MONITORING TOOL WEAR THROUGH FORCE MEASUREMENT

by

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ABSTRACT. The full automation of machine tools requires reliable techniques for on-line sensing of tool wear and breakage. This paper proposes a model-based approach for on-line tool wear estimation. The proposed approach, which is based on cutting force measurements, is designed to operate under varying cutting variables dictated by the workpiece configuration and surface finish requirements. The approach, which uses parameter estimation techniques to track tool wear during cutting, is experimentally demonstrated for a turning operation. The estimated values of tool wear are in good agreement with the actual values of tool wear measured intermittently during the cut.

INTRODUCTION. The full automation of machine tools requires reliable techniques for on-line sensing of tool wear and breakage [1,2]. The on-line sensing of tool wear, an essential part of any realistic adaptive control optimization (ACO) system, is particularly important in efficient scheduling of machine down time for tool changing and for tool failure detection. Unfortunately, despite years of research in this area, a reliable on-line tool wear measurement technique does not exist [3].

The on-line tool wear measurement problem has been investigated by numerous researchers [4]. The proposed methods can be categorized into two groups: direct and indirect. Direct methods, as the name implies, make an assessment of tool wear by either evaluating the worn surface by optical methods, or measuring the material loss of the tool by radiometric techniques. The main difficulty with using optical methods is their long processing time which makes them unsuitable for on-line tool wear measurement, and their limited application to cases where the surface of the tool is visually accessible during the operation [5]. The difficulty with the application of radiometric techniques on the shop floor is their requirements for special preparation of the tool and potential hazards due to radioactivity [6].

Indirect methods, on the other hand, are based on utilizing signals such as force or torque, temperature, tool vibration, or acoustic emissions [7-10]. These techniques which estimate tool wear by correlating it with the measured process variable use different approaches to find such a correlation. Some approaches rely on a detailed mechanistic model of the cutting process (e.g., [11]), while others use empirical relationships between the measured variable and tool wear (e.g., [12]). The mechanistic approach has contributed greatly to the basic understanding of the cutting process, while the empirical approach has been useful for specific tool-workpiece combinations and constant cutting conditions. Both the mechanistic and empirical approach have certain limitations, however, when applied to on-line tool wear estimation.

The mechanistic approach, which relies on the mathematical modeling of the physics of cutting, due to the inherent complexity of the cutting process and our incomplete understanding of it, is limited in applicability. Moreover, since the coefficients and exponents of these models change with tool-workpiece combinations and cutting conditions, extensive off-line testing is required for each case. Another limitation in the utilization of the mechanistic approach is the lack of appropriate sensors. For example, most models developed by this approach emphasize the relationship between tool wear and temperature (e.g., [13]). The absence of a practical temperature sensor limits the application of these models.

The empirical approach, on the other hand, relies on experimentally observed relationships to detect tool failure or estimate tool wear. The empirical methods for tool wear estimation usually consider a "black box" approach with a relationship between variables (e.g., force and flank wear). Therefore, they fail to separate the effect of other variables involved in the process (e.g., the effect of changes in the cutting variables on force). This usually causes serious limitations when the cutting variables are changed due to part configuration.

The objective of this paper is to present an approach which estimates tool wear in the presence of varying depth of cut. This approach uses a mathematical model to identify the effect of tool wear. This model, which uses the cutting force as the measured variable, separates the effect of tool wear from any effects caused by variations in the depth of cut. Therefore, it continues to identify the effect of tool wear despite the varying cutting variable (depth of cut in this case).

The proposed approach uses on-line parameter estimation techniques to estimate the model parameters. Therefore, it does not require a data base and prior off-line testing. The effect of tool wear is identified by estimating a parameter which is proportional to the tool wear.

The next sections present (i) the model proposed and approach used to estimate the tool wear related parameter along with simulation results demonstrating the application of the approach, (ii) the implementation of the proposed approach in an actual case where the depth of cut varies in steps and (iii) analysis and evaluation of the results.

METHODOLOGY. In order to separate the effect of tool wear on the cutting force from any effects caused by variations in the cutting variables, the total cutting force (F) can be separated into two components [14,15] such that

$$F = F_0 + \triangle F \tag{1}$$

where F_0 is the cutting force when the tool is sharp, and $\triangle F$ is a function of the flank wear W. Both F_0 and $\triangle F$ are functions of the cutting variables (cutting speed, feed, and depth of cut).

The methodology used here for tool wear estimation is to identify and subtract F_0 from F so that $\triangle F$, the component affected by wear, can be obtained. The obtained $\triangle F$ is always a function of the cutting conditions. If only depth of cut varies in the process, the model considered for $\triangle F$ has the form [16]

$$\triangle F = C\, d^{\beta}\, W \tag{2}$$

where C is a constant depending on tool and workpiece material and d is the depth of cut. We further assume that for a constant cutting speed and feed the wear rate is almost constant during most of the cut and that it only increases during the accelerated tool wear period where the tool reaches its allowable wear limit very rapidly. This assumption implies that we can write

$$W = \dot{W}\, t \tag{3}$$

where the wear rate $\dot{W}$ is a function of the cutting speed and feed and is independent of the depth of cut. Substituting Eq. (3) into (2) yields

$$\triangle F = X\, d^{\beta}\, t \tag{4}$$

where

$$X = C\, \dot{W} \tag{5}$$

The objective here is to estimate the value of X which is proportional to the wear rate and consequently estimate CW which can be obtained by the intergration of X in time. The estimation of X is based upon measuring the rate of cutting force increase during cutting

$$\frac{F - F_0}{t} = X\, d^{\beta} \tag{6}$$

and separating X from d^{β}.

The approach proposed here to separate X from d^{β} is based on the assumption that W is not a function of d. In order to measure the rate of cutting force increase the abrupt changes in the cutting force signal caused by step changes in the depth of cut are removed from the cutting force signal at each interval k. An interval is defined here as the segment of the cut where the cutting variables are kept constant. Only the segment $\triangle F_k$ affected by wear at constant cutting conditions during the interval is analyzed. The obtained $\triangle F_k$, given by

$$\triangle F_k = X\, d_k^{\,\beta}\, \tau \tag{7}$$

can now be used to estimate X and β (assuming that X is independent of d). Note that $\triangle F_k$ is the force increase in interval k, and τ is the time measured from the beginning of this interval (see Fig. 1).

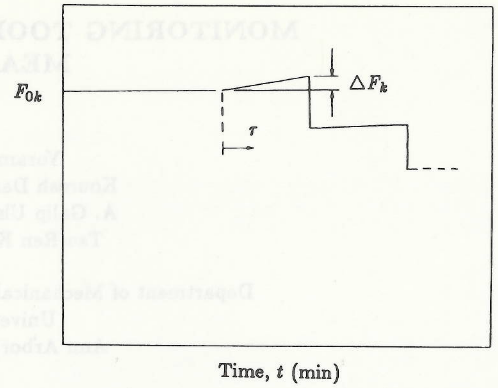

Fig.1 Schematic of the computation of slop S in the proposed approach.

For estimation purposes, the cutting force is sampled at constant sampling rate of 2 HZ. The slope, S, defined as

$$S = \frac{\triangle F_k}{\tau} = X\, d_k^{\,\beta} \tag{8}$$

is fed into the estimator at every sample point and X and β are estimated with a least-squares parameter estimator (the algorithm is shown in the Appendix). It should be emphasized again that we are assuming the change in the slope is solely caused by the different value of the depth of cut and that wear rate is not affected by this depth of cut.

In order to use the ordinary least-squares parameter estimator, the estimation model must be linear in parameters (see the Appendix). For a large signal-to-noise ratio Eq. (8) can be written as

$$\log S = \log X + \beta \log d_k\,. \tag{9}$$

This format fits the linear equation

$$y = \phi^T\, \theta\,, \tag{10}$$

where ϕ is a vector of known variables, defined here as

$$\phi^T = [\ 1 \ \ \log d_k\ ] \tag{11}$$

and θ is a vector of unknown parameters, defined here as

$$\theta^T = [\ \log X \ \ \beta] \tag{12}$$

The performance of the above approach was tested in digital simulation. We assume that only the depth of cut is changed during the cut, and that the wear rate is independent of the depth of cut. The model used for the simulation of the cutting force is

$$F_0 = 500\, d^{0.9}\,,$$

$$\triangle F = 30\, d^{0.6}\, W$$

and

$$W = 0.05\, t + 0.002\, t^2$$

where in this case from Eq. (5)

$$X = 30\, \dot{W}$$

Figures 2 and 3 show the estimated $\widehat{CW}$ and $\hat{\beta}$ respectively. The estimated $\widehat{CW}$, which is proportional to wear, has been obtained by integrating $\hat{X}$ which in discrete-time formulation has the form

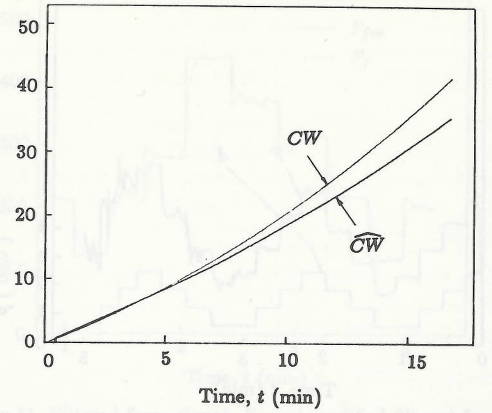

Fig.2 Simulation results of the estimated and the "real" CW (without noise).

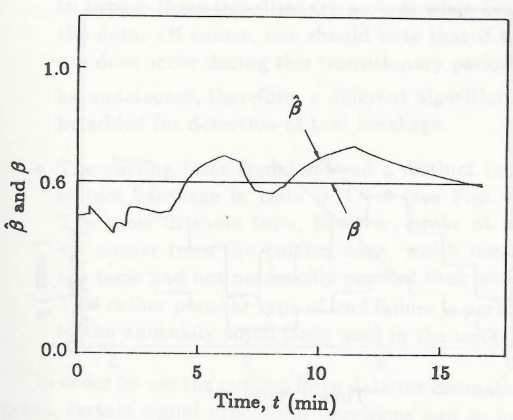

Fig.3 Simulation results of the estimated and the "real" β (without noise).

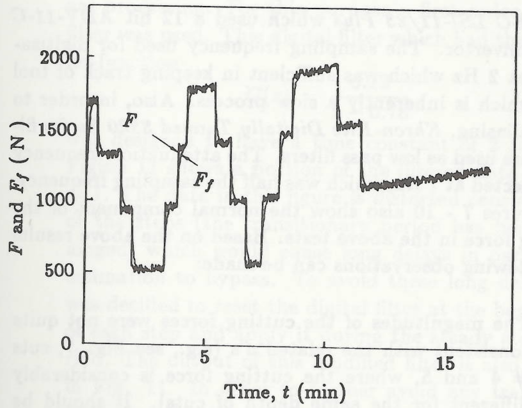

Fig.4 . Unfiltered force signal F and filtered force signal F_f in the simulation.

$$\widehat{CW}(t+1) = \widehat{CW}(t) + \hat{X}\,T \qquad (13)$$

where T is the sampling period.

The difference between the estimated values and the "real" ones in Figs. 2 and 3 is due to the fact that our approach assumes a constant wear rate whereas the "real" wear rate used in the simulation is: 0.05 + 0.004 t.

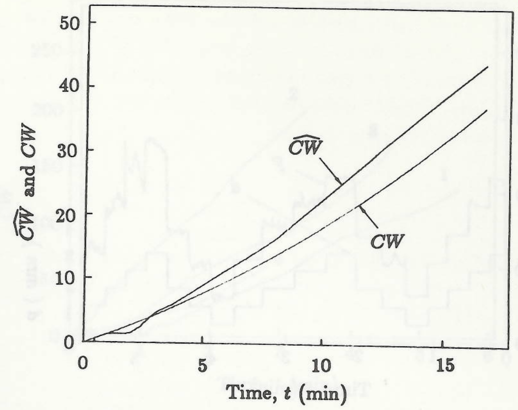

Fig.5 Simulation results of the estimated and the "real" CW (with noise superimposed).

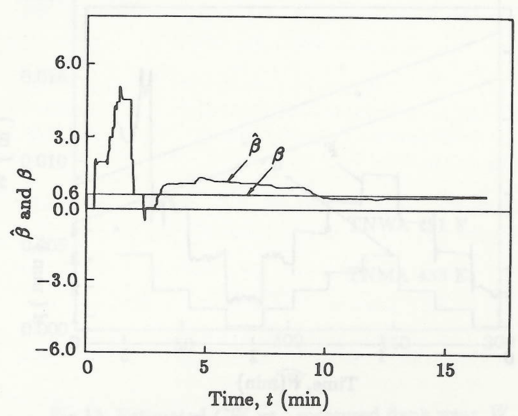

Fig.6 Simulation results of the estimated and the "real" β (with noise superimposed).

In order to study the performance of the approach in presence of noise, a psudo-random binary sequence was added to the simulated signal. Since the presence of noise causes significant problems in identifying the true $\triangle F$, a digital filter was used to reduce the noise. The selected filter, however, introduces certain amount of distortion in the data (see Fig. 4) which affects the identification of $\triangle F$. In order to neutralize this distortion the selection of $\triangle F$ is delayed for a few sampling intervals after each step change in the depth of cut. Figures 5 and 6 show the estimated parameters of the filtered data. Comparing Figure 2 and 5 shows that the difference between the estimated value and the "real" one changes only slightly, which demonstrates that the method can be used with the presence of noise.

EXPERIMENTAL RESULTS. In order to test the performance of the proposed approach in practice, turning experiments were designed and performed. The approach proposed by the authors assumes flank wear to be the dominant type of tool wear. Therefore, cutting conditions were selected to produce only flank wear during the cut. Table 1 shows the cutting conditions as well as the workpiece and tool combination used. These cutting conditions were also selected to generate rapid flank wear, so that long cuts were avoided. Four tests were performed of which three were continued until the tool failed. During all these tests the depth

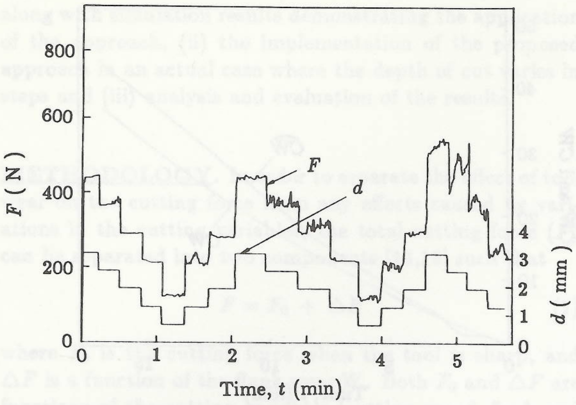

Fig.7 Normal cutting force component, F and the depth of cut, d of the 1st test.

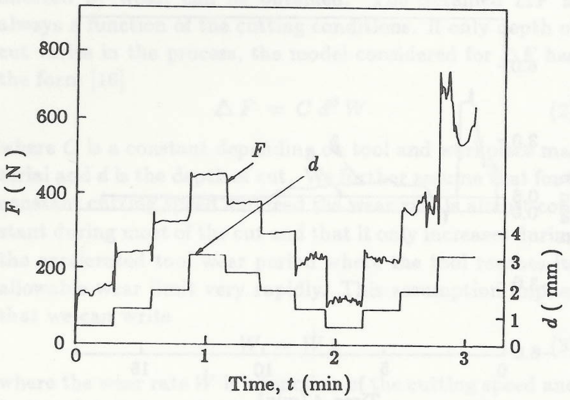

Fig.8 Normal cutting force component, F and the depth of cut, d of the 2nd test.

Table 1 Cutting variables, tool and workpiece material

Test No.	Tool	Workpiece	Feed	Cutting speed
1	TNWA			
2	432E	4340	0.001	1200
3	TNMA	ann'd	in/rev	ft/min
4	434F			

of cut was changed in steps. Figures 7 - 10 show the variations of the depth of cut in the above tests. The length of cut for each step in d was 0.3 inch. The tests were designed to maintain a constant cutting speed at the different diameters caused by the different depth of cuts. The actual flank wear was also measured intermittently during the tests by a tool-makers microscope.

The experiments were carried out on a *Lodge & Shipley 10/25 Bar Chucker CNC* lathe with *General Electric Mark Century 2000T* controller. The transducer used was *Type 9257A Three Component Kistler* force dynamometer with three *Model 5004 Kistler Dual Mode* charge amplifiers. In order to avoid repeating the tests for signal processing purposes the cutting force signals were recorded on an instrumentation tape recorder. A *Model Store 7DS Racal* tape recorder was used for this purpose. The minicomputer used

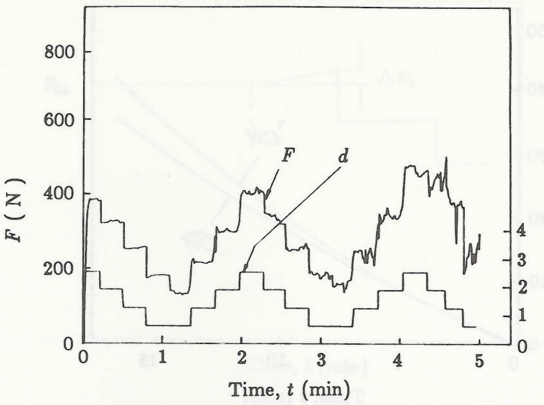

Fig.9 Normal cutting force component, F and the depth of cut, d of the 3rd test.

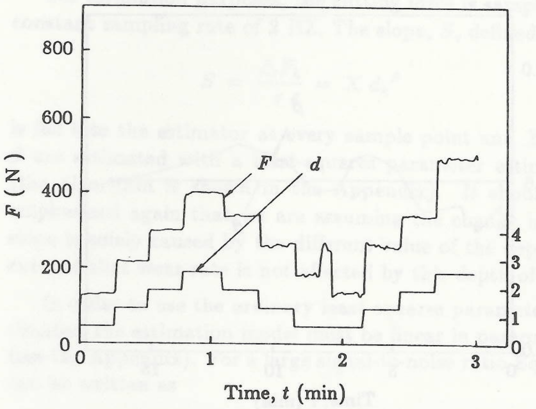

Fig.10 Normal cutting force component, F and the depth of cut, d of the 4th test.

was *DEC LSI-11/23 Plus* which used a 12 bit *ADV-11-C A/D* convertor. The sampling frequency used for digitization was 2 Hz which was sufficient in keeping track of tool wear which is inherently a slow process. Also, in order to avoid aliasing, *Khron-Hite Digitally Tunned 3320 Series* filters were used as low pass filters. The attenuation frequency was selected at 1 Hz, which was half the sampling frequency.

Figures 7 - 10 also show the normal component of the cutting force in the above tests. Based on the above results the following observations can be made:

- The magnitudes of the cutting forces were not quite consistent with the related d's (e.g., see Fig. 7, cuts # 4 and 5, where the cutting force is considerably different for the same depth of cuts). It should be emphasized that particular care was taken in the above tests to maintain the d's at the prespecified values, and that the diameter of the workpiece was measured after each cut to assure accurate results.
- At the points where a cut with a different depth of cut started, the cutting force showed a transitionary period before the steady state was reached. This transitionary period generally contained a rather sharp jump which could be interpreted as tool failure. Since in the proposed approach tool wear estimation is based on the steady state cutting situation, it is necessary

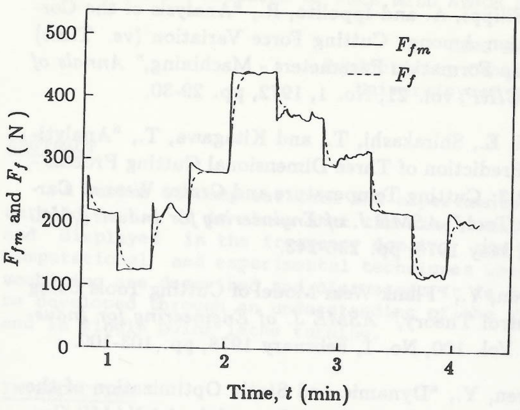

Fig.11 Filtered force signal, F_f and modified filtered force signal, F_{fm}.

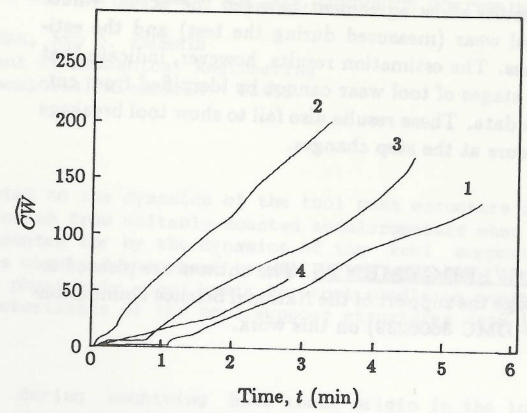

Fig.12 Estimated CW (Test No. are shown.)

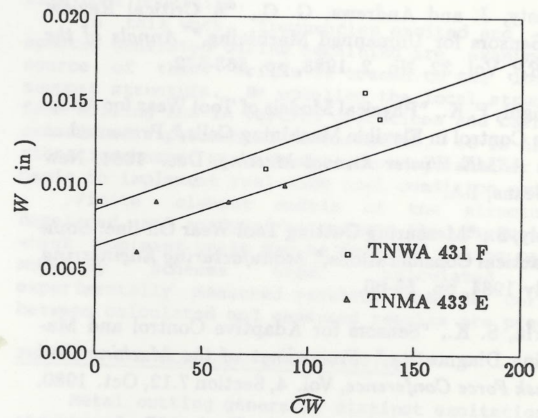

Fig.13 Estimated CW vs. measured flank wear, W.

to bypass these transitionary periods when evaluating the data. Of course, one should note that if tool failure does occur during this transitionary period, it will be undetected, therefore, a different algorithm should be added for detection of tool breakage.

- The cutting force signal showed a distinct indication of tool breakage in tests # 1 - 3 (see Figs. 7 - 9). The tools in these tests, however, broke at a different corner from the cutting edge, which means that the tools had not necessarily reached their wear limit. This rather peculiar type of tool failure is perhaps due to the unusually small feeds used in the tests.

In order to use the cutting force data for estimation purposes, certain signal processing provisions had to be taken into consideration:

- The cutting force signal contained a fair amount of noise which must be eliminated for the purpose of signal processing. For this purpose a first order digital filter was used. This digital filter which had the transfer function

$$G(z) = \frac{0.22}{z - 0.78}$$

was designed to have a time constant of 2 seconds. Figure 11 shows a portion of the filtered data in test # 1. The data in this figure is distorted considerably at the steps (the transitionary period has been prolonged) which would cause long delays in parameter estimation to bypass. To avoid these long delays, it was decided to reset the digital filter at the beginning of each step and apply it during the steady state period. The output of this modified filter is also shown in Fig. 11. In order to further avoid any transients during estimation the data feeding to the estimator was delayed for about 2 sec after each step.

- According to our basic assumption for tool wear estimation the slope of the force signal should be either postive or zero (for cases where tool wear stays constant). The cutting force data obtained from the above tests showed some instances where the slope was negative. Since according to our model a negative slope would mean an impossible reduction in tool wear, the periods of negative slope were taken as zero in estimation.

The filtered cutting force data were used for tool wear estimation. The estimation results are shown in Figs. 12 and 13. Based on these results the following observations can be made:

1. The $\hat{CW}$ values show a continuously increasing trend. These values are also plotted versus the measured tool wear values in Fig. 13. According to this figure there is an initial offset (see Fig. 13) in the estimated results. This could be due to the lesser effect of wear on the cutting force data at the initial stages of tool wear development.

2. The $\hat{CW}$ values, however, do not identify tool failure, which is distinctly clear in the cutting force signal. The ineffectiveness of the estimator in detecting tool breakage is due to neglecting the cutting force variations at the steps.

SUMMARY AND CONCLUSIONS. A model-based approach has been introduced to estimate tool wear despite varying cutting conditions. It uses the normal component of the cutting force as the measured variable and utilizes on-line parameter estimation to keep track of the tool wear increase. The approach has been both tested in digital simulation and implemented on the shop floor. The experimental results show agreement between the actual values of the tool wear (measured during the test) and the estimated ones. The estimation results, however, indicate that the early stages of tool wear cannot be identified from cutting force data. These results also fail to show tool breakage which occurs at the step changes.

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References

[1] Tlusty, J. and Andrews, G. C., "A Critical Review of Sensors for Unmanned Machining," *Annals of the CIRP*, Vol. 32, No. 2, 1983, pp. 563-572.

[2] Wright, P. K., "Physical Models of Tool Wear for Adaptive Control in Flexible Machining Cells," Presented at the *ASME Winter Annual Meeting*, Dec. 1984, New Orleans, LA.

[3] Jetly, S., "Measuring Cutting Tool Wear On-line: Some Practical Considerations," *Manufacturing Engineering*, July 1984, pp. 55-60.

[4] Birla, S. K., "Sensors for Adaptive Control and Machine Diagnostics," *Proceedings of the Machine Tool Task Force Conference*, Vol. 4, Section 7.12, Oct. 1980.

[5] Daneshmand, L. K. and Pak, H. A., "Performance Monitoring of a Computer Numerically Controlled (CNC) Lathe Using Pattern Recognition Techniques," presented at the *Third International Conference on Robot Vision and Sensory Controls (ROVISEC3)*, Cambridge, Mass., USA, Nov. 6-10, 1983.

[6] Jetley, S. K. , "A New Radiometric Method of Measuring Drill Wear," *Proceedings of the North American Manufacturing Research Conference*, Houghton, Michigan, May 1984, pp. 255-259.

[7] De Filippi, A., and Ippolito, R., "Adaptive Control in Turning: Cutting Forces and Tool Wear Relationships for P10, P20, P30 Carbides," *Annals of the CIRP*, vol. 17, 1969, pp. 377-379.

[8] Groover, M. P., Karpovich, R. J., and Levy, E. K., "A Study of the Relationship Between Remote Thermocouple Temperatures and Tool Wear in Machining," *Int. J. Prod. Res.*, Vol. 25, No. 2, 1977, pp. 129-141.

[9] Martin, P., Mutels, B., and Draiper, J. P., "Influence of Lathe Tool Wear on the Vibrations Sustained in Cutting," *Proceedings of the 16th IMTDR*, 1975.

[10] Kannatey-Asibu Jr., E. and Dornfeld, D. A., "A Study of Tool Wear Using Statistical Analysis of Cutting Acoustic Emission," *Wear* , Vol. 76, 1982, pp. 247-261.

[11] Bhattacharyya, A. and Ham, I., "Analysis of Tool Wear-Part 1: Theoretical Models of Flank Wear," *ASME J. of Engineering for Industry*, Aug. 1969, pp. 790-798.

[12] De Filippi, A. and Ippolito, R., "Analysis of the Correlation Among: Cutting Force Variation (vs. Time) - Chip Formation Parameters - Machining," *Annals of the CIRP*, vol. 21, No. 1, 1972, pp. 29-30.

[13] Usui, E., Shirakashi, T., and Kitagawa, T., "Analytical Prediction of Three Dimensional Cutting Process - Part 3: Cutting Temperature and Crater Wear of Carbide Tool," *ASME J. of Engineering for Industry*, Vol. 100, May 1978, pp. 236-243.

[14] Koren, Y., "Flank Wear Model of Cutting Tools Using Control Theory," *ASME J. of Engineering for Industry*, Vol. 100, No. 1, February 1978, pp. 103-109.

[15] Koren, Y., "Dynamic and Static Optimization of the Cutting Processes," *Proceedings of the 1st NAMR Conference*, Hamilton, May 1973, Vol. 3, pp. 67-94.

[16] Koren, Y., "Differential Equation Model of a Flank Wear," *CIRP Manufactuing Systems*, Vol. 6, No. 1, 1977, pp. 67-73.

[17] Goodwin, G. C., and Sin, K. S., *Adaptive Filtering, Prediction, and Control*, Prentice-Hall, Englwood Cliffs, New Jersey, 1984.

APPENDIX

Parameter Estimation Algorithm. A recursive least squares parameter estimation algorithm has the general form [17],

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{\mathrm{P}(k-2)\phi(k-1)}{\beta + \phi(k-1)^T \mathrm{P}(k-2)\phi(k-1)} \bar{\nu}(k) \quad (14)$$

$$\mathrm{P}(k-1) = \frac{1}{\beta}\left[\mathrm{P}(k-2) - \frac{\mathrm{P}(k-2)\phi(k-1)\phi(k-1)^T \mathrm{P}(k-2)}{\beta + \phi(k-1)^T \mathrm{P}(k-2)\phi(k-1)}\right] \quad (15)$$

where $y(k)$ is the value of the measured variable y at time $t = k\triangle t$ for $k = 0, 1, 2, \ldots$. $\mathrm{P}(k)$ is the matrix of estimation gains, β provides exponential data weighting, and $\bar{\nu}(k)$ is the parameter estimation error $\phi(k)$ is the vector of measured (or known) variables, and $\hat{\theta}(k)$ is a vector of parameter estimates. The above algorithm recursively updates the estimated parameter vector $\hat{\theta}(k)$ defined as

$$\hat{\theta}(k) = [\ \hat{a}_1(k)\ \ \hat{a}_2(k)\ \ \ldots\ \ \hat{a}_n(k)\ \ \hat{b}_0(k)\ \ \hat{b}_1(k)\ \ \ldots\ \ \hat{b}_m(k)\ ] \quad (16)$$

for any process whose equations can be written in the form,

$$y(k) = \phi(k-1)^T\,\theta(k) \quad (17)$$

Thus, the process model must be written in a form that is linear in the unknown parameters, which are the elements of the vector $\theta(k)$. The vector $\phi(k)$ and the estimation error $\bar{\nu}(k)$ are defined as

$$\phi(k-1)^T = [\ -y(k-1)\ \ -y(k-2)\ \ \ldots\ \ -y(k-n)\ \ u(k)\ \ u(k-1)\ \ \ldots\ \ u(k-m)\ ] \quad (18)$$

and

$$\bar{\nu}(k) = [y(k) - \phi(k-1)^T \hat{\theta}(k-1)] \quad (19)$$