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Development of an Accelerometer-Based Surface Roughness Prediction System in Turning Operations Using Multiple Regression Techniques

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Introduction

Companies in today's global manufacturing environment compete strongly to produce high-quality products at a low cost. Helping manufacturers meet these goals has been a trend toward increasingly automated manufacturing using modern technology. For example, automated computer numerical control (CNC) cells can lower labor costs and increase production by allowing a single operator to run several cells at once (Mills Manufacturing Technology, 2003). However, the lack of continuous operator monitoring can lead to defects. This limitation must be addressed to optimize automated machining processes.

A typical turning operation produces precision parts with critical features that may require a specified surface roughness. Such applications include bearing surfaces on axles, bearings, and races; ultra-clean surfaces in contaminant-sensitive components; and sealing surfaces on bores and pistons. Producing these products with modern CNC turning equipment can potentially lead to numerous defects due to the lack of continuous operator monitoring. Considering that a typical minimally manned CNC cell is used for very high-volume production, a problem affecting surface roughness may go unnoticed for some time during the operation. Defects may therefore continue to be generated until either a setup person or a quality inspector notices the increase in surface roughness.

One major issue affecting surface roughness is tool wear: a worn tool can go unnoticed until the operator hears chatter or sees the condition of the tool—often too late to prevent defects. Tool condition can be predicted using statistical process control (SPC), other mathematical techniques, or it may be monitored directly or indirectly. All of these methods are in various stages of development and implementation (Dimla, 2002).

However, other factors also affect surface roughness, including tool variations (in addition to wear), work piece variations, and setup variations (Vernon & Özel, 2003). Therefore, it would be more effective to monitor the actual surface roughness rather than individual factors that affect surface roughness. This can be achieved either through intensive post-process inspection, an in-process surface roughness measuring device, or an in-process surface roughness prediction system. While post-process inspection is the easiest to implement at the current time, it adds additional labor and cannot prevent the parts from being processed before a defective batch is discovered. These problems may be avoided by measuring surface roughness in process. Measuring surface roughness in process is a novel idea with high potential; unfortunately, it requires that sensitive components be added to a hostile environment, and is therefore still in a nascent stage of its development. An in-process surface roughness prediction system, however, is an approach that can be used to indirectly determine the surface roughness of a work piece without the concern of components being negatively affected by the cutting process itself.

Effective surface roughness prediction systems, while having been under considerable research and development since the 1980s, have not yet reached their full potential in practical applications (Ulsoy & Koren, 1993). The focus of this type of research in recent years has taken numerous directions, due mainly to the difficulties encountered with the wide range of process variables in real-world applications (Liasi & North, 2003). In-process surface roughness prediction systems, unlike inspections, can be used to either alert the operator of a problem or to be incorporated into an adaptive control system. Therefore, such a system would offer the possibility of a zero-defect work cell without the addition of labor, which would be a major advantage. This type of system therefore encompasses not only Philip Crosby's ideals of eliminating possibilities for defects, but also Joseph Juran and Edward Deming's insistence on designing manufacturing systems (rather than training workers) to avoid defects (Evans & Lindsay, 1996).

Workpiece-tool vibrations have been shown to correlate well with surface roughness (Beauchamp, Youssef, & Masounave, 1995). Surface roughness prediction systems, such as the one described in this study, can utilize this technique; however, deciding how to utilize it can be difficult because there are so many combinations of individual lathe designs and setups, all with different parameters and vibration features. Features of vibration data such as direction relative to the cutting axes, frequencies, and time are good examples of this, as each of them has been investigated to discover its correlation to parameters of various machining setups (Dimla, 2002). Additionally, few studies have mentioned the use of slant-bed lathes. Therefore, given the relative lack of development of this type of technology, as well as the unique nature of an experimental setup in terms of vibration characteristics, it is sensible to continue studies of this nature, using different types of lathes and setup parameters.

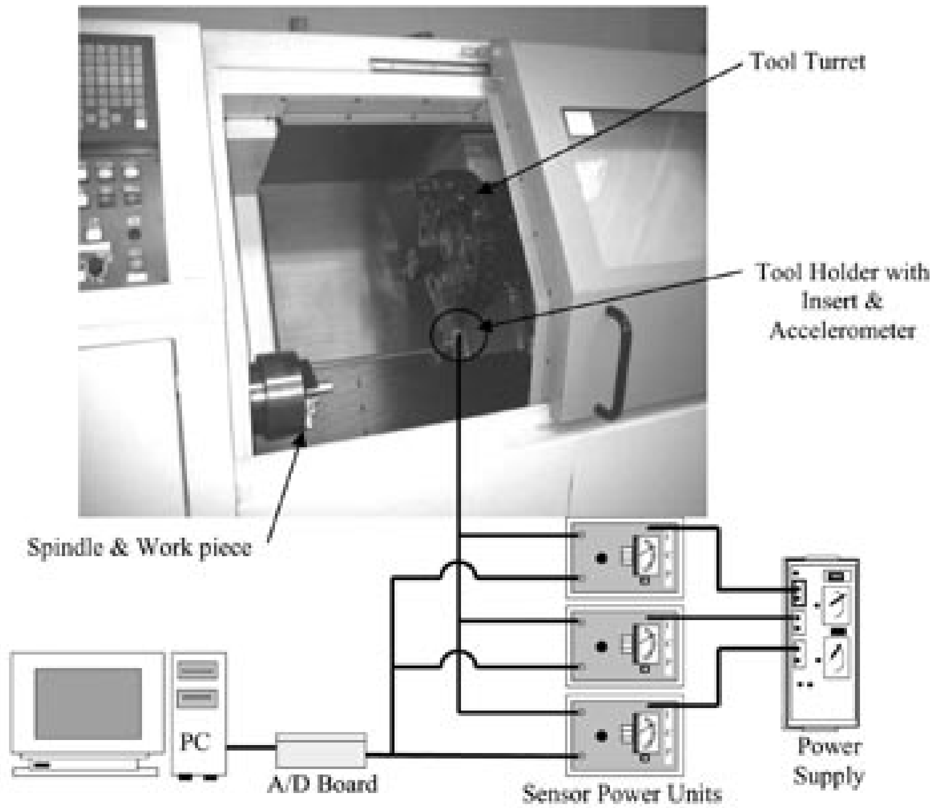

Figure 1. Hardware Setup.

Recently published research on surface roughness prediction, such as that by Huang and Chen (2001) and Risbood, Dixit, and Sahasrabudhe (2002), has found considerable positive results in predicting roughness using vibration in a single direction, as well as the main cutting parameters (feed rate, depth of cut, and spindle speed). However, it has been shown that vibrations in a cutting process occur in all directions and vibration in any direction can affect the cutting conditions (Armarego & Brown, 1969). Additionally, these studies did not explore the idea of substituting vibration data for some cutting parameters in order to minimize the size of the prediction model.

The purpose of this study is to develop an in-process surface roughness prediction system, using an accelerometer and multiple regression techniques, for a CNC slant-bed turning operation. This study will address the following questions:

1. How do various parameters and vibration features relate to the surface roughness of the work piece being turned?
2. What are the minimum turning and vibration parameters that can produce a valid prediction model?
3. Based on the first two questions, what is the best prediction model and can it be repeated in a confirmation run?

The methodology of this research has been created with the specific intent of determining the most significant vibration data for use in an accelerometer-based surface roughness prediction and adaptive control system in turning operations. An experimental design has been employed to address the research questions described in the introduction, including an experimental setup for producing and collecting data, as well as the data collection and analysis procedures. This data analysis is conducted with the intent of answering the research questions and leading to conclusions and recommendations.

Experimental Design and Setup

This experiment involves a basic factorial design, which includes three controlled factors and three response variables. The response variables for this design include surface roughness, measured in micro inches (μin.) R_a, and the vibration signals in the X (radial), Y (tangential) and Z (feed) axes, measured in volts. The controlled factors include the three main parameters controlled in a turning operation (spindle speed, feed rate, and depth of cut), as seen in Table 1.

As shown in Table 1, the spindle speed (SP) has three levels (2500, 3000, and 3500 rpm); the depth of cut (DC) has two levels (0.010 and 0.020 in.); and the feed rate (FR) has six levels (0.002, 0.003, 0.004, 0.005, 0.006, and 0.007 ipr). This results in a total of 36 runs to be conducted to test all combinations of parameter levels. The values for the levels of each parameter were determined based on a review of machinist's literature; recommendations from the cutting tool manufacturer (Green, 1996; Harig, 1978; VNE Corp., 1999); limits of the CNC lathe described previously; and previous experimentation performed on this lathe. These ranges of values will serve to produce a range of finish-cut surfaces using typical finish-cut parameters within the limits of the lathe.

The experimental setup for this methodology is intended to generate samples and collect all data based on the individual experimental runs. This setup includes all hardware and software needed to generate turned surfaces, measure their surface roughness, collect all necessary data, and analyze this data. The hardware used in this experimental setup includes a CNC Lathe, sample work pieces, a vibration data collection system, and a surface roughness measurement setup.

This study was performed using a Clausing/Colchester Storm CNC A50 Slant Bed CNC Lathe. This is a two-axis lathe with both CNC and manual control of the cutting process. This lathe design incorporates a 60º slant-bed setup and other features that help diminish and distribute cutting forces. The cutting process for this lathe was a standard turning process, with the work piece held in a turning chuck. This experiment required the use of dry cutting (without the use of coolant) in order to maintain more constant cutting and vibration conditions. The following are the parameter ranges for this lathe, which apply to this experiment (Clausing/Colchester Co., 1999):

- Spindle speed range: 1000 rpm minimum for full motor power, 4000 rpm maximum.
- Feed rate range: 0.000001-4.000000 inch per revolution (ipr).
- Least input movement increment: X 0.00005 inch, Z 0.0001 inch.

The selected parameter values were set using the NC program, stored in the lathe's Fanuc controller. The cutting process was performed using a new VNE Versa-Turn 80º diamond-shaped carbide tool insert with a nose radius of .016 inch.

The work pieces selected for this experiment were cut from 1.5-inch diameter 6061-T6511 Aluminum Alloy rod, per ASTM B221. Standardized material was selected to ensure consistency of the alloy, which was a common wrought alloy used in industry (Avallone & Baumeister, 1996). To more closely replicate typical finish turning processes and to avoid excessive vibrations due to work piece dimensional inaccuracies and defects, each work piece was rough-cut just prior to the measured finish cut.

The vibration data collection system was comprised of an accelerometer from which signals are amplified, converted to digital data, and processed using Windows-based software. Figure 1 depicts the hardware setup for turning and the schematic for vibration data collection. The accelerometer sensor used was a PCB Piezotronics #356B08 triaxial accelerometer, which was mounted on the shank of the tool holder, directly below the cutting tool. The axes of the accelerometer were aligned with the axes of the lathe (X, Y, and Z), using the applicable surfaces on the tool turret as references. The signal was amplified using three PCB Piezotronics model 480 ICP Sensor Power Units. These are externally-powered DC amplifiers, which amplify each vibration signal from the accelerometer. The power was supplied using an Elenco Precision variable power supply, model XP-656, set at 20 volts. The amplified signals were converted to digital signals with an Omega Engineering Inc. DAQBOOK analog-to-digital converter, which was connected to the parallel port of a standard Windows PC, which housed the software used to record and

Table 1. Design of Experiment

SP	2500		3000		3500	
FR / **DC**	0.010	0.020	0.010	0.020	0.010	0.020
0.002						
0.003						
0.004						
0.005						
0.006						
0.007						

analyze the digitized signal data. The data collection software, which recorded the digital vibration signal data, was Omega Engineering, Inc.'s DaqView, which is a Windows-based application used to process signals it obtains through the A/D converter.

The surface roughness of the finish-turned work pieces was measured using a Federal Pocket Surf stylus profilometer, set up to measure R_a in µ-inch, with a travel length of 0.1 inch. This device, which is certified to ANSI-B46.1, has a resolution of 1 µin. R_a and is calibrated to ±4 µin. R_a. Measurements were obtained with the profilometer and work piece firmly supported, with the stylus motion in the Z-axis (lay) direction.

Data processing and analysis were performed using Microsoft Windows versions of Microsoft Excel, SAS Institute JMP statistical software, and SPSS Inc. SPSS for Windows statistical software.

Experimental and Data Collection Procedures

All data used for this experimental design were generated and collected using the previously described experimental setup. A randomized schedule of runs was created using the design of experiment shown in Table 1. Work pieces from the sample bar were randomly selected and turned using the schedule of parameters. These runs were performed under closely supervised conditions to ensure that no anomalous problems with the cutting tool or turning process occurred. During the finish cut of each run, the vibration signals were collected and stored on the computer for later analysis. After all runs were completed, the surface roughness of the turned work pieces was measured and recorded. Each work piece was measured four times, in approximately 90º increments around the circumference. At this point, all recorded response variable data were ready to be analyzed.

Data Analysis

The vibration signals were analyzed by transforming them into absolute values of amplitude. The mean of vibration data over an equivalent range of 30 spindle revolutions was then determined for use in the model. The parameters and the results of the experimental runs, including surface roughness measurements and mean vibration amplitudes, are shown in Table 2.

Table 2. Factors and Response Data for Experimental Runs

Run #	SP (rpm)	FR (ipr)	DC (in.)	R_a (µin.)	Mean Vibration Signal Amplitudes		
					V_x	V_y	V_z
1	3000	0.003	0.020	21.00	0.0793	0.1603	0.0592
2	3000	0.005	0.010	42.75	0.0844	0.1567	0.0594
3	3000	0.006	0.020	55.75	0.1078	0.2136	0.0826
4	3500	0.004	0.020	28.75	0.1019	0.1893	0.0702
5	2500	0.007	0.010	66.25	0.0762	0.1490	0.0585
6	3500	0.002	0.010	15.25	0.0626	0.1119	0.0430
7	2500	0.004	0.010	30.50	0.0631	0.1201	0.0457
8	2500	0.004	0.020	32.25	0.0705	0.1476	0.0512
9	3500	0.005	0.010	41.50	0.0843	0.1569	0.0587
10	2500	0.005	0.020	43.75	0.0823	0.1671	0.0594
11	3500	0.005	0.020	45.25	0.1094	0.2126	0.0758
12	2500	0.002	0.020	21.25	0.0618	0.1154	0.0441
13	3000	0.007	0.010	63.00	0.0899	0.1693	0.0634
14	3500	0.004	0.010	30.00	0.0717	0.1421	0.0549
15	2500	0.003	0.010	22.00	0.0485	0.0941	0.0370
16	3000	0.007	0.020	66.75	0.1146	0.2391	0.0822
17	3500	0.003	0.010	23.50	0.0716	0.1391	0.0520
18	3500	0.002	0.020	16.50	0.0821	0.1402	0.0559
19	3000	0.005	0.020	43.00	0.0980	0.2103	0.0701
20	3500	0.006	0.010	52.00	0.0884	0.1691	0.0636
21	2500	0.006	0.020	53.25	0.0900	0.1914	0.0677
22	3500	0.007	0.010	69.25	0.1034	0.2004	0.0716
23	3000	0.002	0.010	18.25	0.0486	0.0941	0.0372
24	3000	0.004	0.010	28.25	0.0720	0.1337	0.0496
25	2500	0.003	0.020	21.50	0.0666	0.1337	0.0460
26	3000	0.004	0.020	27.25	0.0885	0.1870	0.0629
27	3000	0.002	0.020	14.00	0.0693	0.1300	0.0489
28	2500	0.007	0.020	69.75	0.0938	0.2219	0.0721
29	3500	0.006	0.020	53.00	0.1260	0.2848	0.0903
30	3000	0.006	0.010	53.75	0.0890	0.1944	0.0652
31	3500	0.003	0.020	19.00	0.0844	0.1731	0.0628
32	2500	0.005	0.010	37.75	0.0661	0.1402	0.0479
33	3000	0.003	0.010	19.25	0.0650	0.1223	0.0470
34	2500	0.002	0.010	19.25	0.0445	0.0867	0.0345
35	2500	0.006	0.010	56.75	0.0697	0.1531	0.0529
36	3500	0.007	0.020	63.75	0.1206	0.2793	0.0956

The data in Table 2 were then used to create a prediction model based on multiple regression. In order to minimize the model, both informal and statistical analyses were performed on these data to determine the minimum and most significant turning parameters and vibration components. Minimizing the model and using the simplest terms would therefore begin with attempting to use the basic parameters and vibration components—feed rate, spindle speed, depth of cut, and the three vibration signals. An initial analysis was performed using SPSS to determine the Pearson correlations between the factors and response. As seen in Table 3, all of the factors except spindle speed and depth of cut were found to have significant correlation coefficients. Therefore, it is likely that spindle speed and depth of cut do not have a significant effect on surface roughness and are probably not necessary for a regression model.

An informal analysis of the trends in the data indicated that vibration in all three directions is affected by depth of cut and spindle speed. Both appear to have a positive effect: as depth of cut or spindle speed increases, vibration magnitudes appear to increase. An analysis of variance (ANOVA) was therefore performed using JMP to explore this observation, the results of which are shown in Tables 4 through 6, respectively.

As seen in Tables 4 through 6, spindle speed, feed rate, and depth of cut all appear to significantly affect the level of vibration. Therefore, it is possible that each of these parameters could be substituted by vibration in the three axes for a regression model. However, since the feed rate has such a high correlation as seen in Table 3, this will be included to create a more robust model. Therefore, a regression model with four factors (feed rate and vibration in all three axes) was created using JMP software. This model has a coefficient of determination (r^2) of 0.96, which indicates a strong relationship between the factors and response. Additionally, as shown in Table 7, an ANOVA performed with JMP indicates a very low p-value, indicating a statistically significant effect on the response among the factors.

Table 3. Pearson correlation of cutting and vibration parameters to the response

Variable	Pearson Correlation Coefficient*
SP	-0.032
FR	0.981**
DC	0.010
V_x	0.668**
V_y	0.703**
V_z	0.707**

*Response = R_a
**Significantly different from 0, with $\alpha = 0.01$.

Table 4. ANOVA for effect of spindle speed and depth of cut on V_x

Source	**DF**	**SS**	**MS**	**F Ratio**	**Prob >F**
SP	2	0.003192	0.001596	79.8805	<0.0001
FR	5	0.006714	0.001343	67.2100	<0.0001
DC	1	0.003367	0.003367	168.5438	<0.0001
Error	27	0.000539	0.000020		
C. Total	35	0.013812			

Table 5. ANOVA for effect of spindle speed and depth of cut on V_y

Source	**DF**	**SS**	**MS**	**F Ratio**	**Prob >F**
SP	2	0.009679	0.0048395	21.2228	<0.0001
FR	5	0.042038	0.0084076	36.8717	<0.0001
DC	1	0.020706	0.0207060	90.8068	<0.0001
Error	27	0.006157	0.0002280		
C. Total	35	0.078579			

Table 6. ANOVA for effect of spindle speed and depth of cut on V_z

Source	**DF**	**SS**	**MS**	**F Ratio**	**Prob >F**
SP	2	0.001339	0.0006695	54.7158	<0.0001
FR	5	0.003992	0.0007984	65.2353	<0.0001
DC	1	0.001804	0.001804	147.4013	<0.0001
Error	27	0.000330	0.000012		
C. Total	35	0.007466			

Table 7. ANOVA for prediction model

Source	**DF**	**SS**	**MS**	**F Ratio**	**Prob >F**
Model	4	10947.928	2736.82	200.4291	<0.0001
Error	31	423.300	13.65		
C. Total	35	11370.597			

Prediction Model

The coefficients calculated with the regression analysis result in the following predictive equation:

$$\hat{R}_a = -7.0674 + 10264.6460FR - 151.1208V_x - 23.4800V_y + 262.1885V_z \quad (1)$$

where
$\hat{R}_a$ = the predicted surface roughness
FR = feed rate
V_x, V_y, & V_z = vibration measured in 3 axes

This equation could be used to test the accuracy of the prediction model using both the experimental data results and a validation run. Initially, accuracy was tested using the experimental data. This involved applying equation 1 to the factors and data for the individual runs in Table 2, then calculating the accuracy using the following equation:

$$\delta = \frac{1}{n}\sum_{i}^{n}\left[\frac{R_{a,i} - \hat{R}_{a,i}}{R_{a,i}} \times 100\%\right] \quad (2)$$

where
δ = the prediction error
n = the total number of measurements
i = the measurement being predicted for a specific run
$R_{a,i}$ = the measured surface roughness for a specific run
$\hat{R}_{a,i}$ = the predicted surface roughness for a specific run

The error rate of this model with the experimental data is calculated to be 9.96%. Considering that the resolution and calibrated accuracy of the profilometer create a possible measurement variance of ±5 µin. R_a, the measurement error for the experiment run data could be as high as 41.67%. Therefore, the prediction model could be considered reasonable and a final determination of the model accuracy using a validation run was in order.

Prediction Model Accuracy

Using identical hardware and software setups for the experimental runs, a validation run was then performed. The run was performed on the same day in order to maintain maximum control over the experimental setup. Parameters selected for a validation run were identical, with a range of cutting parameter values within the range used for the experimental run. Work pieces from the same batch were turned using the selected parameters (in random order) and the resulting surface roughness was measured with the same device and procedure. The results of these measurements, along with the parameters and vibration mean amplitudes for the validation run, are shown in Table 8. Equation 1 was then applied to the data from Table 8 in order to calculate predicted values of R_a. Based on this equation and validation run data, an error rate of 10.77% was calculated using Equation 2.

Table 8. Factors and Response Data for Validation Runs

Run #	SP (rpm)	FR (ipr)	DC (in.)	R_a (µin.)	Mean Vibration Signal Amplitudes V_x	V_y	V_z
1	2750	0.0055	0.005	58.25	0.0451	0.0939	0.0340
2	2750	0.0035	0.005	28.00	0.0336	0.0711	0.0261
3	3750	0.0065	0.015	73.25	0.1055	0.2225	0.0764
4	2750	0.0055	0.015	49.25	0.0725	0.1663	0.0610
5	2750	0.0045	0.015	39.75	0.0637	0.1320	0.0552
6	2750	0.0045	0.005	36.00	0.0391	0.0731	0.0290
7	2750	0.0035	0.015	31.25	0.0559	0.1127	0.0454
8	3250	0.0035	0.005	34.00	0.0292	0.0556	0.0228
9	3250	0.0065	0.015	81.00	0.0881	0.1768	0.0726
10	2750	0.0065	0.005	72.50	0.0487	0.0949	0.0376
11	3750	0.0055	0.015	62.00	0.0834	0.1656	0.0660
12	3750	0.0045	0.015	40.50	0.0806	0.1517	0.0629
13	2750	0.0065	0.015	76.75	0.0769	0.1610	0.0634
14	3250	0.0045	0.005	48.25	0.0444	0.0837	0.0315
15	3250	0.0055	0.005	56.50	0.0420	0.0773	0.0289
16	3250	0.0035	0.015	28.25	0.0579	0.1144	0.0445
17	3250	0.0065	0.005	69.00	0.0507	0.0973	0.0377
18	3750	0.0035	0.005	30.50	0.0383	0.0733	0.0294
19	3250	0.0055	0.015	56.25	0.0828	0.1699	0.0653
20	3750	0.0035	0.015	30.25	0.0711	0.1351	0.0538
21	3750	0.0065	0.005	70.00	0.0543	0.1039	0.0382
22	3750	0.0055	0.005	51.75	0.0520	0.0958	0.0368
23	3250	0.0045	0.015	39.00	0.0685	0.1417	0.0556
24	3750	0.0045	0.005	42.75	0.0549	0.1127	0.0403

Conclusions and Recommendations

The experimental design described herein was used to develop a surface roughness prediction model for a turning operation. A single cutting parameter and vibration along three axes were used to develop a multiple regression model for an in-process surface roughness prediction system. A strong linear relationship among the parameters (feed rate and vibration measured in three axes) and the response (surface roughness) were found using multiple regression and ANOVA. The effectiveness of this system was demonstrated using a validation run of different cutting parameter values. With the experimental design given, predictions were made with errors of 9.96% based on the experimental run and 10.77% based on the validation run. These results are reasonable, given the effective measurement accuracy of the stylus profilometer used. This also demonstrates that spindle speed and depth of cut do not necessarily have to be fixed for an effective surface roughness prediction model.

Given these conclusions, further research into the use of multiple-axis vibration measurements for surface roughness prediction in a turning operation is recommended. This may include using various prediction techniques, applying these techniques to various experimental setups, exploring ways to increase prediction accuracy, and using these concepts in an adaptive control system. Further research should always consider the need for flexibility for variation of parameters in a machining operation, which will make this type of research more adaptable to industry.

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