Study of Ball Nose End Milling of LM6 Al Alloy: Surface Roughness Optimisation using Genetic Algorithm

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***Abstract*— Surface finish is a vital factor in the performance of finished components. Nose ball end milling is being extensively used for finishing of free form surfaces. Aluminium alloys like LM6 find increasing applications in automobile and aerospace industries. This paper presents an investigation of surface finish of LM6 Al alloy using ball nose end mill. Box Behnken approach of the Response Surface Methodology was selected for the design of experiments and mathematical modelling. The developed model was statistically validated using Analysis of Variance with R-squared value obtained at 92.42 %. Cutting speed and feed rate were found to be the most significant parameters. Machining parameters (cutting speed, feed and depth of cut) were optimised with consideration to surface roughness. The minimum optimised value of surface roughness predicted by GA was 0.45 microns (Ra). Validation experiments at optimal parametric settings showed an error of 8.88, which highlights the consistency of the developed model. Thus, this model helps manufacturers to select optimum settings for achieving desired surface quality of contoured finished products.**

Keyword- Surface Roughness, Ball Nose End Mill, LM6 Al Alloy, Response Surface Methodology, Genetic Algorithm.

I. INTRODUCTION

Surface roughness is a widely used index of product quality and in most cases a technical requirement for mechanical products. Achieving the desired surface quality is of great importance for the functional behaviour of a part [1]. Reducing surface roughness is a costly affair, but the surface quality of products is a must to survive in today’s markets [2, 3].

Surface roughness generated in machining operation is influenced by factors such as cutting parameters, cutting tool characteristics, work piece properties and cutting phenomena [1]. These numerous factors make it almost impossible to reach a comprehensive solution to the reduction of machined surface roughness [4]. The most common strategy involves the selection of conservative process parameters, which neither guarantees the achievement of the desired surface finish nor attains high metal removal rates [1]. Therefore, machine operators usually use “trial and error” approaches to set-up milling machine cutting conditions in order to achieve the desired surface roughness. Obviously, the “trial and error” method is neither effective nor efficient and the achievement of a desirable value is a repetitive and empirical process that can be very time consuming. The dynamic nature and widespread usage of milling operations in practice have raised a need for seeking a systematic approach that can help to set-up milling operations in a timely manner and also to help achieve the desired surface roughness [5].

The various approaches of experimental design and analyses provide the necessary tools to determine the optimum cutting conditions and mathematical models to predict the final objective, for example surface roughness.

Fuh and Wu [6] used RSM to study the influence of tool geometries and cutting parameters on surface roughness (Ra) in end milling of Al alloy. Mansour and Abdalla [7] studied the roughness (Ra) in end milling of EN 32 steel in terms of machining parameters using RSM. Benardos and Vosniakos [8] used Taguchi design to consider prediction of Ra in CNC face milling of Al alloy. Bagci and Aykut [9] used the Taguchi optimization method for low surface roughness value (Ra) in terms of cutting parameters in CNC face milling of cobalt based alloy. Hayajneh et al. [10] developed a model, which includes the effect of spindle speed, cutting feed rate and depth of cut, and any two variable interactions, and predicted the surface roughness values of aluminium work pieces with an accuracy of about 12%. Thangarasu and Sivasubramanian [11] used RSM (Box Benkhen Method) to optimise surface finish and material removal rate with equal weightages. Kadirgama et al. [12] used Response Ant Colony Optimisation and Box Benkhen Method to predict surface roughness in end milling. Vakondios et al.

[13] developed and validated mathematical models for different milling strategies by ball end mill on Al7075-T6. Daymi et al. [14] investigated the effect of inclination angle in ball end milling of a titanium alloy. Suresh et al. [15] used Genetic Algorithms to optimise a surface roughness model.In this study, central design runs of Box Behnken methodology were adopted which are essentially the fractions of 3 level factorial designs with additional centre points to preserve the design balance. As per this design, 30 experiments were conducted for 2 levels (each) of speed, feed and depth of cut to obtain surface roughness values, expressed in terms of arithmetic means (Ra). Thereafter, a second order polynomial response surface mathematical model was developed to predict the surface roughness in terms of the said machining parameters and their interactions. Next, Genetic Algorithm was utilised for optimisation of the developed model to obtain the values of machining parameters at which the surface roughness is minimised. Validation experiments were carried out at the optimised values of speed, feed and depth of cut (as obtained from Genetic Algorithm output) and the resulting surface finish values were compared with those predicted by GA.

II. BOX BEHNKEN DESIGN

Box Behnken designs are experimental designs for response surface methodology devised by George E. P. Box and Donald Behnken in 1960. The design should be sufficient to fit a quadratic model, that is, it should contain squared terms and products of factors. The ratio of the number of experimental points to the number of coefficients in the quadratic model should be reasonable (in the range of 1.5 to 2.6). Each design can be thought of as a combination of a two-level (full or fractional) factorial design with an incomplete block design. In each block, a certain number of factors are put through all combinations for the factorial design, while the other factors are kept at the central values [11].

The Box-Behnken Design is normally used when performing non-sequential experiments. That is, performing the experiment only once. These designs allow efficient estimation of the first and second –order coefficients. Because Box-Behnken design has fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box-Behnken Design do not have axial points, thus we can be sure that all design points fall within the safe operation. Box-Behnken Design also ensures that all factors are never set at their high levels simultaneously.

III. GENETIC ALGORITHMS

GAs are search algorithms for optimization, based on the Darwinian theory of evolution. The power of these algorithms is derived from a very simple heuristic assumption that the best solution will be found in the regions of solution space containing high proportion of good solution, and that these regions can be identified by judicious and robust sampling of the solution space. The mechanics of a GA are simple and involve the coding of solution states in chromosomes as series of binary elements (0 and 1). A set (i.e. population) of candidate solution states (i.e. chromosomes) is generated and evaluated. A fitness function is used to evaluate each of the solutions in the population. The chromosomes encoding the better solutions are broken apart and recombined through the use of genetic operators in succession to get a new solution (i.e. offspring) that is generally better in one generation or iteration. These operators are essentially mathematical models of genetic operations that take place in the human body. The simplest form of GA involves three types of operators: selection (copying of the strings into a 'mating pool' (in proportion to their fitness values), crossover (swapping parent strings partially, causing offspring to be generated) and mutation (occasional random alteration with a small probability of the value of a string position, in binary strings, this simply means changing 0 to 1 or vice versa [1]. GA provides alternate solutions to any optimisation problem for different generations and options of the algorithm, such as initial population size, selection function, elite count, crossover fraction, crossover and mutation options etc. Proper fine tuning of the various options in GA is quintessential to the successful minimisation of the objective function (in this case, surface roughness). In particular, decreasing the crossover function to 50% gives better flexibility for mutations to take place, which diversify the parent populations to increase the probability of better children in subsequent generations.

IV. EXPERIMENTAL DETAILS

A. *Selection of Material, Process and Parameters*

Aluminium alloys are being preferred for auto and aerospace structural components. Reasons are: Abundant reserves of the ore, good ductility and malleability, strength to weight ratio, corrosion resistance, machinability and surface finish. Significant scope was identified to optimise surface roughness for LM6 Al alloy. Ball nose end milling is extensively used for finishing of free form surfaces because the ball end cutter adapts well to the job contours [14]. Thus, it holds great importance especially in aerospace applications.

Cutting speed, feed and depth of cut were selected as the most influencing machining parameters for investigation of surface roughness. Among the various available surface roughness parameters, the average surface roughness (Ra) is most commonly used. Hence, Ra was selected for this study.

B. *Plan of Experiments*

Table I shows the levels of the cutting parameters selected for the experimental layout.

TABLE I
CUTTING PARAMETERS AND THEIR LEVELS

Control Parameters	Levels		Observed Value
	Low	**High**	
Cutting Speed, S (rpm)	1500	5000	*Surface Roughness (Ra), µm*
Feed Rate, F (mm/min)	1000	2000	
Depth of Cut, d (mm)	0.5	1.0	

Table II shows the layout of the experimental design runs as per Box Behnken Approach, along with the response values (Ra) obtained for each run. A commercial software (MINITAB 16) was employed to obtain this layout and the resulting mathematical model.

C. *Experimental Setup and Procedure*

The experiments were carried out on a 4-axis CNC vertical machining centre of Bharat Fritz Werner Ltd make, Agni BMV 45 TC 24 model as shown in Fig.1. LM6 aluminium alloy was used as work piece material with hardness of 50-55 BHN. Chemical composition of the work piece was 86.6% Al and 11.6% Si, as confirmed by SEM image (shown in Fig.2). SER 1M 12mm TiNamitite "A" coated ball nose end mill of solid carbide was used as cutting tool for this study (Ø12mm, 4 flutes, 30mm flute length, 70mm OAL). A slot of 20mm in length was machined for each designed run. The experimental setup is shown in Fig. 3.Finish of machined slots were measured using surface roughness tester, Surf test SJ-301 model of Mitutoyo make, and Ra was used for the characterization of surface roughness.

Fig. 1 CNC Vertical Machine Centre

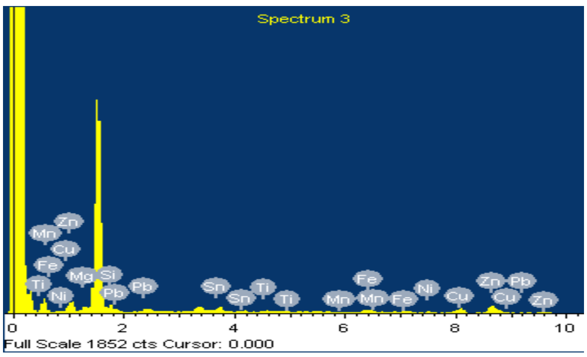

Fig. 2 SEM Image

Fig. 3 Experimental Setup

TABLE II
Experimental Layout and Response: Box Behnken Design

Sr. No.	Cutting Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)	Ra (µm)
1	5000	2000	0.75	1.10
2	5000	1500	0.50	1.00
3	3250	1000	1.00	3.10
4	1500	1500	0.50	2.10
5	5000	1500	1.00	1.10
6	3250	2000	0.50	3.70
7	1500	1000	0.75	3.10
8	1500	1500	1.00	2.50
9	1500	2000	0.75	4.90
10	3250	1500	0.75	1.90
11	3250	1500	0.75	2.30
12	3250	1000	1.00	3.70
13	3250	2000	1.00	4.10
14	3250	1000	0.50	3.20
15	3250	2000	0.50	3.90
16	5000	1000	0.75	1.30
17	1500	1500	0.50	2.30
18	5000	1000	0.75	1.10
19	1500	1500	1.00	3.50
20	1500	1000	0.75	2.40
21	5000	2000	0.75	1.90
22	3250	1000	0.50	2.80
23	3250	2000	1.00	4.10
24	3250	1500	0.75	2.20
25	5000	1500	0.50	0.85
26	3250	1500	0.75	2.20
27	1500	2000	0.75	3.60
28	3250	1500	0.75	2.40
29	3250	1500	0.75	2.10
30	5000	1500	1.00	0.84

V. RESULTS AND DISCUSSIONS

A. *Mathematical Modelling*

To formulate the effect of selected machining parameters on surface roughness, the design modeller software was given inputs of measured responses (Ra values) for all experimental runs. The surface roughness was modelled in terms of speed (S), feed (F) and depth of cut (D) as follows -

Surface Roughness (Ra) = 9.01938 + 0.00194971*S - 0.0101682*F - 6.41036*D - 2.54626E-07*S^2 + 4.08583e-06*F^2 + 5.92333*D^2 - 3.42857E-07*S*F - 4.31429e-04*S*D - 2.00000e-04*F*D

B. *Statistical Validation*

Using Analysis of Variance (ANOVA), the effects of speed, feed, depth of cut and their second order interactions on surface roughness were calculated. (Table III).

TABLE III
ANOVA RESULTS

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	32.89	32.89	3.65	27.09	0.00
Linear	3	17.77	17.77	5.92	43.92	0.00
S	1	14.45	14.45	14.45	107.2	0.00
F	1	2.72	2.72	2.72	20.18	0.00
D	1	0.59	0.59	0.59	4.42	0.05
Square	3	14.10	14.10	4.70	34.85	0.00
S*S	1	5.77	4.49	4.49	33.28	0.00
F*F	1	7.32	7.70	7.70	57.10	0.00
D*D	1	1.01	1.01	1.01	7.50	0.01
Interaction	3	1.01	1.01	0.33	2.50	0.08
S*F	1	0.72	0.72	0.72	5.34	0.03
S*D	1	0.28	0.28	0.28	2.11	0.16
F*D	1	0.01	0.01	0.01	0.04	0.85
Residual Error	20	2.69	2.69	0.13		
Lack of Fit	3	0.27	0.27	0.09	0.64	0.59
Pure Error	17	2.42	2.42	0.14		
Total	29	35.59				

S = 0.367331 PRESS = 6.7424

R-Sq = 92.42% R-Sq (pred) = 81.06% R-Sq (adj) = 89.01%

In Table III, at 95% confidence level, cutting speed and feed rate were most significant parameters (at p-value < 0.05) while depth of cut was less significant (at p-value = 0.05). Similarly, of all the interactions, only the interaction of speed and feed was found statistically significant. Other interactions were insignificant to the surface roughness. The obtained value of the coefficient of determination (R^2) indicates that the developed model explains 92.42% of the surface roughness variation in the ball nose end milling of LM6 alloy. The value of adjusted coefficient of determination (adjusted R^2) at 89.01% shows that the data are fitted well.

C. Optimisation

For minimising response (Ra), the developed mathematical model was converted into a Matlab (R2007a) 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 cutting parameters and the number of variables was set at 3. Multiple runs of the algorithm were carried out at different settings of the available options of GA Toolbox (Matlab) to fine tune the minimum response value. The best response is shown in Fig. 4.

D. Experimental Validations

After optimisation, further experiments were carried out to gauge the accuracy of the developed model. This time, the optimised values of cutting parameters corresponding to the best responses (obtained from GA) were selected for experiments. The resulting surface roughness (experimental) was compared with that predicted by the GA and percentage error was calculated (Table V).

TABLE IV
Accuracy Test of Prediction Model

Run No.	Cutting Speed (rpm)	Feed Rate (mm/ min)	Depth of Cut (mm)	Ra (µm) Predicted	Ra (µm) Actual	% Error
3	3250	1000	1.00	3.38	3.10	8.28
10	3250	1500	0.75	2.18	1.90	12.84
15	3250	2000	0.50	3.82	3.90	2.09
20	1500	1000	0.75	2.66	2.40	9.77
26	3250	1500	0.75	2.18	2.20	0.91
30	5000	1500	1.00	0.83	0.84	1.51
					Average	5.9

The model was experimentally validated at other parameter settings as well. Table V shows the verifications of the model predictions for surface roughness. A good agreement is observed among the predicted and actual results. To assess the accuracy of the model, percentage errors and average percentage error were calculated. The maximum prediction error was 12.84% and the average percentage error of this validation was 5.9%, underlining the satisfactory performance of the prediction model.

TABLE V
Optimum Conditions and Comparison of Results

Parameters	**Optimum values**
Speed (rpm)	5000.00
Feed (mm/min)	1462.82
Depth of Cut (mm)	0.73
Roughness values (Ra - µm)	
Predicted from GA	0.45
Experimental	0.49
% Error	8.88

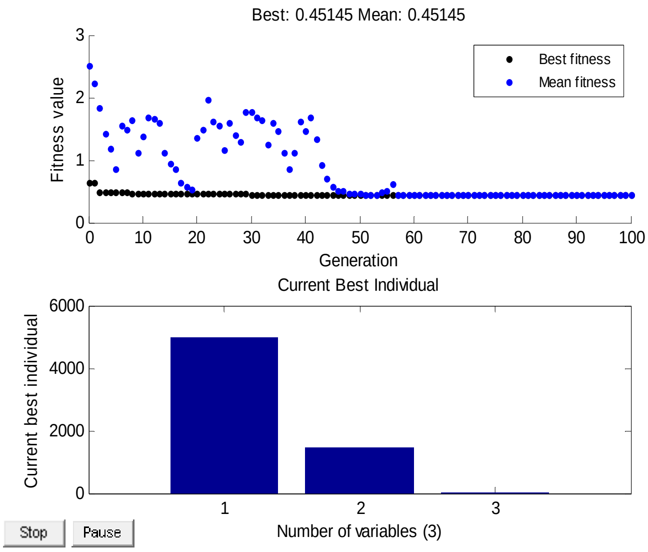

Fig.4 GA Output (Best Response)

VI. CONCLUSIONS

In this work, effect of cutting speed, feed rate and depth of cut on surface roughness was investigated in ball nose end milling of LM6 Al alloy. Box Behnken approach was utilised for the design of experiments. A second order mathematical model was developed to predict surface roughness in terms of the selected machining parameters. Genetic Algorithm was employed for the optimisation of this model and the results were validated by further experiments. Best values of parameters for lowest surface roughness (Ra = 0.45 microns) are: cutting speed, 5000 rpm; feed rate, 1463 mm/min and depth of cut, 0.73 mm.

Comparisons of experimental and predicted results at optimum conditions (Table IV) show errors less than 10 percent. This establishes the reliability of Genetic Algorithms as one of the most accurate optimisation approaches. The results also validate the consistency of the mathematical model developed by following Box Behnken methodology.

LM6 Al alloy is an important new-age material of immense value to the automobile and aerospace industry. It is necessary for the concerned manufacturing industries to have systematic and quick systems to customise parameter settings. The developed model will enable the manufacturers to cater to newer demands of improved finished surface quality, especially in case of free form contoured jobs. This conclusion may be very useful for mass production. Optimal values for spindle speed, feed rate and depth of cut can be set to reduce the manufacturing time without losing surface finish.

The developed model proves to be statistically significant for the description of the process with the necessary accuracy (p-value of each significant term is less than or equal to 0.05 at 95% confidence level). Thus, the model was statistically validated and experimentally verified and can be used for the expected surface quality, while ball end milling of Al LM6 alloy, within the limits of the investigated cutting parameters at 95% confidence level.

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