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Experimental Investigation on Machining of Titanium Alloy (Ti 6Al 4V) and Optimization of its Parameters using ANN

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1. Introduction

Cutting force, tool wear and temperature rise during machining are some of the key considerations for both the designer, manufacturer of machine tools, and to the end user as well. [1, 2]. Manufacturing industries continuously focus on low cost machining solutions with reduced lead time and good surface quality in order to maintain their competitive edge and efficiency [3]. Recent developments in cutting tool grades are intended to permit multipurpose use both in machining and finishing operations and for a wide range of materials [4]. Advancements in coating technologies have produced wide range of tools which have a special wear resistant coating. Coated tools used for metal cutting possess a combination of abrasive wear resistance and chemical stability at high temperature to meet the demands of the application [5-7].

Product quality is a well-known vital factor that has a direct bearing on customer satisfaction. In any industrial sector, be it a small-scale industry or a large industrial sector, surface quality is determined by surface roughness of the product [8]. Measuring and characterizing the surface finish are the two main indicators of machining performance. Since the newer materials are being developed and introduced rapidly in the manufacturing industry, it is very difficult for an operator to select optimum cutting parameters to achieve best surface finish [9, 10]. The cost of machining accounts for a major part of the total value of products in any manufacturing industry and plays a central role in modern manufacturing. Modeling with the help of experimental results forms an integral part in the investigation of the complicated dynamic mechanisms of machining operations. Various approaches have been proposed to model and to simulate the machining processes [11]. Optimization of cutting parameters is necessary for the achievement of minimal surface roughness. The Taguchi method of experimental design is one of the widely accepted techniques for off line quality assurance of products [12, 13]. This method is a traditional approach for robust experimental design that seeks to obtain the best combination of parameters and their levels with the lowest cost to meet customer requirements [14]. Cutting fluids decrease friction between the cutting tool and the work piece material, preventing surface roughness. The conventional cutting fluids utilized in machining are considered as a problem for manufacturers. Environmental concerns have become increasingly important to production processes [15]. Dry machining and minimum quantity lubricant machining have become the focus of attention of researches and technicians in the field of machining as an alternative to conventional fluids [16, 17]. Optimization of machining parameters not only improves machining economics, but also the quality to a greater extent. Developments in modeling surface roughness and optimization of controlling parameters to obtain a surface finish of desired level is possible through proper selection of cutting parameters which produce better performance [18–20]. Influence of built up edge on process forces, surface quality and minimum chip thickness during machining of titanium alloys, reveals that the good surface integrity in terms of favorable stress and surface roughness were achieved in machining of titanium alloys [23–25].

The literature survey reveals that the machining of titanium alloy has not been attempted by many researchers. In the present investigation, an attempt has been made to optimize surface finish and material removal rate on machining Titanium alloy (Ti 6Al 4V) with ceramic coated cutting tool insert. Taguchi parameter design approach and ANN technique has been employed to accomplish the objectives.

2. Experimental details

Based on a number of research works published in the past, three cutting parameters viz., cutting speed, feed rate and depth of cut were selected for the experimental work.

2.1. Machine, material and tool insert

The turning operation was conducted using CNC-Super Jobber 500 LM Industrial type of production lathe machine with a range of spindle speed 30 rpm to 3000 rpm and a 10 kW motor drive. The material used was Ti-6Al-4V titanium alloy round bar of 30 mm diameter and 100 mm long. The specimens were turned, centered and cleaned by removing the skin for 1mm depth, prior to the actual machining. The cutting tool insert used for this study was ceramic coated. Fig. 1 shows the sample of Ti-6Al-4V materials, and Fig. 2 shows the microstructure of the Ti-6Al-4V material. Chemical composition of Titanium alloy (Ti 6Al 4V) is given in Table 1.

Fig. 1 Ti–6Al–4V

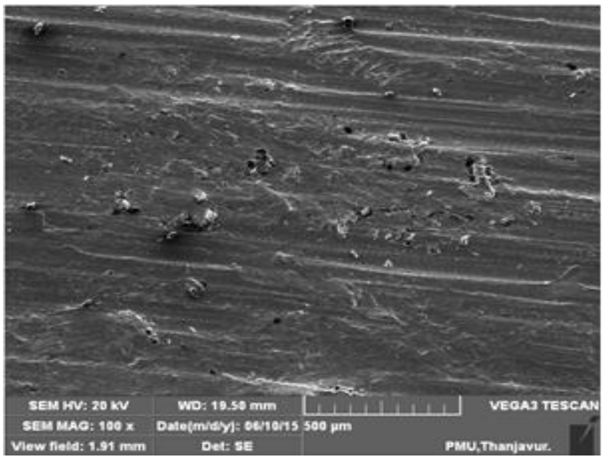

Fig. 2 SEM Image of Ti-6Al-4V

Table 1

Chemical composition of Ti-6Al-4V

Component	C	V	Fe	Al	Ti
Weight %	0.027	3.87	0.11	5.81	Reminder

2.2. Surface roughness measurements & MRR calculations

The roughness readings were recorded at three locations on the work piece and the average value was used for analysis. The Material Removal Rate (MRR) was calculated using:

$$\text{Material Removal Rate} = \frac{W_i - W_f}{\rho s * t}, \tag{1}$$

where: W_i is Initial weight of work piece in grams; W_f is= Final weight of work piece in grams; t is Machining time in seconds; ρs is Density of titanium alloy 4.5 g/cm^3.

3. Taguchi orthogonal array

The Taguchi method is a powerful tool in quality optimization. Optimization is carried out to utilize the available resources effectively to achieve better results. The orthogonal array of twenty seven experiments in a particular order covers all factors. In this method, selected parameters are assumed to have influence on process results, which are located at different rows in a designed orthogonal array [18]. With such an arrangement completely randomized experiments can be conducted. This method is useful for studying the interactions between the parameters, and also it is a powerful design of experiments tool, which provides a simple, efficient and systematic approach to determine optimal cutting parameters [16]. Compared to the conventional approach of experimentation, this method reduces significantly the number of experiments that are required to model the response functions. Hence the optimality is achieved. The three machining parameters were selected as control factors, and each parameter was designed to have three levels as shown in Table 2.

The turning tests were conducted to determine the surface roughness and material removal rate under various sets of turning parameters. Roughness is measured using Mitutoyo Surface roughness tester. The different combinations of speed, feed rate and depth of cut based on which the experiments are conducted is presented in Table 3.

Table 2

Machining parameter and its levels

S.No	Parameters	Units	Levels		
1	Speed	rpm	1000	1500	2000
2	Feed	mm/rev	0.10	0.15	0.20
3	Depth of cut	mm	0.50	0.75	1.00

Table 3

Experimental results for surface roughness and material removal rate

Run No.	S (rpm)	F (mm/rev)	D (mm)	R_a (μm)	MRR (mm^3/sec)
1	1000	0.10	0.50	2.83	424.34
2	1000	0.10	0.75	3.2	452.65
3	1000	0.10	1.00	3.64	472.91
4	1000	0.15	0.50	3.45	465.75
5	1000	0.15	0.75	4.3	483.96
6	1000	0.15	1.00	4.52	496.52
7	1000	0.20	0.50	4.25	485.91
8	1000	0.20	0.75	4.82	502.74
9	1000	0.20	1.00	5.72	523.86
10	1500	0.10	0.50	2.43	512.75
11	1500	0.10	0.75	2.93	534.85
12	1500	0.10	1.00	3.35	552.97
13	1500	0.15	0.50	3.05	524.85
14	1500	0.15	0.75	3.42	542.86
15	1500	0.15	1.00	4.05	560.32
16	1500	0.20	0.50	3.73	553.64
17	1500	0.20	0.75	4.05	571.95
18	1500	0.20	1.00	4.72	592.65
19	2000	0.10	0.50	1.96	581.55
20	2000	0.10	0.75	2.24	598.53
21	2000	0.10	1.00	2.95	620.74
22	2000	0.15	0.50	2.82	596.52
23	2000	0.15	0.75	3.08	621.95
24	2000	0.15	1.00	3.65	640.75
25	2000	0.20	0.50	3.24	620.84
26	2000	0.20	0.75	3.82	642.86
27	2000	0.20	1.00	4.02	660.25

4. Results and discussion

4.1. Optimal setting of machining parameters

In turning operation the surface roughness and MRR are considered important from quality standpoint and economy of machining. After recording the observations, the mean values are calculated and various graphical analyses are done by using Minitab 16 software. The measured response value along with design matrix is furnished in Table 4.

Taguchi method stresses the importance of studying the response variation using the signal-to-noise ratio, resulting in minimization of quality characteristics variation due to uncontrollable parameter. The roughness was considered as the quality characteristics with the concept of “smaller-the-better”. From the response tale of surface roughness, it is found that feed rate is the predominant factor in affecting the roughness value followed by speed and depth of cut.

Table 4

Measured response value along with design matrix

Run Number	S (rpm)	F (mm/rev)	D (mm)	Experimental R_a (μm)	Predicted R_a (μm)	Experimental MRR (mm^3/sec)	Predicted MRR (mm^3/sec)
1	1000	0.1	0.5	2.83	2.873	424.34	428.226
2	1000	0.1	0.75	3.2	3.329	452.65	451.117
3	1000	0.1	1	3.64	3.858	472.91	470.558
4	1000	0.15	0.5	3.45	3.630	465.75	462.919
5	1000	0.15	0.75	4.3	4.086	483.96	483.897
6	1000	0.15	1	4.52	4.614	496.52	499.414
7	1000	0.2	0.5	4.25	4.300	485.91	484.856
8	1000	0.2	0.75	4.82	4.755	502.74	504.337
9	1000	0.2	1	5.72	5.284	523.86	523.318
10	1500	0.1	0.5	2.43	2.318	512.75	512.618
11	1500	0.1	0.75	2.93	2.773	534.85	533.866
12	1500	0.1	1	3.35	3.302	552.97	554.087
13	1500	0.15	0.5	3.05	3.074	524.85	524.354
14	1500	0.15	0.75	3.42	3.530	542.86	543.689
15	1500	0.15	1	4.05	4.059	560.32	559.987
16	1500	0.2	0.5	3.73	3.744	553.64	554.268
17	1500	0.2	0.75	4.05	4.200	571.95	572.106
18	1500	0.2	1	4.72	4.729	592.65	591.867
19	2000	0.1	0.5	1.96	1.879	581.55	577.797
20	2000	0.1	0.75	2.24	2.334	598.53	601.048
21	2000	0.1	1	2.95	2.863	620.74	621.976
22	2000	0.15	0.5	2.82	2.636	596.52	599.847
23	2000	0.15	0.75	3.08	3.091	621.95	621.184
24	2000	0.15	1	3.65	3.620	640.75	638.189
25	2000	0.2	0.5	3.24	3.306	620.84	621.267
26	2000	0.2	0.75	3.82	3.761	642.86	641.108
27	2000	0.2	1	4.02	4.290	660.25	661.576

4.2. Analysis of variance

ANOVA is a statistical tool used to analyse the test for significance individual model coefficients, test for lack of fit. In performing ANOVA, it is essential to identify the dependent and the independent variables. Dependent variables reflect the outcome of the process, and independent variables reflect the factors that influence the dependent variables. Dependent and independent variables are related to each other. For analysing the effect of categorical factors on a response, ANOVA is a useful technique. The response table for MRR shows that the speed is the predominant factor in affecting material removal rate followed by feed rate and depth of cut. The adequacy of the developed model was evaluated using the analysis of variance. It consists essentially of partitioning the total variation in an experiment into components ascribable to the controlled factors and errors. Table 5 and Table 7 represent the results of ANOVA for the responses of surface roughness and material removal rate. The best levels of various parameters are identified by calculating the average values of minimum surface roughness and maximum MRR are tabulated in Table 6 and Table 8 respectively. In the ANOVA table, the sum of squares is used to estimate the square of deviation from the grand mean. The F-ratio is an index used to check the adequacy of the model in which the calculated value of F should be greater than the F-table value. The model is adequate at 95% confidence level.

The main effect plot for Ra and MRR were represented in Fig. 4 and Fig. 6. To summarize the responses, the plots of various interactions with control factors are carried out. The residual plot for means of surface roughness and the residual plot for means of MRR are presented in Fig. 3 and Fig. 5 respectively. The best parameters for surface roughness has been plotted in Fig. 4 as speed 2000 rpm, feed 0.10 mm/rev and depth of cut 0.50 mm. Fig.6 represents the parametric combination of Speed 2000 rpm, feed 0.20 mm/rev and depth of cut 1mm for maximum Material Removal Rate.

Table 5

ANOVA Table for surface roughness (*Ra*)

Source	DOF	SS	MS	F	P	% Contribution C
S	2	15.1250	7.5625	61.93	0.020	24.11
F	2	30.3670	15.1835	124.35	0.026	48.42
D	2	14.8711	7.4356	60.89	0.974	23.71
S*F	4	0.8851	0.2213	1.81	0.220	01.41
F*D	4	0.1781	0.4450	0.36	0.827	00.28
S*D	4	0.3104	0.0776	0.64	0.652	00.49
Error	8	0.9768	0.1221			1.55
Total	26	62.7135				99

Table 6

Response Table for means of surface roughness (*Ra*)

Level	*S*	*F*	*D*
1	4.081	2.837	3.084
2	3.526	3.593	3.540
3	3.087	4.263	4.069
Delta	0.994	1.427	0.984
Rank	2	1	3

Table 7

ANOVA Table for Material Removal Rate (MRR)

Source	DOF	SS	MS	*F*	*P*	% Contribution *C*
S	2	4942456	2471228	3910.17	0.000	84.44
F	2	496518	248259	392.81	0.003	8.48
D	2	382837	191418	302.87	0.005	6.54
S*F	4	23870	5968	9.44	0.004	0.40
F*D	4	398	99	0.16	0.954	0.0068
S*D	4	1698	424	0.67	0.630	0.0290
Error	8	5055	632			0.0863
Total	26	5852832				99.89

Table 8

Response Table for means of Material Removal Rate (MRR)

Level	*S*	*F*	*D*
1	478.7	527.9	529.6
2	549.6	548.2	550.3
3	620.4	572.7	569.0
Delta	141.7	44.8	39.4
Rank	1	2	3

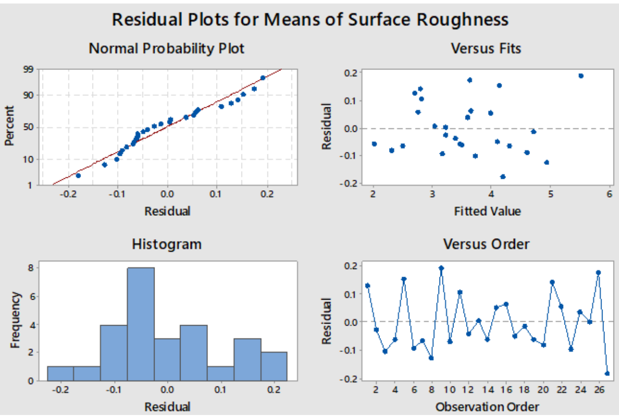

Fig. 3 Effect of residual plots for means of surface roughness

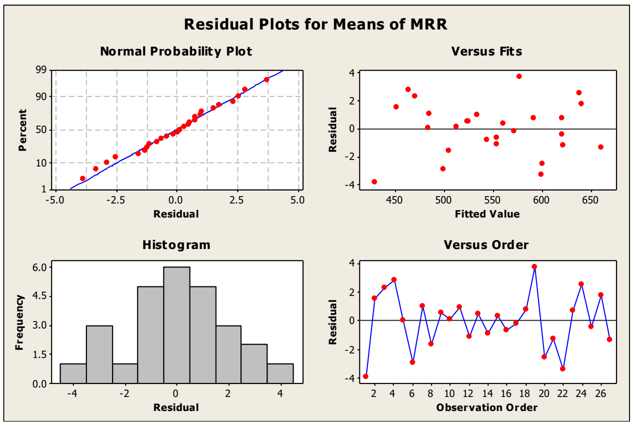

Fig. 5 Effect of residual plots for means of MRR

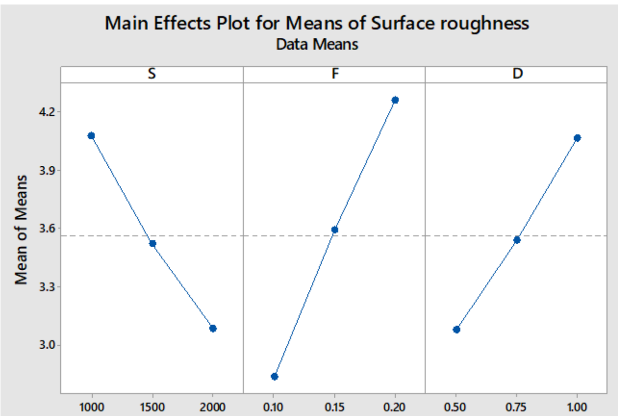

Fig. 4 Main effect plot for surface roughness

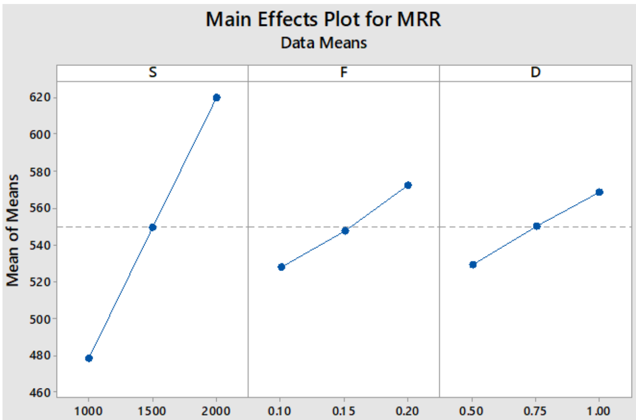

Fig. 6 Main effect plot for MRR

4.3. Artificial neural networks

The multi-layer feed forward ANN is employed in this study which consist of simple processing elements called neurons divided into input layer, output layer and hidden layers. The neurons between the layers are connected by the weight of links. Each neuron has inputs and generates an output as the reflection of local information stored in connections. The output of each neuron is determined by the level of the input signals in relation to the threshold value. These signals are modified by the connection weights between the neurons [21-22]. A Schematic representation of the basic structure of the multi-layered feed forward ANN Architecture is shown in Fig. 7

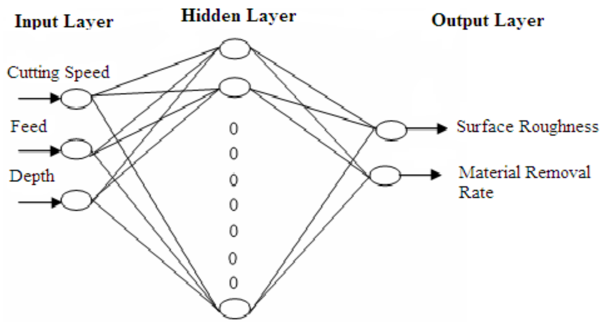

Fig. 7 Multi-layered feed forward ANN architecture

4.3.1. Training and testing of Artificial Neural Network

The training of the ANN with error BB Training algorithm for 27 input-output patterns has been performed using NN toolbox in MATLAB. In the current study, multi-layer feed forward ANN three neurons in the input layers and one hidden layer with ten neurons were considered to estimate surface roughness and Material removal rate of turning process. The network configuration of 3x10x2 was constituted, and it was saved during the determination of training parameters. The ANN training simulation was carried out using the variable learning rate training procedure of the mat lab NN toolbox. The network used in the program is a feed forward network with back propagation learning rule. Training begins with all weights set to random numbers. For each data record, the predicted value is compared to the desired (actual) value and the weights are adjusted to move the prediction closer to the desired value. Numerous trials were made through the entire set of training data with the weights being continually adjusted to produce accurate predictions. The Experimental roughness value along with Artificial Neural Network prediction values are tabulated in Table 9.

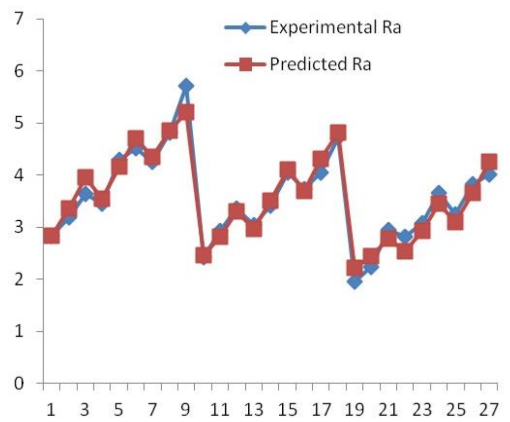

Fig. 8 Experimental value of R_a *Vs* ANN predicted value of R_a

Table 9

Comparison of ANN predictions with experimental results for R_a and MRR

Run Number	*S* (rpm)	*F* (mm/rev)	*D* (mm)	Experimental R_a (µm)	ANN Predicted R_a (µm)	Experimental MRR (mm^3/sec)	ANN Predicted MRR (mm^3/sec)
1	1000	0.1	0.5	2.83	2.843928	424.34	426.7355
2	1000	0.1	0.75	3.2	3.352428	452.65	427.4691
3	1000	0.1	1	3.64	3.950953	472.91	436.0164
4	1000	0.15	0.5	3.45	3.549086	465.75	426.8887
5	1000	0.15	0.75	4.3	4.153815	483.96	427.2054
6	1000	0.15	1	4.52	4.698388	496.52	499.0641
7	1000	0.2	0.5	4.25	4.349427	485.91	431.8641
8	1000	0.2	0.75	4.82	4.852869	502.74	502.7885
9	1000	0.2	1	5.72	5.210794	523.86	524.6546
10	1500	0.1	0.5	2.43	2.457893	512.75	528.7187
11	1500	0.1	0.75	2.93	2.809946	534.85	462.2631
12	1500	0.1	1	3.35	3.308059	552.97	453.7491
13	1500	0.15	0.5	3.05	2.962426	524.85	488.1307
14	1500	0.15	0.75	3.42	3.502533	542.86	435.3345
15	1500	0.15	1	4.05	4.107067	560.32	492.2854
16	1500	0.2	0.5	3.73	3.704767	553.64	475.1508
17	1500	0.2	0.75	4.05	4.304752	571.95	523.2008
18	1500	0.2	1	4.72	4.818412	592.65	555.7671
19	2000	0.1	0.5	1.96	2.22492	581.55	604.8637
20	2000	0.1	0.75	2.24	2.436294	598.53	629.8537
21	2000	0.1	1	2.95	2.776898	620.74	645.8801
22	2000	0.15	0.5	2.82	2.534986	596.52	574.5421
23	2000	0.15	0.75	3.08	2.925417	621.95	600.1156
24	2000	0.15	1	3.65	3.456404	640.75	655.9446
25	2000	0.2	0.5	3.24	3.090565	620.84	552.4539
26	2000	0.2	0.75	3.82	3.65722	642.86	647.7786
27	2000	0.2	1	4.02	4.259511	660.25	654.1854

The results of the comparison between the experimental surface roughness (*Ra*) and material removal rate (MRR) with ANN predicted values are presented in Fig.8 and Fig. 9. Thus, measurement shows that the experimental values and predicted values are comparable.

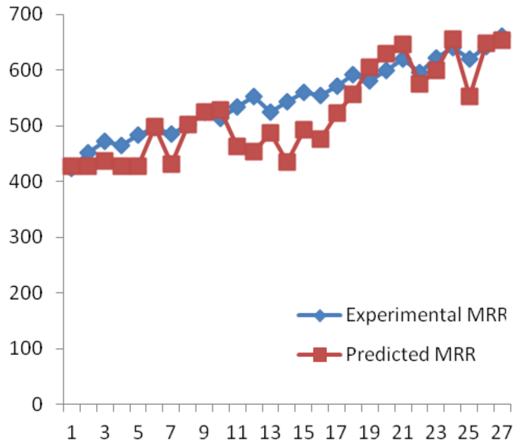

Fig. 9 Experimental value of MRR *Vs* ANN predicted value of MRR

5. Conclusion

The suitability of the ceramic coated insert for machining Ti-6Al-4V alloy was investigated in this study. The surface roughness and MRR after the turning operation were recoded and compared with predicted values using DOE and ANN. The following results can be concluded from the present study.

1. The experiments were conducted by varying the cutting speed, feed rate and depth of cut and the resulting surface roughness and material removal rate was measured for different cutting conditions. The optimum parameter setting for minimization of roughness and maximization of material removal rate was arrived.

2. For surface roughness, the optimal parametric combination is $S_3F_1D_1$ i.e., surface roughness is minimum at the parametric combination of 2000 rpm Speed, 0.1 mm/rev Feed and 0.50 mm depth of cut.

3. For material removal rate, the optimal parametric combination is $S_3F_3D_3$ i.e., material removal rate is maximum at the parametric combination of 2000 rpm Speed, 0.20 mm/rev Feed and 1 mm depth of cut.

4. The modelling performance of the neural network has been evaluated. The results clearly show that there are highly linear relationships between surface roughness and MRR with the cutting parameters. This situation validates the employing of ANN to develop a model for surface roughness and MRR prediction. The ANN model show very good closeness between estimated and measured values.

5. The order of the importance of influential factors based on the Taguchi response is sequenced as feed rate, cutting speed and depth of cut.

6. The adequacy of the developed model is evaluated by using ANOVA with 95% confidence level, and hence the results are quite adequate.

7. The verification test results reveal that the determined combination of the machining parameters satisfies the real requirement of the turning operation in machining of titanium alloy.

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EXPERIMENTAL INVESTIGATION ON MACHINING OF TITANIUM ALLOY (TI 6AL 4V) AND OPTIMIZATION OF ITS PARAMETERS USING ANN

S u m m a r y

Engineering industries continuously face challenges in maintaining a consistently high product quality in terms of dimensional accuracy and surface finish, sustaining a high production rate, and economical processing of materials by minimizing cutting tool wear, rejections and rework. In this study, turning of Titanium alloy (Ti-6Al-4V) has been taken up for optimizing the material removal rate and surface finish, the reason being its wide application in aerospace industry. Cutting speed, feed rate and depth of cut were assigned as the input variables. Design of experiments based on Taguchi technique and L27 orthogonal array was employed to analyze the experimental data and the predicted values. Analysis of variance was used for identify the input parameter exerting maximum influence on surface finish and MRR. It was observed that the experimental results are in good agreement with the predicted values from DOE and multilayered feed forward Artificial Neural Network employed to predict process responses. The optimal values of the input and output parameters are tabulated.

Keywords: surface finish, Titanium alloy, material removal rate, design of experiments, Artificial Neural Network (ANN).

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