

Comparison of Surface Roughness Prediction with Regression and Tree Based Regressions during Boring Operation

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Abstract

Modern manufacturing methods permit the study and prediction of surface roughness since the acquisition of signals and its processing is made instantaneously. With the availability of better computing facilities and newer algorithms in the machine learning domain, online surface roughness prediction will lead to the manufacture of intelligent machines that alert the operator when the process crosses the specified range of roughness. Prediction of surface roughness by multiple linear regression, regression tree and M5P tree methods using multivariable predictors and a single response dependent variable Ra (surface roughness) is attempted. Vibration signal from the boring operation has been acquired for the study that predicts the surface roughness on the inner face of the workpiece. A machine learning approach was used to extract the statistical features and analyzed by four different cases to achieve higher predictability, higher accuracy, low computing effort and reduction of the root mean square error. One case among them was carried out upon feature reduction using Principle Component Analysis (PCA) to examine the effect of feature reduction.

Keywords: Multiple linear regression, Regression Tree, M5P Tree, KNIME Analytics Platform, feature reduction

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1. Introduction

Tool condition monitoring (TCM) and digital signal processing are prominences in manufacturing that prevent damages to workpieces when a faulty condition is about to occur [1]. Prediction of surface roughness during the turning process has always attracted the researchers. This study becomes more relevant in today's context where customer expectations on quality parts within the delivery period are high. Unexpected breakdown or failure of cutting tools increases the downtime, loss of production and maintenance costs. This has triggered industrial persons and academic researchers to focus their attention on such studies using the new techniques and new algorithms available in this field. Tool condition monitoring and diagnosis involve the acquisition of signals, processing, and analysis of data related to tool wear and surface roughness under experimental conditions and interpreted to suit real applications.

Feed rate, depth of cut and speed influence the surface roughness of the inner wall of the work piece. In addition, the conditions of the tool, rigidity of the machine, work material also play a role. A product may require a specified surface roughness as designed by designer either for functional or any other reasonable requirement. These studies have been made to correlate the surface roughness with the machining parameters along with the condition of the tool. The vibration signal acts as an indicator of the surface roughness. Hence, keeping all the other parameter constant, a study can be carried out at various tool conditions (flank wear) and cutting conditions and establish experimentally a relation between vibration (during machining) and surface roughness (Ra). The overhang of the boring bar contributes to chatter and imperfections in the surface finish. F. Kuster and P. E. Gyax explained the importance of keeping the boring bar L/D ratio below 6 for better cutting conditions, low vibrations and better finish [2]. K. Venkata Rao et al. had acquired vibration signal using laser topology on the work-piece and used ANN (Artificial Neural Network) for surface roughness prediction [3]. M. Elangovan et al. also used vibration signal captured using accelerometer but performed feature

reduction using principle component analysis and later applied multiple linear regression method for prediction of surface roughness [4]. S. C. Lin and M. F. Chang confirmed that surface roughness strongly correlates with cutting tool vibration [5]. Shinn-Ying Ho et al. used the image of the work piece to predict the surface roughness by using the gray scale [6]. Lin et al. used the abductive network and regression analysis methods for prediction of cutting force and surface roughness during machining [7]. Machine learning concept introduced in different areas like medical field for predicting the diseases, power distribution, condition monitoring etc. [8-9]. For instance, A. Etemad-Shahidi and J. Mahjoobi used network tree and M5 model tree for prediction of wave height in the lake and stated that M5 model tree results were more accurate than artificial neural networks result [10]. C. J. Poor and J. L. Ullman inferred that regression tree (RT) has higher predictability than multiple linear regression (MLP) [11]. A.M. Handhal showed that both adaptive neuro-fuzzy inference system (ANFIS) and M5 model tree have similar results but ANFIS has a more complex structure than M5 model tree [12].

Among the various regression methods, a study was drawn out to find the one that has the least root mean squared error (RMSE) value and the lowest computational time. The study proposes, prediction of surface roughness during a boring operation by using multiple linear regression (MLR), regression tree and M5P tree then followed by extracting the statistical features from the vibration signal and finally results are compared by analyzed in four cases as follows:

- Case I: the arithmetic mean (statistical features) of the vibration signal
- Case II: First four moments of the statistical features
- Case III: Statistical features of the vibration signal
- Case IV: feature reduction by principle components analysis (PCA)

2. Methodology

In order to evolve a prediction model, surface roughness (Ra) values were recorded for every experiment that was conducted by varying the cutting parameters and flank wear of the cutting tool during a boring operation. Simultaneously, the vibration signals were acquired using a DAQ unit. For every variation of the parameters, surface roughness (Ra) value was measured using a stylus probe type (HandySurf) surface measurement instrument. A cutoff length of 2.5 mm and measuring the length of 12.5 mm was used and the average Ra value is recorded. A prediction model using M5P tree, multiple linear regression and regression tree was carried out using KNIME Analytics Platform. The data was manipulated using 10-fold cross validation.

3. Multiple Linear Regression

If two or more independent variables in a linear regression analysis have one dependent variable is called multiple linear regression (MLR). Multiple linear regression is one of the easiest as well as an excellent method for the prediction of numerical values and it has been widely used technique for statistical application. MLR model develops a relationship in the straight line (linear) form that best approximates of the all the single data points. The basic regression model is of the form $Y = x_0 + g_1x_1 + g_2x_2 + \dots + g_nx_n$ where, Y is the predictand or dependent variable and x_1, x_2, \dots, x_n are the independent variables or predictors that are related to Y. x_0 is the value of Y when all the predictor variables are equal to zero. g_1, g_2, \dots, g_n are the regression coefficients of the predictor variable that are calculated from the training data set. Estimate the mean square error and root mean squared error using statistical software. $Y^2 = \frac{1}{N-P} \sum_{k=0}^n (Y - \hat{Y})^2$ where P is regression coefficient, N-P is degree of freedom and \hat{Y} is measured surface roughness (Ra) value.

4. Regression Tree

A regression tree is a combination of the decision tree and linear regression which is free from constraints like linearity, etc. Regression tree (RT) gives piecewise linear relationship between predictand or dependent variable and predictors or independent variables and this tree can evaluate complex data sets with many interacting predictors. Regression tree has two types of node that are a rounded node which represents splitting node and squared boxes are leaves

node of the tree which represent predictions of the target variable or predictand by using local multiple linear regression (MLR) method. A prediction using regression tree can be attained by dropping the test data set the case down the tree which following the correct nodes according to the output of the test data sets on the input variables. The corresponding prediction of numerical values has been reached the squared node or leaf node.

5. MP5 Tree

M5P tree is similar to a regression tree and has numerical values at its leaf node. An M5P tree is one of the numeric prediction algorithms in machine learning and the linear regression model is stored in the leaf node that predicts the numerical value. To determine the attribute is the best split into the training portion of data which reach a node at the equally split node. To measure of the error at that node using the standard deviation (SD) and calculating the expected reduction in error of the attribute at that node were tested. To reduce the error at that node where split equally. $R = SD (Tr) - \sum_{i=1}^n \frac{|Tr_i|}{|Tr|} \times SD (Tr_i)$ where R is standard deviation reduction and Tr_i is trained data set where $i=1, 2, 3, \dots, n$ are spitting rounded node based on the result. The linear regression models continuous predict the numerical attributes at the leaf node of the M5P model tree.

6. Principle Component Analysis (PCA)

PCA is a feature reduction algorithm that reduces the no. of features from the training data set (for example, from 8 to 2) to provide higher efficiency. M. Elangovan et al. explained that root mean square error value was lowered by dimensional reduction when PCA was used [4].

7. Experimental Setup

The experimental setup constitutes a lathe machine (Kirloskar Turnmaster-40), a National instrument (NI) make data acquisition device -DAQ 9234, a piezoelectric accelerometer (PCB PIEZOTRONICS), and a computer to store digital signals setup shown in Figure 1. The experiments were conducted by varying the cutting parameters of boring operation and the flank wear of the cutting insert. The input cutting parameters are spindle speed (280 rpm, 400 rpm and 630 rpm), feed rate (0.05 mm/rev, 0.071, mm/rev and 0.09 mm/rev) and depth of the cut (0.25 mm, 0.375 mm, 0.50 mm) along with flank wear (good tool, 0.2 mm, 0.4 mm). As per ISO standards when the flank wear of the cutting tool is greater than 0.6 mm, it is considered as failed [3]. A total of 81 experiments were conducted using a full factorial combination of spindle speed, feed rate, depth of the cut and flank wear. After machining each work-piece was measured for its surface roughness using HANDYSURF E-35A/B instrument.



Figure1. Experimental setup

7.1. Tool Wear Measurement

In order to get tool tips with different flank wear, the optical measuring instrument was used to segregate used carbide cutting tool inserts (CCMT090408) based on their flank wear but with the same make and grade.

7.2. Experimental procedure and data acquisition

The experiment procedure consisted of mounting a new uncoated carbide tool tip (CCMT0900408) on a boring bar clamped on the tool post. The piezoelectric accelerometer was fixed on the boring bar using the adhesive mounting technique as shown in the Figure 1. The accelerometer was connected to NI DAQ 9234. The signals were recorded using LABVIEW software and a DAQ unit. The sampling frequency of 51 kHz was set for acquiring the signal. A hollow workpiece of material EN8 and inner diameter as 25 mm and a wall thickness of 15mm was held on a self-centering three jaw chuck. The oxidized layer on the inner wall was removed by giving a small depth of cut and during this process, no signal was recorded. Data acquisition unit (NI DAQ 9234) was switched on and the signals recorded after leaving first few seconds for the signal to get stabilized. Every signal was recorded for 20 seconds using LAB VIEW software and statistical features were extracted from the time domain signals.

8. Results and Discussion

Multiple linear regression (MLR), regression tree (RT) and model tree (M5P) algorithms were used to predict the surface roughness (Ra) of the inner wall of the bored hollow shaft using an uncoated carbide cutting insert. The results are discussed in four states as shown in Table 1. The mean absolute error, the root mean squared error (RMSE) and computational time (CT) of the multiple regression, regression tree and model tree results are compared and shown in Table 2. The measured Ra and predicted Ra in Y-axis against the sample number of rows in X-axis were plotted for the case I of RT to show the conformance of predicted value over the measured value as shown in Figure 2 and Figure 3. The measured Ra and predicted Ra in Y-axis against the sample number of rows in X-axis were plotted for the case I of MLR and M5P tree (first 50 rows) and shown in Figure 4 and Figure 5.

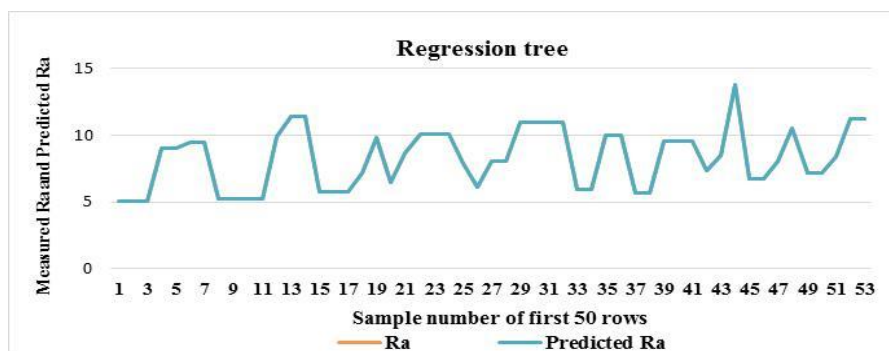


Figure 2. Regression tree

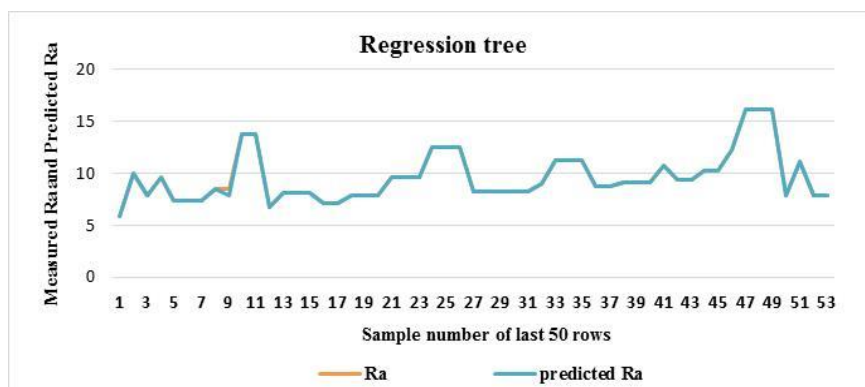


Figure 3. Regression Tree

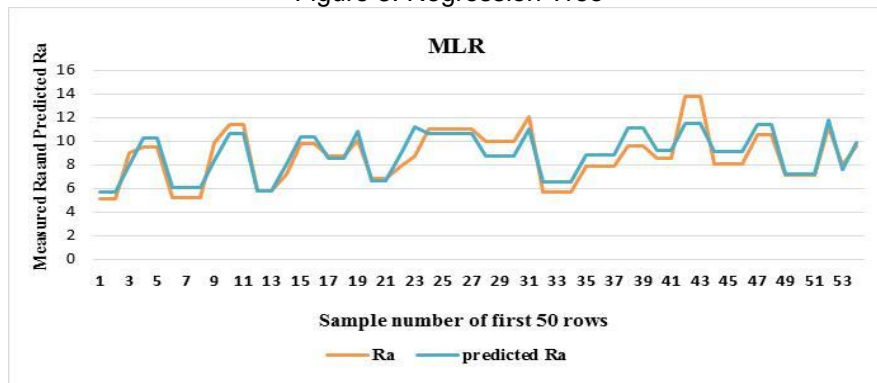


Figure 4. MLR

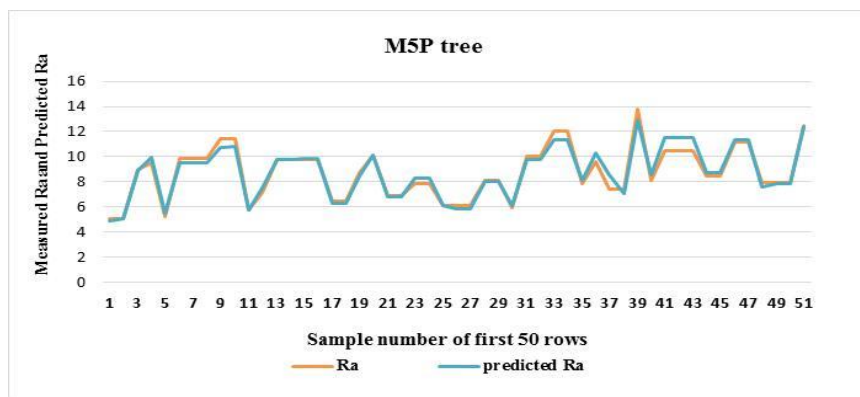


Figure 5. MP5 tree

Table 1. Dependent and Independent Variables

	Dependent variable	Independent variables
Case I	Surface roughness (Ra)	Spindle speed, feed rate, depth of cut, flank wear and mean
Case II	Surface roughness (Ra)	Spindle speed, feed rate, depth of cut, flank wear, mean, standard deviation, kurtosis and skewness
Case III	Surface roughness (Ra)	Spindle speed, feed rate, depth of cut, flank wear, mean, RMS, standard deviation, variance, kurtosis, median, mode and skewness
Case IV	Surface roughness (Ra)	Spindle speed, feed rate, depth of cut, flank wear, RMS and variance

Table 2. Showing S and RMSE Values When Using MLR, RT and M5P Algorithms

	Algorithms	Mean Absolute Error (S)	Root Mean Squared Error (RMSE)	Computation Time (second)
Case I	MLR	1.053	1.39	1.2
	RT	0.02	0.191	1.03
	M5P	0.401	0.4088	2.05
Case II	MLR	1.056	1.391	1.61
	RT	0.059	0.392	1.36
	M5P	0.5596	0.5969	3.3
Case III	MLR	1.05	1.423	2.13
	RT	0.064	0.404	2.41
	M5P	0.4132	0.6232	3.95
Case IV	MLR	1.045	1.381	0.633
	RT	0.007	0.085	0.56
	M5P	0.386	0.525	1.8

The table 2 show that case IV (i.e RT) has the lowest RMSE value of 0.085 than other cases. In case III of RT have the RMSE value of 0.404 when the entire statistical features were included, however the computational time is higher. When the statistical features are reduced from 8 to 2 by PCA, the RT becomes more approximated in case IV. Convincingly, case IV has a lower computational time than the case I, II and III of RT and also has a low 'S' value.

9. Conclusion and Potential for Future Work

Statistical features that were extracted from time domain signals were regressed using MLR, RT and M5P algorithms. Regression tree was found to be better algorithm among the three algorithms that were taken for study. The results show that RSME value obtained by RT is not only low but also has low computational time as shown table 2. Machine Learning approach was used to enhance the reliability and to reduce the RMSE and computational time. This study proves the possibility of usage of Machine Learning algorithms for prediction of surface roughness by simple and costs effective method. The study can be enhanced by using a different type of signals like image, sound etc., and by applying other algorithms. There is a good potential for future work in this direction as different feature reduction methods may be attempted combined with different algorithms and choosing the best feature- algorithm pair. This study will also be a step towards making machine tools more intelligent which are capable of expressing the quality of surface roughness of the workpiece as and when they are being machined.

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