Tool Wear and Breakage Detection Using a Process Model

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On-line sensing of tool wear and breakage in machining has been a long standing goal of the manufacturing community. Wear and breakage detection systems are typically based on force, acoustic emission, current or temperature measurement. They are important for reliable unmanned operation, and also for implementation of an adaptive control optimization system. This paper proposes a model-based approach to on-line tool wear and breakage detection under varying cutting conditions based on force measurement. The proposed model is used together with on-line parameter estimation to track flank wear during cutting. The proposed method is illustrated with a simulation study, the results of which confirm the feasibility of the model-based approach.

1. INTRODUCTION

A successful tool wear/breakage sensor has been a long standing goal of the manufacturing community [1-8]. In addition, a wear sensor has always been regarded as a necessary step toward the implementation of an adaptive control optimization system [6,9,10]. Wear and breakage detection systems are typically based on acoustic emission, motor current, temperature measurement, or cutting force.

Acoustic emission [11-16] and vibration [17] measurements are receiving a great deal of attention due to the non-obtrusive nature of the transducers, but important signal processing problems still remain to be solved. Current monitoring is the simplest method for dc motor driven machine tools[18-19], but suffers from sensitivity and time lag problems. Temperature measurement is particularly important for wear [20-22], however, a practical on-line transducer has yet to be developed [7]. With all these methods the tool wear or breakage are measured indirectly through another system variable. Direct methods based on optical or radiometric techniques have been demonstrated, but not yet proven to be practical [23,24].

Among the indirect methods those based on force and torque sensing [25-28] are perhaps the most developed. Such commercial units have begun to appear on the market in recent years, and have been used with some success in certain limited production situations. With this recent introduction of the first commercial tool wear/breakage sensors it is worthwhile to evaluate these sensors and to reassess their economic advantages [29-30]. For this purpose the machining operations can be divided into roughing and finishing cuts. In roughing operations one can consider two distinct types of production:

1. short production cycles (e.g., $t < 5$ min)
2. long production cycles (e.g., $t > 10$ min)

The first situation is frequently encountered in high volume production, while the second situation occurs in the production of large complex workpieces, or in the machining of hard materials such as titanium.

The importance of wear sensing, breakage detecting, and adaptive control is summarized according to the production mode in Table 1. As can be seen tool breakage detection is economically important in all machining operations except finishing operations. Tool wear sensing is important as a predictor of tool failure due to excessive wear. In long production cycle manufacturing operations, tool wear detection becomes important for surface roughness considerations. Tool wear sensing is also important in finishing cuts due to the effect on product quality.

Commercially available systems for wear and breakage detection are typically based on force or power limits. When the measured force falls outside these predetermined fixed limits the tool is assumed to have failed due to excessive wear or breakage. The disadvantage of the fixed force limit method is that the cutting conditions must remain nearly identical throughout the whole cutting operation, and therefore this is applicable only in very simple cases.

To extend the force limit approach to various cutting conditions, force signature methods typically use "learning" or "averaging" strategies. These methods, however, have the following disadvantages:

1. many parts must be cut to allow the system to learn the force signature
2. the method is not effective in long production cycle situations
3. the method is not applicable in adaptive control(AC), because in AC cutting conditions are not repetitive from one part to another

Table 1 also summarizes the importance of various types of adaptive control systems. Adaptive control is not particularly significant in high volume/short production cycle manufacturing. Geometric adaptive control (GAC) is important in finishing operations [31-34]. In manufacturing operations with a long production cycle, both adaptive control optimization (ACO) and adaptive control with constraint (ACC) type systems are important.

The tool wear sensor is also a necessary component in ACO systems for turning and milling [8-10, 35]. There is a fundamental difference, however, between using a tool wear monitoring system (which operates in open-loop) and applying the same sensor in a closed-loop adaptive control system. ACO systems (e.g., the mid 1960's Bendix System [9]) are based on maintaining the optimal cutting conditions by incrementing the feed and/or cutting speed in small steps. However, in practice an indirect measurement of the tool wear is used, and feeding back the sensor signals in order to close the ACO loop is not a straightforward task.

For example, assume that the tool wear is monitored through measurements of the cutting force. Typically, increasing wear increases the magnitude of the output signal of this sensor. An incremental increase in the feed (as may be executed automatically by the ACO system) will have two effects:

1. Since the cutting force is directly dependent on the feed, an increase in the feed causes a consequent increase in the cutting force. This is the direct effect.
2. An increase in the feed shortens the tool life, namely increases the tool wear rate. As a consequence the wear increases and the force again becomes larger. This is the indirect effect.

An ACO system should use only the latter effect. However, since both mechanisms affect the cutting force similarly, the problem of isolating the second effect from the first is not trivial. One might say that the direct effect happens almost immediately (theoretically after one revolution of the spindle), while the other mechanism affects the force after "some time". However, since the ACO convergence strategy is based upon incremental feed variations, and the signal-to-noise ratio in force measurements is low, it is difficult in practice to isolate the two phenomena by using simple electronics.

A solution to this problem might be obtained by programming a mathematical model of the cutting process and updating it in real time in order to obtain an accurate estimation of the two effects. The separation of the two effects has another significant outcome: it permits the separate detection of tool breakage and excessive tool wear. Tool breakage is detected by a sudden change in the force due to the first (direct) effect, whereas wear can be sensed by changes in the force due to the second (indirect) effect. By contrast to the fixed limits and the force signature approaches, this proposed method does not require the cutting of many parts for the learning mode, and is also effective in long production cycles.

2. THE FORCE EQUATION

Before proceeding to the model-based approach of this paper, we would like to further clarify the problem introduced at the end of the previous section by using a simplified mathematical analysis. The relation between each component of the cutting force F and the flank wear W is approximated by [36]

$$F = F_o + aC_w W \tag{1}$$

where F_o is the initial cutting force (with a sharp tool), a is the depth of cut, and C_w is a constant for a certain tool and workpiece material and a fixed set of cutting conditions (feed f and speed v). Equation (1) has been experimentally verified (see Fig. 1) for cases in which flank wear has the dominant effect on tool life. The initial cutting force is given by

$$F_o = \alpha a f^{\ell} \tag{2}$$

where α and ℓ are constants depending on the tool and workpiece material; typically $0.6 < \ell \leq 1$.

If the wear is assumed to be in its linear progression zone (see Fig. 2) it obeys the equation

$$W = W_o + \frac{W_f - W_o}{T - T_o} t \approx \gamma(t) \frac{W_f}{T} t \tag{3}$$

where T is the tool life, W_f is the corresponding wear at which the tool is replaced, and $\gamma(t)$ is a slowly time varying function used to account for the non-constant slope of the flank wear curve. Combining Eq.(1) and (3) yields the following force equation:

$$F = F_o + F_1 t \tag{4}$$

where

$$F_1 = \gamma(t) a C_w W_f / T \tag{5}$$

An acceptable model for T is the extended Taylor's tool life equation

$$C v^n f^m T = 1 \tag{6}$$

substituting T from Eq.(6) into Eq.(5) yields

$$F_1 = \gamma(t) \beta a v^n f^m \tag{7}$$

where $\beta = CC_w W_f$ and is assumed to be constant in the linear progression zone of the wear curve. The signal that an indirect tool wear detector transmits is proportional to F in Eq. (4). However, only the term $F_1 t$ is proportional to the wear and therefore it should be separated from F (and be inserted as feedback to the ACO control loop). Thus, a wear sensor based on force measurements must resolve the following problems:

1. The real-time separation of the term $F_1 t$ in Eq.(4), particularly under continuously changing cutting conditions.

2. Since the coefficients F_o and F_1 depend on the depth of cut, feed, and speed, any change in these process variables might be interpreted by the system as a change in W.

3. The coefficients (F_o and F_1) in Eq.(4) depend not only on the cutting conditions, but also on the tool and workpiece material. They must be estimated accurately in real time in order to enable the identification of the level of wear increase.

In order to solve these problems, the coefficients (α, β, γ) and the exponents (ℓ, n, and m) in Eqs. (2) and (7) must be known. The exponents n and m of the Taylor's tool life equation have been traditionally determined from off-line experiments [37]. These tool life estimates have not been sufficiently accurate due to variations in material properties and cutting conditions. On-line tool wear monitoring using force measurement was initially based on correlations between force and wear for various constant cutting conditions and known materials [26-28, 36]. These results, although useful, require extensive off-line testing and are limited in applicability. Some of these methods have been extended even further by using "learning" or "averaging" techniques to account for process variability [4,24,25]. These approaches and others [38-40] are all basically empirical, and utilize on-line or off-line estimation methods to develop simple relationships between the measured forces and wear.

Wear and breakage have also been investigated from a more fundamental viewpoint by researchers who attempt to identify and quantify the mechanisms of wear in metal cutting [41-48]. Mechanically activated (e.g., abrasion and adhesion) and thermally activated mechanisms have been proposed for flank wear [43]; and crater wear is generally attributed to thermally activated mechanisms [48]. These mechanistic models have provided a better understanding of the problem of tool wear, but have been too complex to be of practical use.

Our proposed approach, described in the following section, builds on these previous studies to develop a model-based wear and breakage system which uses force sensing and is suitable for variable cutting conditions.

3. ESTIMATION OF PROCESS PARAMETERS

The estimation of the unknown coefficients α and β, and the unknown exponents ℓ, m and n in Eqs. (2), (4) and (7) can be accomplished by on-line (recursive) parameter estimation methods. In this paper the standard recursive least squares (RLS) algorithm is used [49, 50],

$$\boldsymbol{\theta}(k+1) = \boldsymbol{\theta}(k) + \frac{\mathbf{P}(k)\boldsymbol{\phi}(k)[y(k+1) - \boldsymbol{\phi}(k)^T \boldsymbol{\theta}(k)]}{\lambda(k) + \boldsymbol{\phi}(k)^T \mathbf{P}(k)\boldsymbol{\phi}(k)} \tag{8}$$

and,

$$\mathbf{P}(k+1) = \frac{1}{\lambda(k)}\left[\mathbf{P}(k) - \frac{\mathbf{P}(k)\boldsymbol{\phi}(k)\boldsymbol{\phi}(k)^T \mathbf{P}(k)}{\lambda(k) + \boldsymbol{\phi}(k)^T \mathbf{P}(k)\boldsymbol{\phi}(k)}\right] \tag{9}$$

where y(k) is the value of the measured variable at time $t = k\Delta t$ for k = 0, 1, 2, 3, ..., $\boldsymbol{\phi}(k)$ is a vector of measured (or known) variables, $\lambda(k)$ provides exponential data weighting, and $\boldsymbol{\theta}(k)$ is a vector of parameter estimates. The $\mathbf{P}(k)$ is the matrix of estimation gains. The above algorithm recursively updates the estimated parameter vector $\boldsymbol{\theta}(k)$ for any process whose equations can be written in the form,

$$y(k) = \boldsymbol{\phi}(k)^T \boldsymbol{\theta}(k) \tag{10}$$

Thus, the process model must be written in a form that is linear in the unknown parameters, which are the elements of the vector $\boldsymbol{\theta}(k)$.

For the process model presented in the previous section, we first consider the estimation of α and ℓ using Eq. (2). When the tool is sharp, the term $F_1 t$ in Eq. (4) is approximately zero, and one can write

$$F \approx F_o = \alpha a f^{\ell}$$

This, can be rewritten in the form of Eq. (10) by taking natural logarithms of both sides,

$$\ell n F = \ell n \alpha + \ell n a + \ell(\ell n f) \tag{11}$$

or,

$$(\ell n F - \ell n a) = [1 \;\; \ell n f] \begin{Bmatrix} \ell n \alpha \\ \ell \end{Bmatrix} \tag{12}$$

So, initially the estimation algorithm in Eqns.(8) and (9) is used with,

$$y(k) = \ell n F(k) - \ell n a(k)$$

$$\boldsymbol{\phi}(k)^T = [1 \;\; \ell n f(k)]$$

$$\boldsymbol{\theta}(k)^T = [\ell n \alpha \;\; \ell]$$

to estimate α and ℓ. Then, assuming that α and ℓ remain constant during the cutting operation, one can calculate

$$F_o(k) = \alpha a f(k)^{\ell}$$

Next, use the same RLS algorithm with Eq.(4) to estimate β, m, and n in Eq.(7). For example, if we assume that $\gamma(t) = 1$, and β, m, and n are all unknown and constant, taking natural logarithms of both sides of the equation gives,

$$\ell n(F(k) - F_o(k)) = \ell n \beta + \ell n a(k) + m \ell n f(k) + n \ell n v(k) + \ell n t$$

now define,

$$y(k) = \ell n[F(k) - F_o(k)] - \ell n a(k) - \ell n t$$

$$\boldsymbol{\phi}(k)^T = [1 \;\; \ell n f(k) \;\; \ell n v(k)]$$

$$\theta(k)^T = [\ell n\beta \ m \ n]$$

to estimate β, m, and n.

The RLS estimation algorithm requires that one select initial values for θ(k). These selections can either be made from typical values of α, β, ℓ, m, and n as published in the literature [36, 37], or assigned arbitrarily. Initial values of the gain matrix **P**(k) are usually selected to be of the form,

$$\mathbf{P}(o) = \delta \mathbf{I}$$

where **I** is the identity matrix, and the scalar constant $\delta > o$ is chosen by trial and error through simulation studies. The RLS algorithm is typically not too sensitive to the choice of **θ**(0) and **P**(0).

The choice of the weighting factor λ(k) in Eqs.(8) and (9) is more significant. The standard RLS algorithm is obtained when $\lambda(k) = 1$. When it is necessary to track parameters with a value that may jump or vary slowly with time, a value of $o < \lambda(k) < 1$ exponentially weights the data to ensure the "alertness" of the algorithm [49, 50]. In the simulation results presented in the next section a value of $\lambda(k) = 1$ was used. In those simulation studies scaling and factorization of the **P**(k) matrix into upper triangular and diagonal factors was also used. Such measures are often required in practice to eliminate numerical problems [49,50]. For a process model as in Eq.(10) with constant coefficients it can be proven that the RLS algorithm ensures convergence of the estimation error $\varepsilon(k) = y(k) - \boldsymbol{\phi}(k-1)\boldsymbol{\theta}(k-1)$ to zero. To ensure that the parameter estimates **θ**(k) convergence to the actual parameter values, there is an additional requirement on the richness (frequency content) of the process inputs. For further discussion on estimation algorithms the interest reader is referred to [49, 50].

4. SIMULATION RESULTS

In this section we present simulation results to illustrate the model-based approach to tool wear and breakage detection as outlined in the previous sections. The basic scheme is illustrated in Figure 3, where the "process model" block is based on the model presented in Eqs.(2),(4), and (7). The "adaptation algorithm" is based on the RLS algorithm presented in Eqs.(8) and (9). For the purposes of this simulation study the "cutting process" is represented by a model described previously in [48]. That model is more detailed than the simple process model presented here and accounts for crater wear as well as flank wear due to both thermally and mechanically activated mechanisms. Results presented in [48] show that the model gives good results for force, temperature, flank wear, and crater wear. The model equations as well as the cutting conditions used in the simulation are summarized in the Appendix. Under these cutting conditions flank wear dominates, and the effect of crater wear is negligibly small.

To provide sufficient input richness for prameter convergence using the RLS algorithm, the feed f(t) is varied as shown in Fig.4, by ± 0.025 mm/rev about the nominal value of 0.35 mm/rev. The simulated flank wear and force versus time are shown in Figs.5 and 6 respectively. Note that there is initially a rather high wear rate followed by a relatively constant wear rate for $3 < t < 10$ min. For $t > 10$ minutes the wear rate again increases and the useful life of the tool is $T \approx 11$ minutes. The simulated force shows the effects of the variations in feed, and also an increase in level due to increasing flank wear.

The RLS algorithm in Eqs.(8) and (9) is used to first estimate α and ℓ using Eq.(12). This estimation is carried out during the first few sampling periods and leads to constant values of $\alpha = 4300$ and $\ell = 0.877$. Next, assuming that α and ℓ remain constant, F_0 is calculated and used to estimate the F_1 term in Eq.(7). The estimate of F_0 (i.e., $\hat{F}_0$) is shown in Fig. 7, and is quite effective in separating the effects of feed variations on force from those related to the flank wear on the tool. In the simulation v = 300 m/min is constant, a = 2.5 mm is constant, and m = 1 is assumed to be known, so we use the following form of Eq.(7): $F_1 = \gamma(t)\beta f$ where we have found that $\gamma(t) = t^p$ gives good results in the estimation. As shown in Figs.8 and 9, when the wear is in the constant wear rate region the estimated values are,

$$\beta \approx 80$$

$$p \approx -0.1$$

These lead to good agreement between the actual $F_1 t$ and the estimated $F_1 t$ (i.e., $\hat{F}_1 t$), as shown in Figure 10, for the constant wear rate region. When the tool wear rate increases, the error

$$e = F_1 t - \hat{F}_1 t$$

becomes large, and serves as a good indicator of tool failure. Thus, the simulation results shown in Figs.4 - 10 illustrate the potential usefulness of the model-based approach for separating the effects of feed and flank wear on force and for predicting tool failure due to excessive flank wear.

5. SUMMARY AND CONCLUSIONS

This paper has presented a model-based approach to on-line tool wear and breakage detection in metal cutting. Such a model-based approach is considered important for machining under variable cutting conditions, and for use with adaptive control systems that automatically adjust feedrates. The basic approach has been developed, and illustrated with a simple simulation example.

The simulation results confirm the feasibility of the proposed model-based approach, and indicate the need for further research to obtain experimental confirmation. Further research may also be desirable on process modeling, estimation algorithms, and on-line training of the model-based approach by using artificial intelligence methods.

6. REFRENCES

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7. APPENDIX

The "cutting process" in Fig. 3 is simulated using the following model from [48],

$$\dot{W}_1 = (v/\ell_o)(-W_1+K_1 \cos \alpha_r (F/fa))$$

$$\dot{W}_2 = K_2 \sqrt{v}\ \exp(-(K_3/(273+\theta_f)))$$

$$\theta_f = K_4 V^{n1} f^{n2} + K_5(W_1+W_2)^{n3}$$

$$F = [K_6 f^{n4}(1-K_7\alpha_r) - K_8 - K_9 v]\, a + K_{10} a\, (W_1+W_2)$$

where W_1 is the mechanically activated component of flank wear, W_2 is the thermally activated component of flank wear, θ_f is the temperature at the tool flank, v is the cutting speed, f is the feed, a is the depth of cut, and F is the cutting force. The parameters K_i and exponents ni are selected to be typical of turning steel with a carbide tool [48]. The values used in the simulation study are,

a	= 2.5mm	K_6	= 1960
f	= 0.35 mm/rev	K_7	= 0.57
v	= 300 m/min	K_8	= 86
α_r	= 10^o	K_9	= 0.1
ℓ_o	= 500	K_{10}	= 500
K_1	= 5.2×10^{-5}	n1	= 0.4
K_2	= 15	n2	= 0.6
K_3	= 8000	n3	= 1.45
K_4	= 72	n4	= 0.76
K_5	= 2500	Δt	= 0.05 min.

	TYPE OF OPERATION		
	ROUGHING CUT		FINISHING CUT
	SHORT PRODUCTION CYCLE/HIGH VOLUME	LONG PRODUCTION CYCLE	
COMMENTS ON BREAKAGE	Important; force signature method can be used	Important; force signature method not suitable	Not important
COMMENTS ON WEAR	Important only as a predictor of failure due to excessive wear	Important for predicting failure and eliminating excessive surface roughness	Important due to effect on part dimensions and surface finish
COMMENTS ON ADAPTIVE Control	Not important	Both ACO and ACC are important	GAC is important

Table 1. Summary of Comments on the Importance of Wear, Breakage, and Adaptive Control

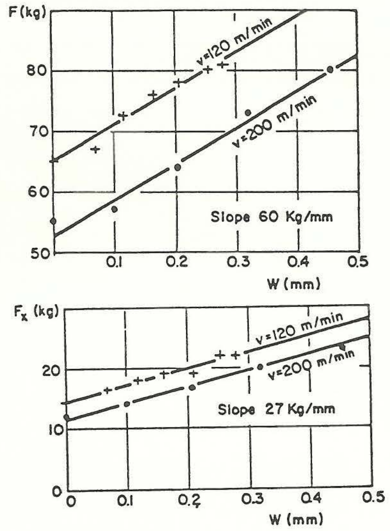

Fig.1 Cutting Force versus Wear [36]

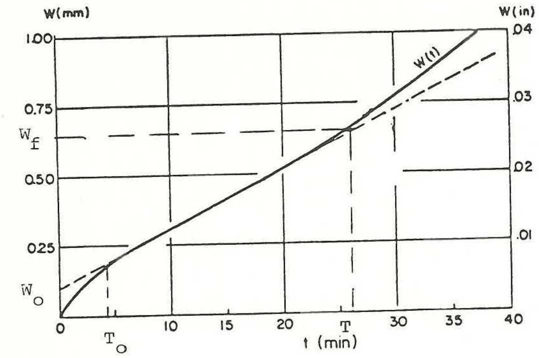

Fig.2 Typical Wear Curve

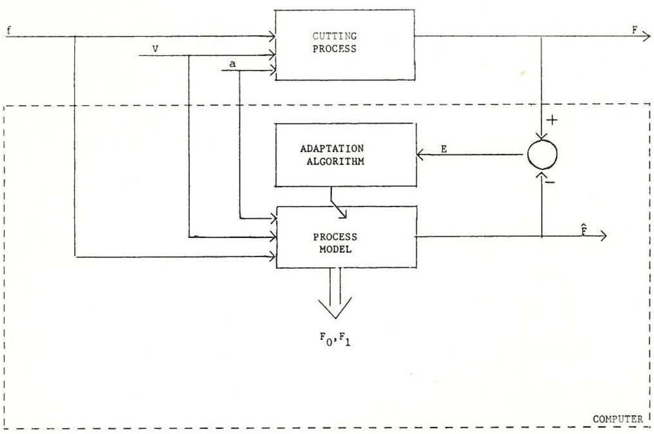

Fig.3 Schematic of the Proposed Model Based Approach

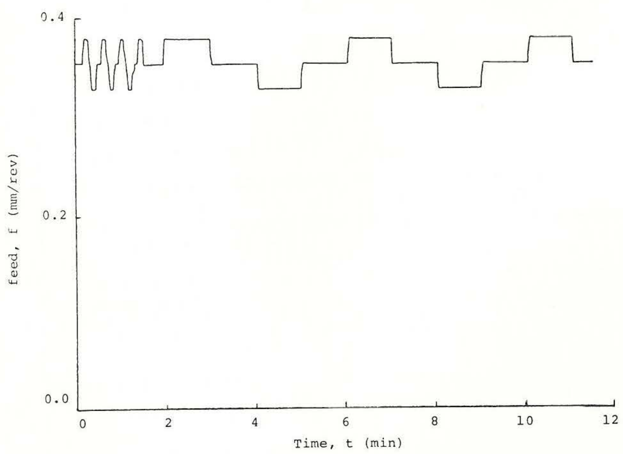

Fig.4 Feed Versus Time for the Simulation Example

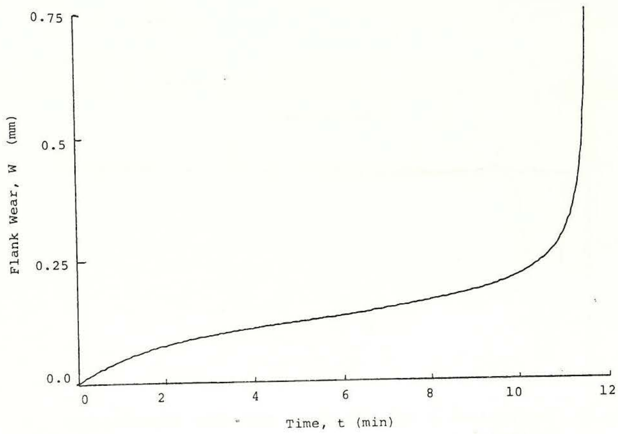

Fig.5 Flank Wear Versus Time for the Simulation

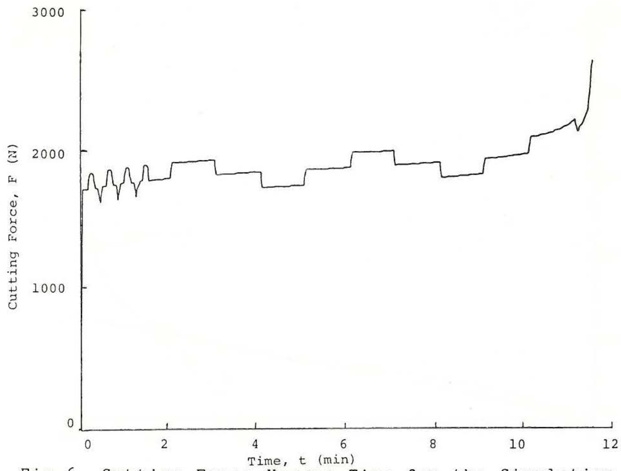

Fig.6 Cutting Force Versus Time for the Simulation

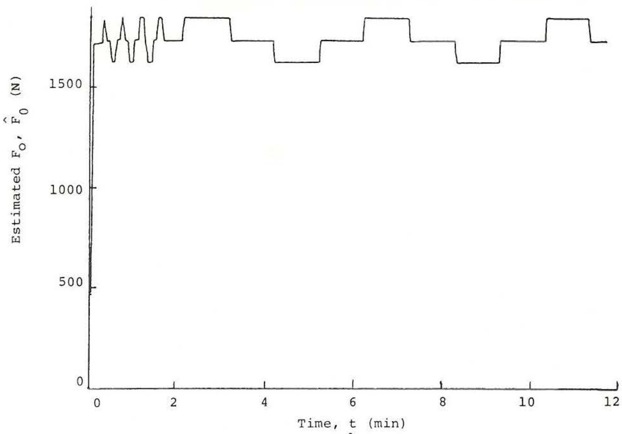

Fig.7 Estimated F_o (i.e., $\hat{F}_o$) Versus Time for the Simulation Example

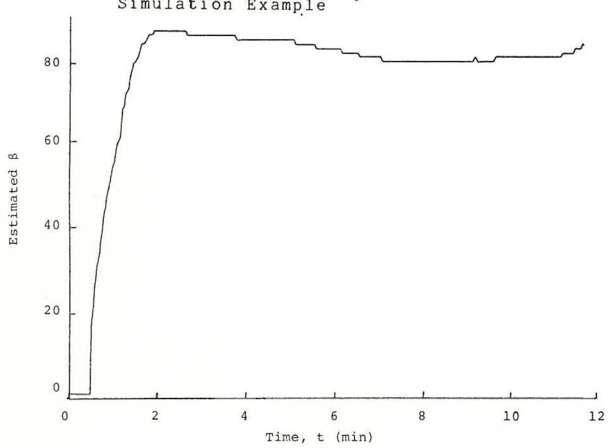

Fig.8 Estimated β Versus Time for the Simulation Example

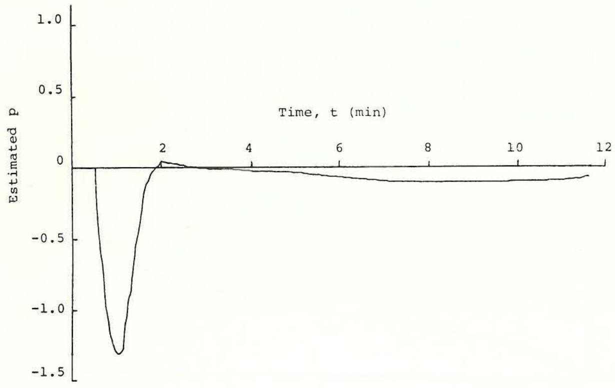

Fig.9 Estimated p versus Time for the Simulation Example

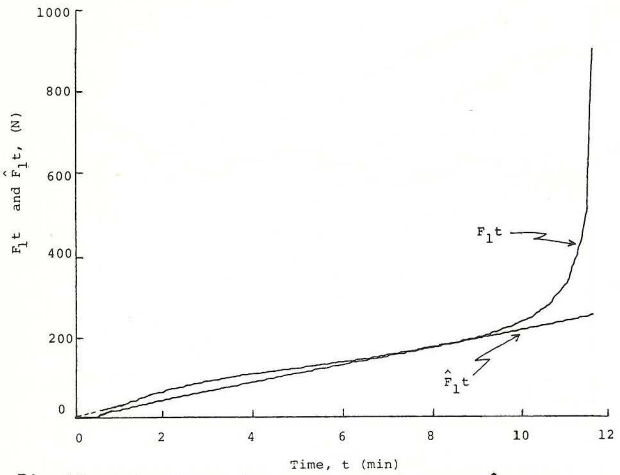

Fig.10 Actual and Estimated F_1t (i.e., $\hat{F}_1t$) Versus Time for the Simulation example