MODEL-BASED TOOL WEAR ESTIMATION IN METAL CUTTING

Final Report of NSF Grant DMC-8606239
Technical Report No. UM-MEAM-89-12

by
A.G. Ulsoy
and
Y. Koren

Department of Mechanical Engineering and Applied Mechanics
Unversity of Michigan, Ann Arbor, MI 48109

October 25, 1989

1 Introduction

An Adaptive Control Optimization(ACO) system can automatically provide optimal cutting conditions, which include optimal feed, depth of cut, and cutting speed, based on on-line measurements of process variables. An ACO system requires reliable sensors which allow manufacturing systems and control computers to be interfaced.

On-line measurement of tool wear is one of the main obstacles to the implementation of ACO systems in industry. Tool wear determines the tool life in most cutting processes, and the prediction of tool life is essential to optimize cutting operations. Also, excessive wear degrades the surface finish and the dimensional accuracy of the finished parts.

Tool wear can be measured through direct measuring techniques, or estimated through indirect measuring techniques. In direct measuring techniques, optical devices or micro-isotope sensors are used. In indirect measuring techniques, tool wear is estimated using other easily measurable cutting process variables which are related to tool wear. Such variables are the cutting force signal, the spindle motor current, the acoustic emission signal, the tool vibration signal, etc.

Indirect measuring techniques are used in most proposed on-line tool wear measuring methods, because direct measuring techniques are inherently off-line methods. The direct measuring techniques monitor the tool only when the tool is disengaged from the workpiece. The indirect measuring techniques, on the other hand, use cutting process variables which can be measured continuously during the cutting operation.

Cutting process models are most important part in indirect tool wear measuring techniques [1]. A cutting process model describes the relationship between tool wear development and the resulting changes in the measured cutting process variable. An indirect measuring method estimates tool wear based on this model and the on-line measurement of the cutting process variable. Therefore, the accuracy of the cutting process model determines the accuracy of tool wear estimation.

Among developed cutting process models, the model describing the relationship between cutting force and tool wear is known to be reliable. Historically, there has been considerable research into relationships between the cutting force and other cutting process variables, including tool wear, using either an empirical or mechanistic approach. Furthermore, measured cutting forces are generally very reliable, and measuring devices (e.g., a force dynamometer) are well developed and widely available.

This project deals with three major problems of cutting force based on-line tool wear estimation methods, as identified in the previous research work by Danai and Ulsoy [2]. The first problem is that cutting process models must be improved to separate the effect of the flank wear on the cutting force from that of the crater wear. The second problem is that on-line tool wear estimation must be achieved under time varying cutting conditions, as would usually occur during cutting processes that are controlled. The third problem is that advanced on-line estimation methodologies must be developed to reduce the dependency on off-line experimental data.

This project also deals with a multi-sensor strategy, where a computer vision based off-line direct measuring technique is integrated with the cutting force based on-line technique. The information from the computer vision intermittently calibrates the on-line estimation scheme. The vision information is collected when the tool is disengaged from the workpiece for part changes or for any other purpose. This strategy increases the accuracy of the tool wear estimation significantly.

The project objective is introduced in Section 2. An overview of the research work is given in Section 3. Conclusions from the research are presented in Section 4. Published articles resulting from this project are listed in the References, and attached in the Appendix.

2 Objective

The objective of this research is to develop a reliable and accurate on-line method that estimates tool wear based on cutting force measurements. This method incorporates tool wear models and advanced estimation techniques. The resulting method should be able to operate under the following conditions:

1. co-existence of crater and flank wear
2. time varying cutting conditions
3. uncertainty in the model parameters
4. cutting force fluctuations

3 Approach

To achieve the aforementioned objective, four separate approaches were developed in parallel. The first approach estimates clearance (flank) wear in the presence of crater wear. The second approach estimates clearance wear with varying cutting conditions. The third approach applies adaptive observer techniques to the tool wear estimation problem. The fourth approach integrates computer vision and the adaptive observer technique by a multi-sensor strategy.

Each of these approaches deals with a different problem in tool wear estimation using the cutting force signal. Based on the results of these approaches, a high level strategy can be devised regarding the implementation of an estimator that can handle all the treated problems simultaneously as shown in Fig. 1.

3.1 Clearance wear estimation in the presence of crater wear

To separately estimate clearance wear (flank wear plus nose-radius wear) and crater wear, we have to know the models which relate the cutting force variations to the development of these two types of wear. For this purpose, a model which describes the cutting force variation due to clearance wear is proposed by extending previously developed flank wear and cutting force models. This proposed clearance wear and cutting force model takes into account the complex cutting tool geometry in practical turning operations. To apply this model to tool wear estimation, assumptions are made to simplify the four physical functions in the model. It is argued that when clearance wear progresses as in the typical three-stage development of flank wear (see Fig. 2), the cutting force variation due to clearance wear is restricted to a single direction.

A model that completely describes the cutting force variation due to crater wear is not available, because of the complex cutting mechanism involved. Therefore, a partial crater-wear force model is proposed for tool wear estimation. This model assumes a certain tool geometrical change due to crater wear, and based on this assumption, the cutting force variation due to crater wear is considered to lie within a fixed plane.

By combining these two models, we can calculate a variable that is proportional to the clearance wear increase after the "run-in" period for constant cutting conditions with clearance wear in its linear stage. This variable is a weighted sum of the three components of the cutting force with the weighting factors determined by the chip flow direction and the tool geometry. In this summing process, the weighting factor of the radial component of the cutting force usually is the largest, since the radial component is least affected by crater wear; the weighting factor of the feed component usually is negative so that the force decrease due to crater wear can be compensated; and the weighting factor of the normal component usually is close to zero and, in some instances, is negligible. Clearance wear is then estimated based on this calculated variable and the initial clearance wear obtained from previous (off-line) measurements.

Three experiments were conducted to test the proposed wear and force models and the estimation algorithm. The experiments showed good agreement with the models, and the estimation results supported our proposed theory [3]. Details of this approach are documented in the dissertation of T.R. Ko [4] and will be described in a forthcoming paper [5].

3.2 Clearance wear estimation with varying cutting variables

To separate the direct effect of cutting variables on the cutting force from the force variation due to tool wear, an accurate model that describes the direct effect of the cutting variable is required. Since tool wear estimation is very sensitive to the variations in the model parameters, it is necessary to estimate the model parameters on line, so that the variations between different cutting conditions can be accounted for.

When one cutting variable changes in steps and crater wear is negligible, a simple model based on the power law formulation can be used for clearance wear estimation. This model can be divided into three different cases corresponding to the cutting condition which changes, i.e., cutting speed, depth of cut, and feed. Three separate methods are proposed to estimate clearance wear for these three cases. These methods use a recursive least-squares estimation algorithm and signal processing techniques to estimate the model parameters on line. Based on the estimated parameters, a variable that is proportional to the clearance wear increase after the "run-in" period can be obtained.

Since the cutting force fluctuates during cutting, the measured force signal contains high frequency noise. This noise affects the quality of the estimated model parameters. The reliability of these estimated parameters becomes an important issue, because the tool wear estimate is based on them. For all three proposed methods, a sensitivity analysis was conducted based on the assumption that the force noise is white and Gaussian. According to the analysis results, a quantitative description of the reliability of the tool wear estimate can be obtained. This type of description is important if sensor fusion is to be implemented in the future.

Simulated cutting forces with realistic noise levels were used to evaluate all three methods. These simulations also accounted for possible wear rate modeling errors, and gave good results. Experimental evaluation of Method II (for changes in depth of cut) was also performed under stepwise changing depth-of-cut in turning. The clearance wear estimates are quite good in all four experiments reported after about the first minute of cutting. These experimental results further reinforce the main conclusion from the simulation studies, that the proposed methods can utilize force measurement to reliably estimate flank wear in turning under varying cutting conditions. Details of this approach are described in [4,6,7,8]. The references [6,7,8] are attached in the Appendix.

3.3 Off-line direct tool wear measurement using computer vision

Among existing tool wear measurement methods, methods using optical devices are known to be very accurate and practical. The most popular device is a microscope, which is also the most accurate. Measuring tool wear using a microscope, however, requires human inspection. To replace the human inspection, a computer vision system has been developed, in which the worn surface and the amount of wear is determined by a computer.

The replacement of human inspectors by computer vision is significant, especially in production lines where one tool cuts many parts. If a tool is inspected by computer vision every time a part is changed, then the tool can be used until tool wear reaches an allowable value. The wasteful discarding of useful tools due to a conservative prediction of the tool life can be avoided, and the machine down time for tool changing can be reduced significantly.

The purpose of this section is to experimentally demonstrate the feasibility of measuring the flank wear using a simple commercially available computer vision system. The flank wear is measured based on the difference between the intensity of the reflected light from the worn tool surface and that from the background. The difference is very significant and an appropriate selection of the intensity threshold level allows acceptable binary images of the flank wear. These images are used by the vision computer to calculate the amount of flank wear. To obtain good images of the worn surface, selection of the light source and its orientation to the flank face are very important. In the experiments, a TN2500 CID (Charge Injection Device) camera and an Optomation II computer vision system made by the General Electric Company are used. The camera has a 244 x 248 pixel resolution and is equipped with a microscopic lens. Figure 3 shows the experimental setup. Carbide inserts are used to cut steel workpiece on a CNC lathe. For the purpose of the laboratory demonstrations, the computer vision system is set up near the lathe, however, it can be designed as an integrated part of a machine tool without difficulty.

Experimental results show excellent agreement between the measured flank wear using computer vision and that using a tool maker's microscope. The flank wear is regarded as the distance between the top of the tool edge and the bottom of the worn surface on the clearance face. Some improvements on the computer vision based tool wear measuring method are necessary before this method is implemented in practice. Because binary images are very sensitive to the selection of the intensity threshold level, and the condition of the light source, it is difficult to obtain good measurements of the entire tool wear development using a predetermined threshold level. This problem can be solved by using gray scale images instead of binary images. In a gray scale image, the texture and the pattern of a worn surface clearly define the boundary of the flank wear even under changing light conditions. This research work will be described in detail in the forthcoming Ph.D. Thesis of J.J. Park [9], and the paper [10].

3.4 On-line tool wear estimation using force measurement and a nonlinear observer

A tool wear model has previously been developed in a nonlinear state space equation form by Danai and Ulsoy [2]. The model uses various components of tool wear (e.g., flank wear caused by abrasion, flank wear by diffusion, and crater wear) as unmeasurable states, and a cutting force component as the measured output. Inputs to the model are cutting speed, the depth of cut, and the feed. However, because the model of crater wear is known to be unreliable, only flank wear dominant cutting processes are considered in the project. These cutting processes are normally found in finishing operations where high cutting speeds and low feeds are required.

The tool wear estimation problem can be formulated as a nonlinear observer design problem. An observer is designed to estimate the unmeasurable states (e.g., tool wear components) by utilizing the process model and the measurement of inputs (e.g., the cutting speed, the depth of cut, and the feed) and outputs (e.g., cutting force). Because the cutting process model is nonlinear, the design of an observer for tool wear estimation requires a difficult nonlinear stability analysis, unlike the well known linear observer design problems.

The stability analysis is carried out for the observer error dynamic system,which describes the dynamical behavior of the error between the true tool wear components and the estimated tool wear components. The observer error dynamic system is shown to be stable by utilizing the Total Stability Theorem and by considering physical limitations of cutting processes, i.e., the fact that tool wear does not increase without bound.

From the stability analysis of the designed nonlinear observer, and from simulation studies, the estimated tool wear is shown to converge to the actual tool wear. The nonlinear observer estimates tool wear with a sufficiently fast speed, which can be controlled by selection of the observer gain. The simulation studies also show that the nonlinear observer is robust against measurement noise typical of cutting force signals. The research is described in detail in [9,11]; note that [11] is included in the Appendix.

3.5 Combined adaptive observer and computer vision for on-line tool wear estimation

An adaptive version of the nonlinear observer is developed, because without adaptation the nonlinear observer approach needs extensive off-line experiments to obtain the parameters used in the tool wear model. In the adaptive observer method, unmeasurable states (e.g., tool wear components) and unknown parameters in the tool wear model are simultaneously estimated using the structure of the cutting process model and the output measurement (e.g., the cutting force signal).

An adaptive observer consists of two part; a state estimation part and a model parameter estimation part. These two parts exchange the estimated information concurrently. The state estimation (i.e., tool wear estimation) is carried out using the developed nonlinear observer, whose parameters are estimated by the parameter estimation part. The parameter estimation can be achieved using a Recursive Prediction Error (RPE) parameter estimation algorithm. The RPE algorithm estimates the model parameters in such a way that the error between the measured cutting force and the cutting force estimated using these parameters is minimized. However, it is not easy to accurately estimate all the parameters in the tool wear model using this method, because many parameters must be estimated and the model is highly nonlinear in terms of these parameters.

Supplementary information on the model parameters can improve the estimation of the parameters and, thus, give an accurate estimation of tool wear. Such information includes the cutting temperature, the diffusion rate of work and tool material combinations, the cutting force when the tool is sharp, the rate of cutting force changes due to the wear development etc.; or at least the range of those parameters. Such information can be obtained by off-line experiments or from machining data bases, but every piece of information is not necessarily available.

The computer vision system, which is described in Section 3.3, is integrated with the adaptive observer to provide supplementary information for accurate tool wear estimation. The computer vision allows the direct measurement of tool wear during times when the part is changed or any other interval when the tool is disengaged from the workpiece. This measurement, along with the previous computer vision measurement and the cutting force measurement, can be used to calculate the rate of cutting force change due to the wear development. The obtained rate is used as a known parameter of the adaptive observer. The adaptive observer estimates the tool wear and the other parameters on-line until the next computer vision measurement is available. Figure 4 shows the schematic of this approach.

This strategy is most effective when several computer vision measurements are available before the tool life ends. A conservatively predicted tool life can be replaced by an actual tool life because the developed adaptive observer estimates the tool wear accurately even while the tool is under a cutting operation. The extended tool life significantly reduces machine down time which otherwise would be required to replace tools.

Simulation studies show good estimates of the tool wear [12], while experimental demonstrations of this strategy are still in progress. Final results of this research work will be presented in [9], which are in preparation.

4 Concluding Remarks

In this research work, four issues associated with on-line tool wear estimation using cutting force signals have been separately investigated. They are (1) clearance wear estimation in the presence of crater wear, (2) clearance wear estimation with varying cutting variables, (3) tool wear estimation using a nonlinear observer, and (4) tool wear estimation using an adaptive observer and computer vision.

The first two approaches do not consider the wear development explicitly. Instead, they investigate the relationship between the cutting force variation and clearance wear. Models were developed to describe the force wear relationship and used to estimate tool wear. In the first approach, clearance wear was estimated in the presence of moderate crater wear by using a weighted sum of the three components of the cutting force. In the second approach, clearance wear was estimated using a least-squares estimation technique, when only one cutting variable changes in steps. These two approaches were tested in simulation as well as experimentally. The results are very promising.

The tool wear development is considered explicitly in the third approach, where a nonlinear observer is designed based on a dynamic tool wear model. When the parameters of the tool wear model are known, the nonlinear observer can provide accurate tool wear estimation, even with a bad initial guess of tool wear and with measurement noise. Since the model parameters may be unknown or time-varying in some cases, an adaptive observer is developed to estimate these parameters together with tool wear in the fourth approach. Computer vision is used to assist this adaptive observer approach by providing intermittent tool wear measurements so that the reliability of the estimated parameters and tool wear can be improved. The fourth approach has been tested in simulation with good results and is currently being tested experimentally.

Several conclusions can be drawn from this research:

- The cutting force signal contains fluctuations. When it is used to estimate tool wear, these fluctuations (noise or high frequency components irrelevant to tool wear process) affect the estimation result. The reliability of the tool wear estimation deteriorates depending on the intensity of these fluctuations.

In most finishing operations, the fluctuations of the cutting force are small, and using the cutting force to estimate tool wear can work well. However, in roughing operations, the cutting force fluctuations can be significant, and certain signal processing schemes have to be adapted to improve the estimation reliability.

- An initial clearance wear develops rapidly during the "run-in" period of a cutting process. Since its effect on the cutting force usually couples with the machine transient at the beginning of a cut and cannot be separated, the initial clearance wear cannot be estimated on line based on the measured cutting force. Therefore, to estimate clearance wear based on the cutting force, we must obtain this initial clearance wear from off-line calibrations.

- A complete model that describes the variation in the cutting force due to crater wear is not available due to the complex cutting mechanisms involved. As a result, crater wear cannot be accurately estimated based on the measured cutting force.

- Tool wear estimation based solely on the cutting force has several drawbacks as mentioned above, therefore tool wear information from other sources can be very valuable to be incorporated into the estimation to increase reliability. Computer vision is a very good choice for this purpose, since it provides automatic tool wear readings accurately while the tool is disengaged from the workpiece.

- When the models used are not derived directly from fundamental physical laws, but from empirical relationships, they may be applicable only within certain domains of the cutting conditions. Therefore, experiments may be needed to define these domains, when the estimation approaches based on the models are used in practice.

To further improve the on-line tool wear estimation using cutting force signals, several subsequent research directions can be suggested. The vision system may be extended to observe the chipflow direction during cutting. The chipflow direction is an important piece of information when the effect of crater wear on the cutting force is to be separated from the effect of clearance wear. The cutting force fluctuations may be modeled so that more effective processing schemes can be devised based on the model. A model describing the relationship between crater wear and the variation of the cutting force is necessary if crater wear is to be estimated using cutting force signal. The incorporation of other tool wear measuring or estimation techniques within the present approach is highly desirable. Multi-sensor approaches combining different sources of tool wear information are expected to produce a more reliable on-line tool wear estimate.

5 References

[1] Y. Koren, 1987, "Flank Wear Model of Cutting Tools Using Control Theory," *ASME J. of Engineering for Industry*, Vol. 100, pp. 103-109.

[2] K. Danai, and A.G. Ulsoy, 1987, "An Adaptive Observer for On-Line Tool Wear Estimation in Turning, Parts I and II," *Mechanical Systems and Signal Processing*, pp. 211-240.

[3] A.G. Ulsoy, Y. Koren, T.R. Ko, and J.J. Park, 1989, "Model-Based Tool Wear Estimation in Metal Cutting," *Proceedings of the 15th NSF Conference on Production Research and Technology*, Berkeley, CA, Jan., pp. 237-239 (included in the Appendix).

[4] T.R. Ko, 1989, *Analytical Study of Tool Wear Estimation Using Cutting Force Signals*, Ph.D. Thesis, Dept. of Mechanical Engineering and Applied Mechanics, The University of Michigan.

[5] T.R. Ko, Y. Koren, and S. Malkin, 1990, "Tool Wear Estimation Using Three Components of the Cutting Forces," in preparation.

[6] Y. Koren, K. Danai, A.G. Ulsoy, and T.R. Ko, 1987, "Monitoring Tool Wear Through Force Measurement," *Proceedings of the 15th NAMR Conference*, Bethlehem, PA, May, pp. 463-468 (included in the Appendix).

[7] Y. Koren, A.G. Ulsoy, and T.R. Ko, 1987, "Estimation of Tool Wear Under Varying Cutting Conditions," *Proceedings of the 14th NSF Conference on Production Research and Technology*, Ann Arbor, MI, Oct., pp. 73-77 (included in the Appendix).

[8] Y. Koren, T.R. Ko, K. Danai, and A.G. Ulsoy, 1989, "Methods for Tool Wear Estimation from Force Measurements Under Varying Cutting Conditions," ASME Winter Annual Meeting, San Francisco, December (included in the Appendix).

[9] J.J. Park, 1990, *Adaptive Observers and a Computer Vision for On-Line Tool Wear Estimation*, Ph.D. Thesis, Dept. of Mechanical Engineering and Applied Mechanics, The University of Michigan (expected completion April 1990).

[10] J.J. Park and A.G. Ulsoy, 1990, "On-Line Tool Wear Estimation Using Adaptive Observers and Computer Vision; Part I Theory and Part II Experiment," in preparation.

[11] J.J. Park and A.G. Ulsoy, 1989, "On-Line Tool Wear Estimation Using Force Measurement and a Nonlinear Observer," ASME Winter Annual Meeting, San Francisco, December (included in the Appendix).

[12] A.G. Ulsoy, 1989, "Estimation of Time Varying Parameters in Discrete Time Dynamic System: A Tool Wear Estimation Example," *Proceedings of the American Control Conference*, Pittsburg, PA, June, pp. 68-74 (included in the Appendix).

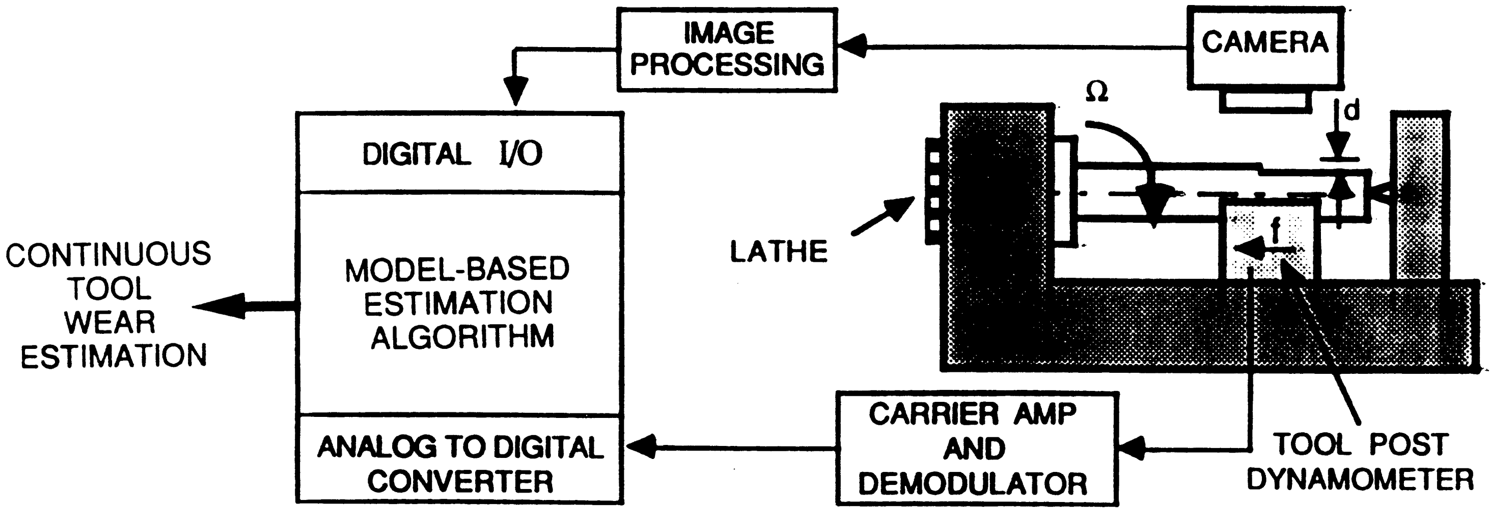

Figure 1: Combined force sensing and computer vision for wear estimation

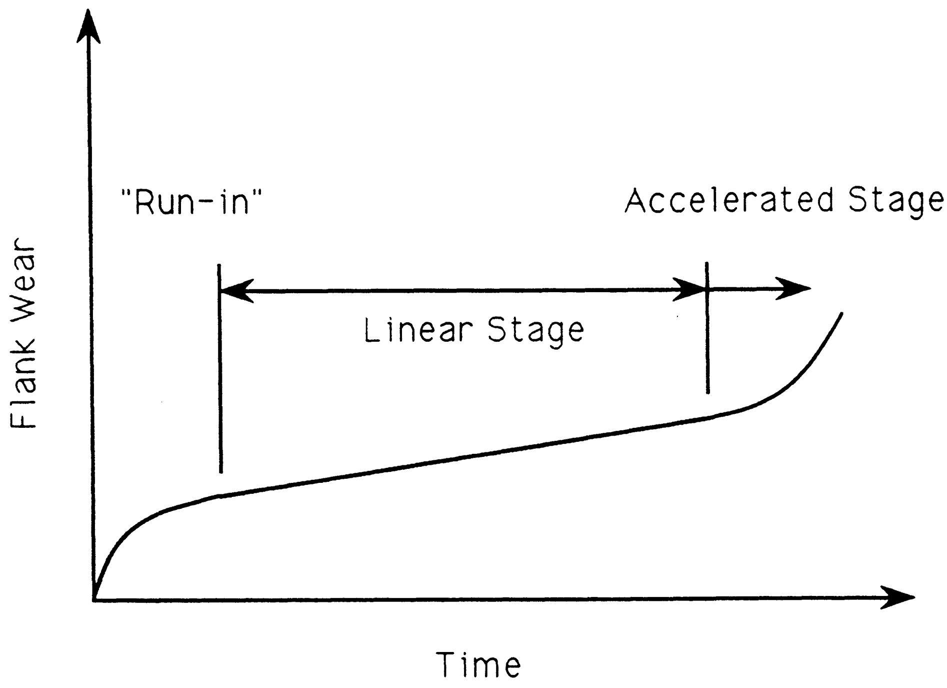

Figure 2: Three typical stages of the flank wear development

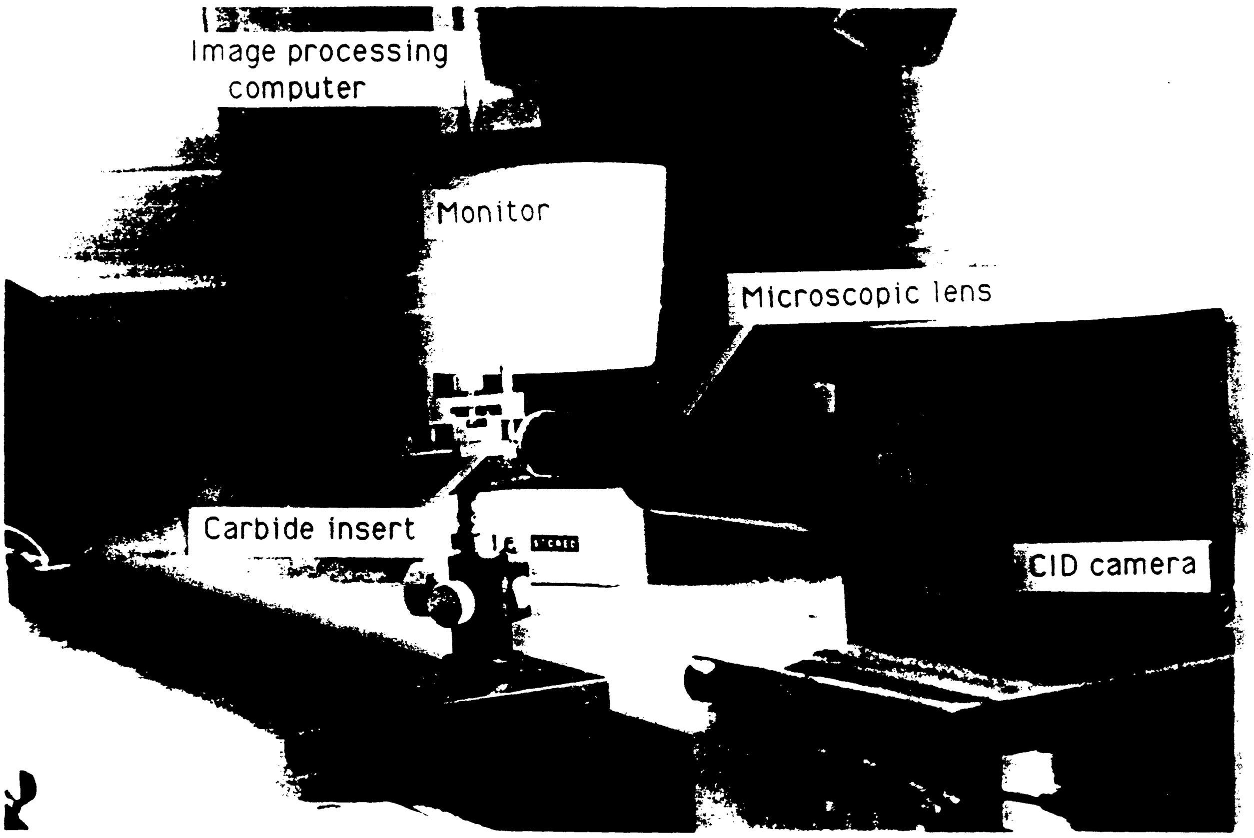

Fig. 3 Experimental setup of computer vision

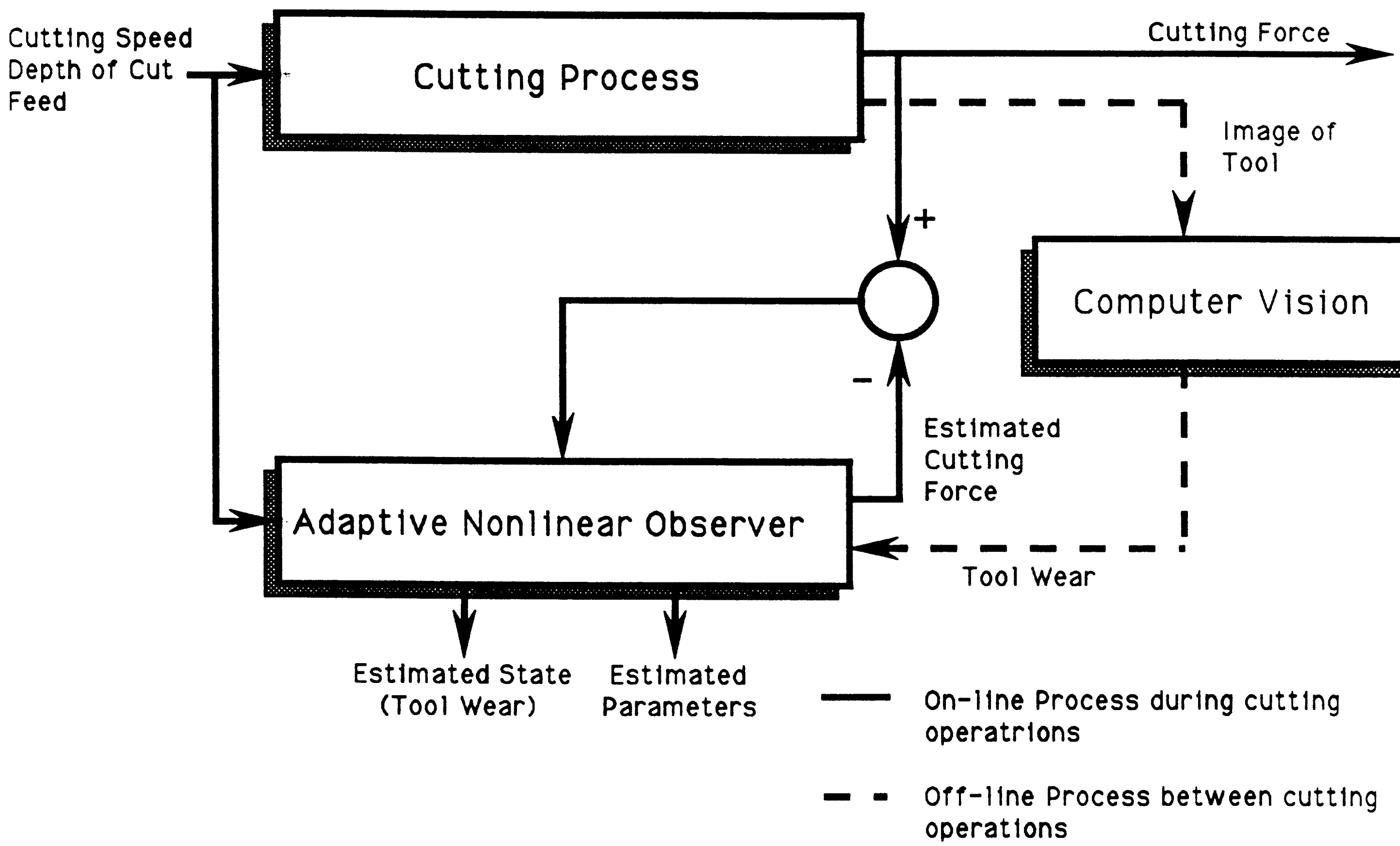

Fig. 4 Schemetic of the adaptive observer combined with computer vision

6 Appendices

MONITORING TOOL WEAR THROUGH FORCE MEASUREMENT

by

Yoram Koren, Professor
Kourosh Danai, Research Associate
A. Galip Ulsoy, Associate Professor
Tsu-Ren Ko, Research Assistant

Department of Mechanical Engineering and Applied Mechanics
University of Michigan
Ann Arbor, Michigan 48109-2125

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

Proceedings of the 15th NAMRC, Bethlehem, PA, May 1987, pp 463 - 468

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

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

where F_0 is the cutting force when the tool is sharp, and ΔF is a function of the flank wear W. Both F_0 and ΔF 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 ΔF, the component affected by wear, can be obtained. The obtained ΔF is always a function of the cutting conditions. If only depth of cut varies in the process, the model considered for ΔF has the form [16]

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

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

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

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 ΔF_k affected by wear at constant cutting conditions during the interval is analyzed. The obtained ΔF_k, given by

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

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

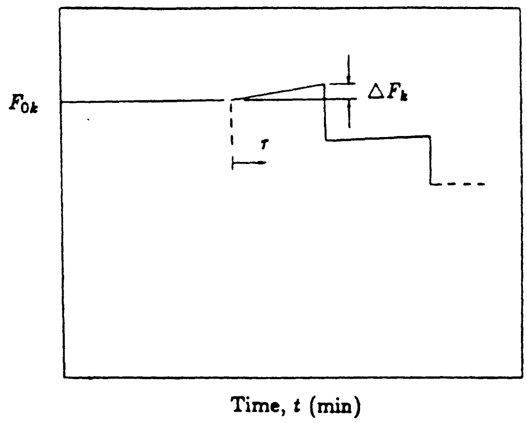

Fig.1 Schematic of the computation of slop S in the proposed approach.

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

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

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

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

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

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

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

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

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

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

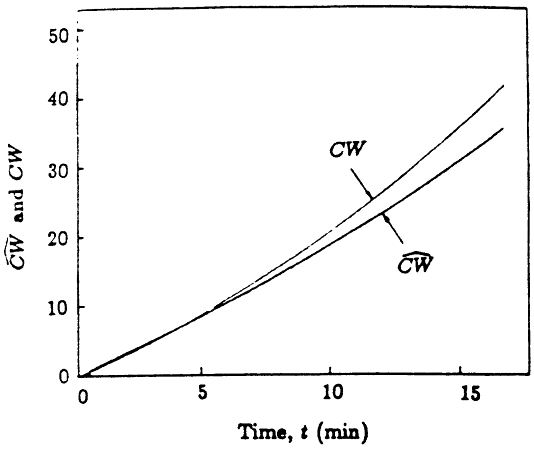

Fig.2 Simulation results of the estimated and the "real" CW (without noise).

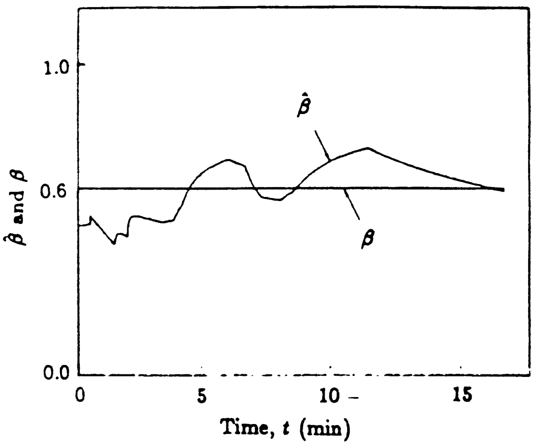

Fig.3 Simulation results of the estimated and the "real" β (without noise).

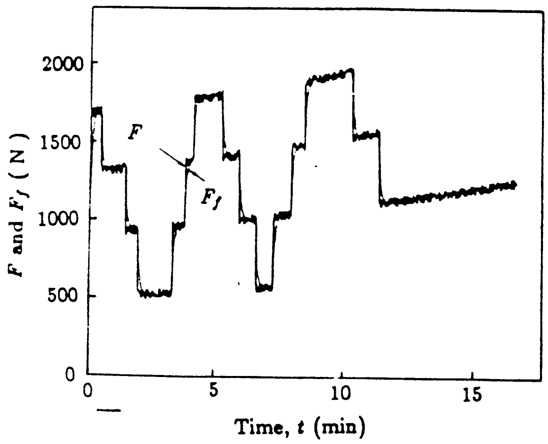

Fig.4 Unfiltered force signal F and filtered force signal F_f in the simulation.

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

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.

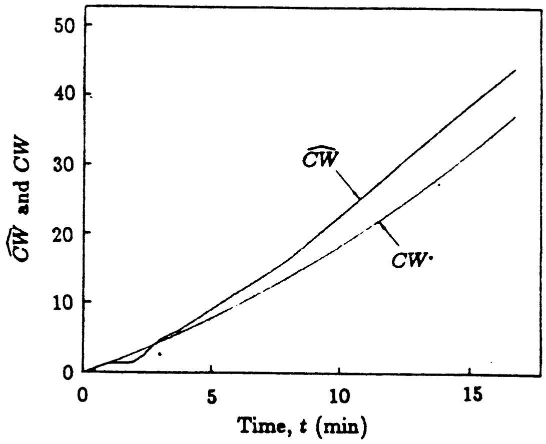

Fig.5 Simulation results of the estimated and the "real" CW (with noise superimposed).

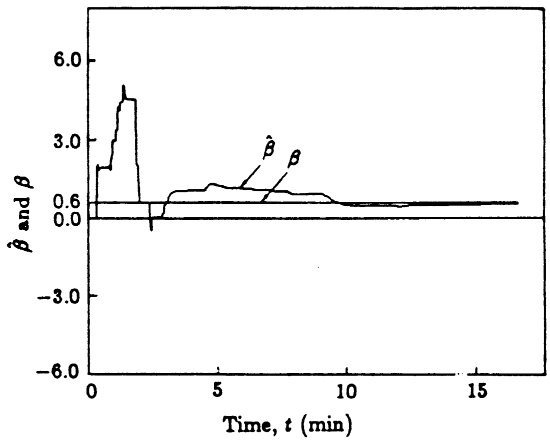

Fig.6 Simulation results of the estimated and the "real" β (with noise superimposed).

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 ΔF, 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 ΔF. In order to neutralize this distortion the selection of ΔF 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

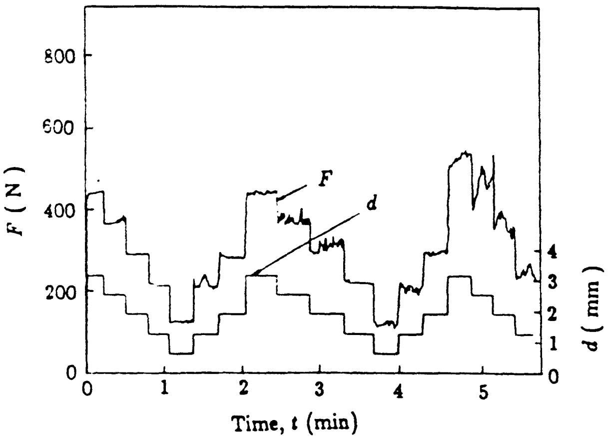

Fig.7 Normal cutting force component, F and the depth of cut, d of the 1st test.

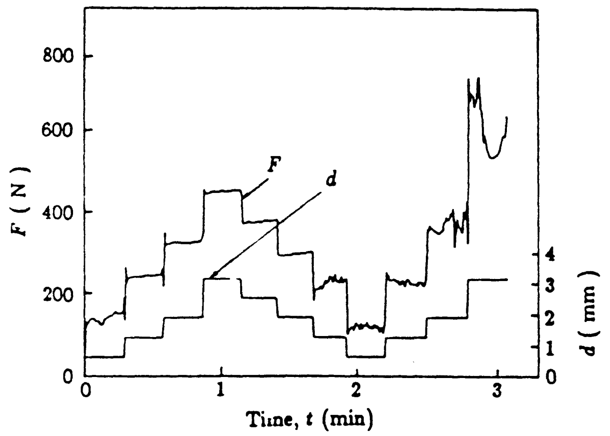

Fig.8 Normal cutting force component, F and the depth of cut, d of the 2nd test.

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

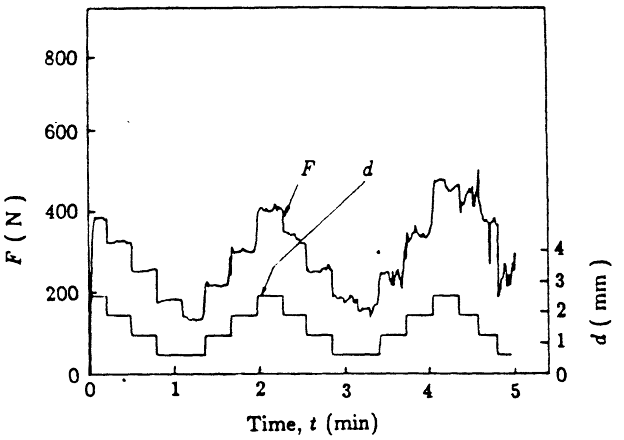

Fig.9 Normal cutting force component, F and the depth of cut, d of the 3rd test.

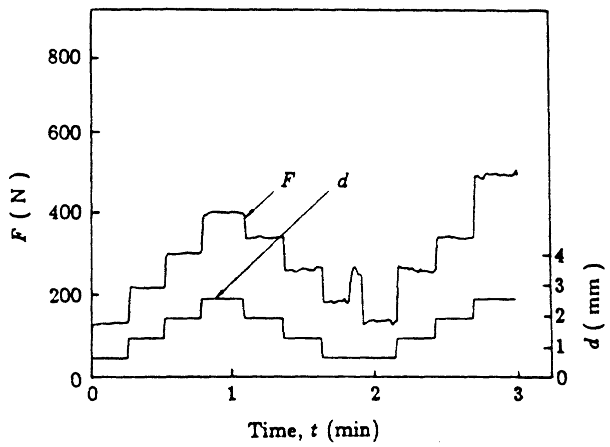

Fig.10 Normal cutting force component, F and the depth of cut, d of the 4th test.

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

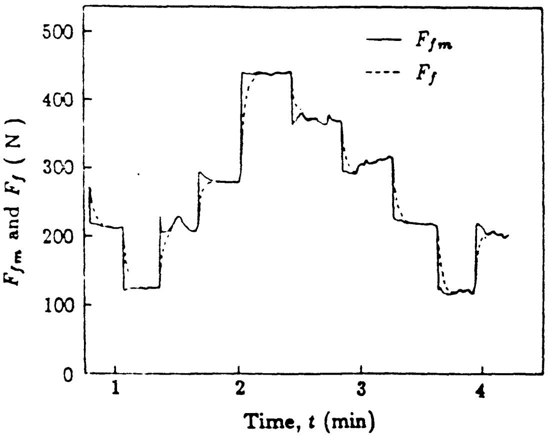

Fig.11 Filtered force signal, F_f and modified filtered force signal, F_{fm}.

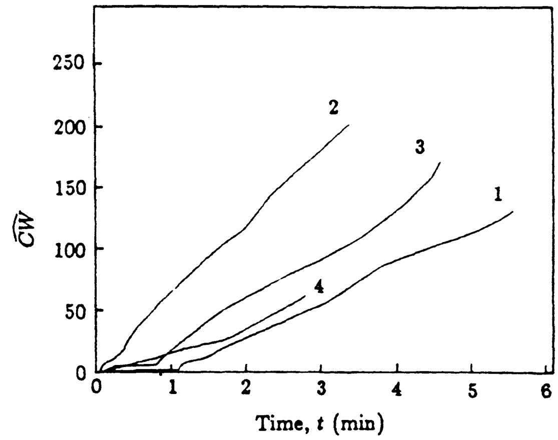

Fig.12 Estimated CW (Test No. are shown.)

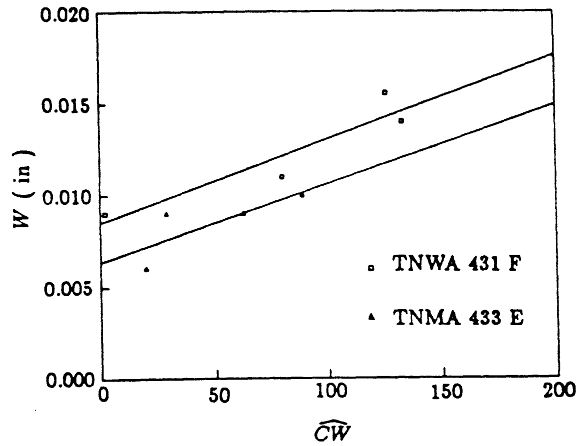

Fig.13 Estimated CW vs. measured flank wear, W.

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.

ACKNOWLEDGEMENTS. The authors are pleased to acknowledge the support of the National Science Foundation (Grant # DMC 8606239) on this work.

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 (ROVISECS)*, 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],

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

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

where $y(k)$ is the value of the measured variable y at time $t = k\triangle t$ for $k = 0, 1, 2, \ldots$. $\mathbf{P}(k)$ is the matrix of estimation gains, β provides exponential data weighting, and $\nu(k)$ 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 $\nu(k)$ 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

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

Proceedings of the 14th NSF Conference on Production Rese and Technology, Ann Arbor, MI, October 1987, pp 73-77

ESTIMATION OF TOOL WEAR UNDER VARYING CUTTING CONDITIONS

by

Yoram Koren, Professor
A. Galip Ulsoy, Associate Professor
Tsu-Ren Ko, Research Assistant

Department of Mechanical Engineering and Applied Mechanics
University of Michigan
Ann Arbor, Michigan 48109-2125

ABSTRACT. 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. 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 difficulties with using optical methods is their long processing time which makes them unsuitable for on-line tool wear measurement, and the presence of chips and coolant in the machining environment [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, (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.

APPROACH. 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

$$F = F_0 + \Delta F \qquad (1)$$

where F_0 is the cutting force when the tool is sharp, and ΔF is a function of the flank wear W. Both F_0 and ΔF 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 ΔF, the component affected by wear, can be obtained. The obtained ΔF is always a function of the cutting conditions. If only depth of cut varies in the process, the model considered for ΔF has the form [16]

$$\Delta F = C\, d^{\beta}\, W \qquad (2)$$

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

$$W = W_0 + \dot{W}\, t \qquad (3)$$

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

$$\Delta F = C\, d^{\beta}\, W_0 + X\, d^{\beta}\, t \qquad (4)$$

where

$$X = C\, \dot{W} \qquad (5)$$

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

$$\frac{F - F_0 - C\, d^{\beta}\, W_0}{t} = X\, d^{\beta} \qquad (6)$$

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 ΔF_k affected by wear at constant cutting conditions during the interval is analyzed. The obtained ΔF_k, given by

$$\Delta F_k = X\, {d_k}^{\beta}\, \tau \qquad (7)$$

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

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

$$S = \frac{\Delta F_k}{\tau} = X\, {d_k}^{\beta} \qquad (8)$$

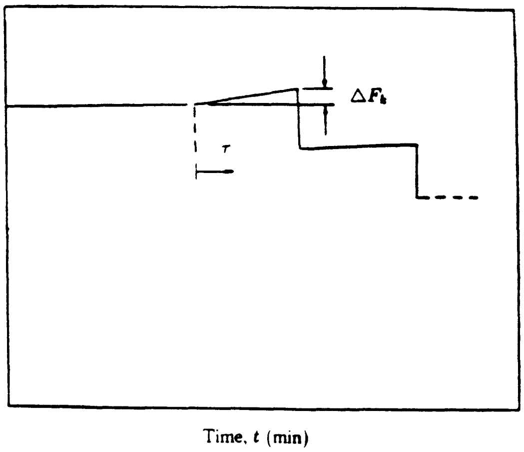

Fig.1 Schematic of the computation of slop S in the proposed approach.

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

$$\log S = \log X + \beta \log d_k \,. \qquad (9)$$

This format fits the linear equation

$$y = \phi^T \theta \,, \qquad (10)$$

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

$$\phi^T = [\ 1 \quad \log d_k\ ] \qquad (11)$$

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

$$\theta^T = [\ \log X \quad \beta] \qquad (12)$$

Thus for every segment k we obtain an setimate $\widehat{X_k}$. The estimates $\widehat{X_k}$ can now be used to estimate the wear,

$$\widehat{W} = W_0 + \frac{\sum_{k=0}^{n} \widehat{X_k}}{C} \qquad (13)$$

where C and W_0 must be determined from off-line tests. When the tool changing criterion is the start of the accelerated wear region, then we are interested only in the wear rate which is proportional to $\widehat{X_k}$. In these cases the off-line determination of C and W_0 is not needed.

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 (without crater 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 of cut was changed in steps of 0.64 mm (0.025 inch).

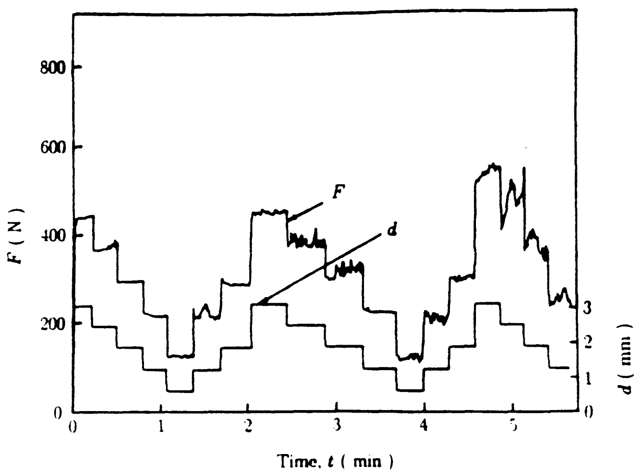

Fig.2 Normal cutting force component, *F* and the depth of cut, *d* of the 1st test.

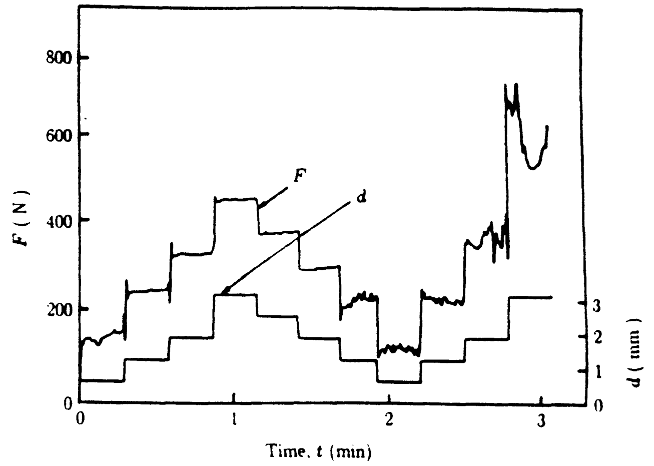

Fig.4 Normal cutting force component, *F* and the depth of cut, *d* of the 3rd test.

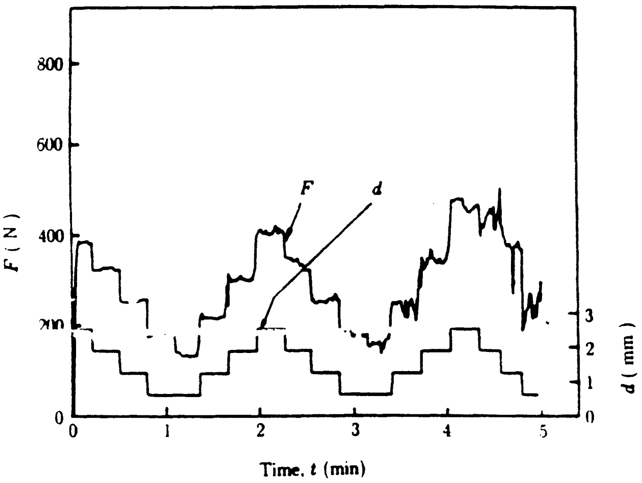

Fig.3 Normal cutting force component, *F* and the depth of cut, *d* of the 2nd test.

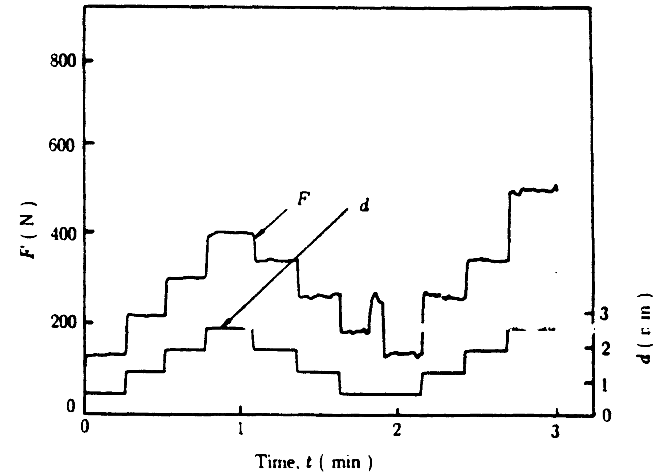

Fig.5 Normal cutting force component, *F* and the depth of cut, *d* of the 4th test.

Table 1 Cutting variables, tool and workpiece material

Test No.	Tool	Workpiece	Feed	Cutting speed
1	TNWA			
2	431F	4340	0.001	1200
3	TNMA	ann'd	in/rev	ft/min
4	433E			

Figures 2 - 5 show the variations of the depth of cut in the above tests (Figure 2 and 3 include also experiments with steps of 1.28mm). The length of cut for each step in d was 7.62 mm (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 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 2 - 5 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. 4, 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.

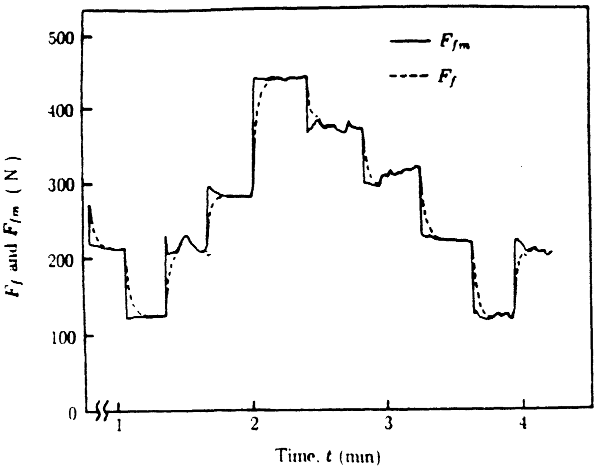

Fig.6 Filtered force signal, F_f and modified filtered force signal, F_{fm}.

- 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 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 by this algorithm. Therefore, a different algorithm, using unfiltered measurements, 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. 2 - 4). 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. Fig. 6 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. 6. In order to further avoid any transients during estimation the data feeding to the estimator was delayed for about 2 sec after each step.

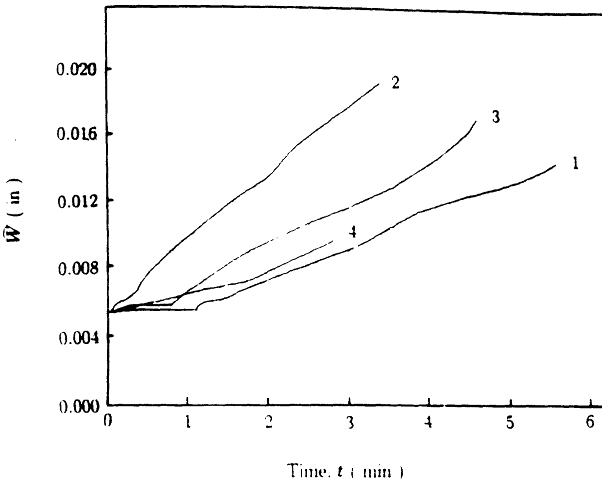

Fig.7 Estimated $\widehat{W}$ (Test No.s are shown.)

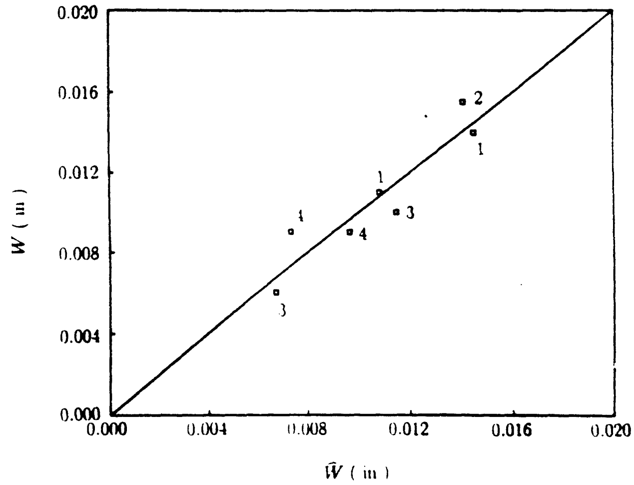

Fig.8 Estimated W vs. measured flank wear, W (Data from different tests are numbered.)

- According to our basic assumption for tool wear estimation the slope of the force signal should be either positive 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 Figure 7. To compare the estimated wear ($\widehat{W}$) and the real flank wear (W), direct measurements using a microscope were taken at regular intervals. Figure 8 shows W vs. $\widehat{W}$ for seven data points. The on-line method allows only the estimation of $(\widehat{CW} - CW_0)$ and not $\widehat{W}$. Thus off-line tool wear measurements are needed to determine the values of W_0 and C, so that $\widehat{W}$ can be calculated from $\widehat{CW}$. In many cases, however, the tool changing criterion is the start of the accelerated wear region. In these cases we are interested only in the wear rate which is proportional to X_k, and the determination of C and W_0 is not needed.

SUMMARY AND CONCLUSIONS. A model-based approach has been introduced to estimate tool wear under 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 implemented and tested in the laboratory. The experimental results show agreement between the actual values of the tool wear (measured during the test) and the estimated ones. While these initial results are promising, further research is needed in improving the estimation algorithm, and in modeling the relationship between tool wear and cutting force.

ACKNOWLEDGEMENTS. The authors are pleased to acknowledge the support of the National Science Foundation (Grant # DMC 8606239) on this work.

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],

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

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

where $y(k)$ is the value of the measured variable y at time $t = k\Delta t$ for $k = 0, 1, 2, \ldots$. $\mathbf{P}(k)$ 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

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

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

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

and

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

-Proceedings of the 15th Conference on Production Research and Technology, Berkeley, CA, January 1989, pp 237-239.

Model-Based Tool Wear Estimation in Metal Cutting

A. Galip Ulsoy
Department of Mechanical Engineering and Applied Mechanics
University of Michigan

Tsu Ren Ko
Department of Mechanical Engineering and Applied Mechanics
University of Michigan

Yoram Koren
Department of Mechanical Engineering and Applied Mechanics
University of Michigan

Jongjin Park
Department of Mechanical Engineering and Applied Mechanics
University of Michigan

ABSTRACT. Monitoring of tool wear in metal cutting under varying cutting conditions is significant, particularly for processes under adaptive control. An approach to tool wear monitoring using force measurements and a process model is being investigated. Last year we reported the results of experiments with varying depths of cut. This year we report results for improved process modeling, improved on-line estimation methods, and some additional experimental results. A newly developed model of the nose and flank wear permits appropriate weighting of the measured force components for use in model based tool wear estimation. The use of an adaptive nonlinear observer, periodically calibrated with vision based wear measurements, provides a sound framework for implementation of a model based approach. Some preliminary results are presented for both cases.

INTRODUCTION. The estimation of tool wear in metal cutting operations has long been regarded as a key step towards the implementation of adaptive control and full process automation [Koren 1983; Ulsoy, Koren and Rasmussen 1983]. Research efforts in this area are extensive, and have been reviewed in studies such as [Tlusty and Andrews 1983; Danai and Ulsoy 1986]. In this research project we are pursuing a model based approach [Isermann 1984] to on-line tool wear estimation and breakage detection using force measurements. Some previous results in this area have been reported in [Koren 1978; Koren and Ulsoy 1983; Ulsoy and Han 1985; Koren, Ulsoy and Danai 1986; Danai and Ulsoy 1987a; Koren, Danai, Ulsoy and Ko 1987].

In this report we summarize our research progress in two separate, but closely related areas. The first is the development of improved process models for use as the basis for model-based estimation. The second is the development of an improved on-line estimation methodology.

A COMPREHENSIVE WEAR MODEL FOR CUTTING TOOLS. Mathematical models relating wear in cutting tools to measured signals, such as cutting forces, have been proposed by various researchers. Some of these models have been described in [Danai and Ulsoy 1987a; Koren 1978; Usui, Shirakashi and Kitagawa 1978], and the flank wear model proposed in [Koren 1978] has been used as the basis for model-based on-line estimation studies [Danai and Ulsoy 1987b, 1987c]. One focus of our current research has been the improvement of this model to include the nose wear as well as the flank wear. Thus, the total clearence wear (including both the nose and flank wear) can be accurately modeled. This is important in non-orthogonal cutting situations which typically occur in practice. The detailed derivation of this comprehensive wear model can be found in [Ko and Koren 1988]. Here only the main points are briefly summarized.

As schematically illustrated in Fig. 1, a coordinate s which runs along the edge of the tool can be defined, and the wear, $w(s)$, along the flank side and the nose expressed as a function of s. Furthermore, if $p(s,w)$ represents the pressure distribution on the clearence wear surface, then the cutting force change due to the pressure on the clearance wear surface can be written as

$$F_p = \int_0^{s_2} \int_0^{w(s)} p(s,w)\,\vec{n}(s)\,dw\,ds, \qquad (1)$$

where $n(s)$ is the inward pointing unit normal vector along the clearance surface. Similarly, the friction force on the clearance wear surface can be expressed as,

$$F_f = \int_0^{s_2} \int_0^{w(s)} \mu(s,w)\,p(s,w)\,\vec{b}\,dw\,ds. \qquad (2)$$

where $\mu(s,w)$ is the friction coefficient on the clearance wear surface, and the unit vector in the direction of the cutting velocity is denoted by $\vec{b}$. Subject to some assumptions about the form of the functions $p(s,w)$, $\mu(s,w)$, $w(s)$, and some assumptions about the directions of the unit vectors, one can use Eqs. (1) and (2) to obtain relationships between the clearance wear and the measured force components.

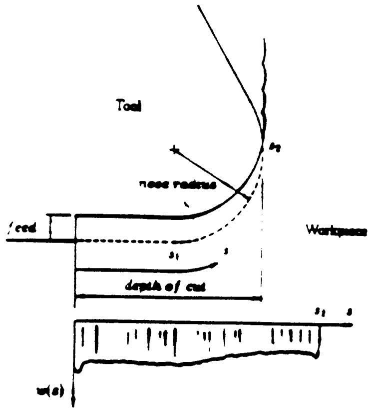

Fig.1 Schematic drawing of the clearance wear in turning operation.

Table 1: The cutting conditions of the three experiments.

Exp. No.	Insert	Depth of cut (in)	Feed (in/rev)	Cutting speed (ft/min)
1	TPG		0.006	800
2	434	0.1	0.004	1200
3	G370			

Three experiments, as summarized in Table 1, were performed to validate the model. Figure 2 shows the cutting force components versus time for Experiment 3. The experiment was stopped three times to measure the actual wear, and then resumed until the tool failed. The results for all three experiments are summarized in Fig. 3 The actual wear measured is plotted as a function of time and compared to the wear estimated by the model. Note that Experiment 3 is a repeat of Experiment 2, while Experiment 1 is at a higher feed and lower cutting speed.

The comprehensive wear model is important because it includes nose wear as well as flank wear to obtain the total clearance wear, and is applicable to non-orthogonal cutting. For the case of orthogonal cutting it simplifies to previous models relating flank wear to cutting force. The model, for a given cutting process, determines how various measured force components should be appropriately weighted to provide an accurate estimate of the clearance wear. Further research is underway to extend this model to crater wear as well as flank and nose wear.

AN ADAPTIVE NONLINEAR OBSERVER FOR TOOL WEAR ESTIMATION. A model based approach to on-line tool wear estimation can be formulated as an adaptive observer design problem. In this formulation

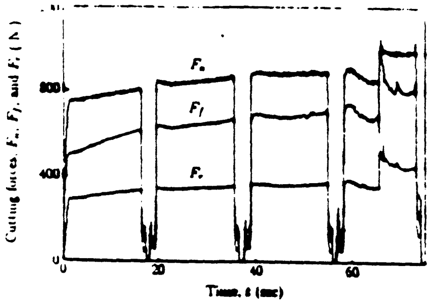

Fig.2 The measured force components of the 3rd Experiment: the main cutting component, F_c, the feed component, F_f, and the radial component, F_r.

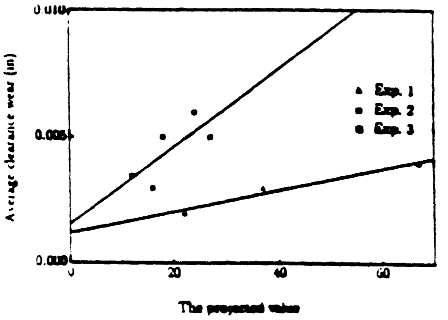

Fig.3 The projected values vs. the measured average clearance wear

the various components of tool wear are assumed to be the unmeasurable states of the process which must be estimated from measured signals such as the force components. This formulation was proposed and experimentally evaluated as described in [Danai and Ulsoy 1987a, 1987b, 1987c]. The refinement of this adaptive observer approach has been another focus of our recent research efforts, and is briefly summarized here.

To improve upon the results reported in [1987c], we have included a vision based tool wear measurement to supplement the force measurement used by the adaptive observer (see Fig. 4). The vision measurement can only occur when the tool is not engaged in the workpiece, and at rather infrequent intervals due to the large computer times required for image processing. The force measurement based adaptive observer gives a wear estimate during the cut, but requires periodic recalibration due to the accumulation of estimation errors. Thus, we propose to combine these two complementary approaches.

The process model describing the state of wear of the tool is rather complex, and so we have concentrated in our recent research on the flank wear problem only. Even in this restricted case the model equations are highly nonlinear[Danai and Ulsoy 1987a]:

$$dw_{f1}/dt = -(v/l_0)w_{f1} + (v/l_0)k_1 \cos\alpha_T(F/fd) \quad (3)$$

$$dw_{f2}/dt = k_2(v)^{1/2}\exp\{-k_3/(273+\theta_f)\} \quad (4)$$

$$F = [k_9 f^{n_7}(1 - k_{10}\alpha_T) - k_{11} - k_{12}v]d + k_{13}dw_f \quad (5)$$

where $\theta_f = k_6 v^{n_1} f^{n_2} + k_7 w_f^{n_3}$ and $w_f = w_{f1} + w_{f2}$. Unlike the studies in [Danai and Ulsoy 1987b, 1987c], where we utilized linearized versions of Eqs. (3)-(5) to design the adaptive observer, we are now basing our adaptive observer design on the full nonlinear equations. The nonlinear observer design requires some results from nonlinear stability theory (Anderson et al 1986) to ensure the stability robustness of the nonlinear observer. The nonlinear observer equations are given by,

$$d\hat{w}_{f1}/dt = -(v/l_0)\hat{w}_{f1} + (v/l_0)k_1 \cos\alpha_T(F/fd) + G_1(F - \hat{F}) \quad (6)$$

$$d\hat{w}_{f2}/dt = k_2(v)^{1/2}\exp\{-k_3/(273+\hat{\theta}_f)\} + G_2(F - \hat{F}) \quad (7)$$

$$\hat{F} = [k_9 f^{n_7}(1 - k_{10}\alpha_T) - k_{11} - k_{12}v]d + k_{13}d\hat{w}_f \quad (8)$$

where $\hat{\theta}_f = k_6 v^{n_1} f^{n_2} + k_7 \hat{w}_f^{n_3}$, $\hat{w}_f = \hat{w}_{f1} + \hat{w}_{f2}$ and $[G_1 G_2]^T$ is the observer gain vector.

The selection of the nonlinear observer gains represent a trade off between stability robustness and rapid convergence characteristics and the effects of measurement noise. This is illustrated in Figs. 5-6, where the flank wear estimation is simulated for two observer gains. With the lower value of the observer gain, the estimates convergence more slowly but are less sensitive to measurement noise.

Future research will be directed at the design of an adaptive version of the robust nonlinera observer, and its implementation in a laboratory system

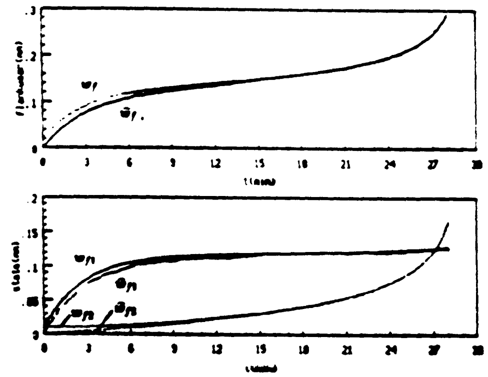

Fig.5 Observed states for $r = 0.2$.
Note: Even though the sufficient condition is not satisfied, the over system is stable. But, in cases when $r < 0.2$, the system is observed to be unstable.

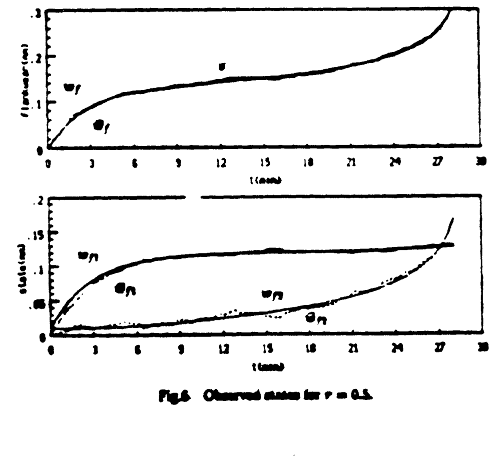

Fig.6 Observed states for $r = 0.5$.

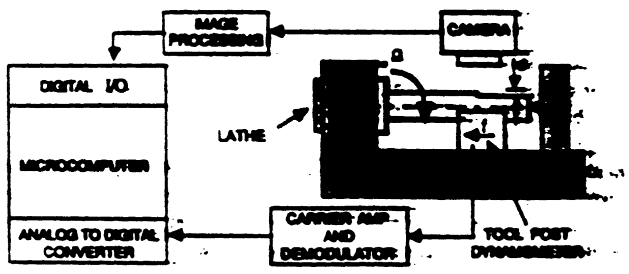

Fig.4 A combined force sensing and vision system for tool wear and breakage detection in turning.

SUMMARY AND CONCLUSIONS. Progress in our research on model-based on-line tool wear estimation in metal cutting using force measurements has been reported. This progress, over the past year, has been focused primarily in two areas: (i) the development of a comprehensive wear model which includes nose as well as flank wear, and (ii) the design of an adaptive nonlinear observer for tool wear estimation which is calibrated using computer vision.

REFERENCES

Anderson, B.D.O., et. al. 1986. *Stability of Adaptive Systems: Passivity and Averaging Analysis*, MIT Press, Cambridge.

Danai, K., and A.G. Ulsoy, 1986, "A Model Based Approach for Tool Wear Estimation in Turning," *SME Manufacturing Technology Review*, Vol. 1, pp. 49-54.

Danai, K., and A.G. Ulsoy, 1987b, "An Adaptive Observer for On-Line Tool Wear Estimation in Turning - Part I: Theory," *Mechanical Systems and Signal Processing*, Vol. 1, No. 2, pp. 211-225.

Danai, K. and A.G. Ulsoy, 1987c, "An Adaptive Observer for On-Line Tool Wear Estimation in Turning - Part II: Results," *Mechanical Systems and Signal Processing*, Vol. 1, No. 2, pp. 227-240.

Danai, K., and A.G. Ulsoy, 1987a, "A Dynamic State Model for On-Line Tool Wear Estimation in Turning," *ASME Journal of Engineering for Industry*, Vol. 109, No. 4, pp. 396-399.

Isermann, R., 1984, "Process Fault Detection Based on Modeling and Estimation Methods - A Survey," *Automatica*, Vol. 20, No. 4, pp. 387-404.

Ko, T.R., and Y. Koren, 1988, *A Comprehensive Wear Model for Cutting Tools*, Technical Report No. UM-MEAM-88-5 Department of Mechanical Engineering and Applied Mechanics, University of Michigan, Ann Arbor, Michigan.

Koren, Y., 1978, "Flank Wear Modeling of Cutting Tools Using Control Theory," *ASME Journal of Engineering for Industry*, Vol. 100, No. 1, pp. 103-109.

Koren, Y., 1983, *Computer Control of Manufacturing Systems*, McGraw-Hill, New York.

Koren, Y., Danai, K., Ulsoy, A.G., and T.R. Ko, 1987, "Monitoring Tool Wear Through Force Measurement," *Proceedings of the 15th North American Manufacturing Research Conference*, Bethlehem, Pennsylvania.

Koren, Y., and A.G. Ulsoy, 1984, "State Model for Flank Wear in Metal Cutting," *Proceedings of the 12th North American Manufacturing Research Conference*, Houghton, Michigan, May.

Koren, Y., Ulsoy, A.G., and K. Danai, 1986, "Tool Wear and Breakage Detection Using a Process Model," *Annals of the CIRP*, Vol. 35, No. 1, pp. 283-288.

Koren, Y., Ulsoy, A.G., and T.R. Ko, 1987, "Estimation of Tool Wear Under Varying Cutting Conditions," *Proceedings of the NSF Manufacturing Systems Conference*, Ann Arbor, Michigan, October.

Takata, S., Ogawa, M., Bertok, P., Ootsuka, J., Matushima, K., and T. Sata, 1985, "Real-Time Monitoring of Tool Breakage Using Kalman Filtering," *Robotics and Computer Integrated Manufacturing*, Vol. 2, No. 1, pp. 33-40.

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

Ulsoy, A.G., 1985, "Applications of Adaptive Control Theory to Metal Cutting," in M. Donath (ed.), *Dynamic Systems: Modeling and Control*, ASME Winter Annual Meeting, November.

Ulsoy, A.G., and E. Ham, 1985, "Tool Breakage Detection Using a Multi-Sensor Strategy," *Proceedings of the IFAC Conference on Control Science and Technology for Development*, Beijing, China, August.

Ulsoy, A.G., Koren, Y., and F. Rasmussen, 1983, "Principal Developments in the Adaptive Control of Machine Tools," *ASME Journal of Dynamic Systems, Measurement, and Control*, Vol. 105, No. 2, pp. 107-112.

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

ESTIMATION OF TIME VARYING PARAMETERS IN DISCRETE TIME DYNAMIC SYSTEMS: A TOOL WEAR ESTIMATION EXAMPLE

A. Galip Ulsoy

Department of Mechanical Engineering and Applied Mechanics
University of Michigan, Ann Arbor, Michigan 48109-2125

ABSTRACT

The recursive least squares, Kalman filter, and basis function methods for the estimation of time varying parameters are described and compared for a particular example problem. A generalization of these methods for estimation of time varying parameters is presented, based on an adaptive Kalman filter algorithm. The adaptive Kalman filter (or adaptive observer) utilizes a state model, with unknown coefficients, of the time varying parameters. All the other estimation methods presented for time varying parameters can be obtained as special cases of the proposed method. The method proposed shows excellent performance on the simple example problem considered, but can be difficult to apply.

1. INTRODUCTION

The on line estimation of the parameters of dynamic systems is an important step in system identification, as well as in adaptive control. Many parameter estimation methods, mainly based on the recursive least squares parameter estimation algorithm, have been developed and succesfully applied[Ljung 87; Goodwin and Sin 84; Ljung and Soderstrom 83; Goodwin and Payne 77].

While most parameter estimation methods assume that the unkown parameters are constant, methods have also been developed for tracking time varying parameters. Such problems arise in many engineering fields, and are of interest to the author in connection with machine tool adaptive control[Ulsoy, Koren and Rasmussen 83], and tool wear estimation in machining[Danai and Ulsoy 87a,b; Koren, Ulsoy and Danai 87]. The main approaches to the estimation of time varying parameters are based on the Kalman filter algorithm (KF), modifications to the recursive least squares (RLS) algorithm, and what we will refer to as basis function (BF) methods[Goodwin and Payne 77; Ljung and Soderstrom 83; Grenier 83; Hall, Oppenheim and Willsky 83; Niedzwiecki 87a,b; Davidov *et al* 87; Bastin and Gevers 88]. These methods are briefly summarized in Section 2, and compared for a simple example problem in Section 4.

This paper also presents, in Section 3, a generalization of the method for estimation of time varying parameters where the parameters of the KF model can be unknown. Such an approach has also been proposed by Clergeot [84]. Adaptive KF (or adaptive observer) methods are directly applied to solve this more general formulation. All the methods described above, including the BF method, are shown to be special cases of the proposed general method. Then, in Section 4, a simple example problem is studied and used to compare the various methods presented for the estimation of time varying parameters. The example problem is motivated by recent research efforts in the on-line estimation of tool wear in metal cutting processes [Danai and Ulsoy 87a,b]. The results of the example problem, as expected, demonstrate that if appropriately applied the KF algorithm and the BF method give better results than the RLS based methods. The adaptive KF method proposed here is, in general, difficult to apply. However, it can be convienently applied in some special cases. Excellent results are obtained for the example problem using the proposed adaptive method.

2. METHODS FOR ESTIMATION OF TIME VARYING PARAMETERS

The Kalman filter algorithm is perhaps the most general of the commonly used methods for estimation of time varying parameters [Goodwin and Payne 77; Ljung 87]. Consider a linear discrete time dynamic system of the form,

$$\theta(k+1) = H(k)\,\theta(k) + \Gamma(k)\,u(k) + w(k) \qquad (1)$$

and,

$$y(k) = \varphi(k-1)^T\,\theta(k) + v(k) \qquad (2)$$

where $y(k)$ is an mx1 output vector, $\varphi(k-1)$ is an mxn measurement matrix, $\theta(k)$ is an nx1 parameter vector, $u(k)$ is an rx1 vector of known deterministic inputs, and $H(k)$ and $\Gamma(k)$ are known coefficient matrices of the appropriate dimensions. The noise terms $v(k)$ and $w(k)$ can be assumed zero mean gaussian and independent with known covariances,

$$E[w(k)w(j)^T] = R_w(k)\delta_{kj} \qquad (3)$$

and,

$$E[v(k)v(j)^T] = R_v(k)\delta_{kj} \qquad (4)$$

The Eqs. (1) and (2) represent, respectively, a state model of the time varying parameter vector $\theta(k)$, and an input output model of a time varying dynamic system in regression form. An estimate $\hat{\theta}(k)$ can be obtained using the Kalman filter (KF):

$$\hat{\theta}(k+1) = H(k)\,\hat{\theta}(k) + \Gamma(k)\,u(k) + H(k)P(k)\varphi(k)[R_v(k) + \varphi(k)^T P(k)\varphi(k)]^{-1}\{y(k+1) - \varphi(k)^T(H(k)\hat{\theta}(k) + \Gamma(k)u(k))\} \qquad (5)$$

Proceedings of the American Control Conference, Pittsburg, PA, June 1989
pp 68-74

and,

$$P(k+1) = H(k)P(k)H(k)^T + R_w(k) - H(k)P(k)\varphi(k)[R_v(k) + \varphi(k)^T P(k)\varphi(k)]^{-1}\varphi(k)^T P(k)H(k)^T \quad (6)$$

where $\hat{\theta}(0)$ and $P(0)$ must be specified, as well as $H(k)$, $u(k)$, $\Gamma(k)$, $R_w(k)$, and $R_v(k)$. The particular KF algorithm in Eqs. (5) and (6) uses the current measurement $y(k)$, rather than the previous measurement $y(k-1)$, to estimate $\hat{\theta}(k)$. The method presented in [Davidov *et al* 87] is a special case of the KF algorithm given above, where the parameter variation model in Eq.(1) is written in terms of high order difference equations rather than in first order form. In applying the above approach to estimation of time varying parameters, one must specify the parameters $H(k)$ and $\Gamma(k)$. Typically one chooses $H(k) = I$ and $(\Gamma(k)u(k)) = 0$ because of a lack of specific prior knowledge of how the parameters actually vary.

The recursive least squares (RLS) algorithm is obtained as a special case of Eqs. (5) and (6) when $H(k) = I$, $\Gamma(k) = 0$, $u(k) = 0$, $R_w(k) = 0$, and $R_v(k) = I$. This corresponds in Eqs. (1) - (4) to constant parameters and only measurement noise. The RLS algorithm with covariance modification (RLS/CM) is a special case of the RLS where $R_w(k)$ is taken to be non zero, or $P(k)$ is periodically reset to $P(0)$. This keeps the algorithm "alert" and permits tracking of time varying parameters. The value of $R_w(k)$ is typically selected based on the expected variation in the parameter values, or by trial and error. The RLS algorithm with a forgetting factor (RLS/FF) exponentially weights the data, so that the influence of past measurements in the parameter estimation is reduced. Again, it is a special case of the RLS with $R_v(k) = \alpha(k)$, and the forgetting factor $0 < \alpha(k) \leq 1$ is typically a constant in the range 0.95 to 0.99. Also for the RLS/FF one chooses,

$$R_w(k) = (\alpha(k)^{-1} - 1)\{P(k) - H(k)P(k)\varphi(k)[R_v(k) + \varphi(k)^T P(k)\varphi(k)]^{-1}\varphi(k)^T P(k)H(k)^T\}.$$

Both these RLS based methods give fairly good results for the estimation of time varying parameters, and their performance is similar in practice[Ljung and Soderstrom 83].

Another approach is based on the expansion of the time varying parameters in terms of known basis functions, with constant unknown coefficients, and will be refered to here as the basis function (BF) method [Grenier 83; Hall, Oppenheim and Willsky 83; Niedzwiecki 87a]. For example, each unknown parameter is written as,

$$\theta_i(k) = \sum_{j=1}^{p_i} \gamma_{ij}\, u_{ij}(k) \quad (7)$$

where the γ_{ij} are unkown constant coefficients and the $u_{ij}(k)$ are known basis functions, such as a polynomial basis: $\{1, k, k^2, k^3, .., k^{(p_i-1)}\}$ (see e.g., [Li 87]). If, without loss of generality, one assumes that the $u_{ij}(k)$ and $p_i = r$ are the same for all i =1,2, ..., n, then Eq. (7), can also be written in the more compact form $\theta(k) = \Gamma\, u(k)$. Thus, Γ is an nxr matrix of unknown coefficients γ_{ij} and $u(k)$ is a rx1 vector of known basis functions $u_j(k)$. Substituting Eq.(7) into Eq.(2) gives,

$$y(k) = \Phi(k-1)^T\, \Theta + v(k) \quad (8)$$

where,

$$\Phi(k-1)^T = [\varphi'_1(k-1)u_1(k), \varphi'_1(k-1)u_2(k), .., \varphi'_1(k-1)u_r(k), \varphi'_2(k-1)u_1(k), .., \varphi'_2(k-1)u_r(k), .., \varphi'_m(k-1)u_1(k), .., \varphi'_m(k-1)u_r(k)] \quad (9)$$

$$\Theta^T = [\gamma_{11}, \gamma_{12}, .., \gamma_{1r}, \gamma_{21}, .., \gamma_{2r}, .., \gamma_{m1}, .., \gamma_{mr}] \quad (10)$$

and $\varphi'_i(k)$ denotes the nx1 vector which is the i^{th} column of the mxn matrix $\varphi(k)^T$, for i = 1, 2, .., m. The estimation of the new constant parameter vector Θ can be carried out using the RLS method as described above. The estimates of the original time varying parameters $\theta(k)$ can then be obtained from Eq.(7) using the estimated $\hat{\gamma}_{ij}$, which are the elements of $\hat{\Theta}$. The BF method is easy to apply, but again requires some prior knowledge about the parameter variations to aid in the selection of appropriate basis functions $u(k)$. Recent results have shown that the BF method is not very robust for large values of p_i [Niedzwiecki 87b]. However, it can work well when the basis functions selected capture the true nature of the parameter variations without too many terms.

In the next section, a general method is presented for estimation of time varying parameters based on a KF approach as in Eqs. (1)-(6), but with $H(k)$ and $\Gamma(k)$ assumed to be unknown. Adaptive KF, or adaptive observer, methods can be directly applied to solve this more general formulation.

3. ADAPTIVE ESTIMATION METHODS

Consider again the dynamic system as represented by Eqs.(1) and (2), and assume that $H(k)$ and $\Gamma(k)$ are constant (or slowly time varying) but unknown. One then tries to estimate $H(k)$ and $\Gamma(k)$ as well as the unkown parameters $\theta(k)$ of the model. Since the time varying parameters have, in Eqs. (1) and (2), been described in a state equation form, this can be accomplished by applying adaptive state estimation algorithms to the parameter estimation problem. There are various adaptive state estimation algorithms that have been formulated[Goodwin and Sin 84; Jacoby and Pandit 87] . Here a KF algorithm for estimation of $\theta(k)$ will be combined with a sequential prediction error method for estimation of the elements of H and Γ. This is schematically illustrated in Fig. 1, and described below.

First assume that estimates of H and Γ are available so that the KF Eqs. (5) and (6) can be used to obtain the parameter estimates $\hat{\theta}(k)$ as well as the predicted output,

$$\hat{y}(k) = \varphi(k-1)^T\, \hat{\theta}(k) = \varphi(k-1)^T(H(k-1)\, \hat{\theta}(k-1) + \Gamma(k-1)\, u(k-1) + H(k-1)P(k-1)\varphi(k-1)[R_v(k-1) + \varphi(k-1)^T P(k-1)\varphi(k-1)]^{-1}\{y(k) - \varphi(k-1)^T(H(k-1)\hat{\theta}(k-1) + \Gamma(k-1)u(k-1))\} \quad (11)$$

The prediction error can then be defined as,

$$\varepsilon(k) = y(k) - \hat{y}(k) \quad (12)$$

The error is considered to be a result of the unkown parameters, which are the elements of H and Γ, in the KF Eqs. (5) and (6). Thus, one defines the new parameter vector,

$\Theta^T = [\gamma_{11}, \gamma_{12}, .., \gamma_{1r}, \gamma_{21}, .., \gamma_{2r}, .., \gamma_{m1}, .., \gamma_{mr}, h_{11}, h_{12}, .., h_{1n}, h_{21}, .. h_{mn}]$ (13)

To determine an estimate $\hat{\Theta}(k)$, minimize a scalar quadratic function of the prediction error

$$\min_{\hat{\Theta}(k)} \quad J[\hat{\Theta}(k), k] = \sum_{i=1}^{k} \varepsilon(i)^T R(k)^{-1} \varepsilon(i) \qquad (14)$$

where $R(k)^{-1}$ is a weighting matrix. As shown in [Goodwin and Sin 84], the recursive algorithm minimizing J is given by

$$\hat{\Theta}(k+1) = \hat{\Theta}(k) + M(k)\Phi(k)[R(k) + \Phi(k)^T M(k)\Phi(k)]^{-1}[y(k+1) - \hat{y}(k+1)] \qquad (15)$$

and,

$$M(k+1) = M(k) - M(k)\Phi(k)[R(k) + \Phi(k)^T M(k)\Phi(k)]^{-1}\Phi(k)^T M(k) \qquad (16)$$

where

$$\Phi(k-1) = [d\,\hat{y}(k)/d\Theta]_{\Theta = \hat{\Theta}(k-1)} = \varphi(k-1)^T [d\,\hat{\theta}(k)/d\Theta]_{\Theta = \hat{\Theta}(k-1)} = \varphi(k-1)^T W(k) \qquad (17)$$

In general, it is difficult to evaluate $\Phi(k-1)$ from Eq.(17), because of W(k), and this is discussed further below. However, if we assume that $\Phi(k-1)$ can be evaluated, then Eqs. (11) and (15) - (17), together with Eqs. (5) and (6), can be used to estimate the original unknown parameters $\theta(k)$ for the time varying system (even when elements of H and/or Γ are unknown). Note that, as illustrated in Fig. 1, the estimated H and Γ from Eqs. (15) - (17) are used in Eqs. (5) and (6), and similarly the estimated $\theta(k-1)$ from Eqs. (5) and (6) are used in Eqs. (15) - (17). Once Eq. (17) is evaluated for a particular system, then this adaptive algorithm can be implemented using standard library software [Goodwin and Sin 84; Jacoby and Pandit 87].

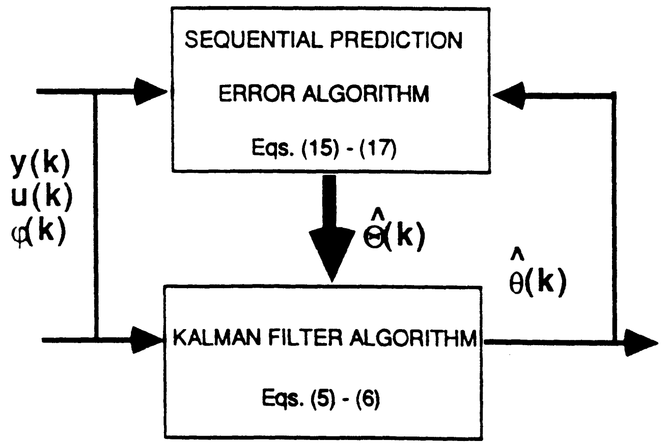

Figure 1. Schematic of An Adaptive Algorithm for the Estimation of Time Varying Parameters

The evaluation of the total derivative in Eq. (17) is, in general, quite complex [Goodwin and Sin 84; Jacoby and Pandit 87]. However, it can be considerably simplified when Eqs. (5) and (6) are replaced by the so called "innovations form observer"[Ljung 87; Jacoby and Pandit 87],

$$\hat{\theta}(k+1) = H(k,\hat{\Theta})\,\hat{\theta}(k) + \Gamma(k,\hat{\Theta})\,u(k) + K(\hat{\Theta})\varepsilon(k) \qquad (18)$$

where $\varepsilon(k)$ is defined in Eq. (12), and the observer (or KF) gain $K(\hat{\Theta})$ is directly parameterized in terms of the $\hat{\Theta}$. Thus, the $K(\hat{\Theta})$ is not the optimally calculated KF gain as in Eqs. (5) and (6). In this formulation the total derivative, W(k), in Eq. (17) can be evaluated as

$$W(k) = \{H(\hat{\Theta}(k-1)) - K(\hat{\Theta}(k-1))\varphi(k-1)^T\}W(k-1) + F_\Theta + K_\Theta \varepsilon(k-1) \qquad (19)$$

where we have defined,

$$F_\Theta = [\partial\{H(k-1,\Theta)\hat{\theta}(k-1) + \Gamma(k-1,\Theta)\,u(k)\}/\partial\Theta]_{\Theta = \hat{\Theta}(k-1)} \qquad (20)$$

and,

$$K_\Theta = [\partial K/\partial\Theta]_{\Theta = \hat{\Theta}(k-1)} \qquad (21)$$

Although considerably simpler than the KF formulation, even Eqs. (18)-(21) may be difficult to implement. However, there are some special cases, such as H=0 or H being constant and known, that facilitate evaluation of the above expressions. These are illustrated by way of an example in the next section.

The proposed method is a general one which includes all the previous methods as special cases [Clergeot 84]. The KF method is obtained when H and Γ are known and do not have to be estimated using Eqs. (11) and (15) - (17), and the RLS methods have already been shown to be special cases of the KF method. The BF method is another special case of this proposed method. When H=0 Eqs. (17) and (13) become, respectively,

$$\Phi(k-1)^T = [\varphi'_1(k-1)u_1(k), \varphi'_1(k-1)u_2(k), .., \varphi'_1(k-1)u_r(k), \varphi'_2(k-1)u_1(k), .., \varphi'_2(k-1)u_r(k), .., \varphi'_m(k-1)u_1(k), .., \varphi'_m(k-1)u_r(k)] \qquad (22)$$

$$\Theta^T = [\gamma_{11}, \gamma_{12}, .., \gamma_{1r}, \gamma_{21}, .., \gamma_{2r}, .., \gamma_{m1}, .., \gamma_{mr}] \qquad (23)$$

and Eqs. (1) and (2) become,

$$\theta(k+1) = \Gamma\,u(k) + w(k) \qquad (24)$$

and,

$$y(k) = \varphi(k-1)^T\,\theta(k) + v(k) \qquad (25)$$

Also Eqs. (5) and (6) become,

$$\hat{\theta}(k+1) = \Gamma\,u(k) \qquad (26)$$

and,

$$P(k+1) = R_w(k) \qquad (27)$$

which is precisely the BF method outlined previously, where the u(k) are the known basis functions, and the elements of Γ

are the unknown coefficients γ_{ij} in Eq. (7). As discussed above, for a particular problem the evaluation of Eq. (17) can be rather difficult. However, when H=0 (i.e., the BF method) this is significantly simplified. Thus, the BF method is seen to be a special case of the adaptive KF method which is particularly easy to apply.

4. EXAMPLE

In this section we present simulation results for a simple example problem to illustrate and compare the various estimation methods discussed in the previous sections. This example problem is motivated by research on the on-line estimation of tool wear in metal cutting operations [Danai and Ulsoy 87a,b]. If the cutting conditions are appropriately selected such that only one type of wear mechanism (i.e., flank wear or crater wear but not both) dominates, then a linear first order model has been experimentally shown to provide good estimation results [Danai and Ulsoy 87b]. However, the parameters of such models depend on cutting conditions, and must be treated as time varying.

Consider the linear single input single output first order discrete time system described by,

$$y(k) = a(k)\, y(k-1) + b(k)\, z(k-1) + v(k) \qquad (28)$$

where y(k) is the system output, z(k) is the system input, and v(k) is zero mean gaussian measurement noise. In the tool wear estimation problem y(k) represents a measured force component which is proportional to the tool wear, and z(k) represents the feed. The parameters a(k) and b(k) are, in general, time varying and perturbed by zero mean independent gaussian noise signals $w_1(k)$ and $w_2(k)$ respectively. For estimation purposes the known input signal z(k) is also assumed to be zero mean and gaussian. The simulation results presented below were all obtained using the International Mathematical and Statistical Library subroutines GGNML to generate the noise signals and FTKALM to implement the KF and/or RLS algorithms as needed [Anonymous 79]. The standard values of the simulation parameters given in Table 1 were used in all the cases presented below. Although numerous simulation studies were performed, due to space limitations, only selected typical results are presented here.

For the results shown in Figs. 2-8, the parameters of Eq. (28) were simulated as follows:

$$a(k) = -0.8 + w_1(k) \qquad (29)$$

and,

$$b(k) = 2.0 + 0.001k + w_2(k) \qquad (30)$$

The estimation results for RLS are shown in Fig. 2, and $\hat{b}(k)$ at k=100 converges to approximately 2.5 rather than the true value of 3.0. The results for RLS/CM are also shown in Fig. 2, and tracking of b(k) is seen to better than for the RLS case. For the RLS/CM algorithm

$$R_w(k) = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}$$

was used. Although not shown here, results with the RLS/FF method were also obtained and found to be similar to the RLS/CM results.

The KF algorithm in Eqs. (5) - (6), applied to the example problem with $R_v(k) = \sigma_v^2$, and

$$H(k) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}, \quad R_w(k) = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma_2^2 \end{bmatrix}$$

$$\varphi(k-1) = [\; -y(k-1) \quad 0 \quad z(k-1) \;]$$

gives the results shown in Fig. 4. These clearly provide improved tracking of the time varying parameter b(k) over the RLS methods. However, the linear nature of the variation in the parameter b(k) must be known so that the appropriate H(k) given above can be selected, and the number of parameters being estimated is now n=3. The estimated parameters are calculated from $\hat{a}(k) = \hat{\theta}_1(k)$ and $\hat{b}(k) = \hat{\theta}_3(k)$.

The use of the BF method with $u_1(k) = 1$ and $u_2(k) = k$ gives the results shown in Fig. 5 when used in conjunction with a standard RLS algorithm. Again, the results are excellent, however three parameters must be estimated and the original time varying parameters calculated from $\hat{a}(k) = \hat{\theta}_1(k)$ and $\hat{b}(k) = \hat{\theta}_2(k) + \hat{\theta}_3(k)k$. Note that this BF result is exactly the same as for the adaptive KF when H=0 is used in modeling the parameter variations.

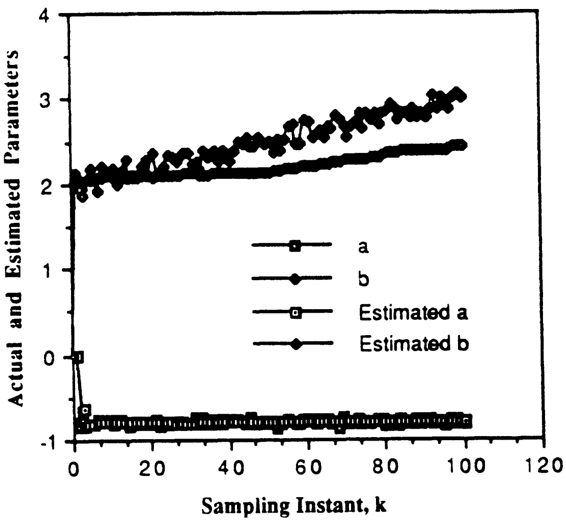

Figure 2. Parameter Estimation Using RLS

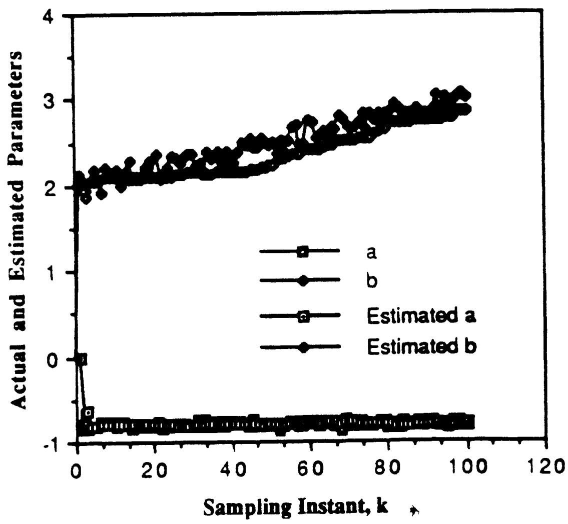

Figure 3. Parameter Estimation Using RLS/CM

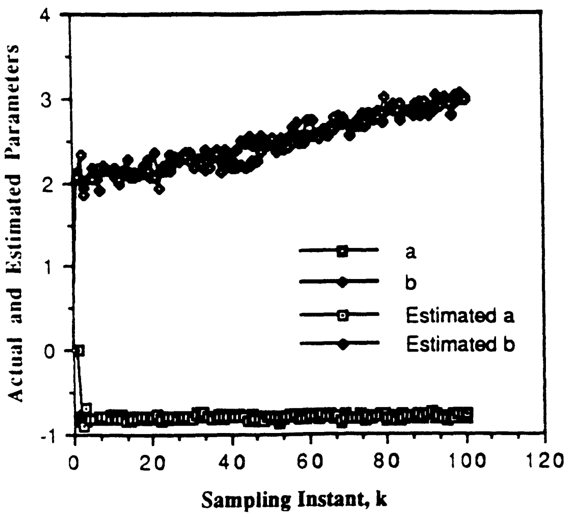

Figure 4. Parameter Estimation Using KF

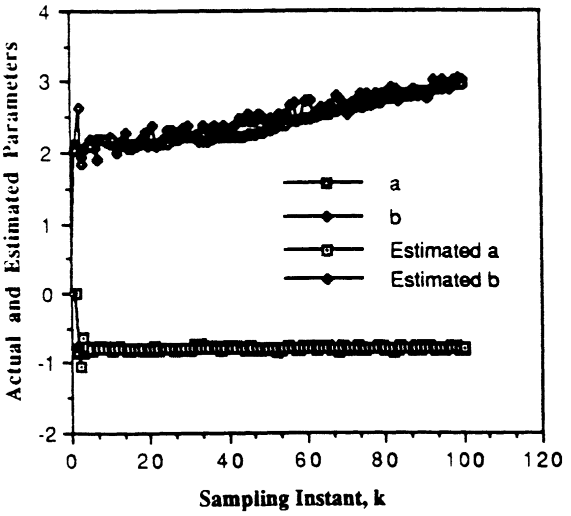

Figure 5. Parameter Estimation Using BF

Figure 6 shows the result when we apply the KF algorithm with a known 2x2 H = I and a known 2x1 $\Gamma u(k) = [0 \;\; 0.01]^T$. We designate this as a KF with a known input (KF w/input). Again the results are excellent, but we need to be able to model the parameter time variations exactly. We must even specify the value (i.e., 0.01) of the slope of the parameter variation as given in Eq. (30). This is essentially repeated in Fig. 7, except we use an innovations form observer with fixed gains rather than a KF algorithm which gives the optimal time varying gains. This case has been designated as OB, and is essentially a prelude to implementing an adaptive observer. The gains used in this particular simulation were $K^T = [-0.035 \;\; 0.1]$ and determined by trial and error. It is difficult to determine these gains using standard observer design methods because the observer error dynamics is governed by the time varying matrix $[H - K\varphi(k-1)]$. This observer, using the same gains, is then implemented in an adaptive version as shown in Fig. 8 and designated as AOB. This adaptive version of the observer uses a known H = I and a $\Gamma u(k) = [0 \;\; \gamma]^T$ where the γ is unknown and must also be estimated. The RLS algorithm is used as in Eqs. (15) - (16) with $M(0) = 1.5\text{x}10^{-5}$ and R(k) = 1. A more general version of the AOB, where the elements of H as well as γ are estimated, would be very difficult to apply and was not attempted here. The difficulty arises from the fact that the time varying matrix $[H - K\varphi(k-1)]$ makes it difficult to obtain an observer gain K which is explicitly parameterized in terms of Θ. Thus, it becomes difficult to obtain the total derivative W(k) required in Eq. (17). This appears to be an important topic for further research.

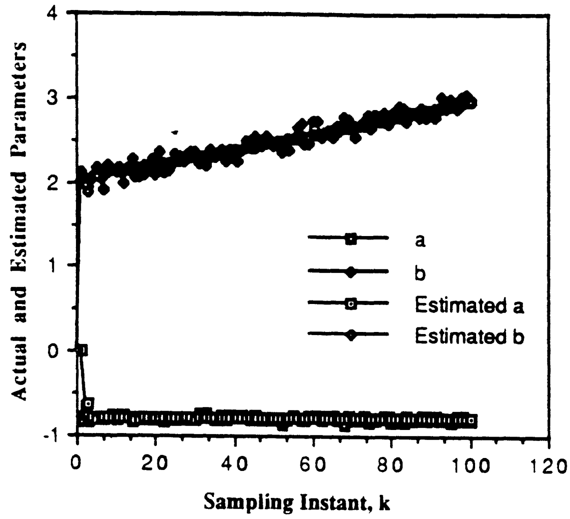

Figure 6. Parameter Estimation Using KF w/input

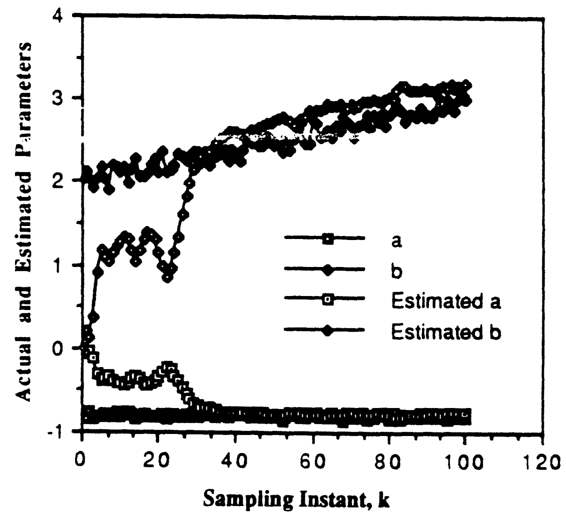

Figure 7. Parameter Estimation Using OB

Finally, consider Eq. (28) with the "jump" type time varying parameters defined by:

$a(k) = -0.8 + w_1(k),$

and

$b(k) = 2.0 + w_2(k)$; if $0 \le k \le 20$; $41 \le k \le 60$; and $81 \le k \le 100$.
$\;\;\;\;\;\; = 3.0 + w_2(k)$; if $21 \le k \le 40$; and $61 \le k \le 80$

Results were presented for this problem in [Ljung and Soderstrom 83] for the RLS, RLS/CM, and RLS/FF methods. Results are presented here for both the KF and BF (i.e., adaptive KF with H=0) methods in Figs. 9-10. In the results presented an N term Fourier Series expansion of the peiodic function b(k) has been assumed:

$$b(k) = b_0 + b_1 \sin(\pi k/20) + b_2 \sin(3\pi k/20) + .. + b_n \sin((2N-1)\pi k/20)$$

where, $b_0 = 2.396$, and $b_i = (2/\pi)(1/(2i-1))$ for $i = 1,2, .., N$. With N = 1 the KF method can be applied with,

$$H(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos(\pi k/20) & \sin(\pi k/20) & 0 \\ 0 & -\sin(\pi k/20) & \cos(\pi k/20) & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$R_w(k) = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_2^2 \end{bmatrix}$$

and,

$$\varphi(k-1) = [\ -y(k-1)\ \ z(k-1)\ \ 0\ \ z(k-1)\ ]$$

The period (i.e., 40 samples) must be known and n = 4 parameters are needed. Similarly, the period must also be known in the BF method, but only n = 3 parameters are required if we use the basis functions: $u_1(k) = 1$ and $u_2(k) = \sin(\pi k/20)$. For both methods, although not shown here, the results improve as N increases. However in the KF the number of parameters is n = 2 + 2N, whereas in the BF method n = 2 + N.

5. SUMMARY AND CONCLUSIONS

Several methods for the estimation of time varying parameters have been reviewed and compared. The recursive least squares (RLS) are known to be special cases of the Kalman filter (KF) algorithm as applied to parameter estimation. The basis function (BF) methods use a series expansion of the time varying parameters in terms of known basis functions with undetermined parameters. Both the KF and BF methods give excellent results, but require some prior knowledge of the functional form of the expected parameter variations. An adaptive version of the KF algorithm can, in theory, eliminate this problem. In practice the adptive KF algorithm can be very difficult to implement. However, there are some special cases where the adaptive KF algorithm can be convienently applied. These include the KF, BF, and RLS based methods described previously. Thus, the adaptive KF method is a generalization of all these other methods for the estimation of time varying parameters.

A simple example problem, motivated by tool wear estimation in metal cutting, has been considered and used to compare the various methods. As expected the KF method gives excellent results when compared to the RLS method and its variants. The BF method is a special case of the adaptive KF method, and gives results very similar to KF. The BF method is especially attractive when a few basis functions can be selected to accurately capture the true parameter variations. Another, somewhat more general, adaptive KF method also gave good results for this example. However, it was more difficult to determine appropriate algorithm gains.

The adaptive KF method provides a very general framework for estimation of time varying parameters, and allows the user to tailor the algorithm to the problem at hand based on available prior information. Further research is needed to develop design techniques that can be convienently applied to the problem of determining the adptive KF method gains.

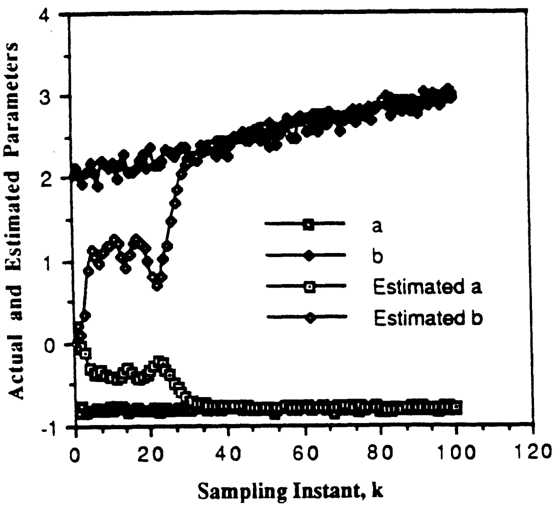

Figure 8. Parameter Estimation Using AOB

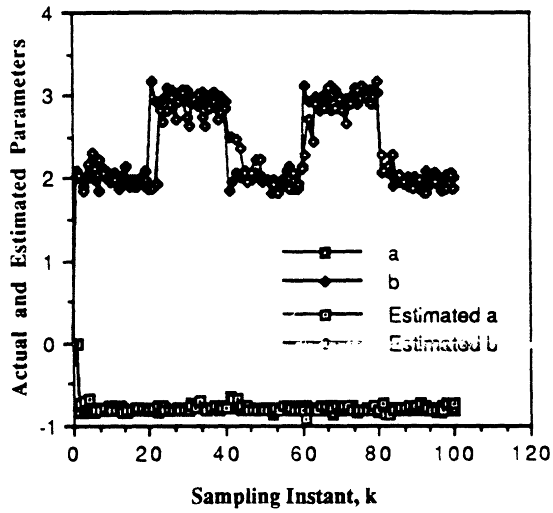

Figure 9. Parameter Estimation Using KF

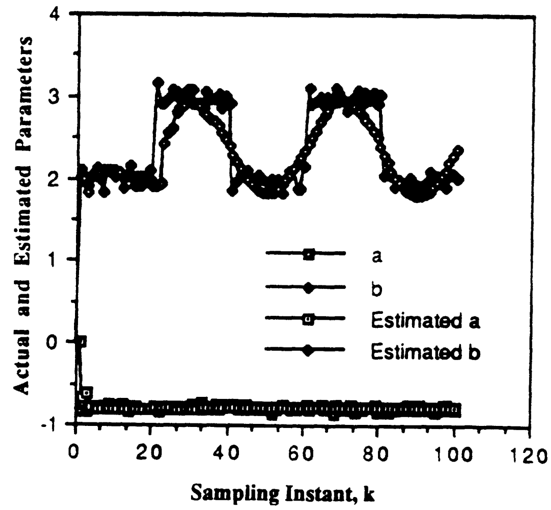

Figure 10. Parameter Estimation Using BF

6. ACKNOWLEDGEMENTS

The author is pleased to acknowledge helpful discussions with Yoram Koren, and the financial support of the National Science Foundation under grant DMC - 8606239. The research was performed in part while the author was on sabatical leave as a Visiting Associate Professor at Bogazici University in Istanbul, Turkey.

7. REFERENCES

Anonymous, 1979, *International Mathematical and Statistical Library (IMSL) Reference Manual*, Houston, Texas.

Bastin, G., and Gevers, M.R., 1988, "Stable Observers for Nonlinear Time Varying Systems," IEEE Transactions on Automatic Control, Vol. 33, No.7, pp 650-658.

Clergeot, H., 1984, "Filter-Order Selection in Adaptive Maximum Likelihood Estimation," IEEE Transactions on Information Theory, Vol. 30, No. 2, pp 199-210.

Danai, K., and Ulsoy, A. G., 1987a, "An Adaptive Observer for On-Line Tool Wear Estimation in Turning, Part I: Theory," *Mechanical Systems and Signal Processing*, Vol. 1, No. 2, pp 211-225.

Danai, K., and Ulsoy, A. G., 1987b, "An Adaptive Observer for On-Line Tool Wear Estimation in Turning, Part II: Results," *Mechanical Systems and Signal Processing*, Vol. 1, No. 2, pp 227-240.

Davidov, G., Shipitalni, M., Shavit, A., and Koren, Y., 1987, "A General Algorithm for Identification of Rapidly Time-Varying Systems," *Proceedings of the IEEE*, Vol. 75, No. 8, pp 1129-1130.

Goodwin, G. C., and Payne, R. L., 1977, *Dynamic System Identification*, Academic Press, New York, New York.

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

Grenier, Y., 1983, "Time-Dependent ARMA Modeling of Nonstationary Signals," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, Vol. ASSP-31, No. 4, August, pp 899-911.

Hall, M. G., Oppenheim, A. V., and Willsky, A. S., 1983, "Time Varying Parametric Modeling of Speech," *Signal Processing*, Vol. 5, pp 267-285.

Jacoby, W., and Pandit, M., 1987, "A Prediction-error-method for Recursive Identififcation of Nonlinear Systems," *Automatica*, Vol. 23, No. 4, pp 497-507.

Koren, Y., Ulsoy, A. G., and Danai, K., 1986, "Tool Wear and Breakage Detection Using a Process Model," *Annals of the CIRP*, Vol. 35, No. 1, pp 283-288.

Li, Zheng, 1987, "Discrete-Time Time Adaptive Control of Deterministic Fast Time-Varying Systems," *IEEE Transactions on Automatic Control*, Vol. 32, No. 5, pp 444-447.

Ljung, L., 1987, *System Identification: Theory for the User*, Prentice-Hall, Englewood Cliffs, New Jersey.

Ljung, L., and Soderstrom, T, 1983, *Theory and Practice of Recursive Identification*, MIT Press, Cambridge, Massachusetts.

Niedzwiecki, M., 1987a, "Functional Series Modeling Approach to Identification of Nonstationary Stochastic Processes," *Proceedings of the American Control Conference*, Minneapolis, Minnesota, June, pp 1143-1148.

Niedzwiecki, M., 1987b, "Recursive Functional Series Modeling Estimators for Adaptive Control of Time-Varying Plants," *Proceedings of the 26th Conference on Decision and Control*, Los Angeles, California, December, pp 1239-1244.

Ulsoy, A. G., Koren, Y., and Rasmussen, F., 1983, "Principal Developments in the Adaptive Control of Machine Tools," *ASME Journal of Dynamic Systems, Measurement, and Control*, Vol. 105, No. 2, June, pp 107-112.

Table 1. Standard Values Used in the Simulation Studies

Simulation Parameter	Standard Value Used
$\hat{\theta}(0)$, $\hat{\Theta}(0)$	0.0
P(0)	10.0 I
σ_z^2	1.0
σ_v^2	0.01
σ_1^2	0.0007
σ_2^2	0.007
k	0, 1, 2, .. , 100

On-Line Tool Wear Estimation Using Force Measurement and a Nonlinear Observer

by
Jong-Jin Park[1]
and
A. Galip Ulsoy[2]

Department of Mechanical Engineering
and Applied Mechanics
The University of Michigan
Ann Arbor, Michigan 48109-2125

Abstract

On-line tool wear monitoring in metal cutting operations is essential for on-line process optimization. In this paper, tool wear is estimated on-line by utilizing a nonlinear observer with feedback of cutting force measurements. Based on a previously developed cutting process model for the turning, the nonlinear observer is designed such that the tool wear is estimated within an acceptable error in the presence of poor initial tool wear estimates. The stability analysis for the tool wear estimation error dynamic system is carried out using the physical limitation on the actual tool wear and the Total Stability Theorem. The simulation results show that the proposed nonlinear observer estimates the tool wear acceptably well, not only in the presence of poor initial estimates but also in the presence of measurement noise.

However, the presented method has drawbacks resulting from modeling errors and difficulties in obtaining model parameters. An adaptive version of the presented nonlinear observer, periodically calibrated by off-line direct tool wear measurements using computer vision, is considered to be a promising strategy for practical implementation.

1 Introduction

The trend in manufacturing is toward production in small batch sizes, especially in the aerospace industry, the ship-building industry, and the tool and die making industry (Miller,1985). In such industries, traditional craftsmanship plays a very important role in producing good quality parts. However, in recent years, the shortage of skilled machinists in those industries has been reported to be very severe (Wright and Bourne,1988). To overcome this problem, manufacturing systems must be automated and machine tools made more intelligent. Computer controlled machines (e.g., robots, computer numerically controlled machine tools, etc.), computer-integrated manufacturing systems, and unmanned manufacturing systems are all evidence of this trend (Koren,1983 and Groover,1980). In such systems, machines are required to have flexible control schemes which can adapt to process changes. Traditionally, such adaptations have been carried out through skilled machinists' knowledge and experiences.

For the metal cutting process, adaptive control, which can automatically adjust process variables such as the feed rate and the cutting speed according to changes in the cutting process, is intended to ensure desired cutting conditions based on in-process measurements (Centner and Idelson,1964, Hinds,1977, Watanabe,1986, Koren and Ulsoy,1989). Such a system has been termed adaptive control with optimization (ACO). The major problem with the use of ACO systems is the need for on-line measurement of cutting process variables, which are necessary in tuning the controller. But reliable on-line sensors are not available for some of these variables, such as the tool wear which determines tool life (Ulsoy *et al.*,1983, Jetly,1984).

An overview of developed tool wear sensors was presented by Cook (1980), and practical implementation issues for several tool wear sensors were discussed by Tlusty and Andrews (1983). Among the developed tool wear sensors, optical sensors measuring the tool wear directly by the use of vision systems (Daneshmend and Pak,1983, Giusti *et al.*,1987), dimensional sensors measuring the distance between the tool holder and the work surface (Suzuki and Weinmann,1985) or measuring the change of the workpiece diameter (El Gomayel and Bregger,1986), and micro-isotope sensors detecting the absence of radioactive particles (Cook and Subramanian,1978) are typical examples of direct tool wear sensing methods. Optical sensors and micro-isotope sensors are fairly accurate, however, they are not practical as on-line sensors. The cutting operation must be stopped and the tool disengaged from the workpiece to take pictures of the tool wear or to measure the radioactivity. The dimensional sensor is generally sensitive to thermal expansion and deflection of the cutting tool, the tool holder, or the workpiece, and also sensitive to vibrations of the workpiece and the tool.

To measure the tool wear on-line, indirect sensing methods have been developed. In these methods, a relationship is estab-

[1]Graduate Research Assistant
[2]Associate Professor and Member of ASME

lished between tool wear and other cutting variables which are easier to measure during the cutting operation. From measured variables, information on the tool wear is obtained by utilizing such a relationship. Some of the easily measurable variables are the cutting force (Koren *et al.*,1986, Danai and Ulsoy,1987a, Lan and Naerheim,1986), the vibration signal (Pandit and Kashou,1982, Jiang *et al.*,1987), the acoustic emission (Moriwaki,1983, Kanatey-Asibu Jr and Dornfeld,1981, Inasak and Yonetsu,1981, Lan and Dornfeld,1984), and the spindle motor current (Takata *et al.*,1985). There are also indirect multisensor strategies which combine cutting force with the vibration signal (Rao,1986), the acoustic emission with the cutting force (Emel,1987, Moriwaki,1984), or the cutting force with a vision system (Daneshmend and Pak,1983). The reliability of these indirect methods depend on how accurately the relationship between the tool wear and measured variables describes the physical phenomena, and also depend on how robust the relationship is to changes in other cutting variables such as different tool-work combinations, time varying cutting conditions(i.e., time varying feed, cutting speed, depth of cut, etc.).

At present, indirect methods suffer from inaccuracy in such relationships, because of difficulties in modeling phenomena such as friction, strain-hardening, unhomogeneity in workpiece materials, etc. For cutting force measuring methods, force measuring devices such as the force dynamometer are widely used, and known to be very reliable. And, there has been extensive research to determine relationships between the cutting force and other cutting variables, including tool wear, using both mechanistic and empirical approaches (Micheletti *et al.*,1968, De Filippi and Ippolito,1969, Nagasaka and Hashimoto,1982). Therefore, it may be possible to develop an acceptable mathematical model, which includes explicit relationships between the cutting force, cutting conditions and tool wear.

Based on various results in the literature, Koren and Lenz (1972) and Koren (1978) developed a flank wear model using concepts from control theory. They considered many of the important variables involved in the cutting process, i.e., the cutting force, the flank wear, the cutting temperature, the feed, the depth of cut, and the cutting speed. Danai and Ulsoy (1987b) combined their flank wear model with the crater wear model developed by Usui *et al.* (1978). Moreover, they formulated the model in a nonlinear state equation form using the tool wear (i.e., flank wear caused by diffusion, flank wear caused by abrasion, and crater wear) as states, the cutting force as the output, and the cutting conditions (the feed, the depth of cut and the cutting speed) as inputs. This is significant in that various mathematical and computational tools from the control and system identification areas can be applied. However, it should be noted that the cutting process is not fully understood and that the crater wear models are known to be less accurate than those of the flank wear.

Based on a linearized version of the developed cutting process model, Danai and Ulsoy (1987a) presented an on-line tool wear estimation scheme using an adaptive state observer. In this method, the tool wear and parameters of the linearized model are simultaneously estimated by measuring the output from the cutting process, i.e., the cutting force signal, and the input to the process, i.e., the feed. Parameters are estimated using the output error parameter estimation method, and the tool wear is obtained using these estimated parameters. However, several off-line direct measurements of the tool wear are also necessary during the cut to obtain the tool wear within an acceptable error. The need for off-line measurements originated from the linearization of the original nonlinear model, and from the transformation of the linearized model into observer canonical form. Such procedures, on the other hand, allow for the straighforward design of the estimation algorithms. This method gives good results when the flank wear is dominant, but not when both types of wear are significant. The main reasons for this are considered to be the inaccuracies in the wear models, the linearization of the model, and the poor conditioning associated with the transformation to observer canonical form.

This study is motivated by the need to overcome the off-line measurement requirement in the adaptive state observer method. If an adaptive nonlinear observer for the original nonlinear model is achieved, the problems originating from linearization and transformation to observer canonical form are avoided. Then off-line measurements are not essential. However, they can be used as a supplementary measurement which makes the on-line estimation more accurate. In this paper, as the first step for achieving the adaptive nonlinear observer, a design of the non-adaptive nonlinear observer for the cutting process model and its convergence characteristics are extensively investigated. Although crater wear is often important, to avoid the problems caused by the inaccuracy in the crater wear model, we consider in this study flank wear dominant cutting processes only. Generalization to processes with both significant flank and crater wear remains a topic for future research.

To design a nonlinear observer, consider a general nonlinear nth-order state equation,

$$\dot{x} = f(t, x)$$

where it is assumed that above system yields a unique solution $x(t)$ starting from any initial state $x(0)$. Measurements described by an output equation of the form

$$y = h(t, x)$$

are to be used as the input to a dynamic state observer,

$$\dot{\hat{x}} = g(t, \hat{x}, y)$$

The observer error dynamic system can be obtained by defining the state estimation error $e = x - \hat{x}$ such that

$$\dot{e} = f(t, x) - g(t, \hat{x}, y)$$

Then, an observer must satisfy the following two basic requirements.

Condition A : If for a certain $t_0, e(t_0) = 0$, then $e(t) = 0$ for all $t \geq t_0$.
Condition B : $e(t)$ should converge sufficiently fast to 0 for $t \to \infty$, irrespective of the initial condition $e(t_0)$.

There have been various attempts to construct such observers for nonlinear systems. However, unlike the linear case, no general design rule is established. Kou *et al.* (1975) presented a nonlinear observer for a class of nonlinear systems, in which the Lyapunov direct method was applied to obtain conditions under which the observer error dynamic system satisfies *Conditions A* and *B*. Recently, there has been considerable research in finding conditions to transform a nonlinear system to a linear form by coordinate transformations; sometimes with output injection. Bestle and Zeitz (1983) and Krener and Isidori (1983) considered a class of nonlinear systems, where a nonlinear coordinate transformation can be used to obtain a linear system plus a nonlinear term depending only on the original system input and output. The transformation makes the nonlinearity become a function of the measurable variables only. Then, a nonlinear observer is designed such that the nonlinearity in the observer error dynamic system is perfectly cancelled. Therefore, the resulting error dynamic system becomes linear, and *Conditions A* and *B* can be satisfied using linear control techniques such as pole assignment. Levine and Marino (1986) used a transformation of the nonlinear system into a higher order linear system, and a standard linear observer is designed for the transformed higher order linear system. These methods are attractive because well developed linear observer design techniques can be applied after the transformation. However, the drawback is to find such a transformation. Most literature on these methods present conditions for existence of transformations. But, for complex nonlinear models such as the cutting process model considered below, it is not necessarily easy to find these transformations.

Nonlinear observer design methods are intended to find globally stable nonlinear observers in the sense that the observer error dynamic system satisfies *Conditions A* and *B* for any $e(t_0)$. A locally stable observer is, however, adequate for some applications, i.e., *Conditions A* and *B* are satisfied for $\|e\| < r$, $0 < r < \infty$, and it is less difficult to design such an observer. For the metal cutting process, the amount of tool wear is actually limited during cutting. Therefore, in this paper, we concentrate on designing a nonlinear observer which is locally stable within such physical limits on the amount of tool wear.

In Section 2 of this paper, the cutting process model developed by Danai and Ulsoy (1987b) is briefly introduced, and the corresponding nonlinear observer is proposed. The stability analysis of the resulting observer error dynamic system is carried out in Section 3. In Section 4, the performance of the nonlinear observer is illustrated using simulation studies. The simulations are designed to include the noise characteristics in typical cutting force signals. Finally, results of the analysis and simulation studies are summarized and discussed in Section 5, which also indicates directions for future research.

2 Nonlinear Observer for the Cutting Process

A detailed description of the cutting process model used in this paper is presented in Danai and Ulsoy (1987b). We consider here flank wear dominated cutting processes only, and neglect crater wear.

In the model, the flank wear is separated into two component: one caused by abrasion(w_{f1}) and the other by diffusion(w_{f2}). These two components are used as state variables. The inputs to the process are the feed f, the cutting speed v, and the depth of cut d. The output, F, is selected to be a component of the cutting force. The resulting model has the form

$$\dot{w}_{f1} = -\frac{v}{l_0} w_{f1} + \frac{v}{l_0} K_1 \cos\alpha_r \frac{F}{fd} \quad (1)$$

$$\dot{w}_{f2} = K_2\sqrt{v}\exp\left(\frac{-K_3}{273+\theta_f}\right) \quad (2)$$

and

$$F = [K_4 f^{n1}(1-K_5\alpha_r) - K_6 - K_7 v]d + K_8 d w_f \quad (3)$$

where α_r is the effective rake angle, l_0 is a constant, w_f is the sum of the two wear components, and θ_f is the tool-work temperature on the flank side of the tool. The tool-work temperature θ_f is calculated using the following relationship

$$\theta_f = K_9 v^{n2} f^{n3} + K_{10} w_f^{n4} \quad (4)$$

The model has been evaluated in Danai and Ulsoy (1987b) using the parameter values given in Table 1 and found to agree with results reported in the literature.

l_0	α_r	K_1	K_2	K_3	K_4	K_5	K_6
500	0.1745	5.2E-5	20	8000	1960	0.57	86
K_7	K_8	K_9	K_{10}	n_1	n_2	n_3	n_4
0.1	500	72	2500	0.76	0.4	0.6	1.45

Table 1: Parameter values used in the model evaluation

Based on the model evaluation results, let us assume that the cutting process model (1)-(4) describes the actual cutting process exactly. Then, the problem is to design a nonlinear observer which estimates the tool wear within an acceptable error despite poor initial estimates. To solve this problem, the following observer is proposed:

$$\dot{\hat{w}}_{f1} = -\frac{v}{l_0}\hat{w}_{f1} + \frac{v}{l_0} K_1 \cos\alpha_r \frac{F}{fd} + G_1(F-\hat{F}) \quad (5)$$

$$\dot{\hat{w}}_{f2} = K_2\sqrt{v}\exp\left(\frac{-K_3}{273+\hat{\theta}_f}\right) + G_2(F-\hat{F}) \quad (6)$$

and

$$\hat{F} = [K_4 f^{n1}(1-K_5\alpha_r) - K_6 - K_7 v]d + K_8 d\hat{w}_f \quad (7)$$

where G_1 and G_2 are observer gains, $\hat{w}_f$ is the sum of the two estimated wear components, and the estimated tool-work temperature on the flank side of the tool, $\hat{\theta}_f$, is calculated using the following relationship,

$$\hat{\theta}_f = K_9 v^{n2} f^{n3} + K_{10}\hat{w}_f^{n4} \quad (8)$$

In the next section, the conditions, under which the proposed observer satisfies the *Conditions A* and *B* presented in Section 1, are investigated.

3 Stability Analysis of the Nonlinear Observer

From the cutting process model given in (1)-(4) and the proposed observer given in (5)-(8), the observer error dynamic system can be formulated as follows. First, the state variables of the error dynamic system are defined as

$$e_1(t) \equiv w_{f1} - \hat{w}_{f1}$$

$$e_2(t) \equiv w_{f2} - \hat{w}_{f2}$$

and the error state vector is defined as

$$x \equiv \begin{pmatrix} e_1 & e_2 \end{pmatrix}^T$$

The error between the measured and the estimated cutting force is

$$F - \hat{F} = K_8 d(w_f - \hat{w}_f) = K_8 d(e_1 + e_2) \quad (9)$$

Subtract (5) from (1), and (6) from (2). Then the error dynamic system is formulated such that

$$\begin{aligned} \dot{e}_1 &= \dot{w}_{f1} - \dot{\hat{w}}_{f1} \\ &= -\frac{v}{l_0}(w_{f1} - \hat{w}_{f1}) - G_1(F - \hat{F}) \\ &= -(\frac{v}{l_0} + G_1 K_8 d)e_1 - G_1 K_8 d e_2 \quad (10) \end{aligned}$$

and,

$$\begin{aligned} \dot{e}_2 &= \dot{w}_{f2} - \dot{\hat{w}}_{f2} \\ &= K_2\sqrt{v}\left[\exp\left(\frac{-K_3}{273 + \theta_f}\right) - \exp\left(\frac{-K_3}{273 + \hat{\theta}_f}\right)\right] - G_2(F - \hat{F}) \\ &= -G_2 K_8 d e_1 - G_2 K_8 d e_2 + g(t, x) \quad (11) \end{aligned}$$

where,

$$\begin{aligned} g(t,x) &= K_2\sqrt{v}\left[\exp\left(\frac{-K_3}{273 + K_9 v^{n2} f^{n3} + K_{10} w_f^{n4}(t)}\right)\right. \\ &\left. - \exp\left(\frac{-K_3}{273 + K_9 v^{n2} f^{n3} + K_{10}(w_f(t) - e_1 - e_2)^{n4}}\right)\right] \quad (12) \end{aligned}$$

Note that $g(t, 0) = 0$ for any $w_f(t) \geq 0$. Finally, the observer error dynamic system is obtained by rewriting (10)-(12) as follows

$$\dot{x} = Ax + f(t,x) \quad (13)$$

where,

$$A = \begin{pmatrix} -\frac{v}{l_0} - G_1 K_8 d & -G_1 K_8 d \\ -G_2 K_8 d & -G_2 K_8 d \end{pmatrix} \quad (14)$$

and

$$f(t,x) = \begin{pmatrix} 0 & g(t,x) \end{pmatrix}^T \quad (15)$$

Note from (13)-(15) that $x = 0$ is an equilibrium point, and consequently *Condition A* given in Section 1 is satisfied by the observer proposed in (5)-(8). To satisfy *Condition B*, the error dynamic system (13) must be stable. Moreover, its convergence rate must be sufficiently fast. The following theorem, presented in Anderson *et al.* (1986), gives sufficient conditions for the stability of the system (13).

Theorem (Total Stability Theorem)
Consider the ordinary differential equation

$$\dot{x} = A(t)x + h_1(t,x) + h_2(t,x) \quad (16)$$
$$x(t_0) = x_0 \in R^n$$

where $A(t), h_1(t,x)$ and $h_2(t,x)$, for each fixed x in the ball $|x| \leq r$, are locally integrable functions of t, and $\forall\ |x_1| \leq r, \forall\ |x_2| \leq r$, and $\forall\ t \geq t_0$:

(A1) $h_1(t,0) = 0$
(A2) $|h_1(t,x_1) - h_1(t,x_2)| \leq \beta_1|x_1 - x_2|$
(A3) $|h_2(t,x_1)| \leq \beta_2 r$
(A4) $|h_2(t,x_1) - h_2(t,x_2)| \leq \beta_2|x_1 - x_2|$

If the unperturbed system

$$\dot{x} = A(t)x \quad (17)$$

is exponentially stable, i.e., if for some constant $a > 0$ and $K \geq 1$ the state transition matrix $F(t_1, t_2)$ of (17) satisfies

$$|F(t_2,t_1)| \leq Ke^{-a(t_2-t_1)}\ \forall\ t_2 \geq t_1 \geq t_0 \quad (18)$$

and if

$$|x_0| < \frac{r}{K} \text{ and } (\beta_1 + \beta_2)K/a < 1 \quad (19)$$

then there is a unique solution $x(t)$ of (16) such that $\forall\ t \geq t_0$,

$$|x(t)| \leq Ke^{-(a-\beta_1 K)(t-t_0)}|x_0| + \frac{K\beta_2}{a - \beta_1 K}r\left(1 - e^{-(a-\beta_1 K)(t-t_0)}\right) \leq r \quad (20)$$

See Anderson *et al.* (1986) for the proof of this theorem.

From (13)-(15), it is observed that the observer error dynamic system has the same structure as the system (16) except that the error dynamic system does not have the nonlinear term corresponding to $h_2(t,x)$ in the Total Stability Theorem (i.e., $h_2(t,x) = 0$ and $\beta_2 = 0$). It is also observed that A and $f(t,x)$ are integrable if the tool wear, w_f, and the estimated tool wear, $\hat{w}_f$, are larger than zero. This is true for w_f, because the actual amount of the tool wear never becomes less than zero. For $\hat{w}_f$, some techniques to be used in designing the observer can ensure that $\hat{w}_f$ remains larger than zero. These techniques will be discussed later in this section. Therefore, the observer error dynamic system can be expected to be stable if it satisfies conditions given in the Total Stability Theorem.

For the error dynamic equation in (13)-(15), the first condition (A1) is obviously satisfied because $g(t,0) = 0$. To obtain the bound β_1 of the nonlinearity $f(t,x)$, apply the mean-value theorem to the nonlinearity (15). Then, one can obtain the following equation.

$$f(t,x_2) - f(t,x_1) = \beta(x^*)(x_2 - x_1) \quad (21)$$

where x_1 and x_2 are error vectors, x^* is a point in the segment between x_1 and x_2, and $\beta(x^*)$ is a matrix such that

$$\beta(x^*) = \begin{pmatrix} 0 & 0 \\ \frac{\partial g}{\partial e_1}(x^*) & \frac{\partial g}{\partial e_2}(x^*) \end{pmatrix} \quad (22)$$

Take the Euclidian norm on both sides of (21) and use the corresponding induced matrix norm;

$$|\beta(x^*)|_i = [\lambda_{max}\overline{\beta(x^*)}^T\beta(x^*)]^{1/2}$$

where $\overline{\beta(x^*)}^T$ is the complex conjugate transpose of $\beta(x^*)$, and $\lambda_{max}\overline{\beta(x^*)}^T\beta(x^*)$ is the maximum eigenvalue of $\overline{\beta(x^*)}^T\beta(x^*)$ (Vidyasagar,1978). Then, from the property of the norm, the following relationship is obtained.

$$|f(t,x_2) - f(t,x_1)| \leq |\beta(x^*)|_i|x_2 - x_1| \quad (23)$$

Here, using equations $\hat{w}_f^* = w_f - e_1^* - e_2^*$, $\hat{\theta}_f^* = K_9 v^{n2} f^{n3} + K_{10}\hat{w}_f^{*n4}$ and (12), (22), $|\beta(x^*)|_i$ can be calculated such as

$$|\beta(x^*)|_i = \left[2K_2\sqrt{v}\exp\left(\frac{-K_3}{273 + \hat{\theta}_f^*}\right)\left(\frac{-K_3}{273 + \hat{\theta}_f^*}\right)\left(n_4 K_{10}\hat{w}_f^*\right)\right]^{1/2} \quad (24)$$

If the maximum value of $\hat{w}_f$ is assumed to be bounded by $\hat{w}_{f_{max}}$, the maximum value of $|\beta(x^*)|_i$ exists in the range $0 \leq \hat{w}_f^* \leq$

$\hat{w}_{fmax}$ and can be calculated from (24). Then (23) can be rewritten as follows

$$|f(t,x_2) - f(t,x_1)| \leq \beta_1 |x_2 - x_1| \tag{25}$$

where $\beta_1 = |\beta(x^*)|_{imax}$ in the range $0 \leq \hat{w}_f^* \leq \hat{w}_{fmax}$. Therefore, condition (A2) of the Total Stability Theorem is also satisfied.

The linear part of the observer error dynamic system (13) has two adjustable gains, i.e., G_1 and G_2. And its poles can be located at any place in the left half s-plane by selecting appropriate gain values. As a result, the characteristic equation of the linear part can be written without loss of generality as

$$s^2 + 2\zeta\omega_n + {\omega_n}^2 = 0$$

where ζ is the damping ratio and ω_n is the natural frequency. The above characteristic equation corresponds to observer gains

$$G_1 = (2\zeta\omega_n - \frac{l_0}{v}{\omega_n}^2 - \frac{v}{l_0})/K_8 d \tag{26}$$

$$G_2 = \frac{l_0}{v}\frac{1}{K_8 d}{\omega_n}^2 \tag{27}$$

The state transition matrix for the second order time invariant linear system is known to be bounded in such a way that

$$|F(t_2,t_1)| \leq e^{-\zeta\omega_n(t_2-t_1)}, \ \forall\, t_2 \geq t_1 \geq t_0$$

Thus, K and a in (18) of the Total Stability Theorem is obtained as $K = 1$ and $a = \zeta\omega_n$. Using these results and the second relationship in (19), the condition which ω_n and ζ of the linear part $\dot{x} = Ax$ must satisfy is obtained as

$$\zeta\omega_n > \beta_1 \tag{28}$$

By selecting a pair of ζ and ω_n, which satisfies the above condition, one can design a nonlinear observer that has observer gains calculated from (26) and (27).

In addition, the initial condition of the observer error dynamic system must satisfy a certain requirement which corresponds to assumptions we made on the range of w_f and $\hat{w}_f$, i.e., $0 \leq w_f$, $0 \leq \hat{w}_f \leq \hat{w}_{fmax}$. Otherwise, the stability of the observer error dynamic system is not assured. And, from the bound given in (20), one can notice that the convergence rate of the observer error dynamic system, $\zeta\omega_n - \beta_1$, can be designed to be sufficiently fast by choosing a sufficiently large $\zeta\omega_n$. Therefore, the resulting nonlinear observer also satisfies *Condition B* given in Section 1.

The design procedure of the nonlinear observer for the cutting process (1)- (4), which has been explained so far, can be summarized as:

Step 1: Select a bound $\hat{w}_{fmax}$ for the estimated tool wear such that $0 \leq \hat{w}_f(t) \leq \hat{w}_{fmax}$, for all $t \geq 0$.
Step 2: Find $\beta_1 = |\beta(x^*)|_{imax}$ from (24).
Step 3: Select an appropriate pair (ζ, ω_n) for the linear part of the observer error dynamic system. Selection is based on the condition (28) and the requirement that the convergence rate must be sufficiently fast.
Step 4: Calculate the observer gain G_1 and G_2 from (26) and (27).
Step 5: Select a suitable initial condition $\hat{w}_f(0)$ which satisfies the bound obtained in Step 1.

Remark: The stability analysis of the error dynamic system is based on the assumption that $0 \leq w_f$ and $0 \leq \hat{w}_f \leq \hat{w}_{fmax}$. The assumption on the range of w_f is exact because the amount of the actual tool wear is never less than zero. It is difficult to know the range of $\hat{w}_f$ *a priori*, however, one reasonable choice of $\hat{w}_f$ is that $\hat{w}_{fmax}$ is the same as the maximum allowable amount of tool wear corresponding to the tool life. By trial-and-error, select ζ and ω_n of the linear part of the system $\dot{x} = Ax$ in such a way that $\hat{w}_f$ remains within the range $0 \leq \hat{w}_f \leq \hat{w}_{fmax}$. From extensive simulation studies, it was observed that such a selection for ζ and ω_n did not require many trials.

4 Simulation Results

It is known that the measured cutting force signal is generally corrupted by process and measurement noise. However, it is also known that the frequency range of the process noise, which is mainly caused by the vibration of the workpiece, is much higher than that of the signal used for tool wear estimation (Danai and Ulsoy,1987a). Thus, it is reasonable to assume that the process noise can be filtered from the signal. The measurement noise contained in the force signal is modeled here as a normally distributed zero mean white sequence whose standard deviation is σ, where σ is estimated to be 1% of the nominal cutting force. In the simulations, the measurement noise is generated using a pseudo-random number generator giving the same distribution and standard deviation as specified in the noise model. The measurement noise modeled in this way is very similar to the noise observed in many actual cutting force signals as illustrated by the experimental data in Fig. 1 (Ulsoy and DeVries,1989).

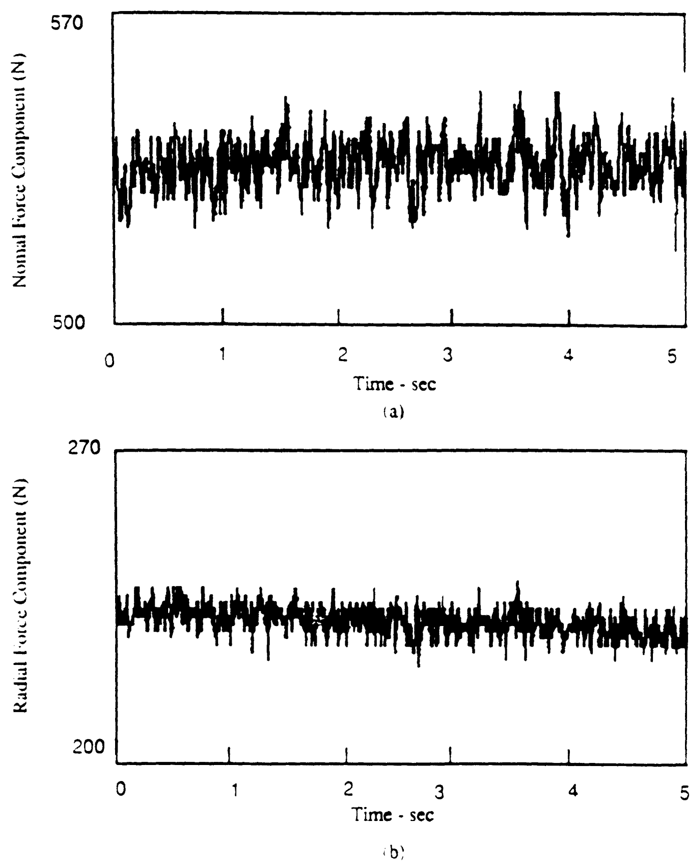

Fig.1 Experimentally obtained cutting force components in turning: (a) normal, and (b) radial.

The cutting conditions used in the simulations are selected to be

$$v = 200\text{m/min},\ f = 0.25\text{mm/rev},\ d = 3.0\text{mm},\ \textit{and}\ \sigma = 20N$$

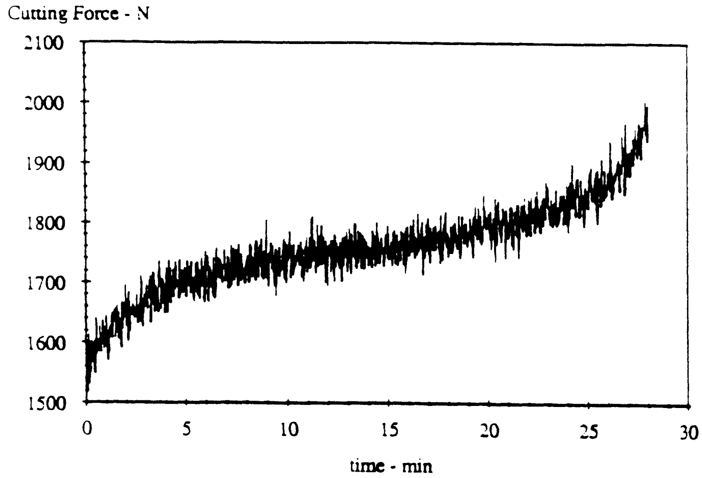

Fig.2 Simulated cutting force signal

And, the model parameter values given in Table 1 are used. For the purpose of simulation, the initial wear on the tool is selected as $w_{f1}(0) = w_{f2}(0) = 0.01$mm and the maximum allowable wear is selected as $w_{f_{max}} = 0.3$mm. Given these conditions, the simulated cutting force signal and the flank wear versus time are shown in Fig. 2 and Fig. 3

To estimate the tool wear, a nonlinear observer is designed by following steps 1 through 4 given in Section 3. The estimated tool wear $\hat{w}_f$ is assumed to be bounded: $0 \leq \hat{w}_f \leq 0.3$. Using this bound, $\beta_1 = 50.8$ is calculated from (24). The condition, which allows the observer error dynamic system to be stable, is obtained from (28) such that the natural frequency and the damping ratio of the linear part of the observer error dynamic system satisfies

$$\zeta\omega_n > 50.8 \tag{29}$$

Based on the above condition, ζ and ω_n are selected to be 0.707 and 80 rad/min respectively. The resulting observer gains, calculated from (26) and (27), are $G_1 = -10.59$ and $G_2 = 6.67$. The simulation is carried out with initial conditions of $\hat{w}_{f1}(0) = \hat{w}_{f2}(0) = 0$, and the result is shown in Fig. 4. From which, one can see that the estimated tool wear follows the actual tool wear progress within a reasonable amount of error. However, the estimated tool wear states are corrupted by a considerable

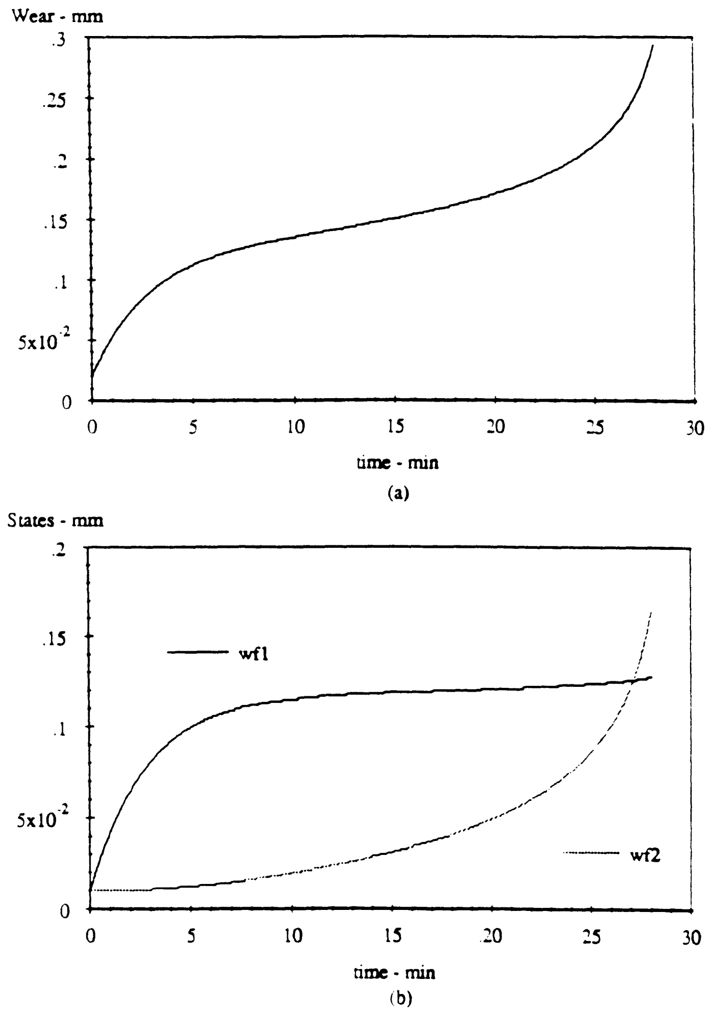

Fig.3 (a) Simulated flank wear progress (b) Simulated two types of flank wear progress

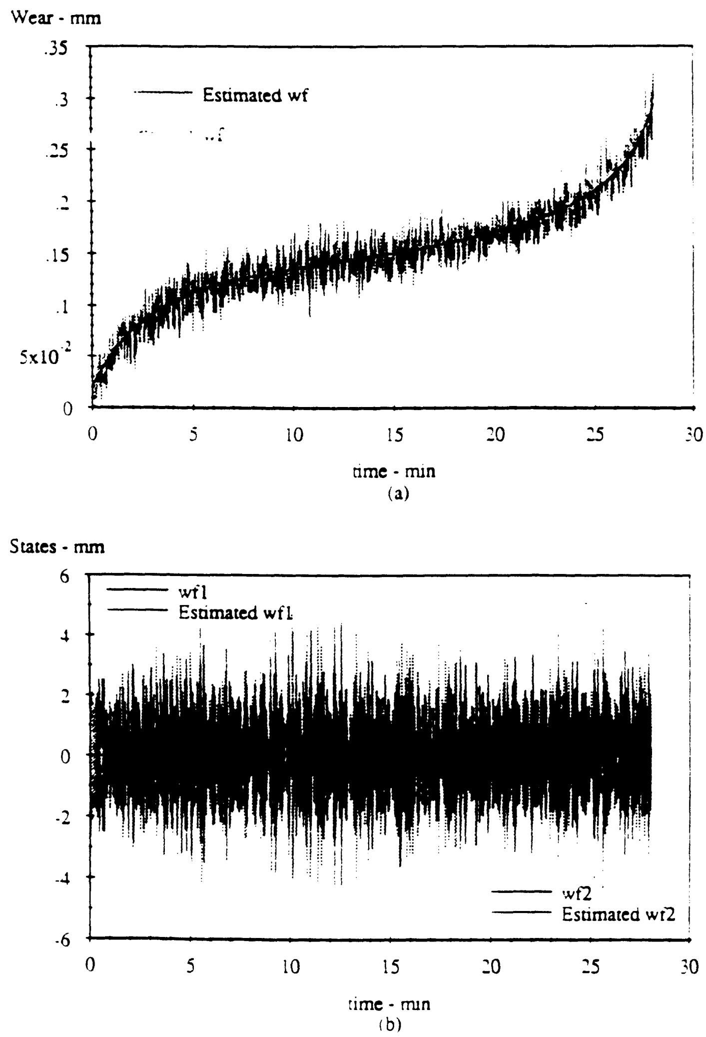

Fig.4 (a) Estimated flank wear (b) Estimated two types of flank wear

amount of noise which originates from the measurement noise in the cutting force signal. After the estimated tool wear and the states are filtered through a low-pass filter, e.g., a 6th order low-pass Butterworth filter with 0.033 Hz cut-off frequency, it is observed that the noise is significantly reduced (see Fig. 5).

To see the response of the observer to the measurement noise, a slower dynamics is chosen in the linear part of the observer error dynamic system, such that $\zeta = 0.707, \omega_n = 5$rad/min are chosen instead of $\zeta = 0.707, \omega_n = 80$rad/min. One can see that this choice violates the condition (29). However, because this condition is a sufficient condition, the violation of the condition does not mean that the error dynamic system will necessarily become unstable. The result of the simulation is shown in Fig. 6. The estimated tool wear follows the actual tool wear within an acceptable error, and the effect of the measurement noise is significantly reduced. From these results, we can see that the noise rejection ability of the nonlinear observer depends on the choice of ζ and ω_n. But, notice that the choice of ζ and ω_n in Fig. 6 does not guarantee the stability of the error dynamic system, since it violates the condition in (29).

Remark: Based on many simulation studies, the sufficient condition for stability in (28) appears to be very conservative. Selection of ζ and ω_n according to (28) is intended to ensure the stability of the observer error dynamic system, even with extremely poor initial estimates. However, in practice, the initial estimates of the tool wear are close to the real tool wear. In such cases, certain ζ and ω_n, which violate the condition (28), can allow acceptable tool wear estimates as shown in Fig. 6. The conservativeness of the sufficient condition for the stability of nonlinear systems is reported in the literature (Craig,1988).

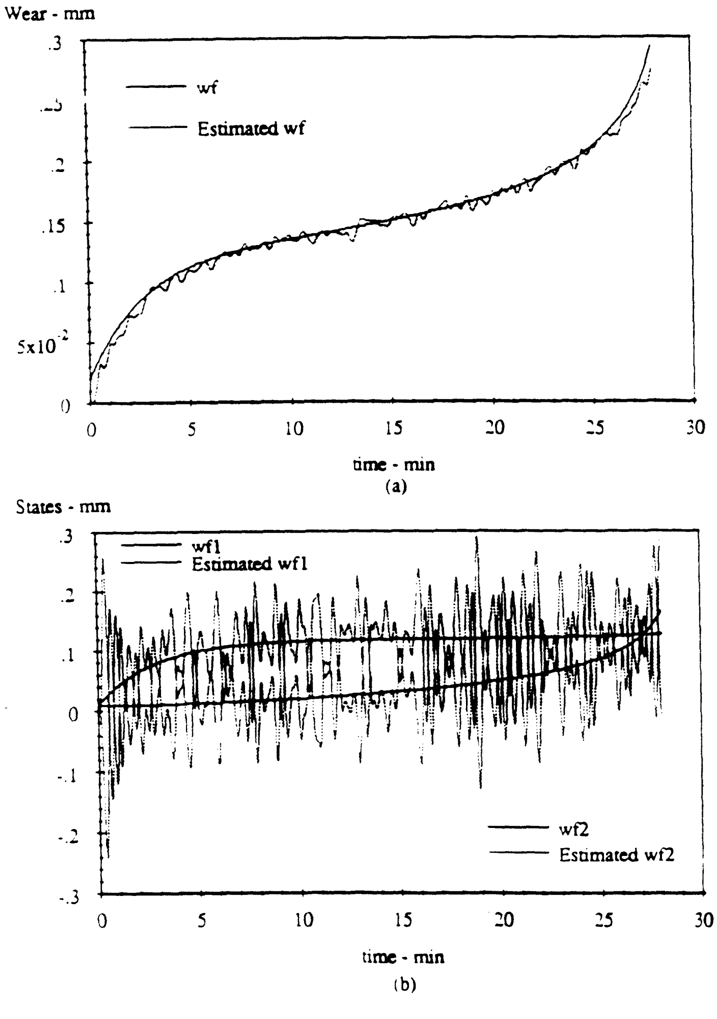

Fig.5 (a) Estimated flank wear (b) Estimated two types of flank wear after filtering

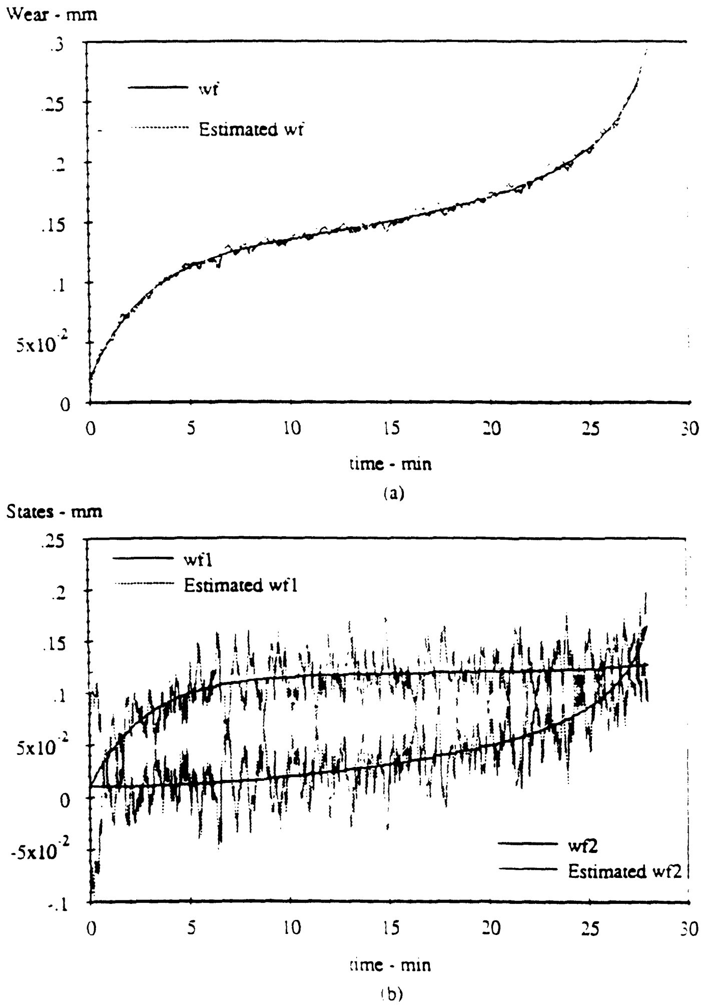

Fig.6 (a) Estimated flank wear (b) Estimated two types of flank wear using a slower dynamics

5 Summary, Conclusions and Future Work

In this paper, a nonlinear observer for the cutting process is presented such that the states(i.e., two types of the flank wear) are estimated using the output(i.e., the cutting force signal) and inputs(i.e., the feed, the depth of cut, and the cutting speed). The basic assumption in designing the nonlinear observer is that the model structure and model parameter values are exactly same as those of the actual cutting process. Under this assumption, the stability condition of the observer error dynamic system is obtained by utilizing the physical limitation of the actual tool wear progress and the Total Stability Theorem. The nonlinear observer is designed in such a way that the obtained stability condition is satisfied by a suitable selection of the observer gain. Simulation studies show that the presented nonlinear observer estimates the tool wear acceptably well even in the presence of poor initial estimates and measurement noise.

The implementation of the presented method using a microprocessor requires a discrete time version of the nonlinear observer. Because the development of tool wear is a relatively slow process, it can be well approximated using a simple backward difference approximation to the time derivative, given a high enough sampling frequency. Therefore, the presented method can be implemented on a computer system without difficulty.

The perfect modeling assumption we have used here is, of course, impractical. The model probably has errors in the model structure and errors in the model parameters. We can conjecture that the error between the estimated tool wear and the actual tool wear remains bounded, the size of the bound depending on the modeling errors. The conjecture is based on the Total Stability Theorem given in Section 3, where modeling errors cause the nonlinear function $h_2(t,x)$ to be non-zero. If the bound of the error in tool wear estimation is small enough to be ignored in practice, the nonlinear observer presented in this paper can be used.

In addition to the problem caused by modeling errors, identification of the parameters of the model (1)-(4) is not a trivial problem in practice. It generally requires a large number of experiments for each combination of tool and workpiece. Moreover, parameters may be time varying due to changes in cutting conditions. An adaptive version of the nonlinear observer presented here is considered to be a possible solution for this problem. In the adaptive nonlinear observer, the tool wear and model parameters are to be simultaneously estimated by using the cutting force signal and input signals (i.e., the feed, the cutting speed, the depth of cut). However, in the adaptive nonlinear observer, some problems (such as the local minima problem which frequently occurs in nonlinear parameter adaptation) may deteriorate the accuracy of the tool wear estimation. To avoid this, off-line direct tool wear measurements using computer vision will be combined with the adaptive nonlinear observer. These studies will be reported in future articles.

ACKNOWLEDGEMENT

The authors are pleased to acknowledge the financial support of the National Science Foundation under Grant No. DMC-8606239.

References

Anderson, B. D. O. *et al.* (1986) *Stability of Adaptive systems: Passivity and Averaging Analysis*, The MIT Press.

Bestle, D. and Zeitz, M.(1983) Canonical form observer design for non-linear time-variable systems, *Int. J. Control*, Vol.38, No.2, pp.419-431.

Centner, R. M. and Idelson, J. M. (1964) Adaptive Controller for a Metal Cutting Process. *Proceedings of IEEE ASME Joint Automatic Control Conference*, pp.154-161.

Cook, N. H. (1980) Tool Wear Sensors. *Wear*, Vol.62, pp.49-57.

Cook, N. H. and Subramanian, K. (1978) Micro-Isotope Tool Wear Sensor. *Annals of the CIRP*, Vol.27, No.1, pp.73-78.

Craig, J. (1988) *Adaptive Control of Mechancal Manipulators*. Addison-Wesley, Reading, Massachusetts.

Danai, K and Ulsoy, A. G. (1987a) An Adaptive Observer for On-Line Tool Wear Estimation in Turning, Part I: Theory, Part II: Results. *Mechanical Systems and Signal Processing*, 1(2), pp. 211-240.

Danai, K. and Ulsoy, A. G. (1987b) A Dynamic State Model for On-Line Tool Wear Estimation in Turning. *ASME Journal of Engineering for Industry*, Vol.109, November, pp.396-399.

Daneshmend, L. K. and Pak, H. A. (1983) Performance Monitoring of a Computer Numerically Controlled (CNC) Lathe Using Pattern Recognition Techniques. *3rd International Conference on Robot Vision and Sensory Controls (ROVISEC 3)*. Cambridge, Massachusetts.

De Filippi, A. and Ippolito, R. (1969) Adaptive Control in Turning: Cutting Forces and Tool Wear Relationships for P10. P20, P30 Carbides. *Annals of the CIRP*, Vol.17, pp.377-385.

El Gomayel, J. I. and Bregger, K. D. (1986) On-Line Tool Wear Sensing for Turning Operations. *ASME Journal of Engineering for Industry*, Vol.108, February, pp.44-47.

Emel, E. (1987) *Identification of the Metal Cutting Process by Pattern Recognition Analysis of Acoustic Emission and Force Signals.* PhD Thesis, University of Michigan, Ann Arbor, Michigan.

Giusti, F., Santochi, M, and Tantussi, G. (1987) On-Line Sensing of Flank and Crater Wear of Cutting Tools. *Annals of the CIRP*, Vol.36, No.1, pp.41-44.

Groover, M. P. (1980) *Automation, Production Systems, and Computer-Aided Manufacturing.* Prentice-Hall Inc., Englewood Cliffs, New Jersey.

Hinds, B. K. (1977) Control of Tool Wear During Metal Cutting Using a Computer and On Line Measurements. *International Journal of Production Research*, Vol.15, No.3, pp.291-301.

Inasak, I. and Yonetsu, S. (1981) In-Process Detection of Cutting Tool Damage by Acoustic Emission Measurement. *Proceedings of 22nd MTDR Conference*, pp.261-268.

Jetly, S. (1984) Measuring Cutting Tool Wear On-line: Some Practical Considerations. *Manufacturing Engineering*, July, pp.55-60.

Jiang, C. Y., Zhang, Y. Z. and Xu, H. J. (1987) In-Process Monitoring of Tool Wear Stage by the Frequency Band-Energy Method. *Annals of the CIRP*, Vol.36, No.1, pp.45-48.

Kanatey-Asibu Jr, E. and Dornfeld, D. A. (1981) Quantitative Relationships for Acoustic Emission from Orthogonal Metal Cutting. *ASME Journal of Engineering for Industry*, Vol.103, pp.330-340.

Koren, Y. (1978) Flank Wear Model of Cutting Tools Using Control Theory. *ASME Journal of Engineering for Industry*, Vol.100, February, pp.103-109.

Koren, Y. (1983) *Computer Control of Manufacturing Systems*, McGraw-Hill Co., New York.

Koren, Y. and Lenz, E. (1972) Mathematical Model for the Flank Wear While Turning Steel with Carbide Tools. *CIRP Proceedings on Manufacturing Systems*, Vol.1, No.2, pp.127-139.

Koren, Y and Ulsoy, A.G. (1989) Adaptive Control in Machining, Chapter in the *Metals Handbook 9th ed.*, Vol.16, ASM International, Cleveland, Ohio.

Koren, Y., Ulsoy, A. G. and Danai, K. (1986) Tool Wear and Breakage Detection Using a Process Model. *Annals of the CIRP*, Vol.35, No.1, pp.283-288.

Kou, S.R., Elliott, D. L., and Tarn, T.J.(1975) Exponential Observers for Nonlinear Dynamic Systems, *Information and Control*, Vol.29, pp.204-216.

Krener, A. J. and Isidori, A.(1983) Linearization by output injection and nonlinear observers, *Systems & Control Letters*, Vol.3, pp47-52.

Lan, M. and Dornfeld, D. A. (1984) In-Process Tool Fracture Detection. *ASME Journal of Engineering Materials and Technology*, Vol.106. April, pp.111-118.

Lan, M. and Naerheim, Y. (1986) In-Process Detection of Tool Breakage in Milling. *ASME Journal of Engineering for Industry*, Vol.108, August, pp.191-197.

Levine, J. and Marino, R.(1986) Nonlinear system immersion, observers and finite dimensional filters, *Systems & Control Letters*, Vol.7, pp.133-142.

Micheletti, G. F., De Filippi, A. and Ippolito, R. (1968) Tool Wear and Cutting Forces in Steel Turning. *Annals of the CIRP*, Vol.16, pp.353-360.

Miller, S.M. (1985) Impacts of robotics and flexible manufacturing technologies on manufacturing costs and employment, *The Management of Productivity and Technology in Manufacturing*, edited by P.R. Kleindorfer. Plenum Press, pp.73-110.

Moriwaki, T. (1983) Application of Acoustic Emission Measurement to Sensing of Wear and Breakage of Cutting Tool. *Bull. Japan Soc. of Prec. Engg.*, Vol.17, No.3, pp.154-160.

Moriwaki, T. (1984) Sensing and Prediction of Cutting Tool Failure. *Bull. Japan Soc. of Prec. Engg.*, Vol.18, No.2, pp.90-96.

Nagasaka, K. and Hashimoto, F. (1982) The Establishment of a Tool life Equation Considering the Amount of Tool Wear. *Wear*, Vol.81, pp.21-31.

Pandit, S. M. and Kashou, S. (1982) A Data Dependent Systems Strategy of On-Line Tool Wear Sensing. *ASME Journal of Engineering for Industry*, Vol.104, August, pp.217-223.

Rao, S. B. (1986) Tool Wear Monitoring Through the Dynamics of Stable Turning. *ASME Journal of Engineering for Industry*, Vol.108, August, pp.183-190.

Suzuki, H. and Weinmann, K. J. (1985) An On-Line Tool Wear Sensor for Straight Turning Operations. *ASME Journal of Engineering for Industry*, Vol.107, November, pp.397-399.

Takata, S., Ogawa, M., Bertok, P., Ootuka, J, Matushima, K. and Sata, T. (1985) Real- Time Monitoring System of Tool Breakage Using Kalman Filtering. *Robotics & Computer-Integrat Manufacturing*, Vol.2, No.1, pp.33-40.

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

Ulsoy, A.G. and DeVries, W.R. (1989) *Microcomputer Applications in Manufacturing*, John Wiley and Sons, New York.

Ulsoy, A. G., Koren, Y., and Rasmussen, F. (1983) Principal Developments in the Adaptive Control of Machine Tools. *ASME Journal of Dynamic Systems, Measurement, and Control*, Vol.105, June, pp.107-112.

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

Vidyasagar, M. (1978) *Nonlinear Systems Analysis*, Prentice-Hall Inc.

Watanabe, T. (1986) A Model-Based Approach to Adaptive Control Optimization in Milling. *ASME Journal of Dynamic Systems, Measurement, and Control*, Vol.108, March, pp.56-64.

Wright, P.K and Bourne, D.A. (1988) *Manufacturing Intelligence*, Addison-Wesley, Reading, Massachusetts.

METHODS FOR TOOL WEAR ESTIMATION FROM FORCE MEASUREMENTS UNDER VARYING CUTTING CONDITIONS

by

Yoram Koren, Professor[1]
Tsu-Ren Ko, Research Assistant[1]
Kourosh Danai, Assistant Professor[2]
A. Galip Ulsoy, Associate Professor[1]

BSTRACT A general model-based methodology for on-line esti-
nation of tool wear rate based on cutting force measurements is intro-
uced. The proposed methodology is designed to operate under vary-
ng cutting conditions dictated by the workpiece geometry or adaptive
ontrol strategies. This methodology, which uses parameter estima-
ion techniques to track tool wear during cutting, is demonstrated in
imulations and cutting experiments. The experiments, conducted for
urning operations with a varying depth of cut, show good agreement
etween estimated wear values and the actual values of tool wear mea-
ured intermittently during the cut.

Introduction

The full automation of machine tools requires reliable techniques or on-line sensing of tool wear and breakage [1,2]. Since tool wear has direct influence on the part dimensions, on-line tool wear information indispensable in precision machining [3]. The on-line sensing of tool ear is an essential part of any realistic adaptive control optimization ACO) system [4], and is important in adaptive scheduling of machine own-time for tool changing. Unfortunately, despite years of research this area, a reliable on-line tool wear measurement technique does ot exist [4,5].

The on-line tool wear measurement problem has been investigated numerous researchers [6]. The proposed methods can be categorized to two groups: direct and indirect wear sensing. Direct methods, as e name implies, make an assessment of tool wear by either evaluat- g the worn surface by optical methods [7], or measuring the material ss of the tool by radiometric techniques [8]. Since the surface of the ol is visually inaccessible during the operation, optical methods can used only during workpiece loading, which limits their application, pecially for parts with long machining times. The difficulty with the plication of radiometric techniques on the shop floor is their require- ents for special preparation of the tool and the potential hazards due radioactivity [9].

Indirect methods, on the other hand, are based on measuring vari- les which are related to wear such as force, torque, temperature, tool

[1]Department of Mechanical Engineering and Applied Mechanics, The University Michigan, Ann Arbor.

[2]Department of Mechanical Engineering, The University of Massachusetts, herst.

on-line tool wear estimation.

The physical model approach, which relies on mathematical modeling of the physics of cutting, is limited in applicability because of the inherent complexity of the cutting process. Moreover, since parameters in these models change with tool-workpiece combinations, off-line testing is required for each case. Another limitation in the utilization of the physical modeling 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., [18]). The absence of a reliable practical tool-edge 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" with a relationship between the measurement and tool wear (e.g., acoustic emission and flank wear). Therefore, they cannot accomodate the full range of cutting variables involved in the process. This causes serious limitations when the cutting variables are changed due to part geometry or control strategies.

Most of the above model-based approaches have been developed for fixed cutting conditions. In practical applications, however, the cutting conditions are not fixed. The depth of cut changes because of the part geometry, and the feed might change according to control strategies. Since the measured variable is affected by both tool wear and the changing cutting conditions, the detection of tool wear by indirect measurements becomes more challenging. The problem is to separate the direct effect of the wear on the measurement from the other effects. So far, this problem has not been thoroughly addressed in the literature.

The objective of this paper is to present methods that estimate in real time the rate of tool wear by using cutting force measurements. The methods use a mathematical model to separate the effect of tool wear on the measured variable from the effects caused by variations in the cutting variables, and therefore they may operate even in the vibration, or acoustic emission [10-15]. These techniques estimate tool wear by correlating it with the measured process variable. Some approaches rely on a detailed physical model of the cutting process (e.g., [16]), while others use empirical relationships between the measured variable and tool wear (e.g., [15,17]). Both the physical and empirical model approaches have certain limitations, however, when applied to presence of varying cutting variables. On-line parameter estimation techniques are used to estimate the model parameters. Therefore, they require neither a data-base nor prior off-line testing. The effect of tool wear is identified by estimating a parameter which is proportional to the tool wear.

The following sections present (i) the proposed model and the approaches used to estimate the rate of tool-wear, (ii) simulation results, (iii) the implementation of the proposed approach in cases where the depth of cut varies in steps, and (iv) analysis and evaluation of the results.

2 Approach

Experiments have shown that when the flank wear is the dominant wear, the total cutting force (F) can be separated into two components [19,20] such that

$$F = F_0' + \Delta F' \tag{1}$$

where F_0' is the cutting force when the tool is sharp and $\Delta F'$ is a force proportional to the total flank wear (W_T) :

$$\Delta F' = K_f(v, f, d)\, W_T(v, f, d, t)$$

Both F_0' and $\Delta F'$ are functions of the controllable cutting variables : the cutting speed (v), the feed (f), and the depth of cut (d). If only one of the cutting variables varies in the process, the model considered for $\Delta F'$ is assumed to have the form

$$\Delta F' = C\, b^\beta\, W_T(b^\gamma, t) \tag{2}$$

where C, β, and γ are empirical constants, and b is the manipulated cutting variable (i.e., b might be v, f, or d).

A relatively large wear W_0 is developed rapidly in the first few seconds of the cut [21]. The total flank wear width after this short period may be written as

$$W_T(b^\gamma, t) = W_0 + W(b^\gamma, t) \tag{3}$$

Substituting Eq. (3) into (2) yields

$$\Delta F' = \Delta F_0 + \Delta F \tag{4}$$

where

$$\Delta F_0 = C\, b^\beta\, W_0$$

and

$$\Delta F = C\, b^\beta\, W(b^\gamma, t) \tag{5}$$

Using these definitions we may rewrite Eq. (1) as

$$F = F_0 + \Delta F \tag{6}$$

where

$$F_0 = F_0' + \Delta F_0 \tag{7}$$

F_0 is the initial *measured* cutting force. Note that in practice separate measurements of F_0' and ΔF_0 are impossible. Equations (5) and (6) express the fundamental relationships needed for wear estimation.

After the initial transient, it is assumed for constant cutting conditions that the flank wear rate remains constant during most of the cut, and that it only increases during the final accelerated tool wear period, where the tool reaches its allowable wear limit. This assumption implies that we can write

$$W(b^\gamma, t) = \dot{W}(b^\gamma)\, t \tag{8}$$

and Eq. (5) may be rewritten as

$$\Delta F = C\, b^\beta\, \dot{W}(b^\gamma)\, t \tag{9}$$

The objective of this paper is to introduce methods to estimate flank wear from force measurements, even under varying cutting conditions. Depending on the cutting variable manipulated during the cut, one of three possible cases exists for Eq. (5):

case # 1	$\beta \simeq 0$	$\gamma \neq 0$,	
case # 2	$\beta \neq 0$	$\gamma \simeq 0$,	and
case # 3	$\beta \neq 0$	$\gamma \neq 0$.	

In the first case, the change of the cutting force is due to the change of flank wear, and the wear rate changes with b. A typical example is when $b = v$: changes in the cutting speed strongly affect the wear rate, but their direct effect on ΔF is small [22]. In case # 2, the change of b has a direct effect on ΔF, while the wear rate is almost unaffected by b. A practical case is when $b = d$; the effect of the depth of cut on flank wear is very small [23], but it is almost proportional to ΔF [19,24]. The case where both exponents in Eq. (5) are nonzero (case # 3) is the most complicated one, since the effect of the variations in b are felt both directly, through b^β, and indirectly, through an affected wear rate. In practice, $b = f$ fits this case [25].

For the first two cases, the proposed methods are based on estimating a variable X defined by

$$X = C\, \dot{W}(b^\gamma) \tag{10}$$

This estimation is done by measuring the rate of the cutting force increase during cutting, given by combining Eqs. (6) and (9) as

$$\frac{\Delta F}{t} = \frac{F - F_0}{t} = X(b^\gamma)\, b^\beta \tag{11}$$

and subsequently separating X from b^β.

The real-time estimation of flank wear becomes even more challenging when the variable b is changed during the cut. A step change from b_{k-1} to b_k at time t_k will cause an abrupt change in the cutting force from F_{k-1}' to F_k, as shown in Fig. 1. As will be shown later, in the first two cases $F_k(b_k, t_k)$, or in short F_k, might be considered as a reference point for the segment machined with b_k, and the corresponding $\Delta F_k(b_k, \tau_k)$, or in short ΔF_k, is used in the estimation processes. In these cases, for $b = b_k$, Eq. (11) becomes

$$\frac{F(b_k, t) - F_k(b_k, t_k)}{\tau_k} = \frac{\Delta F_k(\tau_k)}{\tau_k} = X(b_k^\gamma)\, b_k^\beta \tag{12}$$

where

$$\tau_k = t - t_k$$

Equation (12), however, cannot be used in the third case. In this case $\Delta F(b_k, t)$, rather than $\Delta F_k(b_k, \tau_k)$, must be used for the estimation, and therefore the model parameters of $F_0(b_k)$ must be estimated as well; this will be explained below (Section 3.3).

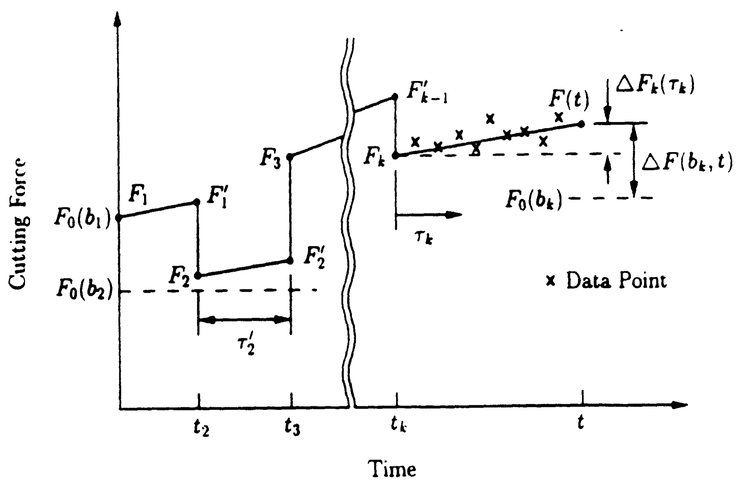

Fig.1 Schematic of the cutting force, F, when the cutting condition changes in steps

For the three cases above, three corresponding estimation methods will be introduced, which are designed to allow the identification and separation of F_0 and ΔF from F and the subsequent estimation of the value of CW (see Eq. 5).

- *Method I*: This method is suitable for case # 1, where the rate of the cutting force increase $(F - F_k)/\tau_k$ represents X (Eq. 12 with $\beta = 0$). X can be estimated by the identification of F_k and its subsequent subtraction from the total cutting force F. The variable CW is then estimated by integrating X (see Eq. 10). With this method, the sudden changes in the cutting force caused by step changes in b are related to changes in F_0 but not in the flank wear.

- *Method II*: This method is developed for case # 2, in which $(F - F_k)/\tau_k$ is a direct function of b and a constant wear rate $\dot{W}$ ($\gamma = 0$). In this method, F_k is identified and subtracted from F as in Method I. Since in case # 2 the rate of the cutting force is affected directly by b, any change in the cutting force rate after a step change in b is solely due to the new b. This enables the simultaneous estimation of both β and X, and the subsequent estimation of CW.

- *Method III*: This method is suitable for case # 3, in which $(F - F_k)/\tau_k$ is affected directly by b as well as by $\dot{W}$ which is a function of b. The two effects must be separated for estimation, and measuring the incremental changes in the cutting force ΔF_k is not sufficient in this case. The separation of CW from b^β is based on Eq. (5), for which ΔF should be known. To estimate ΔF, an additional model equation for F_0 is needed. The parameters of this model are estimated at the beginning of the cut where W is very small (i.e., $\Delta F \approx 0$ in Eq. 6). The model of F_0 is then used with other cutting conditions at the later stages of the cut. The estimated F_0 is subtracted from the total F to obtain ΔF (see Fig. 1). The obtained ΔF can be subsequently used to estimate β, and then CW may be identified.

Methods I and II do not rely on a mathematical model of F_0 for estimation, and therefore random variations in F_0 (or errors in the estimated F_0) will not affect the estimation of the wear rate. Method III, however, is sensitive to errors in the estimation of F_0. Therefore, applying the first two approaches is preferred wherever possible.

3 Analysis

This section provides a detailed description of the above methods and studies their performance in simulation. The model used in the simulations is

$$F = F_0' + \Delta F' + noise \tag{13}$$

where the initial cutting force is

$$F_0' = K_0' b^\alpha \tag{14}$$

and the additional force is

$$\Delta F' = C\, b^\beta W \tag{15}$$

where b is the cutting variable, and K_0', C, α, and β are constants. The simulated noise is a white Gaussian noise of 5% (peak-to-peak) of the total cutting force signal F. This particular noise distribution has been chosen based upon observations of actual cutting forces, as seen for example in Fig. 2.

3.1 Method I

In this method, the abrupt changes in the cutting force caused by sudden changes in b are removed from the total cutting force at each interval k, and the resultant signal ΔF_k is analysed. An interval k is

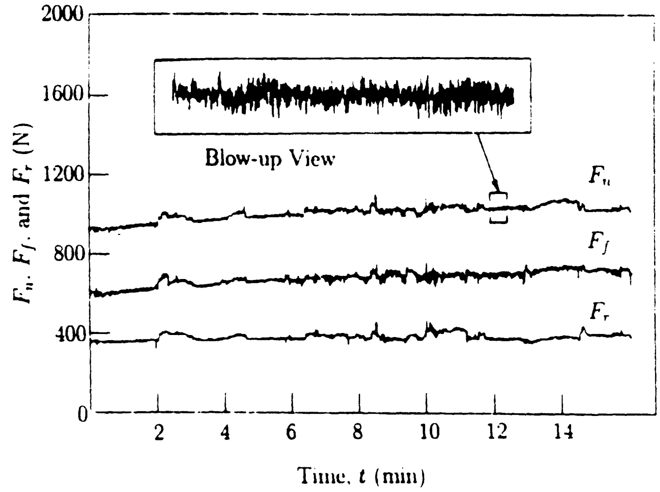

Fig.2 A cutting force record of turning 4340 steel by a carbide insert (F_n, the normal component; F_f, the feed component; and F_r, the radial component)

defined here as a segment of a cut in which the cutting variable b_k is kept constant. In this interval, ΔF_k is given by substituting $\beta = 0$ into Eq. (12) which yields

$$\Delta F_k = X_k \tau_k \tag{16}$$

Note that ΔF_k is the force increase in interval k, and τ_k is the time measured from the beginning of this interval. Equation (16) might be used to estimate X with a two-variable least-square estimation algorithm as explained below. The method requires sampling the measured cutting force at a constant rate (on our experimental system the sampling rate is 2 Hz).

The force increase ΔF_k is calculated at every sampling period i by

$$\Delta F_{ki} = F_i(b_k) - F_k(b_k) \tag{17}$$

where $F_i(b_k)$ is the measured force at the i th period, and $F_k(b_k)$ is the initial cutting force of interval k (at t_k) and is a constant reference for the interval k. This constant, however, must also be estimated since its direct measurement at $t = t_k$ is unreliable because of noise and possible overshoot. (We observed in our experiments that at t_k the force signal usually has an overshoot or undershoot.) Errors in the measurement of $F_k(b_k)$ at the beginning of the interval cause severe errors in ΔF_k and, in turn, in the estimated X. For these reasons we must simultaneously estimate both X and $F_k(b_k)$. Combining Eqs. (16) and (17) yields the estimation model

$$F_i(b_k) = X_k \tau_k + F_k(b_k) \tag{18}$$

This is a linear model of the form

$$y = \phi^\top \theta$$

where ϕ is a vector of known variables

$$\phi^\top = [\tau_k \quad 1] \tag{19}$$

and θ is a vector of the unknown estimated parameters

$$\theta^\top = [X_k \quad F_k(b_k)] \tag{20}$$

The recursive least-square estimator described in Appendix A is used to estimate X_k and $F_k(b_k)$ at each sampling period. Note that τ_k is the time measured from the beginning of the interval. At $\tau_k = 0$ the estimation gain matrix P in Eq. (55) is reset and the estimation of X_k and F_k starts. A numerical value proportional to the estimated wear may be calculated at each sampling period by the equation

$$\widehat{CW}(t) = \sum_{j=1}^{k-1} \widehat{CW}_j + \hat{X}_k \tau_k \tag{21}$$

where

$$\widehat{CW}_j = \hat{X}_j \tau_j'$$

with τ_j' being the total time elapsed during interval j. Note that $\widehat{X}_j$ indicates the rate of tool wear (see Eq. 10), and the actual tool wear can only be estimated when C is known.

The performance of Method I was tested in digital simulation. The simulation model is given in Eqs. (14) and (15), which in this case ($\beta = 0$) are

$$F_0' = 3000\, b^{-0.1} + noise \tag{22}$$

and

$$\triangle F' = 1200\, W + noise \tag{23}$$

The wear model for the simulation is

$$W = 0.04 + (0.03\, t + 0.0005\, t^2)\,(b\,/\,b_0)^{\delta} \tag{24}$$

where the forces are in Newtons, W is in mm, and $b_0 = 150$ and $\delta = 3$. (These numbers as well as the coefficients in Eqs. (22) through (24) are obtained from cutting steel with carbide tools with b being the cutting speed in m/min.) Notice that the parabolic component in the wear model simulates the accelerated wear at a large t, but the estimation method does not accomodate this term. This results in an estimation error, but it corresponds to practical situations where the wear increase is not precisely linear. Equation (24) is valid for constant cutting conditions. Here, however, we assume variations in the parameter b, and therefore it has to be modified to

$$W = W_0 + \sum_{i=1}^{n} T\,\dot{W}_i = 0.04 + \sum_{i=1}^{n} T\,(0.03 + 0.001\, iT)\,(\frac{b_i}{b_0})^{\delta} \tag{25}$$

where T is the sampling period (in our experiments and simulations $T = 0.5$ second). Note that from Eq. (23), $C = 1200$. Equation (25) was simulated for a varying b_i as shown in Fig. 3a. The resultant force which is used for the estimation includes 5% peak-to-peak Gaussian noise, and is shown at the top of Fig. 3b. The noise intensity in the simulation appears higher than that encountered in practice. Figure 3b also shows the "true" wear and the estimated wear that is obtained by applying a 10-second low-pass filter on the result of Eq. (21), and by assuming known C and W_0 ($C = 1200$ and $W_0 = 0.04$). The error between the "true" and the estimated wear is below 0.05 mm during the entire cutting cycle, which is a good result for practical applications.

3.2 Method II

The second estimation method is used when $\beta \neq 0$ and $\gamma = 0$ in Eqs. (5) or (12). In this case, the relationship defining ΔF_k has the form

$$\triangle F_k = X\, {b_k}^{\beta}\, \tau_k \tag{26}$$

By comparing Eqs. (16) with (26), one might observe that the estima-

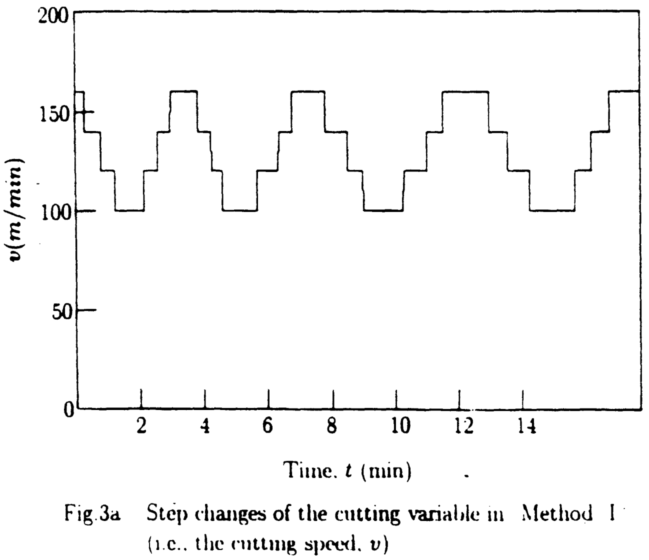

Fig.3a Step changes of the cutting variable in Method I (i.e., the cutting speed, v)

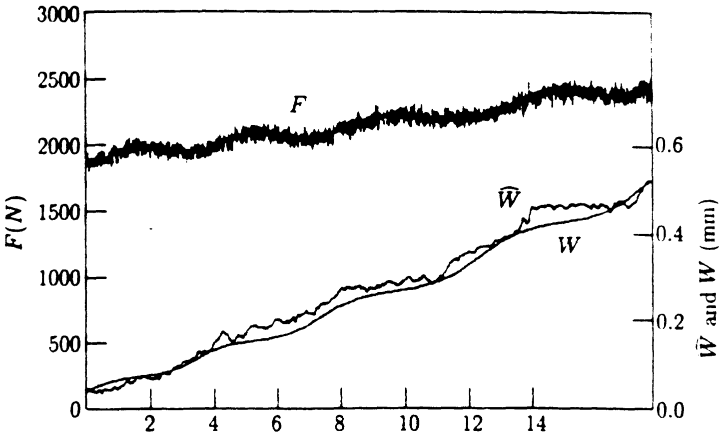

Fig.3b The simulated cutting force, F, and the estimation result (the estimated wear, $\widehat{W}$, verse the true wear, W) in Method I

tion problem is more complex here, since the two parameters X and β must be estimated simultaneously. It should be re-emphasized that in this case we assume that the wear rate, and consequently X, are independent of b. For estimation purposes, the cutting force $F_i(b_k)$ is sampled at constant sampling rate, and a slope, S, defined by

$$S = \frac{\Delta F_k}{\tau_k} = X\, {b_k}^{\beta} \tag{27}$$

is estimated. Each segment has a different slope. In principle S may be calculated from ΔF_k at each sampling period, and then X and β can be estimated by the algorithm presented in Appendix A. However, direct calculation of S from Eq. (27) causes enormous errors, which forces us to introduce a two-step estimation method. First, S is estimated by the method introduced in Method I, using the model

$$F_i(b_k) = \widehat{S}\, \tau_k + F_k(b_k) \tag{28}$$

instead of the model given previously in Eq. (18). The estimated $\widehat{S}$ is subsequently fed, at every sampling point, into a second estimator, by which X and β are calculated. This second estimator is based on the least-squares parameter estimation algorithm given in Appendix A.

In order to use this ordinary least-squares estimator, the estimation model must be linear in its parameters, but the model in Eq. (27) is nonlinear. This requires modification in the model representation. For $S = \widehat{S}$ and a large signal-to-noise ratio, Eq. (27) may be written as

$$\log \widehat{S} = \log X + \beta \log b_k \tag{29}$$

This form of Eq. (29) corresponds to the linear equation

$$y = \boldsymbol{\phi}^{\mathsf{T}}\, \boldsymbol{\theta} \tag{30}$$

where $\boldsymbol{\phi}$ is a vector of known variables, defined here as

$$\boldsymbol{\phi}^{\mathsf{T}} = [\ 1 \quad \log b_k\ ] \tag{31}$$

and $\boldsymbol{\theta}$ is a vector of unknown constant parameters, defined here as

$$\boldsymbol{\theta}^{\mathsf{T}} = [\ \log X \quad \beta\ ] \tag{32}$$

In the second step of the estimation algorithm, $\log X$ and β are determined using the estimated $\widehat{S}$ obtained at the first step. The wear rate is proportional to X, as given by Eq. (10). The estimated wear is subsequently calculated by the accumulation process given in Eq. (21).

The performance of the above method was tested in a simulation. The model used for the simulation of the cutting force is given in Eqs. (14) and (15), with $\alpha = 0.96$ and $\beta = 0.95$, namely

$$F = F_0' + \Delta F' + noise$$

with a noise of 5% of the total cutting force F

$$F_0' = 750 b^{0.96} \tag{33}$$

$$\triangle F' = 500\, b^{0.95}\, W \tag{34}$$

and the wear model in the simulation is

$$W = 0.04 + 0.03\,t + 0.0005\,t^2 \tag{35}$$

namely, the wear is almost a linear function for small t, but also includes a parabolic function of t. The latter simulates the wear acceleration period just before the tool fails. The wear, however, is independent of the cutting variable b, a model that fits the case in which b is the depth of cut.

The estimation process of Method II was tried in a simulation with a varying b. The changes in b are shown in Fig. 4a, and the corresponding cutting force is shown in Fig. 4b. In the estimation process, the force signal is filtered to assure the large signal-to-noise ratio needed to perform the transformation from Eq. (27) to Eq. (29). A low-pass filter with time constant of 2 seconds is used for this purpose. The values of $\log X$ and β are then estimated, and X is subsequently calculated. The variable CW is estimated by the accumulation process given in Eq. (21).

The estimation of CW by the accumulation process does not start until the estimation of β becomes reliable. Figure 4c shows the estimated variable $\hat{\beta}$ which is very sensitive to noise. Reliability of $\hat{\beta}$ is determined by an algorithm that checks the changes in the diagonal component that corresponds to $\hat{\beta}$ in the gain matrix P in Eq. (55). In this case, the accumulation starts automatically at the beginning of the 5th step (after 1.6 minutes). By assuming known C (500) and W_0 (0.04), the estimated wear $\widehat{W}$ may be drawn. Figure 4d shows the values of W and $\widehat{W}$ as estimated by Method II. The differences between the estimated values and the "real" ones are because of the noise sensitivity of the estimation due to taking logarithms in Eq. (29) and due to the fact that Method II assumes a constant wear rate, whereas the "real" wear-rate used in the simulation is $\dot{W} = 500(0.03 + 0.001t)$. The estimation results are good, and the error is less than 0.04 mm. Since we simulate realistic conditions, we believe that practical experiments will provide similar results.

3.3 Method III

This method handles the most comprehensive case in which ΔF in Eq. (5) is affected by the manipulated cutting variable both directly and indirectly (through W). In order to separate these effects, a model of the initial force F_0 must be estimated in the earlier stages of the cut (where the effect of W on the cutting force is small) and used later to estimate the variable CW.

The model of the initial *measured* force is given by Eq. (7) and has the form

$$F_0(b) = K_0'\, b^{\alpha} + C\, b^{\beta}\, W_0 \tag{36}$$

where W_0 is an initial wear developed during the first seconds of the cut. Since in practice the term containing W_0 is small and $\alpha \approx \beta$ (e.g., for b being the depth of cut $\alpha \approx \beta \approx 1$), we obtain

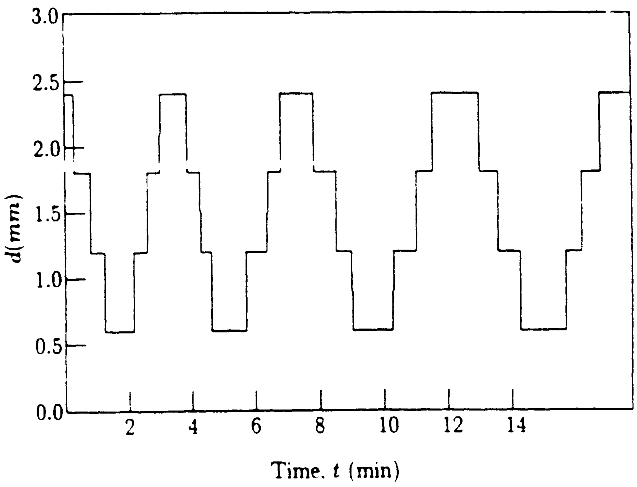

Fig.4a Step changes of the cutting variable in Method II (i.e., the depth of cut, d)

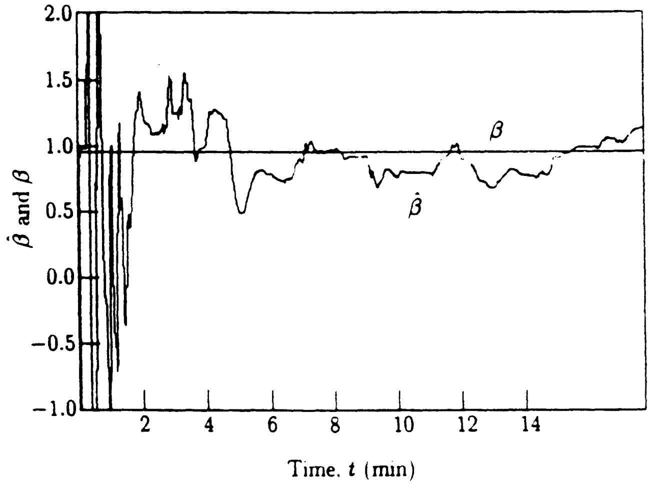

Fig.4c The estimated variable $\hat{\beta}$ verse the true β in Method II

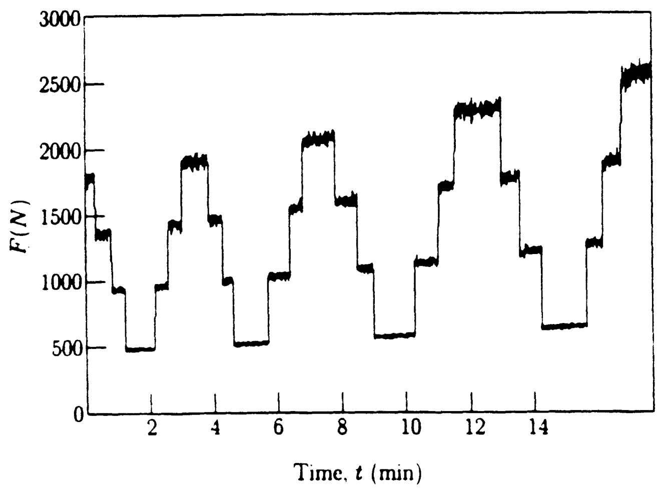

Fig.4b The simulated cutting force, F, in Method II

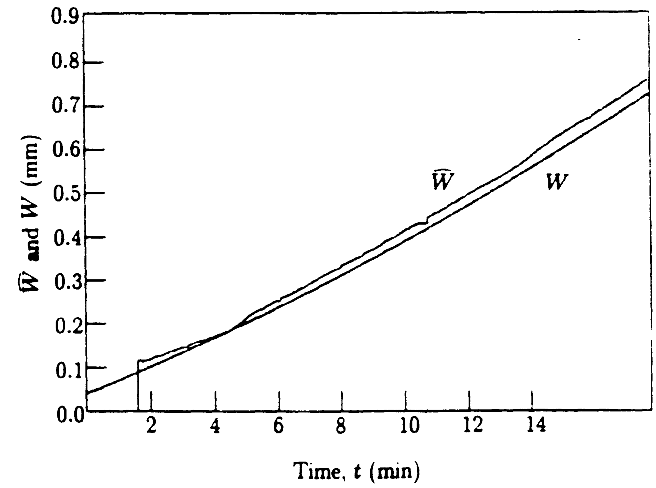

Fig.4d The estimation result (the estimated wear, $\widehat{W}$, verse the true wear, W) in Method II

$$F_0(b) \approx K_0 b^{\alpha} \quad (37)$$

where

$$K_0 = K_0' + C W_0 \quad (38)$$

K_0 and α are the model parameters that should be estimated. In order to use a linear least-squares parameter estimation algorithm, the above model is written in the form

$$\log F_0 = \log K_0 + \alpha \log b \quad (39)$$

The linear least-squares estimation algorithm requires a rich input, namely enough variation on b. For a two-parameter estimation problem, we have to operate the process with at least three values of b. The problem is that during these initial stages the tool wears, which means that the value of W_0 in Eq. (38) varies. Consequently K_0 in Eq. (39) is not constant, and the conventional estimator does not work. To compensate for the tool wear we have developed a special four-step algorithm to estimate the initial-force-model parameters. This estimation algorithm is explained below.

For small wear ($K_0' >> CW$ in Eq. 38) the force model has the form

$$F = K_0 b^{\alpha} \quad (40)$$

where $K_0 = K_0' + CW$. The estimation algorithm is based on the fact that a step change in b (from b_{k-1} to b_k) immediately affects the cutting force, but the wear at this instant remains constant (namely K_0 does not change). This means that the force before the step change is

$$F_{k-1}' = K_0 b_{k-1}^{\alpha_k}$$

and immediately after the step is

$$F_k = K_0 b_k^{\alpha_k}$$

where F_{k-1}' and F_k are shown in Fig. 1. Dividing these two equations yields

$$\alpha_k = \frac{\log(F_{k-1}'/F_k)}{\log(b_{k-1}/b_k)} \quad (41)$$

At each step change of the cutting condition, a value of α_k is obtained. However, as we stated in the discussion of Method I and II, an estimation based on one measured point (i.e., F_{k-1}' or F_k) is unreliable. Therefore we use a linear least-squares estimation algorithm to estimate at each segment the initial force $\widehat{F_k}$ and the slope $\widehat{S}$ from the equation

$$F_i = \widehat{F_k} + \widehat{S_k}\tau_k \quad (42)$$

These estimated values are utilized to calculate the end-of-segment value

$$\widehat{F_k'} = \widehat{F_k} + \widehat{S_k}\tau_k' \quad (43)$$

where τ_k' is the total time elapsed during the segment k. This is the first step of the algorithm. In the second step, the values of $\widehat{F_k}$ (calculated from Eq. 42) and $\widehat{F_{k-1}'}$ (calculated from Eq. 43 for segment $k-1$) are used to calculate α_k in Eq. (41).

Obviously τ' is not long, since we try to keep the estimation period of the initial force model as short as possible. The estimation error in Eqs. (42) and (43) is approximately inversely-proportional to τ', the total observation time of a segment [26]. We have found that the inclusion of the observation time in the estimation of α improves substantially the reliability of the model. This time inclusion is done as follows. First, since according to Eq. (41), α_k depends on the measurements at segments $k-1$ and k, weighting factors m_k defined by

$$m_k = 1/(\frac{1}{\tau_k'} + \frac{1}{\tau_{k-1}'}) = \frac{\tau_k'\tau_{k-1}'}{\tau_k' + \tau_{k-1}'} \quad (44)$$

are calculated. Subsequently, these m_k are used to estimate α by

$$\hat{\alpha} = \sum_{j=2}^{n} m_j\alpha_j / \sum_{j=2}^{n} m_j \quad (45)$$

Finally K_0 in Eq. (37) is calculated by

$$\widehat{K_0} = \widehat{F_1}/b_1^{\hat{\alpha}} \quad (46)$$

with $\widehat{F_1}$ estimated by Eq. (42) for the initial cutting period. (Note that $\widehat{F_1} = \widehat{F_0}(b_1)$.)

To conclude, the estimation algorithm of the initial force model has four steps:

1. Using a least-squares estimation for $\widehat{F_k}$ and $\widehat{F_k'}$ at each of the initial segments.
2. Using these values to estimate α_k by Eq. (41) at the end of each segment.
3. Using a weighting average to obtain $\hat{\alpha}$ by Eq. (45).
4. Using Eq. (46) to obtain $\widehat{K_0}$.

Once the parameters K_0 and α of the force model F_0 in Eq. (37) are identified, the model can be used for different b's during cutting. The model of F_0 with the appropriate b is subtracted from the measured F to compute the variable ΔF during the later stages of the cut for any cutting conditions (see Eq. 10). The obtained ΔF is subsequently used to estimate the flank wear through Eq. (5).

To obtain reliable results, however, the use of ΔF is not straightforward, and the estimation process requires another multi-step algorithm as explained below. Let us assume that the cutting condition changes from b_{k-1} to b_k at time t_k. Based on Eqs. (5) and (6), the force equation before the change is

$$F_{k-1}' = F_0(b_{k-1}) + C b_{k-1}^{\beta} W \quad (47)$$

and after the change in b is

$$F_k = F_0(b_k) + C b_k^{\beta} W \quad (48)$$

Namely, the change in the cutting force ($F_k - F_{k-1}'$) is attributed to two mechanisms : a change in the basic force F_0 and a change caused by the varying contact zone at the tool's flank. Note that W remains constant at t_k. Using the above two relationships one can estimate β_k at each step change :

$$\beta_k = \frac{\log[(F_{k-1}' - F_0(b_{k-1}))/(F_k - F_0(b_k))]}{\log(b_{k-1}/b_k)} \quad (49)$$

The estimation of $\widehat{CW}$ is based on another four-step algorithm, similar to the one used to estimate the initial force model.

1. $\widehat{F_{k-1}'}$ and $\widehat{F_k}$ are estimated by the same procedure used in the estimation of α in Eqs. (42) and (43).
2. At each step, β_k is calculated by Eq. (49), and the force change is calculated by

   $$\Delta \widehat{F(b_k)} = \widehat{F_k} + \widehat{S_k}\tau_k - F_0(b_k) \quad (50)$$

3. Weighting factors m_k' are assigned to each estimated β_k. They are calculated by

   $$m_k' = 1/(\frac{F_k}{F_k - F_0(b_k)}\frac{1}{\tau_k} + \frac{F_{k-1}'}{F_{k-1}' - F_0(b_{k-1})}\frac{1}{\tau_{k-1}'}) \quad (51)$$

   where the terms $F_k/(F_k - F_0(b_k))$ and $F_{k-1}'/(F_{k-1}' - F_0(b_{k-1}))$ are needed for normalization. Subsequently, β is estimated by the following averaging process

   $$\hat{\beta} = \sum_{j=n}^{k} m_j'\beta_j / \sum_{j=n}^{k} m_j' \quad (52)$$

4. The estimated $\hat{\beta}$ and the estimated change at the step $\Delta\widehat{F(b_k)}$ by Eq. (50) are used to estimate $\widehat{CW}$ from the equation :

$$\widehat{CW} = \frac{\Delta \widehat{F(b_k)}}{b_k^{\widehat{\beta}}} \quad (53)$$

As mentioned earlier, this method is sensitive to any random variations in F'_{k-1} and F_k, estimation errors, or modeling errors of F_0 (see Appendix B for a sensitivity analysis). However, as demonstrated by the simulation result below, our algorithm is very robust and gives good results despite this high sensitivity. It should be emphasized again that the changes in b should be made in steps, and the method does not work for cases where a cutting condition is changed gradually (e.g., the depth of cut in cutting a cone on a lathe).

The performance of Method III was tested in simulation. The model used for the simulation is defined by Eqs. (14), (15), and (24) with $\alpha = 0.64$, $\beta = 0.6$, $\delta = 1.5$, $K'_0 = 4400$, $C = 2800$ and $b_0 = 0.25$. This model fits perturbations on the feed, given in *mm/rev*, and force given in Newtons. Figure 5a shows the changes in b in the simulation. The simulated force signal which contains 5% noise is shown in Fig. 5b. To decrease the effect of the noise on the estimation of F'_{k-1} and F_k, the force signal passes through a low-pass filter. The two four-step estimation algorithms are then applied. The resulting estimated wear (filtered with a 10-second low-pass filter) is plotted in Fig. 5b together with the "true" wear. The tool wear estimation does not start until the estimation of β becomes reliable. The reliability of β is tested by an algorithm that checks the magnitude of $\sum m'_j$. The estimated β for the simulated case is shown in Fig. 5c, and tool wear estimation starts only after 3.9 minutes. As seen in Fig. 5b, the estimated tool wear follows the "true" wear closely with a maximum error of 0.06 mm, which is acceptable for many applications in which the tool wear is needed.

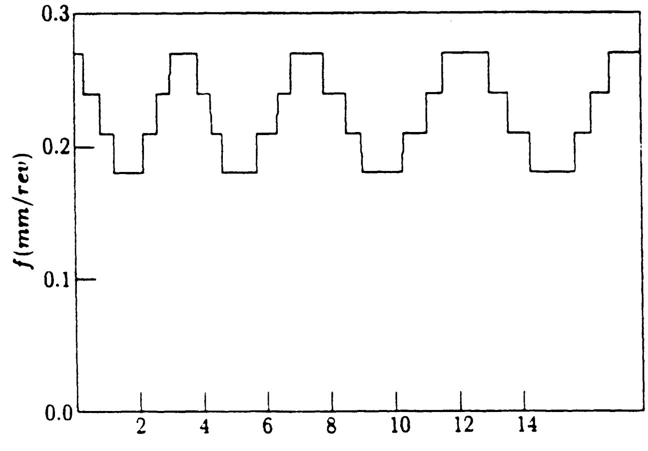

Fig.5a Step changes of the cutting variable in Method III (i.e., the feed, f)

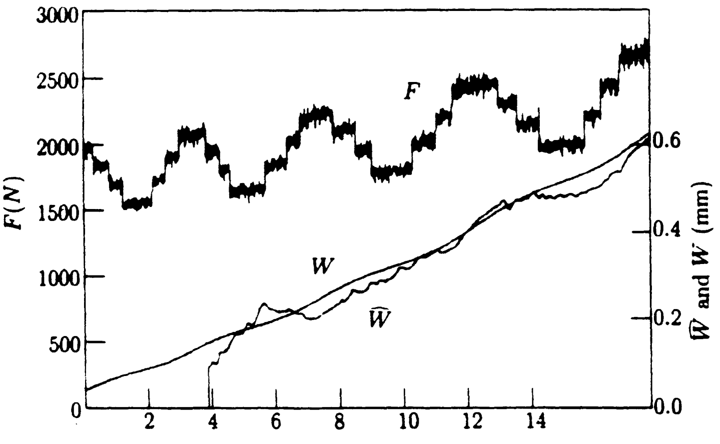

Fig.5b The simulated cutting force, F, and the estimation result (the estimated wear, $\hat{W}$, verse the true wear, W) in Method III

Table 1: Cutting variables, tool and workpiece material

Test No.	Tool	Workpiece	Feed	Cutting Speed
1	TNWA 431F	4340 ann'd	0.0254 mm/rev (0.001 in/rev)	366 m/min (1200 ft/min)
2				
3	TNMA 433E			
4				

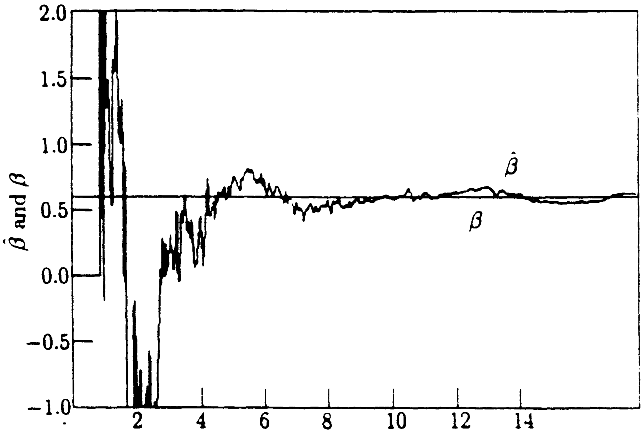

Fig.5c The estimated variable $\hat{\beta}$ verse the true β in Method III

4 Experiments

In order to test the performance of the estimator in practice, turning experiments were designed and performed. Only Method II was tested, which requires changes in the depth of cut.

The methods proposed assume flank wear to be the dominant type of tool wear. Therefore, cutting conditions were selected to produce mainly 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 (without crater wear), so that long cuts were avoided. Four tests were performed, of which three were continued until the tool failed. During these tests the depth of cut was changed in steps of 0.64 mm (0.025 inch) or 1.28 mm. Figures 6 and 7 show the variations of the depth of cut in two of the above tests and the normal component of the cutting force. The length of cut along the bar for each cutting segment was 7.62 mm (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 using 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 was *DEC LSI-11/23 Plus* which used a 12 bit *ADV-11-C A/D* converter. The sampling frequency used for digitization was 2 Hz which was sufficient in keeping track of tool wear that 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.

The sampled cutting force signal contained a fair amount of noise which had to be filtered. For this purpose a first order software filter with a time constant of 2 seconds.

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

was applied. More elaborate filter designs may give better results [27].

According to our basic assumption for tool wear estimation, the slope of the force signal should be either positive 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 the estimation.

The filtered cutting force data were used for tool wear estimation. The estimation results are shown in Figure 8. To compare the estimated wear ($\widehat{W}$) and the real flank wear (W), direct measurements using a microscope were taken at regular intervals. Figure 9 shows W vs. $\widehat{W}$ for seven data points. The on-line method allows only the estimation of ($\widehat{CW} - CW_0$) and not $\widehat{W}$. Thus off-line tool wear measurements are needed to determine the values of W_0 and C, so that $\widehat{W}$ can be calculated from $\widehat{CW}$. In many cases, however, the tool changing criterion is the start of the accelerated wear region. In these cases we are interested only in the wear rate which is proportional to X_k, and the determination of C and W_0 is not needed.

5 Discussion

Though the force signals, with which the proposed methods were tested, were generated by simulations, these signals are very similar to those obtained in real production. They contain noise of realistic intensity, and a realistic wear model that contains a parabolic component that simulates the acceleration in wear rate. Therefore, the simulation studies provide a realistic assessment of the methods proposed.

Note that the wear estimates are based on the assumption of availability of the values of the initial tool wear W_0, and of the parameter C which relates the cutting force and tool wear. These two values may not be readily obtainable. The initial tool wear for each new tool appears to be scattered around a certain value [28] and to be independent of the initial cutting conditions. Due to this uncertainty in the initial wear value, the tool wear estimation might have an additional error. However, if the initial wear varies within the range of 0.04 ± 0.02 mm, the accuracy of the tool wear estimation will not be greatly affected. Also note that if only the wear rate is needed, then the value of W_0 is not required at all. The parameter C is related to the material properties of the tool and workpiece [29], and may be considered a constant if these properties remain unchanged. Usually, the value of C is obtained from off-line experiments.

An alternative method to obtain the values of W_0 and C might be to use a few direct measurements of tool wear (e.g., with a vision system) for calibration. These measurements may be taken during loading of the workpieces. In principle, only two such measurements are needed to calibrate the estimated wear curve, but in practice more measurements are required.

The last point to be considered is that, in Methods II and III, tool wear can be estimated only after some initial observation period. Thus no wear estimation is available at the beginning of the cut. This does not create a problem, however, since the tool wear information is needed only at the later stages of the cutting process, when the tool wear approaches some allowable limits at which on-line dimensional compensation should start, or when the tool should be replaced.

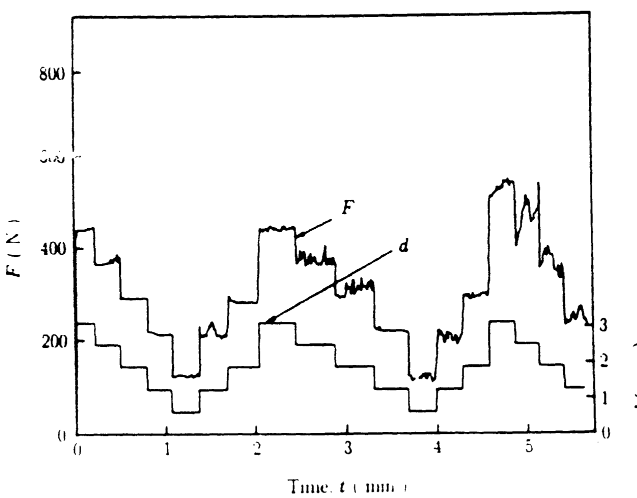

Fig 6 Normal cutting force component, F, and the depth of cut, d, of the 1st test

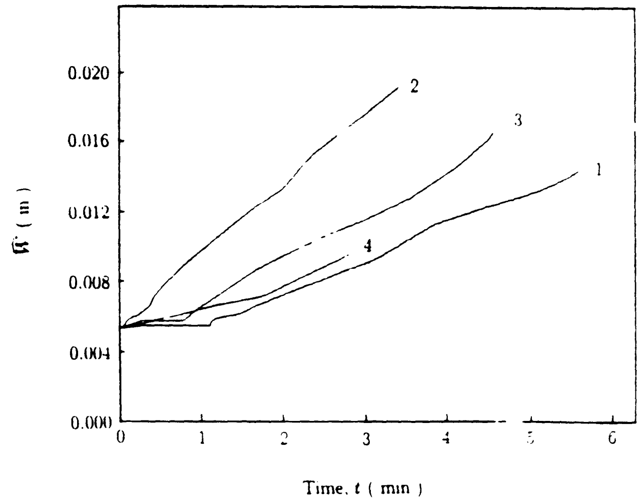

Fig 8 Estimated wear, $\widehat{W}$ (Test numbers are shown)

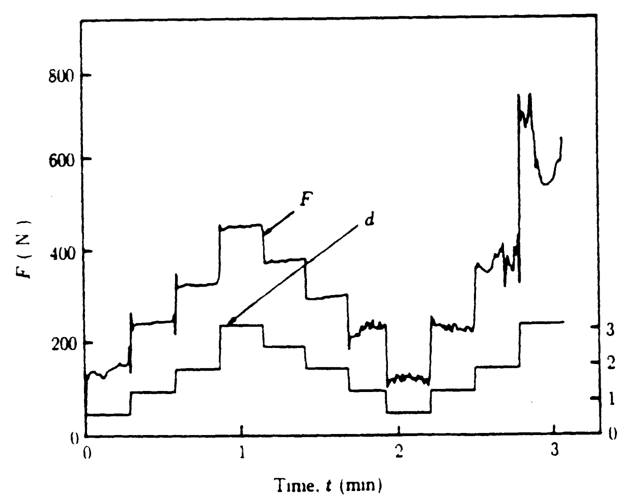

Fig 7 Normal cutting force component, F, and the depth of cut, d, of the 3rd test

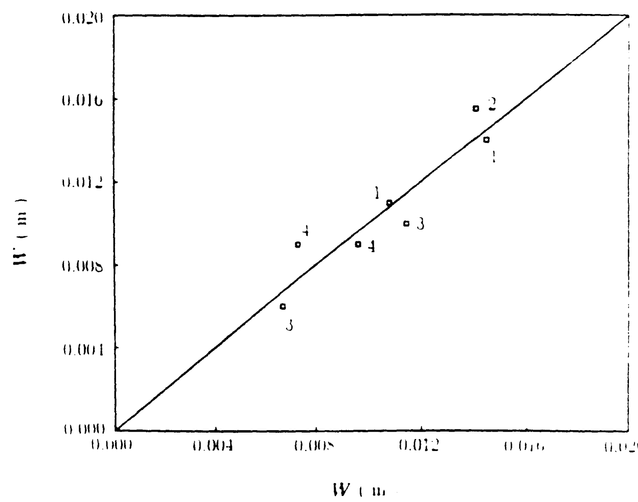

Fig 9 Estimated wear, $\widehat{W}$, verse measured wear W (Data from different tests are numbered)

6 Conclusions

Three methods were proposed to estimate flank wear for varying cutting conditions in turning. These methods may be applied when one cutting condition varies in steps, and utilize simple and practical models for which only a few parameters need to be estimated. Recursive least-squares methods are used for the estimation of these parameters. Simulated cutting forces with realistic noise levels are used to evaluate all the methods. These simulations also account for possible wear rate modeling errors, and give good results. These methods, therefore, are considered to be applicable in real cutting processes. When implemented, they can provide on-line flank wear information between isolated off-line measurements and reduce the uncertainty of wear prediction based on off-line models. Experimental evaluation of Method II was also performed, under stepwise changing depth-of-cut in turning. The flank wear estimates are quite good in all four experiments reported after about the first minute of cutting. These experimental results further reinforce the main conclusion from the simulation studies, that the proposed methods can utilize force measurement to reliably estimate flank wear in turning under varying cutting conditions. The cutting variables must vary one at a time in a stepwise constant manner and the effect of crater wear must be negligible.

7 Acknowledgement

The authors are pleased to acknowledge the support of the National Science Foundation (Grant # DMC 8606239) for this work.

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] Peklenik, J., "Geometrical Adaptive Control of Manufacturing Systems," *Annals of the CIRP*, Vol. 18, No. 2, 1970, pp. 265-272.

[4] Koren, Y., *Computer control of Manufacturing Systems*, Chap. 8, McGraw-Hill Book Co., New York, 1983.

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

[6] 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.

[7] 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.

[8] Cook, N. H., Subramanian, K., and Basile, S. A., "Survey of the State of the Art of Tool Wear Sensing Techniques," M.I.T. report for NSF Grant No. GI-43861, Sep. 1975.

[9] 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.

10] 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.

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

[12] Pandit, S. M., and Kashou, S., "A Data Dependent Systems Strategy of On-Line Tool Wear Sensing," *ASME Journal of Engineering for Industry*, Vol. 104, August 1982, pp. 217-223.

[13] 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.

[14] Rao, S. B., "Tool Wear Monitoring Through the Dynamics of Stable Turning," *ASME Journal of Engineering for Industry*, Vol. 108, Aug. 1986, pp. 183-190.

[15] 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.

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

[17] Jiang, C. Y., Zhang, Y. Z., and Xu, H. J., "In-Process Monitoring of Tool Wear Stage by the Frequency Band-Energy Method," *Annals of the CIRP*, Vol. 36, No. 1, 1987, PP. 45-48.

[18] Usui, E., Shirakashi, T., and Kitagawa, T., "Analytical Prediction of Cutting Tool Wear," *Wear*, Vol. 100, 1984, pp. 129-151.

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

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

[21] Ber, A., and Kaldor, S., "The first seconds of cutting, wear behaviour," *Annals of the CIRP*, Vol. 31, No. 1, 1982, pp. 13-15.

[22] Von Turkovich, B. F., "Metal Cutting : A Look Towards the Future," ASME, PED-Vol. 1, pp. 1-16, 1980.

[23] Trent, E. M., "Tool Wear and Machinability," *Institution of Production Engineers Journal*, March 1959, pp. 3-28.

[24] Danai, K., and Ulsoy, A. G., "Dynamic Modeling of Cutting Forces in Turning, Drilling, and Milling from Experimental Data," *Control Methods for Manufacturing Process*, DSC-Vol. 9, ASME, 1988, pp. 27-34.

[25] Kronenberg, M., *Machining Science & Application*, Chap. 9, Pergamon Press Inc., 1966.

[26] Ko, T. R., *Ph.D. Thesis*, 1989, U. of Michigan.

[27] Tomizuka, M., "Zero Phase Error Tracking Algorithm for Digital Control," *Journal of Dynamic Systems, Measurement, and Control*, Vol. 109, 1987, pp. 65-68.

[28] Koren, Y., "A Variable Cutting Speed Method for Tool Life Evaluation," *Proceedings of the 4th International Conference on Production Engineering*, Tokyo, 1980, pp. 530-534.

[29] Zorev, N. N., *Metal Cutting Mechanics*, Pergamon Press, 1966.

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