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Original Research

Determining the Effect of Cutting Parameters on Surface Roughness Using Genetic Algorithm

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Abstract

The aim of present research focuses on the prediction of machining parameters that improve the quality of surface finish. The surface roughness is one of the important properties of work piece quality in the CNC (Computer Numerical Control) turning process. An effective approach of optimization techniques genetic algorithm (GA) and response surface methodology (RSM) was implemented to investigate the effect of the cutting parameters such as cutting speed, feed rate, and depth of cut on the surface roughness. In this study, the surface roughness is measured during turning operation at different cutting parameters such as speed, feed, and depth of cut on Alumunium 6063 using coated carbide tool. The second order mathematical model is developed using RSM of central composite method to predict the surface roughness standards. The regression equation is solved using genetic algorithm approach for optimizing the cutting parameters for minimizing surface roughness, this study attempts the application of GA technique using Matlab 8.0 is recommends 1.512μm as the best minimum predicted surface roughness value for the optimal solution of the cutting conditions was 80 m/min, 0.18 mm/rev,0.3mm.

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INTRODUCTION

Alumninium (Al) Alloy 6063 is a combination of magnesium and silicon as the alloying elements. It has generally good mechanical properties and is heat treatable and wieldable. Alumninium 6063 is mostly used in extruded shapes for architecture, particularly window frames, door frames, roofs, and sign frames. But some of the limitations during machining of aluminum 6063 are lower strength at elevated temperatures and limited formability affects quality of desired output (Arun *et al.*, 2010).

Regression Equation: Computer-generated experimental designs, such as the D-optimal design, have some advantages over traditional response surface designs such as the central composite design. One major advantage is much greater flexibility in selecting response surface model types and the number of experimental runs. There are three-factor and one response surface experiment; the following second-order model is the standard model for CCD (Ilhan and Harun, 2011).

$$Y=\beta_0+ \beta_1x_1+ \beta_2x_2+ \beta_3x_3+ \beta_{11}x_1^2+ \beta_{22}x_2^2+ \beta_{12}x_1$$

Genetic Algorithms: The system is mainly based on a powerful optimization technique tool. GA is a part of the evolutionary algorithms that copy intelligence of nature in order to find global extremities on the given function problem (Azlan, Habibollah and Safian Sharif, 2010).

In order to ascertain the effect of geometry parameters of the tool in the surface roughness during turning RSM was used and a prediction model was developed relating to the average surface roughness (Ra) from experimental data (Suleyman, Suleyman and Erol, 2010).

The developed model can be used in the metal machining industries in order to determine the optimum cutting parameters for minimum surface roughness. Optimum cutting conditions which correspond to maximum value of surface roughness depth (Rz) value, were found for the cutting speed, feed rate and for the depth of cut has been achieved (Ilhan and Harun, 2011).

The influence of cutting speed, feed rate and depth of cut on the surface roughness is examined. The results indicate that the feed rate is the dominant factor affecting surface roughness, which is minimized when the feed rate and depth of cut are set to the lowest level, while the cutting speed is set to the highest level. These results demonstrated that this optimization method was efficient and greatly reduced the machining cost and the design process (Ilhan and Süleyman, 2011). In this study, the effects of cutting speed, feed rate, workpiece hardness and depth of cut on surface roughness and cutting force components in the hard turning were experimentally investigated and analysis of variance were performed.

The best surface roughness was achieved at lower feed rate and the highest cutting speed (Hamdi *et al.*, 2011).The results indicate that the hybrid approaches applied for modeling and optimization of the LBC process are reasonable (Amit and Vinod, 2011).

The machining parameters (cutting speed, feed rate, depth of cut, nose radius and cutting environment)are optimized with considerations of the multiple performance measures surface roughness, tool life, cutting force and power consumption. The result analysis shows the process parameters were significant (Anil and Hari, 2010). The surface roughness is measured during turning at different cutting parameters such as speed, feed, and depth of cut. Full factorial experimental design is implemented to increase the confidence limit and reliability of the experimental data. Parameter optimization in metal cutting processes is suggested for the benefits of selection of an appropriate approach (Indrajit and Pradip, 2006).

Machining with CNC requires that an operator select the process parameters such as feed rate, spindle speed and depth of cut, thus the process still depends on knowledge and experience. To prevent an unsatisfactory surface finish, the most common strategy involves the selection of conservative process parameters such as feed rate, spindle speed and depth of cut, which neither guarantees the achievement of desired surface finish (Suleyman, Suleyman and Erol, 2010). To overcome these problems, the various approaches has been used to predict the surface roughness by considering the optimal process parameters (Ilhan and Süleyman, 2011).

The perusal of the literature survey indicates that there are no literatures available on the cutting condition value for minimizing the surface roughness for Aluminium 6063. In this research effective optimization techniques approach response surface methodology was used to develop mathematical model and genetic algorithm was utilized for finding the optimal cutting conditions for best surface finish and also to develop the second order mathematical model for process parameters and analysis of variance measured for process parameters to ensure the significant effects.

MATERIALS AND METHODS

Experimental Setup

For different sets of machining conditions experiments are conducted in order to obtain the surface roughness. Twenty sets of experiments were conducted as per DOE (Design of Experiments).The turning operations are carried out with the coated carbide insert on Aluminium 6063.

Work Piece Material

The work piece material, Aluminium 6063 of dimensions radius 20mm and perimeter is 100 mm considered. Its chemical compositions and hardness are tested and hardness value is found to be 43 HRC. The table below shows the chemical composition of Aluminium 6063 (Table 1).

Table 1: Chemical Composition for Aluminium 6063.

Al 6063	Weight (%)
Si	0.2 to 0.6
Fe	0.0-0.35
Cu	0.0-0.1
Mn	0.0-0.1
Mg	0.45-0.9
Zn	0.0-0.1
Ti	0.0-0.1
Cr	0.1 Max
Others Each	0.05 Max

CNC Lathe

The CNC Lathe is an automated machine used for machining Purpose and it has greater accuracy and productivity (Figure 1) shown below along with specification.

Figure 1: CNC Lathe Used for Machining.

Turning centre specification

FANUC series 0i mate-Tc
FANUC-Furic Arrow Numerical Control
Mode-0i Mate-Tc
Turning Diameter- 250mm
Maximum speed- 3500RPM
Maximum feed – 3.00mm
Maximum depth of cut – 1mm
Turning length- 300mm
Chuck diameter – 200mm

Surface Tester

Mitutoyo SJ 201 Surf tester (Figure 2) is a surface roughness measuring device which is provided with exchangeable diamond stylus of radius of 5μ, which sensing the horizontal and vertical deflection from any surface gives roughness value.

Figure 2: Surface roughness testing.

Procedures of experiment

1. Checking the adequacy of the models developed
2. Comparing the optimization results with the experimental results and finding out the percentage error between them
3. Presenting the effects of the process parameters on the mechanical properties in graphical form and analyzing the results
4. Validation

Process Parameters and their Levels

In this experimental analysis of process parameters has been chosen from the industry for turning process in three levels -1, 0, 1 and were represented in table 2.

Table 2: Process parameters and their levels.

SL	Cutting parameters	unit	-1	0	1
1	Cutting speed (X_1)	m/min	80	100	120
2	Feed rate (X_2)	mm/rev	0.18	0.27	0.36
3	Depth of cut (X_3)`	mm	0.3	0.5	0.7

Experimental Values

The design of experiment developed in central composite method of response surface methodology used to conduct the experiments and develop the mathematical model for prediction of optimal cutting parameters and surface roughness (Ra) (Table 3). The parameters are:

Input parameters:

X1=cutting speed m/min
X2=feed rate mm/rev
X3=depth of cut mm

Output parameter:

Surface roughness µm

Table 3: Experimental values with responses.

Cutting parameter (Actual values)				
Cutting speed m/min	Feed rate mm/rev	Depth of cut mm	Surface roughness Ra(Exp)	Surface roughness Ra (Pred)
120	0.18	0.7	2.5	3.6
133.6359	0.27	0.5	2.7	4.7
100	0.27	0.163641	1.89	3.52
100	0.27	0.5	1.91	3.44
100	0.421361	0.5	1.85	4.3
100	0.27	0.5	1.62	3.4
80	0.18	0.3	1.66	2.3
100	0.27	0.836359	1.86	3.44
120	0.36	0.7	1.92	4.54
80	0.36	0.3	1.71	3.43
80	0.18	0.7	1.69	2.55
66.36414	0.27	0.5	1.54	2.6
80	0.36	0.7	1.83	3.42
120	0.36	0.3	2.38	4.83
120	0.18	0.3	2.45	3.76
100	0.118639	0.5	1.89	2.6
100	0.27	0.5	1.95	3.44
100	0.27	0.5	1.9	3.44
100	0.27	0.5	1.93	3.44
100	0.27	0.5	1.89	3.44

Regression Equation

The second order mathematical model is developed using the experimental values and responses to predict the surface roughness. Regression equations were formed using design expert 8.0 software for surface roughness Ra (**Y**) is

surface roughness= 0.36898- 0.010530*x(1)+ 5.98023*x(2)+ 2.04872*x(3)0.058333*x(1)*x(2)-0.017500*x(1)*x(3)2.91667 *x(2)*x(3)+0.000254063*x(1)*x(1)+1.63417*x(2)*x(2)+0.3751 1*x(3)*x(3)

Statistical Analysis

The effects of cutting speed, feed rate, and depth of cut on surface roughness were experimentally investigated and calculated with a statistical analysis of variance (ANOVA) were performed. The ANOVAs table 4 shows that the parameter experimented have been significant effect is sufficient.

Table 4: Analysis of variance

Analysis of variance table [Partial sum of squares - Type III]					
Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	1.686917	9	0.187435	12.68699	0.0002*
A-cutting speed	1.360759	1	1.360759	92.10615	< 0.0001
B-feed rate	0.020357	1	0.020357	1.377926	0.2677
C-depth of rate	0.007057	1	0.007057	0.477695	0.5052
AB	0.0882	1	0.0882	5.970024	0.0346
AC	0.0392	1	0.0392	2.653344	0.1344
BC	0.02205	1	0.02205	1.492506	0.2498
A^2	0.148835	1	0.148835	10.07425	0.0099
B^2	0.002525	1	0.002525	0.170913	0.6880
C^2	0.003245	1	0.003245	0.219612	0.6494
Residual	0.147738	10	0.014774		
Lack of Fit	0.072405	5	0.014481	0.961125	0.5168*
Pure Error	0.075333	5	0.015067		
Cor Total	1.834655	19			

* Significant

RESULTS AND DISCUSSION

Prediction Vs Actual

The graph is obtained from the experimental and prediction responses (Figure 3) using design expert software 8.0, shows the significant error in normal line.

The obtained experimental data is used to predict the surface roughness 'Ra' by developing the regression model and design of experiment. The Figure 3 Prediction Vs Experimental shows that the surface finish responses obtained from actual and prediction is lies closer in normal line, so thus the process parameters optimized for surface finish has been achieved best result.

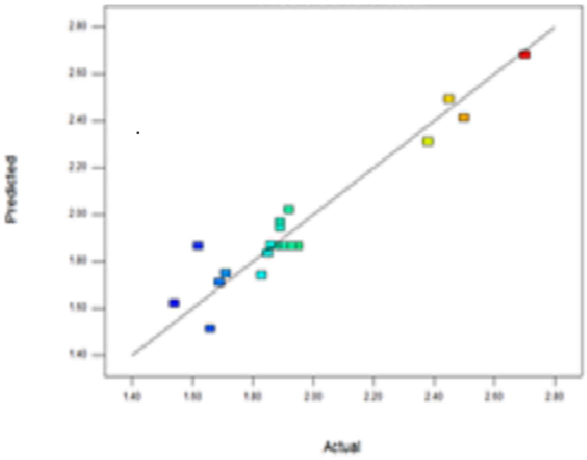

Figure 3: Prediction Vs Experimental.

Confirmation Report

The confirmation report (Table 5) shows that the confidence level is 95% is preferred for the factors cutting speed, feed rate, depth of cut for finding the significant adequacy in analysis of variance.

Table 5: Confirmation Report.

Confirmation Report						
Two-sided		**Confidence = 95%**		**n = 1**		
Factor	**Name**	**Level**	**Low Level**	**High Level**	**Std. Dev.**	**Coding**
A	cutting speed	100	80	120	0	Actual
B	feed rate	0.27	0.18	0.36	0	Actual
C	depth of Cut	0.5	0.3	0.7	0	Actual
Response	**Prediction**	**Std Dev**	**SE (n=1)**	**95% PI low**	**95% PI high**	
surface roughness	1.864822	0.121548	0.131268	1.572338	2.157305	

Best Fitness Using Genetic Algorithm Tool

In optimization, the Plot functions best fitness preferred so it enables to display various plots of the results of the genetic algorithm considering Population 100, Current generation 52.The Figure 4 shows achieved optimization values for cutting parameters are Cutting speed is 80m/min, Feed rate is 0.18mm/rev, Depth of Cut is 0.3mm and best fitness of surface roughness is 1.512µm.

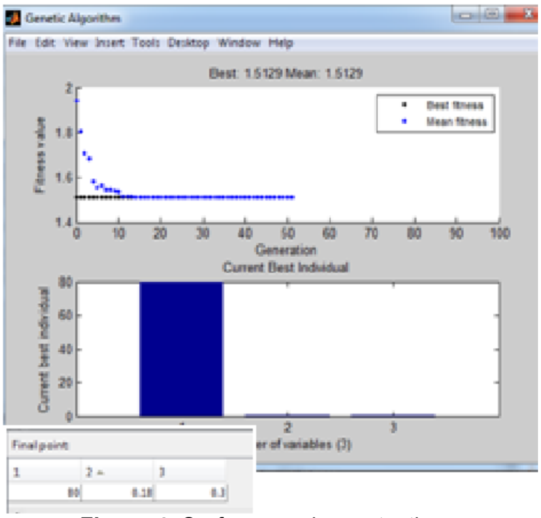

Figure 4: Surface roughness testing.

CONCLUSION

This investigation utilizing the application of genetic algorithm and recommends that optimal solution of the cutting conditions obtained on cutting speed is 80m/min, feed rate is 0.18 mm/rev and depth of cut =0.3mm for achieving the minimum value of surface roughness 1.512µm using matlab software 8.0. The confirmatory test was conducted and found that the percentage of error within 0.69.

REFERENCES

Amit, S., Vinod, Y. (2011). Modeling and optimization of cut quality during pulsed laser cutting of thin Al-alloy sheet for straight profile. *Optics and Laser Technology* 44(1): 159-168.

Anil, G., Hari, S., Aman, A. (2010). Taguchi-fuzzy multi output optimization (MOO) in high speed CNC turningof AISI P-20 tool steel. *Expert Systems with Applications* 38(6): 6822-6828.

Arun, P.A., Alwarsamy, T., Abhinav, T and Adithya, K.C., (2012). Surface roughness prediction by response surface methodology in milling of hybrid Aluminum composites. *Procedia Engineering* 38: 745- 752.

Azlan, M., Habibollah, H., Safian Sharif (2010). Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process. *Expert Systems with Application* 37(6): 4650-4659.

Hamdi, A., Mohamed, A.Y., Kamel Chaoui., Tarek Mabrouki., Jean-François Rigal. (2011). Analysis of surface roughness and cutting force components in hard turning with CBN tool: Prediction model and cutting conditions optimization. *Measurement* 45(3): 344-354.

Ilhan, A., Harun, A. (2011). Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method. *Measurement* 44(9): 1697-1704.

Ilhan, A., Süleyman, N. (2011). Multi response optimization of CNC turning parameters via Taguchimethod-based response surface analysis. *Measurement* 45(4): 785-795.

Indrajit, M., Pradip, K. R., (2006). A review of optimization techniques in metal cutting processes. *Computers and Industrial Engineering* 50(1-2): 15-34.

Suleyman, N., Suleyman, Y., Erol, T., (2010). Optimization of tool geometry parameters for turning operations based on the response surface methodology. *Measurement* 44(3): 581-587.