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PARAMETRIC OPTIMIZATION OF CUTTING TOOL FLANK WEAR DURING HIGH SPEED TURNING OF AL 6061+ B4C (4%) METAL MATRIX COMPOSITE TURNING USING PVD COATED TOOL

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Abstract - This paper presents the influence of process parameters like cutting speed, feed and depth of cut on Tool Flank wear (Vb) in turning Al6061+B_4 C (4% by weight) metal matrix composites using PVD coated cutting insert under dry environment. The experiments have been conducted based on Taguchi's L9 orthogonal array. Optimization of three machining parameters cutting speed, feed rate and depth of cut, was done using three levels. The study spotlights the determination of the optimal machining conditions and the predictive modeling for the response while dry turning. Analysis of variance (ANOVA) showed that cutting speed (60.02%) is the most significant parameter followed by feed (37.42%).A notable improvement observed in Vb (4.503dB) after conducting confirmation tests. The optimal parametric combination for surface roughness is found to be v_3–f_1–d_1. The mathematical model for Tool Flank wear is found to be statistically significant.

***Key Words*:** Anova, Taguchi Method,Orthogonal array,Flank wear.

1.INTRODUCTION

Dry Machining is a processing method that consciously does not use cutting fluid and performs machining without cold liquid, mainly to protect the environment and reduce costs. And this dry machining is not simply to stop using cutting fluid, but to ensure high efficiency, high product quality, high tool durability and reliability of the cutting process while stopping the use of cutting fluid. This requires the use of dry machining tools, machine tools and auxiliary facilities with excellent performance to replace the cutting fluid in traditional cutting to achieve true dry machining. Cutting fluid is usually one of the indispensable production factors in most machining, and plays an important role in ensuring machining accuracy, surface quality and production efficiency. As global environmental awareness increases and environmental regulations become more stringent, the negative effects of cutting fluid was less than 3% of the cost of the work piece. At present, in high-productivity manufacturing enterprises, the supply, maintenance and recycling costs of cutting fluids accounts for 13-17% of the manufacturing cost of the work piece, while the tool costs only account for 2%-5%. About 22% of the total cost associated with cutting fluids is the processing cost of cutting fluid. It is estimated that if 20% of the cutting process uses dry machining, the total manufacturing cost can be reduced by 1.6%Green manufacturing that is environmentally friendly is considered a modern manufacturing model for sustainable development. Dry cutting without any cutting fluid during processing is a green manufacturing process that controls the source of environmental pollution. It can obtain clean, non-polluting chips, eliminating the need for cutting fluids and their disposal, which can further reduce production costs. Therefore, the direction of future machining is to use as little cutting fluid as possible. With the development of high temperature tool materials and coating technology, dry machining has become possible in the field of machine building. Dry machining technology emerged in this historical context and has developed rapidly since in the mid-1990s.Its development history has only been ten years, and it is a frontier research topic of advanced manufacturing technology. Cutting fluid is usually one of the indispensable production factors in most machining, and plays an important role in ensuring machining accuracy, surface quality and production efficiency.

2. Experimental Setup

We have used the Machinery that is CNC Turning and Microscope.

A CNC machine is a motorized maneuverable tool and often a motorized maneuverable platform, which are both controlled by a computer, according to specific input instructions. Instructions are delivered to a CNC machine in the form of a sequential program of machine control instructions such as G-code and M-code, and then executed. The program can be written by a person or, far more often, generated by graphical computer-aided design (CAD) or computer-aided manufacturing (CAM) software. In the case of 3D printers, the part to be printed is "sliced" before the instructions (or the program) are generated. 3D printers also use G-Code.

DIGITAL MICROSCOPE

A digital microscope is a variation of a traditional optical microscope that uses optics and a digital camera to output an image to a monitor, sometimes by means of software running on a computer. A digital microscope often has its own in-built LED light source and differs from an optical microscope in that there is no provision to observe the sample directly through an eyepiece. Since the image is focused on the digital circuit, the entire system is designed for the monitor image. The optics for the human eye are omitted.

Digital microscopes range from, usually inexpensive, USB digital microscopes to advanced industrial digital microscopes costing tens of thousands of dollars. The low price commercial microscopes normally omit the optics for illumination (for example Kohler Illumination and phase contrast illumination) and are more akin to webcams with a macro lens. An optical microscope can also be fitted with a digital camera.

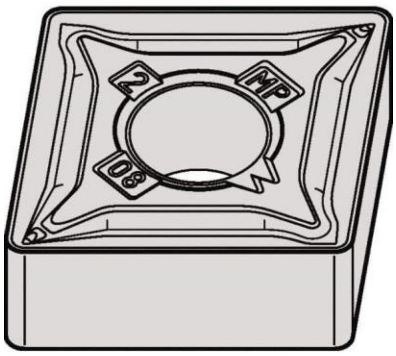
Figure 1.1 Digital Microscope

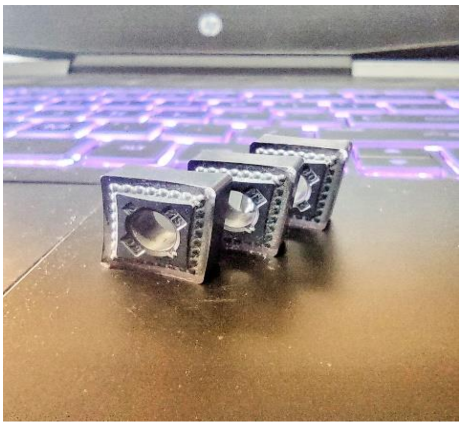
Figure:3.2 Ace Microsmatic SJ 500 XL CNC Lathe Machine, Length: 500 mm

Figure1.3 Workpiece

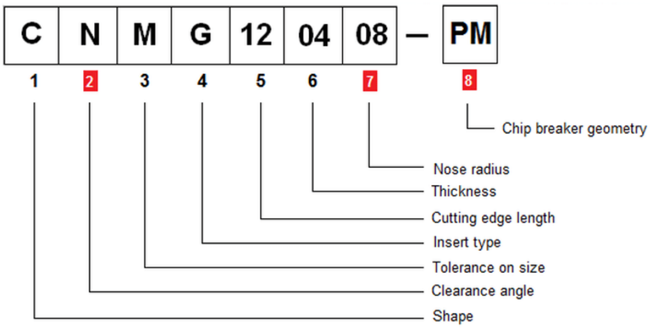
2. DESCRIPTION OF CUTTING TOOL.

In order to determine the surface roughness of under different cutting parameters CNMG120408MS KCS10 grade PVD coated carbide turning Insert AlTiN Finish, 80° Diamond, 1/2" Insert Circle, 3/16" Thick, 1/64" Corner Radius cutting insert was used.





Nomenclature



Inserts - ISO nomeclature

Table -1: Operational Factors

STD ORDER	RUN ORDER	PT TYPE	BLOCKS	SPEED	FEED	DEPTH OF CUT
1	1	1	1	150	0.05	0.05
2	2	1	1	270	0.05	0.05
3	3	1	1	150	0.1	0.05
4	4	1	1	270	0.1	0.05
5	5	1	1	150	0.05	0.15
6	6	1	1	270	0.05	0.15
7	7	1	1	150	0.1	0.15
8	8	1	1	270	0.1	0.15
9	9	-1	1	150	0.075	0.10
10	10	-1	1	270	0.075	0.10
11	11	-1	1	210	0.05	0.10
12	12	-1	1	210	0.1	0.10
13	13	-1	1	210	0.075	0.05
14	14	-1	1	210	0.075	0.15
15	15	0	1	210	0.075	0.10
16	16	0	1	210	0.075	0.10
17	17	0	1	210	0.075	0.10

3. Flank Wear Testing:

1. Now the machine specimens will undergo flank wear test
2. Place the tool insert under microscope for measuring (average of the absolute values of profile over elevation length)
3. Repeat the process for 21 trails.
4. Now the values are used to check the presence of the curvature (non-linearity) in a model.
5. If the curvature is significant additional experiments are added to build the non-linearity model.
6. If the curvature is not significant in the model in first stage additional experiments are not required to performed.

Table 4.1. Experimental results

Trail no	**Speed** (m/min)	**Feed** (mm/rev)	**Doc** (mm)	**Flank wear** (µm)	**S/N ratio (dB)**
1	200	0.10	0.375	0.88	1.11035
2	200	0.15	0.500	1.00	0.00000
3	200	0.20	0.625	1.12	-0.98436
4	300	0.10	0.500	0.80	1.93820
5	300	0.15	0.625	0.87	1.20961
6	300	0.20	0.375	0.87	1.20961
7	400	0.10	0.625	0.64	3.87640
8	400	0.15	0.375	0.79	2.04746
9	400	0.20	0.500	0.88	1.11035

4.1 S/N RATIO ANALYSIS

Taguchi used the S/N ratio as the quality characteristic of choice to analyze the data. S/N ratio is used as a measurable value instead of standard deviation due to the fact that as the mean decreases, the standard deviation also decreases and vice versa. The methods for calculating the S/N ratio are classified into three main categories, depending on whether the desired quality characteristics are smaller the better, larger the better or nominal the better. In the case of flank wear, the smaller values are always preferred. The S/N ratio functioned as a performance measurement to develop processes insensitive to noise factors. The degree of predictable performance of a product or process in the presence of noise factors could be defined from S/N ratio values. For each type of the characteristics, the higher the S/N ratio the better is the result.

The desired *"smaller the better"* criteria implies that the lowest flank wear would be the ideal result, while the largest S/N ratio response would reflect the best response which results in the lowest noise. This is the criteria employed in this study to determine the optimal machining parameters. The S/N ratio response graphs of the resultant flank wear for selecting the best combination levels for minimum flank wear are shown in Figs 1.

As seen in Fig 1based on the higher the S/N ratio the better is the result, the cutting speed (400 m/min), with the feed rate (0.1 mm/rev) and the lowest depth of cut (0.375 mm), are determined to be the best choices for obtaining the lower flank wear. Therefore, the optimal parameters combination for flank wear is 4-1-1.

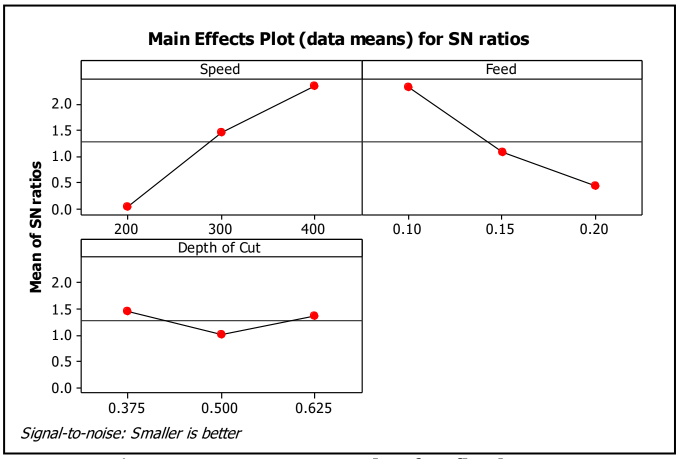


Figure 4.1. S/N ratio plot for flank wear

4.3 CONFIRMATION EXPERIMENTS:

After identifying the most influential parameters, the final step of the Taguchi method is the confirmation experiments performed to examine the quality characteristics. The model used in the confirmation test is defined with the total effect generated by the control factors and the factors are equal to the sum of each individual effect. The *4-1-1* is an optimal parameter combination for flank wear. Therefore, the condition *4-1-1* of the optimal parameter combination of the turning process was treated as a confirmation test. The optimal settings with a cutting speed of 400 m/min, 0.1 mm/rev of the feed rate, a cut depth of 0.375 mm gives the flank wear average (i.e., Vb) of **0.524 µm.**

In order to predict the S/N ratio $\eta_{pred.}$ for flank wear by using Tables 4.1 and 4.3a and, the following equation can be employed as (Nalbant et al., 2007),

$$\eta_{pred.} = \eta_{msn.} + \sum_{k=1}^{j} (\overline{\eta_k} - \eta_{msn})$$

Where $\eta_{msn.}$ the total mean of S/N ratio is, $\overline{\eta_k}$ represents mean S/N ratio at optimal set, and *j* is the number of input parameters that significantly affect the flank wear. The outcome of the conformation experiments and estimated values are shown in the Table 4.3b. From the results, a noteworthy improvement (4.503dB for flank wear) in S/N ratio was observed.

Table 4.3a. Response table mean S/N ratio for flank wear

Level	*v*	*f*	*D*
1	0.04200	**2.30832**	**1.45581**
2	1.45248	1.08569	1.01618
3	**2.34474**	0.44520	1.36722
Range (Max-Min)	2.30274	1.86312	0.43962
Rank	**1**	**2**	**3**

5.MATHEMATICAL MODELING

The performance of any manufacturing process can be predicted using mathematical models that can originate from either introspection or observation (or both). However, the intention of developing the mathematical models is to understand the combined effect of involved parameters and to facilitate the optimization of the machining process. In the present work, multiple linear regression models were developed using Minitab-14 software.

Linear regression model

$$Y = a_0 + \sum_{i}^{l}{}_{1} a_i X_i + \varepsilon_{ij}$$
Eq(1a)

Herea_0, a_i, a_{ij}, a_{ii} are the regression coefficients.X_i , denotes process parameters and ε_{ij} represents error of fit of regression equation.

For flank wear the model was hypothesized in acquiring the association between the VB and the turning parameter. The model equation is given as:

VB = 0.882 - 0.00115*Speed + 1.83* Feed + 0.120* Depth of Cut

MODEL ADEQUECY CHECKING

The assumption of normality of disturbances is very much needed for the validity of the results for testing of hypothesis, confidence intervals and prediction intervals. Small departures from normality may not affect the model much but gross non-normality is more serious. The normal probability plots help in verifying the assumption of normal distribution. If the errors are coming from a distribution with thicker and heavier tails than normal, then the least squares fit may be sensitive to a small set of data. Heavy tailed error distribution often generates outliers that "pull" the least squares too much in their direction. In such cases, other estimation techniques like robust regression methods should be considered. The normal probability plot is a plot of ordered standardized residuals versus normal scores. The normal probability plot is a graphical technique to identify substantive departures from normality. This includes identifying outliers, skewness, kurtosis, a need for transformations, and mixtures. Normal probability plots are made of raw data, residuals from model fits, and estimated parameters.

To measure the strength of the relationship between the developed model and dependent variable (flank wear in this work) on a suitable scale of 0-100%, coefficient of determination (R-sq) is used. In a simple way, the higher the R-sq value, the more explanation of variations in the output variable by input variables. In the current work, R-sq value is obtained as 91.2 %, means 91.2% variations in flank wear is explained by the machining parameters.

In a normal probability plot (also called a "normal plot"), the sorted data are plotted vs. values selected to make the resulting image look close to a straight line if the data are approximately normally distributed. Deviations from a straight line suggest departures from normality.

The model adequacy checking has been performed through residual analysis for the developed models. The residual plots are shown in Figs 5.1. This demonstrates Theodore Anderson and Donald Darling normal probability diagram. The p-value (0.277) is greater than the value of significance level 0.05; this implies that the data distribution is normal (i.e the null-hypothesis is true). The data points in the plot should in approximate linear form. The plot follows the normality as the residuals are close to the straight line. Finally, the proposed model for flank wear is adequate for good prediction.

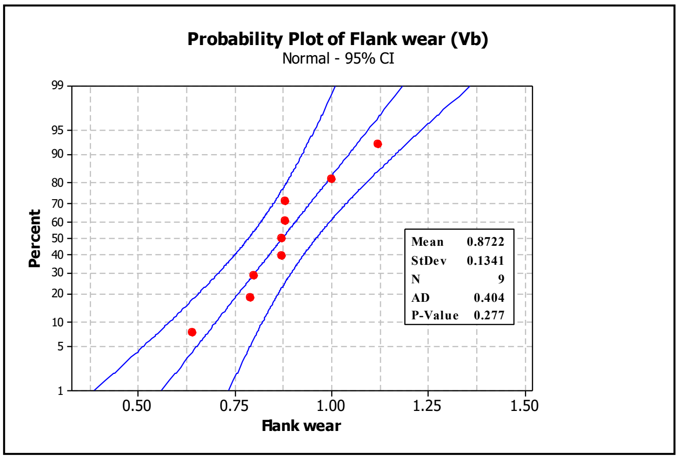


Figure 5.1. Probability plot of flank wear

6.CONCLUSION

This study has discussed an application of the Taguchi method for optimizing cutting parameters in the aim to minimize flank wear in dry turning on Al606+B4C (4%) MMC. The important findings are mentioned in the following specific conclusions:

- It is observed that cutting speed (60.02%) is the most significant parameter followed by feed (37.42%).
- Based on the Taguchi optimization approach, the optimal cutting parameters for minimizing flank wear (VB) are found to be as follows: v = 400 m/min, f = 0.1 mm/rev and DOC = 0.375 mm.
- The multiple regressions were obtained to predict flank wear whose value of R^2 is 91.2%. The predicted values and measured values are fairly close which indicates that the developed VB model can be effectively used to predict the flank wear from the cutting process, with 95% confident intervals.
- A good agreement between the predicted value and the experimental value can be seen. The increase of the S/N ratio from the initial cutting parameters to the optimal cutting parameters is 4.503dB.

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