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MODELING OF MATERIAL REMOVAL RATE IN ULTRASONIC MACHINING OF TUNGSTEN CARBIDE USING THE REGRESSION METHOD

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ABSTRACT

This paper describes the application of regression method in investing the effects of the electrical and physical parameters on the material removal rate in ultrasonic machining of tungsten carbide. Tungsten carbide as a super hard and high wear-resistant material has been used widely in industries. Powder metallurgy technology is the common method for producing tungsten carbide components. However, this method is obviously too costly and time consuming for small quantity production, such as product prototyping. It is expected to make the prototypes by a material removal process, such as ultrasonic machining. A brief explanation of the material removal rate is presented and the parameters influencing this output factor are identified. The statistica 7.0 software has been used for the regression method to obtain mathematical model .The validity of the results is verified since it predicts results which are in good agreement with experimental findings.

Keywords: *Regression, Hardness, Model.*

1. Introduction

Currently techniques for mechanical working of ordinary materials are highly developed and machine tools have been greatly improved in recent years. Engineering ceramic materials have many attractive properties such as high hardness, high thermal resistance, chemical stability and low electrical conductivity etc. Recent years have been seen the introduction of many new materials such as tungsten and titanium carbides, diamonds, rubies, sapphire, hard steels, magnetic alloys and corundum. Another group of materials such as germanium, silicon, ferrites, ceramics, glass, quartz etc gives difficulty on account of more brittleness. These materials often can not withstand the forces needed for mechanical working.

The need for methods of working these “unworkable” materials has led to the introduction of non-traditional methods such as electrochemical, electro erosion, electron beam and ultrasonic machining is one of them. The ultrasonic machining is a modern machining process with decisive advantages and as a result its use is becoming more and more widespread. Last five decades have witnessed rapid developments of advanced metals and alloys, hence increasing demand for their machining and fabrication. For better performance of machining of components made from such materials to close tolerances, higher surface finish is a must [1]. Hence, for the sake of economy, the components must be machined at a fast rate in minimum number of set ups. Ultrasonic machining is often used in the combination with other chip less machining techniques, such as electric discharge machining in the manufacturing of precision components.

Ultrasonic machining is a form of abrasion; the brittle material is removed by blows from grains of a harder abrasive. This action is under the control of a tool, which vibrates with small amplitude. The abrasive also causes wear in the tool but this is minimized by making the tool of viscous material. The particles of abrasive are themselves cleaved in the process and so must be gradually replaced by running into the working area. A liquid carrying fresh abrasive which also serves to flush away products. The material is cut away as very small particles, but these are produced by many abrasive grains. The tool vibrates at a high frequency so the total rate of removal can be sufficient for practical purposes. Tool may be advanced in the direction of vibration, in which case a cavity is produced whose profile corresponds precisely to that of the tool. Combinations of movements allow one to perform a variety of operations on brittle materials analogous to those of ordinary milling, shaping, profile milling etc.The noise resulting from this process is minimized by choosing a frequency in the low ultrasonic range (16-25 Kc / s). Earlier, the assessment

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of ultrasonic machining of cobalt based super alloy was studied using the taguchi methodology [2].The effects of various parameters of ultrasonic machining including tool material, types of abrasives, slurry concentration ratio, power rating, abrasive grit size, surface quality and material removal rate were discussed. The taguchi method is a powerful experimental design tool uses simple, effective and systematic methodology for deriving of the optimal machining parameters. Also this methodology requires minimum experimental cost and efficiently reduces the effect of the source of variation. An inexpensive and easy to operate methodology must be designed to improve the machined surfaces as well as maintain accuracy. The methodology uses taguchi experimental design for setting suitable machining parameters in order to effectively produce the complicated precise components. However, in this paper, effort has been made using the regression method to obtain the mathematical model for the material removal rate of tungsten carbide in ultrasonic machining process.

2. Experimental Details

The experiments were performed on a stationary Sonic-Mill, 500W (Albuquerque, USA) as shown in Fig. 1. The machining of tungsten carbide was done using different input parameters. The tool material used was titanium alloy (Titan15). The Fig. 6 represents the geometry of the tool.

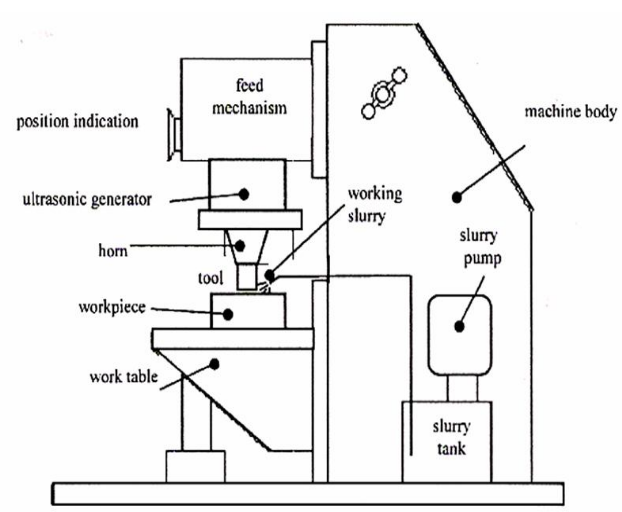

Fig.1 Schematic Diagram of the Ultrasonic Machine Tool (Type: Sonic Mill, USA)

The frequency was varied from 18 to 22 kHz. The three different values of power rating taken were (25, 50, 75) percent. The abrasive slurry silicon carbide (SiC) of three grit sizes (220, 320 and 500) with percentage concentrations by volume with water (20, 25, and 30) was used. The properties of SiC are (Hardness: 3000-3500 BHN, relative cutting power: 0.25-0.45), density: 3150 Kg/m^3, color: grey). The percentage chemical composition of tungsten carbide as the work material was (C=27.24%, O=3.51%, Co=4.57%, W=64.67%). The fixing of tool on the shank was performed by silver soldering.

The stresses were relieved by heat treatment after silver soldering. There was no withdrawal of the tool during the tests. The abrasive slurry feed circulation and frequency amplitude was maintained constant [3].The frequency measurement was performed with the help of a frequency meter. The trials were carried out under maximum material removal rate conditions with a tool rotation of 350 r.p.m.The regression analysis of results has been performed using the statistica 7.0 software.

3. Regression Method

The regression method is a technique which examines the relation of a dependent variable (response variable) to specified independent variables (explanatory variables) [4]. The objective here is to determine how the predicted or dependent variable y (the variable to be estimated) reacts to the variations of the predicator or independent variables. The regression analysis builds a mathematical model that helps to make accurate predictions about the impact of variable variations. The regression analysis can be used as a descriptive method of data analysis (such as curve fitting) without relying on any assumptions.

The values of regression parameters are determined using the experimental data. When a regression model is used, the dependent variable is modeled as a random variable because of either uncertainty as to its value or inherent variability [6, 7]. The data is assumed to be sample from a probability distribution, which is usually assumed to be a normal distribution. In this analysis, main objective was to determine machining parameter settings for maximization of material removal rate. The multi-objective optimization requires quantitative derivation of the relationship between the material removal rate with combination of machine setting parameters. The empirical expressions were developed to evaluate the relationship between input parameters and output parameter. The average output values of material removal rate were used to formulate the empirical expressions. The second order model is given below where x_1, x_2 and x_3 presents the abrasive slurry, concentration of abrasive slurry and power rating.

$$y = c_1x_1 + c_2x_2 + c_3x_3 + c_4x_1^2 + c_5x_2^2 + c_6x_3^2 + c_7x_1x_2 + c_8x_1x_3 + c_9x_2x_3 \quad (1)$$

The parameters of the above second-order model were estimated using regression method. It was observed that relative error between predicted and observed output values of material removal rate was well within limits of 0.924%. The following steps are involved when fitting data with nonlinear regression. The data obtained from the experimentation work has been used to develop the empirical model for material removal rate is given below:

$$y = 0.089x_1 + 8*10^{-5}x_2 + 0.020x_3 - 0.0011x_1^2 - 16*10^{-5}x_3^2 - 8*10^{-5}x_1x_2 + 2*10^{-5}x_1x_3 - 10^{-5}x_2x_3 \quad (2)$$

3.1 Choose a model and initial values

The non-linear regression fits a model to the data. Therefore, a model has to be selected. With most programs, this model must be expressed as a mathematical function. The non-linear regression is an iterative procedure. The program must start with estimated values for each variable that are in the right "ball park" say within a factor of five of the actual value[8,9]. It then adjusts these initial values to improve the fit.

3.2 Decide whether to constrain any parameters

When performing nonlinear regression, no need to fit each parameter in the equation [10]. Instead, one or more of the parameters may be fixed to constant values.

3.3 Decide on a weighting scheme

The non-linear regression programs generally weight each point equally and there are many ways to differentially weight the points [11].

3.4 Decide how to handle replicate values (If any)

If y values replicate at every value of x, there are two ways to fit a model to the data. It can treat each replicate as a separate point or average the replicate y values and treat the mean as a single point. It has to be considered each replicate a separate point when the replicates are independent.

3.5 Regression diagnostics

When a regression model has been constructed, it is important to confirm the goodness of fit of the model and the statistical significance of estimated parameters [12, 13]. The commonly used checkness of fit includes R-squared and analysis of pattern of residuals. Interpretations of these diagnostics heavily rest on the assumptions. Also statistics inference is needed such as confidence intervals for parameters or a test of whether or not the fitted model agrees well with the data [14].The appropriate computational procedures for polynomial regression are procedures of multiple linear regressions with two predictor variables such as x and x^2. However, on occasion it is suggested that non linear regression is needed for fitting polynomials. Practical consequences of the misunderstanding include that a non linear optimization procedure may be used when the solution is actually available in closed form [15].

3.5 Report of regression analysis

It includes examine the plots and the final regression line. Examine the residuals of the regression for normality (equally spaced around zero), constant variance and the outliers. Report the regression equation, the significance of the model, the degrees of freedom and the significance of each of the parameters (t-statistics and p-values for the slope and intercept) [16, 17].

3.6 R_2 from nonlinear regression

The value R_2 quantifies goodness of fit. It is a fraction between 0.0 and 1.0 and has no units. Higher values indicate that the model fits the data better. The R_2 can be interpreted from nonlinear regression. When R_2 equals 0.0, the best-fit curve fits the data no better than a horizontal line going through the mean of all y values. In this case, knowing x does not help for predicting y. When R_2=1.0, all points lie exactly on the curve with no scatter.

3.7 Residuals from nonlinear regression

Residual analysis creates predicted and residual values for all cases (observations). A residual is the distance of a point from the curve. A residual is positive when the point is above the curve, and is negative when the point is below the curve [18]. The residual table has the same x values as the original data, but the y values are the vertical distances of the point from the curve.

4. Results and Discussion

4.1 Diagnostic checking of the fitted model

The predicted values cluster fairly closely and homogeneously around the diagonal line in this plot and indicating a good fit of the model. It appears that the residuals follow the normal distribution very closely.

Table.1 shows the computational results in terms of signal to noise ratio and residuals for the various experiments. The process parameters taken are presented by A: Slurry concentration, B: Abrasive grit size, C: Power rating). The predicted and residual scores have been examined. The histogram as shown in Fig.2

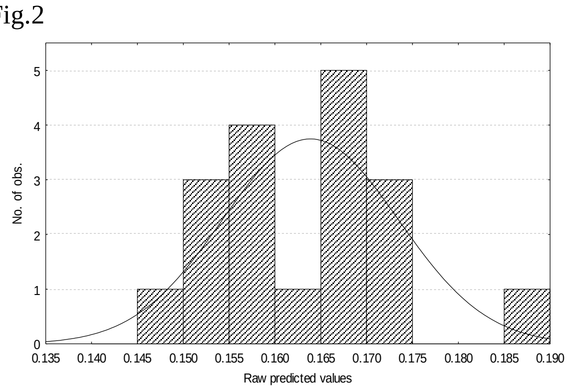

Fig. 2 Histogram of Raw Predicted Values

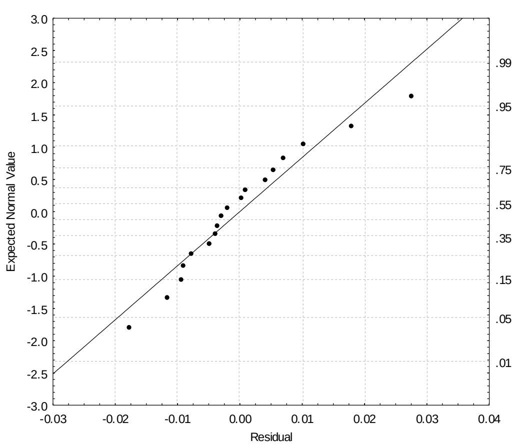

Fig.3. Normal Probability Plot

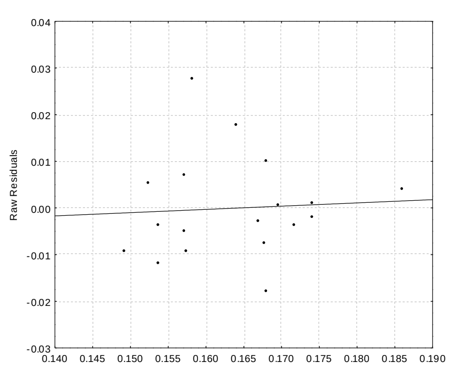

Fig.4 Predicted Vs. Raw Residuals

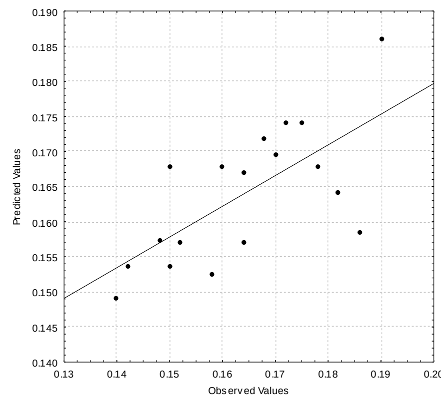

Fig. 5 Observed Vs. Predicted Values

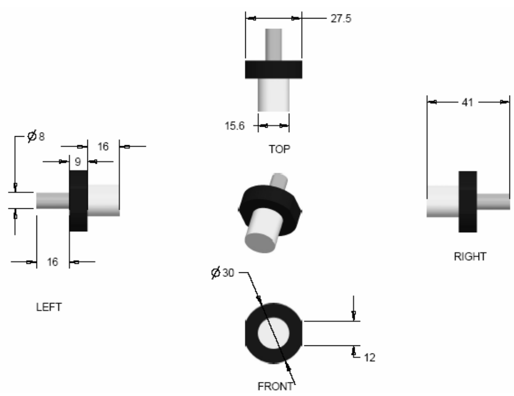

Fig.6 Presentation of Tool Geometry

Table: 1 Computational Result

A	B	C	Mean (MRR)	S/N ratio	Y (Residuals)
20	220	25	0.176	-15.4938	-0.0038
25	320	50	0.171	-16.0268	0.0054
30	500	75	0.202	-14.7985	0.0178
25	320	75	0.174	-15.1392	0.0009
30	500	25	0.156	-15.9176	-0.0078
20	220	50	0.179	-14.4249	0.0040
20	500	50	0.11	-15.7031	-0.0031
25	220	75	0.142	-14.9915	0.0100
30	320	25	0.115	-15.8096	0.0069
30	320	50	0.229	-15.2894	-0.0020
20	500	75	0.168	-16.4781	-0.0037
25	220	25	0.181	-16.5947	-0.0094
30	220	75	0.171	-16.3631	-0.0050
20	320	25	0.175	-16.7129	-0.0179
25	500	50	0.161	-16.9542	-0.0117
25	500	25	0.129	-14.6097	0.0276
30	220	50	0.124	-17.0774	-0.0092
20	320	75	0.137	-15.391	0.0003

represents the variation of raw predicted values. It indicates the results are satisfying the ±95% confidence limits.

4.2 Normal probability plots

The normal probability plot of residuals gives an indication of whether or not gross violations of the assumptions have occurred. If the residuals are not normally distributed, then they will deviate from the line. The outliers may also become evident in this plot. If there is a general lack of fit, and the data seem to form a clear pattern (e.g., an S shape) around the line, then the dependent variable may have to be transformed. The variation of predicted Vs residuals, observed Vs predicted has been shown in Figs.4 and 5. From the fig.5 it is concluded that the observed and predicted values are close to each other. Therefore the validity of results is verified since it predicts results which are in good agreement with the experimental findings.

5. Conclusion

The ultrasonic machining of tungsten carbide has been done using the titanium alloy (TITAN15) as tool material. A mathematical model of the material removal rate using regression analysis has been formulated by identifying both the physical and electrical parameters of the process. A second order empirical model was developed to reduce the predicted errors. It has been determined that maximum predicted error was only 0.924%.It has been concluded that this model fits the data and the prediction residuals for this model are well normally distributed. Also it has been found that the raw residuals are normally distributed as all values fall on to a straight line in the plot. All points follow the line very closely as concluded from the graphical presentations.

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