Empirical model for Surface Roughness in hard turning based on Analysis of Machining Parameters and Hardness values of various Engineering Materials

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ABSTRACT

This paper investigates the machining parameters affecting the roughness of surfaces produced in hard turning process for three different materials like EN8 steel, Aluminium alloy and Copper alloy under dry conditions. Three parameters were selected for study: cutting speed, feed and material hardness.

For the three materials like Aluminium alloy, copper alloy and EN8 steel impact of increase in feeds versus decrease in cutting speeds with constant depth of cut adopted to analyze the influence of these parameters on the generated surface roughness.

Regression analysis using MINITAB software for all the three material turning operation data mining was used to create model for the prediction of the average surface roughness (Ra) in terms of cutting speed, feed and material hardness and 67.2% of R^2 and 47.52% of R^2(adj) were obtained.

Keywords: Roughness, Engineering Materials, Regression Analysis, MINITAB.

1. INTRODUCTION

Metal cutting technology has grown rapidly with a common goal of achieving higher machining process efficiencies and high surface roughness. As the Surface roughness is one of the most important properties and is an indicator of surface quality specified by most of the customer requirements in machining process, it really necessitates the products to be of a very high surface quality to grab the product appearance, function, utility, heat transmission and reliability. To have high surface roughness, one has to do several machining cuts of each and every product, thereby making its processing time and production costs to be increasing. So, Hard turning of various engineering materials in a single cut operation, in order to reduce processing time, production cost and setup time with high surface roughness came into existence. Failures of mechanical parts due to surface roughness, sometimes leads to high cost damages, as in case of engine cylinder blocks, pistons etc. The quality of the produced components surface roughness can not only be evaluated using machining parameters like cutting speed, feed rate, depth of cut and their relative interactions but also with inclusion of the tool geometry wear.

The term “**Regression**” was introduced in the eighteenth century by Sir Francis Galton, cousin of C. Darwin, and had a pure biological connotation.

Regression analysis models the predictor–response relationship between independent variables and dependent variables. By the use of regression, curve fitting can be done as generalized linear, nonlinear, Poisson regression, log-linear, regression trees, least square, spline, Parametric, fractal etc.

2. LITERATURE REVIEW

Literature on the measurement of surface roughness using single and multi-point cutting tool on a ***single work piece materials*** using different machining parameters like feed, speeds, depth of cut and tool geometry are well documented [1-4]. In turning processes, a proper selection of cutting conditions generates high surface roughness finish and less dimensional errors. Hence, proper estimation of surface roughness based on cutting parameters and tool geometry has focused on number of researchers study.

T. Tamizharasan et al.**[1]** analyzed 18 different machining conditions on commercially available engine crank pin material, with three different grades of polycrystalline cubic boron nitride (PCBN) tool inserts for describing the various characteristics in terms of component quality, tool life, tool wear, effects of individual parameters on tool life and material removal, and economics of operation in hard turning operation performed on a lathe and measured surface roughness using MITUTOYO SURF III tester. Dilbag Singh. P. Venkateswara Rao **[2]** investigated the effects of cutting conditions and tool geometry on the surface roughness in the finish hard turning of the bearing steel (AISI 52100) with Mixed ceramic inserts made up of Aluminium oxide and titanium carbonitride (SNGA). This study showed that the feed is the dominant factor determining the surface finish followed by cutting velocity and then tool rake angle and a mathematical model for the surface roughness were developed by using the response surface methodology. Turnad L. Ginta et. Al **[3]** focused on developing an effective methodology to determine the performance of uncoated WC-Co inserts in predicting minimum surface roughness in end milling of titanium alloys Ti-6Al-4V under dry conditions. Response surface methodology was employed to create an efficient analytical model for surface roughness in terms of cutting parameters and Surface roughness values were measured using a surface roughness measuring instrument- Mitutoyo Surftest model SV-500. R.A. Mahdavinejad, H. Sharifi Bidgoli **[4]** highlighted the methods of predicting the surface roughness, like based on the trends of machining theories, .Based on the designed tests, based on Artificial intelligence such as Neural networks, GA, Fuzzy etc and methods based on lab research such as statistics and regression model analysis. Experiments were conducted to research on optimization of machining process under dry conditions in order to predict surface roughness on two steel blocks. Experimental data was used to create fuzzy rules and their processing via neural networks. So that, first the prediction model is created with some experimental data and then the results of this model are compared with the real surface roughness. The combination of adaptive neural fuzzy intelligent system is used to predict the roughness of dried surface machined in turning process.

Recent works extended in predicting surface roughness based on not only on cutting parameters (such as feed rate, spindle speed, and depth of cut), but also vibration signals detected by an accelerometer sensor [5,6] and also extended on to the surface roughness prediction on composite materials machining [7-10].

Julie Z. Zhang et. Al **[5]** developed an in-process surface roughness adaptive control (ISRAC) system in turning operations using Artificial neural network (ANN) employing two subsystems: the neural network-based, in-process surface roughness prediction (INNSRP) subsystem and the neural network-based, in-process adaptive parameter control (INNAPC) subsystem and predicted surface roughness during the finish cutting process with an accuracy of 92.42%. Abouelatta, O.B. and Mádl, J. **[6]** focused on the study of finding correlation between surface roughness and cutting vibrations in turning and derived mathematical models for the predicted roughness parameters based both on cutting parameters and machine tool vibrations.

Rajesh Kumar Bhushan et. Al **[7]** attempted to investigate the influence of cutting speed, depth of cut, and feed rate on surface roughness during machining of 7075 Al alloy and 10 wt.% SiC particulate metal-matrix Composites using tungsten carbide and polycrystalline diamond (PCD) inserts on a CNC Turning Machine and found machining with tungsten carbide tool, lower in the feed range of 0.1 to 0.3 mm/rev and depth of cut (DOC) range of 0.5 to 1.5 mm as compared to surface roughness at other process parameters to be considered and above cutting speed of 220 m/min surface roughness of SiC composite during machining by PCD tool was less as compared to surface roughness at other values of cutting speed considered. V. Anandakrishnan & A. Mahamani **[8]** investigated on the machinability parameters such as cutting speed, feed rate, and depth of cut on flank wear, cutting force and surface roughness were analyzed during turning operations of a in situ Al-6061–TiB2 metal matrix composite (MMC) prepared by flux-assisted synthesis basing on the composites characterization using scanning electron microscopy, X-ray diffraction, and micro-hardness analysis. Li Zhou et. Al **[9]** investigated a two-dimensional orthogonal cutting experiments and simulation analysis on the machining of SiCp/Al composites with a polycrystalline diamond tool. Using two kinds of finite element models, the cutting force and Von-Mises equivalent stress at different cutting conditions were studied in detail.

A. Manna. B. Bhattacharyya **[10]** investigated influence of cutting conditions on surface finish during turning of Al/SiC-MMC with a fixed rhombic tooling system using Taguchi method for optimizing the cutting parameters for effective turning. Taking significant cutting parameters into consideration and using multiple linear regression mathematical models relating to surface roughness height Ra and Rt were established.

The measurement of surface roughness of the workpiece by comparing with the maximum flank wears of the tool using machine visions systems, cutting parameters and vibrations using vibrometer has also been attempted for online prediction of surface roughness, as recent trends prefers automation of operations [11-14]. Researchers like H. H. Shahabi & M. M. Ratnam **[11,12]** studied the effect of nose radius wear using the 2-D profile using a toolmaker's microscope on the roughness profile and dimensional changes of workpiece of turned parts in a lathe operation using the machine vision (CCD camera) method. B. Srinivasa Prasad et. Al **[13]** developed a methodology for extracting the relevant information the cutting process, tool wear monitoring, vibrations and effect on the machined surface topography. Vibrational data acquisition and signal processing were grabbed using acousto-optic emission sensor (i.e., laser Doppler vibrometer) and the surface topography analysis of machined surfaces during the progression of the tool wear was done with vision-based surface textural analysis. Fatih Basciftci and Huseyin Seker **[14]** generated on-line prediction of tool wears using artificial neural networks and fuzzy logic, considering cutting parameters as combination of different cutting speeds and feeds with constant depth of cut.

Development of Regression models based on experimental tests of turning/machining operations are widely in exercise for predicting the behaviour and effects of machining parameters on surface roughness of the components or to aid the selection of working parameters given a required surface roughness [15-18]. C. X. (Jack) Feng et. Al **[15]** developed an empirical model for the prediction of surface roughness in finish turning basing on work piece hardness (material), cutting parameters, tool geometry and cutting time by means of nonlinear regression with logarithmic data transformation and their applications in determining the optimum machining conditions. Sahin, Yusuf and Motorcu, Riza A. **[16]** studied the development of surface roughness model when turning the mild steel hardened with mixed alumina ceramic (KY1615) and coated alumina ceramic cutting tools (KY4400). The model was developed in terms of main cutting parameters such as cutting speed, feed rate and depth of cut, using response surface methodology. A.M.A. Al-Ahmari [**17**] developed empirical models for tool life, surface roughness and cutting force in turning operations basing on the process parameters (cutting speed, feed rate, depth of cut and tool nose radius). Response surface methodology and neural networks were used on turning experiments done on austenitic AISI 302 to generate, compare and evaluate the proposed models of tool life, cutting force and surface roughness. K. Kadirgama et. al**[18]** investigated the surface roughness prediction of 6061-T6 Aluminium alloy in milling operation with carbide coated insert using statistical method and studied the influence of feed, speed, axial depth and radial depths as dependent variables.

Researchers focused more, on combination of various cutting parameters using single-point cutting tool in turning operations and the regression model generation of surface roughness. However, the empirical model generations were limited to only one material study. Hence this paper focuses on study of combination of cutting parameters along with three different materials hardness into account on surface roughness prediction and model generation.

3. EXPERIMENTAL DESIGN AND CONDITIONS

3.1. Machining Tests

In this work, turning operations were conducted on fully automated all geared headstock lathe machining center under dry condition, as shown in figure 1. Each turning operation were carried out with new carbide inserts for avoiding tool geometry wear impact, crater and chatter impact on disturbing the surface roughness finish in hard turning operations.

Figure 1: Experimental setup of turning operation

Three materials like Aluminium alloy, copper alloy and EN8 steel were chosen for studying the impact of increase in feeds versus decrease in cutting speeds with constant depth and were experimented to analyze the influence of these parameters along with the material hardness, on the generated surface roughness.

Surface roughness tester as shown in figure 2 of Mitutoyo SURFTEST SJ-301, range of traverse 0.25-0.5mm, Stylus (Diamond) differential induction method detection unit with detector retraction function in range of 21mm, V-Way bottom configuration, line voltage 100–240 V AC, power 12V, 3.5A, measuring in the range of -200 to 150microns, was used to measure the surface roughness on the turned surfaces. As the surface of turned components are cylinder in shape, surface roughness were measured on four diametrical points and the average of them was taken as surface roughness of that operation [2].

The effect of machinability parameters such as cutting speed, feed rate and material hardness on surface roughness with constant depth of cut [2,14] were analyzed during turning operations and a regression model was developed.

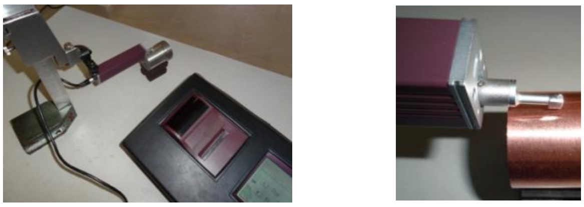


Figure 2: Experimental setup of measuring surface roughness using MITUTOYO SJ-301 surface roughness tester

3.2 Cutting inserts

Commercially available tungsten-based uncoated flat faced cemented carbide inserts (grade: WIDIA gray DCMT 11T312) were used. These inserts have geometries identical with the ones designated by ISO as DCMT 11T312 THM and ANSI as DCMT 3253 (rhombus shape insert of length 11.63, with thickness of 3.97 and 1.2mm nose radius).

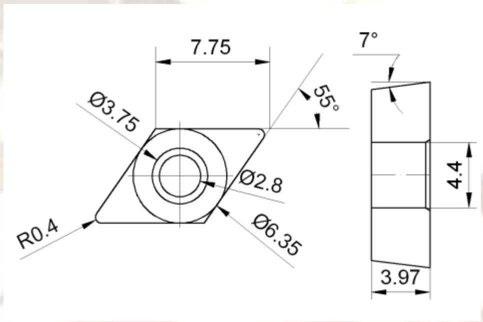


Figure 3: Carbide Insert Geometry

3.3 Workpiece material

Hardness test is practical and provide a quick assessment and the result can be used as a good indicator for material selections. It also employed for quality assurance like wear, strength, fatigue etc. The nomenclature of hardness comes in various terms depending on the techniques used for hardness testing and also depends on the hardness levels of various types of materials.

In this work, Brinell hardness testing machine was used for measuring the hardness of all the materials on which cutting tests were performed like on EN8 steel (152-207HB) and found the hardness to be 170.4HB. This material was chosen for its well-known properties and for its relevance to the automotive and heavy equipment industries. Aluminium alloy having hardness of 69HB are widely used in engineering structures and components where light weight or corrosion resistance is required and Copper alloy having hardness of 85HB are widely used in deep draw and flat stamped products because of their excellent electrical and thermal performance, good resistance to corrosion, high ductility and relatively low cost, non-magnetic, non-sparking and non-bacterial and is slow to corrode.

The three workpiece materials used as test pieces were in the form of solid cylindrical bars.

$$BHN = \frac{2P}{\pi D\left[D - \sqrt{D^2 - d^2}\right]} \quad (1)$$

Where BHN *is* the Brinell hardness value, P is applied load (kg-f), D is diameter of the indent ball (mm), d is the diameter of the indentation (mm).

Using the Eq: (1) and $P/D^2 = 10mm$ & $P/D^2 = 30mm$ for Aluminium alloy, Copper alloy and EN8 steel respectively with indent ball diameters of 5mm and 2.5mm respectively, the hardness values of the materials were determined.

The test piece taken are of 12cm each and as the machining done on them is hard turning, the temperature raised does not influence on the change in material hardness and so the hardness of the materials taken remains same through out the experiments.

4. EXPERIMENTAL DATA AND REGRESSION MODEL

This work postulates the model for the surface roughness prediction in the turning operations, in terms of the independent variable investigated based on lab research such as regression model analysis and using Taylor tool life equation in metal cutting [2,3,4,10,14], the variables can be expressed as:

$$R_a = Cf^a v^b H^d \tag{2}$$

Where R_a Average surface roughness (µm), v is the cutting speed (m/min), f is the feed (mm/min), and H is hardness of the material (BHN) under consideration. C, a, b and d are model parameters to be estimated from experimental results.

Converting the exponential form of surface roughness R_a to linear model with help of logarithmic transformation, we generate the model as

$$\log R_a = \log C + a * \log f + b * \log v + d * \log H \tag{3}$$

The proposed first order model developed from the above functional relationship using RSM method is as follows [2]:

$$Y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \tag{4}$$

Where Y is the true response of surface roughness on a logarithmic scale $x_0 = 1$ (dummy variable), x_1, x_2, x_3 are logarithmic transformations of feed, speed and material hardness respectively, while $\beta_0, \beta_1, \beta_2, \beta_3$ are the parameters to be estimated. Eq (4) can be expressed as:

$$Y_1 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \tag{5}$$

Where Y_1 is the estimated response and y the measured surface roughness on a logarithmic scale, ε the experimental error and the b values are estimates of the β parameters.

The second-order model can be extended from the first-order model's equation as:

$$Y_2 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_{11} x_1^2 \\ b_{22} x_2^2 + b_{33} x_3^2 + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{23} x_2 x_3 \tag{6}$$

Where Y_1 is the estimated response based on second order model.

Table 1: Experimental test values of turning operations on Aluminium alloy having hardness of 69HB using Carbide insert and constant depth of cut of 1.5mm

Test Piece	Average Surface Roughness (microns)	feed (mm/rev)	Spindle Speed (rpm)	Cutting speed (m/min)
1	3.38	0.15	1250	184.475
2	2.39	0.17		190.36
3	2.96	0.19		184.475
4	2.49	0.2		196.25
5	4.08	0.2	900	132.82
6	2.20	0.22		137.06
7	4.59	0.24		137.06
8	3.24	0.25		141.3
9	8.95	0.25	560	82.65
10	6.75	0.28		85.28
11	7.14	0.3		87.92

Table 2: Experimental test values of turning operations on EN8 steel alloy having hardness of 170.4HB using Carbide insert and constant depth of cut of 1.5mm

Test Piece	Average Surface Roughness (microns)	feed (mm/rev)	Spindle Speed (rpm)	Cutting speed (m/min)
1	3.50	0.15	1250	184.475
2	3.28	0.17		190.36
3	2.05	0.19		184.475
4	2.53	0.2		196.25
5	4.14	0.2	900	132.82
6	3.53	0.22		137.06
7	5.09	0.24		137.06
8	2.71	0.25		141.3
9	5.18	0.25	560	82.65
10	5.90	0.28		85.28
11	3.50	0.3		87.92

Table 3: Experimental test values of turning operations on Copper alloy having hardness of 85HB using Carbide insert and constant depth of cut of 1.5mm

Test Piece	Average Surface Roughness (microns)	feed (mm/rev)	Spindle Speed (rpm)	Cutting speed (m/min)
1	3.92	0.15	1250	184.475
2	2.80	0.17		190.36
3	2.22	0.19		184.475
4	1.92	0.2		196.25
5	4.09	0.2	900	132.82
6	3.57	0.22		137.06
7	6.05	0.24		137.06
8	3.30	0.25		141.3
9	4.04	0.25	560	82.65

10	4.63	0.28		85.28
11	3.38	0.3		87.92

Each workpiece material of length "L" were divided into 11 parts using the combination of three speeds and four feeds in such a way that as the cutting speed increases, the feed decreases, as shown in tables 1,2 and 3 and are been cut using hydraulic power hacksaw machine. As the surface is cylindrical, surface roughness was measured on the four diametrical end points and average of them was considered as the surface roughness of the test material.

In this paper, after conducting the first pass of the 11 cutting experiments for each material, the surface roughness readings are used to find the parameters appearing in the postulated first-order and second-order model (Equation 4 & 5). In order to calculate these parameters, the least square method was used with the commercially available data mining technique software packages like MINITAB software. The first-order and second order linear equation used to predict the regression constants and exponents and the regression equation of surface roughness generated as:

$$R_a = 12.942 - 14.02 f - 0.0384 v - 0.00445 H$$

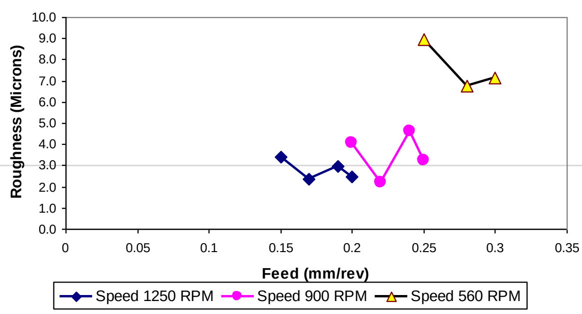
$$\text{with } R^2 = 67.20\% \;\; \& \;\; R^2(adj) = 47.52\%$$

5. RESULTS

In this paper, regression analysis generates comparable results with its competing data mining method. The established regression equation indicates that the feed affects the surface roughness the most, but other parameters like cutting speed and the hardness of materials had a slight effect on surface roughness values.

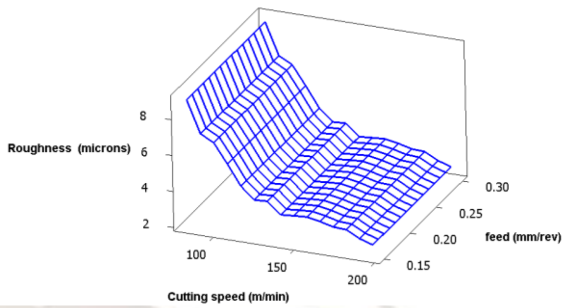
Table 1,2 and 3 presents the experimental results, when machined with considering cutting parameters (like feed, speed with constant depth of cut) and material hardness as a measure of surface roughness. So, three parameters are involved in predicting the model. Graph 1a, 2a and 3a indicates that the surface roughness decreases gradually at high speed like at 1250rpm and Graph 1b, 2b and 3b depicts that the Aluminium alloy at low machining speeds generates high roughness on surface and can be reduced with low feeds and hence Aluminium alloy is suitable for high speeds. EN8 steels generate high surface finish at high speeds with high feeds. Whereas Copper alloy shows the surface roughness will be good at high speeds with high feeds and even at low speeds with high feeds, the surface roughness can be maintained same as that of average speeds with increase in feeds.

Fitted curve approximates very close to the observed values and predicts the regression model with a good precision and it appears to be a better model with R-sq of 67.20%. Furthermore, the average surface roughness value of Ra is 4.38 um for Aluminium alloy, 3.67 um for EN8 steel and 4.12 um for copper alloy using



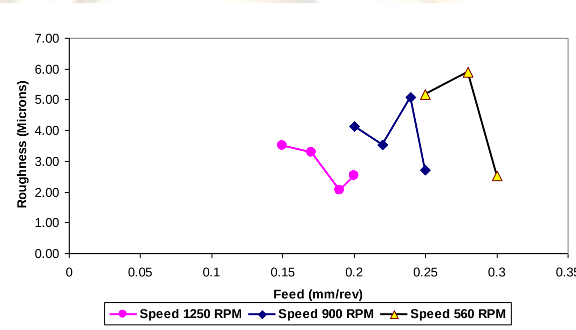
new carbide inserts each time, respectively.

(a)



(b)

Graph 1: Surface Roughness Vs Feed and cutting speeds for Aluminium alloy



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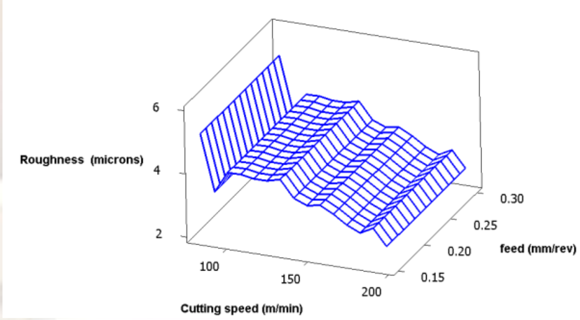
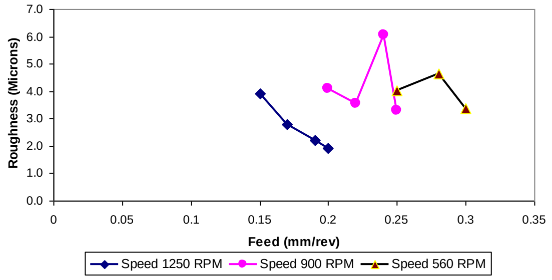
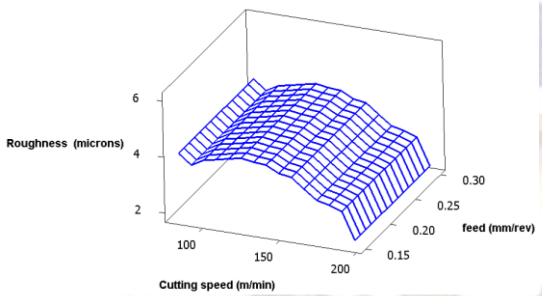


(b)

Graph 2: Surface Roughness Vs Feed and cutting speeds for EN8 steel alloy



(a)
(b)



Graph 3: Surface Roughness Vs Feed and cutting speeds for Copper alloy

The adequacy of using analysis of variance on regression model, shown in Table 4. At a level of confidence of 95%, the model was checked Surface Roughness Prediction Model of Machining Using Statistical Method for its adequacy. As shown in Table 4, P value shows no evidence of lack of fit (P>=0.1) and this implies that the model could fit and it is adequate.

Table 4: Analysis of Variance

Source	Degree of Freedom	Sum of Squares	Mean Squares	F-ratio	P-Value
Regression	3	40.796	13.599	9.22	0.00
Residual Error	29	42.794	1.476		
Total	32	83.590			

6. CONCLUSIONS

The investigations of this study indicate that the cutting parameters like cutting speeds and feeds are the primary influencing factors, which affect the surface finish when machining with new tool inserts. The results indicate that feed is the dominant factor affecting the surface roughness, followed by cutting speed and hardness of the material.

Empirical model for surface roughness developed in this paper based on metal cutting experiments with various speeds and feeds and material hardness by means of nonlinear regression data mining technique done in MINITAB. It can be used to estimate the values of surface roughness at certain turning parameters like speeds and feeds or to aid the selection of working parameters and material, when given a required surface roughness.

With the regression equation generated, the best combination of design variables between feed, cutting speed and material hardness for achieving optimum surface roughness can be worked out.

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