

Empirical model for estimating the surface roughness of machined components under various cutting speed

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ABSTRACT: The increasing importance of turning operations is gaining new dimensions in the present industrial age, in which the growing competition calls for all the efforts to be directed towards the economical manufacture of machined parts as well as surface finish is one of the most critical quality measure in mechanical products. In the present work, empirical models for estimating the surface roughness of machined components under various cutting speed have been developed using regression analysis software. The centre lathe was used to turn the components (stainless steel, mild steel and aluminum cast) at different cutting speed ranging between 76 rev/min to 600 rev/ min at a constant depth of cut of 1 mm/pass and feed rate of 0.5 mm/rev. and surface roughness of machined components measured with a digital portable surface roughness tester (TR100 Model) using centre line average method. The values obtained from the empirical models were found to compare favourably with the experimental values. The Mean Absolute Percent Deviation (MAPD) which measures absolute error as a percentage was found to be 1.46% (stainless steel), 4.55 %(mild steel) and 4.76% (aluminum cast) respectively. These values were insignificant and below the maximum recommended value of 10%. These model performances were therefore found to be satisfactory and show good predictability. @JASEM

Keywords: cutting speed, centre lathe, empirical model, surface roughness, Mean absolute percentage deviation

Today s manufacturing industries are very much concerned about the quality of their products. Surface Roughness (finish) is one of the crucial performance parameters that have to be controlled within suitable limits for a particular process (Saadat, 2008). Therefore, prediction or monitoring of the surface roughness of machined components has been an important area of research. Surface roughness is harder to attain and track than physical dimensions are, because relatively many factors affect surface roughness. Some of these factors can be controlled and some cannot. Controllable process parameters include feed, cutting speed, tool geometry, nose radius and tool setup. Other factors, such as tool, work piece and machine vibration, tool wear and degradation, and work piece and tool material variability cannot be controlled as easily (Saadat, 2008). Surface roughness also affects several functional attributes of parts, such as contact causing surface friction, wearing, light reflection, heat transmission, ability of distributing and holding a lubricant, coating or resisting fatigue (Saadat, 2008. Therefore the desired finish surface is usually specified and the appropriate are selected to reach the required quality.

Several works have been reported in the area of models to predict surface roughness of machined component. Ozcelik and Bayramoglu, 2006 developed statistical models to predict the surface roughness estimation in a high-speed flat end milling process under wet cutting conditions, using machining variables such as spindle speed, feed rate, depth of cut, and step over. First- and second-order models were developed using experimental results of a rotatable central composite design, and assessed by means of various statistical tests. Palanikumar et al ,2008 developed an empirical model for predicting surface roughness in machining A356/SiC/20p composites with the lathe. Response surface regression and analysis of variance (ANOVA) are used in order to study the effects of machining parameters. Saadat, 2008 adopted, a Regression Analysis to construct a prediction model for surface roughness such that once the process parameters (cutting speed, feed, depth of cut, Nose Radius and Speed) are given, the surface roughness can be predicted. The work piece material was EN8 which was processed by carbide-inserted tool conducted on CNC lathe. Ozel, and Karpat, , 2004 used a neural network modeling approach to predict surface roughness and tool wear in turning operation.

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The factors considered were work piece properties ,tool material, tool geometry and cutting conditions in it a prediction system was developed which was capable of accurate surface roughness and tool wear prediction. Jiao et al (2004), used fuzzy adaptive networks in machining process modeling to predict surface roughness in turning operation and found that this approach is more powerful than the classical regression approach. Pal and Chakraborty (2005) developed a back propagation neural network model for the prediction of surface roughness in turning operation. Sundaram et al (1981) developed mathematical models to predict surface finish in fine turning of AISI 4140 steel using TiC coated tungsten carbide throw-away tools. For tools that exhibited lack of fit for the first-order models, a second-order model was developed. Multiple regression analysis was used in developing these prediction models. Feng and Wang (2002) developed a model considering the following working parameters: workpiece hardness (material), feed, cutter nose radius, spindle speed and depth of cut. Two competing data mining techniques, nonlinear regression analysis and computational neural networks were applied in developing empirical models for predicting surface roughness. Researchers are trying to develop a robust and accurate model that can find a correlation between the cutting parameters and the surface roughness of the machined products. This work therefore focus on the development of empirical model for estimating the surface roughness of some frequently machined components (stainless steel, mild steel and aluminum cast) under various cutting speed using previous experimental data.

MATERIALS AND METHODOLOGY

Materials: The materials used for this study were Stainless steel, Mild steel iron and Aluminum cast obtained from a scrap yard in Benin City, Nigeria. Cutting tool used was High Speed Steel (HSS)

Experimental Procedures: A centre lathe machine (Geomatic Harrison M300 model), with a speed range of 76 rev/min to 600 rev/ min and driven by a motor(Artriesbst 380/220v and a scale factor of 0.37) was used for the machining using High Speed Steel (HSS) cutting tool. Stainless steel iron, mild steel and aluminum cast iron were machined using different cutting speed of 76 rev./min,150 rev./min,240 rev./min,305 rev./min, and 600 rev./min at a constant depth of cut of 1mm/pass and feed rate of 0.5mm/rev. to a of diameter 25mm and 40mm length each . A digital portable surface roughness tester (TR100 Model) was used measure the surface roughness value using centre line average method at five different equidistant points along the surface of each of the machined component .The surface roughness of values was recorded and the average for each component determined. Fig. 1 shows some of the machined component.

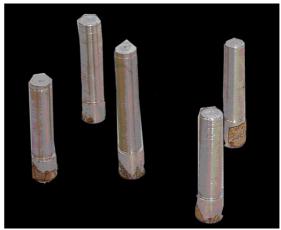


Fig.1: Some of the machined component

Model Formulation: In this work all empirical model was developed using the experimental values obtained from previous experimental investigation (Osarenmwinda and Edafiga ,2010). The empirical model was used to predict the surface roughness of the machined components which was the output y taking the inputs as spindle speed x. The empirical model was developed using regression analysis software program expressing the outputs in linear form as shown in Equation 1

$$Y = a + bx$$
(1)

Where the input is x which is spindle speed and the output is y which is surface roughness while a and b are constants.

The mean absolute Percent deviation: The Mean Absolute Percent Deviation (MAPD) which measures absolute error as a percentage was determined using Equation 2. Where Y_E and Y_P are experimental and predicted surface roughness values respectively.

$$MAPD = \frac{\Sigma ||YE - YP||}{YE} - \cdots (2)$$

RESULTS AND DISCUSSION

Developed Empirical Models: The developed empirical model for estimating the surface roughness of the machined components stainless steel, mild steel and aluminum cast are shown in Eqns. 3, 4 and 5 respectively. Where Yps, Ypm and Ypa are predicted surface roughness for stainless steel, mild steel and aluminum cast respectively.

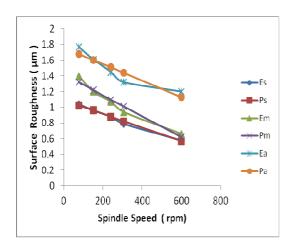
$$Y_{ps} = 1.08913 - 0.0087229x$$
....(3)

$$Y_{pm} = 1.42269 - 0.001344x$$
(4)

$$Y_{va} = 1.75392 - 0.0010354x \dots (5)$$

The plot of surface roughness Experimental values (Es, Em, and Ea) and Predicted values (Ps, Pm and Pa) against spindle speed for three different machined components stainless steel, mild steel and aluminum cast respectively is shown in Figures 2.

Accuracy and validity of model: The model was validated by comparing the predicted values with experimental values. The predicted values were found to compare favourably with experimental values (see Fig.2). The Mean Absolute Percent Deviation (MAPD) which measures absolute error as a percentage was determined using Eqn. 2 were found to be 1.46% (stainless steel), 4.55% (mild steel), 4.76% (aluminum cast) respectively. These values are insignificant and below the maximum error of 10% proposed by Liping and Deku (1992). These values were therefore found to be satisfactory and show good predictability of the model. The empirical model developed are reasonably accurate to predict surface roughness properties of the machined components and will serve as useful guide for researchers, industrialist and small-scale machinist.



 ${f Fig.2:}$ Cutting speed (rev./min.) against surface roughness(μm). Es,Em, and Ea are curves for experimental values while Ps, Pm and Pa are for predicted values stainless steel, mild steel and aluminum cast respectively.

Conclusion: The empirical model developed are reasonably accurate to estimate surface roughness of machined components (stainless steel, mild steel and

aluminum cast) using spindle speed as input. The model performance was found to be satisfactory and show good predictability. It hoped that this study will be of immense help to researchers, industrialist and guide to machinist in the selection of appropriate machining parameter for turning operations.

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