A Multiple-Regression Model for Monitoring Tool Wear with a Dynamometer in Milling Operations

Jacob C. Chen and Joseph C. Chen

Introduction

A major goal of the manufacturing industry is increasing product quality. The quality of a product is strongly associated with the condition of the cutting tool that produced it. Catching poor tool conditions early in the production will help reduce defects. However, with current CNC technology, manufacturers still rely mainly on the operator's experience to operate and monitor machines to avoid defects from poor tool conditions. Since operator experience can be unreliable, recent research has focused on integrating a tool condition monitoring system within the machine to allow online, real-time monitoring to reduce the dependence on human judgment.

Any effective monitoring system must be able to sense tool conditions, allow for effective tool change strategies when tools deteriorate, and maintain proper cutting conditions throughout the process (Lee, Kim, & Lee, 1996). Among the many possible machining conditions that could be monitored, tool wear is the most critical for ensuring uninterrupted machining.

The traditional process for predicting the life of a machine tool involves Taylor's (1906) equation $VT^n=C$, where V is cutting speed, T is tool life, and n and C are coefficients. This equation has played an important role in machining tool development (Kattan & Currie, 1996). Since advanced machining was introduced in the mid-1900s, various tool wear monitoring methods have been proposed to expand the scope and complexity of Taylor's equation. However, none of these extensions has been successfully adopted in industry universally due to the complex nature of the machining process. Therefore, there have been many attempts to explore other more promising methods for monitoring tool wear online using computers and sensing techniques (Atlas, Ostendorf, & Bernard, 2000; Li & Tzeng, 2000; Pai, Nagabhushana, & Rao, 2001; Roth & Pandit, 1999; Wilkinson, Reuben, & Jones, 1999). Again, none of the in-process monitoring systems has ever been applied in any form in industry because research is still at the estimation stage; the systems are too immature to implement for monitoring (Waurzyniak, 2001).

Therefore, researchers saw a need to explore an experimental and statistical approach in developing an in-process tool wear monitoring (ITWM) system. In order to accomplish this goal, this ITWM system requires an integration of sensing and decision-making techniques. For any in-process machining monitoring system, the sensing techniques are used to give the machine the capability of "seeing" that is equivalent to the human's eyes. However, the signals from the sensor have to be processed in order to determine whether or not something abnormal has occurred. The decision-making techniques are developed for the purpose of processing the signals from the sensors and data from other resources to determine whether or not the machining is satisfactory. Therefore, the decision-making techniques function like the "brain" of machines to make them intelligent.

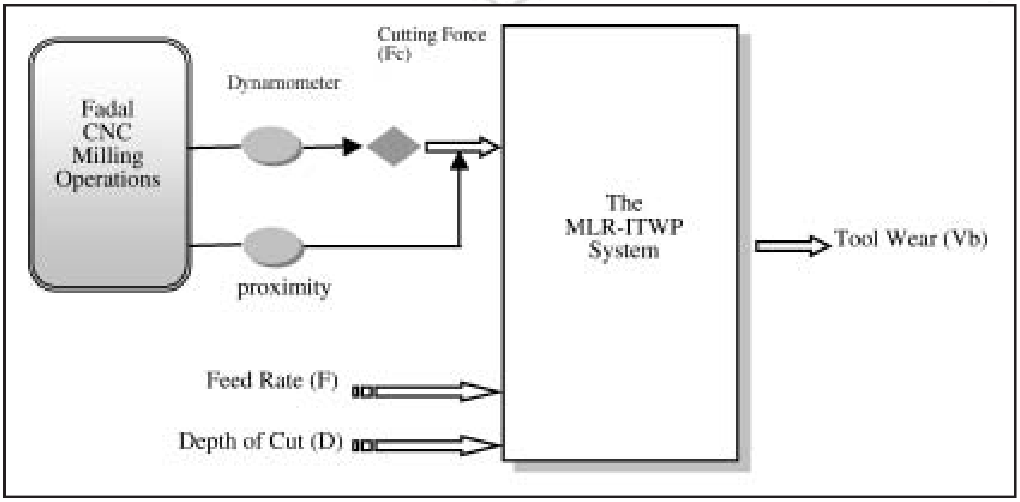
Studies in the past have shown that the dynamometer sensor was much more effective than any other sensors in the field of tool wear (Dutta, Kiran, & Paul, 2000; Wilkinson et al., 1999). However, cutting force is very complex—it varies in different directions and varies throughout the whole revolution of the spindle. As a result, when tool wear occurs, it is sensible to conduct a cutting force analysis experimentally and statistically to find the cutting force representation that best predicts tool wear.

There is no doubt that the dynamometer is the most effective sensor available for monitoring tool wear. However, past studies of building tool wear prediction systems have used different decision mechanisms—either classic mathematical equations (Cho, Choi, & Lee, 2000; Sarhan, Sayed, Nassr, & El-Zahry, 2001) or expert systems (Dutta et al., 2000; Susanto & Chen, 2002)—based on different interests. In this study, a multiple regression approach was used as the decision mechanism in the proposed ITWM system.

Purpose of Study

The purpose of this study was to develop an ITWM system using cutting force as a sensing signal and integrating the multiple regression approach as the decision mechanism. In order

Figure 1. The architecture of the MLR-ITWP system.



to develop the proposed ITWM system, the following two research outcomes were expected:

1. Identify the cutting force representation that could best predict tool wear.
2. Build and test an in-process tool wear prediction system, which was a multiple-regression model in this study, with the cutting force identified from the first task.

Architecture of In-Process Tool Wear Prediction System

In this study, the ITWM system that integrated multiple-linear regression can be named the multiple-linear-regression-based in-process tool wear prediction (MLR-ITWP) system. The input variables were feed rate (*F*), depth of cut (*D*), and cutting force (*Fc*), while the only output variable was tool wear (*Vb*). The architecture of the MLR-ITWP system is illustrated in Figure 1.

In the MLR-ITWP system, the three inputs entered the system as follows: both feed rate and depth of cut were controlled and programmed into the Fadal machine, while cutting force signals were collected through a dynamometer and converted to digital format through an A/D (analog/digital) converter. The digitized cutting force data per revolution of the spindle were simplified to a representative value, which was selected based on the force analysis. The following section shows the experimental setup for the study.

Experimental Setup

The experimental setup is illustrated in Figure 2. The dynamometer sensor was mounted on the feeding table of the Fadal vertical machining center with the workpieces/tool holder on top of the sensor. The proximity sensor was mounted on the spindle and connected to a power supply. Through an A/D converter, the signals from both sensors were collected and converted into digital codes on the computer.

Hardware

Two sensors were used in the study: a Kistler 9257B type dynamometer sensor, which is capable of detecting force signals in three orthogonal directions (*Fx*, *Fy*, and *Fz*), and a Micro Switch 922 series 3-wire DC proximity sensor, which is used to determine the starting point of each revolution of the spindle in the force diagram (see Figure 3). Together, these two sensors were used to determine the cutting force magnitude.

An RCA WP-703A power supply was used to provide about 2.5V of electromotive force to operate the proximity sensor. A Kistler Type 5010 amplifier was used to amplify the force signals from the dynamometer to the maximum of 10V. An Omega CIO-DAS-1602/12 A/D converter was used to convert cutting force data from analog to digital. A P5 133 personal computer was used to collect data from the A/D converter, which originated from the proximity sensor and the dynamometer sensor.

The workpiece material used in the study was 1018 steel. A VNE90-1250C 3-insert mill with 1.25" cut diameter was used to hold inserts. APKT 160408R coated carbide inserts

Figure 2. Experimental setup.

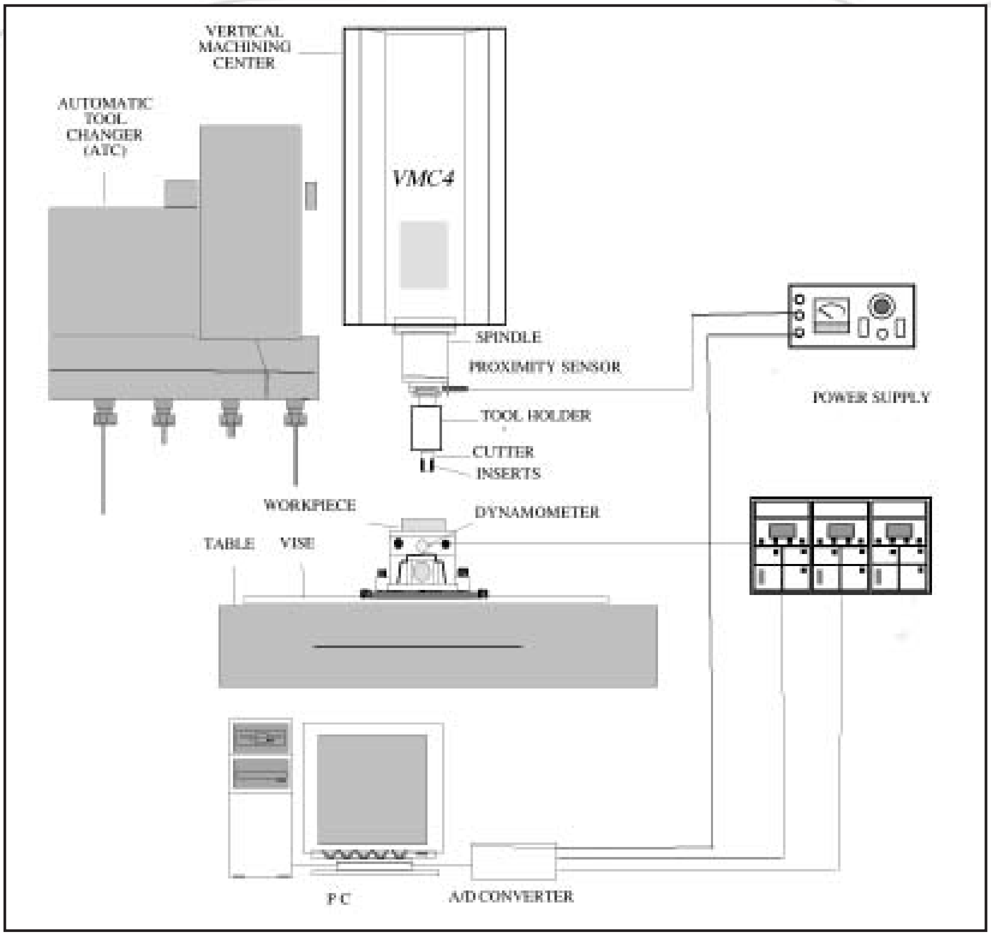
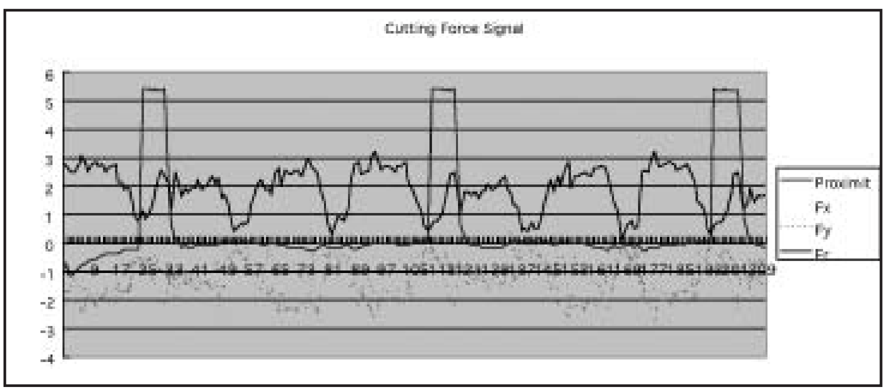


Figure 3. An example of cutting force signal converted as collectable digital data.



were mounted on the tool holder for the milling machining. A Meiji EMZ-5TR Zoom Stereo Microscope was used to observe and measure the flank wears on the inserts.

Identifying the Best-Predicting Cutting Force Representation

The goal of the first experimental run and data analysis was for force analysis, in order to identify the best cutting force representation for predicting tool wear.

Force Analysis Experiment

The first part of the study included determining the cutting force representation to be recorded and entered into the prediction system in the second part of the study.

Past experiments have revealed that in end-milling operations, the Z direction (the vertical direction) of the cutting force can be ignored because it is insignificant relative to tool wear monitoring compared to the X and Y orthogonal directions. Therefore, the selection of the force directions was limited to the forces in the X and Y directions and the resultant force of the two: F_x, F_y, and F_r, where $F_r = \sqrt{{F_x}^2 + {F_y}^2}$.

For each of these three directions of cutting force, one could identify two possible cutting force representations: average force ($\overline{F}$) and average peak force ($\hat{F}$). Therefore, six cutting force representations were identified:

$$\overline{F}_x = \frac{\sum_{i=1}^{m} |F_x^i|}{m}$$

$$\overline{F}_y = \frac{\sum_{i=1}^{m} |F_y^i|}{m}$$

$$\overline{F}_r = \frac{\sum_{i=1}^{m} F_r^i}{m}$$

$$\hat{F}_x = \sum_{\lambda=0}^{n-1} \{Max\{|F_x^i| \mid i = \lambda[\frac{m}{n}]+1, \lambda[\frac{m}{n}]+2, \ldots, \lambda[\frac{m}{n}]+[\frac{m}{n}]\}\} \;/n$$

$$\hat{F}_y = \sum_{\lambda=0}^{n-1} \{Max\{|F_y^i| \mid i = \lambda[\frac{m}{n}]+1, \lambda[\frac{m}{n}]+2, \ldots, \lambda[\frac{m}{n}]+[\frac{m}{n}]\}\} \;/n$$

$$\hat{F}_r = \sum_{\lambda=0}^{n-1} \{Max\{F_r^i \mid i = \lambda[\frac{m}{n}]+1, \lambda[\frac{m}{n}]+2, \ldots, \lambda[\frac{m}{n}]+[\frac{m}{n}]\}\} \;/n$$

In the equations, m is the total number of cutting force signals collected in a revolution, and n is the number of the mill inserts (in the study, n = 3).

To decide the best cutting force representation for predicting tool wear, the only independent variable was the flank wear (Vb) of the tool, and the only dependent variable was the cutting force. The remaining cutting conditions were set to fixed values: feed rate = 5 in/min, spindle speed = 1800 rpm, and depth of cut = 0.05 inches.

Figure 4. A typical flank wear geometry on an edge of an insert.

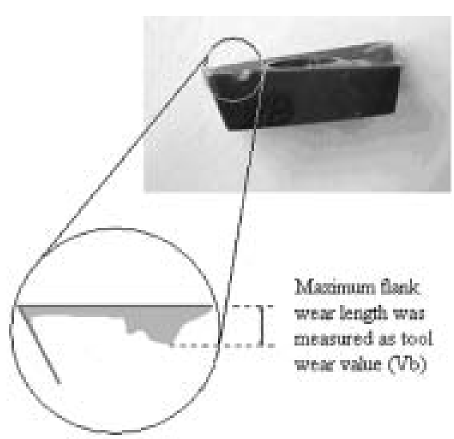
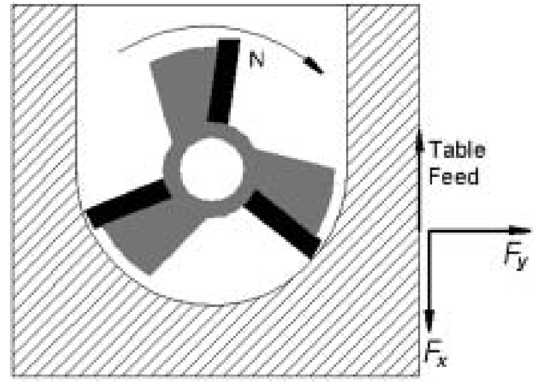


Figure 5. Definition of cutting force directions.



Correlations of Six Cutting Force Combinations and Tool Wear

One of the easiest ways to identify the best cutting force representation out of the six was to compare the correlations of these cutting force combinations and tool wear. The correlation coefficients were determined using Microsoft Excel, and the formula for the correlation coefficients is:

$$1)\quad \rho_{Vb-Fc^k} = \frac{\sum_{i=1}^{n}(Vb_i - \overline{Vb})(Fc^k{}_i - \overline{Fc^k})}{\sqrt{\sum_{i=1}^{n}(Vb_i - \overline{Vb})^2 (Fc^k{}_i - \overline{Fc^k})^2}}$$

where ρ_{Vb-Fc^k} is the correlation coefficient between tool wear (Vb) and cutting force combination k (Fc^k); Vb_i is the tool wear value of the i^{th} cut, while n is the total number of the training data sets. In this study, n = 13, $\overline{Vb} = \sum_{i=1}^{n} Vb_i \big/ n$ and $\overline{Fc^k} = \sum_{i=1}^{n} Fc^k{}_i \big/ n$.

With six cutting force combinations, six different correlation coefficients were obtained: $\rho_{Vb-\overline{F}_x}$, $\rho_{Vb-\overline{F}_y}$, $\rho_{Vb-\overline{F}_r}$, $\rho_{Vb-\hat{F}_x}$, $\rho_{Vb-\hat{F}_y}$, and $\rho_{Vb-\hat{F}_r}$. The largest correlation coefficient among the six indicates that the correlation is the greatest and the cutting force combination in that correlation is the best to predict tool wear.

Results of Force Analysis

From the analysis (please contact the authors for the details), it can be concluded that the average peak forces in one revolution in the Y direction had the greatest correlation coefficient (0.78) with a p value of 0.002. However, the Y direction here is from the dynamometer, which is oriented differently from the machine. Therefore, the Y direction in this study is better defined as the direction perpendicular to *the direction of the table feed* (see Figure 5). The theoretical reasons, although not included in the study, definitely merit further study in the future.

Developing the MLR-ITWP System

After the best cutting force representation for predicting tool wear had been identified as the average peak forces in one revolution in the Y direction ($\hat{F}_y$), all the input values for the MLR-ITWP system were clearly defined. The second run of experiments and data analyses were then conducted.

Tool Wear Monitoring Experiment

Cutting Condition Selection

General cutting conditions usually refer to three major cutting parameters: feed rate, spindle speed, and depth of cut. From the body of research concerning tool wear (Lin & Lin, 1996; Susanto & Chen, 2002), spindle speed was not a significant factor in predicting tool wear. To simplify the study, spindle speed was therefore fixed in the study; only feed rate and depth of cut varied. The values of the cutting conditions were as follows:

Feed rate (x4): 5, 7, 9, 11, and 13 inches/minute

Depth of cut (x3): 0.02, 0.03, 0.04, 0.05, and 0.06 inches

Spindle speed: 1,200 rpm

Tool Wear

In the beginning of the experiment, all of the tool wears of the industry-used inserts were classified into five range groups (0.20-0.29, 0.30-0.39, 0.40-0.49, 0.50-0.59, and 0.60-0.69 mm), with the first group considered the lightest wear and the last group the heaviest wear. During the experiment, two sets of the inserts in the 0.60-0.69 mm group were worn out quickly and fractured in the third cut, which was quite different from the other inserts (which remained almost intact during the experiment). For this reason, it could be concluded that the tool life ends for this kind of coated carbide insert when it reaches the wear range of 0.60 mm.

Because many more industry-used inserts broke during the experiment with no replacements available, the researchers decided to artificially grind new inserts to the appropriate level of wear. In the study, the inserts were finely ground to even artificial tool wear with values of 0.25, 0.35, 0.45 and 0.55 mm (the 0.60 mm tool wear limit was observed).

Experimental Design

With two factors from the cutting condition and one factor from the tool wear, the experimental design was a factorial design with three factors: feed rate (x5), depth of cut (x5), and tool wear (x4). Therefore, 100 experiments were needed for the purpose of training the monitoring system. The data to be collected were the cutting forces (that is, the best predicting cutting force representation concluded from the first part of the study: the average peak forces in the Y direction).

Results of Monitoring Tool Wear

The multiple-linear-regression model of tool wear, the MLR-ITWP system in Figure 1, was built with the help of the statistical software package JMP. The regression model considers the interactions among these three factors in the analysis, according to the following equation:

$$Vb = \beta_0 + \beta_1 F + \beta_2 D + \beta_3 Fc + \beta_4 F*D + \beta_5 D*Fc + \beta_6 Fc*F + \beta_7 F*D*Fc \quad (2)$$

Where Vb = tool wear (flank); F = feed rate; D = depth of cut; $\hat{F}_y$ = cutting force (the most significant force representation revealed previously); and β_i (i = 0, 1, … 7) = the coefficients to be decided.

Using the JMP software, all the coefficients β_i in the model were decided, and the following regression model was obtained:

$$Vb = 0.1615 + 0.0454*F + 5.965*D - 0.0429*Fc + 0.1397*F*D - 0.0781*F*Fc - 8.2053*D*Fc + 1.3551*F*D*Fc \quad (3)$$

The analysis of variance of the regression model showed that the F ratio was smaller than .0001, which shows that this model is very significant for predicting tool wear.

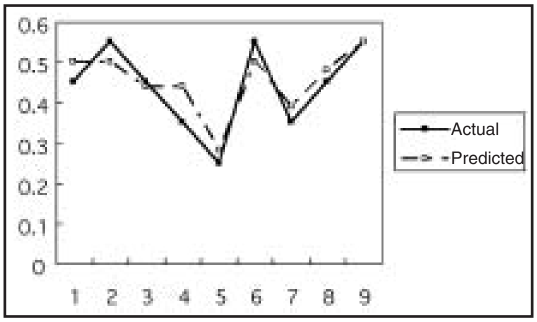
Verification of the MLR-ITWP System

Once the regression model was formed, the MLR-ITWP system was built. To evaluate the performance of the developed system, nine sets of data were used for testing. The testing data sets were different from the 100 sets of training data used to produce the regression models.

The actual tool wear and the tool wear predicted with the testing data through the regression model were then compared. Nine sets of testing data were used to compare the actual wear with the predicted wear. The average error is ± 0.039 mm.

Figure 6 compares predicted and measured tool wear magnitude for all nine test cuts. The results suggest that the proposed MLR-ITWP system reasonably predicted tool wear in an online, real-time fashion.

Figure 6. The comparisons of the actual and predicted tool wears.



Conclusions

A new in-process tool wear prediction (MLR-ITWP) system in milling operations has been set up, developed, and examined. The system showed the capability of predicting tool wear during the machining process.

The conclusions of this study are summarized as follows:

1. The average peak forces in the Y direction in a revolution best predict the tool wear among the force directions and the modes considered in the current study.
2. This proposed MLR-ITWP system can predict the tool wear value to have average error of ± 0.039 mm compared with the actual tool wear.
3. The proposed ITWP system has some limitations, which suggest the following possible directions for further research:
   a. The tool wear used for developing the system was changed from industry produced to artificially ground. The difference between the two wears needs further study.
   b. During the experiment, the researchers found that tool wear prediction is strongly affected by the existence of tool chatter. Therefore, the study of chatter prediction and control is also necessary for the development of automated machining.
   c. A MLR model has the limitation that it lacks the capability to learn—it does not allow any future data inputs. It is valuable to explore tools such as SPC, EMP, and DOE to assist in overcoming the problem in the future research.
   d. A MLR model is limited in its ability to simulate complex, nonlinear phenomena. Other ITWM systems that employ expert systems as decision mechanisms have value for future research.
   e. This research is limited to one type of tool insert and one type of workpiece material. Enlarging this system to include more cutting tools and materials for workpieces could make the results of this line of research more practical for implementation in industry.

In summary, this study provides the authors with a better position in continuing the tool monitoring system to enable an automated machining process for more efficient manufacturing in the future.

Dr. Jacob C. Chen is an assistant professor in the Department of Industrial Engineering and Management at Ching-Yun University, Taiwan.

Dr. Joseph C. Chen is a professor in the Department of Agriculture and Biosystems Engineering at Iowa State University, and is a member of Alpha Xi Chapter of Epsilon Pi Tau.

References

Atlas, L., Ostendorf, M., & Bernard, G. D. (2000). Hidden Markov models for monitoring machining tool-wear. *Proc. of ICASSP, 6*, 3887-3890.

Cho, D. W., Choi, W. C., & Lee, H. Y. (2000). Detecting tool wear in face milling with different workpiece materials. *Key Engineering Materials, 183*(1), 559-564.

Dutta, R. K., Kiran, G., & Paul, S. (2000). Assessment of machining features for tool condition monitoring in face milling using an artificial neural network. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 214*(1), 535-546.

Kattan, I. A., & Currie, K. R. (1996). Developing new trends of cutting tool geometry. *Journal of Materials Processing Technology, 61*, 231-237.

Lee, J. H., Kim, D. E., & Lee, S. J. (1998). Statistical analysis of cutting force ratios for flank-wear monitoring. *Journal of Materials Processing Technology, 74*, 104-114.

Li, C. J., & Tzeng, T. C. (2000). Multimilling-insert wear assessment using non-linear virtual sensor, time-frequency distribution and neural networks. *Mechanical Systems and Signal Processing, 14*(6), 945-957.

Lin, S. C., & Lin, R. J. (1996). Tool wear monitoring in face milling using force signals. *Wear, 198*(1-2), 136-142.

Pai, P. S., Nagabhushana, T. N., & Rao, P. K. R. (2001). Tool wear estimation using resource allocation network. *International Journal of Machine Tools and Manufacture, 41*(5), 673-685.

Roth, J. T., & Pandit, S. M. (1999). Using multivariate models to monitor end-mill wear and predict tool failure. *Technical Papers of NAMRI/SME, 27*, 63-68.

Sarhan, A., Sayed, R., Nassr, A. A., & El-Zahry, R. M. (2001). Interrelationships between cutting force variation and tool wear in end-milling. *Journal of Materials Processing Technology, 109*(3), 229-235.

Susanto, V., & Chen, J. C. (2002). Fuzzy logic based in-process tool-wear monitoring system in face milling operations. *International Journal of Advanced Manufacturing Technology, 21*(3), 186-192.

Taylor, F. W. (1906). On the art of cutting metals. *ASME Journal of Engineering for Industry, 28*, 310-350.

Waurzyniak, P. (2001, November.). Moving toward the e-factory. *Manufacturing Engineering*, pp. 42-56.

Wilkinson, P., Reuben, R. L., & Jones, J. D. C. (1999). Tool wear prediction from acoustic emission and surface characteristics via an artificial neural network. *Mechanical Systems and Signal Processing, 13*(6), 955-966.