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Optimization of the Machining parameter of LM6 Alminium alloy in CNC Turning using Taguchi method

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Abstract. Due to widespread use of highly automated machine tools in the industry, manufacturing requires reliable models and methods for the prediction of output performance of machining process. In machining of parts, surface quality is one of the most specified customer requirements. In order for manufactures to maximize their gains from utilizing CNC turning, accurate predictive models for surface roughness must be constructed. The prediction of optimum machining conditions for good surface finish plays an important role in process planning. This work deals with the study and development of a surface roughness prediction model for machining LM6 aluminum alloy. Two important tools used in parameter design are Taguchi orthogonal arrays and signal to noise ratio (S/N).Speed, feed, depth of cut and coolant are taken as process parameter at three levels. Taguchi's parameters design is employed here to perform the experiments based on the various level of the chosen parameter. The statistical analysis results in optimum parameter combination of speed, feed, depth of cut and coolant as the best for obtaining good roughness for the cylindrical components. The result obtained through Taguchi is confirmed with real time experimental work.

1. Introduction

Two important issues in manufacturing process of modeling and optimization. A greater attention is given to accuracy and surface roughness of product by the industry these days. Surface finish has been one of the most important considerations in determining the machinability of materials. The predictive modeling of machining operations requires detailed prediction of the boundary conditions for stable machining. Most surface roughness prediction models are empirical and are generally based on experiments in the laboratory. In addition, it is very difficult in practice; to keep all factors under controls as required obtaining reproducible results. Generally these models have a complex relationship between surface roughness and operational parameters not only increase the utility for machining economics, but also the product quality to a great extent.Column number represents the influencing factor and row number represents the trial number. The other numbers represent the level of the factor represented by their column number.

Optimization process involving seven parameters at two levels. Experiments have been conducted based on the orthogonal array and these data obtained have been analyzed using ANOVA and response curves [1].Statistical model for surface roughness estimation in a high-speed flat end milling process under wet cutting conditions. The variables taken are spindle speed, feed rate, depth of cut, and step over. This work deals with obtaining parameter settings for both minimum surface roughness and long tool life [2].Optimized the turning operation with multiple performance characteristics. Taguchi method of optimization was applied to optimize three control factors such as cutting speed, feed rate, and depth of cut considering the performance characteristics such as Tool life, cutting force, surface Roughness which was designed in L9 orthogonal array [3].Optimal value of cutting force by an optimal setting of turning process parameters while machining En24 alloy steel with TiC coated carbide inserts. The effects of the selected parameters have been accomplished using Taguchi's parameter design approach. The results indicate that the selected process parameters –speed, feed, and depth of cut, as well as interaction between cutting speed and depth of cut significantly affect the mean and variance of cutting force [4]. Predict the surface roughness of machined parts in the end milling process was developed to assure product quality and increase reproduction rate by predicting the surface finish parameter in real time [6].

2. Orthogonal array

Column number represents the influencing factor and row number represents the trial number. The other numbers represent the level of the factor represented by their column number which is shown in Table 1.

Table 1. Standard L9 (3^4) Array

Trial number	COLUMN NUMBER			
	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

2.1Details of experiments conducted

Taguchi experiments to identify the optimum surface roughness and to find the percentage contribution of parameters namely speed, feed rate, depth of cut and coolant flow rate shown in Table 2. Taguchi L 9(34) orthogonal array was used to design the experiments as shown in Table 3.

Table 2. Variables factor levels

Controllable factors	Level 1	Level 2	Level 3
Depth of cut (mm)	0.4	0.6	0.8
Spindle speed (rpm)	1400	2000	2600
Feed (mm)	0.05	0.15	0.25
Coolant flow rate (lit/sec)	0.02	0.05	0.1

Table 3. Orthogonal array L_9 (3^4)

Exp. no	Control factor assignment and column number				Noise factor (measurement location)		
	Depth of cut	Speed	Feed	Coolant flow rate	1	2	3
1	0.4	1400	0.05	0.02	0.69	0.72	0.67
2	0.4	2000	0.15	0.05	2.22	2.40	2.20
3	0.4	2600	0.25	0.1	2.74	2.56	2.87
4	0.6	1400	0.15	0.1	2.03	2.06	2.02
5	0.6	2000	0.25	0.02	1.90	1.80	2.14
6	0.6	2600	0.05	0.05	0.71	0.68	0.76
7	0.8	1400	0.25	0.05	1.75	1.76	1.75
8	0.8	2000	0.05	0.1	0.68	0.69	0.74
9	0.8	2600	0.15	0.02	0.84	0.73	0.88

3. Results and discussion

The results of the experiments for nine trials conditions with three measurement locations the average response vales and the S/N ratio were recorded in Table 4.

Table 4. Result of the $L_9 (3^4)$ experiment

Experiment number	$(R_{aij})j =1,2,3$ Response value			(R_{ai}) Average response vale	(dBi) S/N value
	1	2	3		
1	0.69	0.72	0.67	0.69	3.17
2	2.22	2.40	2.20	2.27	-7.14
3	2.74	2.56	2.87	2.72	-8.71
4	2.03	2.06	2.02	2.03	-6.17
5	1.90	1.80	2.14	1.94	-5.80
6	0.71	0.68	0.76	0.71	2.88
7	1.75	1.76	1.75	1.75	-4.87
8	0.68	0.69	0.74	0.70	3.09
9	0.84	0.73	0.88	0.82	1.70
				$\bar{y}$ =1.4,8	$\bar{y}$ =-21.85

The average effects and S/N ratios for each level of cutting parameter are summarized and referred to in the average effects response table and S/N ratios response table roughness (Ra), as shown in Table 5 and 6.

Table 5. Average effect response the raw data

Levels	Depth of cut (A)	Spindle speed (B)	Feed rate (C)	Coolant flow rate (D)
1	1.89	1.49	0.70	1.45
2	1.56	1.62	1.70	1.57
3	1.09	1.41	2.13	1.82
Max- Min	0.80	0.22	1.42	0.66
Rank	2	4	1	3

Table 6. Average effect response for S/N ratio

Levels	Depth of cut (A)	Spindle Speed (B)	Feed rate (C)	Coolant flow rate (D)
1	-5.46	-2.62	3.05	-0.31
2	-3.04	-3.28	-3.87	-3.04
3	-0.02	-1.37	-7.86	-3.93
Max-Min	5.44	1.91	10.91	3.62
Rank	2	4	1	3

4. Pareto anova

It is a quick and easy method for analyzing result. This method enables the significance of factors and allows the optimal levels of factors to be obtained, as shown in Table 7.

Table 7. Pareto anova

Factor		A	B	C	D	Total
Sum at factor levels	1	5.67	4.47	2.10	3.45	
	2	4.68	4.91	5.12	4.73	13.62
	3	3.27	4.25	6.41	5.45	
Sum of squares of differences		8.72	0.67	29.46	6.14	44.88
Contribution ratio (%)		19.42	1.49	65.37	13.68	100
Overall optimum conditions for all factors		A_3 =0.8 mm B_3 =2600 rpm C_1=0.05 feed rate mm D_1= 0.02 lit/sec				

Table 8. Pareto anova for raw data factor

Pareto ANOVA for raw data Factor		A	B	C	D	Total
Sum at factor levels	1	-12.62	-7.86	9.07	-0.79	
	2	-9.03	-9.82	-15.06	-9.09	-21.69
	3	-0.04	-4.01	-19.32	-11.80	
Sum of squares of differences		251.82	51.66	1290.14	197.43	1791.05
Contribution ratio (%)		14.05	2.88	72.03	11.023	100
Overall optimum conditions for all factors		A_3 =0.8 mm B_3 =2600 rpm C_1=0.05 feed rate mm D_1= 0.02 lit/sec				

4.1. Response graphs are drawn with parameters and levels
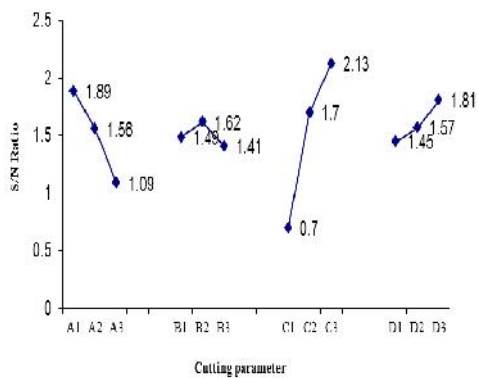

Figure1. Average effect response chart for the raw data
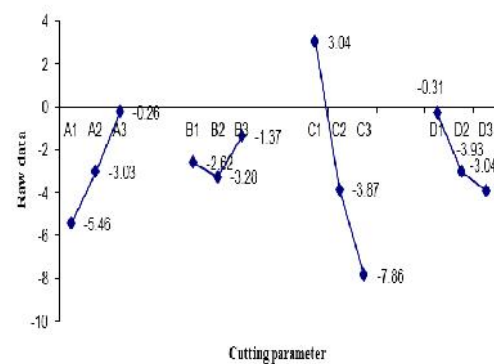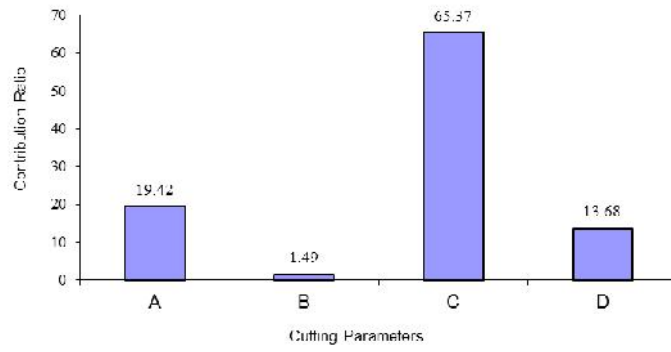

Figure 2. Average effect response chart for S/N ratio
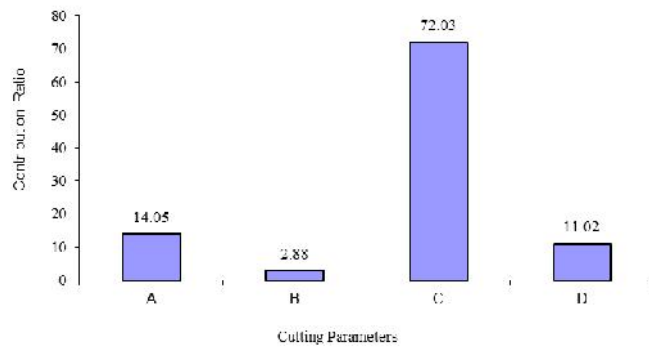
Figure 3. Pareto ANOVA for Raw Data

Figure 4. Pareto ANOVA for S/N Ratio

Table 9. ANOVA for raw data

Square of variation	Sum of square	Degree of freedom	Mean of square	F_{cal}	F_{tal}
Depth of cut	2.95	2	1.47	32.22	6.01
Spindle speed	0.22	2	0.11	2.51	6.01
Feed rate	9.74	2	4.87	108.20	6.01
Coolant flow rate	1.56	2	0.78	17.30	6.01
	0.81	18	0.04		
Error	15.28	26			
Total					

In order to determine which cutting parameter significantly affect the quality characteristic for S/N Ratio. Table 9 shows the results of ANOVA analysis of S/N Ratio for surface roughness. From Table 10 it is apparent that the F values of factor A (depth of cut), and factor C (feed rate) were all greater than $F_{(0.01,2,18)}$ =6.01. Figure 1 and Figure 2 represents average effect response chart for raw data and S/N ratio respectively. Figure 3 and Figure 4 represents Pareto ANOVA for the raw data and S/N ratio respectively.

Table 10. ANOVA for raw data

Square of variation	Sum of square	Degree of freedom	Mean of square	F_{cal}	F_{tal}
Depth of cut	83.63	2	41.81	13.02	6.01
Spindle speed	17.40	2	8.7	2.71	6.01
Feed rate	431.0	2	215.5	67.13	6.01
Coolant flow rate	8.09	2	4.04	1.25	6.01
Error	58.33	18	3.27		
Total	598.45	26			

4.2. Predicting optimum performance

The optimal surface roughness and S/N ratio are predicted at the selected optimal setting of process parameter is shown in Table 11. The significant parameters with optimal levels are selected as**:**

$$\text{Predicted optimal surface roughness} = \overline{A}_3 + \overline{C}_1 + \overline{D}_1 - 2(\overline{y}) \qquad (1)$$
$$= 1.09 + 1.70 + 1.45 - 2(1.48)$$
$$= 0.30 \, \mu m$$

$$\text{Predicted optimal S/N ratio} \quad = \overline{A}_1 + \overline{C}_3 - (\overline{y}) \qquad (2)$$
$$= (-5.46) + (-7.86) - (-21.85)$$
$$= 8.23 dB$$

4.3. Confirmation Experiment.

Conformation experiment was contacted at the optimum setting Ra values at optimum are

Table 11. The values obtained in the experiments are in the Predicted limits

Trial 1	Trial 2	Trial 3	mean	S/N Ratio
0.59	0.49	0.55	0.54	5.72

5. Conclusion

Table 12. The Optimal setting process parameter for optimal surface roughness

S.NO	Parameter	Optimal levels
1	Depth of cut	0.8
2	Spindle speed	2600
3	Feed rate	0.05
4	Coolant flow rate	0.02

Table 13. The percent contribution of raw data

1	Parameter	Percent contribution on surface roughness
1	Depth of cut	19.42
2	Spindle speed	1.49
3	Feed rate	65.37
4	Coolant flow rate	13.68

The predicted optimal surface roughness = $0.01 \leq Ra \leq 0.59$ (μm)

The calculation C.I for confirmation runs =±0.29.

The predicted optimal range (99% C.I) of the surface roughness for confirmation runs: $Ra<0.59$(μm).

The average value of surface roughness for confirmation runs at the optimal setting of turning process parameters was found to be 0.54μm. this result was within the predicted optimal surface roughness therefore, the optimum surface roughness was verified in turning operations is shown in Table 12 and 13.

Table 14. The percent contributions of S/N ratio parameters in affecting variation in surface roughness while machining aluminum turning operation.

S.NO	Parameter	Percent contribution on surface roughness
1	Depth of cut	14.05
2	Spindle speed	2.88
3	Feed rate	72.03
4	Coolant flow rate	11.02

The predicted optimal surface roughness = 5.39 ≤Ra ≤11.37 dB

The calculation C.I for confirmation runs = ±2.84

 The predicted optimal range (99% C.I) of the surface roughness for confirmation runs: Ra<11.37dB

The S/N Ratio value of surface roughness for confirmation runs at the optimal setting of turning process parameters was found to be 5.72dB. This result was within the predicted optimal S/N Ratio therefore, the optimum surface roughness was verified in turning operations are shown in Table 14.

6. References

[1]   Avani Gandhi 2003, Problem solving using Taguchi DOE techniques *Industrial engineering Journal* No.**12** p 16-25.

[2]   Babur Ozcelik Mahmut Bayramoglu 2005 The Statistical modeling of surface roughness in high speed flat end milling *International Journal of machine tool and manufacture.* No. **14** p65-72.

[3]   Nian.C Y ,Yang W H ,Tarng Y.S, 1999, Optimization of turning operations with multiple performance characteristics *Journal of material processing and technology* No.**24** p90 – 96.

[4]   Hari Singh & Pradeep Kumar, 2005, Optimizing cutting force for turned parts by Taguchi's parameter design approach *Indian journal of engineering & Material sciences*, No.**12**, p97-103.

[5]   Juan.H,Yu.S.F,Lee B.Y, 2003,The Optimal cutting parameter selection of production in HSM for SKD61 tool steels, *International Journal of Machine Tools and manufacture*,No.**43** p679-686.

[6]   Yu-Hsuan Tsai Joseph C Chen Shi-Jer Lou 1999 An in process surface recognition system based on neural networks in end milling cutting operations *International journal of machine tool and manufacture* No.**39** p583-605.

[7]   John L Yang & Joseph C Chen, 2004 A systematic approach for identifying surface roughness performance in end milling operations *Journal of industrial technology* No **17** p125-134.

[8]   EI Baradie 1993 Surface roughness model for turning grey cast iron (154BHN) Proceeding of Institution of Mechanical Engg Part B, *Journal of Engineering Manufacture 207*No.**23**, p43-54.