Journal of
INDUSTRIAL
TECHNOLOGY

Volume 17, Number 2 - February 2001 to April 2001

A Multiple Regression Model to Predict In-process Surface Roughness in Turning Operation Via Accelerometer

By Mr. Luke Huang & Dr. Joseph C. Chen

KEYWORD SEARCH

CIM
Manufacturing
Machine Tools
Research
Quality
Quality Control

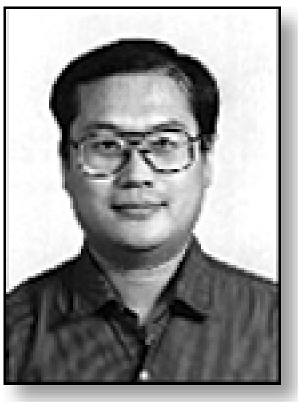
Reviewed Article

The Official Electronic Publication of the National Association of Industrial Technology • www.nait.org

A Multiple Regression Model to Predict In-process Surface Roughness in Turning Operation Via Accelerometer

By Mr. Luke Huang & Dr. Joseph C. Chen

Mr. Luke H. Huang is an Assistant Professor in the Department of Industrial Technology at the University of North Dakota. He teaches course in Manufacturing Automation, Computer Integrated Manufacturing, Facilities planning, Manufacturing Materials, etc.. His research interest is in CAD/CAM/CNC process, fuzzy system-related intelligent control, and manufacturing system design and control.



Dr. Joseph C. Chen, PE is an associate professor in the Department of Industrial Education and Technology at Iowa State University. Recently, he received the Early Achievement in Teaching Award from Iowa State University. His research interests are in cellular manufacturing systems, machine tool dynamics, and intelligent control as it relates to neural networks and fuzzy control.

Introduction

Although the lathe is the oldest machine tool, it is still the most commonly used machining operation in the manufacturing industry. Many cylindrical parts are products of turning operations. Some of these cylindrical parts, such as shaft, axis, and bearing, are crucial in machining motions.

The traditional way to monitor the surface quality of a machined part is to measure the surface roughness by using a surface gauge. The most used surface gauge is the stylus type surface gauge. It has a diamond stylus dragging along the test surface, of which, the up and down movement is recorded and calculated for the surface roughness. Since this measuring method requires that the stylus have direct contact to the measured surface, measurement cannot be conducted unless the test surface is in a stationary mode. In other words, the stylus measuring method cannot be applied to an in-process work piece on a lathe when the work piece is spinning.

Other measurement techniques must be used to obtain in-process surface roughness in turning operations. Since there is no actual in-process measuring available, the surface roughness is predicted by the use of other technologies, such as optical, acoustic, electromagnetic, force, and vibration. However, the optical, acoustic, and electromagnetic technologies are not practical in the machining environment because chips and coolant interfere with the travel of these signals. Cutting force and machining vibration can be used to predict the surface roughness of a machined surface. Practically, a dynamometer (the force sensor) is expensive and difficult to mount to a lathe. On the other hand, an accelerometer (the vibration sensor) is inexpensive and easy to mount. Therefore, an accelerometer has the potential to be applied in collecting vibration information for the prediction of a machined surface.

Machining vibration exists throughout the cutting process. While influenced by many sources, such as machine structure, tool type, work material, etc., the composition of the machining vibration is complicated. However, at least two types of vibrations, force vibration and self-excited vibration, were identified as machining vibrations. (Kalpakjian, 1995). Force vibration is a result of certain periodical forces that exist within the machine. The source of these forces can be bad gear drives, unbalanced machine-tool components, misalignment, or motors and pumps, etc. Self-excited vibration, which is also known as chatter, is caused by the interaction of the chip-removal process and the structure of the machine tool, which results with disturbances in the cutting zone. Chatter always indicates defects on the machined surface (Rakhit, Osman, and Sankar, 1973; Jang's et al., 1996). Therefore, vibration, especially self-excited vibration, is associated with the machined surface roughness.

Attempts have been made to use vibration signals in predicting tool wear and tool life in turning operations and other machining operations (Fang, Yao, and Arndt, 1991; Yao, Fang, and Arndt, 1991; Bonifacio and Diniz, 1994; Fernandes and Diniz, 1997). Results showed that vibration signals were promising in the predictions of these applications. Vibration signals were also employed to predict the surface roughness of machined parts using milling operation (Lou and Chen, 1999). Lou and Chen found that the prediction accuracy was as high as 96%. However, no work has been done in the prediction of surface roughness in turning operation by using vibration signals.

Purpose of Study

Based on the above analysis, the purpose of this study was to set up a multiple regression model that was capable of predicting the in-process surface roughness of a machined work piece using a turning operation. The model was expected to have the following features:

1. Use machining parameters, such as feed rate, spindle speed, and depth of cut, as predictors.
2. Apply vibration information that was collected with an accelerometer as another predictor.
3. The prediction accuracy is high to above 90%.

Experimental Setup

The hardware setup is shown in Figure 1. Two sensing systems were set on a lathe (Enterprise 1550, Mysore Kirloskar Inc., Karnataka, India). The accelerometer (PCB356B08, PCB Piezotronics, Depew, NY) was secured at the tool holder below the insert. The vibration signal that was generated by the accelerometer was sent to a signal conditioner, in which the signal's voltage was amplified to between –1 V and +1 V. A multifunction data acquisition board (OMB-Daqbook/100, Omega Engineering Inc., Stamford, CT) received the conditioned signals and had them stored in a dedicated computer. Simultaneously, a proximity sensor (Honeywell 922AC08YI micro-switch, Honeywell Inc., Minneapolis, MN) was mounted over the chuck and counted the spindle's rotations by detecting the holes on the chuck. The signals from the proximity sensor were also sent to the multifunction data acquisition board. Wiring of these devices is shown in Figure 2.

The proximity sensor was a micro switch. It was turned on and released a high voltage when there was ferrous material detected. When there was no ferrous material in the hole positions close to it, it was turned off and released a low voltage. Therefore, signals from the proximity sensor were pulses that indicated the position of the chuck rotation with holes on the chuck as references (Figure 3). Since there were six holes around the chuck, six pulses represented a revolution. The proximity signals were graphed along with the vibration signals, and they serve as identifications of revolutions for the vibration signals. This made it possible to separate the vibration signals revolution by revolution.

The lathe was modified with an additional digital positioning device (Wizard, Alilam Electronic Corp, Miami, FL). With this device, the position of the tool could be displayed digitally to ten-thousandth of an inch.

The work material was aluminum 6061T2, dimensioned in ϕ1´2 inches. The lathe chuck held this work piece with about 1.5 inches extending out the chuck as shown in Figure 4. Before the data-collecting cut, each piece was cut to 0.98 inches in diameter to eliminate variance in raw material size. Vibration data was collected when the tool cut to about 1.25 inches (measuring zone) from the chuck. The surface roughness was measured immediately after the work piece was cut with a pocket surface gauge (PocketSurf, Mahr Federal Inc. Providence, RI). The measuring length was five micro-inches. Each piece was randomly measured around the measuring zone ten times, as shown in Figure 4.

Data were arranged in two groups. One group was designed for training the model, and another was designed to only test the model for accuracy. These

Figure 1. Hardware set up.

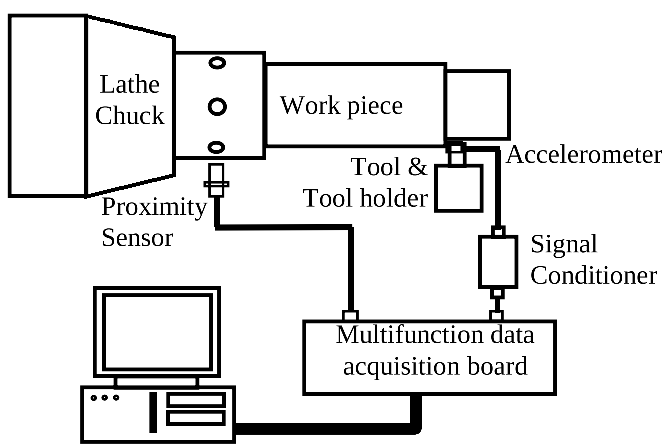
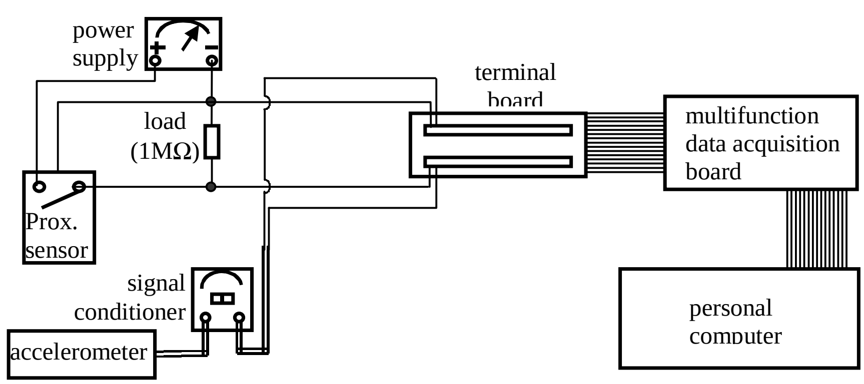


Figure 2. Wiring of the signal system



two groups of data were independent from each other. Data were also collected from tools of different nose sizes. One tool had a nose radius of 0.016 inches, and the other had a nose radius of 0.031 inches. As combinations, there were four groups of data, Train 16, Train 31, Test 16, and Test 31. The organization of data is illustrated in Figure 5.

All data sets have four independent variables, which are spindle speed (S), feed rate (F), depth of cut (D), vibration amplitude average (V), and one dependent variable, surface roughness average (R). In the training data set, there are three sampling levels for spindle speed and depth of cut and six for feed rate. In the testing data set, there are three for spindle speed and feed rate and two for depth of cut. Vibration and surface roughness respond to these independent variables. The sampling level of vibration and surface roughness varied. With three duplicates, there are 162 sets of data in total for each training data set and 54 for each testing data set.

Processing Vibration Signals

The vibration signals were voltages generated by the accelerometer in response to vibration and were converted from analogue to digital. With the help of the proximity signals, the vibration signals were separated revolution by revolution. Next, the voltage signals of each revolution were averaged (Equation 1). The mean served as the centerline of vibration. Then, the absolute differences of the centerline and each voltage value were averaged to obtain the Vibration Amplitude Average (V) (Equation 2).

$$V_{ave} = \frac{1}{c}\sum_{1}^{c} v_i \quad , \qquad (1)$$

where

V_{ave} – the centerline value of vibration voltages in a revolution,

V_i – an individual vibration voltage,

c – the number of voltage value a revolution has.

Figure 3. Identifications of revolution in the vibration signals (Data came from cutting conditions of 630rpm spindle speed, 2ipm feed rate, and 0.015in depth of cut.)

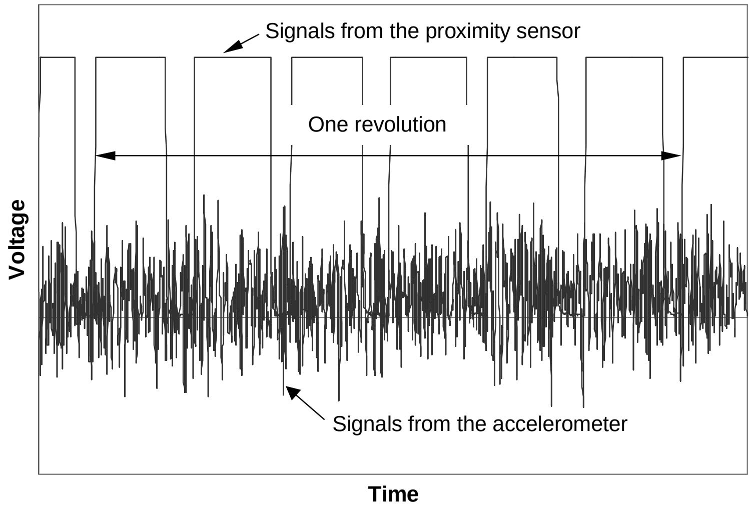


Figure 4. Setup of the work piece and the measuring zone.

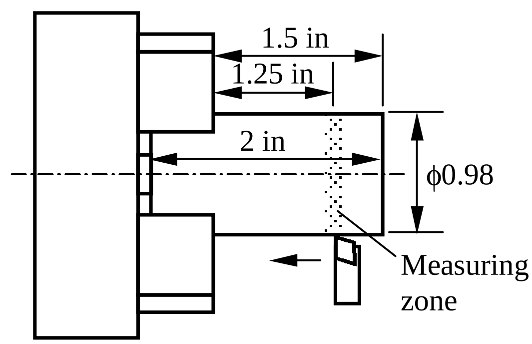
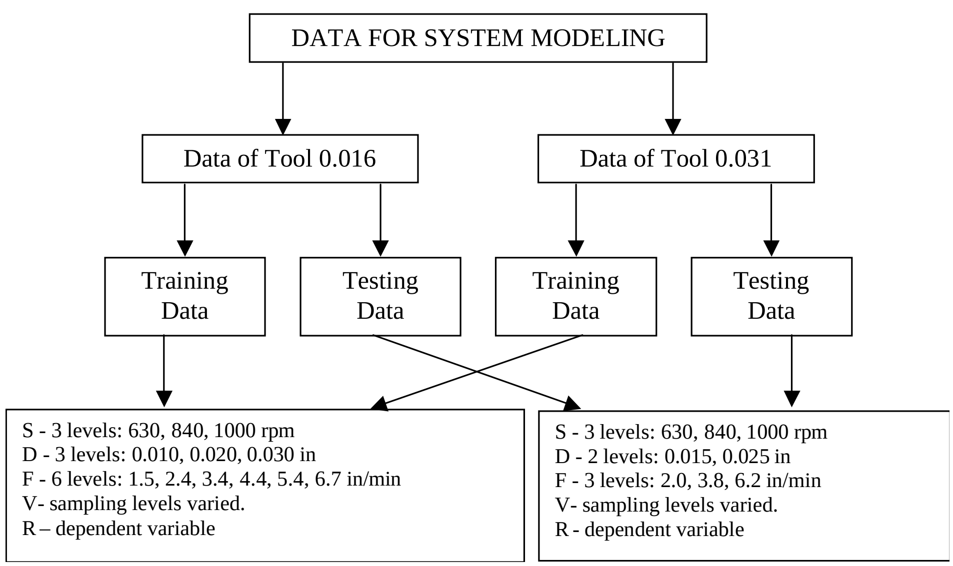


Figure 5. Sampling data structure



$$V = \frac{1}{c}\sum_{1}^{c}\left|v_i - V_{ave}\right| \quad , (2)$$

where
V - vibration amplitude average.

Multiple Regression Modeling

The goal of the multiple regression analysis was to determine the dependency of surface roughness to vibration and other selected machining parameters. In addition to the main effects of these variables, effects of the interactions of them were included in the analysis. The model was expressed as:

$$R = \beta_0 + \beta_S S + \beta_F F + \beta_D D + \beta_V V + \beta_{SF} SF + \beta_{SD} SD + \beta_{SV} SV + \beta_{DF} DF + \beta_{DV} DV + \beta_{FV} FV + \beta_{SDF} SDF + \beta_{SDV} SDV + \beta_{SFV} SFV + \beta_{DFV} DFV + \beta_{SDFV} SDFV, \quad (3)$$

where
R – surface roughness average,
F – feed rate,
S – spindle speed,
D – depth of cut,
V – vibration amplitude average,
β – linear constants.

With the significance level set to 0.01 ($\alpha = 0.01$), the null hypothesis and alterative hypothesis for the model were:

H_0: $\beta_S = \beta_F = \beta_D = \beta_V = \beta_{SF} = \beta_{SD} = \beta_{SV} = \beta_{DF} = \beta_{DV} = \beta_{FV} = \beta_{SDF} = \beta_{SDV} = \beta_{SFV} = \beta_{DFV} = \beta_{SDFV} = 0$.

H_a: at least one of the βs does not equal to zero.

A statistical software program, SPSS version 8.0, was employed in model training. Two training data sets, Train 16 and Train 31, were applied to train the above model to obtain two resulted models, MR16 and MR31, respectively. For the involvement of the interactive predictor variables, a total of 15 predictor variables were used in the training of the model, as shown in Equation 3.

Correlations of the predictor variables with the predicted variable from two data sets were reported as Pearson correlation coefficients by the linear multiple regression analysis with SPSS 8.0 (Table 1). They both showed that feed rate had the greatest correlation coefficient. Other primary variables were much smaller than feed rate. Interactive variables associated with feed rate have greater correlation coefficients as well. Among the primary variables, vibration had the second greatest correlation coefficient, which suggested that vibration information should not be ignored in the prediction.

As shown in Table 2, both MR16 and MR31 models had high regression coefficients (0.970 and 0.966, respectively). The square values of the regression coefficients were 0.940 and 0.933, respectively, which indicated high association of the regression coefficients with variances in the predictor values. All these evidences showed a strong linear relationship between the predictor variables (S, F, D, and V) and the predicted variable (R) for both models.

The results of analysis of variance (ANOVA) of the models also supported strong linear relationships in the models (Table 3). The F values of regression were 153.375 and 145.154 for MR16 and MR31, respectively. These high F values indicated a great significance ($\alpha = 0.000$) for both models in rejecting the null hypothesis (H_0) that every coefficient of the predictor variables in the model was zero. Instead, the alterative hypothesis, at least one of these coefficients did not equal to zero, was accepted. Therefore, the linear relationship between the predicted variable (R) and

Table 1. Correlations of predictor variables to the predicted variable

Predictor Variables	Pearson Correlation Coefficients*	
	Train 16	Train 31
S	-0.022	-0.015
F	0.958	0.954
D	0.088	0.019
V	0.180	0.214
SF	0.868	0.854
SD	0.082	0.009
SV	-0.094	-0.141
FD	0.748	0.683
FV	0.808	0.759
DV	-0.004	-0.087
SFD	0.712	0.629
SFV	0.677	0.621
SDV	0.011	0.072
FDV	0.607	0.511
SFDV	0.553	0.446

*The predicted variable is R

Table 2. Model Summaries

Model	r	r square
MR16	0.970	0.940
MR31	0.966	0.933

predictor variables significantly existed. The coefficients of all predictor variables and the constants of the model are listed in Table 4. According to these coefficients, the multiple regression models are built as shown in Equations 4 and 5 for MR16 and MR31, respectively.

MR16:
R = 52.3789 - 0.0270S + 3.5737F - 4397.9309D + 6.6156V + 0.0042SF + 4.3124SD - 0.0131SV + 864.4383FD + 14.0982FV + 17543.4834DV - 0.8091SFD - 0.0202SFV - 17.6585SDV - 4272.3100FDV + 4.4396SFDV (4)

MR31:
R = 11.4265 + 0.0490S + 6.2586F - 746.4256D + 77.1254V - 0.0074SF - 0.6270SD - 0.2350SV + 24.6572FD - 0.5641FV + 0.0000DV + 0.3218SFD + 0.0339SFV + 6.5832SDV + 658.9529FDV - 2.2918SFDV (5)

The Model Accuracy

Accuracy is a measure of the closeness of the predicted value to the measured one. For each single data set, the accuracy is the ratio of the absolute difference of the predicted and the measured R-values to the measured value. The accuracy is expressed in percentage (Equation 6). The model accuracy is the average of the accuracy values of all data sets (Equation 7).

$$\delta_i = \frac{\left|R_i - R_i^o\right|}{R_i} \times 100\% \,, \quad (6)$$

where
d_i – prediction accuracy of data set i,
R_i – predicted R by data set i,
R^o_i – measured R corresponding to data set i.

$$\Delta = \frac{1}{n}\sum_{i}^{n} \delta_i \,, \quad (7)$$

where
Δ – model prediction accuracy,
n – number of data sets in the training data set.

There were four groups of data available for testing the model accuracy because of the sampling design (Figure 5). They were Train 16, Train 31, Test 16, and Test 31. Table 5 lists the calculated accuracy values in percentage as well as the accuracy differences between the training and testing data sets. The training data gave higher and consistent model accuracy, which were 94.98% and 94.53% for Train 16 and Train 31, respectively. The model accuracy from the testing data varied. While the accuracy (92.18%) of Test 31 was close (2.35% less) to that of Train 31, the accuracy of Test 16

Table 3. The ANOVA Table of the regression models

Model	Item	Sum of Squares	df	Mean Square	F	Sig.
MR16	Regression	32218.714	15	2147.914	153.375	0.000
	Residual	2044.626	146	14.004		
	Total	34263.340	161			
MR31	Regression	19634.746	14	1402.482	145.154	0.000
	Residual	1420.318	147	9.662		
	Total	21055.064	161			

Dependent Variable: R

Table 4. Coefficients of the model

MR16		MR31	
Predictor variable	Coefficients	Predictor variable	Coefficients
(Constant)	52.379	(Constant)	11.426
S	-0.027	S	0.049
F	3.574	F	6.259
D	-4397.943	D	-746.426
V	6.616	V	77.125
SF	0.004	SF	-0.007
SD	4.312	SD	-0.627
SV	0.013	SV	-0.235
FD	864.441	FD	24.657
FV	14.098	FV	-0.564
DV	17543.527	DV	0.000
SFD	-0.809	SFD	0.322
SFV	-0.020	SFV	0.034
SDV	-17.659	SDV	6.583
FDV	-4272.321	FDV	658.953
SFDV	4.440	SFDV	-2.292

Dependent Variable: R

(81.55%) dropped far away (13.4% less) from that of Train 16. Since the model was trained with the training data set, it was reasonable that the model better fitted the training data set than the test data sets. Therefore, it was understandable that the training data set generated higher model accuracy than the testing data set did. Nevertheless, with the evidence that three accuracy values out of four ranged from 92% to almost 95%, the model accuracy was considered high.

Verification of Using Vibration Information

The necessity of using vibration information in the model was verified with two other models, MR16-noV and MR31-noV (Equations 8 and 9), which were also generated with SPSS 8.0. Data sets Train 16 and Train 31 with the vibration part subtracted were the training data for these two models, respectively. These models served as controls to verify the effectiveness of the vibration information in the model.

MR16-noV:

$$R = 42.926 - 0.0146S + 7.5123F - 388.5937D - 0.0008SF + 0.3998SD + 26.9933FD + 0.0299SFD \quad (8)$$

MR31-noV:

$$R = 47.3237 - 0.0277S + 0.2928F - 1423.8583D + 0.0073SF + 1.7856SD + 388.8863FD - 0.4383SFD \quad (9)$$

Accuracy values with vibration information and without vibration information are compared by applying a t-test. The results are listed in Table 6. Significant differences between accuracy values with vibration information and without vibration information were found when the training data sets were applied; whereas, basically no statistical significance was found from the testing data sets. However, it seemed a trend that the accuracy values from data sets with vibration information were numerically larger than those from without. On average, the accuracy value from with vibration information is 1.55% greater than that from without vibration information. From these evidences and the previous correlation analysis (Table 1), the use of vibration information was found valuable.

Conclusion and Discussion

The experimental design and setup to develop a multiple regression model for an on-line, real-time surface roughness prediction system have been demonstrated. The experiment of collecting data for training and testing have been conducted. Using the training data, a multiple regression model has been developed to be integrated in the prediction system. A group of testing data are also conducted to evaluate the accuracy of this proposed surface roughness prediction model. With these data and results, one could conclude:

1. With linear correlation coefficients of 0.940 and 0.933 for models MR16 and MR31, respectively, using the experiment data, the predictor variables, such as feed rate, vibration amplitude average, spindle speed, and depth of cut, have strong linear correlation with the predicted variable. The ANOVAR results also show that both models are valid at a high significance (a = 0.000). Therefore, the proposed regression approach for an in-process surface roughness prediction model is reasonably adapted.
2. The vibration amplitude average has Pearson correlation coefficients of 0.18 and 0.24 for data obtained by using two different tools, respectively. These coefficients rank vibration amplitude average the second among the four predictor variables in having strong correlation with surface roughness. Without the vibration data, the prediction accuracy of the proposed multiple regression

Table 5. Model accuracy

Model	Data sources	Data sets	Model accuracy	Standard Deviation	Acc. Diff. by sources
MR16	Training	162	94.976%	3.929	13.426%
	Testing	54	81.550%	14.693	
MR31	Training	162	94.530%	3.608	2.351%
	Testing	54	92.179%	6.435	

Table 6. Comparison of accuracy values from with and without vibration information by paired t-test.

Paired Sources	Accuracy	Standard Deviation	p Values	Difference of accuracy
Train16	94.976	3.929	0.000	3.007
Train16-noV	91.968	5.558		
Train31	94.530	3.608	0.000	2.000
Train31-noV	92.530	6.363		
Test16	81.550	14.693	0.883	0.181
Test16-noV	81.369	8.702		
Test31	92.179	6.435	0.248	0.992
Test31-noV	91.187	4.841		

model declines by about 1.55%. Therefore, the use of the accelerometer is valuable.

3. Established by using 162 data sets and tested by using 54 data sets for each tool condition, the proposed regression model basically possesses accuracy of above 90% on predicting the in-process surface roughness from feed rate, vibration amplitude average, spindle speed, and depth of cut. This is considered as enough to be applied in most manufacturing shops.

Taking these conclusions as the foundation, further research will be conducted to develop other prediction systems that could enhance the accuracy for surface roughness prediction in an on-line, real-time fashion, which could eventually be adapted by industry.

References

Bonifacio, M. E. R. and Diniz, A. E., (1994). "Correlating tool wear, tool life, surface roughness and tool vibration in finish turning with coated carbide tools", *Wear, 173*(1-2), pp. 137-144.

Fang, X. D., Yao, Y. and Arndt, G., (1991). "Monitoring groove wear development in cutting tools via stochastic modeling of three-dimensional vibrations", *Wear, 151*(1), pp. 143-156.

Fernandes, R. and Diniz, A. E. (1997). "Using wavelet transform to analyze tool vibration signals in turning operations", *Journal of the Brazilian Society of Mechanical Sciences, 19*(3), pp. 426-437.

Jang, D. Y., Choi, Y., Kim, H. and Hsiao, A. (1996). "Study of the correlation between surface roughness and cutting vibrations to develop an on-line roughness measuring technique in hard turning", *International Journal of Machine Tools Manufacturing, 36*(3), pp. 453-464.

Kalpakjian, S., (1995). "Manufacturing Engineering and Technology (3rd Ed.)", Addison-Wesley, Reading, MA.

Lou, M. S. and Chen, J. C., (1999). "In-process surface roughness recognition (ISRR) system in end-milling operations", *International Journal of Advanced Manufacturing Technology, 15*(3), pp. 200-209.

Rakhit, A. K., Osman, M. O. M. and Sankar, T. S., (1973). "Machine tool vibration; Its effect on manufactured surfaces", *Proceedings of the Fourth Canadian Congress of Applied Mechanics*, June 1973, pp. 463-464.

Yao, Y., Fang, X. D. and Arndt, G., (1991) "On-line estimation of groove wear in the minor cutting edge for finish machining", *CIRP Annals, 40*(1), pp. 41-44.