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Optimization of Surface Roughness during Turning of Aluminium based Metal Matrix Composites

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Abstract

Application of aluminum based metal matrix composites can be found in many manufacturing industries such as aircraft and aerospace components, marine fittings, transport, drive, shafts, brake components, valves, couplings. Metal matrix composites are heterogeneous material and they impose machinability issues with conventional turning process. This causes the deterioration of surface finish after machining. Thus, this paper aimed at conducting experiments on aluminum based metal matrix composites and investigating the influence of machining process parameters such as cutting speed (m/min), feed rate(mm/rev), depth of cut (mm) and nose radius (mm) on surface roughness. Experiments were carried out on CNC machine tool and coated tungsten carbide inserted cutting tool was used for machining. Further in this study an empirical model was developed for predicting surface roughness in terms of spindle speed, feed rate, depth of cut and nose radius using multiple regressions modeling method. At last, genetic algorithm has been employed to find out the optimal setting of process parameters that optimize surface roughness value. This provides a good flexibility to the manufacturing industries by selecting the good parameters setting as per the requirement.

***Keywords**: metal matrix composite, surface roughness, empirical model, multiple regression modeling method, genetic algorithm.*

1. Introduction

Surface roughness is primarily dependent on the production process. Surface roughness is affect by input parameters such as spindle speed, feed rate, depth of cut, cutting speed, type of lubrication used, nose radius, tool angle, tool height, properties of tool used for cutting operation etc. Manufacturing industry aims at producing a large number of products within relatively lesser time. But it is felt that reduction in manufacturing time may cause severe quality loss. In order to embrace these two conflicting criteria it is necessary to check quality level of the item either on-line or off-line. The purpose is to check whether quality lies within desired tolerance level which can be accepted by the customers. Quality of a product can be described by various quality attributes. The attributes may be quantitative or qualitative. This invites optimization problem which seeks identification of the best process condition or parametric combination for the said manufacturing process. Though much work has been reported in literature to improve the process performance, proper selection of process parameters still remains a challenge. There are several optimization techniques for the same like goal programming, simulated annealing (SA), grey relation, and genetic algorithms (GA). GA is very different from most of the traditional optimization methods. GA finds applicability in the field of conventional machining processes. It works with a random population of solution points and a set of Pareto-optimal solutions is obtained for the best performance measures. I developed a mathematical model for predicting value of surface roughness while machining mild steel using response surface methodology and optimized the developed model using genetic algorithm, in order to attain the required surface quality. Then was demonstrated an efficient method for determining the optimal turning operation parameters for a specified surface finish through the use of parameter design experiment methods. It was found that the feed rate and spindle speed had significant effects on surface roughness, while depth of cut had an insignificant effect. This parameter design yielded an optimal treatment combination well as a predictive equation that yielded realistic values. Furthermore, optimized turning parameters based on the Taguchi's method with regression analysis. Then developed model for prediction of surface roughness and material removal rate in machining of unidirectional glass fiber reinforced plastics composites with a polycrystalline diamond tool. Moreover, formulated a multi-characteristics response optimization model based on Taguchi and utility concept to optimize process parameters, such as speed, feed, depth of cut, and nose radius on multiple performance characteristics namely, surface roughness and material removal rate during turning of AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool. Finally, investigated the effect of feed rate, cutting speed and depth of cut on surface roughness, cutting temperature and cutting force in turning of aluminum 7075 alloy using diamond like carbon coated cutting tools. Then was developed a model for predicting the surface roughness based on cutting speed, feed and depth of cut using response surface methodology. Surface roughness contour for cutting speed – depth of cut is developed to describe the values resulting from the cutting parameters selected. Investigation of the effects of process parameters on surface finish and material removal rate in turning of AISI 304 using PVD coated cermet inserts, to obtain the optimal setting of these parameters was done. Further, investigation of multi-response optimization of turning process for an optimal parametric combination to yield the minimum power consumption, surface roughness and frequency of tool vibration using a combination of a grey relational analysis was carried out. The aim of this study was to optimize the process parameters for obtaining minimum surface roughness. Experiments were carried out using Taguchi orthogonal array under with and without coolant condition by varying spindle speed, feed rate, depth of cut and nose radius.

2.Material and Methods

Experiments were carried out on HAAS make CNC lathe machine. Aluminium based metal matrix composites were used as work piece material of dimension ϕ15 mm x 50 mm long. Coated Tungsten carbide insert cutting tool (tool holder- SVJBL 2020K 11 and insert- DCMT 11T308- PM 4225) was used for machining work pieces. In this study, spindle speed, feed rate, depth of cut and nose radius were considered as machining parameters and turning was carried out with and without application of cutting fluid. Experiments were designed using $L_{16}(2^4)$ Taguchi orthogonal array. Table 1 shows the machining parameters and their levels. The experimental design and observed values of responses are shown in table 2

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Table 1 Machining parameters with their levels

Level	Spindle Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)	Nose Radius (mm)
1	1500	0.1	0.75	0.4
2	2500	0.2	1	0.8

Work pieces were cleaned prior to the experiments by removing 0.2 mm thickness of the top surface in order to to remove any surface defects and wobbling. Surface roughness of the machined surfaces was measured by Surface roughness tester (TURBO RAUHEIT V6.14).

3.Results and Discussions

The turning experiments were conducted by using the parametric approach of the Taguchi's method and table 2 shows the orthogonal array with observed values.Regression analysis has been performed to find out the relationship between input factors and responses using Minitab 16 statistical software. During regression analysis it was assumed that the factors and the responses are linearly related to each other.

Table 2 Taguchi orthogonal array with observed values

Sr. No.	Coolant	SiC %	Spindle speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)	Nose radius (mm)	Ra (μm)
1	With	3	1500	0.1	0.75	0.4	1.71
2	With	3	1500	0.1	0.75	0.8	1.85
3	With	6	2500	0.2	1	0.4	4.55
4	With	6	2500	0.2	1	0.8	2.43
5	Without	3	1500	0.2	1	0.4	4.79
6	Without	3	1500	0.2	1	0.8	2.68
7	Without	6	2500	0.1	0.75	0.4	4.44
8	Without	6	2500	0.1	0.75	0.8	2.33
9	With	3	2500	0.1	1	0.4	1.59
10	With	3	2500	0.1	1	0.8	0.6

							4
11	With	6	1500	0.2	0.75	0.4	4.67
12	With	6	1500	0.2	0.75	0.8	2.56
13	Without	3	2500	0.2	0.75	0.4	4.86
14	Without	3	2500	0.2	0.75	0.8	2.75
15	Without	6	1500	0.1	1	0.4	4.37
16	Without	6	1500	0.1	1	0.8	2.26

The average values of surface roughness for each parameter at levels 1 and 2 for S/N data are plotted in figure 1.

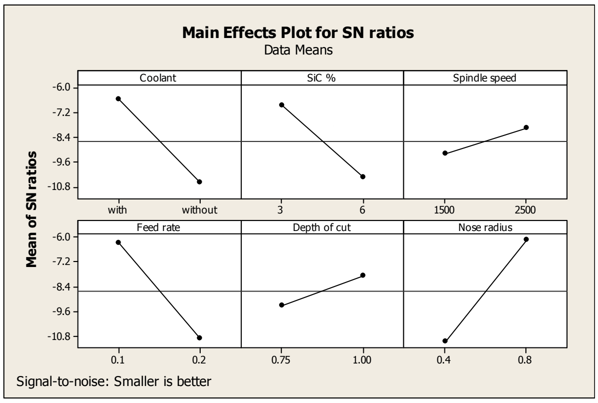

Fig. 1 Main Effects Plots for SR

Figure 1 shows that the surface roughness increases with the increase in spindle speed. Surface roughness decrease with increase in feed rate and also it increases with increase with depth of cut and nose radius. From the cutting theory it is known that an increase in spindle speed will significantly reduce the surface roughness. At low spindle speed, the unstable larger built up edge (BUE) is formed and also the chips fracture readily producing the rough surface. As the spindle speed increases, the BUE vanishes, chip fracture decreases, and, hence, the roughness decreases. An increase in feed will increase surface roughness. Increase in feed rate increases the chatter and heat generation, which increases the surface roughness. Increasing the depth of cut would slightly increase the surface roughness. The best surface finish was achieved at the lowest feed rate and highest spindle speed combination. This conclusion may be very useful for mass production and optimal values for spindle speed and feed rate can be set to reduce the manufacturing time without losing surface finish.

Residual plots are used to evaluate the data for the problems like non normality, non-random variation, non-constant variance, higher-order relationships, and outliers. It can be seen from figure 2 that the residuals follow an approximately straight line in normal probability plot and approximate symmetric nature of histogram indicates that the residuals are normally distributed. Residuals possess constant variance as they are scattered randomly around zero in residuals versus the fitted values. Since residuals exhibit no clear pattern, there is no error due to time or data collection order.

It is seen from the figure 3 that there is very weak interaction between the process parameters in affecting the surface roughness since the responses at different levels of process parameters for a given level of parameter value are almost parallel.

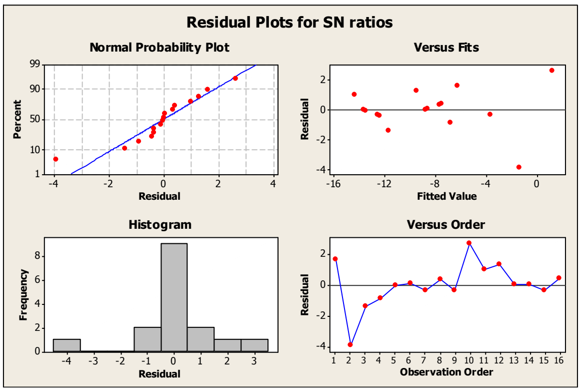

Fig. 2 Residual Plots for SR

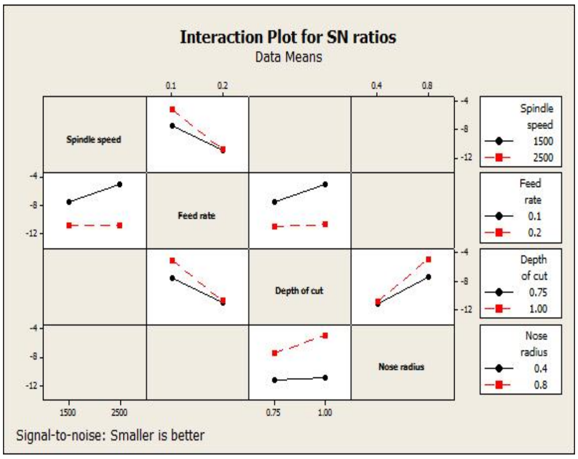

Fig. 3 Interaction plot for SN ratios

In order to study the significance of the process variables towards surface roughness, analysis of variance was performed at a confidence interval of 95% i.e. a significance level of 0.05. It was found that nose radius is greatest significant parameter for surface roughness. Feed rate and depth of cut have moderate effect on surface roughness. Significant process variables were predicted with an R^2 value of 95.4% and R^2 adjusted of 89.3%. The response table 3 shows the average of each response characteristic for each level of each factor. The table includes ranks based on delta statistics, which compare the relative magnitude of effects. The delta statistic is the highest minus the lowest average for each factor. Minitab assigns ranks based on delta values; rank 1 to the highest delta value, rank 2 to the second highest, and so on. The ranks indicate the relative importance of each factor to the response. The ranks and the delta values show that nose radius have the greatest effect on surface roughness and is followed by feed rate. As surface roughness is the "smaller the better" type quality characteristic and from the S/N data analysis, it can be seen from figure 1 that the second level of spindle speed, first level of feed rate, second level of depth of cut and second level of nose radius provide minimum value of surface roughness.

Table 3 Signal to noise for Ra

Level	Coolant	SiC%	Feed rate	Nose-radius
1	-7.111	-7.392	-6.834	-11.057
2	-10.627	-10.347	-10.905	-10.681
Delta	3.516	2.955	4.071	4.376
Rank	3	4	2	1

Table 4 Analysis of Variance for Ra

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Coolant	1	24.722	24.722	24.722	13.63	0.034
SiC%	1	17.463	17.463	17.463	9.63	0.053
Feed rate	1	33.150	33.150	33.150	18.28	0.023
Nose radius	1	38.297	38.29	38.29	21.1	0.019
Error	3	5.840	5.840	1.813		
Total	7	119.072				
S = 1.347 R-sq = 95.4% R-sq (adj) = 89.3%						

Regression analysis was carried out to ensure a least squared fitting to error surface in Minitab 16 software. Regression analysis has been performed to find out the relationship between input factors and Ra. During regression analysis it was assumed that the factors and the response are linearly related to each other. The general first order model was developed to predict the Ra over the experimental region can be expressed as equations 1 and 2. In general, the R^2adjustedstatistic will not always increase as variables are added to the model. In fact, if unnecessary terms are added, the value of R^2adjustedwill often decrease. When R^2 and R^2 adjusted differ dramatically, there is a good chance that no significant terms have been included in the model.For this experiment the R^2 value indicates that the predictors explain 95.4% of the response variation. Adjusted R^2 for the number of predictors in the model 89.3% values shows that the data are fitted well.

Coolant

With R = 1.86883 + 0.281823 SiC % + 12.6297 Feed rate - 4.21367 Nos radius (1)

Without R = 2.9318 + 0.281823 SiC % + 12.6297 Feed rate - 4.21367 Nose radius (2)

Single optimization of surface roughness

The developed mathematical model from regression method was used for minimization of surface roughness in turning of Al based MMCs. The developed mathematical model was converted into a MATLAB function. This function was input to the GA Toolbox of MATLAB as the objective function. Upper and lower bounds were specified as per the levels of the machining parameters and the number of variables was set at 4. The population type was set to double vector, population size of 20 and a generation of 100 was used for the analysis. Constraint dependent creation function and scattered type of cross over function were used for the analysis. Multiple runs of the algorithm were carried out at different settings of the available options of GA Toolbox to fine tune the minimum response value. The best response is shown in figure 4. The best response value for surface roughness obtained from GA was 0.606474 µm with SiC of 3%, feed rate of 0.1 mm/rev, and nose radius of 0.8 mm.

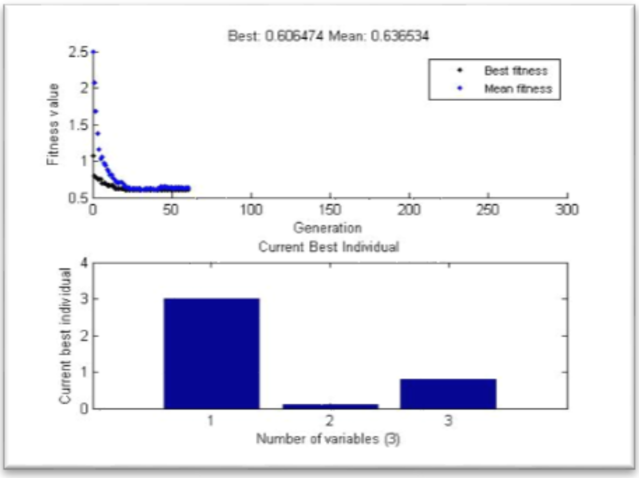

Fig. 4 GA Toolbox to fine tune the minimum response value

The model was experimentally validated and the results were tabulated in table 5. A good agreement was observed among the predicted and actual results. After optimization, further experiments were carried out to test the accuracy of the developed model. This time, the optimized values of cutting parameters corresponding to the best responses (obtained from GA) were selected for experiments. The resulting SR (experimental) was compared with that predicted by the GA and percentage error was calculated.

Table 5 Validation experiment results

Responses	**Optimal Values**	**Predicted**	**Actual (Avg. of three)**	**%Error**
SR (µm)	SiC of 3%, feed rate of 0.1 mm/rev, and nose radius of 0.8 mm	0.606474 µm	0.57712 µm	4.48

4. Conclusions

In this study turning experiments were conducted by using the parametric approach of the Taguchi's method. Regression analysis has been performed to find out the relationship between input factors and responses using Minitab 16 statistical software. General first order model was developed to predict the surface roughness over the experimental region. Based on single objective optimization by genetic algorithm gave the best surface roughness value obtained was 0.6064 µm. For surface roughness, confirmation experiments resulted in a maximum percentage error of 6.89% and an average percentage error of 4.84%, underlining the satisfactory performance of the prediction model. This establishes the reliability of genetic algorithms as one of the most accurate optimization approaches.

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