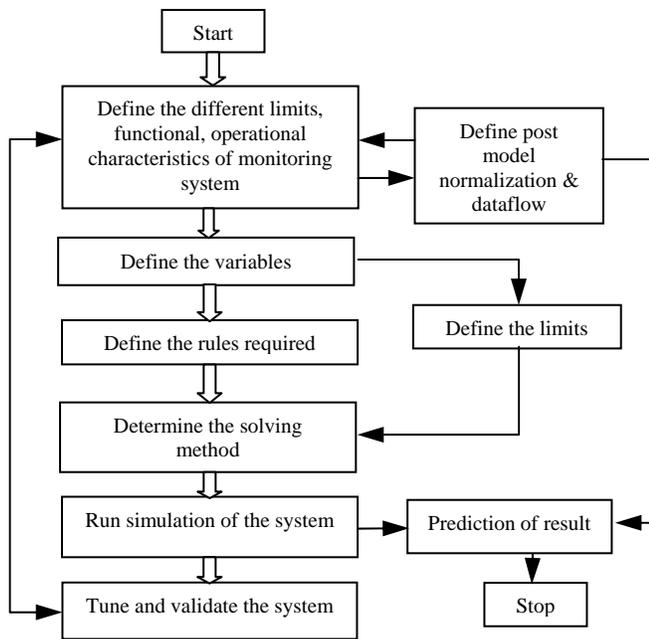


Fig 1. Methodology adopted

HV @ 500 gms load. The tool insert used is RCMT10T300MT TT3500 (ISO) – CVD coated carbide (Fig.2) of Taegutec, Korea. The performance of CVD - TiN-TiCN-Al₂O₃-TiN coated round (ϕ 10 mm) inserts were evaluated at three levels of cutting speeds, three levels of feeds and three levels of depth of cut. The level of the factors are decided on the availability of experimental condition and also based on the literature. The factors considered and their levels are presented in Table 1. Taguchi's L_{27} (3^{13}) orthogonal array (Montgomery, 1997) is considered for experimentation and input parameters are assigned to columns. The machining trials were carried out in dry conditions as shown in Fig. 3. For each experiment a new cutting point profile was used on the round insert. The surface roughness of the Titanium alloy (Gr 5) has been measured by using a stylus type instrument. Surface roughness tester Surtronic 3+ manufactured by Taylor Hobson with a cut-off length of 0.8 mm. The surface roughness used in this study is the arithmetic mean average surface roughness value (R_a), which is mostly used in industries. The experiments are repeated for three times and average values are used for analysis. The results are presented in Table 2.

Table 1. Factors and levels used for the experimentation

<i>Cutting Parameters</i>	<i>Symbol</i>	<i>Unit</i>	<i>Level 1</i>	<i>Level 2</i>	<i>Level 3</i>
Feed rate	f	mm/rev	0.065	0.13	0.22
Cutting Speed	V	m/min	10	40	60
Depth of cut	d	mm	0.5	0.75	1.0

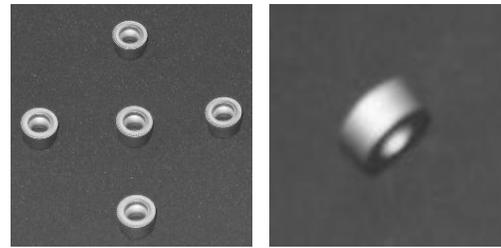


Fig. 2. CVD - coated round inserts



Fig. 3. Experimental Set-up (Dry Cutting)

Table 2. Experimental Results for CVD - TiN-TiCN-Al₂O₃-TiN coated round inserts – RCMT 10T300MT.

<i>Trial No.</i>	<i>V, m/min</i>	<i>f, mm/rev</i>	<i>d, mm</i>	<i>R_a, μm</i>
1	10	0.065	0.50	0.68
2	10	0.065	0.75	0.64
3	10	0.065	1.00	0.66
4	10	0.13	0.50	0.69
5	10	0.13	0.75	0.70
6	10	0.13	1.00	0.72
7	10	0.22	0.50	0.72
8	10	0.22	0.75	0.70
9	10	0.22	1.00	0.74
10	40	0.065	0.50	0.64
11	40	0.065	0.75	0.62
12	40	0.065	1.00	0.62
13	40	0.13	0.50	0.66
14	40	0.13	0.75	0.68
15	40	0.13	1.00	0.67
16	40	0.22	0.50	0.69
17	40	0.22	0.75	0.70
18	40	0.22	1.00	0.71
19	70	0.065	0.50	0.59
20	70	0.065	0.75	0.6
21	70	0.065	1.00	0.62
22	70	0.13	0.50	0.67
23	70	0.13	0.75	0.69
24	70	0.13	1.00	0.71
25	70	0.22	0.50	0.82
26	70	0.22	0.75	0.84
27	70	0.22	1.00	0.89

4. ARTIFICIAL NEURAL NETWORK MODEL

Artificial neural networks are capable computational models for a wide diversity of problems. The Neural Network models stems from the studies on the working of human brain systems and serve as an associative memory between the input and output patterns. Basically these contain many densely interconnected elements called “Neurons or Nodes”, which are nothing more than computational elements non-linear in nature.

The neuron has a set of n inputs x_j where the subscript j takes values from 1 to m and indicates the source of the input signal. Each input x_j is weighted before reaching the main body of the processing elements by the connection strength or weight factor W_j . In addition, it has a bias term and a summation that has to be reached a value of “ a ” (Hassoun 1995).

$$a = w_1x_1 + w_2x_2 + \dots + w_Nx_N + \text{Bias} \quad (1)$$

$$\text{Output} = \text{Threshold} [a] \quad (2)$$

Where

$$\text{Threshold} [a] = \begin{cases} -1 & \text{for all } a \leq 0 \\ 1, & \text{for all } a \geq 0 \end{cases} \quad (3)$$

The basic model of neuron is illustrated in the Fig. 4.

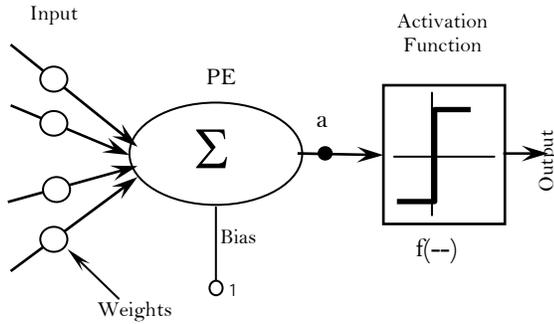


Fig.4. Basic Processing Element NN Model

In the present work, a multilayer perceptrons with each layer consisting of number of computing neurons, have been used. The algorithm used in this work is back propagation (BPA) algorithm. Back propagation (BP) is a systematic method for training multi-layer networks. Rumelhart, Hinton and Williams presented a clear and concise description of this algorithm (Rumelhart et al 1986). Basically the idea is to measure error across the output units and then to propagate the error backwards through the network making any necessary weight changes at each layer of units, including hidden layers.

This procedure is repeated for all the training patterns. At the end of iteration, test patterns are presented to network, and the classification performance of network is evaluated. Further training of ANN is continued till the desired classification performance is reached. The weights w and the threshold values θ are adjusted until the error value comes within the limit. The steps involved in training ANN by using BPA are (Bershad et al 1993, Das et al

1996, and Purusothaman et al 1998, Eyup Bagci et al 2006).

Step1: The weights and thresholds are randomly initialized between layers.

Step2: The input of a pattern is presented to the input layer and the outputs of the neuron are computed as follows:

The activation function $f(x)$ used here is the Sigmoid function and is given by:

$$f(x) = \frac{1}{1 + \exp(-x)} \quad (4)$$

Between the input and hidden layer,

$$x = \sum_{i=1}^m w_{ji}u_i + \theta_j, \quad j = 1 \text{ to } n \quad (5)$$

and between the hidden and output layer,

$$x = \sum_{i=1}^n w_{ij}v_j + \theta_k, \quad k = -1 \text{ to } 1 \quad (6)$$

Where m is the number of input nodes, n is the number of hidden nodes, l is the number of output nodes (here it is 1), u are the input node values, and v are the hidden node values

Step3: The error of a pattern is calculated as follows:

The overall error, E , of all the patterns is given by:

$$E = \sum_{p=1}^n \frac{1}{2} \sum_{i=1}^m (T_{pi} - O_{pi})^2 \quad (7)$$

Where m is the number of outputs in the layer and n is the number of patterns; T_{pi} is the i^{th} component of the desired output vector; and O_{pi} is the calculated output of the i^{th} neuron in the output layer.

Step4: The error δ for each node in the output layer is computed by:

$$\delta_{pj} = O_{pj}(1 - O_{pj})(T_{pj} - O_{pj}) \quad (8)$$

Step5: The weights between layers are updated by:

$$w_{ij}(n+1) = w_{ij}(n) + \eta \delta_{pj} O_{pj} + \alpha(w_{ij}(n) - w_{ij}(n-1)) \quad (9)$$

Step6: The error for the nodes in the hidden layer is calculated by:

$$\delta_{pj} = O_{pj}(1 - O_{pj}) \sum_k \delta_{pk} w_{jk} \quad (10)$$

In these equations, η is a constant real number called the learning rate, which determines the influences of error over weight changes and α is the momentum or accelerating factor, δ_{pj} is the error owing to the p^{th} pattern connected to the j^{th} neuron and O_{pi} is the i^{th} neuron output when the p^{th} pattern is processed by the neural network.

Step7: For each training pattern, steps 5 and 6 are repeated till the input layer is reached.

Step8: The iteration process continues until the desired goal is reached.

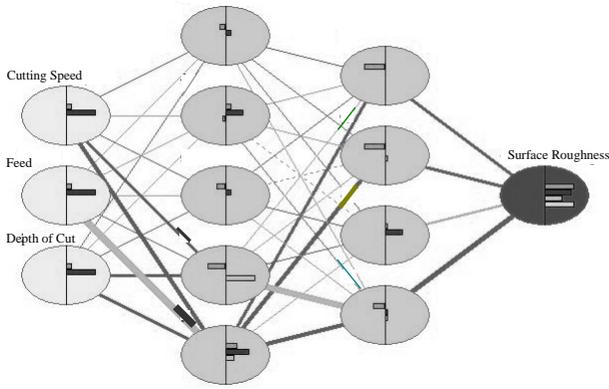


Fig.5. Topology of Neural network structure used for the investigation

When the ANN training is over, the network can monitor the state of the tool using the feed forward mechanism. Unfortunately there is little guidance, other than experience, which is based on trial-and-error. Another very significant limitation of BP is that there is no easy way to select learning parameters and network architecture (Luong et al, 1995).

The main objective of the present work is to investigate the ability of neural networks in predicting the surface finish of the work material (Ti64) using the BP paradigm. The neural network architecture designed for the present investigation is shown in Fig. 5. The inputs of a pattern are cutting speed, feed and depth of cut. The output of the network obtained in the output layer is compared with the desired output. The difference between the calculated output of the network and the desired output is called error (MSE) of the network for the pattern presented. This error is propagated backwards, such that the weights connecting the different layers are updated. By this process, the MSE of the network for the pattern presented is minimized. The training of the network can be stopped, by considering MSE.

The network model is trained by using a typical sample of patterns and tested for new patterns. The training pattern should be representative of all the patterns observed during machining trials. The data values are normalized to bring all the values in the range of 0 to 1.

The results of surface roughness estimates were obtained from the network and the percentage error deviations were computed with reference to the experimental values.

5. RESULTS AND DISCUSSION

A software package called “EasyNN-plus” Version 8.0i (2002) was used for network development, training and testing. The network works on the back propagation algorithm. In calculation of weight variables, often referred to as network training, the weights are given quasi-random, intelligently chosen initial values. The performance of the network was measured by mean square error (MSE), for both the training and testing stages. The optimal ANN architecture was designed by using trial and error method.

Feng et al (2002), in his study stated that two hidden layers perform better than a one hidden layer and hence two hidden layers have been used. In this present work, the inputs are fully connected to hidden layers and hidden layers are fully connected to output layer. The input layer has three neurons corresponding to three input parameters and output layer has one neuron corresponds to surface roughness. The ANN model used has five neurons in first hidden layer and four neurons in second hidden layer (i.e. a 3-5-4-1 net). There are 18 patterns are used for training the network from the experimental results. The trained network model was tested using 9 experimental results, which were not used in the training process and known as testing experiments. The details of BP parameters and their values are shown in Table 3.

Table 3. BP parameters and their values

<i>BP networks parameters</i>	<i>Value</i>
Networks topology structure	3-5-4-1
Learning rate (α)	0.9
Momentum rate (β)	0.8
Initial weights	Random of (0.5)

Table 4. Comparison of ANN predictions with experimental results

<i>Trial #</i>	<i>Expt. results</i>	<i>ANN</i>	<i>Error</i>	<i>Accuracy %</i>	
1	0.68	0.677	0.003	99.7	<i>(Ave 99.46) Values used for Training the N/W</i>
2	0.70	0.689	0.011	98.9	
3	0.74	0.738	0.002	99.8	
4	0.62	0.624	-0.004	99.6	
5	0.67	0.667	0.003	99.7	
6	0.69	0.698	-0.008	99.2	
7	0.62	0.625	-0.005	99.5	
8	0.67	0.669	0.001	99.9	
9	0.84	0.829	0.011	98.9	
10	0.64	0.653	-0.013	98.7	<i>(Max 99.2, Min 88.2, Ave 96.69) Values used for Testing the N/W</i>
11	0.66	0.628	0.032	96.8	
12	0.69	0.688	0.002	99.8	
13	0.72	0.690	0.03	97	
14	0.72	0.688	0.032	96.8	
15	0.70	0.696	0.004	99.6	
16	0.64	0.641	-0.001	99.9	
17	0.62	0.623	-0.003	99.7	
18	0.66	0.687	-0.027	97.3	
19	0.68	0.682	-0.002	99.8	
20	0.70	0.748	-0.048	95.2	
21	0.71	0.828	-0.118	88.2	
22	0.59	0.623	-0.033	96.7	
23	0.6	0.622	-0.022	97.8	
24	0.69	0.648	0.042	95.8	
25	0.71	0.641	0.069	93.1	
26	0.82	0.759	0.061	93.9	
27	0.89	0.834	0.056	94.4	

The error at the beginning of the iteration process is around 0.65. When the iteration continues, the error has been reduced. At the 426th iteration, the error reached to the target error of 0.00099. At the outset the average error for the performance of the ANN when testing all the training and testing pattern is only up to 4.0%.

In the Table 2, the first column indicates the number of experimental trials used for training the network and the next three columns indicates cutting parameters symbols viz; cutting speed (V), feed rate (f) and depth of cut (d). These three columns are considered as input parameters for the network configuration. In the Table 4, the second column indicates the experimental output obtained as surface roughness. The predicted ANN surface roughness using 3-5-4-1 architecture is given in column 3. The difference between the experimental results and ANN is presented in column 4 and is denoted by Error.

After training for various configurations finally, 3-5-4-1 was found to be feasible by trial and error method and the network is tested using the 18 untrained patterns. The average error obtained was very less for the 9 set of patterns. The results predicted from the ANN model are compared with those obtained by experimental test, and is shown in Table 4. The 1-9 rows are used for training purpose and its training accuracy can be witnessed along with untrained fresh values in 10-27 rows expressed in italic font. The learning curve of the present investigation is presented below shows in Fig 6.

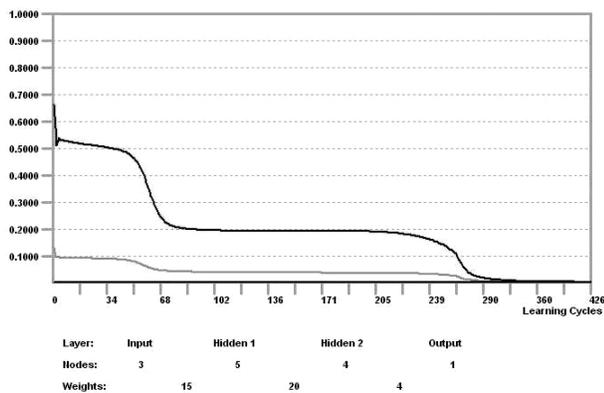


Fig.6. Learning progress curve for the 3-5-4-1 net

The associations found in Round Insert Dat.tvq

List of up to 4 associations in 4 columns. The list is finished.
The last association found was for column number 3 named "Surface Roughness".

Associated columns	Strength
1 feed 3 Surface Roughness	15.142242
3 Surface Roughness 1 feed	10.538907
0 Cutting Speed 2 doc	5.228829
2 doc 1 feed	3.788689

Round Insert Dat.tvq 426 cycles. Target error 0.0010 Average training error 0.000999
The first 3 of 3 Inputs in descending order.

Column	Input Name	Importance	Relative Importance
1	feed	8.7626	
0	Cutting Speed	8.6801	
2	doc	7.4023	

Fig.7. Associations and relative importance of each input

Fig. 7 indicates the associations and relative importance of each input during training the ANN model. From the illustration it is noticed that feed rate is the main contributing factor and its value shows 8.76 points. The next very closing one is cutting speed with a value of 8.68 points.

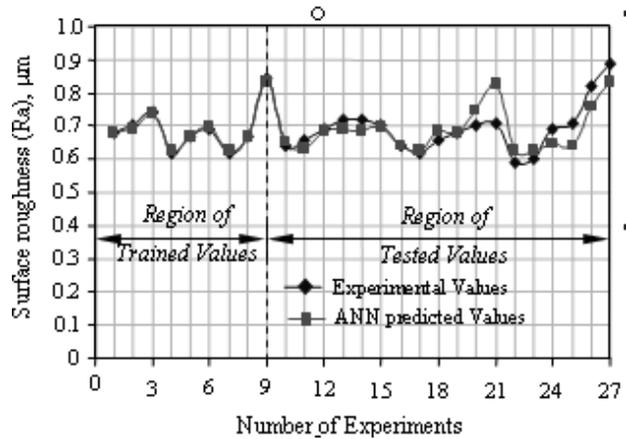


Fig.8. Comparison of ANN predictions with experimental results

Fig. 8 shows the comparison of experimental results with artificial neural network (ANN) model. From the figure it can be confirmed that the developed artificial neural network model has good interpolation with the regions in test values and trained values and are very close to the experimental results. Further it can be observed from the Fig. 8, that comparison of trained values region gives exact fit (99.46%) with experimental results to claim the training accuracy of the network. At the same time, comparison of test values region gives approximately 96.69% error free fit over the experimental results.

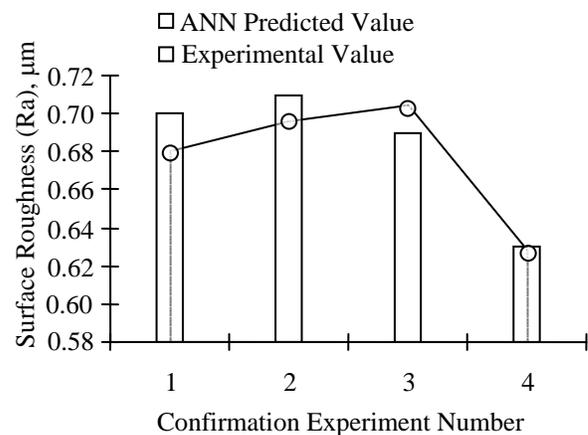


Fig.9. Comparison of NN prediction with confirmation experimental results

The confirmation results in comparison with ANN are presented in Fig. 9. It is seen from figure that ANN prediction is in good agreement with the experimental results. From the results with reference to Table 4 and Figs. 8 and 9, it is found that the developed ANN model has good interpolation capability and can be used as an

efficient predictive tool for surface roughness. Increasing the number of nodes increases the computational cost and decreases the error Benardos et al (2003).

Since the turning of titanium alloy is difficult, the quality of surface finish is poor and uncontrollable. Titanium alloy and the round inserts have more attention towards cost reduction in efficient manufacturing. In this circumstances ANN is considered as an economically influenced offline tool to develop prediction models for finding surface roughness of machined component. Using the predicted machining parameters it is possible to optimize the machining of titanium alloys in real time manufacturing.

5. CONCLUSION

In this study, the experimental observations were incorporated into the ANN model for turning of titanium alloy (Gr-5). A feed forward neural network model was developed to predict surface roughness after the turning process. Models were also compared to predict surface roughness accurately within a wide range of cutting parameters based on DOE. Good agreement was shown between the predictive models results and the experimental measurements.

The neural network method can be considered as an alternative and competent modeling for estimating the surface roughness based on the cutting conditions and machining time. The model has been validated by using typical training patterns for inference on test patterns. The method seems to have prediction potentials for non experimental patterns additionally.

Tool nose radius is a geometric parameter in machining and its effects on Ti64 turning have been investigated. Large tool nose radii seem to only have the advantage of finer surface finish over the previous studies.

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