WALIA journal 31(1): 6-16, 2015
Available online at www.Waliaj.com
ISSN 1026-3861

Optimization of machining parameters in end milling of Al 2024-SiC_p metal matrix composite using Taguchi method for surface roughness

Atul Kumar [1, *], Dr. Sudhir Kumar [2], Dr. Rohit Garg [2]

[1]*Research Scholar, Suresh Gyan Vihar University, Jaipur, India*
[2]*Professor in Mechanical Engineering (GNIT), Greater Noida (U.P.) India*

Abstract: The quality of the surface finish of the machined job is one of the most important product quality characteristics. In the present study the Taguchi methodology has been used for modelling and optimization of surface roughness in end milling of aluminium silicon carbide composite plates (Al2024-SiC_p) using carbide end mills. Four machining parameters, the spindle speed (rev. /min.), the feed rate (mm/min.), the depth of cut (mm) and number of flutes were used in the experiment. The average surface roughness (R_a) was chosen as a measure of surface quality. The experiment was designed and carried out on the basis of standard L27 Taguchi orthogonal array. The data set of the experimental values was used for conducting the optimization using Taguchi design methodology. The results of calculations were in good agreement with the experimental data. A minor discrepancy between the experimental results and calculations could be inferred due to the presence of random errors and uncontrollable errors of the machining process, as well as environmental effects. Using Taguchi method for design of experiment (DOE), other significant effects such as the interaction among milling parameters are also investigated.

Key words: *Stir casting; End milling; Surface roughness (R_a); Taguchi optimization technique; ANOVA*

1. Introduction

The advancement in automation and accuracy of machine tool has made it possible to produce high quality industrial products. One of the main perceptions of quality in mechanical products is its physical appearance. One of the most important factors in physical appearance is the surface roughness. A number of research publications addressed this issue of surface roughness measurement and analyses. This paper evaluates surface quality in end milling operation of Al 2024-SiC_p metal matrix composite. This material is selected as this is most widely used in automobile and aerospace industry. The effect of spindle speed, feed rate, depth of cut, number of flutes with respect to varying percentage weight of silicon carbide is studied on surface roughness. Alloy 2024 plate products are used in Sheet products, usually Alclad, are used extensively in commercial and military aircraft for fuselage skins, wing skins and engine areas where elevated temperatures to 250°F (121°C) are often encountered.

Among several CNC industrial machining processes, milling is a fundamental machining operation. End milling is the most common metal removal operation encountered. The most common cutting tool used with a vertical milling is an end-mill, which looks like a stubby twist drill with a flattened end instead of a point. An end mill can cut into a work piece either vertically, like a drill, or horizontally using the side of the end mill to do the cutting. This horizontal cutting operation imposes heavy lateral forces on the tool and the mill, so both must be rigidly constructed. By making a series of horizontal cuts across the surface of a work piece, the end mill removes layers of metal at a depth than can be accurately controlled to about one one-thousandth of an inch (.001"). The surface generated during milling is affected by different factors such as vibration, spindle run–out, temperature, tool geometry, feed, cross-feed, tool path and other parameters. During finish milling, the depth of cut is small. Technological parameter range plays a very important role on surface roughness [1]. In end milling, use of high cutting speed, low feed rate and low depth of cut are recommended to obtained better surface finish for the specific test range in a specified material [2]. Cutting feed is the most dominated factor for surface finish. The most important interactions, that effect surface roughness of machined surfaces, are between the cutting feed and depth of cut, and between cutting feed and cutting speed [11]. Surface Roughness is affected negatively if the applied force is increased [14]. Surface roughness at the same feed rate becomes higher when a small nose radius is used [13]. With the more precise demands of modern engineering products, the control of surface texture together with dimensional accuracy has become more important.

The experiment is conducted on Al 2024-SiC_p stir cast plates. The processing of the job is done by solid

* Corresponding Author.

carbide two, three and four fluted end-mill tools under finishing conditions. The machining parameters evaluated are spindle speed, feed rate, depth of cut and number of flutes. The experiments are conducted by using L-27 orthogonal array as suggested by Taguchi. Signal-to-Noise (S/N) ratio and Analysis of Variance (ANOVA) is employed to analyse the effect of milling parameters on surface roughness.

2. Literature review

P.S. Sivasakthivel et al. (2010) conducted experiments on aluminum Al 6063 by high speed steel end mill cutter and tool wear was measured using tool maker's microscope. The helix angle is the most significant parameter which reduces tool wear. The tool wear is minimal in between 400 – 450 helix angles. The increase in spindle speed and axial depth of cut reduces the tool wear. The decrease in radial depth of cut reduces tool wear. Sundara Murthy *et al.* (2010) studied provides the optimum cutting conditions for end milling of Aluminum 6063 under minimum quantity lubrication machining. The highest cutting speed, medium feed rate and medium depth of cut produces lowest surface roughness. Kromanis et al. (2008) developed a technique to predict a surface roughness of part to be machined according to technological parameters & find relationships between surface roughness (Average absolute deviation of the surface) of machined workpiece and used technological parameters (cutting speed; feed; depth of cut). They concluded that technological parameter range also plays a very important role on surface roughness. Study results can be used by technologists and other manufacturing specialists to set up cutting parameter in end-milling. Jaharah A. G et al. (2008) found that new challenge in machining (High speed milling of Ti-6Al-4V using coated carbide tools) is to use high cutting speed in order to increase the productivity. Effect of feed rate on surface roughness is more significant compared to other cutting parameters. The top layer of the machined surface experiences work hardening process, which is higher than the average hardness of the work piece material.

3. Methodology

3.1. Quality as par Taguchi

According to Taguchi, quality of a manufactured product is loss by that product incurred to the society from the time it is shipped. Financial loss or Quality loss may be given by:

$L(y) = k(y-m)^2$

Y objective characteristic

M target value

K constant

k = Cost of defective product / $(\text{Tolerance})^2 = A/\Delta^2$

3.1.1. Taguchi design approach

The Taguchi technique involves reducing the variation in a process through robust design of experiments. To achieve desired product quality, Taguchi suggested a three-stage process:

1. System Design: Right combination of materials, parts, processes and design factors that will satisfy functional and economical specifications.
2. Parameter Design: To find the appropriate control factor levels to make the system less sensitive to variations in uncontrollable noise factors, i.e., to make the system robust.

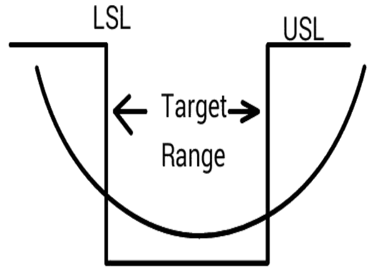

Fig. 1: Taguchi loss function

4. Tolerance design

Tolerances of those factors which have the largest influence on variation are adjusted to achieve the target quality level.

The overall objective of the method is to produce high quality product at low cost to the manufacturer. Taguchi's parameter design offers a single and systematic technique to optimize the design performance, quality and cost (Phadke, 1989).

Determine the quality characteristics to be optimized

↓

Identify the noise factors and test conditions.

↓

Identify the control factors and their alternative levels

↓

Design the matrix experiment and define the data analysis procedure.

↓

Conduct the matrix experiment.

↓

Analyse the data and determine optimum levels for control factors.

↓

Predict the performance at these levels.

Fig. 2: Steps in Taguchi design methodology

Two major tools used in robust design are:

1. Orthogonal arrays(OA), which accommodate many design factors simultaneously ;
2. Signal to noise ratio(S/N), which measures quality with emphasis on variation.

The columns in the OA indicate the control factor and its corresponding levels and each row in the OA forms an experimental trial run which is performed at the given factor settings. To select the number of levels and amount constitutes the major effort in planning robust design experiments. The S/N ratio helps in choosing control levels that best cope with noise. The S/N ratio may be defined as the ratio of the mean (signal) to the standard deviation (noise). S/N ratio is given by a formula having negative of logarithmic value, which is a monotonic decreasing function. So S/N ratio should be always kept at maximum value. While statistical process control attempts to control the factors which affect the quality of manufacturing, Taguchi methods focus on creating superior performance designs (combinations of output products and input machining or manufacturing processes) to produce better quality.

Normally three S/N equations are applicable in the various situations as described below:-

- Smallest is better quality characteristic (contamination, surface finish) $\frac{S}{N} = -10\log(\frac{1}{n\sum_i y^2})$
- Nominal-is-best quality characteristic (dimension) :$\frac{S}{N} = 10\log(\frac{\bar{y}^2}{s^2})$
- Largest-is-better quality characteristic(yield, material removal),$\frac{S}{N} = -10\log(1/n\sum_i \frac{1}{y_i^2})$

4.1. Standard orthogonal array L27

The orthogonal array is selected based on the DOF. Here, For 4 parameters each at three levels (degree of freedom =2+2+2+2) and two interaction (degree of freedom=4+4), so the total DOF=16, the number of DOF for orthogonal array should be greater than or equal to the number of DOF required. L27 orthogonal array has got 26 degrees of freedom which is obviously more than 16. Hence here L27 orthogonal array is selected. In this experiment with three factors at three levels each, the fractional factorial design used is a standard L27 (3x13) orthogonal array. The standard L27 (3x13) orthogonal array table (as shown in Table 2) with factors A(speed), B(feed) , C(depth of cut) and D (number of flutes) arranged in columns 1, 2,5 and 9 respectively. The interactions among factors are indicated as in column 3, 4, 6, 7, 8, 9 and 13(Singh and Kumar, 2004).

4.2. Analysis of variance (ANOVA)

In addition to the Signal to Noise Ratio (S/N ratio), the results have been subjected to Analysis of Variance (ANOVA) to evaluate the impact of control factors (process parameters) on surface roughness. In addition to the Signal to Noise Ratio (S/N ratio), the obtained results have been tested using statistical Analysis of Variance (ANOVA) to indicate the impact of process parameters on surface roughness.

$$SN_i = 10\log\frac{\bar{y}_i^{\,2}}{s_i^{\,2}}$$

$Where$

$$\bar{y}_i = \frac{1}{N_i}\sum_{u=1}^{N_i} y_{i,u}$$

$$s_i^2 = \frac{1}{N_i - 1}\sum_{u=1}^{N_i}(y_{i,u} - \bar{y}_i)^2$$

$i = Experiment\ number$

$u = Trial\ number$

$N_i = Number\ of\ trials\ for\ experiment\ i$

The group mean for group is:

$$\bar{y}_{i,.} = \frac{\sum_{j=1}^{n_i} y_{i,j}}{n_i}$$

The grand mean is:

$$\bar{y} = \bar{y}_{.,.} = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n_i} y_{i,j}}{n}$$

$$n = n_1 + n_2 + \cdots + n_k$$

$y_{i,j}$ = the measurement from *group i*, *observation-index j*.

k = number of groups

n_i = number of observations in group *i*

n = total number of observations,

The hypothesis that means of a given set of normally distributed populations, all having the same standard deviation, is equal. This is perhaps the best-known *F*-test, and plays an important role in the analysis of variance [17]. The name was coined by George W. Snedecor, in honour of Sir Ronald A. Fisher. Fisher initially developed the statistic as the variance ratio in the 1920s.

$$F = \frac{Explained\ Variance\quad or\quad between\ group\ variability}{Unexplained\ Variance\quad or\quad within\ group\ variability}$$

A type I error (raising a false alarm), also known as an error of the first kind, occurs when the null hypothesis (H_0) is true, but is rejected. The type I error rate or significance level is the probability of rejecting the null hypothesis given that it is true. [19]. It is denoted by α (alpha) and is also called the alpha level. By convention, the significance level is set to 0.05 (5%), implying that it is acceptable to have a 5% probability of incorrectly rejecting the null hypothesis. [18]

A type II error, also known as an error of the second kind, occurs when the null hypothesis is false, but erroneously fails to be rejected. (e.g., fire breaking out and the fire alarm do not ring).The rate of the type II error is denoted by the Greek letter β (beta) and related to the power of a test (which equals 1−β).

4.3. P-values

Hypothesis tests are used to test or check the validity of a claim that is made about a data set. This claim that's on trial is called the null hypothesis. The alternative hypothesis is the one you would believe if the null hypothesis is untrue.

The evidence in the trial is your data and the statistics that go along with it. All hypothesis tests ultimately use a *p*-value to weigh the strength of the evidence [20]. The *p*-value is a number between 0 and 1 and interpreted in the following way:

- A small *p*-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so you reject the null hypothesis.

- A large *p*-value (> 0.05) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis.
- *P-values* very close to the cut-off (0.05) are considered to be marginal (could go either way). Always report the *p*-value so your readers can draw their own conclusions.

This ANOVA analysis was done for a significance level of 0.05 (α), i.e., for a confidence level of 95%.

5. Experimental details

5.1. Materials and method of fabrication

5.1.1. Matrix material

Aluminium alloy Al 2024 was used as matrix material. Density of Al 2024 alloy is 2.78 g/cm^3 and Young's Modulus is 73 GPa .The main alloying element of Al 2024 alloy is copper. The second is magnesium, which is predominantly added to increase the wetting between matrix and reinforcement. Composition of Al 2024 is shown in Table 1.

5.1.2. Reinforcement material

Silicon carbide particulates are used as reinforcement material. Silicon carbide was purchased from Thermo-Technologies, Ghaziabad. The type of the silicon carbide is F320. Density of silicon carbide is 3.6 g/cm^3 and the mesh size is 29.2 ± 1.5 µm. The Fig. 3 shows the Al-2024 slabs whereas Fig. 4 shows the SiC powder.

5.2. Stir casting

The silicon carbide (SiC) is used as the reinforcement material in the preparation of the Al-2024-SiC metal matrix particulate composite. The process involves heating up of the Al-2024 metal to a temperature higher than the melting point about 850°C.This was done in an underground furnace and once aluminum melts; the SiC is added to the molten aluminum. It was degassed by purging hexachloroethane tablets. The furnace is then enclosed by the cover and a stirrer is introduced upon the cover of the furnace. The stirrer is attached to the motor which rotates the stirrer blades which are inserted into the molten metal. The motor rotates the blades at the speed of 500 rpm for about 5 minutes. The molten composite is then poured into the mould made by sand moulding of pattern 8” x 6” x 1”.The molten composite is then allowed to solidify which takes some 25 minutes and then the solidified composite is then allowed to cool in atmospheric temperature and pressure.

Table 1: Chemical composition of Al 2024 [% elements]

Si	Fe	Cu	Mn	Cr	Mg
0.5	0.5	3.8-4.9	0.30-0.9	0.1	1.2-1.8
Zn	Ti	Others (each)	Others (total)		Balance
0.25	0.15	0.05	0.15		Aluminum

Fig. 3: Plates of Al 2024

Fig. 4: SiC powder

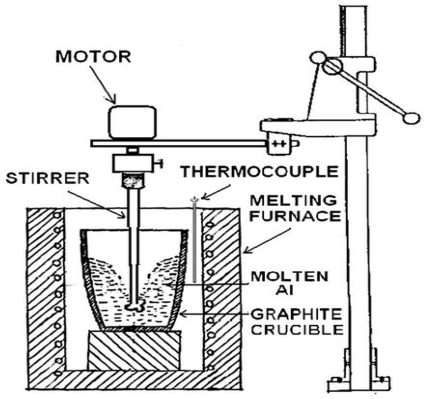

Fig. 5: Stir casting Arrangement

Fig. 7: Stir Cast Plate of Al 2024 -SiC Composite

5.3. Characterization of Al 2024- SiCp Plates

5.3.1. Metallographic examination and characterization

Microstructures of stir cast aluminium composite samples were examined by metallography. The photographs of samples were taken. Samples were freshly cut and mounted. Then they were grinded, polished and etched with Keller solution which contains 1.5% HCl, 2.5% HNO_3, 1% HF and 95% H_2O. At the end, micrographs (Figs. 8 & 9) were taken by a metallurgical microscope fitted with a digital camera.

5.3.2. SEM, EDX & XRD testing of the prepared composite plates:

In order to get detailed and close views of interior structures of aluminium samples SEM studies were done. Especially the precipitates that should form after casting were examined. The percentages of alloying elements were analysed and their graphs were obtained (Fig. 13). SEM studies were done with JSM-6400 Electron Microscope (JEOL). XRD analysis was carried out on X-ray diffraction machines of Shimadzu make (model XRD 6000) whereas SEM EDAX was carried out on Oxford instrument's ZEISS EVO 18 series machine (Figs.11 & 12). For SEM an accelerating voltage of 10 KV was used.

5.4. XRD Observations

Table 2: XRD data of Al 2024- 10% SiC

S. No.	Peak No.	2 Theta (deg)	d (A)
01	1	38.5993	2.33065
02	2	39.0200	2.30649
03	3	44.5400	2.03261
04	4	44.8451	2.01948
05	5	65.2552	1.42866
06	6	65.5800	1.42237
07	7	78.4419	1.21823

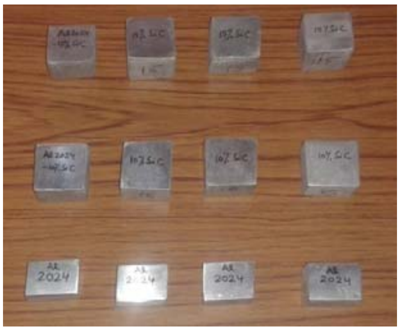

Fig. 8: Cut Specimens for characterization

Fig. 9: Underground furnaces for melting Al & SiC

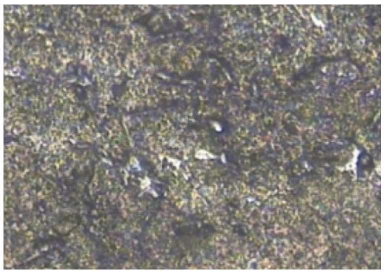

Fig. 10: LOM OF Al 2024- 10 % SiCp @10 X

*** Basic Data Process ***

Group : Standard
Data : Al2024

Strongest 3 peaks

no.	peak no.	2Theta (deg)	d (A)	I/I1	FWHM (deg)	Intensity (Counts)	Integrated Int (Counts)
1	1	38.5993	2.33065	100	0.23740	1606	21492
2	4	44.8451	2.01948	41	0.27740	658	9785
3	5	65.2552	1.42866	21	0.29760	339	5823

Peak Data List

peak no.	2Theta (deg)	d (A)	I/I1	FWHM (deg)	Intensity (Counts)	Integrated Int (Counts)
1	38.5993	2.33065	100	0.23740	1606	21492
2	39.0200	2.30649	3	0.16000	50	916
3	44.5400	2.03261	5	0.14220	83	986
4	44.8451	2.01948	41	0.27740	658	9785
5	65.2552	1.42866	21	0.29760	339	5823
6	65.5800	1.42237	3	0.10500	50	463
7	78.4419	1.21823	17	0.38820	281	6398

Fig. 11: XRD Data of Al 2024- 10% SiC

Table 3: Interpretation of the Composite Plates

S. No	Peak	Reference Peak	Measures Peak
1	Al, Si-C	38.452	38.5993
2	Al	44.8451	44.8451
3	Al	65.004	65.2552

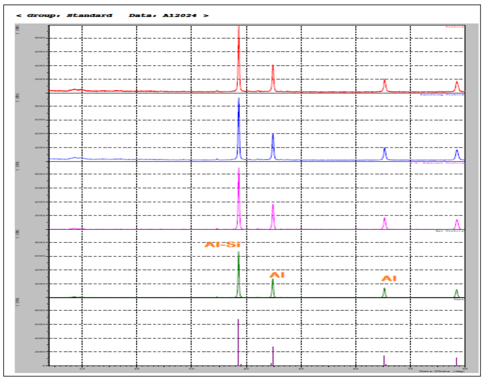

Fig. 12: XRD Data of Al 2024- 10% SiC

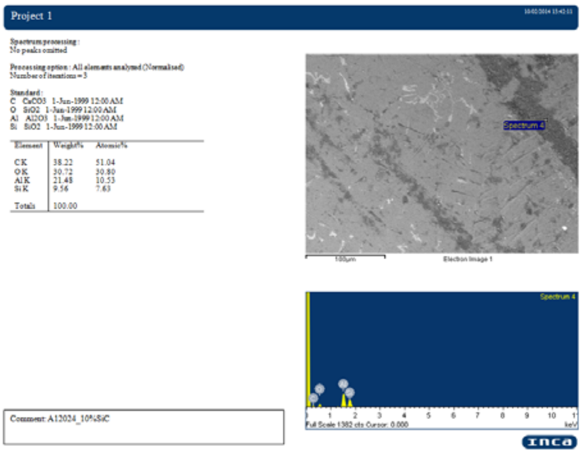

Fig. 13: SEM &EDS (Energy Dispersive Spectroscopy) of Al 2024-10%SiC

Fig. 14: TAKUMI CNC vertical machining centre

Fig. 15: End Mills used in the study

Fig. 16: End Milled (Slot) Al 2024-SiC plates

Fig. 17: Minitab Logo

5.5. Machining (end milling) conditions

From Table 3 it is confirmed that Aluminium, Silica and Carbon are present in the sample.

The experiments were carried with 2, 3 & 4 fluted carbide end mills on a highly precise CNC *Vertical* Machining Center of TAKUMI make with Maho controller (Fig. 14). The maximum travel of X-Y stage is 70mm whereas the maximum travel of Z stage is 100 mm.

The spindle speed varies from 100 to 24000 rpm**.** Total 27*2=54 runs were performed on Al 2024 -10% SiC and Al 2024 -15%SiC plates having dimensions 8” x 7” x 1”. Carbide end mill tools of diameter 12.7 mm (1/2 inch) were used to make horizontal slots as can be seen in the Fig. 13. The process parameters or control factors used were speed of the spindle (rpm), feed (mm/min), depth of cut (mm) and number of flutes as detailed in the Table 4.Three levels were used for each control factor. End milled plates having slots can be seen in Fig. 16.

The output characteristics considered was surface roughness. The surface roughness (R_a) of the end milled surface was measured using ITI surftest (see Fig. 18)

Table 4: Process parameters (factors) and their levels

Machining Parameters & Abbreviation	Code	Units	Levels		
			1	2	3
Spindle Speed (SPEED)	A	rev./min	1000	2000	3000
Feed (FEED)	B	mm/min	400	600	800
Depth of Cut (DOC)	C	mm	0.3	0.6	0.9
No. of flutes (NFL)	D	Nos.	2	3	4

The output characteristics considered was surface roughness. The surface roughness (R_a) of the end milled surface was measured using ITI surf test

5.6. Software used for analysis (Minitab 14)

In this project we have used the Minitab 14 software for the Taguchi design of experiment with signal to noise ratio and ANOVA approach

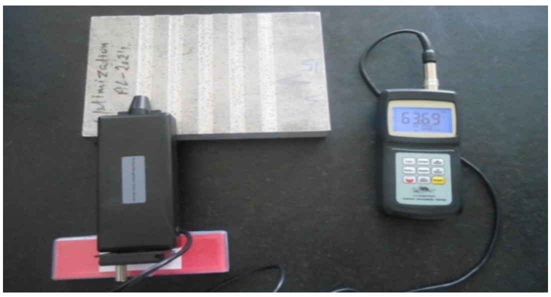

Fig. 18: ITI Surftest to measure Surface roughness

6. Results and discussions

6.1. Characterization of the Al 2024-SiCp composite plates

The results of LOM, SEM, SEM-EDAX and XRD showed that:

1. There is proper dispersion of SiC reinforcement in Aluminium matrix material as per LOM.
2. Mechanical characterization proved that there is increase in hardness and strength after reinforcement.
3. XRD and EDX showed the presence of SiC in alloy matrix

6.2. Analysis of surface roughness

The number of degree of freedom (DOF) for orthogonal array should be greater than or equal to the number of DOF required. Hence here L27 orthogonal array is selected. In this experiment with three factors at three levels each, the fractional factorial design used is a standard L27 (3x13) orthogonal array. The standard L27 (3x13) orthogonal array table (as shown in Table 2) with factors A, and C arranged in columns 2, 5, and 6 respectively. The interactions among factors are indicated as in column 1, 7, 8,9,11 and 12. (Singh and Kumar, 2004).This orthogonal array is chosen due to its capability to check the interactions among the factors. The factors and levels are assigned as in Table 4.

The experimental results are then transformed into a signal-to-noise (S/N) ratio. The S/N ratio can be used to measure the deviation of the performance characteristics from the desired values. Regardless of the category of the performance characteristic, a larger S/N ratio corresponds to better performance characteristic. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio.

6.2.1. Surface roughness of end milled Al 2024-10% SiC plates

Predicted surface roughness = 0.96333: D3= 0.987category of the performance characteristic, a larger S/N ratio corresponds to better performance characteristic. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio.

Table 5: Experimental data of Surface roughness of End Milled Al 2024-10% & 15% SiC plates

Trial	Coded Factors				Mean R_a (10% SiC) µm	η = S/N ratio (dB)	Mean R_a(15% SiC) µm	η = S/N ratio (dB)
	A	B	C	D				
1	1	1	1	1	0.8	1.9378	0.92	0.7238
2	1	1	2	2	1.23	-1.7995	1.56	-3.8664
3	1	1	3	3	1.46	-3.2877	4.6	-13.298
4	1	2	1	2	1.71	-4.673	3.34	-10.486
5	1	2	2	3	2.37	-7.5019	4.13	-12.362
6	1	2	3	1	1.23	-1.7987	0.98	0.175
7	1	3	1	3	2.7	-8.6342	3.94	-11.953
8	1	3	2	1	2.97	-9.4828	4.37	-12.853
9	1	3	3	2	3.13	-9.9386	4.75	-13.577
10	2	1	1	2	2.88	-9.1948	1.15	-1.2144
11	2	1	2	3	1.52	-3.65	2.11	-6.4965
12	2	1	3	1	1.83	-5.2621	2.53	-8.0733
13	2	2	1	3	2.01	-6.0748	2.86	-9.1382
14	2	2	2	1	1.91	-5.6315	1.98	-5.9372
15	2	2	3	2	1.84	-5.3072	2.95	-9.4073
16	2	3	1	1	3.38	-10.613	4.1	-12.299
17	2	3	2	2	3.5	-10.909	4.86	-13.776
18	2	3	3	3	2.99	-9.5411	3.57	-11.097
19	3	1	1	3	1.03	-0.2582	1.19	-1.5114
21	3	1	3	2	1.22	-1.7286	1.85	-5.3473
22	3	2	1	1	1.17	-1.3651	1.3	-2.2793
23	3	2	2	2	2.11	-6.4965	3.86	-11.775
24	3	2	3	3	1.32	-2.4121	1.63	-4.2477
25	3	3	1	2	3.07	-9.7705	3.5	-10.892
26	3	3	2	3	2.43	-7.7191	3.18	-10.059
27	3	3	3	1	1.95	-5.8115	1.4	-2.9265

Table 6: Predicted values (10% SiC)

S/N Ratio	Mean	St Dev	Log(St Dev)
-1.82224	1.30778	0.0550758	-3.97225
Factor levels for predictions			
Speed	Feed	DOC	NFL
3000 (A3)	400 (B1)	0.3 (C1)	2 (D1)

Predicted surface roughness = 1.3078 µm: Optimum values of factors & predicted values of response: A3-B1-C1-D1= 1.354 µm

6.2.2. Surface roughness of end milled of Al 2024-15% SiC plates

Table 7: Predicted Values (15% SiC)

S/N Ratio	Mean	St Dev	Log(St Dev)
-0.0205295	0.963333	0.0157512	-4.28208
Factor levels for predictions			
Speed	Feed	DOC	NFL
3000 (A1)	400 (B1)	0.6 (C2)	4 (D3)

Table 8: ANOVA of Surface roughness of Al 2024-10% SiC plates

Source	DF	Seq. SS (sum of squares)	Adj. SS (Variance)	Adj. MS (Variance ratio)	F	P	% SS (% contribution)
Speed (A)	2	55.291	55.291	27.6455	3.63	0.093	15.68 ⍰
Feed (B)	2	205.986	205.986	102.993	13.52	0.006	58.4154 ⍰⍰

DOC (C)	2	4.654	4.654	2.327	0.31	0.748	1.3199
NFL (D)	2	3.423	3.423	1.7115	0.22	0.805	0.9708
A*B	4	17.429	17.429	4.35725	0.57	0.694	4.9427
A*C	4	4.346	17.429	1.086	0.14	0.96	1.2325
A*D	4	15.779	4.346	3.945	0.52	0.727	4.4748
Residual Error	6	45.716	45.716	7.619			12.9646
Total	26	352.623=SS_T					100
S = 2.760 R-Sq = 87.0% R-Sq(adj) = 43.8%							
Critical F-ratio F0.05,2,6= 5.14, F0.05,4,6= 4.53							
Significant factor – Feed; Sub- significant factor – Spindle Speed							
Where S	An estimate of σ, the estimated standard deviation of the error in the model. Note that S^2= MS Error.						
R^2 (R-Sq)	Coefficient of determination; indicates how much variation in the response is explained by the model. The higher the R^2, the better the model fits your data. The formula is:$1 - \frac{SS_{Erroe}}{SS_{Total}}$						
Adjusted R^2 (R-SqAdj)	Another presentation of the formula is : $\overline{R}^2 = 1 - \frac{SS_{res}/df_e}{SS_{tot}/df_t}$						

Table 9: Response Table for Signal to Noise Ratios of Al 2024-10% SiC plates

Process Parameters	Code	Levels for 10% SiC			Delta (Δ) MAX. - MIN.	RANK
		1	2	3		
Speed	A	-5.02	-7.354	-3.922	3.432	2
Feed	B	-2.553	-4.585	-9.158	6.605	1
Depth of Cut	C	-5.826	-4.858	-5.611	0.968	3
No. of Flutes	D	-5.405	-5.881	-5.05	0.871	4

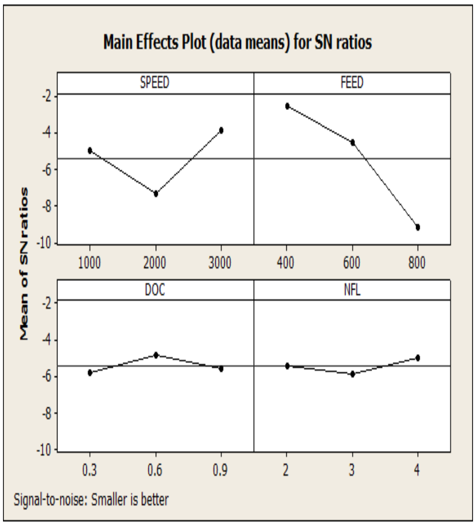

Fig. 19: Plot of SN Ratios of Al2024-10%SiC

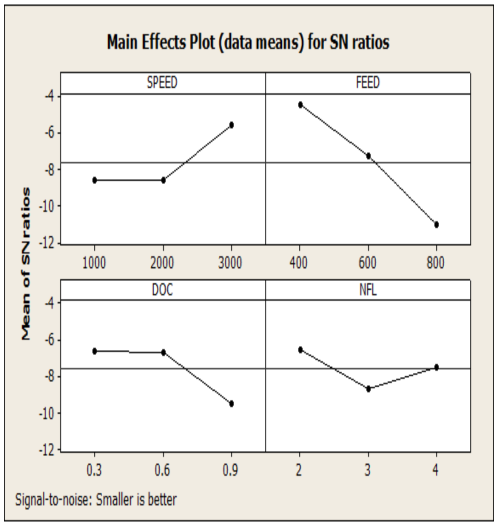

Fig. 21: Plot of SN Ratios of Al2024-15%SiC

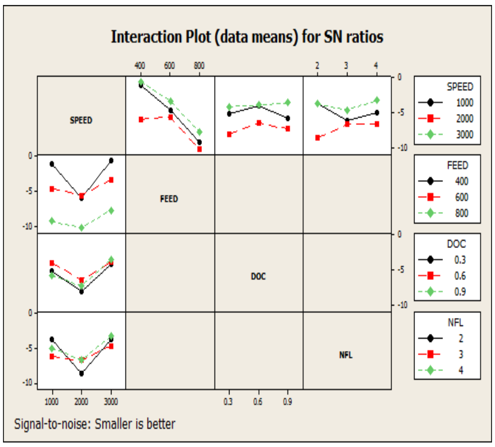

Fig. 20: Plot of Interactions of Al2024-10%SiC

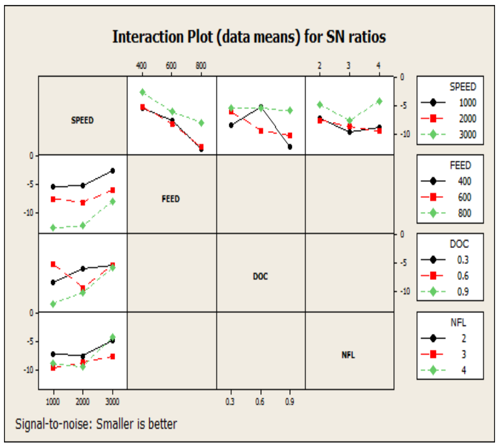

Fig. 22: Plot of Interactions of Al2024-15%SiC

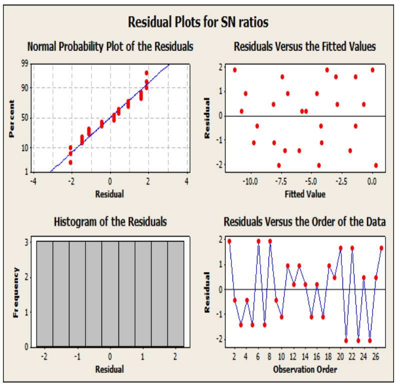

Fig. 23: Residual Plots for SN ratios of Al 2024- 10% SiC

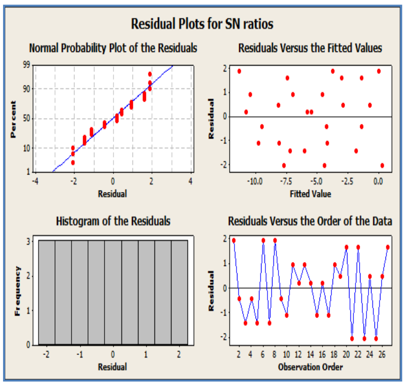

Fig. 24: Residual Plots for SN ratios of Al 2024- 15% SiC

Table 10: ANOVA of R_a of Al 2024-15% SiC plates

Source	DF	Seq. SS	Adj. SS	Adj. MS	F	P	% SS
Speed (A)	2	54.862	54.862	27.431	0.86	0.469	9.282 ✲
Feed (B)	2	195.71	195.71	97.855	3.07	0.121	33.109 ✲✲
DOC (C)	2	47.697	47.697	23.8485	0.75	0.513	8.07
NFL (D)	2	20.733	20.733	10.3665	0.33	0.734	3.508
A*B	4	9.48	9.48	2.37	0.07	0.987	1.604
A*C	4	56.284	56.284	14.071	0.44	0.776	9.522
A*D	4	15.228	15.228	3.807	0.12	0.97	2.577
Residual Error	6	191.121	191.121	31.8535			32.333
Total	26	591.114=SS_T					100
S = 5.644R-Sq =67.7% R-Sq(adj) = 39.4%							
Critical F-ratio F0.05,2,6= 5.14, F0.05,4,6= 4.53							
✲✲ Significant factor – Feed; ✲ Sub- significant factor – Spindle speed							

Table 11: Response Table for S/N Ratios of R_a of Al2024-15% SiC plates

Process Parameters	Designation	Levels For 15% SiC			Delta (Δ) = MAX. - MIN.	RANK
		1	2	3		
Speed	A	-8.611	-8.604	-5.584	3.027	2
Feed	B	-4.478	-7.273	-11.048	6.57	1
Depth of Cut	C	-6.631	-6.689	-9.479	2.848	3
No. of Flutes	D	-6.561	-8.704	-7.533	2.143	4

6.3. Discussion on above results

Using Taguchi method for design of experiment (DOE), other significant effects such as the interaction among milling parameters are also investigated.

6.3.1. Response tables

The S/N ratio helps in choosing control levels that best cope with noise. The S/N ratio may be defined as the ratio of the mean (signal) to the standard deviation (noise). S/N ratio is given by a formula having negative of logarithmic value, which is a monotonic decreasing function. So S/N ratio (see tables 9 &11) should be always kept at maximum value. So, in finding the optimum parameter setting, the levels of input factors are chosen in such a way that the S/N ratios for those levels have maximum values for each input factor (Antony & Kaye, 1999).

6.3.2. ANOVA tables

ANOVA is a computational technique which gives relative contribution of each control factor on the overall output response. ANOVA generalizes t-test to more than two groups.

The sum of squares SS_T estimates the square of deviation with respect to grand mean. Mean sum of squares are obtained by dividing SS_T by degree of freedom (DOF). F-ratio indicates adequacy of the model. When p-value is less than 0.05 (for 955 confidence level) the tested model can be said to statistically significant. The % contribution gives the effect of a control factor on the output. Factor with maximum % contribution is termed as most significant factor.

The ANOVA analysis (see Tables 8 & 10) revealed that feed is the most significant factor followed by speed and depth of cut for obtaining optimum surface finish, i.e., minimum value of R_a. Interactions do not have much effect on the output response. Only interaction between feed and speed affects the surface roughness to some extent.

6.3.3. Plots

The optimum parameter levels of input factors are given by S/N ratios having maximum values (for each input factor) (Antony & Kaye, 1999). So, Maximum value of a factor on an S/N plot of that particular factor indicates optimum level of that factor.

6.3.4. S/N plots

Figs. 19 & 21 clearly indicate the level of a control factor for optimum output. From Fig. 19; a combination of speed of 3000 rpm, feed of 400 mm /min, DOC of 0.6 mm and 4 flute end mill will provide better surface finish for Al 2024-10%SiC composite.

From Fig. 20; a combination of speed of 3000 rpm, feed of 400 mm /min, DOC of 0.3 mm and 2 flute end mill will provide better surface finish for Al 2024-15% SiC composite. As the content of SiC increases; end mill tool with lesser flutes generates a better surface finish.

6.3.5. Interaction plots

Figs. 20 & 22 show the effect of interaction among various input control factors. In Fig. 20, plot of factor A & C intersect each other indicating interaction of speed and DOC. In Fig. 22, plot of factor A & D intersect indicating interaction of speed and number of flutes. But as can be seen from ANOVA table the quantum effect of interaction is not major.

6.3.6. Residual plots

Residuals were scattered above and below the zero-line of the residual plot implying that the proposed models are adequate and the variance of the experimental measurements is constant at all values of responses. Hence, there is no reason to suspect any violation of the independence or constant variance assumption (Montgomery, 2013). As clear from residual plots (Fig. no. 23 & 24) residual form a straight line distribution implying model fits the data well. In second plot of Figs. 23 & 24 fitted values vs. residuals the values are scattered randomly below and above zero line showing data is independent.

7. Confirmation tests of optimum levels of the surface roughness

7.1. Experimental verification

The combination of input control factor levels, for which optimum output responses will be obtained, is given in Table 12 which shows the results of the confirmation test with optimized input control factors for output responses namely surface roughness. The verification between the predicted values and experimental data for both MMCs is in good agreement for a 95% confidence level.

Table 12: Confirmation test results

Expt. No.	Spindle speed	Feed	Depth of cut	No. of flutes	Surface roughness (Ra)	
					10% SiC	15% SiC
1	3000	400	0.6	4	0.987	---
2	3000	400	0.6	2	---	1.354

A minor discrepancy between the experimental results and calculations could be inferred due to the presence of random errors and uncontrollable errors of the machining process, as well as environmental effects.

8. Conclusions

The analysis of the result of the surface roughness shows that the optimal combination higher spindle speed, low feed rate, lower depth of cut (DOC) and for number of flutes it's a mixed one. But as the content of SiC increases in the metal matrix composite an end mill with lesser flutes generates better surface finish. The following conclusions were drawn from the analysis:

- Taguchi's robust design method is suitable to analyse the end milling problem as described in the present work.
- In end milling, increase in spindle speed, decrease in feed rate and decrease in depth of cut and less flutes will decreases the surface roughness within specified test range.
- In end milling, use of high spindle speed (3000 rpm), low feed rate (400 mm/min.) and low depth of cut (0.3 mm) and 4 fluted end mill tool are optimized parameters to obtained better surface finish for the specific test range in a Al2024-10% SiC composite while the values of same control factors for Al 2024-15%SiC are (3000 rpm), low feed rate (400 mm/min.) and low depth of cut (0.3 mm) and 2 fluted end mill tool.
- The feed rate and spindle speed are by far the most dominant factor than the depth of cut for surface finish.

References

A. Ravikiran, M.K. Surappa "Effect of sliding speed on wear behaviour of A356 Al-30wt.%SiCp MMC" In: Wear, 206 (1-2). Pp

C.Y. Chung and K.C. Lau: Mechanical Characteristics of Hipped SIC Particulate- Reinforced Aluminum Alloy Metal Matrix Composites, 0-7803-5489-3/99/$10.00109 99 IEEE. P. 1023-28

D. Huda, M.A. El Baradie& M.J.S. Hashmi, "Metal Matrix Composites: Materials aspects. Part II" Journal of material processing technology, Vol.37 (1993), 528-541.

D. J. Lloyd, "Particulate Reinforced Composites Produced by Molten mixing," High Performance Composites for the 1990's, eds. S. K. Das, C.P. Ballard and F. Marikar, TMS-New Jersey, 1990, pp 33-46.

D. Mahto and Anjani Kumar, Optimization of Process Parameters in Vertical CNC Mill Machine Using a Taguchi's Design of Experiments, Journal of Arab Research Institute in Sciences & Engg. (Industrial Engg.), ARISER, Vol. 4 No. 2 (2008), pp. 61-75, (UAE).

Davea, H. K., Patel, L. S., and Raval, H. K.,2012, " Effect of machining conditions on MRR and surface roughness during CNC Turning of different Materials Using TiN Coated Cutting Tools – A Taguchi approach," International Journal of Industrial Engineering Computations 3.

Han Jian-min, Wu Zhao-ling, Cui Shi-haia, Li Wei-Jing and Du Yong-ping, Investigation of defects in SiCp/A356 composites made by a stir casting method Journal of Ceramic Processing Research. Vol. 8, No. 1, pp. 74~77 (2006)

I. Adeqoyin, F. A. Mohamed and E. J. Lavernia, 'Particulate Reinforced MMCs-A Review, J. Mat Sci., Vol.26, 1991, pp 1137-1156.

Jaharah A.G , Nagi Elmagrabi, Che Hassan C.H, ,F.M. Shuaeib ,High Speed Milling of Ti-6Al-4V Using Coated Carbide Tools ,European Journal of Scientific Research ISSN 1450-216X Vol.22 No.2 (2008), pp.153-162 © Euro Journals Publishing, Inc. 2008

Jasmi Hashim "The production of cast metal matrix composite by a modified stir casting Method", Journal technology, Malaysia, pp 9-20, 2007

Lindenmayer, David; Burgman, Mark A. (2005). "Monitoring, assessment and indicators". Practical Conservation Biology (PAP/CDR ed.). Collingwood, Victoria, Australia: CSIRO Publishing. pp. 401–424. ISBN 0-643-09089-4.

Lomax, Richard G. (2007). Statistical Concepts: A Second Course. p. 10. ISBN 0-8058-5850-4.

M.K. Jain, V. V. Bhanu Prasad, S.V. Kamat, A. B. Pandey, V. K. Varma, B.V.R. Bhat and Y.R. Mahajan, "Processing Microstructure and properties of 2124 Al- SiCp Composites", Int. J Pow. Met., Vol. 29(3), 1993, pp 267-275

M.K. Surappa and P. K. Rohatgi, 'Preparation and Properties of Cast Aluminum Ceramic Particle Composites, 'J. Mat. Sci., Vol.16, 1981, pp.983-993.

Moheb M. Hanna, Arthur Buck, and Roger Smith, (1996) "Fuzzy Petri Nets With Neural

Networks To Model Products Quality from a CNC-Milling Machining Centre" IEEE, Vol. 26, No. 5.

Raviraj Shetty, Laxmikanth Keni, R. Pai and V. Kamath "Taguchi's Technique in machining of Metal Matrix Composites'', VOL. 3, NO. 5, OCTOBER 2008 ISSN 1819-6608 ARPN Journal of Engineering and Applied Sciences ©2006-2008 Asian Research Publishing Network (ARPN). All rights reserved. www.arpnjournals.com

Schlotzhauer, Sandra (2007). Elementary Statistics Using JMP (SAS Press) (1 ed.). Cary, NC: SAS Institute. pp. 166–423. ISBN 1-599-94375-1.

Statistics For Dummies, 2nd Edition. Deborah J. Rumsey. ISBN: 978-0-470-91108-2. 384 pages. May 2011. Statistics For Dummies, 2nd Edition.

Sundara Murthy, K. And Rajendran, I. (2010) , A study on optimization of cutting parameters and prediction of surface roughness in end milling of aluminum under MQL machining ,Int. Journal of Machining and Machinability of Materials, Vol. 7, Nos. 1/2, pp.112–128.

Wassanai Wattanutchariya and Bunyalith Pintasee, 'Optimization of Metallic Milling Parameters for Surface Finishing', Proceedings of the 7th Asia Pacific Industrial Engineering and Management Systems Conference 2006 17-20 December 2006, Bangkok, Thailand