INVESTIGATING MACHINABILITY AND HARDNESS OF ALUMINIUM ALLOY (Al-6063) WITH VARIOUS PROCESS PARAMETERS BASED ON TAGUCHI METHOD BY CNC MILLING MACHINE

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Abstract

In the metalworking and cutting industries, the surface finish and strength of the product are very important in determining the quality of the product. A good surface finish ensures the quality of the product. The effect and optimization of machining parameters on the surface roughness in a milling process is examined using the Taguchi method. The experimental investigations are carried out with different cutting speeds, feeds and depths of cut and considering the aluminum alloy 6063. In this project, the Taguchi Engineering and Utilization Concept, a multiple-response optimization method was employed to determine the optimal process parameters to simultaneously minimize surface roughness when milling an aluminum alloy on a CNC milling machine using a coated carbide tool . The experiments are designed according to the orthogonal matrix L9, i.e. considering three levels and three factors, and the optimization is performed using the S/N ratio.

*Keywords:*Optimization,CNC,Miling,Surface Roughness

1.Introduction

Aluminum is a composite element with the symbol Al and the nuclear number 13. In the boron gathering, it is a gleaming white, fragile, nonmagnetic, and flexible metal. Aluminum is a composite element with the symbol Al and the nuclear number 13. In the boron gathering, it is a gleaming white, fragile, nonmagnetic, and flexible metal. Bauxite is the primary mineral of aluminum. Because aluminum is so artificially responsive, local occurrences are infrequent and limited to exceptional decreasing conditions. Rather, it is observed consolidated in over 270 distinct minerals. Aluminum is fantastic because of its thinness and ability to resist consumption through the marvel of passivation.Aluminium and its alloys are critical in the aeronautics industry, as well as in transportation and building endeavors such as building veneers and window outlines. The oxides and sulphates are the most beneficial aluminum mixtures.

Selection of material:

6000 association are alloyed with magnesium, silicon and iron. They are whatever however hard to machine, are wieldable, and may be precipitation solidified, but now no longer to the excessive traits that 2000 and 7000 can reach. 6063 alloy is a standout among the most customarily applied universally beneficial aluminum combinations.

Table 1. Control Factors and Levels

Properties	Values	Properties	Values
Density	2.69g/cm^3	Melting temp.	615 °C
Young's modulus	68.3 GPa	Thermal conductivity	201–218 W/[m·K]
Tensile strength	145–186 MPa	Linear thermal expansion co-efficient	2.34·10−5/K

Properties	Values	Properties	Values
Poisson's ratio	0.3	Specific heat capacity	900 J/kg·K
Elongation at break	18–33%	Volume resistivity	30-35 n Ohm

1.2 LITERATURE REVIEW:

Groover and Mikell et. al.(1996) [1] described the influence of three factors, namely feed, corner radius and cutting angle, on surface roughness..

Srikanth and Kamala et. al.(2008)[2] proposed a real coded genetic algorithm (RCGA) to find optimal cut-off parameters and explained several RCGA problems and their advantages over the existing binary coded genetic algorithm (BCGA) approach.

Rabindra Thamma et. al.[3] had found different models to obtain optimal machining parameters for the required surface roughness for a work piece made of AL 2017 T4. He concluded that spindle speed and feed rate are significant control factors for surface roughness. Smoother surfaces are produced when machining at higher spindle speeds, lower feeds and tip radius. The depth of cut has a significant impact on the roughness of the surface.

David et al. (2006) [4] described an approach to predict surface roughness in high speed milling process and used artificial neutral meshes (ANN) and statistical tools to develop different predictors for surface roughness.

Bajic et al. (2008) [5] focused on the modeling of the machined surface roughness and the optimization of the face cut parameters and investigated the influence of the cutting parameters on the face roughness.

Azouzi et. al.(1997) [6] proposed online prediction of surface finish and dimensional error in turning using sensor fusion based on neural networks.

Biswajit Das. al. [7] had investigated the surface roughness, which affects the parameters during turning, using a CNC lathe. The most affected control factors in the experiments were spindle speed, feed rate, and depth of cut. They found that feed rate is the parameter affecting surface roughness.

Hossain et al. (2008) [8] developed an artificial neural network algorithm to predict the final milled surface roughness of Inconel 718 alloy.

Ali Abdallah et. al.[9] had optimized machining parameters for surface roughness using AL 2017 T4 material on a CNC lathe. Based on the surface roughness result, it was found that the feed rate affects both the surface roughness and the metal removal rate. Spindle speed is a more important control factor for surface roughness than metal removal rate.

Sakir et. al.(2008) [10] worked on surface roughness prediction using an artificial neural network of a lathe and studied the effect of tool geometry on surface roughness on a universal lathe and performed a machining process of AISI 1040 steel under dry cutting conditions using different insert geometries at 0 .5 mm depth of cut. The optimization of the processing parameters not only increases the efficiency of the processing, but also the product quality.

Yang and Tarng et. al.(1998) [11] used the Taguchi method to optimize the design for surface quality. An orthogonal matrix, signal-to-noise (S/N) ratio, and analysis of variance (ANOVA) were used to examine the cut-off properties.

Feng and Hu et. al. (2001) [12] addressed a comparative study of the ideal and actual surface roughness in finish turning and also applied the fractional factorial experiment approach to study the influence of turning parameters on the roughness of turned surfaces and used analysis of variance to determine the influence to investigate. of spin factors and factor interactions on surface roughness.

Suresh et. al. (2002) [13] developed an optimal surface roughness prediction model using a binary coded genetic algorithm (BCGA). This GA program provides a minimum and maximum surface roughness value and their respective optimum machining conditions.

H.M. Somashekera et. al. [14] used manipulate elements e.g. slicing velocity, feed charge and intensity of reduce to optimize floor roughness whilst machining AL2017 T4 with uncoated carbide tool. They used Taguchi technique to optimize the system parameters. They concluded that velocity has a extra impact on floor roughness.

1.3 Alloys Selected:

The alloys selected is Al 6063. These are the 6000 collection that are alloyed with magnesium and silicon. These are discovered broadly in manufacture industry, applied transcendently as expulsions and consolidated in several simple parts. Magnesium-silicate is produced through including magnesium and silicon to aluminum.

1.4 Experimentation

Total nine number of experiments were conducted to study the effects of various parameters with milling operation on aluminum alloys 6063 which is operated by CNC machine. This project works on experimental investigation and optimization control factors like cutting speed, feed, depth of cut and material in order to obtain the optimized value for good surface finish using Taguchi design methodology.

1.4.1 MINITAB:

It is particularly interactive software program which makes coming into information, engaging in regression analysis, ANOVA analysis, designing experiments the usage of DOE, appearing Taguchi analysis, drawing manipulate charts for processes, appearing reliability/ survival tests, plotting time collection plots, etc. very clean and time saving. It is the great device for information pushed high-satisfactory development programs.

1.4.2 Control Factors And Levels

A total of four process parameters with three levels are chosen as control factors, with the levels spaced sufficiently apart to span a wide range."The process parameters and their ranges are gathered from the literature. A-Spindle Speed, B-Feed Rate, C-Depth of Cut ,are the four control factors chosen. In experiments, a coated carbide CNMg120408 tool is employed. Table 2 shows the control parameters and their alternative levels.

Table 2. Control Factors and Levels

Factors	Level 1	Level 2	Level 3
Speed (A) rpm	1050	1250	1450
Feed rate(B) mm/min	35	55	75
Depth of cut (C) mm	0.3	0.5	0.7

1.4.3 Selection Of Orthogonal Array:

Selection of the orthogonal network of the O.A. norm requires a minimum number of experiments to be conducted, this is based on the number of factors, the levels of each factor and the total degrees of freedom.

Number of control factors =3

Number of levels for each control factor =3

Total degrees of freedom of factors =3*(3-1) = 6

Minimum number of experiments to be conducted =6+3=9

2. CNC Milling Machine:

The milling on aluminum alloys 6063 work pieces are done on CNC machine by dumping the codes into machine. A series of nine experiments using different values of speed, feed, depth of cut are performed

Fig.1CNC Milling Machine

In order to examine the influence of machining parameters in the roughness of the surface, experiments are performed in aluminum alloys (Length-9mm,Breath-9mm,Height-10mm) using the HSS containing cobalt content tool, as shown in

Fig.2 Tool Bit

2.1 Tool Specification

The HSS tool was used in this experiment. The specification of the tool is given below.

Total length: approx.100 mm

Shank diameter: 12 mm

Material: High Speed steel(HSS)

3.Surface Roughness Tester

The shape is measured using a surface roughness tester. It is a portable surface roughness tester featuring a touch-screen LCD and an integrated printer. The LCD window makes it simple to view measurement results and evaluate graphs.

Fig.3 Surface Roughness Tester

The key masking function makes limitations to the touch panel operation so that it prevents the detector calibration data & measuring conditions from being altered or deleted as shown in above

4. Analyze Taguchi design

After determining the surface roughness for each of the nine components, use the Taguchi approach in Minitab to analyses it. In the worksheet, enter the surface roughness values provided in the table. Now, choose Analyze Taguchi Design and double-click the E. (surface roughness).The S/N ratio and mean features are selected on that tab, as illustrated in Table 3

Table 3. Data of Surface Roughness

Experiment No	Speed rpm A	Feed mm/min B	DOC mm C	surface roughness µm R
1	1050	35	0.3	1.86
2	1050	55	0.5	3.452
3	1050	75	0.7	5.562
4	1250	35	0.5	3.440
5	1250	55	0.7	3.967
6	1250	75	0.3	1.755
7	1450	35	0.7	3.249
8	1450	55	0.3	2.869
9	1450	75	0.5	3.759

S/N ratio computation since it is a surface roughness calculation, the lower the roughness value, the better the

machined surface. As a result, the smaller-the-better S/N ratio calculation is used for computation.

S/N ratio, first experiment = -10*log(1.86^2)=-5.390

Experiment 2 S/N ratio = -10*log(3.452^2)= -10.761

Experiment 3 S/N ratio = -10*log(5.562^2)= -14.904

S/N ratio is determined in a similar manner for the remaining operations, and the values for S/N ratio are given below. Table 4.

Table 4. Data for S/N ratio

Experiment No	A Rpm	B mm/min	C mm	R µm	S/N Ratio
1	1050	35	0.3	1.86	-5.390
2	1050	55	0.5	3.452	-10.761
3	1050	75	0.7	5.562	-14.904
4	1250	35	0.5	3.440	-10.731
5	1250	55	0.7	3.967	-11.969
6	1250	75	0.3	1.755	-4.885
7	1450	35	0.7	3.249	-10.234
8	1450	55	0.3	2.869	-9.154
9	1450	75	0.5	3.759	-11.501

Minitab generates a response chart for each response characteristic, such as signal-to-noise ratio and mean.

The response chart indicates which factors have the most influence on the response and which degree of factor is associated to greater or lower response characteristic values.

1. With each factor level combination, this function computes the specified response characteristic.
2. Minitab calculates this same response characteristic at every level of the factor for each factor.
3. S/N ratio, factor A, level 1 is S/N =(-5.390-10.761-14.904)/3=-10.352
4. After that, delta values are generated, which are the differences between the greatest and smallest average response attributes for that factor's levels.
5. Delta = -10.352-(-9.195)=1.157
6. Using the delta values, rankings are assigned from high to low.
7. The factor with the largest delta value is listed first, followed by the next factor, and so on.
8. As seen in the response chart for signal-to-noise, smaller is preferable. Table 5.

Table 5. Response Table for S/N Ratio

Levels	Spindle Speed	Feed Rate	Depth Of Cut
1	-10.352	-8.785	-6.477
2	-9.195	-10.628	-10.998
3	-10.297	-10.431	-12.370
Delta	1.157	1.843	5.893
Rank	3	2	1

The response for each factor is calculated as

For factor A, S/N ratio

level 1 = (-5.390-10.761-14.904)/3= -10.352

level 2 = (-10.731-11.969-4.885)/3= -9.195

level 3 = (-10.234-9.154-11.501)/3= -10.296

Similarly, the S/N ratio of B and C factors is computed.

The delta value is computed after calculating the mean S/N ratios for every component.

Delta value for

Factor A =(-10.352+9.195)= 1.157

Factor B =(-10.628+8.785)= 1.843

Factor C =(-12.370+6.477)= 5.893

Of these, the value of factor B is the highest, so it is ranked first, the value of factor C is the second highest, and then the value of factor A is the third highest. The averages shown in Table 6 below.

Table 6. Response table for Mean

Levels	Spindle Speed	Feed Rate	Depth Of Cut
1	3.625	2.850	2.161
2	3.054	3.429	3.550
3	3.292	3.692	4.259
Delta	0.571	0.842	2.098
Rank	3	2	1

After getting the response table, the optimal state is predicted. H. Select the highest value for each element and record the level of that particular value. This gives the optimum value that affects the surface roughness. The maximum value in factor Spindle Speed, i.e., is in level 1 of the S/N ratio response table. The highest value in factor Feed Rate is, which corresponds to level 3. The greatest value in component Depth Of Cut is, which corresponds to level 3 Entering this level into the prediction popup box yields the best results, as shown in Table 7.

Table 7 shows the prediction level

Spindle Speed	Feed Rate	Depth Of Cut
1	3	3

The values in the response table are displayed in graph format. This chart shows the X-axis and S / N factor levels Y-axis ratio value. The purpose of these charts is to maximize the signal-to-noise ratio values, as shown in Figure below. And Figure

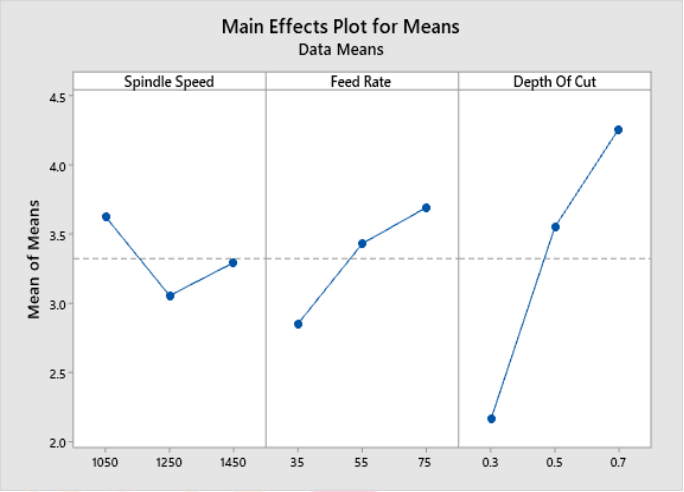


Fig No 4: Graph for Surface Roughness

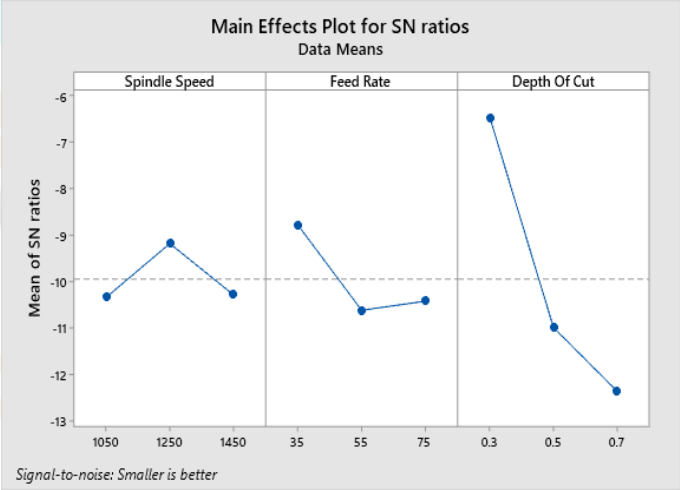


Fig No.5: Graph for Signal to Noise Ratio

The figure 4 it shows that for factor Spindle Speed, the S/N ratio is more for level 1(1250 rpm).
For factor Feed Rate, the S/N ratio is larger for level 3(75 mm/min)
For factor Depth of Cut, the S/N ratio is larger for level 3(0.3mm)
These are the best conditions to obtain the better surface finish as shown in below Table 8.

Table 8. Optimum set of Control Factors

Control factor	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)
Optimum	1250	75	0.3

By prediction the mean and signal-to-noise ratio values are
S/N ratio =-5.71809
Mean = 1.98833

5.Hardness:

The Brinell hardness test is still the oldest test method that is regularly used. The Brinell hardness tester used in this test is a spherical penetrator. In the Brinell hardness test, a ball with a diameter of [5] mm is usually pushed into the investment casting surface and tested. Contact pressure [250kgf] can be adjusted according to the material to be inspected. The Brinell hardness value for investment casting is displayed in h

Calculation of hardness:(Al6063 brinell hardness) :

First hardness before machining:-
Load [P] = 250 kgf
Diameter [D]= 5mm
Time= 30 sec
Dia [d]=1ST=2.1 mm
2nd =2 mm
3rd =2.2 mm

1st test □ h1 =1/2[$\frac{D}{D2-d2}$] =0.1214181641573

2nd test □ h2 =1/2[$\frac{D}{D2-d2}$] =0.1190476190476

3rd test □ h3 =1/2[$\frac{D}{D2-d2}$] =0.1240079365079

Hardness Table. 1

Dia	h	BHN	Avg.before m/c
2.1	0.1214(h1)	131.080011	0.12147
2	0.1190(h2)	133.690152	
2.2	0.1240(h3)	128.342546	

The hardness is determined in a similar manner for the remaining operations, and the values for hardness value are given below. Table 4.

5.1 First hardness after machining:-

1st test □ h_1 =1/2[$\frac{D}{D2-d2}$] =0.1190476190476

2nd test □ h_2 =1/2[$\frac{D}{D2-d2}$] =0.1240079365079

3rd test □ h_3 =1/2[$\frac{D}{D2-d2}$] =0.121418164

Hardness Table. 2

Dia	h	BHN	Avg.After m/c 1
2	0.119047619(h1)	133.690152	0.12146
2.2	0.124007937(h2)	128.342546	
2.1	0.121418164(h3)	131.080011	

5.1.1 Second hardness after machining:-

1st test □ h1 =1/2[$\frac{D}{D2-d2}$] =0.11904762

2nd test □ h2 =1/2[$\frac{D}{D2-d2}$] =0.121418164

3rd test □ h3 =1/2[$\frac{D}{D2-d2}$] =0.121418164

Hardness Table. 3

Dia	h	BHN	Avg.After m/c 2
2	0.11904762(h1)	133.690152	0.12062
2.1	0.121418164(h2)	131.080011	
2.1	0.121418164(h3)	131.080011	

5.1.2Third hardness after machining:-

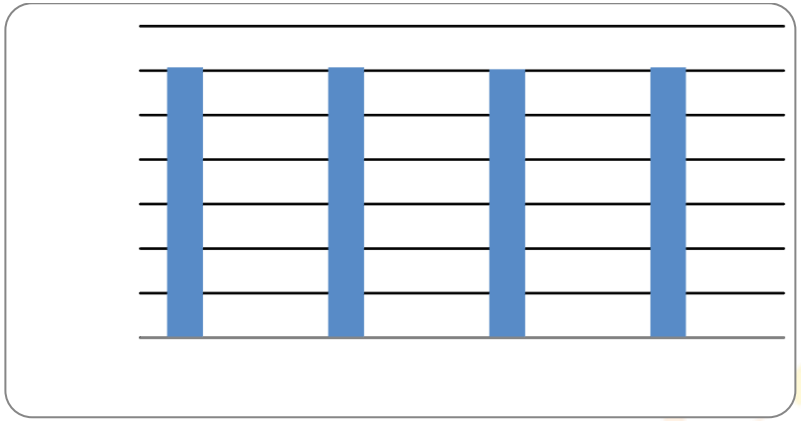
1st test □ h1 =1/2[$\frac{D}{D2-d2}$] =0.124007937

2nd test □ h2 =1/2[$\frac{D}{D2-d2}$] =0.121418164

3rd test □ h3 =1/2[$\frac{D}{D2-d2}$] =0.119047619

Hardness Table. 4

Dia	h	BHN	Avg.After m/c 3
2.2	0.124007937(h1)	133.690152	0.12149
2.1	0.121418164(h2)	128.342546	
2	0.119047619(h3)	131.080011	



By prediction the hardness values are
Increasing Hardness=0.12149
Mean =0.16281

6. Results:

By conducting the experiment on CNC machine with Speed = 1450rpm, and including all parameters, Increasing hardness = 0.12149,Mean = 0.16281 and the optimum conditions i.e. Speed = 1250rpm, Feed Rate = 75mm/min, Depth of Cut = 0.3mm and Material = 6063. By machining 6063 component, the results are

Surface Roughness =1.755µm
S/N ratio = -10*log((1.755)^2)
S/N ratio =-4.885

7. Conclusion:

Based on the results of this experimental investigation, the following conclusions can be drawn:

The cutting performance of aluminum alloy 6063 shows a favorable result. By conducting the experiment on CNC machine with Speed = 1450rpm, and including all parameters, Increasing hardness value is quit negligible i.e.0.12149,Mean = 0.16281. The Taguchi shows that the 6063 material has a good surface finish when machined under optimal conditions., i.e. by keeping 1250rpm, Feed Rate = 75mm/min, Depth of Cut = 0.3mm . The predicted values obtained from Taguchi are S/N ratio = -5.71809and the S/N ratio obtained by conducting the experiment is -4.885By this we are able to finish that the most efficient situations are adoptable for any machining.

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