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A SYSTEM FOR MONITORING THE MACHINING OPERATION IN AUTOMATIC MANUFACTURING SYSTEMS

By

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CHAPTER 1

AUTOMATIC OPERATION OF MANUFACTURING SYSTEMS (INTRODUCTION)

1.1 INCENTIVES, AIMS

As the investment into manufacturing hardware increased, better utilization of equipment became a serious problem. Continuous (three shift) operation not only augments the throughput, but also has the benefit of eliminating warm-up of machines which takes up time otherwise usable for machining. Notwithstanding, due to changing social circumstances it becomes more and more difficult to have operators in night shifts and week-ends [4]. Untended operation has become a key problem in present manufacturing systems, but existing methods offer only a limited solution, e.g. [12], [16], [20]. The main concern is to improve the quality of operation, since the quantitative benefit -the increase in output- is achieved already by the safe operation of additional workshifts. In other words securing workpiece quality and machining safety is more important at present then augmenting the number of products.

The rapid technological development of the last decades provided new means for automation of factories too. New electronic devices, familiar in other fields, are moving into the factory; they solve many problems in providing good throughput of manufacturing systems. The new tools do not change the fundamentals of manufacturing, but rather improve the organization and enhance the performance. Nevertheless, full automation of factories is a very complex task, and although many problems have already been solved, several breakthroughs are necessary before laying down the foundations of this new manufacturing technology. This study is intended to make an investigation into the new ways of manufacturing, especially it deals with the problem of operating the machines without the presence of a human attendant.

1.2 AUTOMATIC OPERATION OF MANUFACTURING SYSTEMS

In a manufacturing system various kinds of tasks have to be performed in order to maintain the continuous operation. The most important of them are:

- to provide the smooth work and tool flow to and from the place of machining
- machining the workpiece
- carrying away the chips removed in machining
- surveillance of the operation, e.g. to measure the finished workpiece, detect abnormal events, etc.

In a conventional manufacturing system an operator performs all these tasks. The automation of them began in mass production, as the few motions repeated frequently posed an easier problem, and the operation itself was very predictable enabling automated surveillance of the operation. Small and medium size production followed it with considerable delay. Although batch orientation of the latter systems differs from a random like operation, it is still very different from manufacturing in large volumes, and the intelligence of a human operator is necessary in many situations. In the following the small and medium size manufacturing systems are the main subject of consideration.

Today already many of these manufacturing systems operate with a few operators only, nevertheless, full automation in this field has not been achieved yet [5]. The tasks listed previously can be divided into two groups, the first being connected with maintaining the normal operation, and the second with handling abnormal events. They need different approaches, since the tasks have basically different properties. Efficient operation under normal circumstances needs careful planning accompanied by proper preparations. The manufacturing schedule has to be set up, and materials, tools have to be in the right place at the right time. The normal operation is foreseeable and predictable. Abnormal events, on the other hand, come about unexpectedly, neither their occurences nor their consequences can be predicted. When the continuous operation is interrupted by an abnormal event, actions depending on the actual situation have to be taken to restore the normal state.

The automation of normal operation is a relatively easier task, since the planning and preparatory work is performed off line; the help of CAD and CAPP (computer aided design and process planning) systems are available for the purpose. For automatic detection and elimination of unexpected events a comprehensive, intelligent system is required. The main task of such a system is to restore the normal operation as soon as possible. This can not always be done real time, some cases, e.g. the repair of a damaged machine tool part, may need a long time. In this case the task is easier, immediate stop of the operation, which prevents the system incurring additional damages, helps in reducing the time spent on repair. In general, the automatic resumption of normal operation can be divided into four phases.

1. Failure detection: This requires continuous or at least continuously repeated check of the operation.
2. Damage assessment: The cause of failure must be localized, the extent of damage must be determined. No recovery procedure can be initiated before a complete image of the trouble has been obtained.
3. Recovery: All components failed or damaged have to be replaced, and/or their normal state restored in order to be able to continue the operation.

4. Resumption of the operation: There are two possible ways to restore the operation
   - resumption of the machining at the point where it was interrupted
   - beginning to machine a new workpiece, and the previous, not finished one is put aside for further inspection and possible repairs.

   To be on the safe side usually the second method is selected even when the workpiece is not damaged irreparably.

The actual state of the system is recognized and analyzed in the first two phases, while steps to continue the operation are taken in the second two phases. Depending on the type of failure detected, different actions have to be taken, no general methods or directions can be formulated.

Looking at a highly automated manufacturing system we can see that smooth workpiece flow is achieved by proper scheduling of the transport system,which uses pallets with automatic changers or robots to load and unload the machines. The CNCs need no operator to load or change part programs, their memory or connection with a central computer can supply the programs necessary to the operation. Cleaning the machine tools from chips has already been solved by using special conveyor belts and other methods. Surveillance of the operation is the least automated in manufacturing. It poses more problems, which can be divided into three main groups:

- inspection of workpiece quality
- check of proper operation of machinery
- supervision of machining.

When checking a workpiece, geometrical accuracy and quality of surfaces are examined. Three-coordinate measuring machines gauge the size of the workpiece, and the quality of surfaces are checked by measuring light reflected from the surface [39]. The check of machinery is usually built into the machines. Early systems had only simpler checks, e.g. not rotating spindle prohibited feed motion. New, advanced systems have already comprehensive check and give detailed information. Component failure detection is always system dependent, since both failures and actions to be taken when a failure is detected differ from system to system. In the next section methods for detecion of failure in the cutting process is discussed.

1.3 DETECTION OF FAILURE IN MACHINING

1.3.1 FUNCTIONAL OVERVIEW

One of the most pressing problems of manufacturing systems is detection of failures during operation. The necessity of recognition of failures has already been acknowledged more than ten years ago, and different systems have been developed to detect accidents, malfunctions, irregularities in manufacturing systems. Some of the functions are performed off-line, before or after the machining process. For instance, a common method is checking the tool and the workpiece by mechanical [24]-[25], or optical [38] devices. The size and position of the workpiece can be checked before or after machining as well. The major setback of these methods is that the check is performed off-line, while the machining process remains without supervision. Abnormal events have to be detected before they cause further damages, and this can be performed only by continuous monitoring of the operation, e.g. [15], [18]. If a monitoring system is combined with a powerful automatic failure diagnostics and control system, proper actions can be taken to eliminate the problem and the operation can continue after a short break. The continuous operation improves the production utilization of machines and results in higher productivity. At the same time by detecting abnormalities when they occur and not letting them to cause a chain reaction of further damages, higher quality products and reduced scrap are also the benefits of a well designed real time monitoring system.

Initially automation has been applied to mass production systems with large run of identical parts. As this operation is rather predictable, a few relatively simple devices can continuously check it and respond to breakdowns and abnormal events [3]. Small and medium size batch oriented production, on the other hand, handles a wide variety of workpieces, and the continuous check of the operation is a more difficult task. It is fraught with many kinds of unexpected disturbances: the variability of work causes irregularities in stock, uneven tool wear, etc., eventually all being possible sources of failures.

Computer integrated manufacturing, the way of automation in small and medium size manufacturing, can facilitate the monitoring of the operation too. On one hand, data serving later for monitoring purposes can be generated at design or preparation to manufacturing. On the other hand, computers can be directly used for monitoring. Especially the continuous increase in the performance of computers, combined with steady decrease in prices, makes them attractive for direct application to monitoring. An important question is, how much diagnostics to incorporate in any machine. Adding diagnostic features also increases the number of components in the system and its overall complexity, thereby increasing the chances of a failure, although they are expected to improve the performance of the monitored or checked devices. It is essential to note that diagnostic systems, by themselves, do not improve the reliability of an equipment, and do not increase the mean time between failures (MTBF). But they do facilitate the problem identification and thus reduce the mean time to fix (MTTF).

In the following an overview of the existing methods is given. The guiding line will be the principle of operation, as some methods provide a solution for more problems, and it would be difficult to classify them strictly according to their functions.

1.3.2 OPERATION SURVEILLANCE METHODS

Touch probe methods

One method to examine tool and workpiece is the use of touch sensitive devices [24]-[25]. To check the tool usually a switch is built onto the machine. During check the tool is sent into a predetermined position, where it has to touch this switch. The workpiece can be examined by a touch probe in several points. By using the data of tool location, tool offset data can automatically be adjusted. The measuring probe supplies data about the location of the workpiece, such as position of holes or planes, and a modification of the actual zero shift can compensate the inaccuracies.

One of the greatest drawbacks of the method is, that it is off line, the measurement is performed before or after machining. The measurement is also very sensitive to dust; chips and dirt can hinder the accurate measurement. In spite of the similarity with measuring machines it can not be used for workpiece inspection, the measuring reference must be more accurate than the manufacturing.

Nontouch size measuring

Dependence on the accuracy of the manufacturing machine can be eliminated by using an independent measuring device. One possible solution is using laser interferometry [22]. The measurement is stable in time and there is no need for calibration, it can even measure thermal deformation during machining. A feedback of the measured data to the NC can significantly increase the accuracy of the next workpieces.

As a laser is a very delicate equipment, it must be well protected against the sprinkling metal chips and coolant being common in every workshop. The measurement is sensitive to dust, not clean surfaces deteriorate the accuracy. Finally it must be noted, that a laser is very expensive.

On line monitoring methods

The monitoring methods are to detect abnormal events during machining. They measure different signals, during machining, and detect abnormalities in them. Some methods use vibration analysis technics [21], [35]. The method has been used to detect excessive wear of drills, as an increase in the vibrations. Similar methods have been used in grinding to detect wear of the grinding wheel. Apparently it works well for single edged tools and continuous cutting, but multipoint tools and intermittent processes -as milling-have not been tested yet.

There are experiments to detect tool wear and prevent tool failure by using heat sensing methods [22], [36], [37]. A heat sensor is placed close to the machining point to measure the radiation during operation. The method, however, meets with difficulties when coolant is used in machining.

Much attention has been paid to the application of acousto-emission (AE) technics to tool wear and breakage detection [27]-[32]. The sound produced by excessive tool wear, tool breakage, entanglement of continuous chips and possibly by other events can be used to detect these abnormalities. Proper filters suppress the unwanted noises, and the interesting -mainly ultrasonic- sounds inform about the cutting state. The method is said to be able to work in finishing and moderate roughing cuts with a single point tool.

Monitoring the cutting torque or the feed forces is a sensitive method to detect machining troubles, since the torque and the feed forces reflect the cutting state well, but their direct measurement is a complicated task. When the tool is not rotating, as on a lathe, the installation of a measuring device is fairly easy [10], but the torque measurement on a rotating tool -as in case of milling- needs expensive devices [13]. The output coupling of the analog signal can be performed by using slip rings [33], which make the data noisy and less reliable, or by employing more expensive signal transmitters [34]. An easier method is to measure the torque indirectly via spindle motor current or the feed forces via feed motor current. This measuring method does not require additional sensors, as currents are usually measured in drive circuits for control purposes. The transfer function between cutting torque (or feed force) and motor current is linear to such extent that monitoring can be based on this method. The price for easy sensoring is more complicated data processing. The monitoring methods using current measurement are reviewed in section 4.2.

The method of monitoring the cutting process by spindle motor current measurement has been opted in the present study. The main target was to provide reliable monitoring algorithms, while benefiting the cheap and easy sensoring.

1.4 STRUCTURE OF THE PRESENT STUDY

The study concerns on line monitoring of the machining operation. It describes methods to detect troubles and their application to real cutting experiments. The parameter monitored is the cutting torque measured via spindle motor current.

First the validity of the sensoring method is proved by determining the cutting torque - spindle motor current transfer function of the machine tool used. Chapter two describes the experiments performed and the determination of the transfer function.

The next three chapters describe two monitoring methods and their practical implementations. The first method, discussed in chapter three, is a stand alone method, not using auxiliary information. The method is primarily for tool breakage detection. The analyzing method and application experiments are presented.

Chapter four describes a cutting torque estimation system aimed at providing a reference pattern of the cutting torque for comprehensive monitoring. The solution opted also helps in performing the geometrical and technological verification of the NC part program. The structure of the torque calculation system is described together with validation and application experiments.

Next the implementation of the two methods into a 16 bit microcomputer is explained in chapter five. The necessary adjustments are presented with experimental results.

The study is concluded with a summary of the main results achieved.

CHAPTER 2

MEASUREMENT OF THE CUTTING TORQUE - SPINDLE MOTOR CURRENT TRANSFER FUNCTION

2.1 INTRODUCTION

Monitoring needs a reliable data acquisition from the cutting operation. The parameter monitored is expected to reflect the state of the process well, and the sensors used should be durable and accurate. The cutting torque is a parameter reflecting the cutting state well, but its direct measuring on some machine tools may meet with difficulties. In case of a milling machine, or a machining centre, the difficulties of measuring in a place where sharp metal chips and coolant fluid sprinkle are combined with the problem of a rotating tool. Measuring the torque indirectly, via spindle motor current, is a more suitable way, as it overcomes these difficulties. In order to prove that sensoring of the cutting torque via spindle motor current is correct, the connection between torque and current has to be determined.

CHAPTER 2

2.2 THE EXPERIMENTAL SYSTEM

2.2.1 CONFIGURATION OF THE EXPERIMENTS

The cutting experiments were performed on a vertical machining centre (MAZAK V 7.5 with a FANUC System 7 numerical controller). The tool used in the experiments was a face mill cutter with six throw-away cutting edges. The cutting edges used in the experiments were NX55 type (of the Mitsubishi Kinzoku Corp.). The material of the workpiece was carbon steel, with C = 0.45 %.

2.2.2 DATA ACQUISITION SYSTEM

The schematics of the data acqisition is shown in figure 2.1. The spindle motor current was measured in the electronic spindle drive unit.

The cutting torque was measured by strain gauges. The gauges were attached to a specially made workpiece, and the signals were led to a gauge amplifier combined with a low pass filter.

Torque measurement

For torque measurements a special workpiece was made of carbon steel. The workpiece, performing the functions of a dynamometer, comprised of two parts. The lower part,

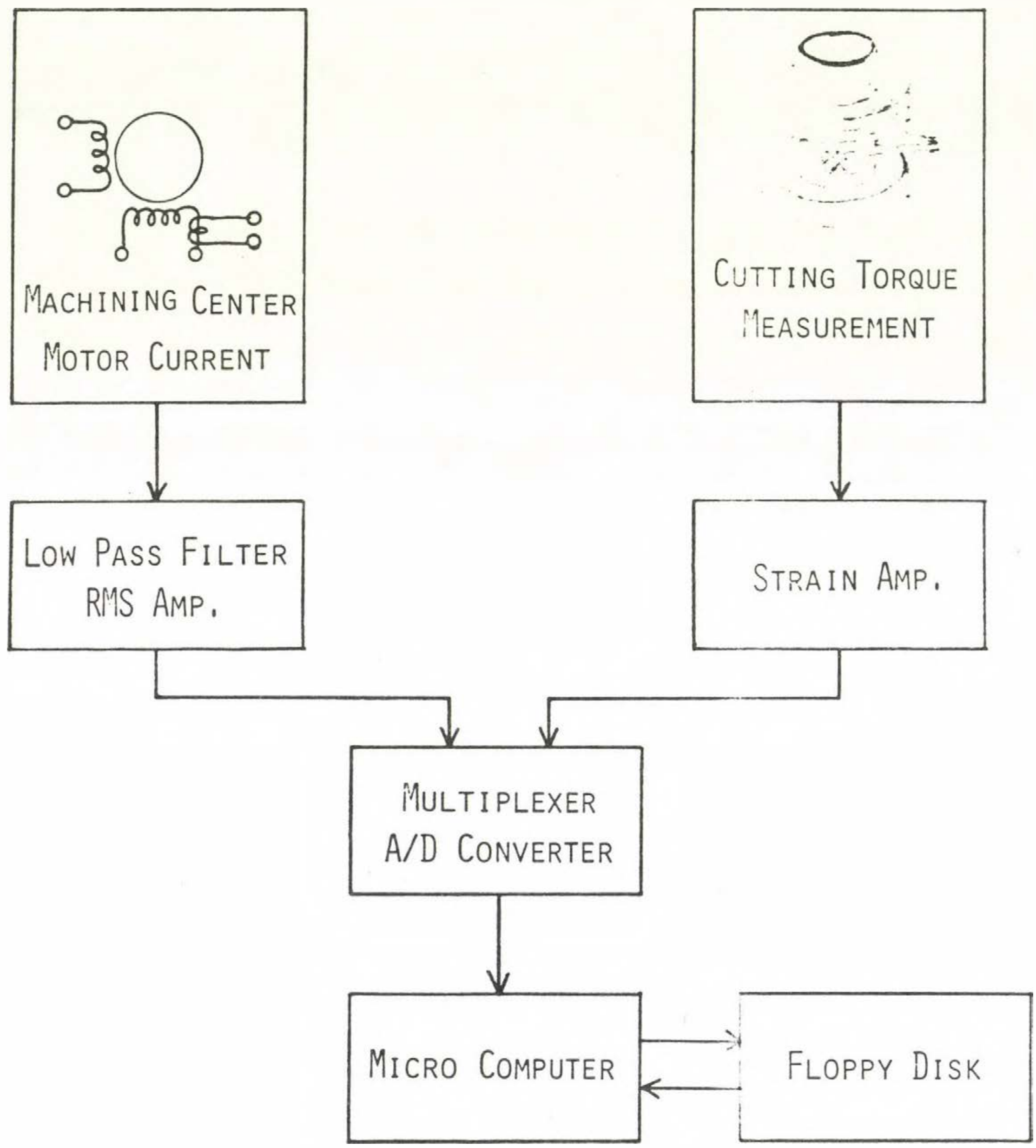


Fig. 2.1 Data Acquisition System

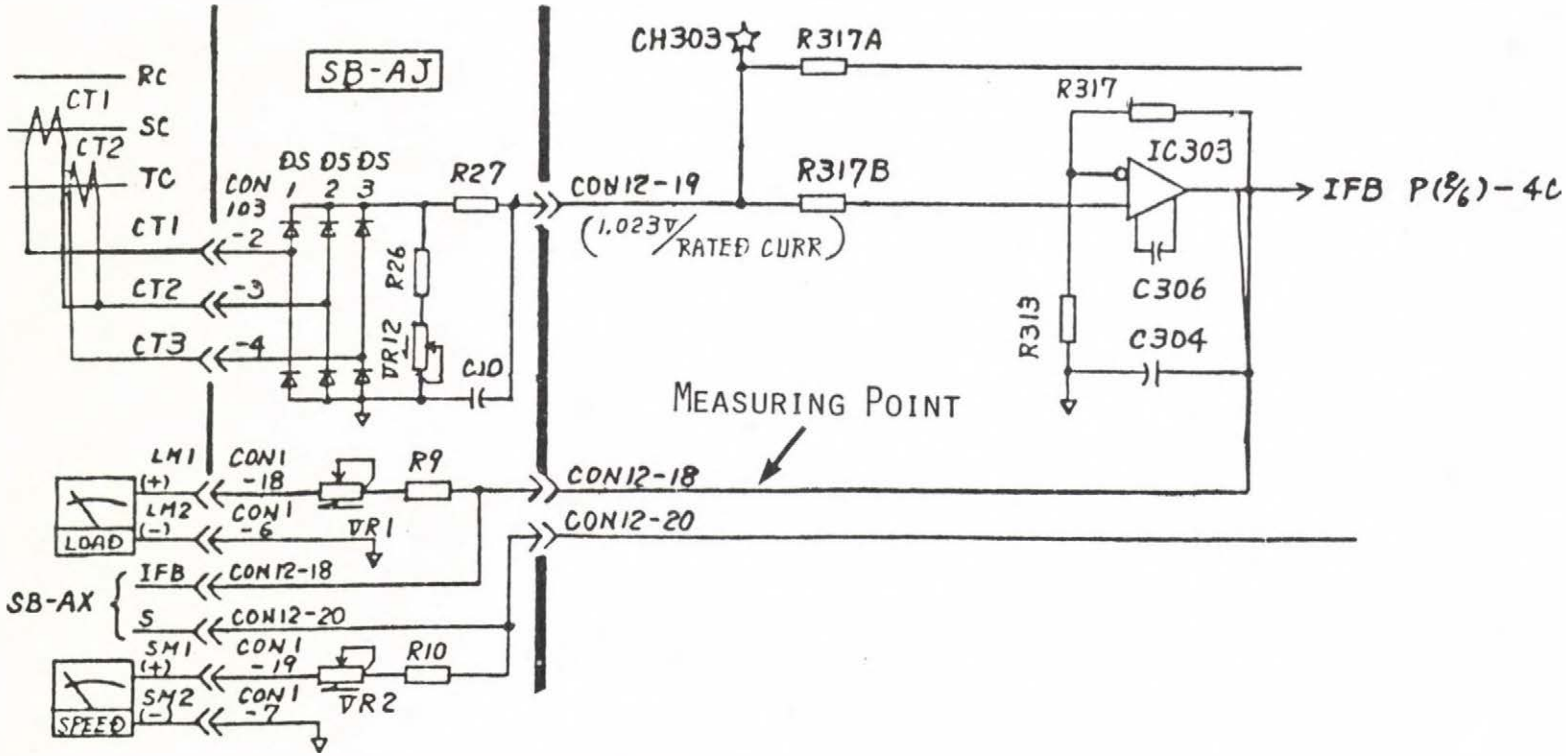


Fig. 2.2   The Spindle Motor Current Measuring Circuit

fastened directly on the machine tool table, served as a stand holding the part machined. The two components were fixed together with M14 bolts. The torque was measured on the stand.

Spindle motor current measurement

The spindle motor current was measured in the DC spindle drive unit. The measured current was smoothed by a lowpass filter and a root-mean-square amplifier before the A/D converter sampled the signal.

2.3 CUTTING TORQUE - MOTOR CURRENT TRANSFER FUNCTION MEASUREMENT

2.3.1 TRANSFER FUNCTION CALCULATION METHOD

The input signal 'x(t)' has the spectral density 'Pxx(f)', the output signal 'y(t)' has 'Pyy(f)'. A cross spectral density 'Pxy(f)' between input and output signals is defined as the Fourier transform of the cross correlation function. The relationship among these functions can be described with the help of the transfer function 'G(f)'. One relationship describes the connection of the functions as:

$$Pxy(f) = G(f)\ Pxx(f) \qquad 2.1$$

or

$$G(f) = Pxy(f) / Pxx(f) \qquad 2.2.$$

The coherence function

$$ABS\ [Coh(f)]^2 = ABS\ [Pxy(f)]^2 / Pxx(f)Pyy(f) \qquad 2.3$$

measures the reliability of the calculations.

2.3.2 CUTTING EXPERIMENTS

Experiments of two types were performed. As can be seen from figure 2.3, in experiment 'A' a workpiece of round shape was cut vertically. The mean diameter of the workpiece and the diameter of the tool were the same. The workpiece in experiment 'B', a half cylinder, was cut horizontally. The rim thickness of the workpiece was much less than the diameter of the tool, so the displacement of point of application along the cutting path was negligible. The resultant cutting torque - spindle motor current transfer function obtained by summarizing the results of different experiments is shown in figure 2.12. The figure indicates that the transfer function is constant in the lower frequency range, at least below log omega = 2 , i.e. below 16 Hz. As the system is supposed to be linear, the break point of the transfer function must be at the highest frequencies of the examined range, or above. As the frequency range examined was that of real cutting experiments, we can conclude that the transfer function of the system is constant in the frequency range used.

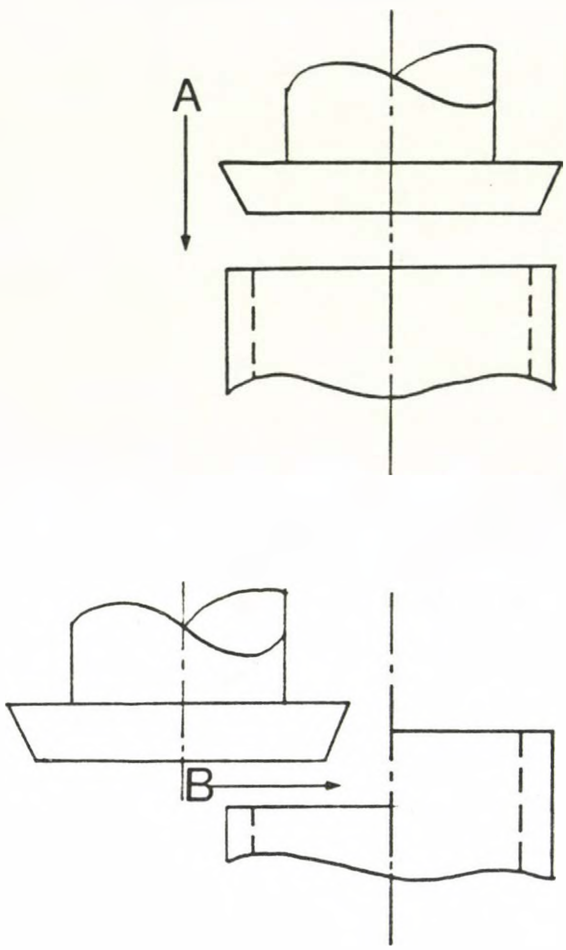


Fig. 2.3 Cutting Experiments
(A & B Type of Cutting)

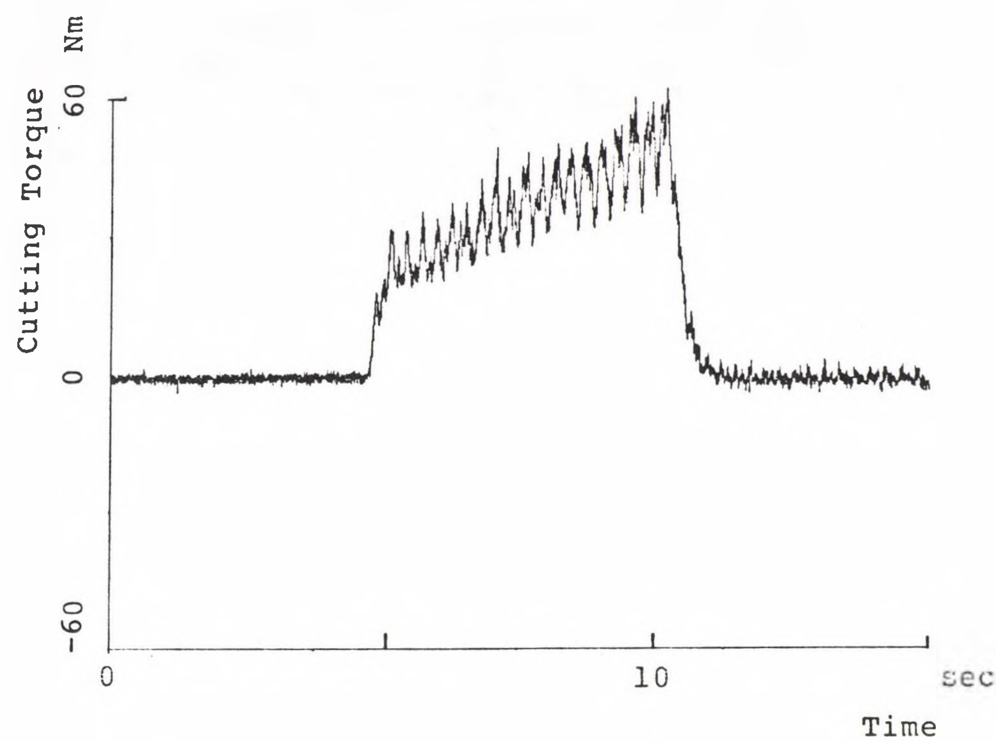


Fig. 2.4 Measured Torque in Cutting Experiment A

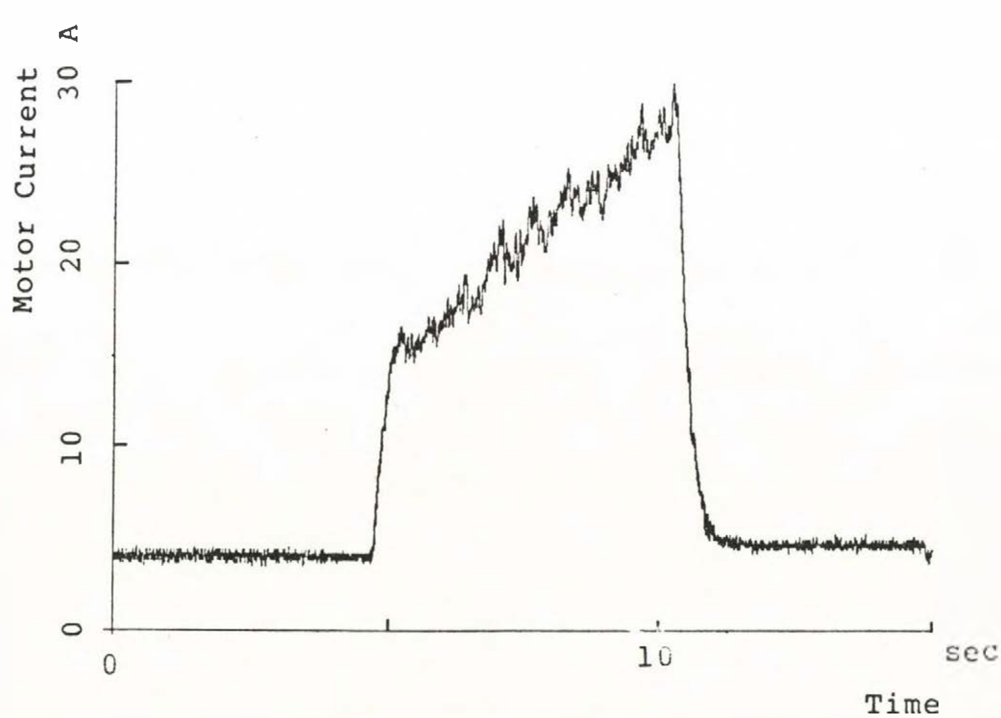


Fig. 2.5 Measured Current in Cutting Experiment A

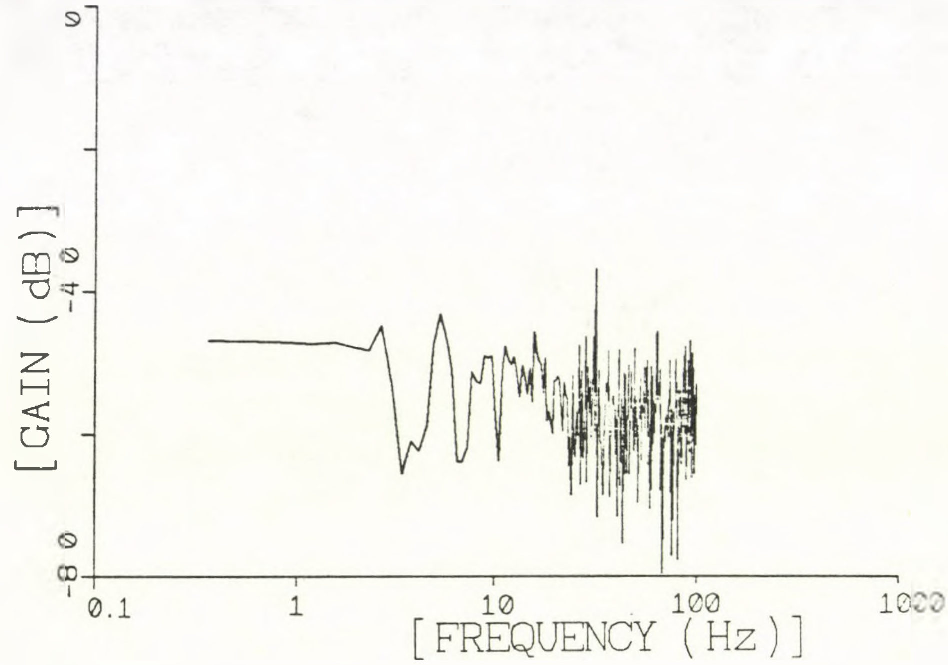


Fig. 2.6 The Calculated Transfer Function in Case A

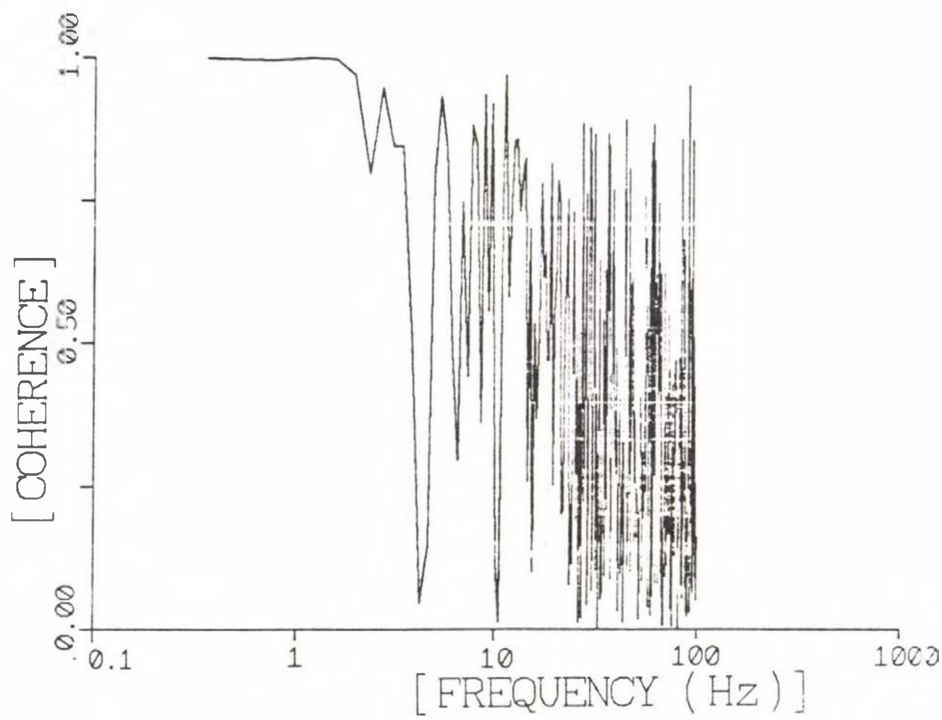


Fig. 2.7 The Calculated Coherence Function in Cas A

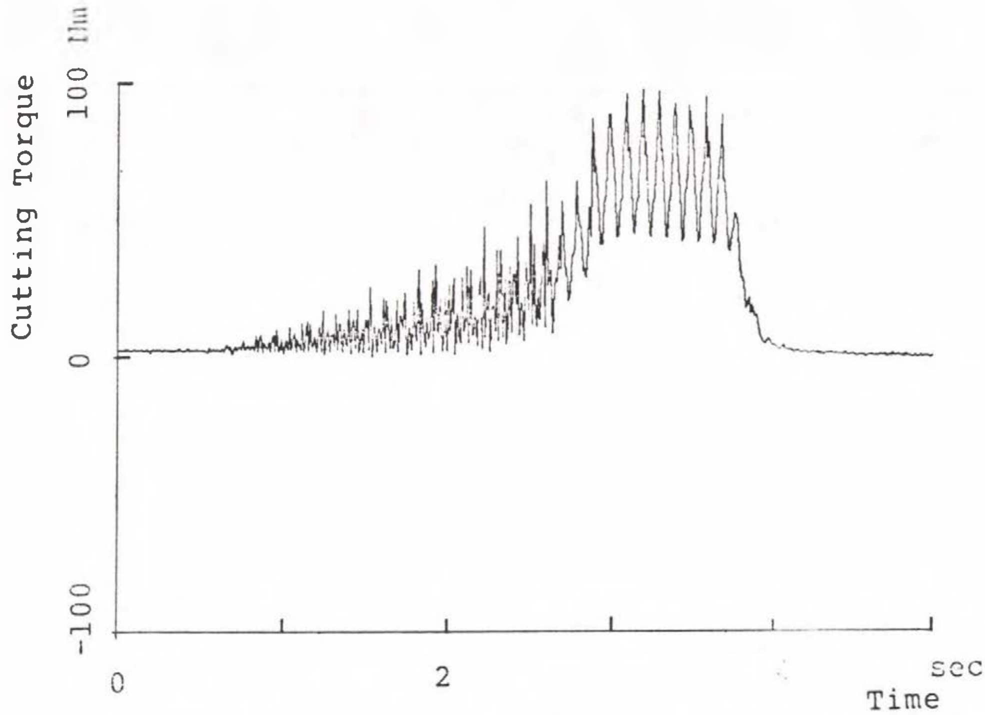


Fig. 2.8 The Measured Torque in Experiment B

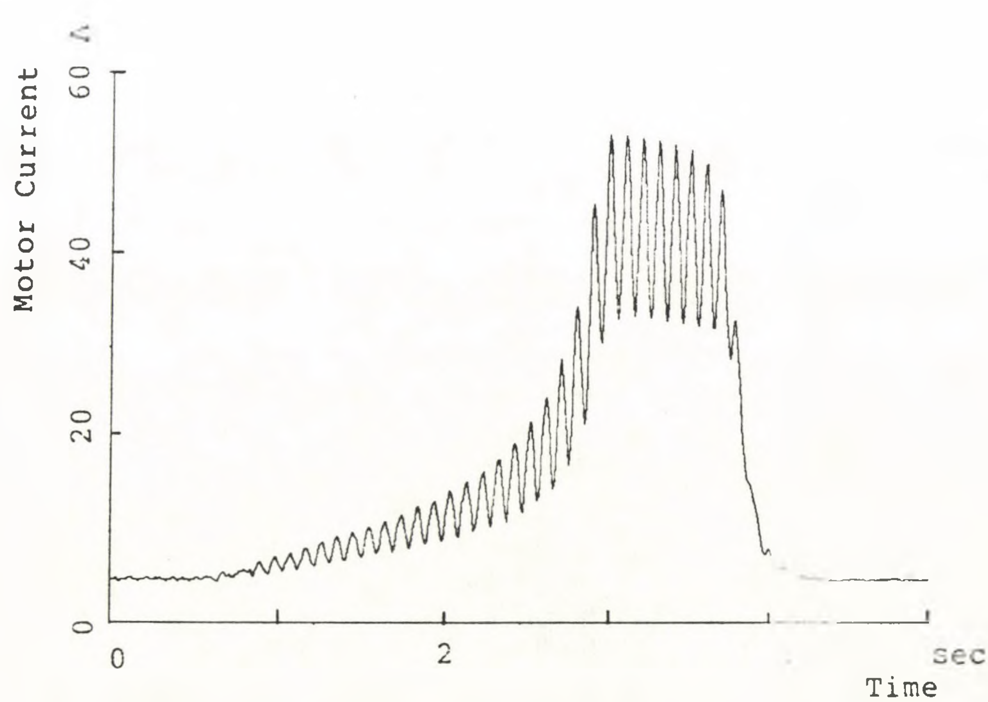


Fig. 2.9 The Measured Current in Experiment B

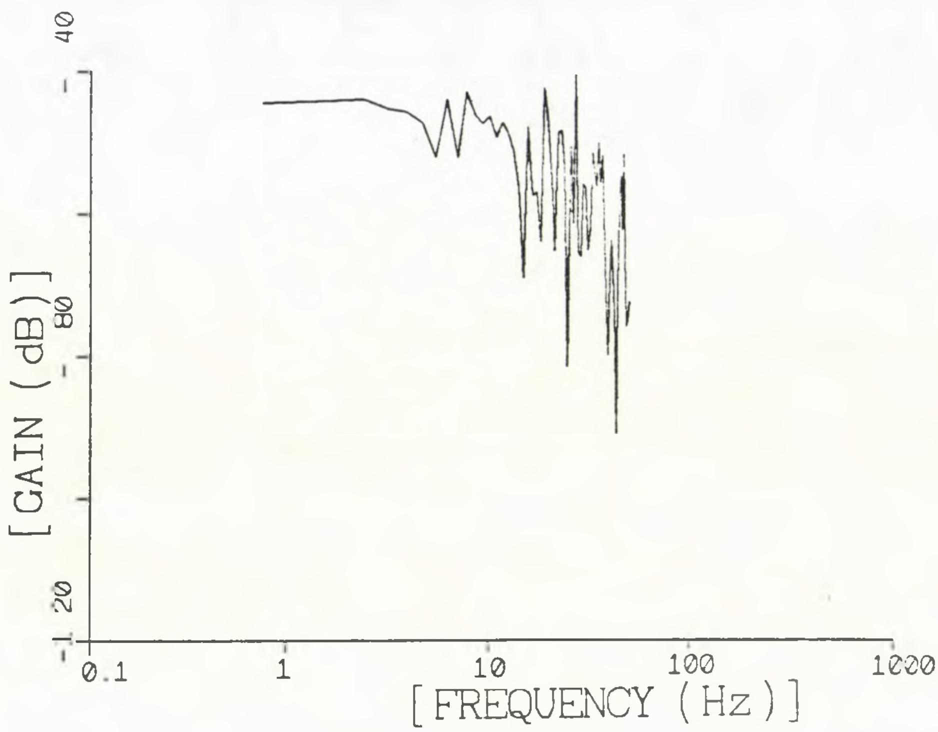


Fig. 2.10 The Calculated Transfer Function in Case B

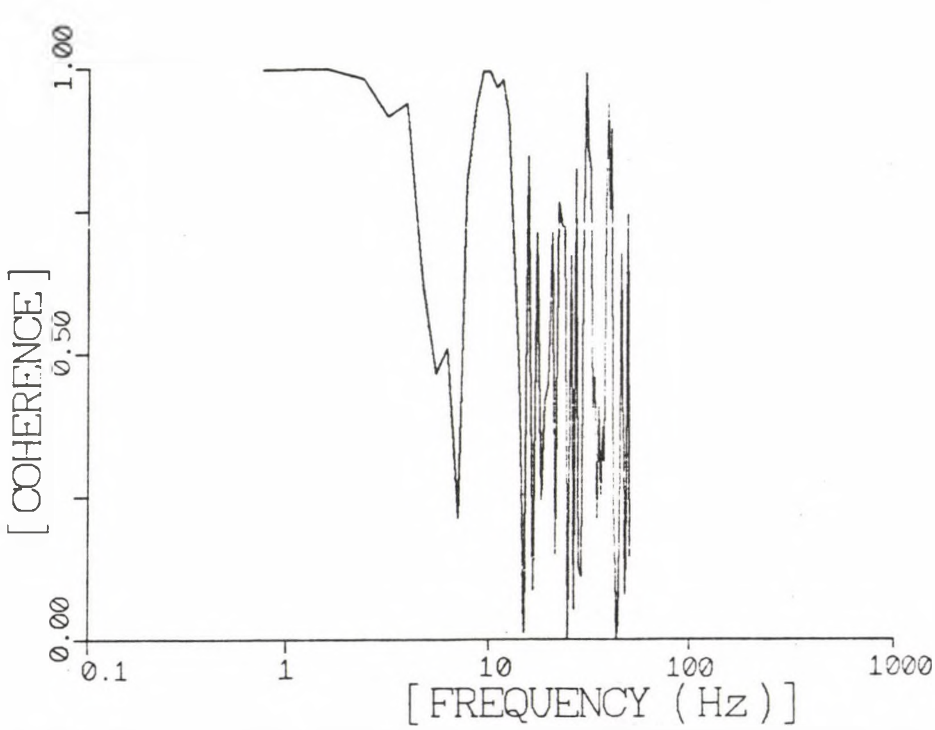


Fig. 2.11 The Calculated Coherence Function in Case B

Fig. 2.12 The Transfer Function obtained in the Different Experiments

2.4 CONCLUSION

The results indicate that the spindle motor current reflects reliably the cutting torque in the used frequency range. The calculated transfer function was constant in the lower frequency range (about 0 - 16 Hz). The spindle motor current is very easy to measure, as spindle drive units measure it for control purposes. On the other hand, as the measuring point is relatively far from the actual cutting point, the information obtained about the cutting process is less accurate. The inertia of the tool and of the spindle gear unit was neglected in the experiments. For a more precise measurement, however, this factor must also be taken into consideration. Finally we can conclude that the cutting state can be reliably monitored via the spindle motor current, as the cutting torque - spindle motor current transfer function can be regarded as constant in the range of cutting signals used.

CHAPTER 3

DETECTION OF THE BREAKAGE OF A MULTIPLE EDGED TOOL BY AUTOREGRESSIVE MODELLING

3.1 INTRODUCTION

3.1.1 THE MONITORING METHODS OF THIS STUDY

One of the two monitoring methods of this study is presented in this chapter. The two methods use different approaches, as they have different targets. The method described here is to detect tool breakages by detailed analysis of the spindle motor current, and uses no preliminary information about the cutting process in contrast with the comprehensive method described in chapter four. The two methods are complements of each other as far as their applications are concerned, and make up a monitoring system described in chapter five.

Here, after a short section revealing the connection between estimation theory and the examined phenomenon the theoretical background of this method is summarized, then the monitoring method itself and the application experiments are presented. The theoretical summary is based on existing literature. The main points are discussed in respect of the application and special attention is paid to practical problems, such as initialization. The application method is described by relying on the theoretical background. Finally application experiments illustrate the method's performance.

3.1.2 TOOL BREAKAGE AND ESTIMATION (FILTERING) THEORY

In case of single edged tools an efficient solution has been described in [28] for tool brekage detection. Here the case of a tool with more cutting edges is examined.

Our main purpose is the study of small, sometimes microscopic breakages, when the dimensions of the damaged surface on the cutting tip are only within a few millimeters, but we would like to detect greater damages too. Small breakages cause usually small changes in the cutting process, hence their reflection in the cutting torque is also very weak. The mean of the signal does not change significantly, therefore a method monitoring it can detect no abnormality in the signal. The methods comparing the signal with maximum values or with a reference pattern are monitoring the running average of the signal, in order to include some tolerances, so they miss this kind of failures. This type of phenomena are usually examined by using spectrum analytical methods. There are some new methods in spectrum analysis, which offer advantages over classical methods in computation and evaluation as well. These methods are closely related to estimation and filtering theory, in fact they are a special application of it.

Based on linear estimation and filtering theory a method for detection of cutting edge breakage in case of a tool with more cutting edges is proposed in this chapter.

3.2 THE WAY OF MODELLING THE CUTTING PROCESS

3.2.1 ESTIMATION

The estimation problem consists in determining a model, which approximates to the time history of the system from the erroneous measurement.

A problem of great importance is determining the parameters of a model based on observations of the physical process being modelled. In some cases the system parameters can not be determined a priori or they vary during system operation. In such case a model can be used, which depends explicitly on these parameters. Based on data from the physical plant and from the model a parameter identifier adjusts the model on-line, thus performing a real time system identification. The method described here follows a similar way. A model describing the physical process is chosen, and its parameters are estimated recursively. The tool breakage is detected as a change in the physical process, which is reflected in the system model updated real time.

3.2.2 STOCHASTIC LINEAR ESTIMATION

3.2.2.1 PROBLEM FORMULATION

We consider a dynamic system whose state in time is described by the function 'x(t)'. The discrete case is discussed here only, i.e. when the state of the system is given at (usually equally spaced) time instants. We are interested in knowing the value of 'x(k)' for some fixed 'k', but this 'x(k)' is not directly accessible to us for observation. On the other hand we have a sequence of measurements z(1), z(2), ... z(j), which are causally related to x(k). The estimation problem is to determine a function between 'x' and 'z' in some rational and meaningful manner. If k=j the problem is called filtering, if k>j it is prediction and if k<j it is smoothing or interpolation.

3.2.2.2 THE FILTERING METHOD

The filter we consider has the following equations:

$$X(n,n-1) = H(n)\, X(n,n) \qquad 3.1$$

$$P(n,n-1) = H(n)\, P(n-1,n-1)\, H'(n) \qquad 3.2$$

$$P(n,n) = [P^{-1}(n,n-1) + M'(n)V^{-1}(n)M(n)]^{-1} \qquad 3.3$$

$$G(n) = P(n,n)\, M'(n)\, V^{-1}(n) \qquad 3.4$$

$$X(n,n) = X(n,n-1) + G(n)\, [z(n) - M(n)X(n,n-1)] \qquad 3.5.$$

These equations mean that first, in equation 3.1, the previous estimation is updated according to the state transition equation. Then correction gain 'G' is computed with the help of estimation covariance 'P', observation mechanism 'M' and noise variance 'V' in equations 3.2 - 3.4. Finally equation 3.5 gives the new estimate . Using the so called matrix inversion lemma equations 3.3 - 3.4 can be transformed into a different form, and a new, algebraically equivalent algorithm is resulted in:

$$X(n,n-1) = H(n)\, X(n-1,n-1) \tag{3.6}$$

$$P(n,n-1) = H(n)\, P(n-1,n-1)\, H'(n) \tag{3.7}$$

$$G(n) = P(n,n-1)\, M'(n)[V(n)+M(n)P(n,n-1)M'(n)]^{-1} \tag{3.8}$$

$$P(n,n) = [E - G(n)M(n)]\, P(n,n-1) \tag{3.9}$$

$$X(n,n) = X(n,n-1) + G(n)\, [z(n)-M(n)X(n,n-1)] \tag{3.10}$$

where 'E' is the unit matrix [7]. Equations 3.6 - 3.10 represent a simpler form of the Kalman filter, when the plant noise is omitted from the model. The previous form, equations 3.1 - 3.5, is usually titled the sequential estimator, and as it can be derived by using Bayes' theorem on conditional probability sometimes it is also referred to as Bayes-filter. The filters satisfy the minimum variance criterium, in fact they are recursive formulations of it.

As far as computational features are concerned, the two formulas have significant differences. The Kalman formulation requires the inversion of only one matrix, which has the same order as the observation vector. The other formulation calls for the inversion of at least one matrix of the order of the state vector. The simpler calculation can be a deciding factor in some applications.

A problem with the Kalman formulation is the initialization. In the first formulation we can select an initial vector 'X(1,0)' completely arbitrarily, and then by setting the inverse of the covariance matrix singular, i.e.

$$P^{-1}(1,0) = 0 \qquad 3.11$$

we make the subsequent estimate totally independent of 'X(1,0)'.

In the Kalman formulation, however, this can not be done, since setting

$$P(1,0) = c\ E \qquad 3.12$$

('c' means a very great scalar and 'E' is the unit matrix), and substituting it into 3.8 and 3.10 we will get a result, in which 'X(1,0)' will enter into the first estimate. Therefore in order to start the filtering succesfully, a preliminary information included in the initial vector 'X(1,0)' is necessary.

Too accurate measurements, i.e. when the variance of the measurement error is very close or equal to zero (V=0), can also cause troubles: the estimation variance matrix

'P(n,n)' will be singular. Theoretically it is impossible, but due to finite accuracy of our computers a small noise variance can be wiped out completely by computer roundoffs, and the matrix 'P' will be positive definite only marginally and then degenerate into indefinite. This makes the whole process unreliable and the filter be divergent. Thus the Kalman formulation runs into trouble in trying to process too precise observations. In this work larger noise variances were used to circumwent this problem.

3.2.2.3 PROCESS MODELLING, AUTOREGRESSIVE MODEL (SYSTEM IDENTIFICATION)

In many applications the so called autoregressive moving average (ARMA) models have proven to approximate deterministic and stochastic discrete time processes well. They are especially popular in human speech analysis, seismic data, ocean wave data analysis and others [8], [10]. Here an attempt is made to apply it to cutting data analysis.

The model expresses the output sequence with the following equation:

$$\sum_{k=0}^{p} a'(k)\ X(n-k) = \sum_{\ell=0}^{q} b'(l)\ u(n-l) \qquad 3.13$$

or

$$X(n) = -\sum_{k=1}^{p} a(k)\ X(n-k) + \sum_{\ell=0}^{q} b(l)\ u(n-l) \qquad 3.14.$$

where 'X(n-k)' denotes the outputs and 'u(n-l)' the inputs of the system. The coefficients 'a(k)' and 'b(l)' have to be determined by some parameter identification method. The first term on the right side of equation 3.14, which contains only the signal's past is called the self regressive or autoregressive (AR) branch, the second is the moving average (MA) branch of the model. It is very interesting that a general ARMA or an AR process can be represented by a MA model, and an ARMA or MA process can be modelled by an AR one, but in the adequate model the order will be higher, maybe infinite [9]. The AR model, requiring only linear equations for parameter identification, has a computational advantage over the other two.

For sequential estimation of AR parameters the recursive least square method gives a straightforward solution with a fair computational load. The procedure can be interpreted as a Kalman filter. The basic problem is to find the least sqare solution of the AR parameter estimate vector for the observed process. Considering the following system equations:

$$X(k+1) = X(k) \qquad 3.15$$

$$z(k) = M(k)\, X(k) + v(k) \qquad 3.16$$

an estimation can be performed either with equations 3.1 - 3.5 or 3.6 - 3.10.

3.2.2.4 THE RESIDUAL

The difference of estimated and actually measured data has great importance in estimation technics and usually it is referred to as the residual. It is used in the algorithms to correct the estimation, as we have seen. New observations bring new information about the physical process, and in this way the estimator's knowledge about the process is innovated, therefore it is also termed innovation process [13], [14], [15]. The residual will increase when the process changes abruptly, because the model follows the process with a delay, and the change appears in the model only after a time lag. This suggests, that the residual can be monitored to detect abrupt changes in the process.

3.3 TOOL BREAKAGE DETECTION BY AUTOREGRESSIVE MODELLING

3.3.1 BREAKAGE DETECTION PRINCIPLE

A model of the cutting process is built up in the computer, and its output is regularly compared with the physical process. When the physical process changes due to a breakage, the approximation by the original model deteriorates, giving worse results, and the difference between the output of the model and the monitored parameter of the current physical process increases. Accordingly, an unexpected increase in the difference between the model output and the monitored process parameter shows the deterioration of the model, which, on the other hand, indicates an unexpected change in the machining process: a tool breakage.

Practical considerations

The first step towards computerized processing of cutting data is to find an adequate model of the cutting process. It is not our aim to find a general comprehensive model as far as cutting dynamics is concerned. On the other hand, the model should be in good correspondence with the real process and give a similar output, in order to be able to use it for monitoring purposes. An AR model is easy to handle in a computer, as the system equations are linear. And even if the process turns out to have a moving average branch, an AR model of higher order will give satisfactory results. In the following a method for describing the cutting process by an AR model and its application to detect tool breakage caused changes in the signal will be discussed.

3.3.2 EXPERIMENTAL RESULTS AND DISCUSSIONS

For cutting data analysis and tool breakage experiments the milling operation was examined. The face milling process has been chosen for the experiments, since

- in face milling the cutting forces are large, which may cause more frequent breakages

- the use of throw-away tips in face mill cutters and their easy replacement make the experiments easier to perform

Nevertheless, it must be stated that cutting experiments suggest very close similarity between face and end milling.

3.3.2.1 EXPERIMENTS AND RESULTS

An example of a typical small breakage is shown in figures 3.1 - 3.3. The experiment was performed on a vertical machining centre (Yamazaki V7.5). The tool used was a six-tooth face mill cutter, 125 mm in diameter, which cut a workpiece made of carbon steel (C= 0.45 %). The cutting conditions were the following:

cutting speed = 15.625 m/min (250 rpm)
feed rate = 0.4 mm/tooth (600 mm/min)

The experiment can be followed in figure 3.1. First the tool was rotating in the air while moving ahead in feed direction, this was the "air cutting". At point 'B' the foremost part of the tool entered the workpiece material, then at 'C' the full cutting width was reached. The breakage occured at point 'D', and at point 'E' the cutting width began to decrease as the tool went out of the workpiece. The periodicity of the signal corresponds to the spindle speed, the distance in time between two peaks is one revolution. The signal before the breakage is shown in figure 3.2, after enlarging along both axes. The graph reveals, that the tool had some eccentricity, one of the

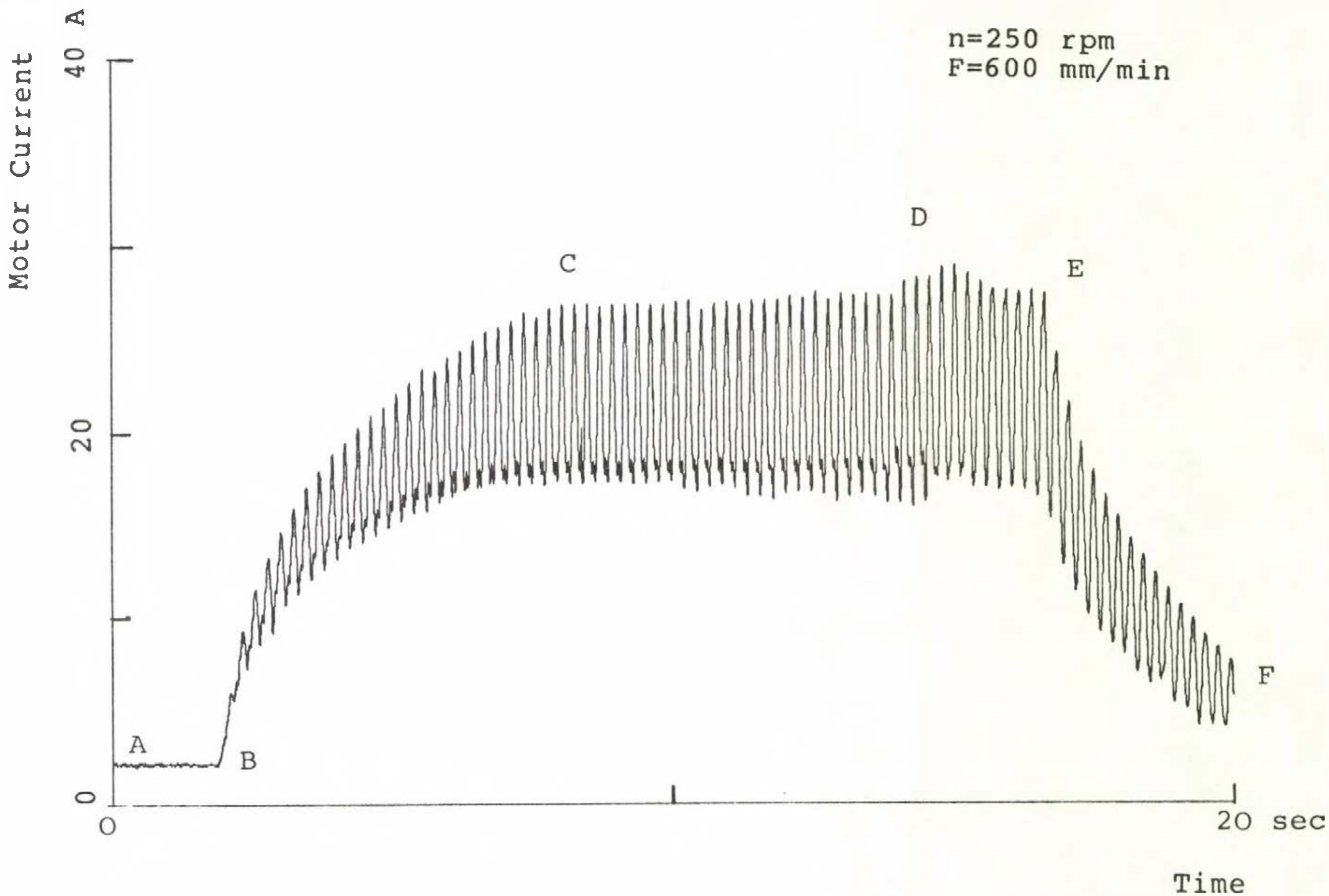


Fig. 3.1 Measured Spindle Motor Current (Sampling Interval=5msec)

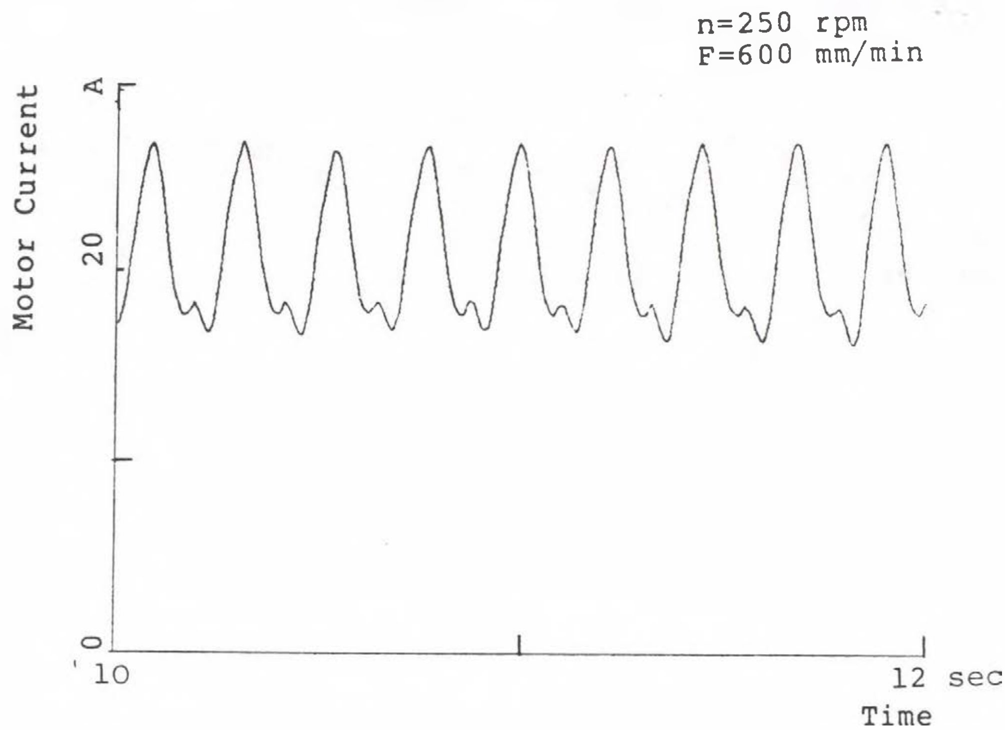


Fig. 3.2 Measured Spindle Motor Current before Tool Breakage

Sampling Interval = 5 msec

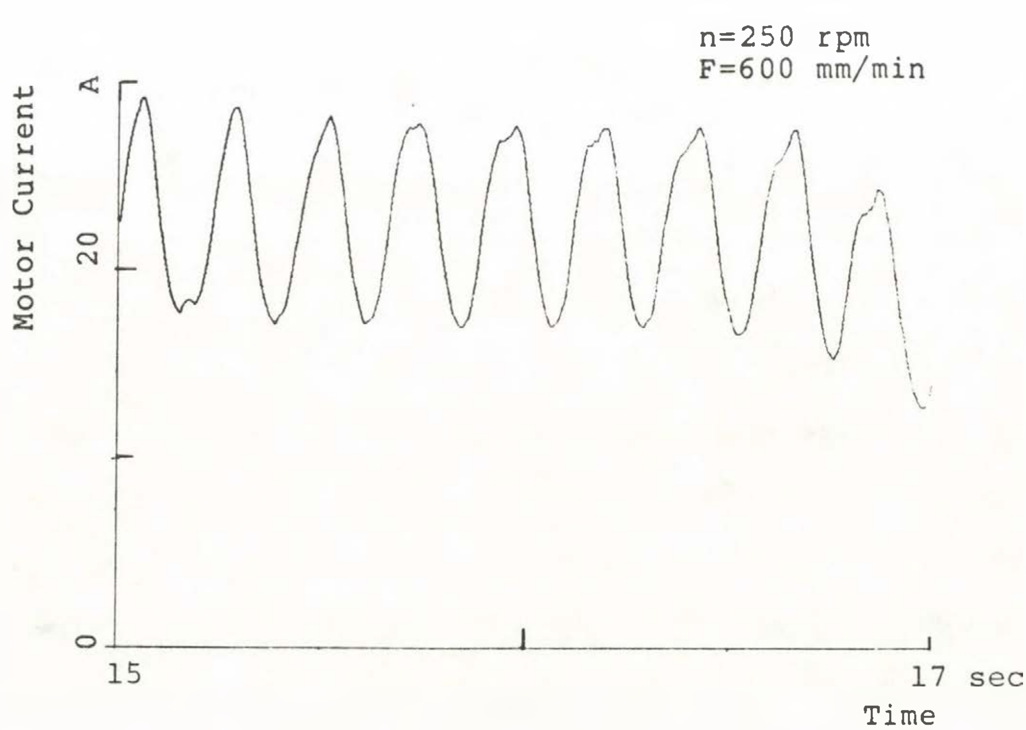


Fig. 3.3 Measured Spindle Motor Current after Tool Breakage

Sampling Interval = 5 msec

teeth had a greater share from cutting than the others. The high peaks preceded by falls in the signal suggest, that a tooth had to cut thicker chips than the others. Figure 3.3 shows the signal after the breakage. A smaller peak is present yet at the left side of the graph, but it disappears in the following revolution by rising to the level of the higher peak. This can be explained in that way, that one tooth has broken but continued cutting. Cutting with a broken edge required greater force, which caused a rise in the torque.

The detection signal

The calculated detection signal is shown in figure 3.5. Figure 3.4 shows again the measured motor current, but here the sampling time was twenty milliseconds. (Only every fourth data of the original set were used.) The change in the current (torque) signal became more difficult to recognize with human eye, but it is still visible. The output of the monitoring system, the residual, was enlarged by twenty times in figure 3.5 in order to make it visible. Between points 'A' and 'A1' the AR model is adjusting itself to the process and there is no output. After point 'A1' the output is already valid. The real cutting begins at point 'B'. As the physical process changed, i.e. the tool began to cut the workpiece, there is some difference between the model and the process, and this is reflected in the increase of fluctuations in the residual. After a transient period

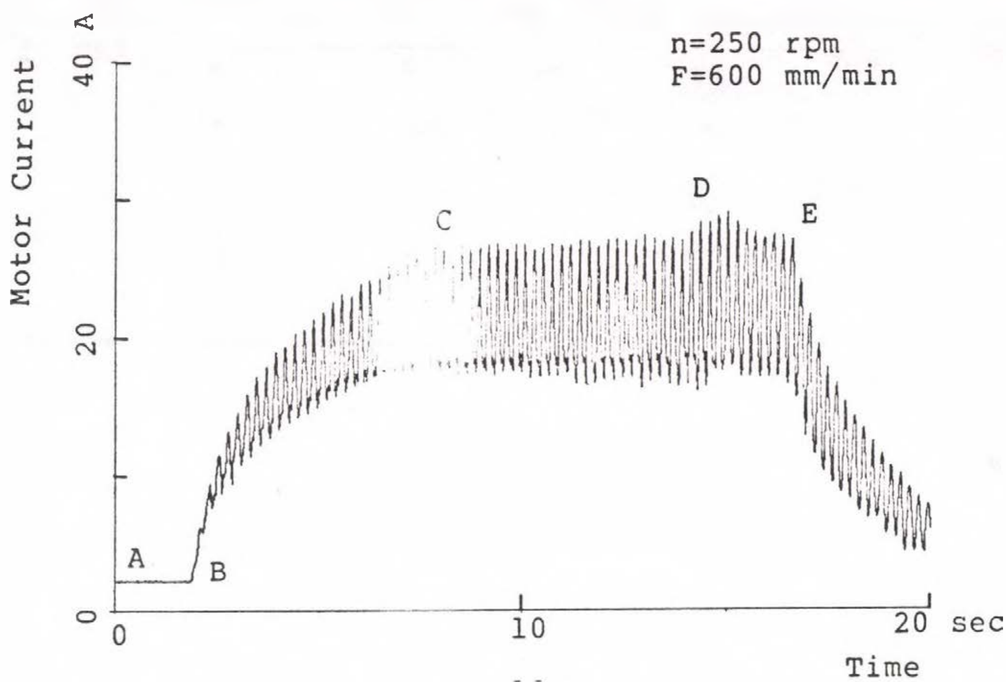


Fig. 3.4 Measured Spindle Motor Current

Sampling Interval = 20 msec

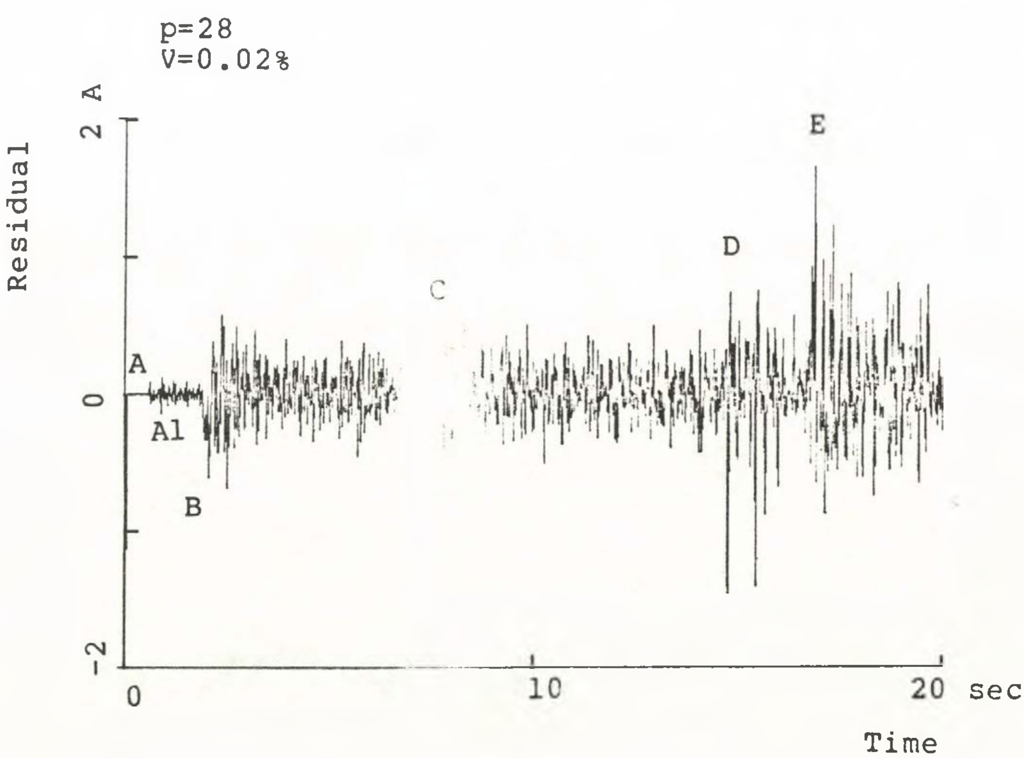


Fig. 3.5 Tool Breakage Detection Signal

the fluctuations decrease, the greater peaks fade away, which shows that the model readjusted itself to the process. The residual does not show any special mark at point 'C' where the tool reached the full width of cut. In point 'D' there is a large spike indicating the tool breakage. As the cutting process changed abruptly, the amplitude of the peaks is about twice as great as in point 'B'. Also, there are large individual peaks rather than a general increase in the amplitude of the fluctuations. The peaks fade away similarly to point 'B', indicating that the model readjusts itself to the changed process. In point 'E' the foremost point of the cutter reached the end of the workpiece, and began to leave the workpiece. Comparing the points 'B', 'D' and 'E' we can see that the peaks are the smallest at 'B'. It is also apparent that at 'B' and 'E' the fluctuations increase in the residual, while at 'D' only individual peaks can be observed. From a different point of view we can say that while the changes in the process at points 'B' and 'E' are fairly slow and can be predicted if the workpiece is known, the change of the process at point 'D' is fast and unpredictable.

3.3.2.2 THE AR MODEL FOR FACE MILLING

The method of AR modelling was that the coefficients of the model, expressing the actual data as a linear combination of the previous data, were recursively estimated by a Kalman filtering algorithm. In other words, the AR model says that each time an additional observation of the signal 'z' was attained, it was expressed in the form:

$$z(k) = M(k)\,X(k) + v(k) \qquad 3.17$$

where 'M' denotes the vector of prevoius observations, 'X' is the coefficient vector to be determined and 'v' is some unknown disturbance supposed to be a zero mean white noise process independent of the observed signal. The updating of 'M' is a simple shifting operation, the new data steps in and the oldest one is dropped out of the observation vector. Applying the set of equations to this case we get the following:

$$P(n) = P(n-1) - P(n-1)M'(n)\left[V+M(n)P(n-1)M'(n)\right]^{-1} M(n)P(n-1) \qquad 3.18$$

$$X(n) = X(n-1)+P(n)M'(n)V^{-1}(n)\left[z(n)-M(n)X(n-1)\right] \qquad 3.19$$

where 'P' is the estimation covariance and 'V' is the noise variance. The noise variance was supposed to be constant. Using 3.18 and 3.19 the coefficient vector of the AR model, 'X', was recursively estimated. Then by using the coefficients an AR model was built up and the output was calculated at every step. The initial value of every variable was taken as zero, except for the estimation covariance, which was taken as unit matrix.

3.3.2.3 PRACTICAL ASPECTS OF AR MODELLING

Determination of the model order

Several criteria have been introduced for selection of the AR model order, i.e. to determine how many previous data are needed to estimate the signal reliably [19] - [25]. These criteria give considerable help in selecting a proper order. Nevertheless, when using them against actual data rather than simulated processes, their performance may worsen [26], and in the final analysis subjective judgement can not be eliminated.

The first method discussed is called the final prediction error (FPE). The FPE for an AR process is defined as

$$FPE(p) = s^2(k)\ (N+p+1)(N-p-1)^{-1} \qquad 3.20$$

where s(k) is the average prediction error of the model, 'N' is the number of data samples and 'p' is the model order. The FPE increases as 'p' approaches 'N', which reflects the increasing uncertainity of the estimation. The order 'p' selected is the one for which FPE is the least.

Another selection criterion determines the model order by minimizing an information theoretic function introduced by Akaike. Assuming the process has Gaussian statistics, this information criterion (AIC) is defined as

$$AIC(p) = N \ln FPE + 2p \qquad 3.21.$$

Here again the model selected is the one for which the AIC is the least. As 'N' increases, the two criteria, FPE and AIC, will approach each other.

Figure 3.6 shows the AIC against model order for the example shown previously. It can be seen that for very low model orders AIC decreases sharply when the order increases. When the order reaches three, the curve becomes almost flat. The next significant decrease in AIC is at order 9 - 11, then a very slight decrease between 26 and 30, and finally between 43 and 46. In other words AIC suggests the following model orders: 3, 11, 30, 46; as the ones which offer good AR models with relatively little computational load. Next, figure 3.7 - 3.10 show the residuals, calculated with different model orders, against time for the same process. Looking at the diagrams it becomes obvious that order eight does not give any result, as far as breakage detection is concerned. The next model, with order 16 improves the result, the detection signal becomes apparent as the fluctuations in the residual decreased. Repeated increases in the model order result in some additional decrease in the fluctuations of the residual, without any augment in the breakage detection signal. The examples later were computed with model order 28, in order to show the possible influence of the breakage on the AR model.

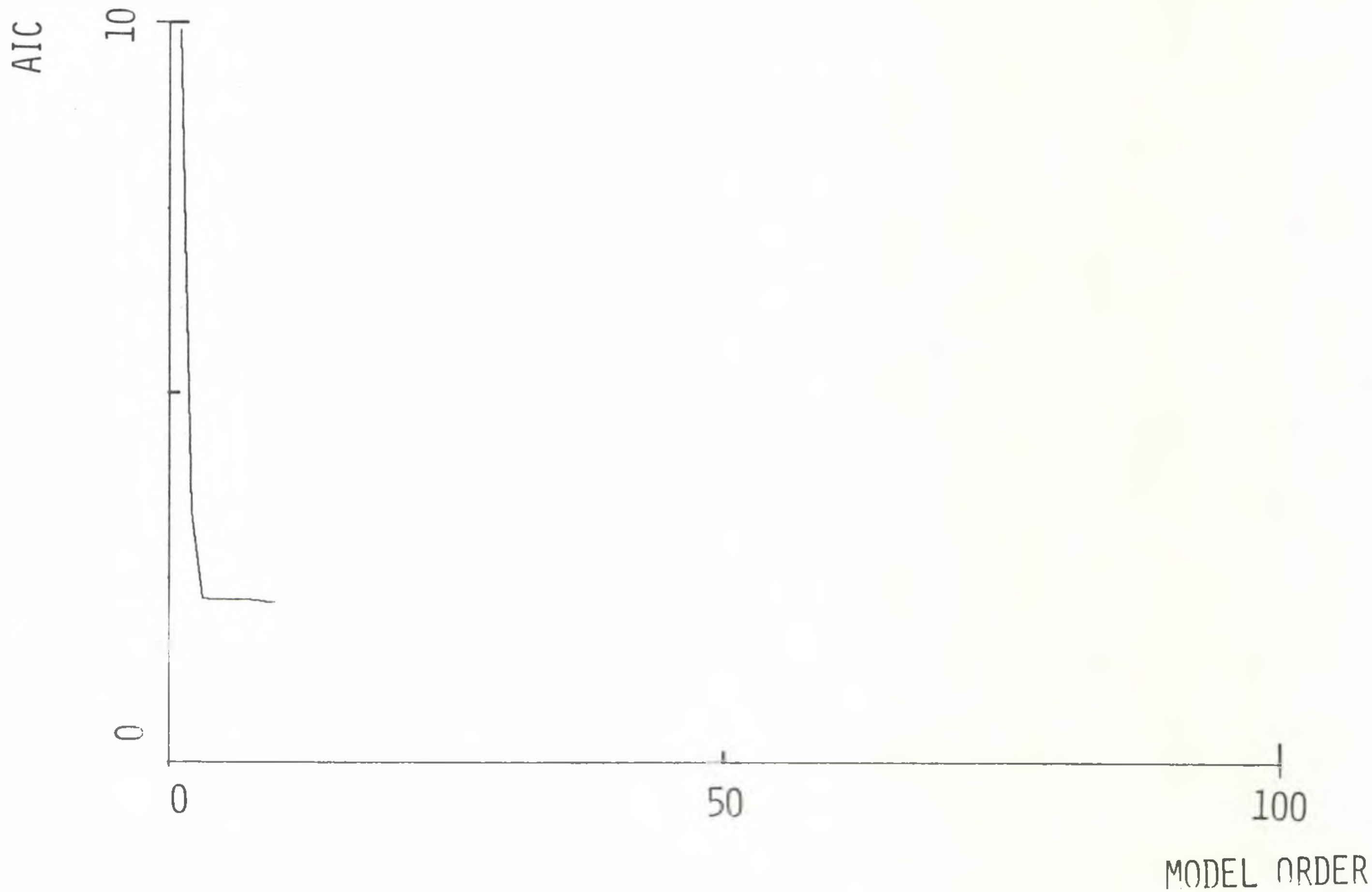


Fig. 3.6 Information Criterion by Akaike

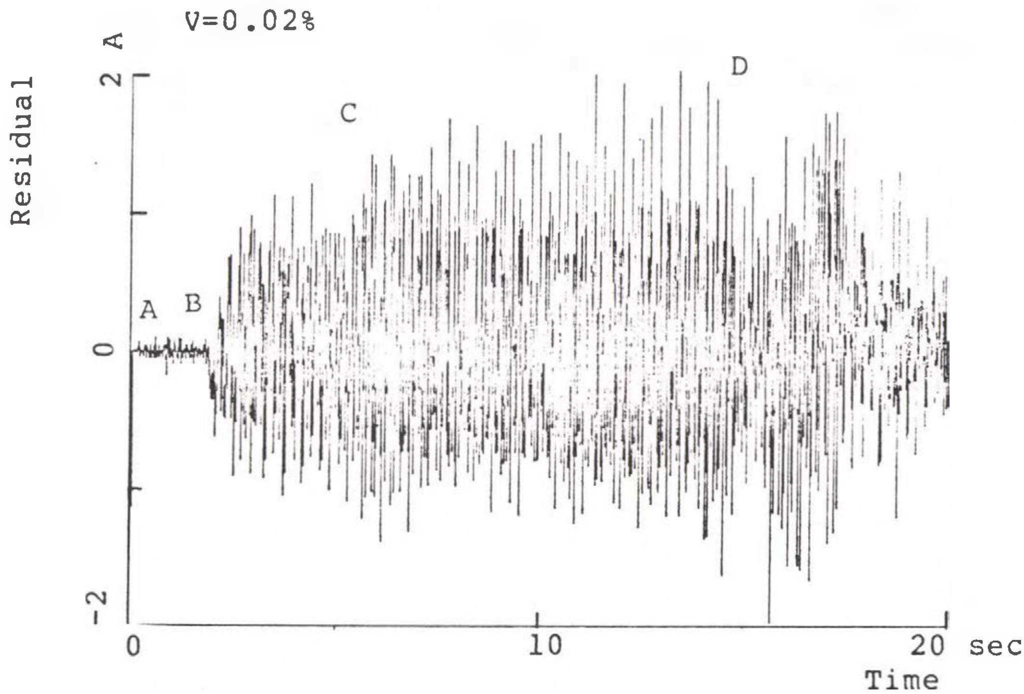


Fig. 3.7 Calculated Residual

Model Order p=8

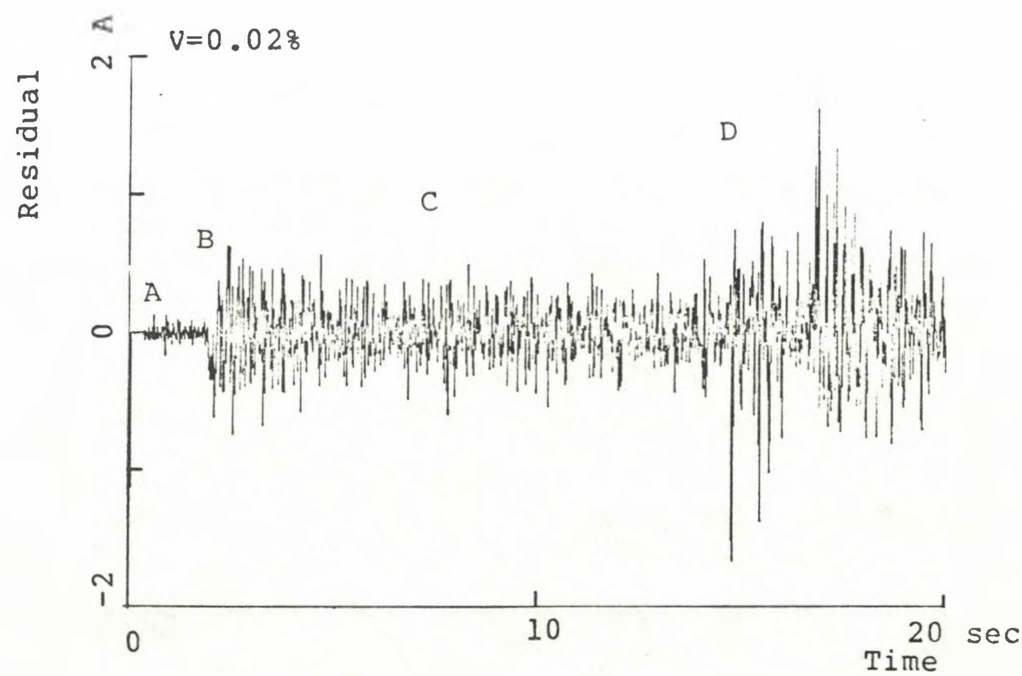


Fig. 3.8 Calculated Residual
Model Order p=16

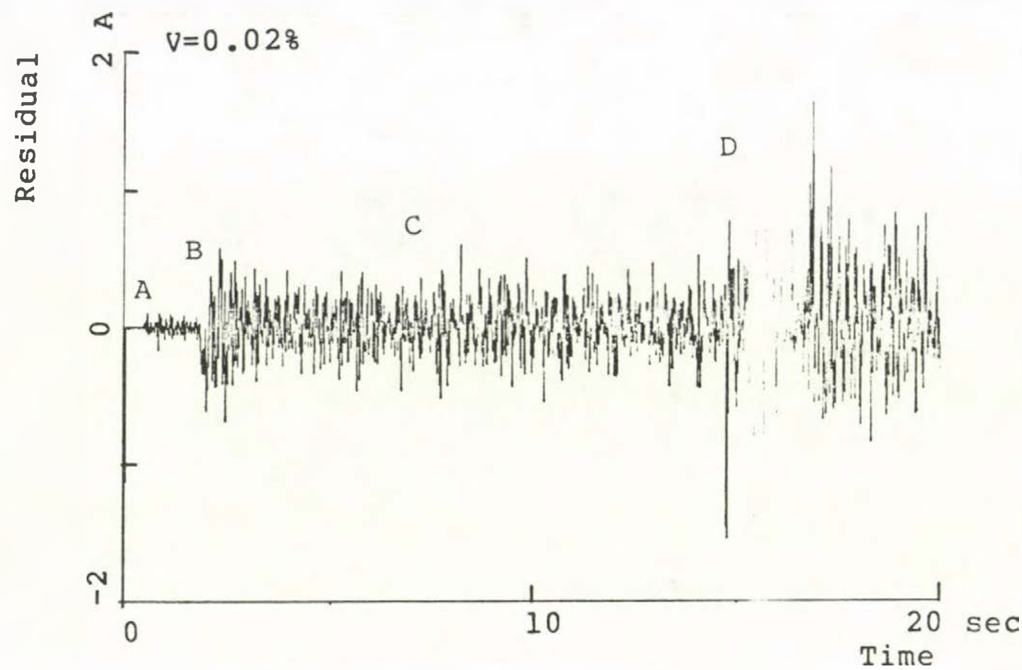


Fig. 3.9 Calculated Residual
Model Order p=24

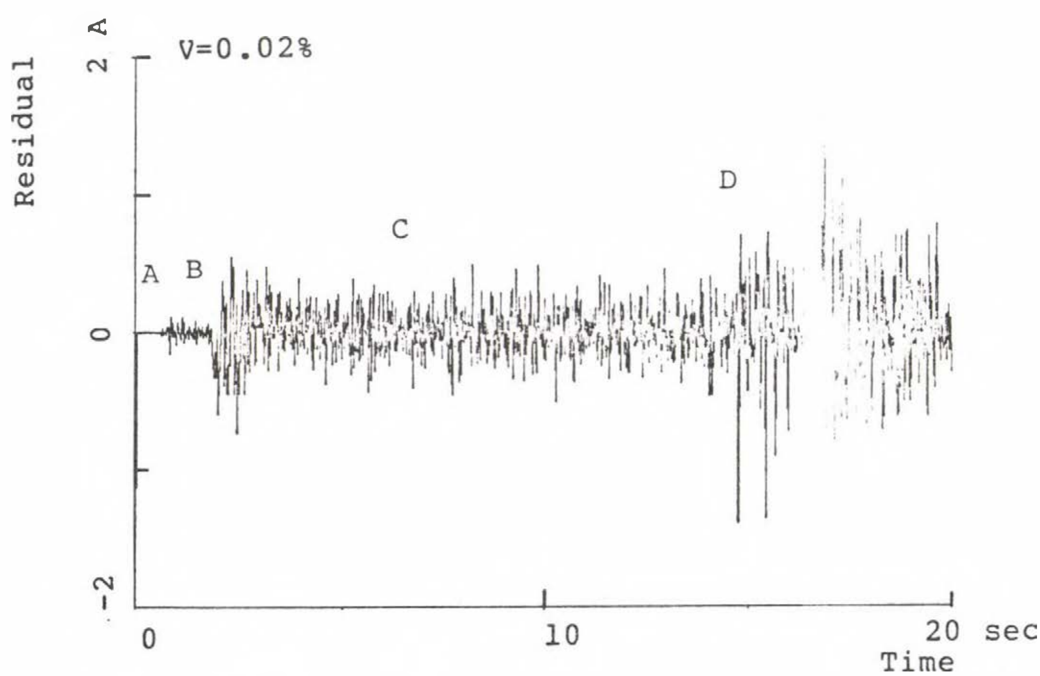


Fig. 3.10 Calculated Residual
Model Order p=32

Summarizing the results on model order determination we may conclude that although there are some theoretical criteria, the best and most reliable method is finally a subjective judgement. At least one whole revolution must be included in the data processed (twelve samples were taken from every revolution), and further increase in the order may be useful, as the breakage may cause change in higher coefficients of the model too. The inclusion of two revolutions proved to be sufficient. The detection signal not necessarily improves when the order of the model increases, but the tendency exists, and an optimum must be found.

The observation noise variance

Although the supposition of a noise describing the uncertainities and inaccuracies in the measurement system is well founded, there are no good methods to measure any parameter of it. The assumption that it is a zero mean white noise independent of the observed cutting process is plausible and all we need to estimate the model is the noise variance 'V'; it was supposed to be constant in the experiments. Figures 3.11 - 3.12 show the results of different calculations: the residuals calculated with different noise variance against time. The order of the model was 28. The smallest value of the noise variance was about 0.02 % of the signal mean, its absolute value being 0.1. The result shown in figure 3.11 is very good, the

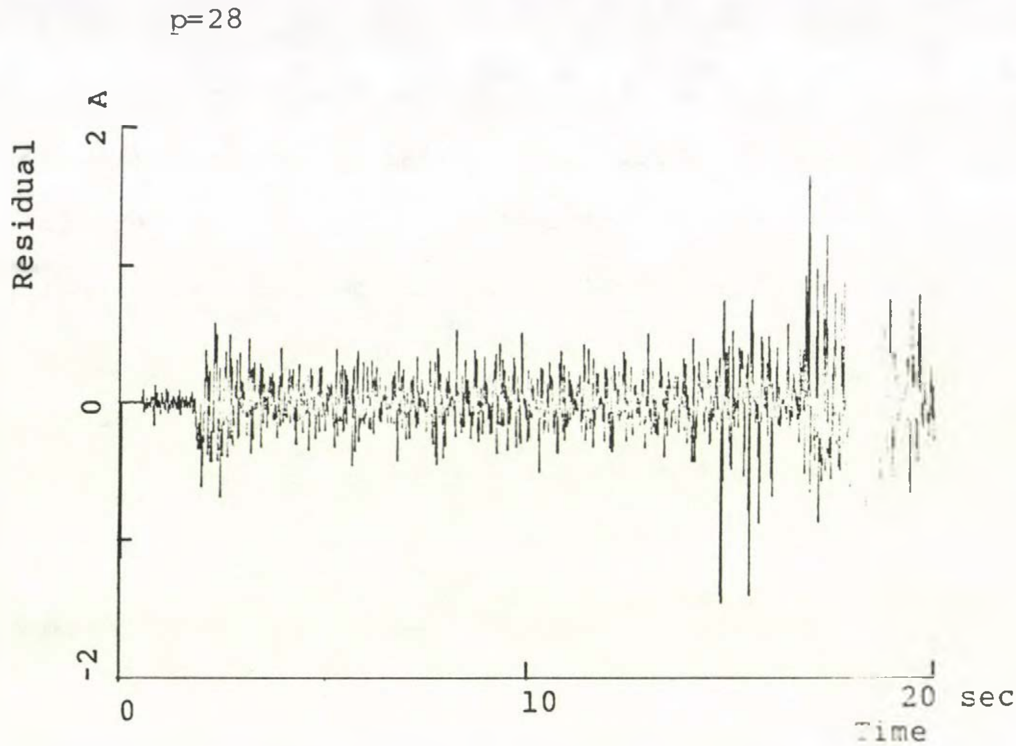


Fig. 3.11 Calculated Residual
Noise Variance V=0.02%

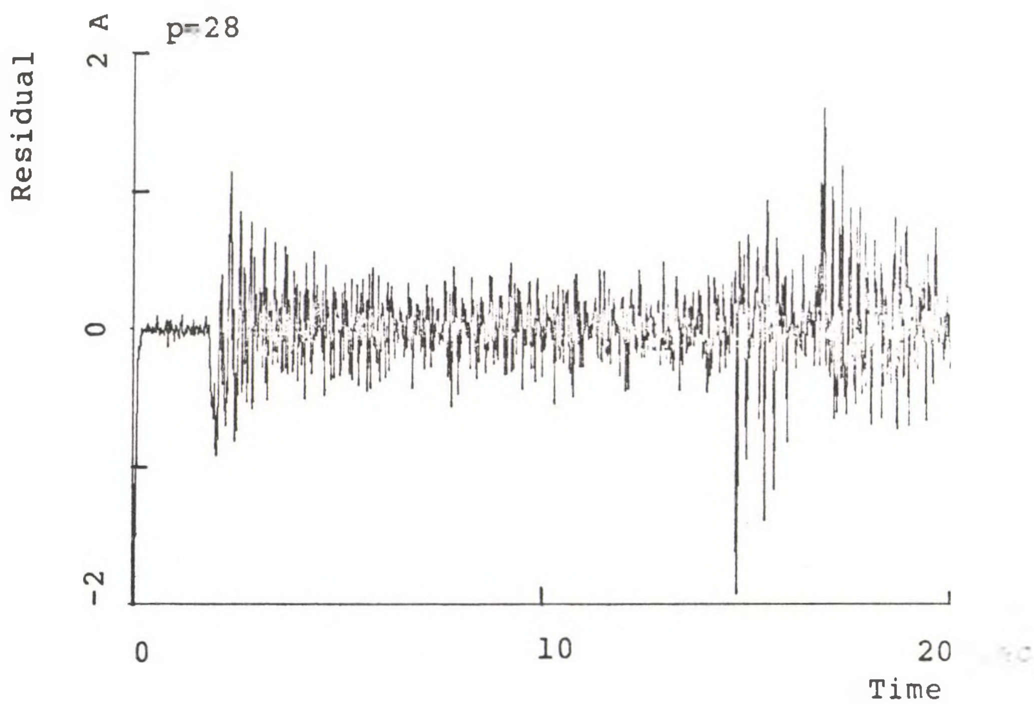


Fig. 3.12 Calculated Residual
Noise Variance V=20%

detection signal is very clear. The residual shown in figure 3.12 was calculated with a variance about 20 % of the signal. The fluctuations are considerably greater, but an augment in the pulse at the breakage can yet be observed. It must be noticed that the great fluctuations around the points where the cutting process changed, e.g. 'B' and 'D', fade away slower. This feature is easily understandable from equation 3.19: the correction factor of the estimation, the second term, is inverse proportional to noise variance 'V'. The results discussed above clearly indicate that the noise variance must be kept at a low level. It may be interesting to see how low they can be kept. As it has been discussed, due to roundoffs in the computer the estimation covariance matrix, 'P' in the equations, can become singular which can cause the filtering method to diverge. The model output in figure 3.13 clearly indicates the singularities in the covariance matrix as great peaks. Here scales different from the previous ones were used. The result shown in figure 3.14 is extremely good, as the spike at the point of breakage exceeds over any other peak in the residual. Unfortunately these results are not enough for a detection method to be based on. As the point where the covariance matrix becomes singular depends on the actual process (and on the computer's roundoffs), individual noise variance has to be found for every process. To find a general method in this way is beyond the scope of this work.

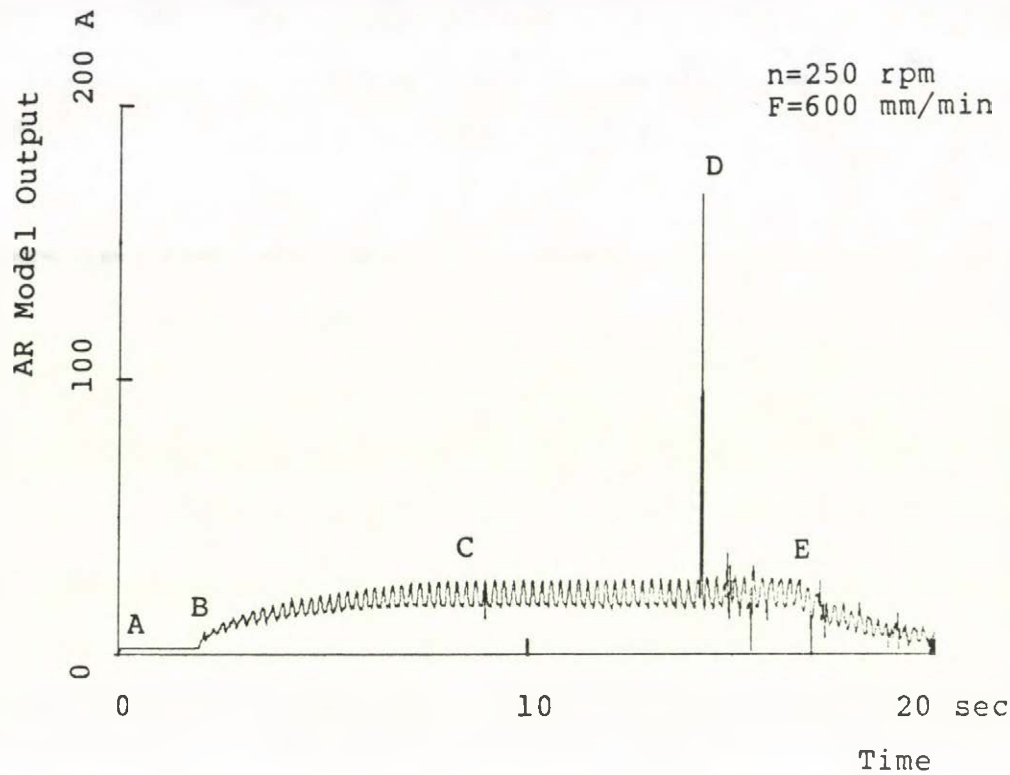


Fig. 3.13 AR Model Output p=28 V=0.00318

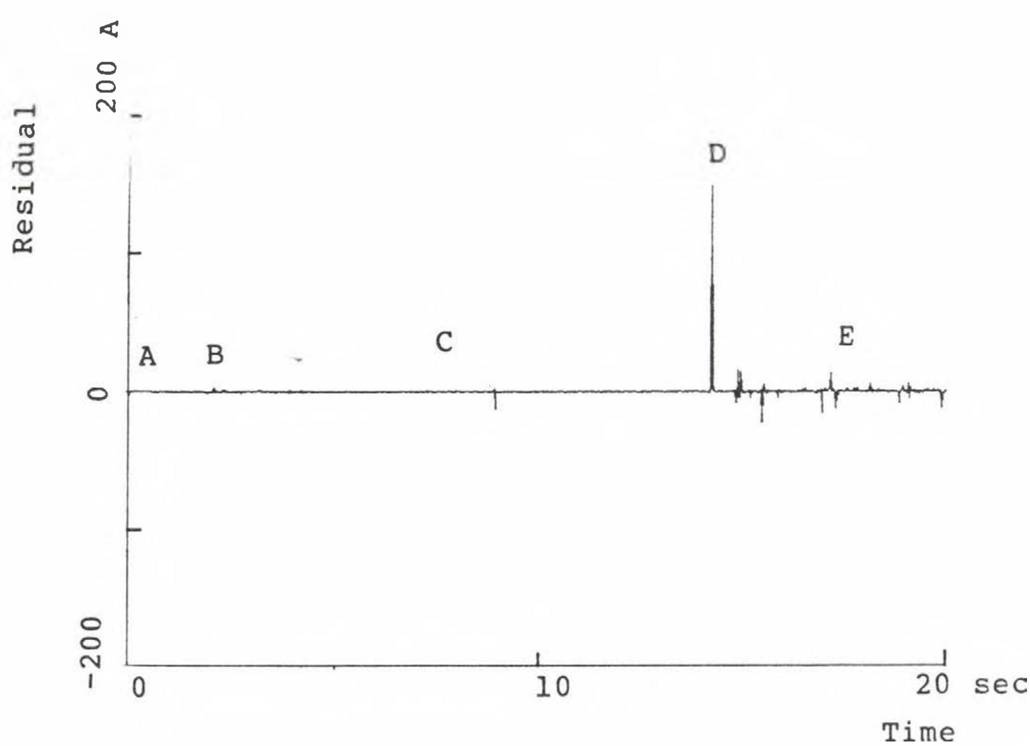


Fig. 3.14 Calculated Residual

It can be seen from the results, that a wide range of noise variance values provide satisfactory detection signals. Notwithstanding, extremely great values can cause the detection signal to disappear in the enormous fluctuations of the residual, and extremely small values make the estimation variance matrix singular in the course of calculations.

3.4 APPLICATION EXPERIMENTS

Figure 3.15 shows the spindle motor current measured during another cutting experiment, and figure 3.16 shows the calculated residual. The tool began to cut the workpiece at point 'B'. At point 'C' a small breakage occured, which upset the normal course of the process. This is clearly indicated in the augmented fluctuations of the residual between 'D' and 'E'. In this interval the mechanical, and probably also the heat load of one cutting edge was very heavy resulting in a fast wear of the edge between 'E' and 'F', where the minimum values of the wave gradually increased, indicating that an edge being idle beforehand became active.

The experiment shown in figure 3.17 was also not a simple breakage. The tool entered the material at point 'B'. The cutting process was normal until a breakage at point 'C' occured. The cutting process continued with broken edge, but as the process seemed to be very dangerous

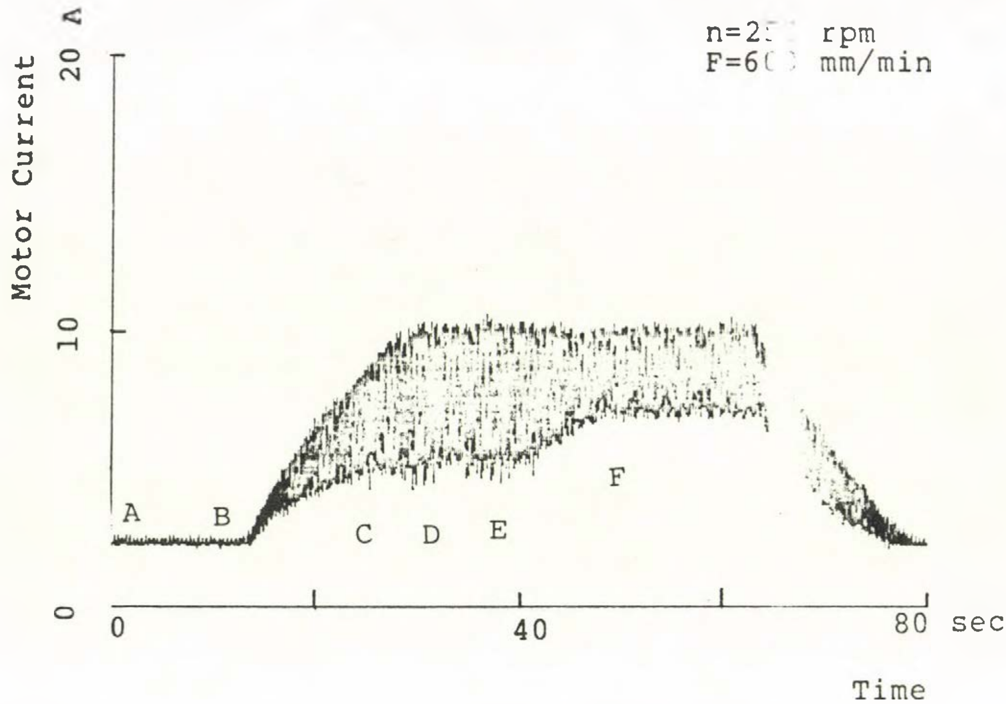


Fig. 3.15 Measured Spindle Motor Curr nt
Sampling Interval 40 msec

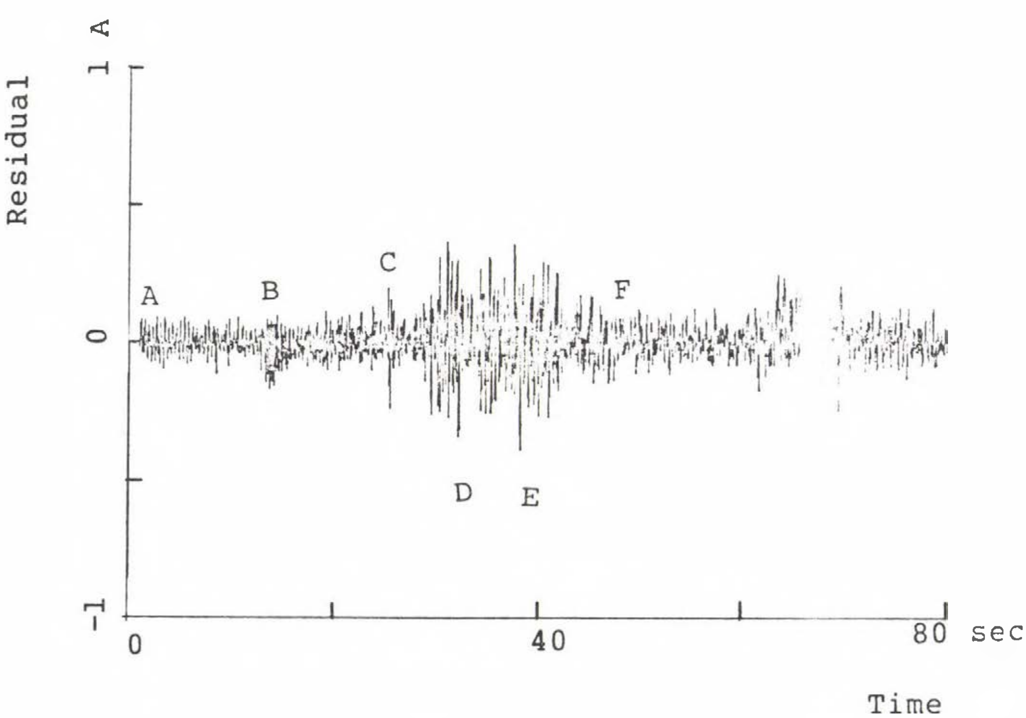


Fig. 3.16 Calculated Residual p=28 =0.01%

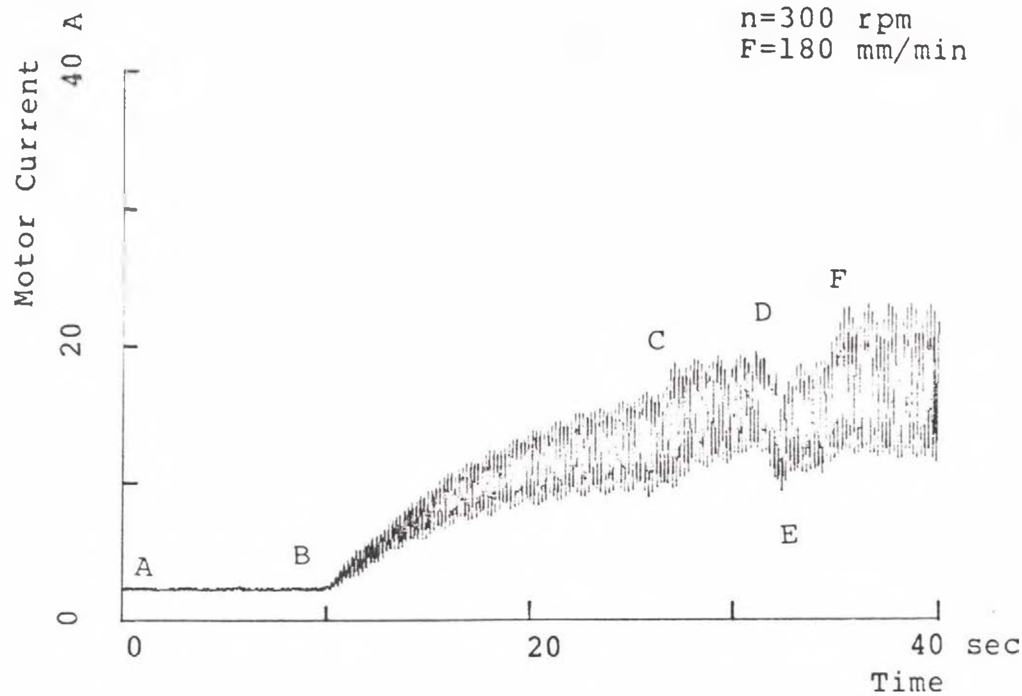


Fig. 3.17 Measured Spindle Motor Current
Sampling Interval 40 msec

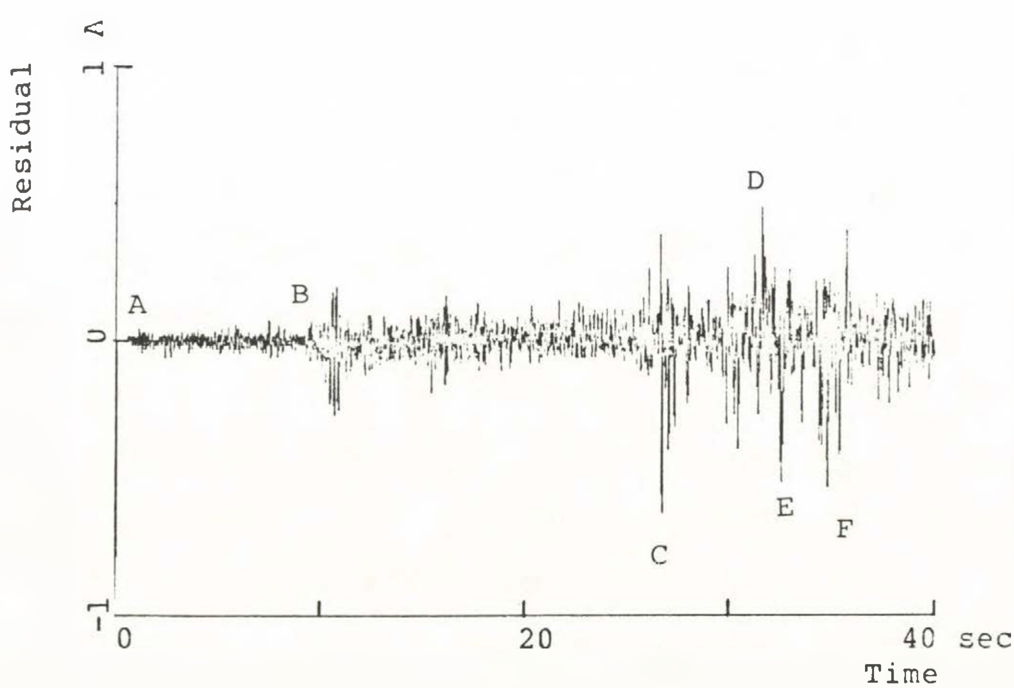


Fig. 3.18 Calculated Residual p=28 V=0.01%

a human interaction became necessary, and the feed rate was reduced to half at point 'D'. This caused a decrease in the torque between 'D' and 'E'. The improvement was temporary, as the increasing tendency of the torque continued, and finally at point 'F' another edge broke. The two broken edges followed each other immediately on the tool, which means that the second edge broke due to the overload caused by the first breakage. The corresponding residual in figure 3.18 clearly indicates these events.

3.5 CONCLUSIONS

A monitoring method for cutting operation was described in this chapter. As being one of the most pressing problems, the detection of tool breakages was targeted. The efforts were bent towards breakages having negligible immediate consequences but being possible sources of further problems, which can end in serious damage or loss. In order to find a general method, the face milling process, where the tool has more cutting edges, was selected. Microscopic breakages during the experiments caused small but distinct change in the cutting process. The different cutting edges of the tool had different load in the experiments, i.e. due to not uniform setting of the tool some edges had wider cut, which was reflected in greater cutting torque. It was interesting to see, that the broken edge was not always the one having the widest cut. Considering that breakages are caused usually by some defect in the workpiece material or in the cutting edge rather than by simple overload, this fact is easily understandable. The most common consequence of the breakages in the experiments was that the load of the next cutting edge increased, as it had to cut for the broken one too. This overload brought about additional breakages or very intensive wear in many cases, which then resulted in dangerous cutting conditions. This fact emphasizes the necessity of detecting very small breakages too.

The sensoring method was the one described in the previous chapter, i.e. the resultant cutting torque was measured via the spindle motor current. The breakage caused a change in the cutting torque. The change was very small, the waveform of the monitored signal was affected slightly, no significant rise in the signal mean or enormous increase of the fluctuations were detectable as immediate consequences of small breakages. Hence a mathematical method was used to filter the change out of the process.

The process observation was regarded as a stationary signal measured by using noisy instruments. The process was described by an autoregressive model, and the coefficients of the model were estimated recursively. Due to the advantageous property of the AR model, its equations being linear and easy to handle , a relatively simple updating method, a simpler form of Kalman filter algorithm, was used for system identification. The algorithm for sequential estimation had a predictor - corrector structure, i.e. the current estimation was always modified by a factor computed from the difference between the previous estimation and the measured signal. The difference between the estimated and measured data, called residual, served for detection of a change in the process. The change in the process induced the deterioration of the model, and an increase in the residual. This increase in the residual was always sharp and distinct at tool breakages, since the change caused by the breakage in the process was abrupt.

The basic problem in AR modelling was the determination of model order. It became clear that to get a detection signal satisfactory in amplitude at least one whole revolution had to be involved in the data processed, good detection signal required about two revolutions. Further increase in the model order improved the detection signal to a certain degree, a tendency was apparent. It can not be stated, however, that higher model order results in greater or clearer detection signal without limits. In spite of existing criteria for model order determination subjective judgement proved to be also necessary. It has also become clear that proper care has to be taken in the calculations. The noise variance can vary within a wide range, but extremely great or extremely small values can lead to difficulties in detection or in calculations. To initialize the calculations some preliminary knowlegde is necessary about the process. In this case, however, the solution of setting the variables at zero and taking the estimation variance as unit matrix has given satisfactory results.

CHAPTER 4

CUTTING TORQUE ESTIMATION SYSTEM
(FOR MONITORING THE CUTTING OPERATION)

4.1 COMPREHENSIVE MONITORING
(INTRODUCTION)

The purpose of monitoring the machining operation is to detect any abnormality which may result in inferior products or breakdown of machines. Methods monitoring only main parameters of a system, e.g. cutting torque, motor current etc., give a good general overview of the system's operation, but proper interpretation of the measured data is a difficult task. The parameters change in time according to the operating conditions, and their normal values have to be known by the monitoring system. Furthermore, any diagnostic procedure requires not only the expected values of parameters, but sufficient knowledge about the process taking place on the machine. The development of CAD-CAM technology brought about the integrated planning of the manufacturing process. Failure detection can also be involved into the CAD process, since the expected values of parameters can also be calculated during design.

Not only failure of machines but human mistakes can also result in scraps in manufacturing. At present the verification of NC programs is a time consuming work. Recent development of geometric modelling systems and their application to CAD-CAM enables the NC data verification to be carried out on a computer [1], [2]. NC data verificaton, however, must be performed not only geometrically, but also technologically.

To cope with these problems this chapter presents a cutting torque estimation system primarily for face and end milling operation. After a short description of existing monitoring systems, the functions and the structure of the system are described, which are followed by discussions on the results of validation experiments and application examples.

4.2 EXISTING COMPREHENSIVE MONITORING SYSTEMS BASED ON CURRENT MEASUREMENT

The most simple is the overlimit method, when the measured parameter (current) is compared with a limit set before the operation, the cutting, begins. When a parameter exceeds over one of these limits, the monitoring system gives an alarm signal. In most cases fatal errors cause enormous increase in the process parameters, what makes their detection easy. Nevertheless, the method has important shortcomings. As these limits are set to be greater than the values expected during normal operation, an enormous increase of a weak signal can remain undetected, if it does not rise above the limit. Another type of failure, when the measured signal is significantly smaller than expected, needs different treatment. A simple comparison with a minimum threshold level can not be used, since the signals may be inactive at any time, e.g. during tool change, and therefore the minimum expected value is zero. The method used most generally refers to a preliminarily defined signal pattern. The parameter's expected value, a function of time, is inputted to the system, and during operation the measured value is compared with the reference. When the system detects significant discrepancies, it generates an alarm signal. Unfortunately in most cases this method uses an inconvenient reference data input: the reference pattern is obtained by recording the signal during a test run (therefore it is also called teaching playback). Carrying out test cuts is inefficient in small or medium size manufacturing. In some cases the workpiece is very expensive, and test cuts can not be afforded at all.

4.3 BASIC FEATURES AND FUNCTIONS OF THE SYSTEM

In this chapter an attempt is made to involve failure diagnostics into a CAD-CAM system, and also to base monitoring of the manufacturing process on CAD-CAM. The main idea is to calculate the monitored parameter changing in time prior to machining, and to input these values as a reference to the monitoring system. This method, giving the parameter's value after the design step and before the physical process takes place on the machine, can serve for verification of the design as well.

The monitored parameter in our case is the cutting torque, its value has to be determined by calculations. The basic aim of developing a cutting torque prediction system was to provide a powerful tool for the following:

1. monitoring the machining operation
2. failure diagnostics
3. NC data verification
4. optimization of cutting conditions.

A classical monitoring system helps only in the first task, and even there it gives a worse performance, since the best method -the teaching playback- needs a test cut to obtain the reference. The cutting torque estimation is based on a CAD-CAM system, shares a common data base with it, hence in addition to the reference cutting torque it can transfer technological data about the machining operation, tool or material data to the monitoring system. Using these data the monitoring system can be extended into a diagnostic system which has enough knowledge about the actual process, and can identify the causes of failures. Accordingly, upon detection of abnormal conditions the diagnostic system can take proper actions, and the normal operation may resume without human interaction.

CHAPTER 4

As far as NC data verification is concerned, the system can accomplish the geometrical verification by the precise cutting simulation performed in the first phase of the cutting torque calculation, the simulation resulting in the model of the finished workpiece. For geometric modelling a three-dimensional geometric modelling system is used, consequently, potential collisions between tool and fixtures can be checked by inputting the model of the fixture instead of that of the workpiece.

In addition to geometrical verification, improper cutting conditions leading to excess cutting torque can easily be discovered before cutting. The calculated cutting torque can be used for estimation of thermal and elastic deformations, and the resultant machining error can be evaluated and compared with the accuracy required.

Technological conditions of the NC program can be optimized by using the estimated torque data; e.g. feed rate, spindle speed, depth of cut etc. can be set to provide minimum manufacturing time while not exceeding force, torque and other limits allowed for the actual tool and machine tool.

4.4 SYSTEM DESCRIPTION

4.4.1 SYSTEM ARCHITECTURE

A system has been built to perform the tasks listed in the previous section. The geometric model and material data of the workpiece together with the NC part program are inputted to the system; the supplementary data about tools are stored separately, as shown in figure 4.1. The system consists of two main parts, the first is called geometric simulation, the second is torque estimation. Based on a geometric model of the workpiece and of the tool the material removed by cutting is determined, i.e. the cutting operation is simulated in a computer. Then in the second phase the cutting torque is estimated by using the results of geometrical calculations as well as other, technological data. As the calculations are divided into two phases, a repetition of the torque estimation with different technological parameters does not require a repetition of the geometrical simulation, and the optimization of cutting conditions becomes faster.

The output of the system is a series of torque values.

4.4.2 GEOMETRICAL SIMULATION

The geometric simulation is performed with the GEOMAP-I modelling system. The procedure is illustrated in

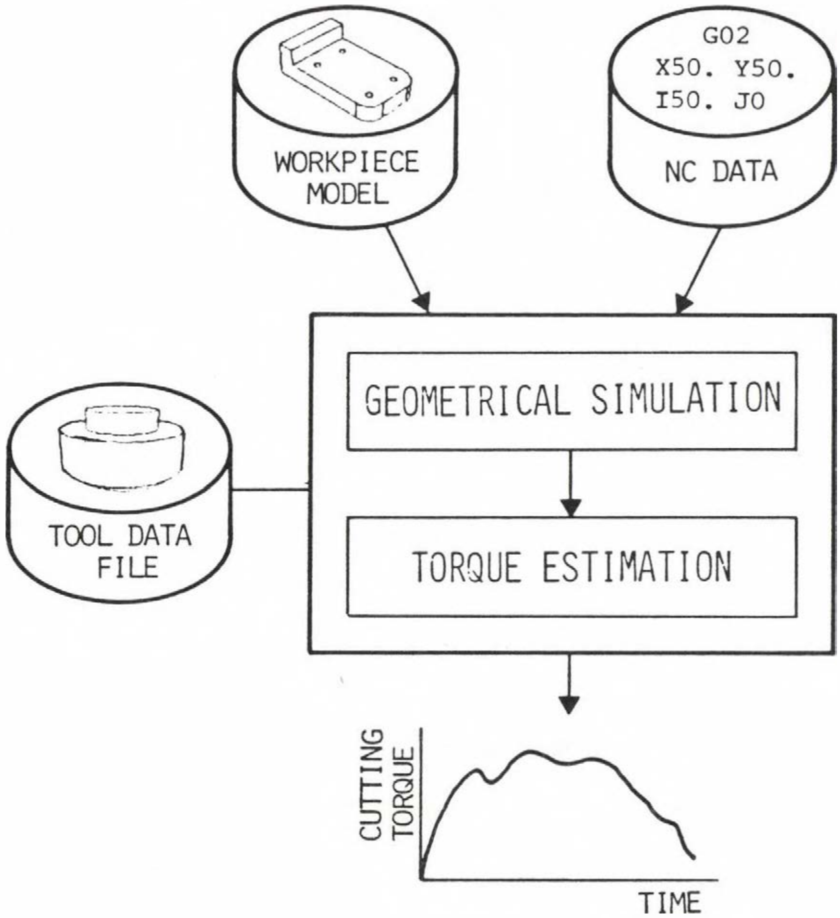


Fig. 4.1 System Architecture

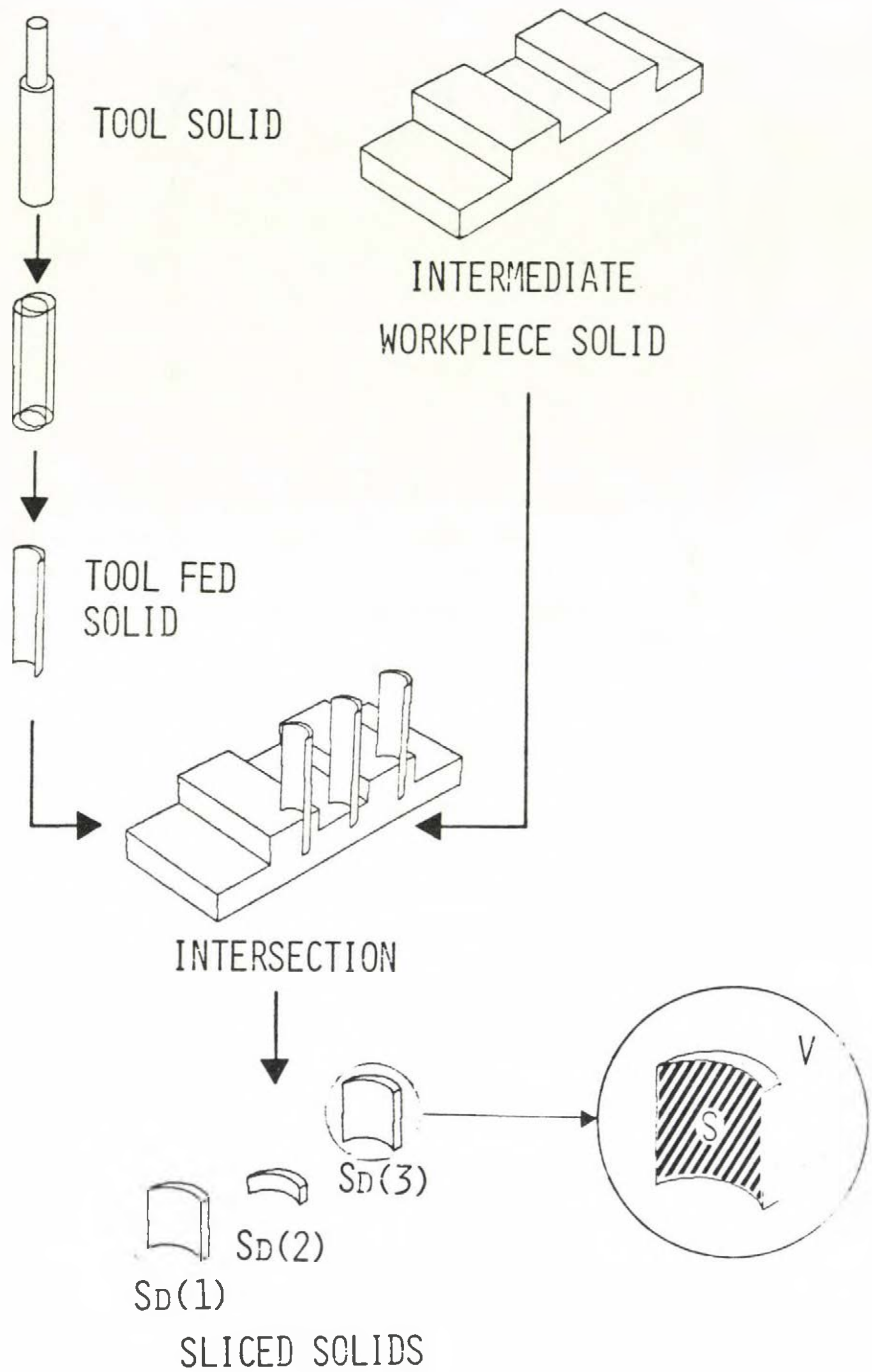


Fig. 4.2 Geometrical Simulation

figure 4.2. First a tool solid is generated from the attributes tool size and type, which are supplementary input to the system. Next the advance of the tool is simulated. During cutting the tool, moving along the programmed path, sweeps a space and any workpiece material in this space will be removed during cutting. This process is modelled in the following way. Determining the space swept by the tool between time 'i' and 'i+1' and subtracting the tool model at time 'i' will result in the space, from which any material is removed between time 'i' and 'i+1'. When the distance covered by the tool in unit time is small, this space can be well approximated by subtracting the tool model at time 'i' from that at time 'i+1'. The modelling system uses this approximation, as can be seen from the left side of the figure, and the result is called the tool fed solid at time 'i'. This tool fed solid represents only the possibility of material removal, cutting will be performed only in that space where there is material actually. Hence to determine the segment of material removed between time 'i' and 'i+1' the intersection of the workpiece solid and the tool fed solid is taken, the outcome being the sliced solid. By repeating this in several points along the programmed path, the cutting torque can be approximated in a series of points. The points can be determined completely arbitrarily if so desired. In the examples discussed the steps were uniform in length, and the length of one step was equal to the width of the tool fed solid, which means that the whole space swept by the tool in a block was involved in the

simulation. The result of the geometrical simulation for one block is a series of sliced solids - as shown in the lower part of the figure.

The procedure described above is executed for each block of the NC part program. During cutting the shape of the workpiece changes continuously as the tool removes the material. The system simulates the change in the geometry of the workpiece by subtracting the space swept by the tool in the whole NC block from the workpiece solid input to the actual block. This is performed upon completion of torque calculation for the given block. As illustrated in figure 4.3, the resultant body of this operation is used as input workpiece model to torque calculations in the next NC block. This simulation is performed from the first NC block to the last one step by step, and in this way the system generates a series of changing shapes of the workpiece, from the initial workpiece model, the blank part, through intermediate workpieces to the final result, the finished part.

The cutting simulation serves for geometrical verification of the operation as well, which can be performed by examining the changes in the shape of workpiece model.

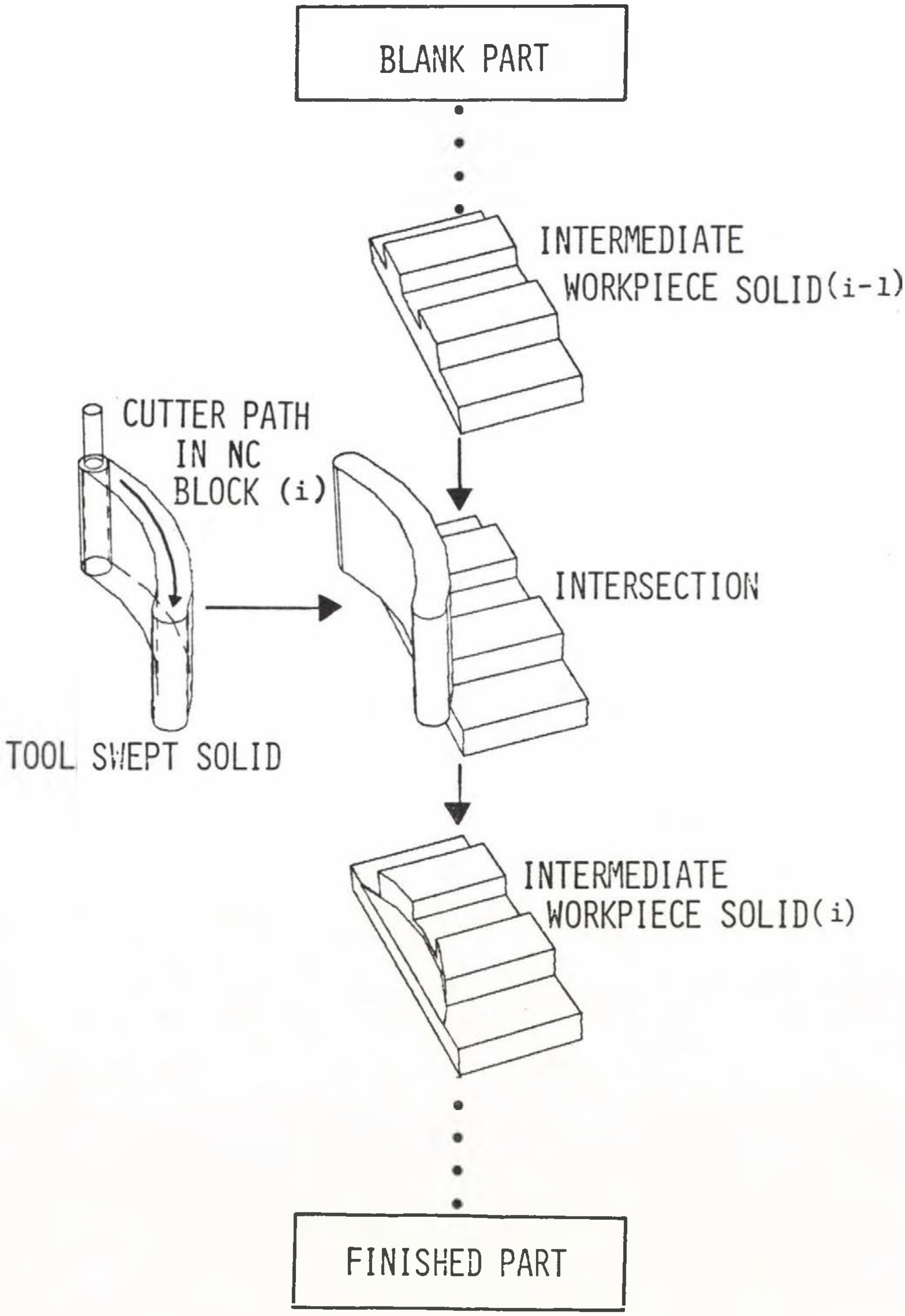


Fig. 4.3 Tape Verification

4.4.3 TORQUE ESTIMATION

The cutting torque is estimated in the second part of the system by using the result of geometrical simulation, some additional technological information obtained from the NC part program, material and tool data. The torque is estimated by using an empirical equation of the following form:

$$M = k1*V*f + (k2*f+k3)*S \qquad 4.1,$$

where 'V' is the volume of material removed while the tool advances a unit distance, 'S' is the tool-workpiece contact surface area, 'f' is the feed rate (per tooth) and 'k1', 'k2', 'k3' are constants depending on the material of workpiece and the type of tool used.

As can be seen from figure 4.2, the material removed 'V' and the tool-workpiece contact surface area 'S' can easily be calculated from the sliced solid.

4.5 VALIDATION OF THE SYSTEM

4.5.1 VALIDATION EXPERIMENTS

To evaluate the effectiveness of the cutting torque estimation system, cutting experiments using milling cutters were performed on a vertical machining centre (MAZAK V 7.5). The average torque was calculated for every revolution of the tool, and this value was compared to the estimate. As one cycle of the process is one revolution of the tool, during which the amount of material removed is constant, data calculated in this way give better results than a running average of the signal.

Figure 4.4 shows data measured in a cutting experiment performed with an endmill, 20 mm in diameter. The spindle motor current was sampled at 40 millisec intervals. The real cutting took place between points 'B' and 'E', in the intervals 'AB' and 'EF' the tool was rotating in the air, as it approached or moved away from the material. In intervals 'AB' and 'EF' the average torque is greater than zero, since the input torque was measured, and it takes some energy to rotate the tool. Examining the torque signal measured during cutting, we can observe that the measured torque (current) decreases below the initial level. This is due to huntings in the spindle control system, and does not have importance. Figure 4.5 shows only the initial part of the signal around point 'B', so the alterations are clearer here. The information obtained from the fluctuations can be processed with high efficiency by using other methods, such as described in chapter three.

The result of cutting simulation is shown in figure 4.6, the measured and estimated cutting torque under various cutting conditions are shown in figures 4.7 - 4.9. The workpiece was made of carbon steel (C = 0.45 %). The

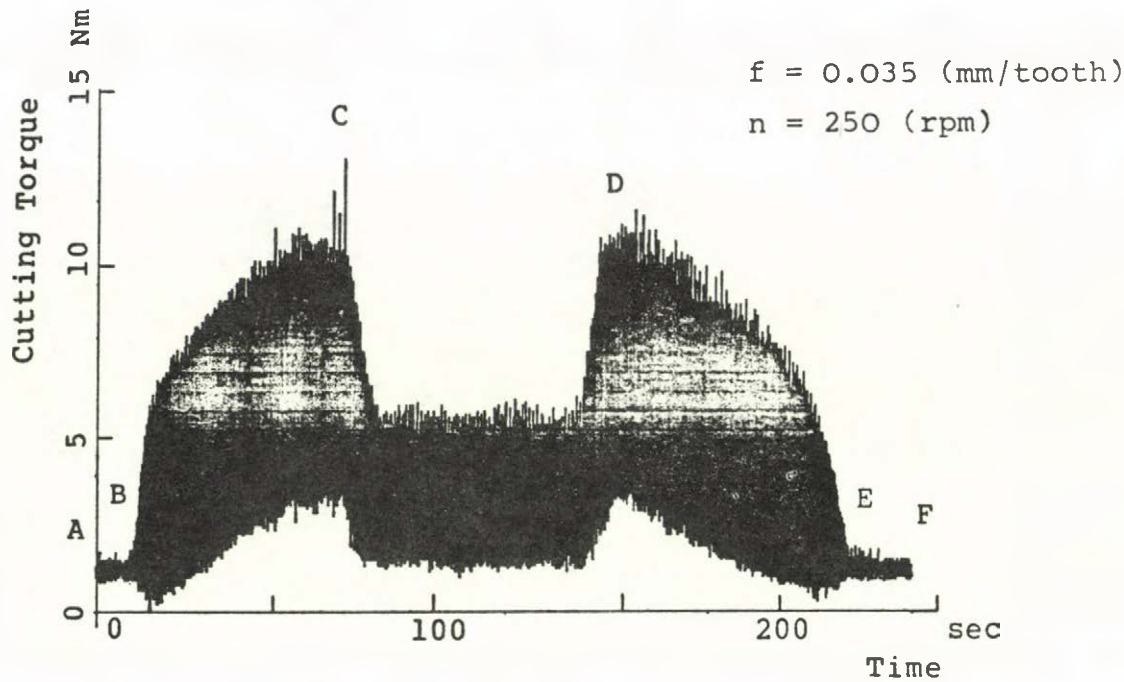


Fig. 4.4 Measured Cutting Torque

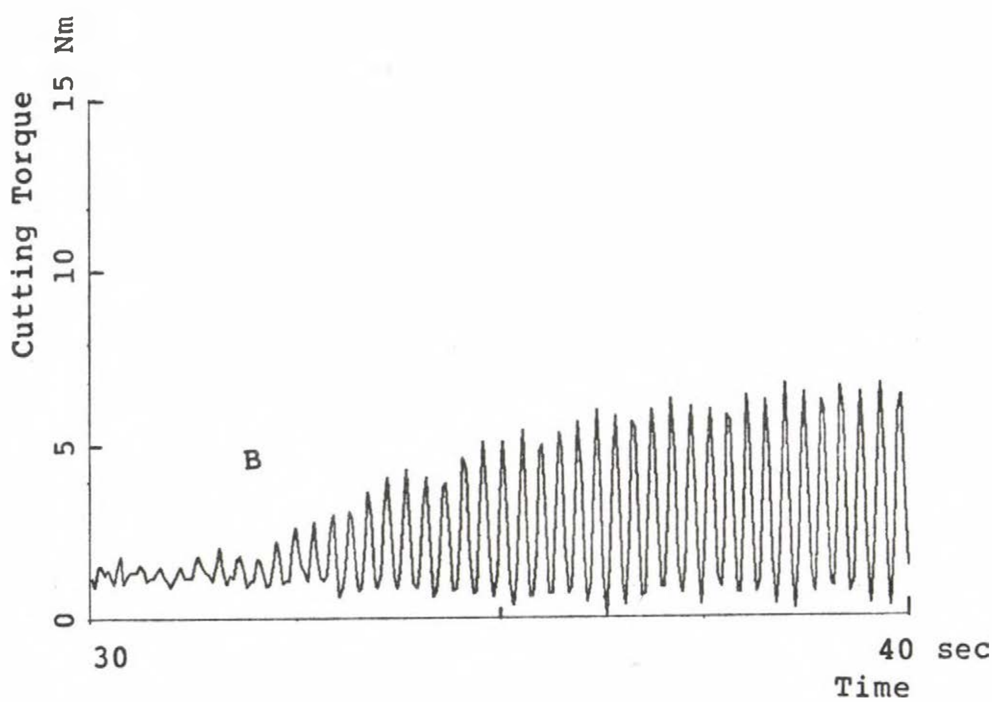


Fig. 4.5 Measured Cutting Torque

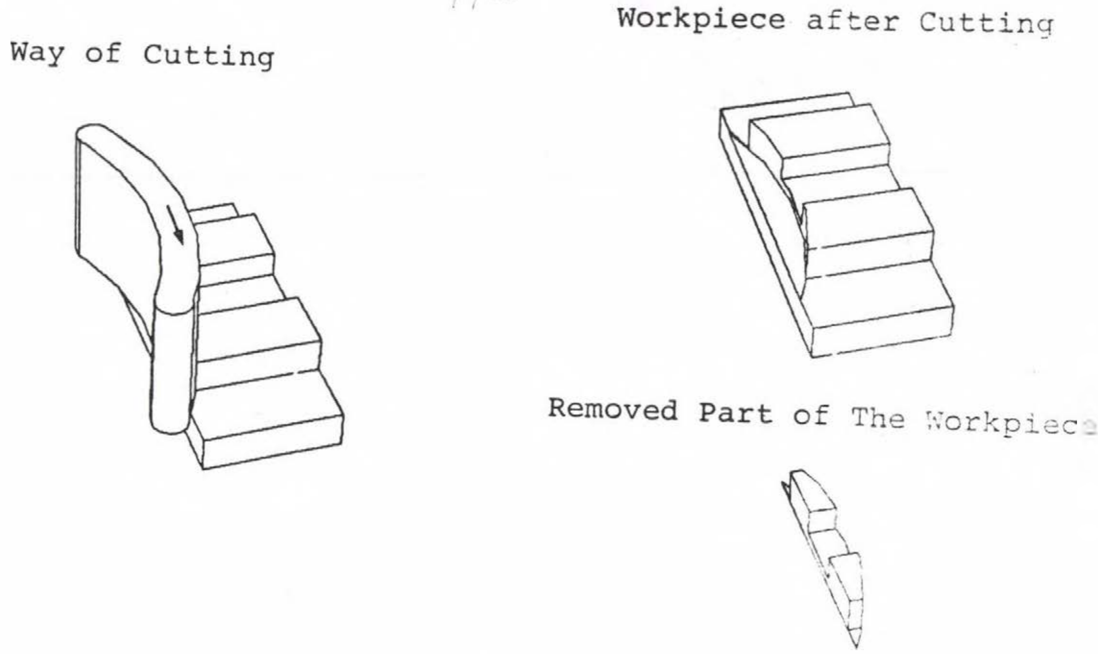


Fig. 4.6 Cutting Simulation

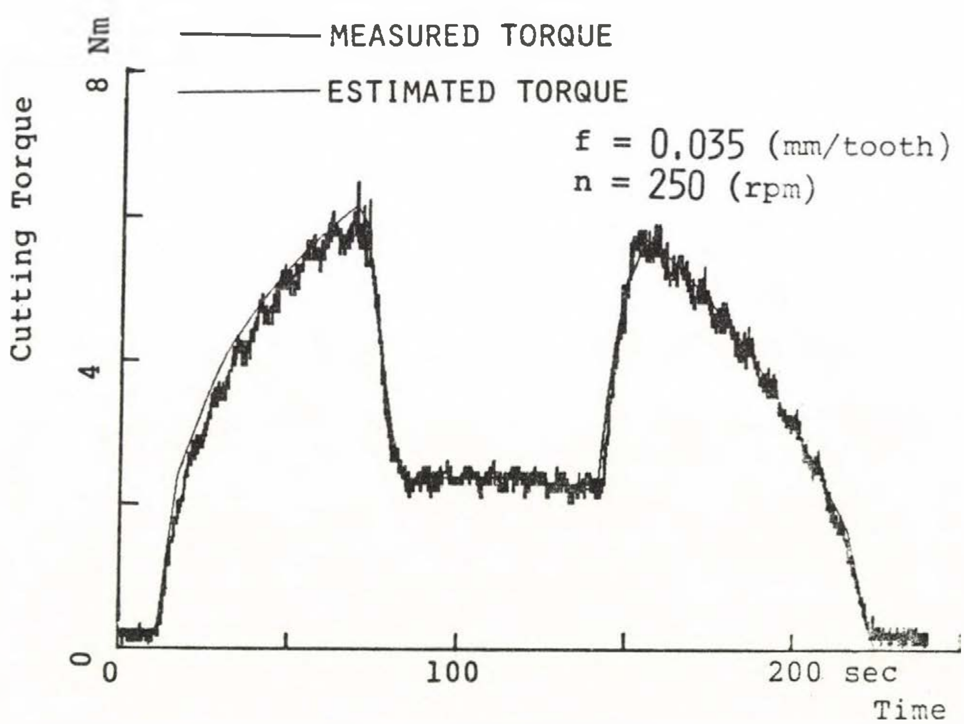


Fig. 4.7 Measured and Estimated Cutting Torque

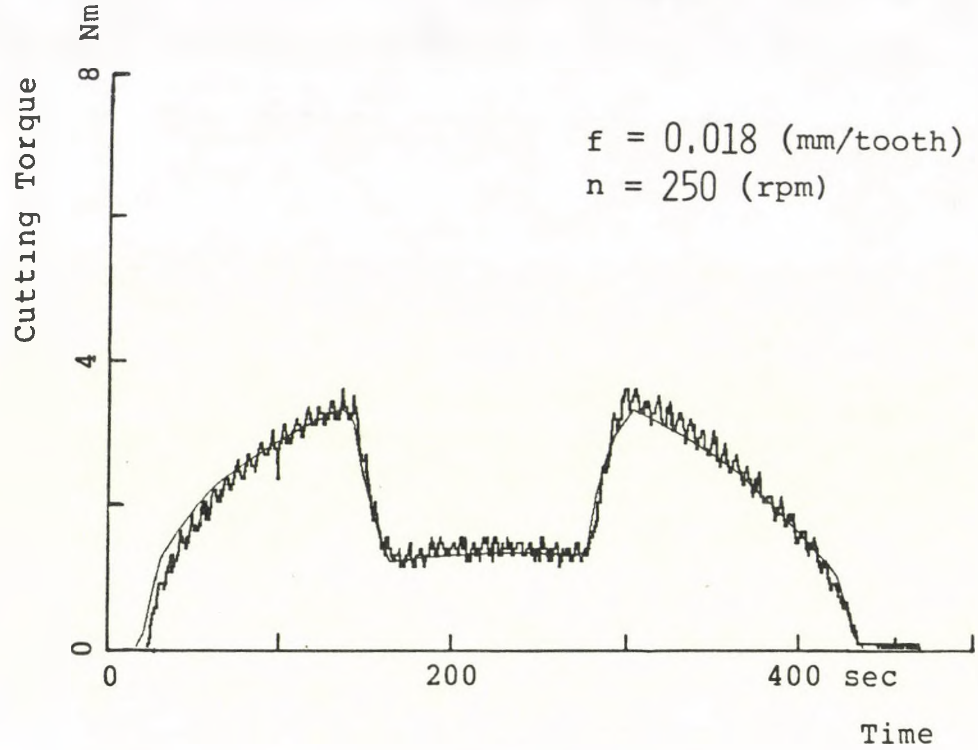


Fig. 4.8 Measured and Estimated Cutting Torque

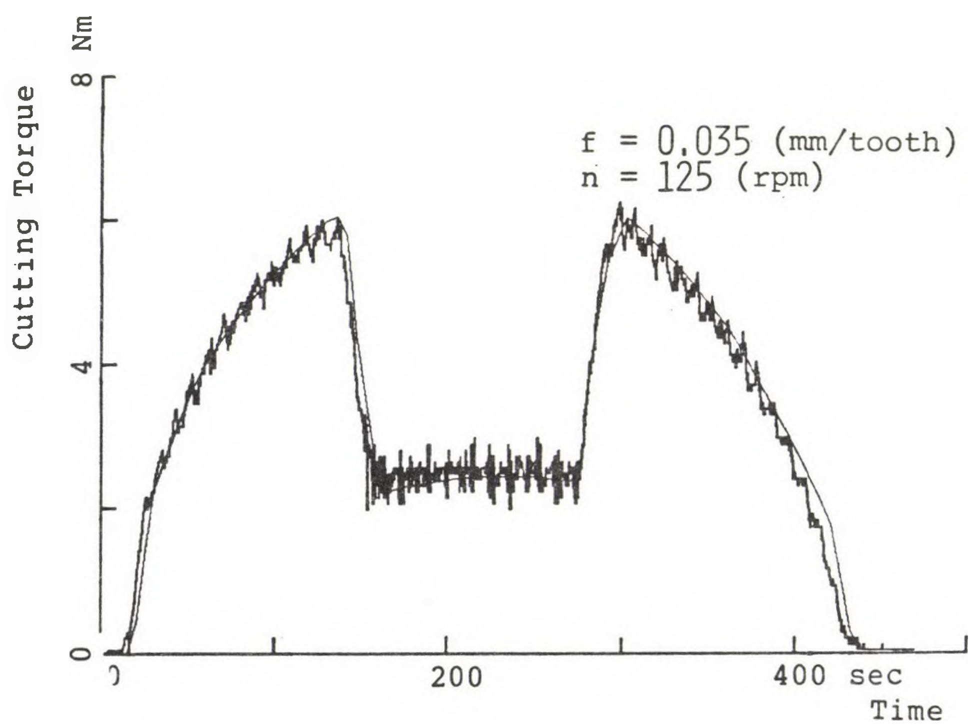


Fig. 4.9 Measured and Estimated Cutting Torque

tool used was an endmill, 20 mm in diameter. These examples are to show the influence of spindle speed and feed rate on the cutting torque.

As can be seen in figure 4.6, one side of a grooved workpiece was cut along a circular arc, and both radial and axial depth of cut were changed within a wide range. In order to get true cutting torque from the measured torque, the average of the torque measured during air-cutting was subtracted from the torque measured during metal cutting. The correspondence between estimated and measured cutting torque both in magnitude and timing is satisfactory, the time difference during an about 200 sec cutting being less than 1.2 %.

The torque calculation equation has also been verified for different geometric configurations. Figure 4.10 - 4.11 show the results of experiments with the same tool and workpiece but the way of cutting was different.

4.5.2 DERIVATION OF THE CUTTING TORQUE EQUATION AND ITS ANALYSIS

Previous investigations of the cutting process

The first very detailed investigation of the cutting process was that of Martellotti [5]. In that article power requirement of the milling process was also studied. The results indicated that the metal removal efficiency,

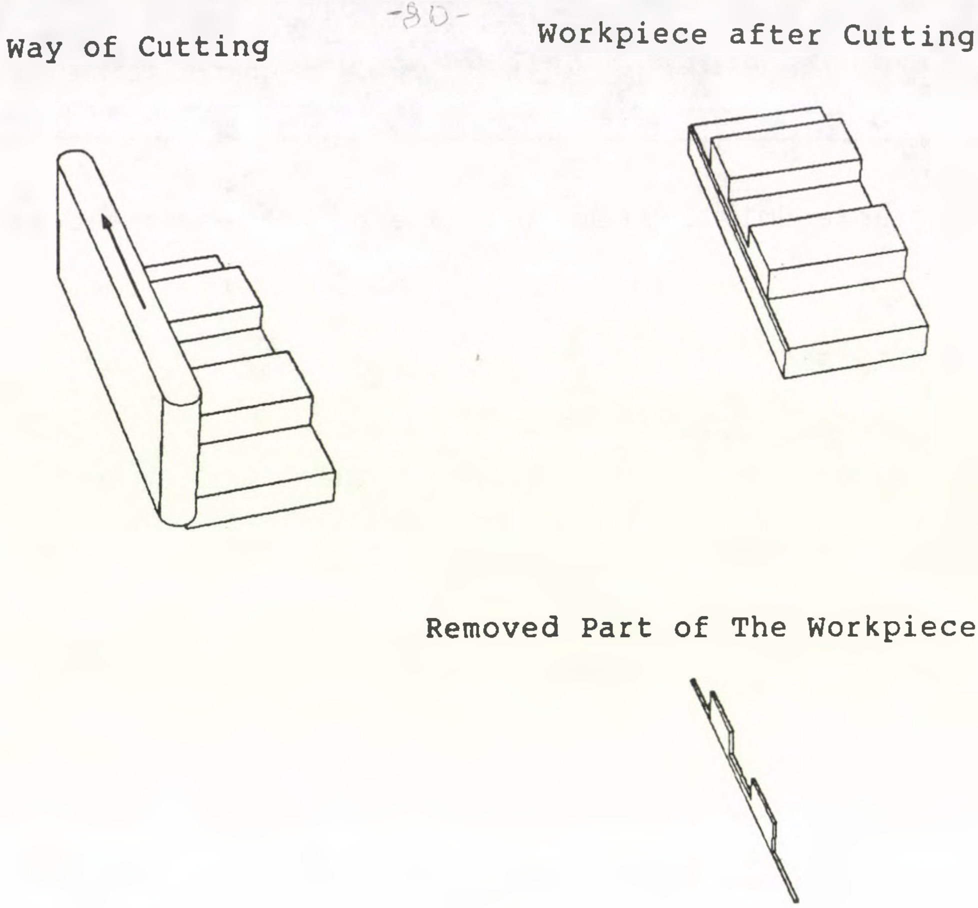


Fig. 4.10 Cutting Simulation

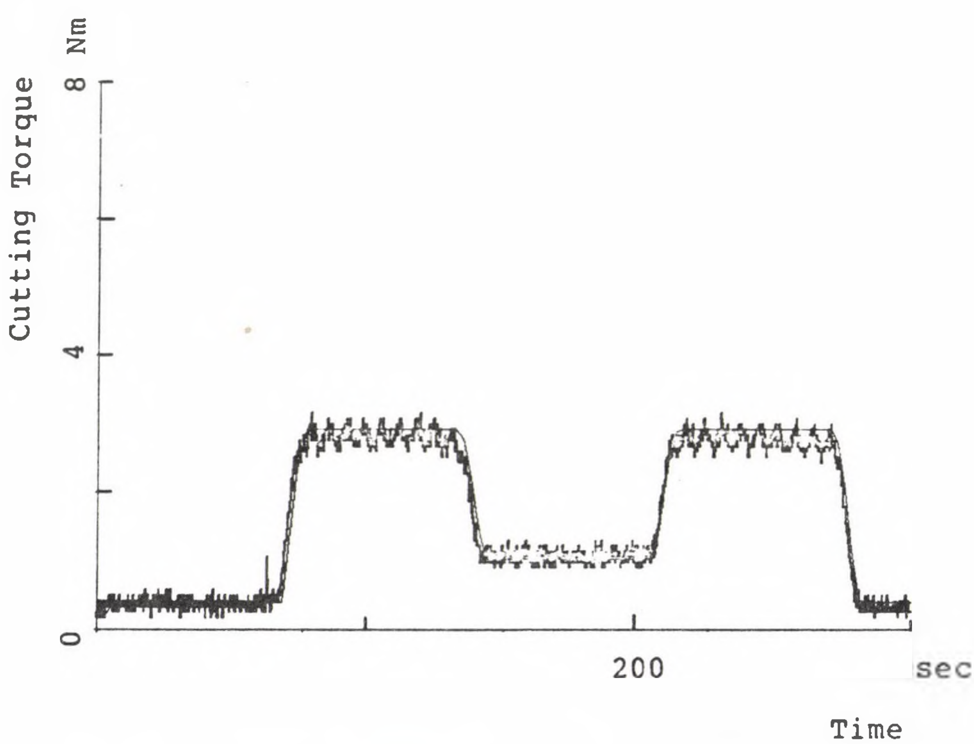


Fig. 4.11 Measured and Estimated Cutting Torque

measured in volume per energy, decreases when the amount of material removed decreases.

Another investigation [6], examined the radial and tangential forces in zero helix peripheral up milling. The authors found intercept forces positive and statistically significant. In order to explain experimental results on specific energy, shear stress and friction angle, the intercept forces were supposed to be "tool edge forces" in the article.

The next article [7] mentions again the edge force, as the cutting force component due to rubbing or ploughing at the cutting edge. The results of investigations on milling operation showed that the cutting torque -or the tangential cutting force- is basically proportional to the volume of material removed. Detailed examinations, however, indicate that the cutting torque can not be calculated with proper accuracy by considering only the volume of material removed, some additional information about the cutting configuration is also necessary.

The torque calculation equation

Discussion

The results of our experiments have shown a tendency similar to the results of previous investigations. As shown in figure 4.12, the cutting torque per removed volume is nearly constant at greater radial depth of cut, and it increases sharply at very small radial depth. The difference between its values for small and great radial depth of cut is above 50 %. End mill cutters frequently work at relatively small radial depth of cut, so it is desirable to find a formula which describes the cutting torque well even if the radial depth of cut is small. The experiments substantiated that

- the removal of smaller quantity of material needs relatively more energy: the metal removal efficiency is worse,
- increasing chip thickness decreases the energy required to remove the material: the specific cutting pressure decreases.

Considering the geometry of the experimental configuration it was easy to observe that the endmill cutter's edge was engaged with the material along a relatively longer path when the amount of material removed was small. The situation is illustrated in figure 4.13, the cutting edge of the tool is engaged with the material along 'L' while the radial depth of cut is 'a'. In the actual torque calculation the third dimension was also involved; the line, along which the cutting edge is engaged with the workpiece material, has been extended to the tool-workpiece contact surface area. The empirical equation 4.1 was formulated, which gives the cutting torque as a linear combination of the volume cut and the tool - workpiece

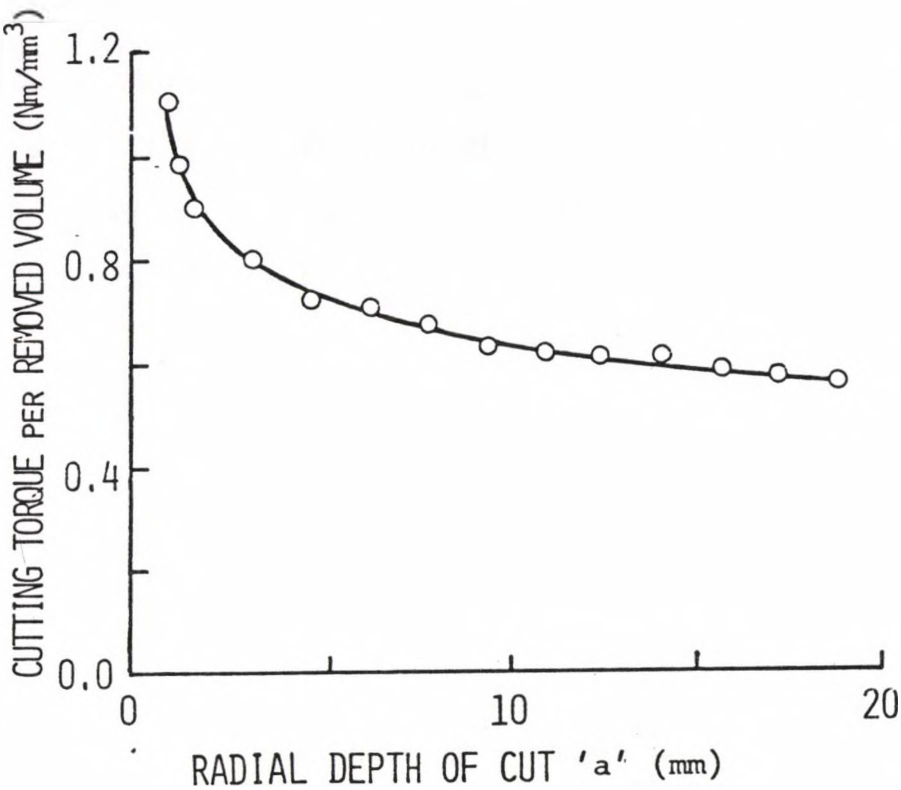


Fig. 4.12 Example of the Size Effect

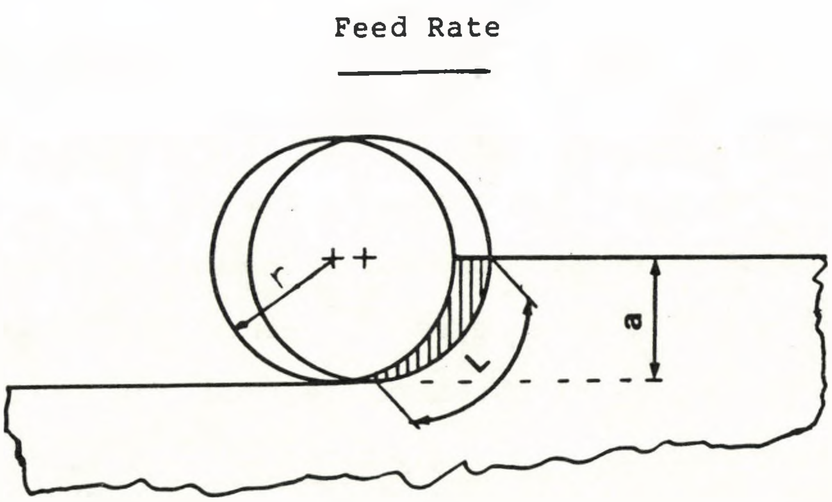


Fig. 4.13 Illustration of The Cutting Parameters

contact surface area. When radial depth of cut 'a' and axial depth of cut 'b' and feed rate 'f' remain constant during cutting, the volume of material removed while the tool advances unit distance is

$$V = a * b * 1$$

and the tool workpiece contact surface area is

$$S = L * b$$

where 'L' is the cutting edge - workpiece contact length. In this special case eqution 4.1 can be written in form

$$M = k1*a*b*f+(k2*f+k3)*L*b \qquad 4.2.$$

To make this equation plausible, it can be transformed into the form

$$M = k1*a*b*f*[1+c2*L/a+c3*L/(f*a)] \qquad 4.3.$$

The notation 'k2/kl=c2' and 'k3/kl=c3' has been used.

In equation 4.3 the first term in the brackets indicates that the torque is basically proportional to the volume of material removed. The second and third term represent a "side effect", since they become significant when the volume of material removed is small. Both are proportional to 'L/a', the ratio of cutting edge - workpiece contact length to radial depth of cut. The third term in the brackets indicates that the cutting torque increases for small feed rates.

The constants 'k1', 'c2', and 'c3' were determined from experiments. First the share of volume and of tool - workpiece contact area in the cutting torque was determined by using least sqare estimation method, then the coefficient of contact area was divided into feed rate dependent and independent parts. In case of a carbon steel material (C=0.45 %) and an endmill cutter, 20 mm in diameter, the constants were k1 = 1.39, k2 = 0.36 and k3 = 0.00316, so the equation is:

$$M = 1.39*a*b*f+(0.36*f+0.00316)*L*b \tag{4.4}$$

or

$$M = 1.39*a*b*f*[1+0.259*L/a+0.00227*L/(f*a)] \tag{4.5}$$

where distances 'a' and 'b' were measured in mm, feed rate 'f' in mm/tooth and torque 'M' in Nm. When the radial depth of cut is about half of the tool radius, the second term is about 27 % of the first one. When the radial depth of cut is about 15 % of the cutter radius, it increases to 95 %.

It has to be noted, that in geometrical simulation the tooth path was supposed to be circular instead of calculating with a trochoidal path. In the experiments this proved to be acceptable.

4.6 APPLICATIONS

4.6.1 APPLICATION EXAMPLE

The practical applicability of the method was proved in an experiment, where one surface of a cast workpiece was machined. The workpiece was a transmission box made of gray cast iron. The complete manufacturing of the workpiece was fairly complicated, it involved face milling, centre drilling, drilling, reaming and tapping, but only the face mill operation is described here.

The model of the blank part and the face mill cutter used are shown in figure 4.14. As only one surface of the workpiece was machined, the workpiece model was built up with regard to the relevant parts, the complicated shape was not modelled in full details. The model of the tool is fairly precise, as it describes the space from which the rotating tool removes any material.

The face milling operation was executed in three steps (three NC blocks). The ways of cutting, the removed parts of the workpiece and the resultant bodies after execution of the NC blocks are shown in the upper part of figures 4.15 - 4.17. Face milling was the first operation, the tool cut an irregular surface. Some differences were expected between the estimated and measured cutting torque, since the geometric modelling system assumes the face to be

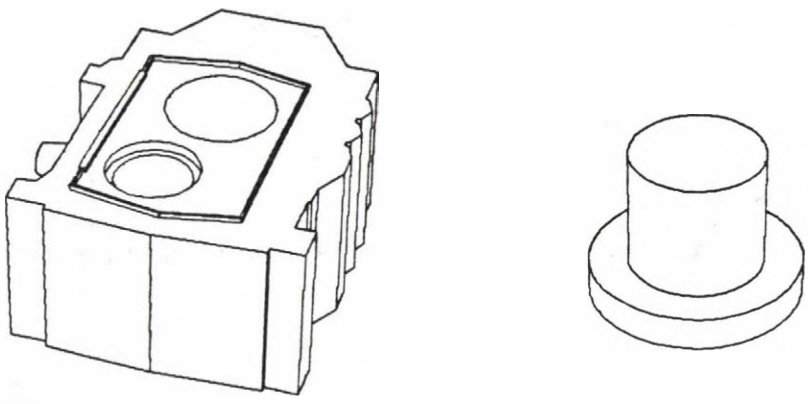


Fig. 4.14 Geometric Model of the Workpiece and the Face Mill Cutter

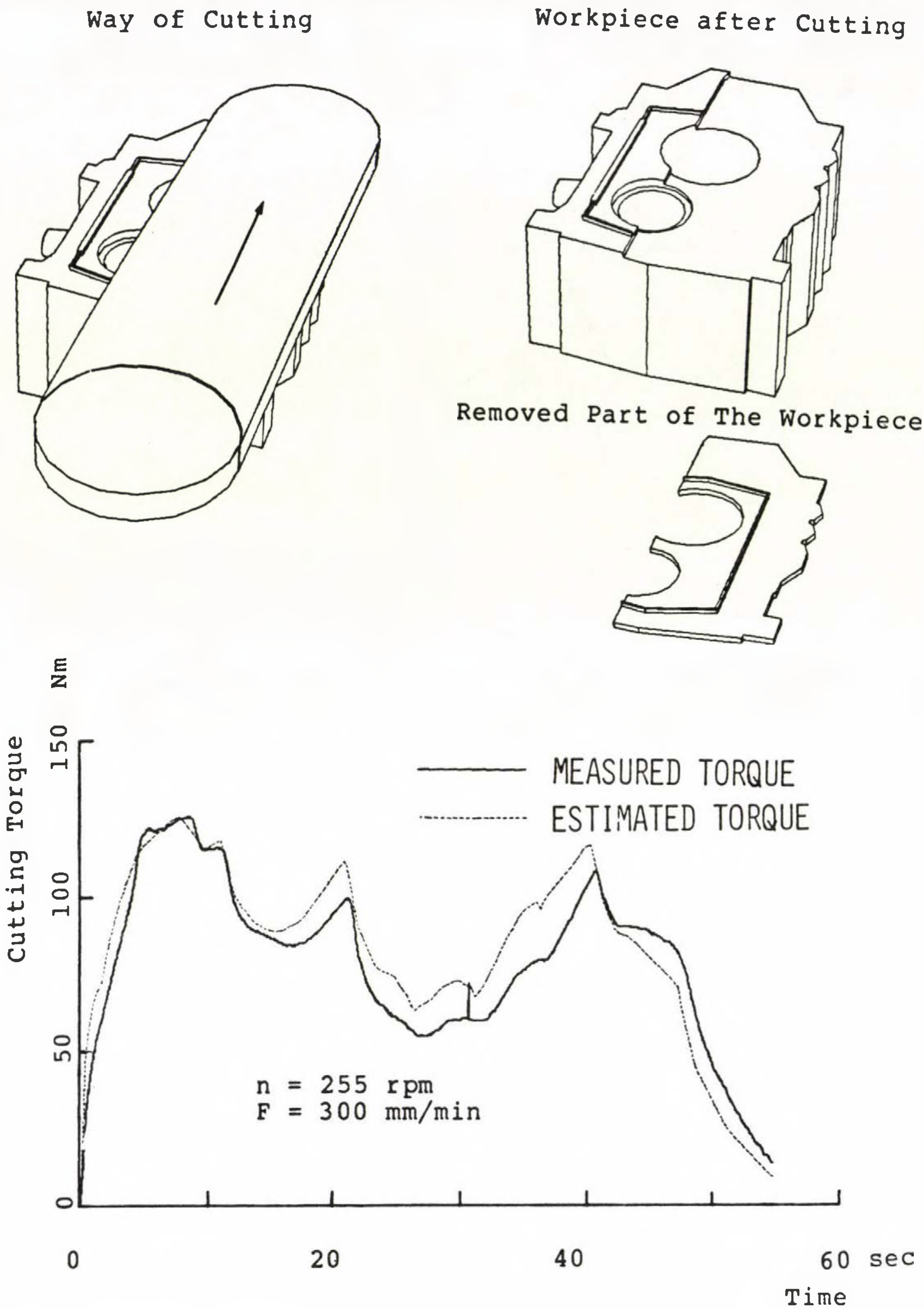


Fig. 4.15 Cutting Simulation
and the Corresponding Cutting Torque (1)

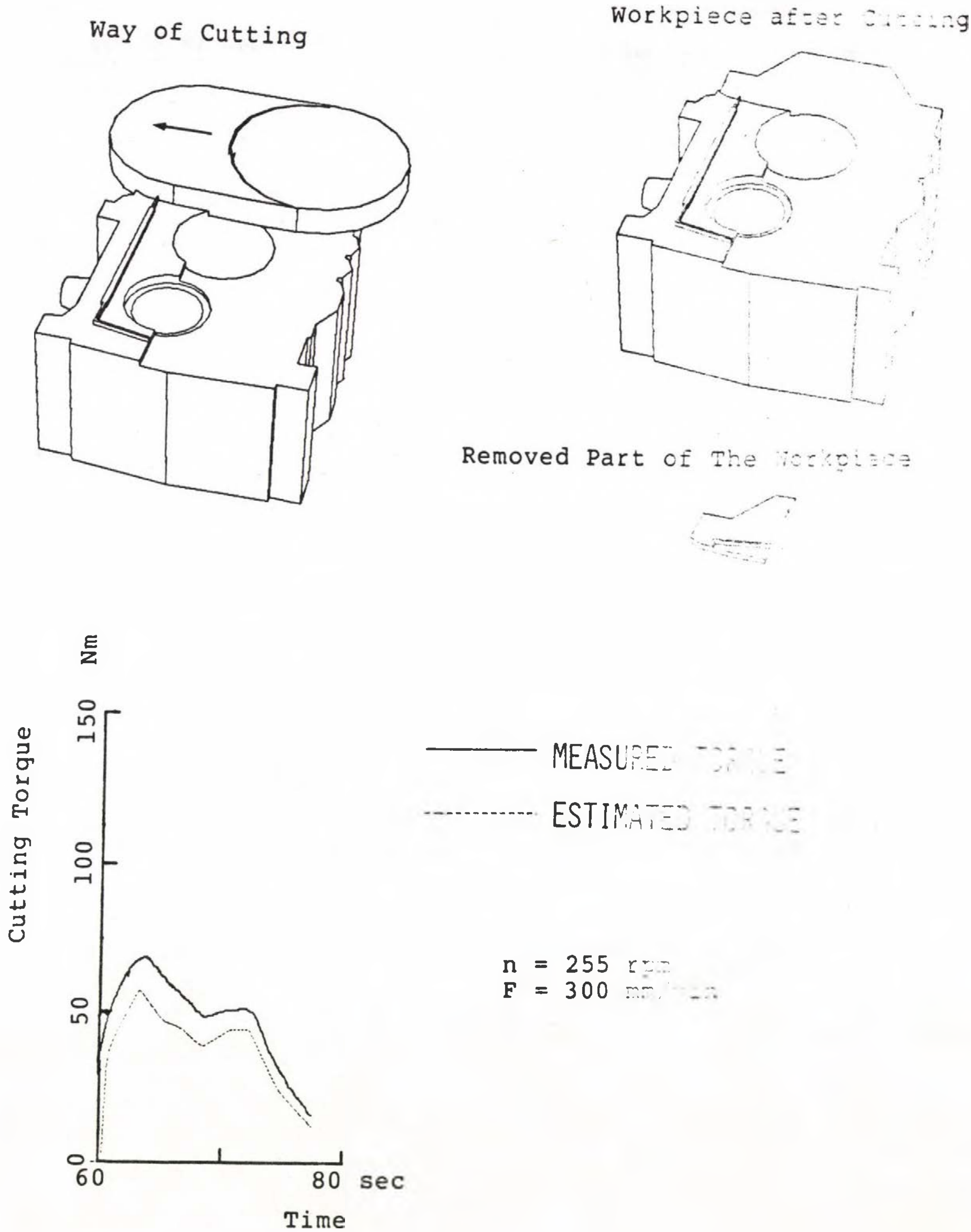


Fig. 4.16 Cutting Simulation
and the Corresponding Cutting Torque (2)

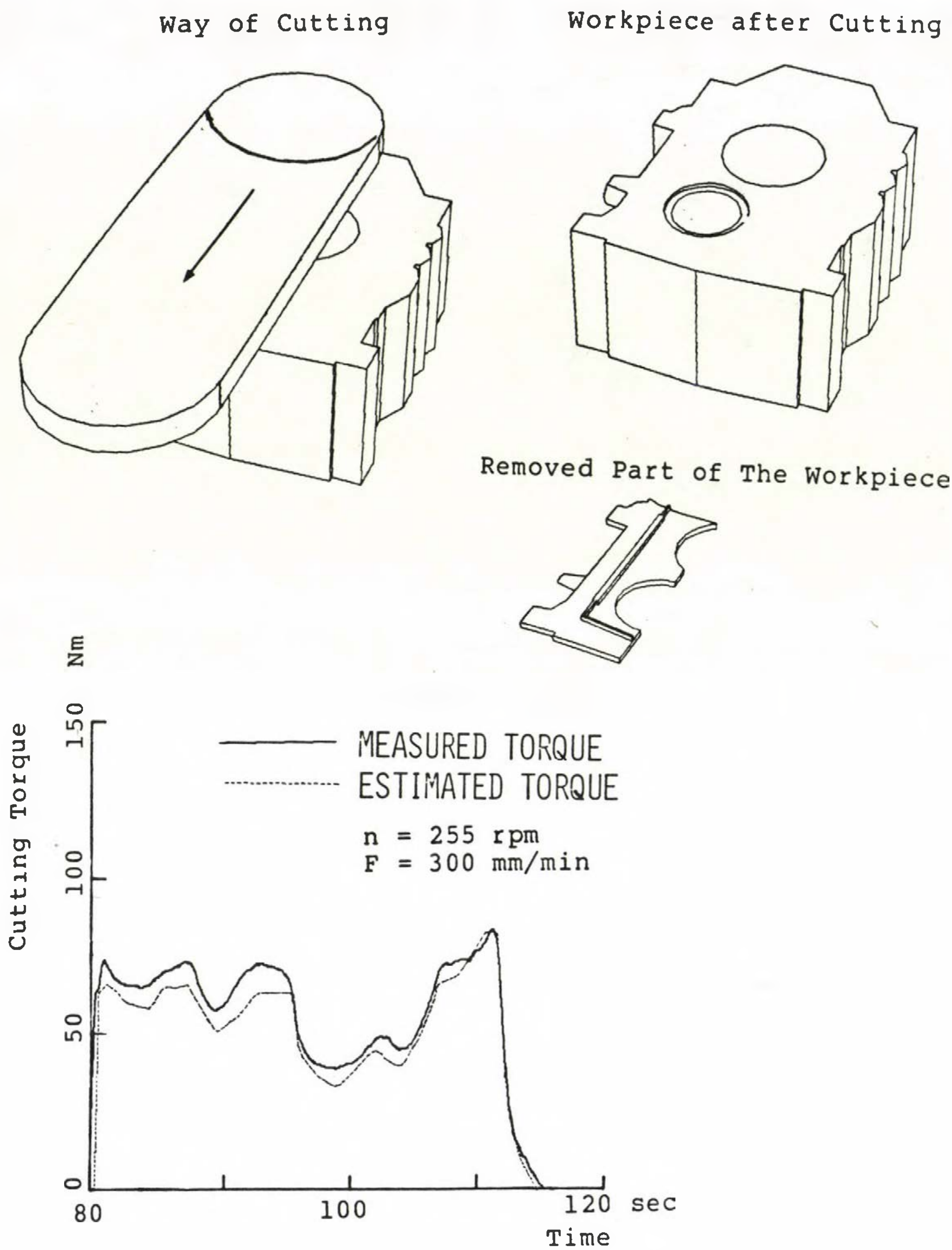


Fig. 4.17 Cutting Simulation
and the Corresponding Cutting Torque (3)

completely flat. In spite of these differences, which are clearly visible in the cutting torque signals, the agreement between calculated and measured cutting torque is fairly good. The changes in magnitude of the torque due to the shape of the workpiece show good agreement. The alterations in the measured signal are small, because the tool runout was small and a lowpass filter with a low breakpoint frequency was inserted into the measuring circuit.

The agreement in timing is also good. Nevertheless, the agreement is lower in this case than in the previous examples, owing to the geometrical irregularities of the workpiece. The torque was calculated by using equation 4.2. The ratios 'k2/kl' and 'k3/kl' - which correspond to the constants 'c2' and 'c3' in equation 4.3- were the same as in equations 4.4 - 4.5, but 'kl' was different because of the different tool type and workpiece material. Its value was half of the value determined in the previous experiments.

4.6.2 NC PROGRAM VERIFICATION

The upper part of figures 4.15 - 17 illustrate not only the way of cutting, but also the tape verification process. The intersect of the tool swept solid and the workpiece is removed at every step from the latter one, and step by step the workpiece gets its new shape. The workpiece going through this intermediate phases reaches the shape of the finished part, exactly in the same way, as it is in real cutting.

4.6.3 MONITORING THE CUTTING PROCESS

The accuracy of the estimated torque value enables an on-line monitoring of the cutting process by referring to the estimated quantity. Sampling the cutting torque at certain time intervals and referring to the preliminary estimate a monitoring system is able to detect abnormal events. At the beginning of every NC block a signal taken from the controller can initialize the monitoring, and during execution of the block the measured torque is compared continuously with the precalculated one. In case of significant discrepancies the system is to give an alarm signal. As geometrical inaccuracies of the workpiece effect the magnitude of the torque and timing, some tolerance is necessary for both. Abnormal events which influence the cutting torque can be detected by this monitoring system.

4.7 CONCLUSION

A system to predict the cutting torque in machining operation was developed. Based on a geometric modelling system the method chosen suits both geometrical and technological verification of the input NC data. The predicted cutting torque can also be used in monitoring the machining operation. In the system a geometrical simulation of the cutting process is performed by using the NC data and the model of the workpiece as well as additional data of the tool. The simulation enables geometric verification of the

NC program. The workpiece model changes in shape from block to block exactly in the same way as the workpiece changes during cutting. The examination of the workpiece can approve the machining or the points wanting corrections can be picked out.

The geometrical simulation also gives the basis of torque estimation. The removed material segment being determined in several points along the programmed path was a reliable basis of torque calculations. In accordance with other previous investigations the results indicated that although the torque is basically proportional to the volume of material removed, other factors describing the cutting configuration have also to be involved into the calculations to achieve acceptable results. An empirical equation is proposed here for torque calculations, which calculates the torque by using easily accessible data. Geometrically the volume of the material removed and the tool - workpiece contact surface area provide sufficient information about the cutting process. Technological parameters of the NC part program and additional information about the workpiece material and tool data are sufficient for the torque estimation to be based on.

Experiments performed on a machining centre gave confirming results. In case of an endmill cutter, when machining a surface cut to accurate size previously, the agreement between measured torque and estimate was very good both in magnitude and in timing under various cutting conditions. In case of a face mill cutter, when machining a cast surface, fairly good agreement has been reached between measured data and estimate, in spite of the geometrical irregularities of the workpiece.

CHAPTER 5

A MICROCOMPUTER BASED REAL TIME MONITORING SYSTEM

5.1 INTRODUCTION

Two methods have been described in the previous chapters to monitor the machining operation by analyzing the spindle motor current. The methods were discussed in detail already, but some slight modifications or rather adaptations are necessary to implement them in a real time monitoring system. This chapter presents a microcomputer based system for monitoring the machining operation by using these methods.

5.2 STRUCTURE OF THE MONITORING SYSTEM

5.2.1 FUNCTIONAL STRUCTURE

As shown in figure 5.1, the monitoring system consists of two main parts, the first is an analytical and the second is a comprehensive monitoring subsystem. The analytical subsystem is to detect irregularities in machining, which do

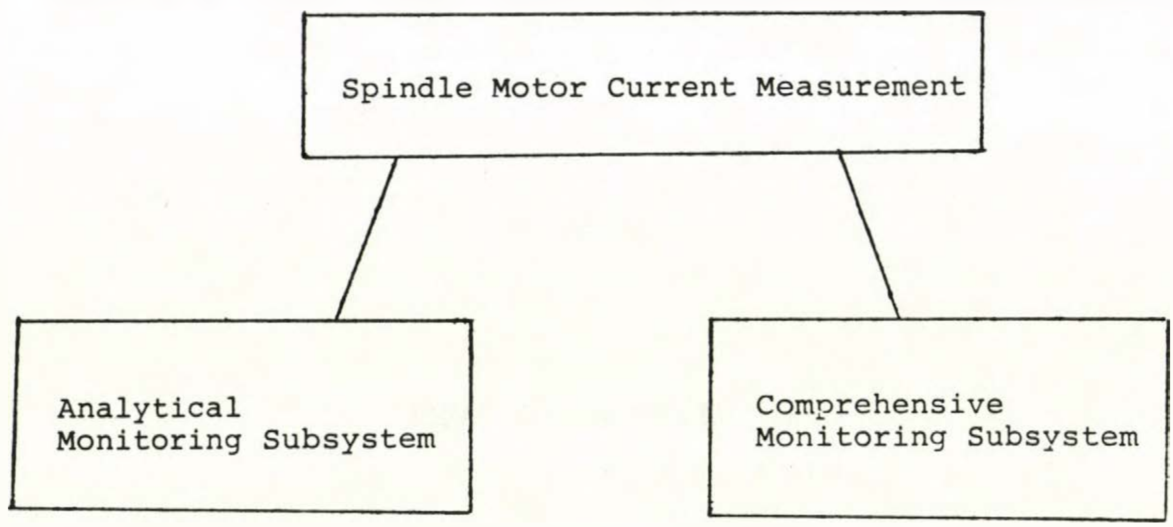


Fig. 5.1 Functional Structure of The Monitoring System

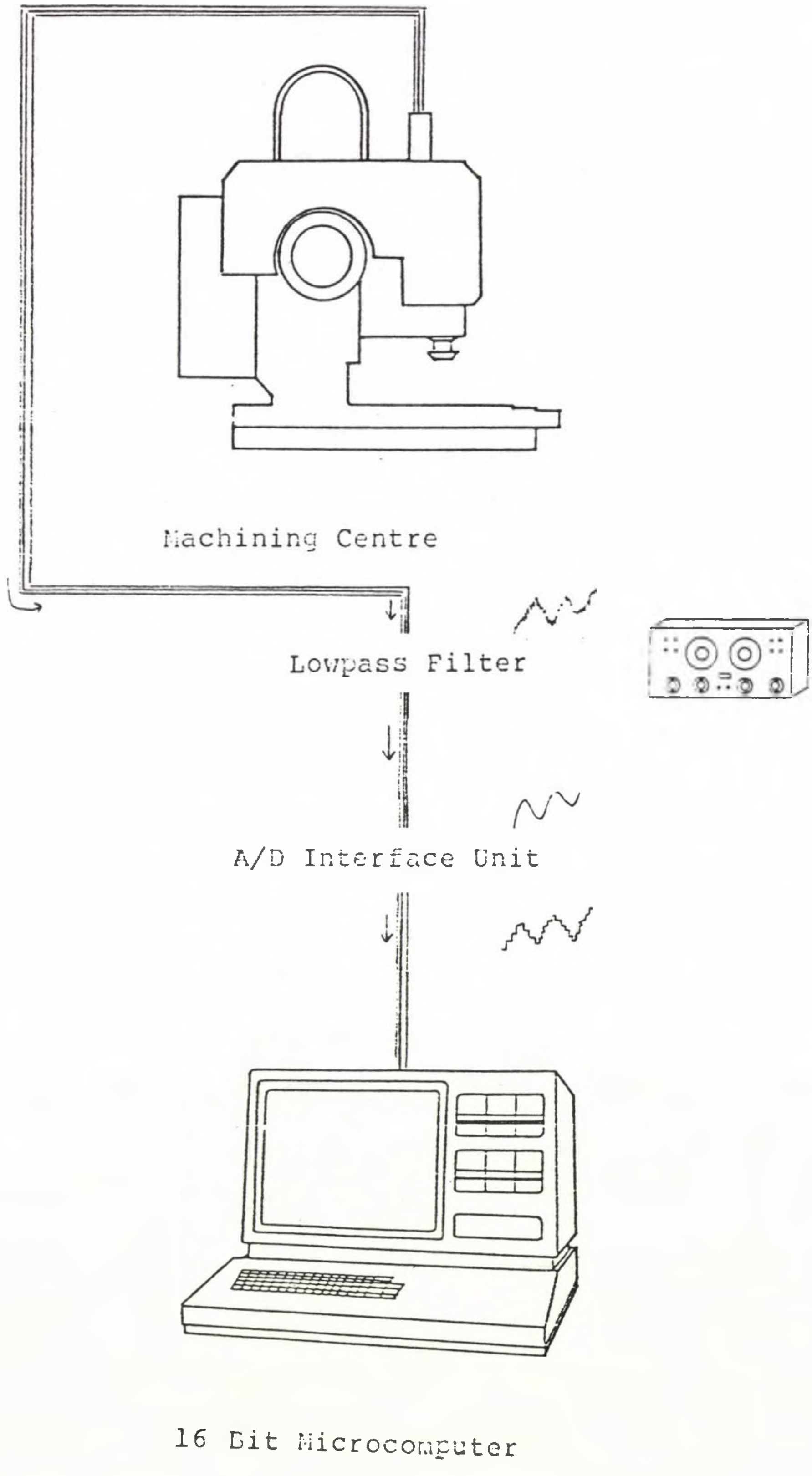


Fig. 5.2 Monitoring Configuration

not cause significant change in the monitored signal, but can lead to serious problems if not detected in time. The comprehensive monitoring subsystem is to detect failures which cause greater deviation of the cutting torque from its normal value, but the failures are not necessarily fatal problems. The analytical subsystem is a stand alone one, which does not use any preliminary information about machining. It processes the measured signal directly by using an autoregressive modelling method described in chapter three. The comprehensive subsystem monitors the operation by referring to a predicted cutting torque pattern. The method used in the analytical part for autoregressive modelling slightly differs from that in chapter three. The updating algorithm with the order required proved to be so slow, that it did not allow a real time application, therefore a faster updating algorithm has been chosen, which met the requirements. An improved method to detect tool breakage is also included in the subsystem.

The two subsystems can detect different kinds of failures. The first part detects tool breakage by analysing the measured signal. The second part has detailed information about the process taking place on the machine. Hence it can detect many types of failures such as

1. incorrect selection of workpiece or defect in the workpiece
2. misorientation of the workpiece
3. misarrangement of fixtures

4. incorrect preparation of the tool
5. excess tool wear
6. failure in the spindle unit or in the feed drive unit etc.

5.2.2 DATA PROCESSING

The analytical part was written in FORTRAN and assembly languages, in order to achieve short execution time. The comprehensive part allowed slower program execution, therefore it was written in BASIC, which also enabled colour graphics.

5.3 ANALYTICAL MONITORING OF THE MACHINING PROCESS

5.3.1 AUTOREGRESSIVE MODEL CONSTRUCTION USING A FAST CALCULATION ALGORITHM

The equations used in chapter three are the following:

$$P(n) = P(n-1) - P(n-1)M'(n)[V+M(n)P(n-1)M'(n)]^{-1}M(n)P(n-1) \qquad 5.1$$

$$X(n) = X(n-1)+P(n)M'(n)V^{-1}[z(n)-M(n)X(n-1)] \qquad 5.2$$

where 'P' is the estimation covariance, 'M' is the vector of previous observations, 'V' is the noise variance, 'z' is the actual observation and 'X' is the estimated coefficient vector of the AR model. Equation 5.1 is in expanded form,

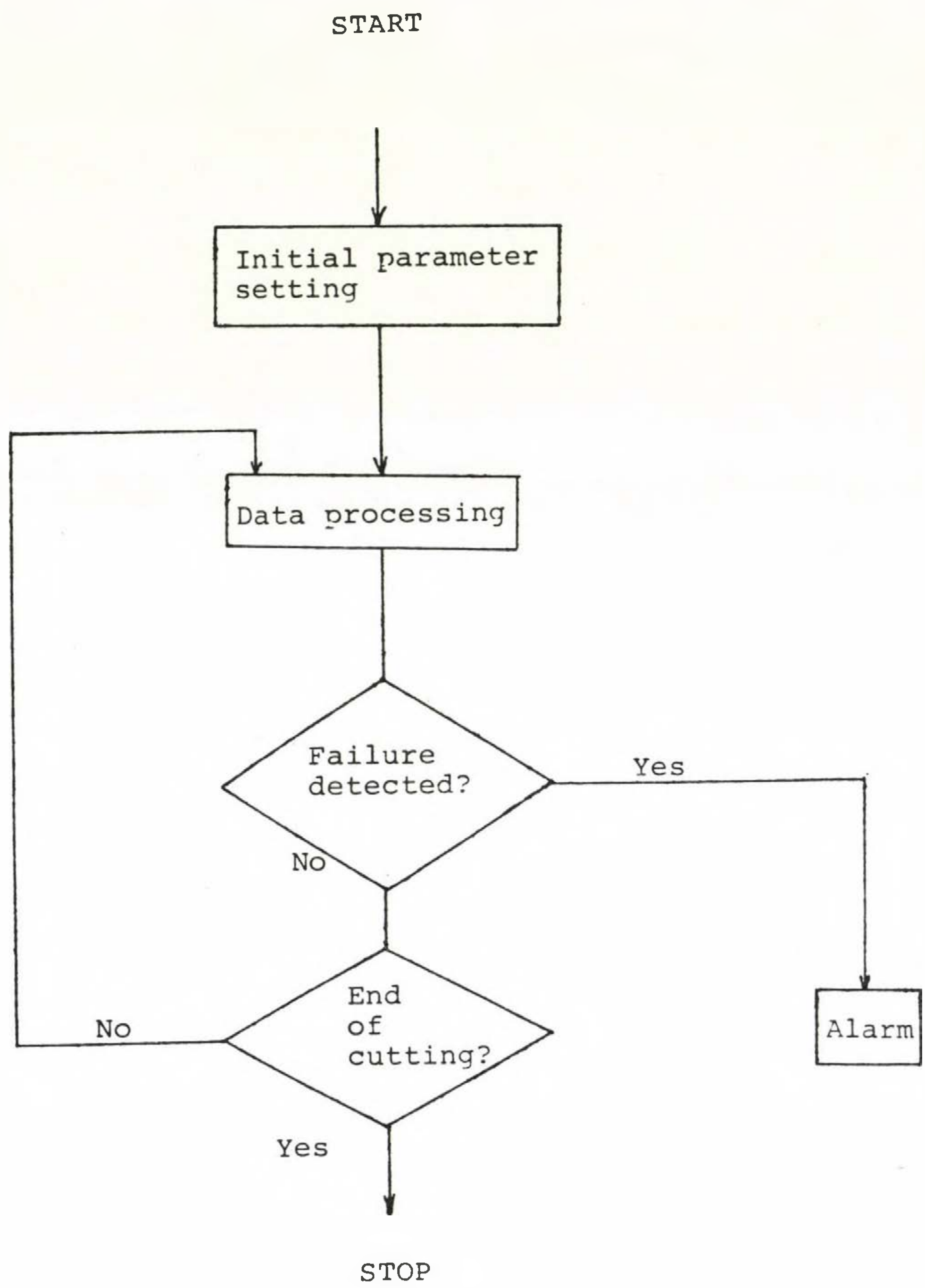


Fig. 5.3 Data Processing Structure of The Monitoring System

i.e. it has been transformed into this form in order to make the matrix inversion calculations easier. (The transformation is based on the so called matrix inversion lemma.) The unexpanded form of equation 5.1 is:

$$P(n) = (P^{-1}(n-1) + M'(n)\,V^{-1}\,M(n))^{-1} \qquad 5.3.$$

A fast method for calculating the sequence of vectors of the form

$$k(n) = \Big(\sum_{j=0}^{n} x(j)z'(j)\Big)^{-1} x(n) \qquad 5.4$$

is proposed in [1]. The similarity between the previous equations and 5.4 becomes clear if 'x(j)' and 'z(j)' are replaced by M'(j)V**-1 and 'M(j)' respectively.

This fast calculation algorithm is based on the shifting property of the squence of vectors 'x(j)' and 'z(j)'. The shifting property is inherent in AR modelling, since 'M(j)' represents the system's state from point 'j' back until 'j-p' (where 'p' is the model order), according to the definition of the AR model.

We denote the vector of previous observations at time instant 'j' by 'z(j)', and the product of noise variance 'V' and 'z(j)' by 'x(j)', i.e.

$$x(n) = \begin{bmatrix} ksi(n-1) \\ \cdot \\ \cdot \\ \cdot \\ ksi(n-k) \end{bmatrix} \quad \text{and} \quad z(n) = \begin{bmatrix} zeta(n-1) \\ \cdot \\ \cdot \\ \cdot \\ zeta(n-k) \end{bmatrix}$$

The gain

$$G(n) = P^{-1}(0) + \left(\sum_{j=1}^{n} x(j)z'(j)+\right)^{-1} x(n))$$

can be determined recursively as

$$epsilon0(n) = zeta(n) + A'(n-1)z(n) \quad 5.5$$

$$A(n) = A(n-1) - g(n)epsilon0'(n) \quad 5.6$$

$$B(n) = B(n-1) + z(n)ksi'(n) \quad 5.7$$

$$epsilon(n) = ksi(n) - B'(n)g(n) \quad 5.8$$

$$SIGMA(n) = SIGMA(n-1) + epsilon(n)epsilon0'(n) \quad 5.9$$

$$gl(n) = \begin{bmatrix} SIGMA^{-1}(n)epsilon(n) \\ g(n)+A(n)SIGMA^{-1}(n)epsilon(n) \end{bmatrix} \quad 5.10$$

'gl(n)' is partitioned as

$$gl(n) = \begin{bmatrix} m(n) \\ mu(n) \end{bmatrix} \quad 5.11$$

then

$$eta0(n) = zeta(n-k)+D'(n-1)z(n+1) \quad 5.12$$

$$D(n) =[D(n-1)-m(n)eta0(n)][E-mu(n)eta0'(n)]^{-1} \quad 5.13$$

$$g(n+1) = m(n)-D(n)mu(n) \quad 5.14.$$

Here the variables denoted by greek names (ksi, zeta, epsilon, SIGMA, mu, eta) are scalars, lower and upper case letters indicate vectors of dimension 'p' -the model order-, and 'gl' is of dimension 'p+l'. The initial conditions are taken as

$$g(1)=0 \quad A(0)=0 \quad B(0)=0 \quad SIGMA(0)=1 \quad D(0)=0 \quad .$$

The measurements clearly indicated the differences between the two algorithms. Figure 5.4 shows the calculation time against model order for both algorithms. The calculation time on the vertical axes was measured as the average time needed by a 16 bit microcomputer (SEIKO 9500) to process one input data. The time was measured while processing real cutting data. The average computation time when using the faster algorithm is within a few ten milliseconds, and this enables a real time application. Nevertheless, further decrease in the computation time would allow even shorter time for sampling the signal, and this may improve the system's performance by increasing the maximum spindle speed allowed.

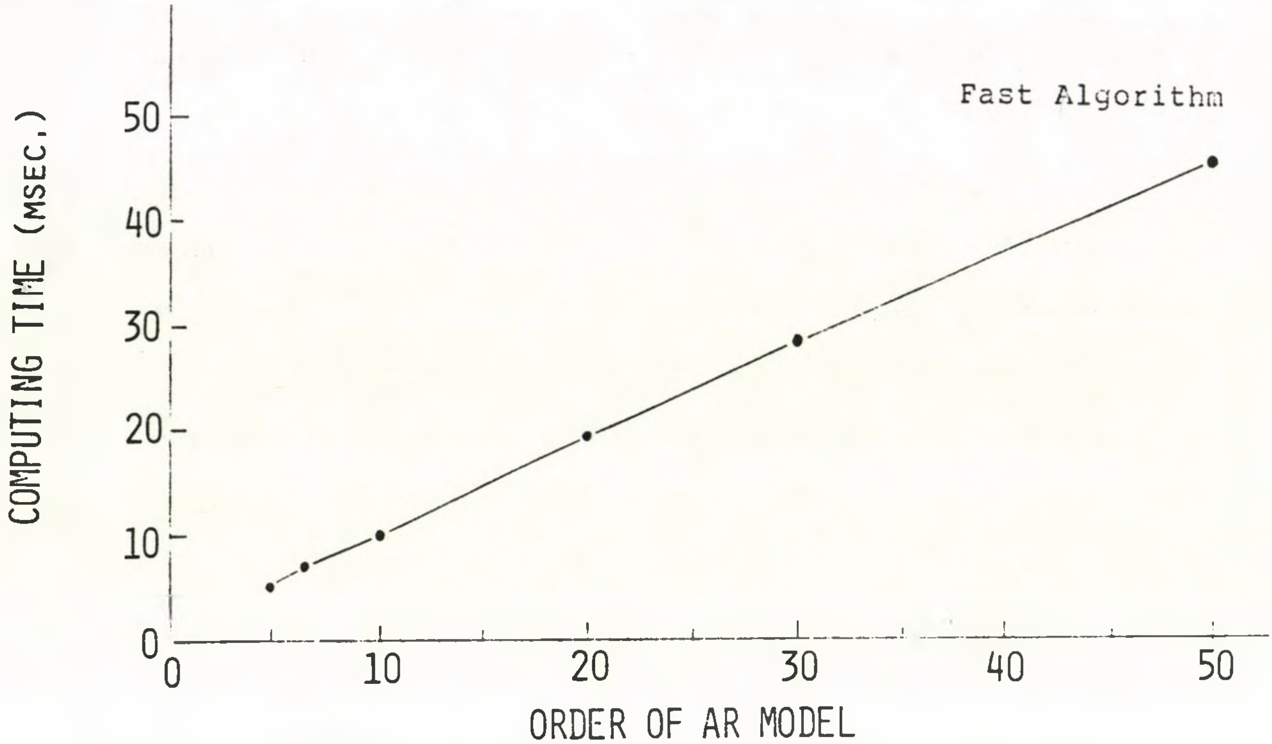
5.3.2 TOOL BREAKAGE DETECTION ALGORITHM

The basis of the detection algorithm used here is the calculation of a moving threshold. The monitoring and failure detection is performed then by comparing the actual residual value with this threshold. The moving threshold is computed repetitively from the residual. The fluctuations in the residual can be described mathematically by the variance. The variance, the expected fluctuation of the signal around its mean, is well approximated in practice by

$$V^2 = \sum_{i=1}^{n} [x(i)-xm]^2 / n \qquad 5.15$$

where

$$xm = \sum_{i=1}^{n} x(i)/n \qquad 5.16$$



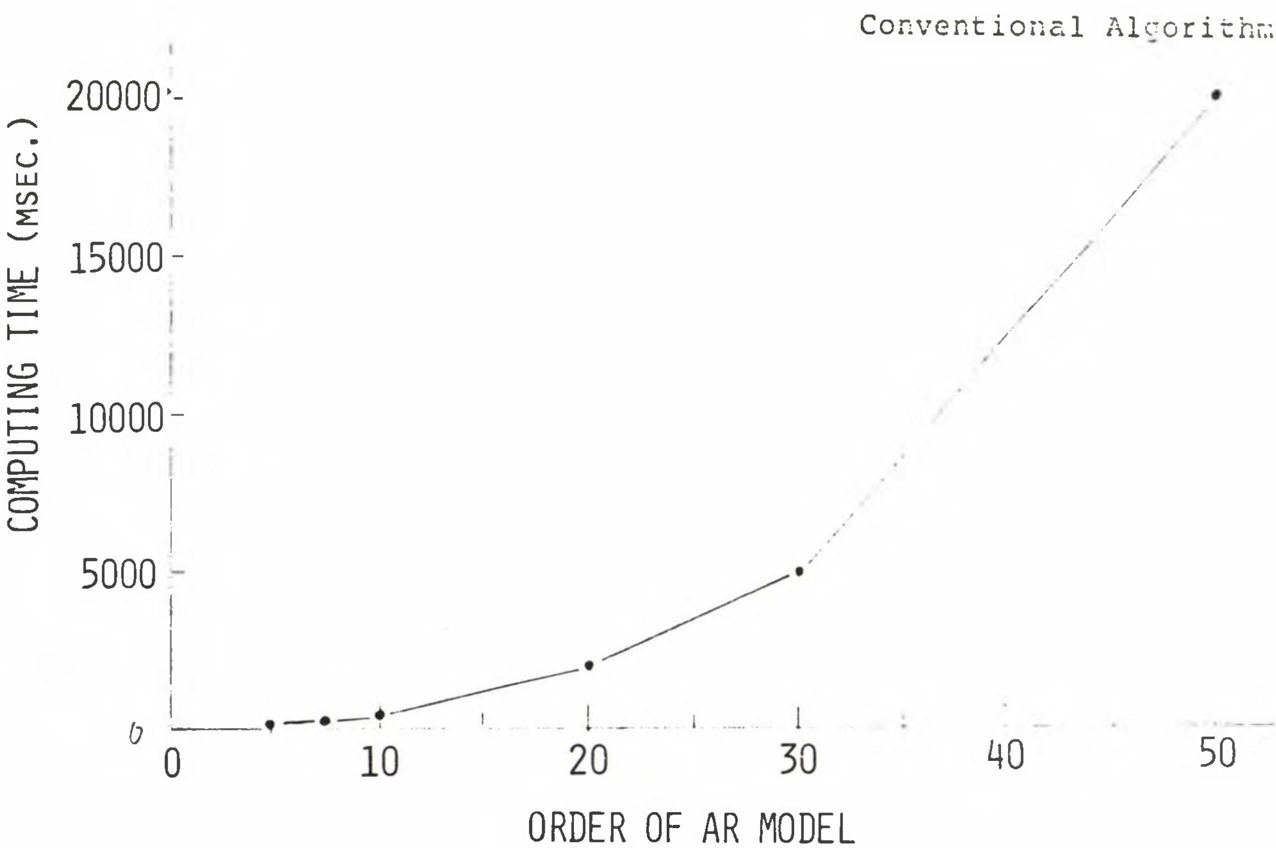


Fig. 5.4 AR Model Computing Time as a Function of the Order

is the mean of the signal. As comes from the initial condition of the filtering algorithm, the residual is a zero mean white noise process, i.e.

$$xm = 0 \qquad \text{and} \qquad V^2 = \sum_{i=1}^{n} x(i)^2 /n \qquad 5.17.$$

The actual value of the residual is always compared with the variance calculated in the close neighbourhood of the actual data, and when their ratio exceeds over a limit an alarm signal is generated. In mathematical form the ratio

$$R = x(k)/\sqrt{\sum_{i=1}^{n} x(k-i)^2 /n} \qquad 5.18$$

is calculated and compared with a value set preliminarily. The equation contains a square root, which is time consuming to compute and in our case has no significance, therefore it is omitted from the real time calculations, the value of the square of 'R' is used instead. After very simple transformations 5.18 becomes

$$x^2(k) = R^2 \sum_{i=1}^{n} x^2(k-i)/n \qquad 5.19.$$

The actual decision is made by comparing the two sides of 5.19. The flow chart of the decision algorithm is shown in figure 5.5. The effectiveness of the algorithm was tested by applying it off-line to data measured. The results of this off line test are described in the following.

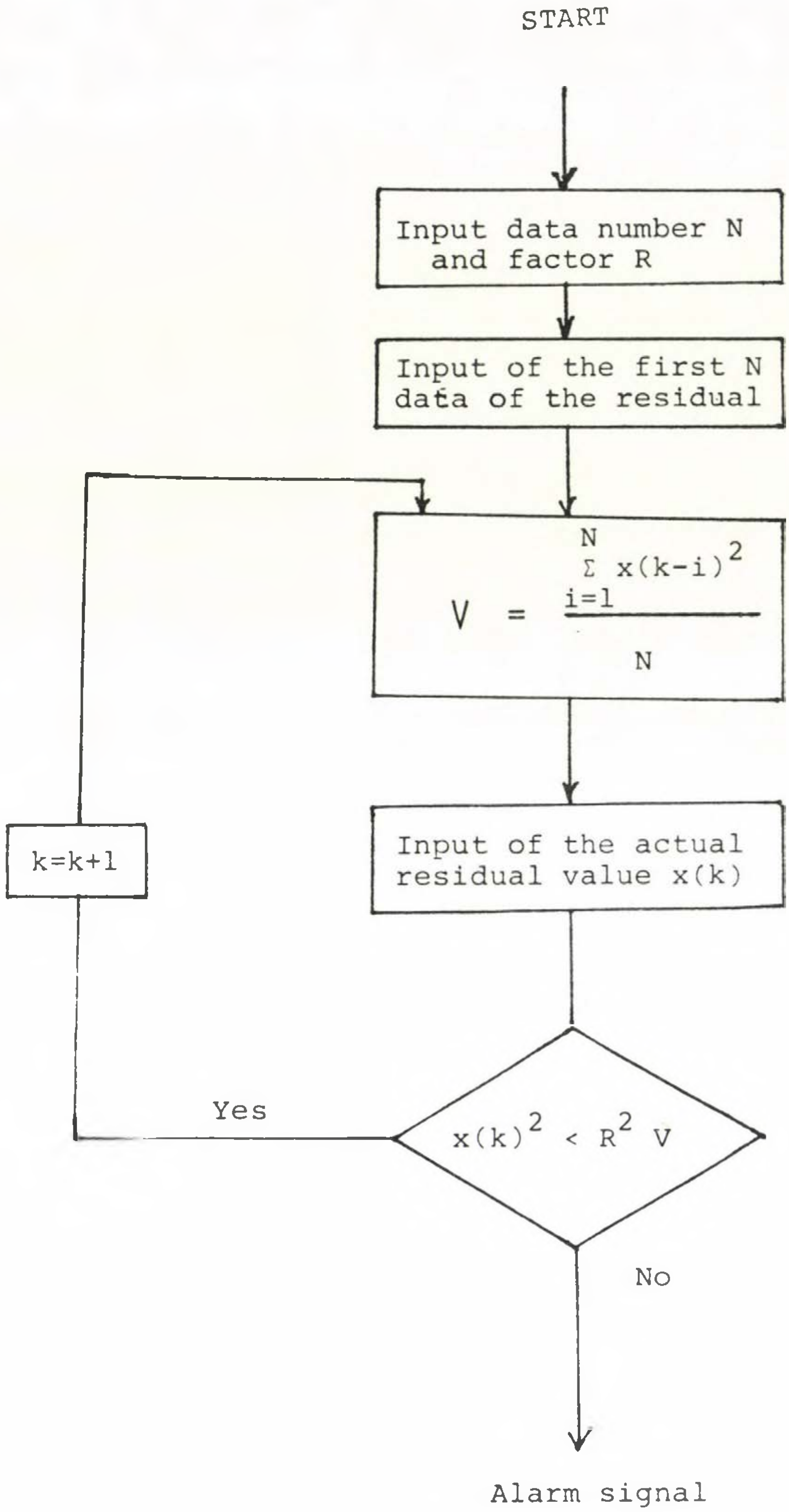


Fig. 5.5 Failure Detection Decision Algorithm

5.3.3 OFF-LINE TOOLBREAKAGE DETECTION TESTS

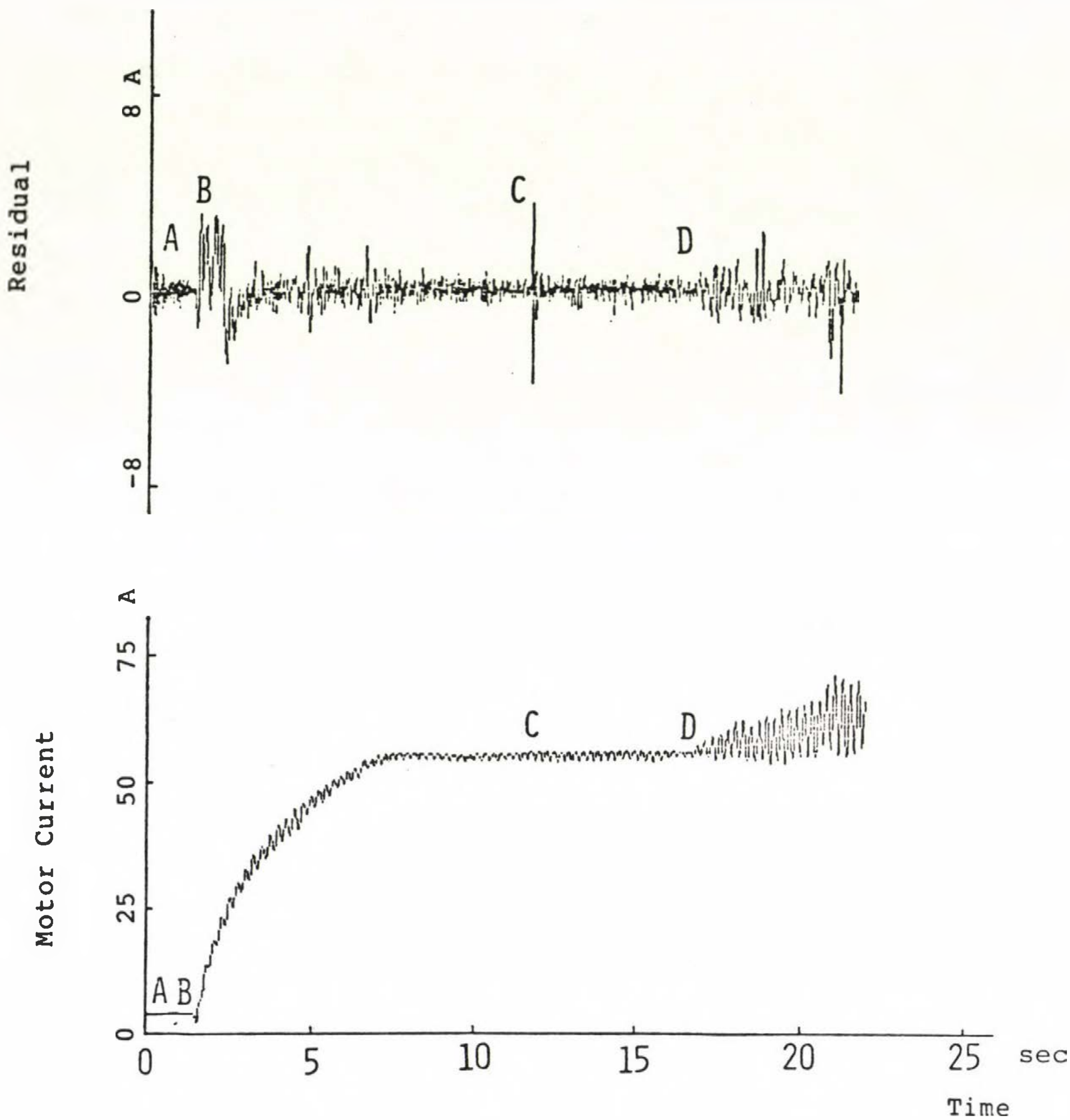
In order to prove the method to be effective first it was applied to tool breakage data recorded earlier. The conditions in the cutting experiments were:

spindle speed = 250 rpm

feed rate = 600 mm/min

axial depth of cut = 2 mm

and the tool used was a face mill cutter with six teeth. The cutting process can be followed on the measured spindle motor current shown in the lower part of figure 5.6. The tool was rotating in the air from the start 'A' until point 'B'. Then normal cutting was performed until point 'C', where one cutting edge broke. The breakage did not have serious immediate consequences, but this more intensive stress led to other problems in point 'D', where a very fast wear began, and later the cutting had to be stopped for safety reasons. The calculated residual is shown in the upper part of figure 5.6. The beginning of cutting at point 'B' caused some increase in the fluctuations, which gradually decreased, then at point 'C' a short but high peak indicates a change in the process. Finally from point 'D' the fluctuations increase, it has very high peaks. The next step is calculation of the actual value - variance ratio. By using equation 5.18 the ratio was calculated in different cases, when the number of data involved in variance calculation varied, its value being n = 5, 10. The result



V = 0.1 Sampling Interval = 48 (msec.)

Fig. 5.6 Measured Spindle Motor Current and the Residual

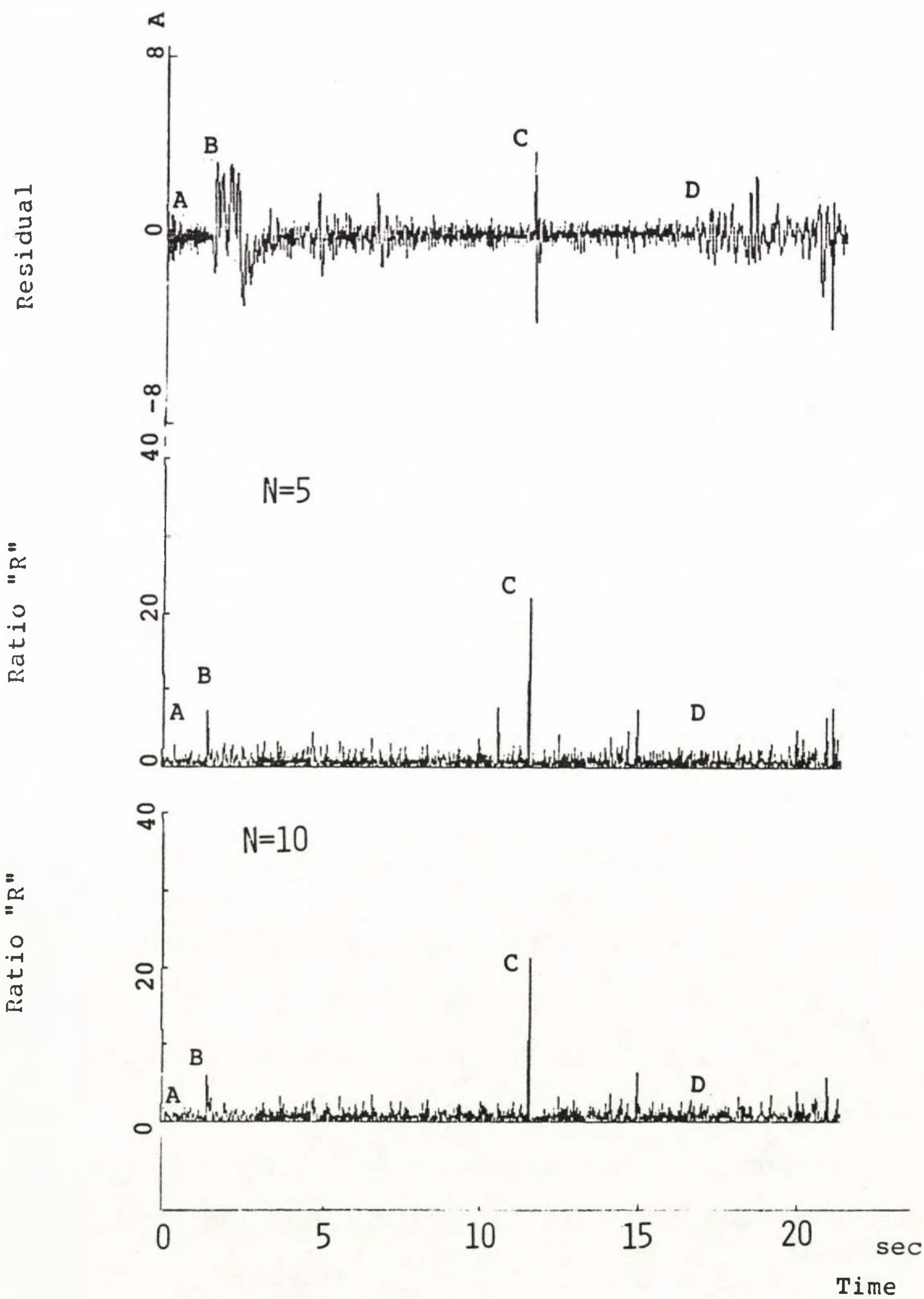


Fig. 5.7 Residual And The Ratio "R"

is shown in figure 5.7. When the variance was calculated by using five data, as shown in the middle part of figure 5.7, the calculated ratio shows large fluctuations, and in point 'C' there is a spike. After increasing the number of data in variance calculation to ten, the fluctuations became almost uniform, but the peak at point 'C' remained almost unchanged, thus it became clearer. Further increase in the number of data used for variance calculation caused a decrease in the peak at point 'C'.

5.4 COMPREHENSIVE MONITORING OF THE MACHINING PROCESS

5.4.1 TOLERANCE CALCULATION

Tolerance in magnitude is easy to consider, but it is not enough, since positional inaccuracies, appearing as shift along the time axis, can lead to enormous magnitude differences.

This means that proper tolerance has to be considered in timing too. The time tolerance is defined in that way, that the upper and lower limit in a point are the greatest and smallest value in the point's neighbourhood defined by the time tolerance, respectively. When both magnitude and time tolerances are considered, first the magnitude tolerance is calculated in the normal way, then the timing tolerance is considered. The proper tolerance in time can be determined by considering geometrical inaccuracies of the workpiece as well as feed rate. As far as the magnitude of torque is concerned, geometrical inaccuracies of the workpiece have to be considered together with inhomogenities in workpiece material and tool sharpness. The tolerance in the experiments was calculated prior to monitoring, as an additional step to torque estimation.

5.4.2 MONITORING

Monitoring is performed by comparing the measured torque with the given upper and lower limits. When it is not within the limits, an alarm signal is generated. A few monitoring examples are given here. Tolerances in the examples were chosen as the minimum values not causing an alarm. An example of detected error is given later in the application examples.

Figure 5.8 shows the upper and lower tolerances selected for the example discussed previously, and in figure 5.9 the measured torque appears between these limits. The next example, shown in figure 5.10 - 5.11, presents the cutting of the same grooved workpiece along a straight line.

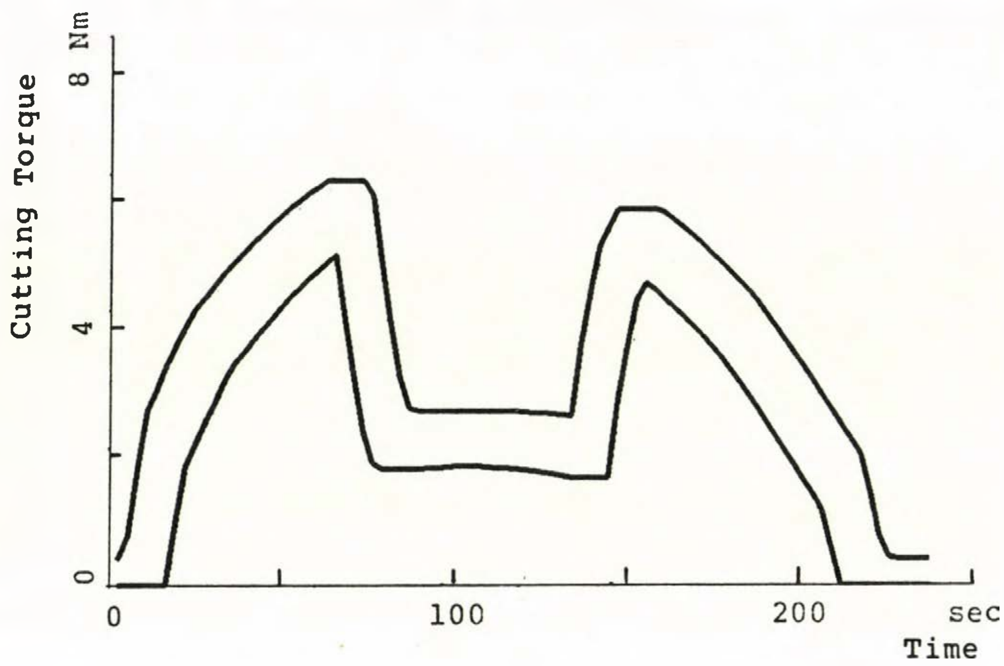


Fig. 5.8 Calculated Tolerance

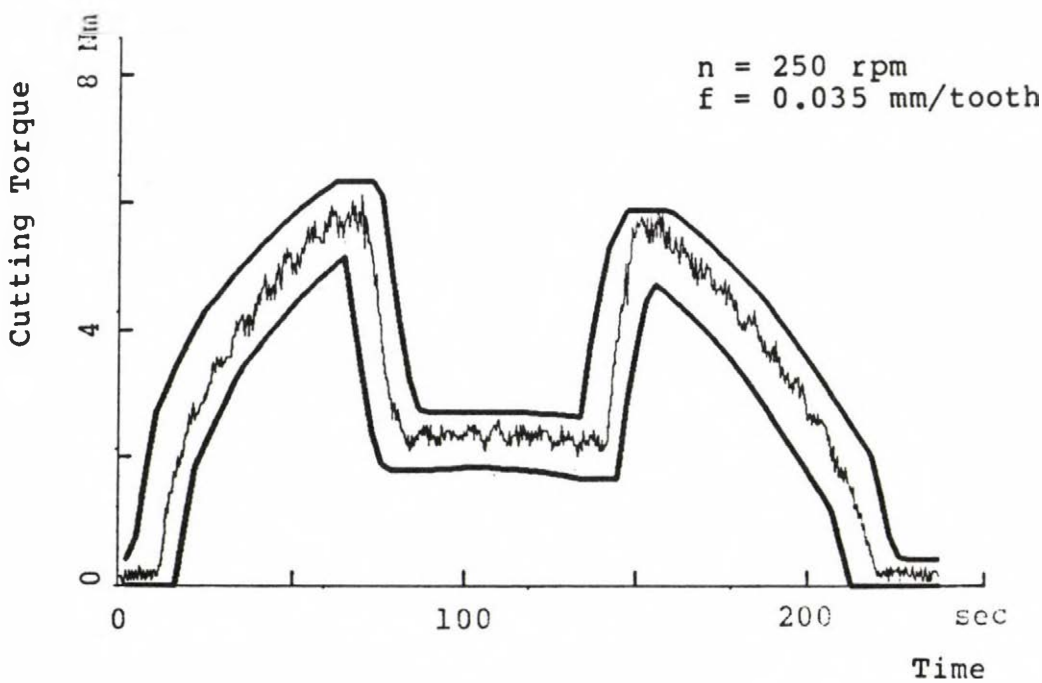


Fig. 5.9 Calculated Tolerance And Measured Torque

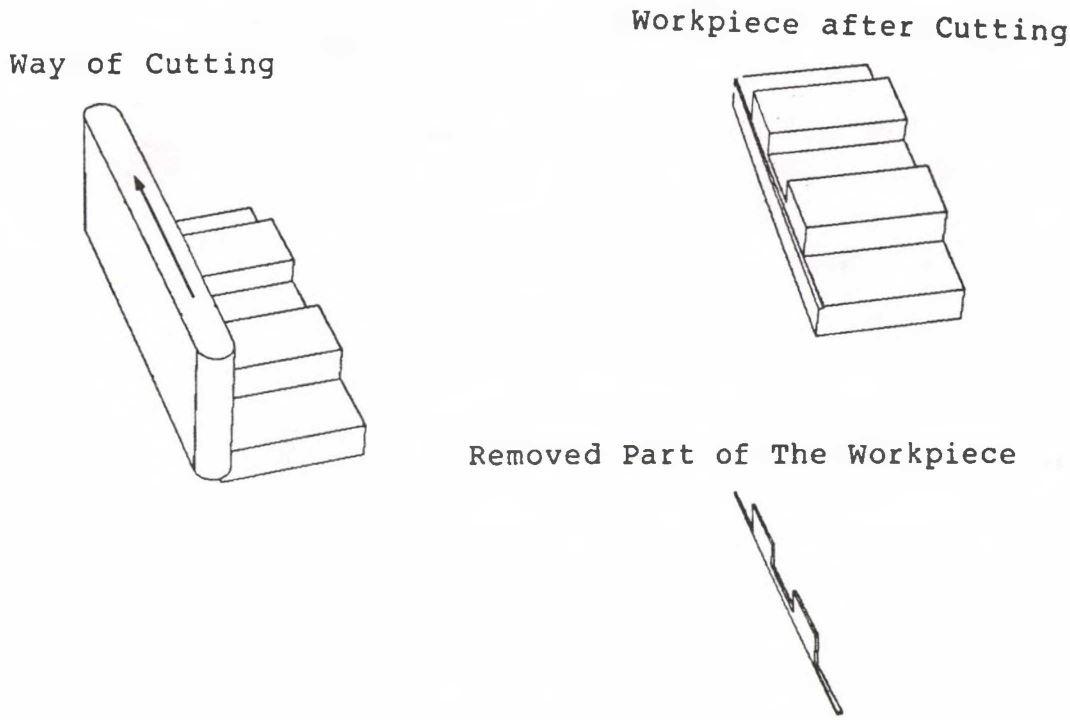


Fig. 5.10 Cutting Illustration

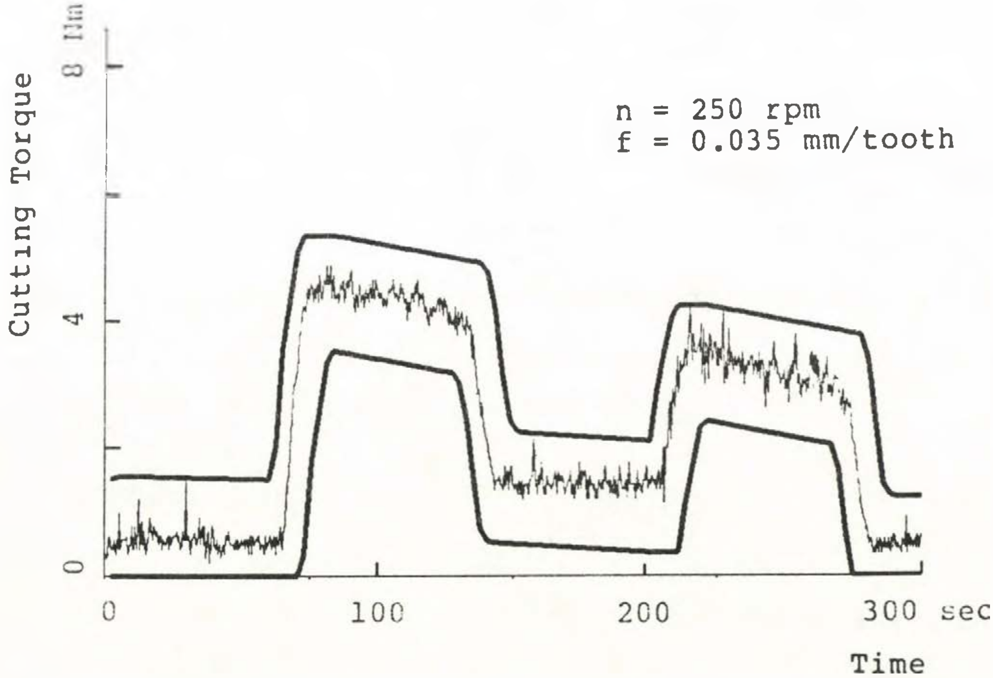


Fig. 5.11 Calculated Tolerance And Measured Torque

5.5 APPLICATION EXAMPLES

5.5.1 ANALYTICAL MONITORING

In the following an example of on-line tool breakage detection is analyzed, the diagrams of the measured spindle motor current, residual and detection signals are given. The cutting conditions in the experiment were:

spindle speed = 250 rpm
feed rate = 600 mm/min
axial depth of cut = 0.7 mm in the first example
0.8 mm in the second example
radial depth of cut = 61 mm.

The main parameters of the monitoring system were:

AR model order = 27
noise variance = 0.01
sampling time = 48 msec
data involved in the moving threshold calculations = 10
threshold value of 'R' in detection = 10.

Example

The example is explained by using figure 5.12, which shows the spindle motor current during the experiment. The detection result, a message from the monitoring system, is shown on the upper part of the figure. The message indicates that the breakage was at data number 751. As the sampling time was 48 msec, the breakage was indicated to

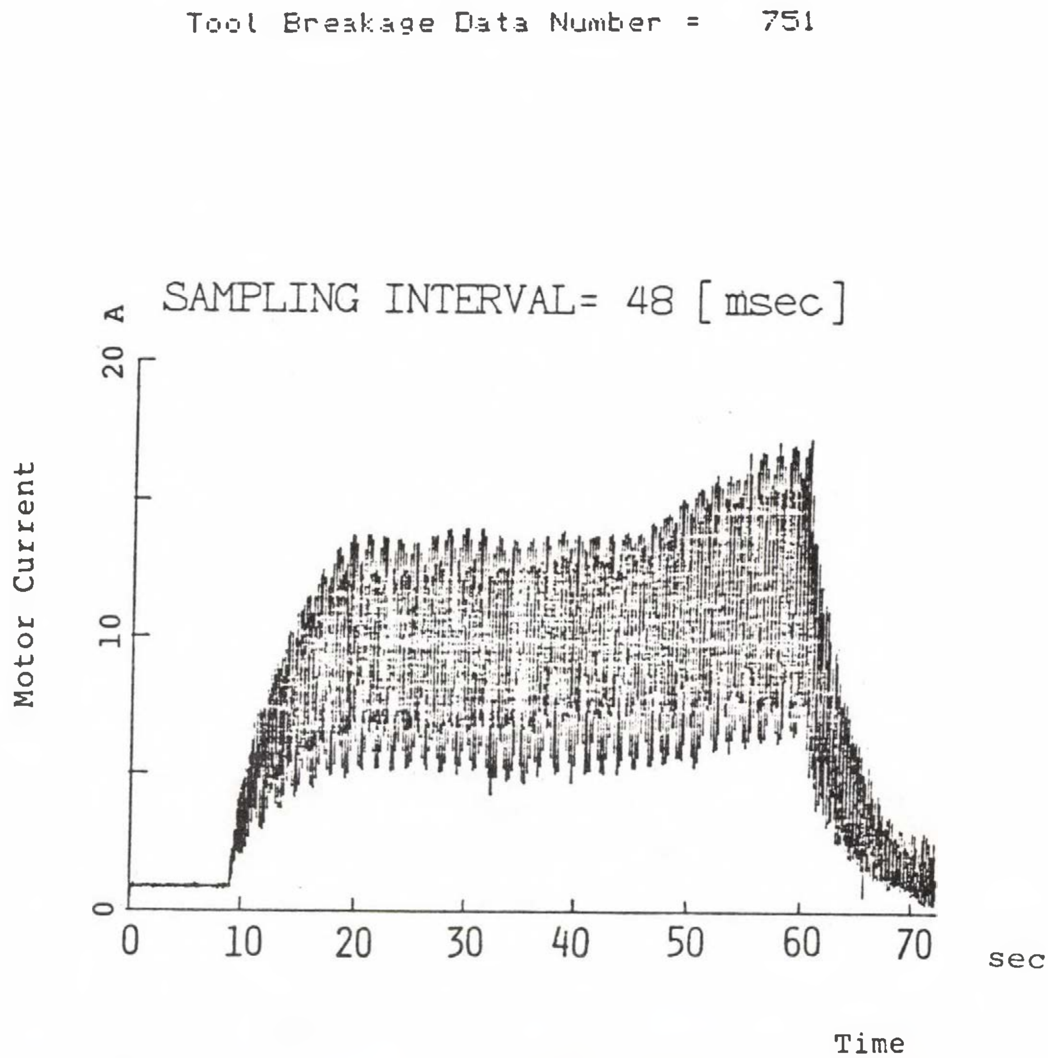


Fig. 5.12 On-line Experiment

Measured Spindle Motor Current

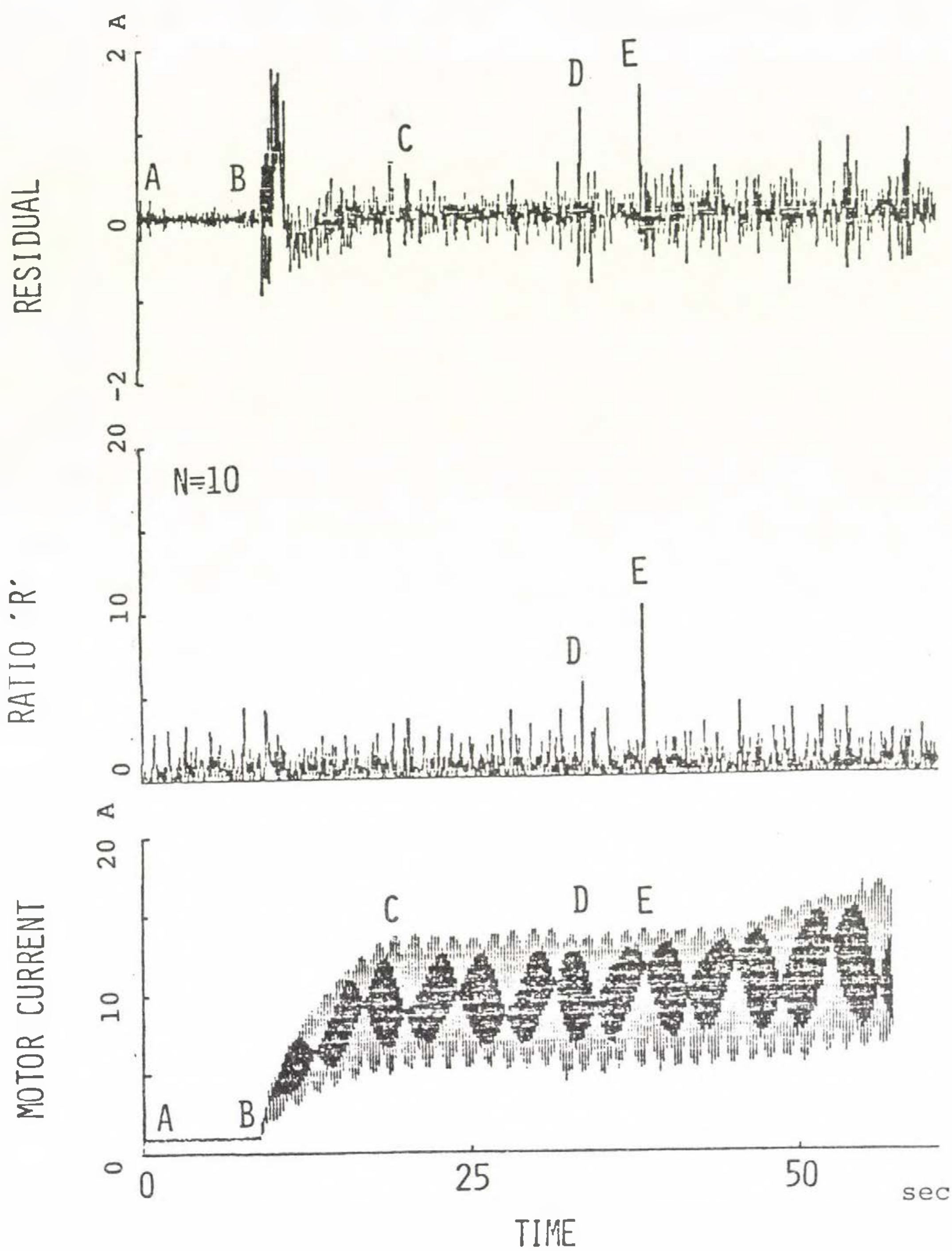


Fig. 5.13 The Residual , Detection Signal and the Measured Spindle Motor Current

have happened 751 * 0.048 = 36 sec after the sampling started. After the breakage the tool wear began to increase, as the rise in the torque indicates. The process is shown in more details in figure 5.13. The 'AB' interval is air cutting, then at point 'C' the tool reached the full radial depth of cut. There were two tool breakages at points 'D' and 'E'. The second breakage could have been avoided if the process had been stopped at point 'D'.

5.5.3 COMPREHENSIVE MONITORING

In the experiments a grooved workpiece was machined. The cutting conditions were:

spindle speed = 250 rpm

feed rate =0.035 mm/tooth

The radial and axial depth of cut varied in the experiments. The synchronization of the measured and calculated data was performed manually. The monitoring was performed by continuously examining, whether the measured cutting torque was within the tolerance limits or not. The monitoring system indicated only the error, but did not stop the process. In the following example a detection of a machining trouble is shown.

Example

A workpiece was machined in a way different from what was supposed in the cutting torque calculations. As shown in figure 5.14 - 5.15, the torque had been calculated for constant radial depth of cut, but in the experiment it was varied, it continuously increased. The allowed tolerance and the measured cutting torque are shown in figures 5.16 - 5.17.

5.6 CONCLUSION

Two approaches were described in this chapter to real time monitoring of the cutting process. The two systems are to detect different kinds of failures. The first method is to detect tool breakages, while the second one is to monitor the machining process comprehensively. The first method uses an analytical procedure and needs no preliminary information about the process taking place on the machine. This enables a stand alone use of it. An autoregressive model of the process was built up in the computer, and it was updated after the arrival of every new data. A fast calculation algorithm was used to update the model. The algorithm, running more than hundred times faster than a conventional one, already allows real time application. Further increase in the calculation speed probably can improve the monitoring system's performance. An adaptive method to detect the failures was also developed. The algorithm calculates a moving threshold, and uses it to

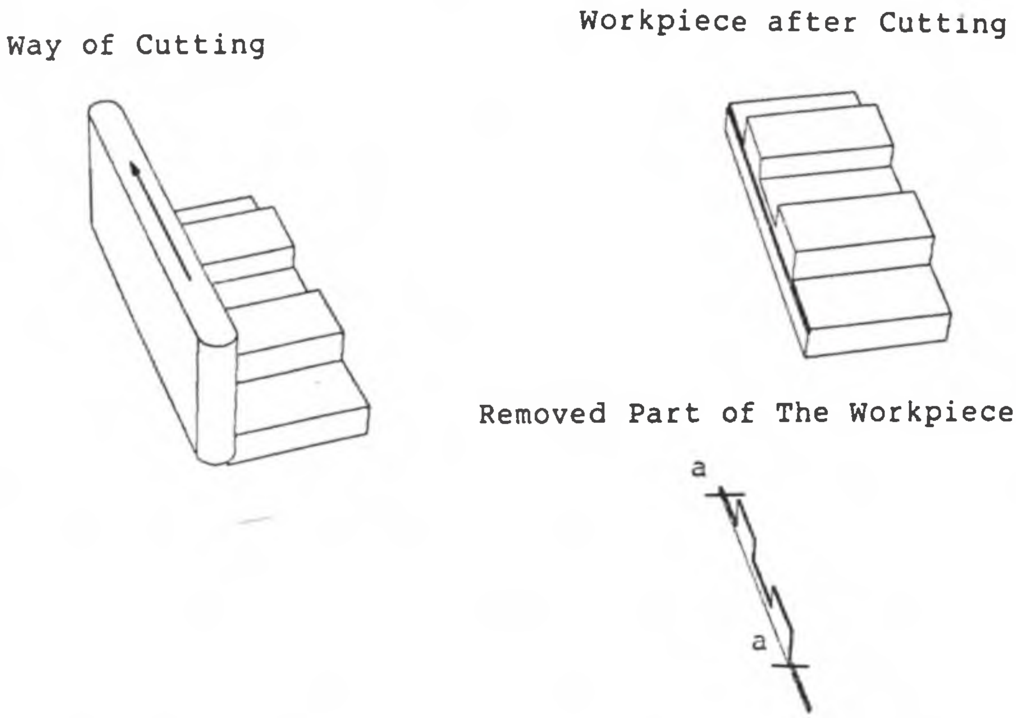


Fig. 5.14 Cutting Model for Torque Calculation

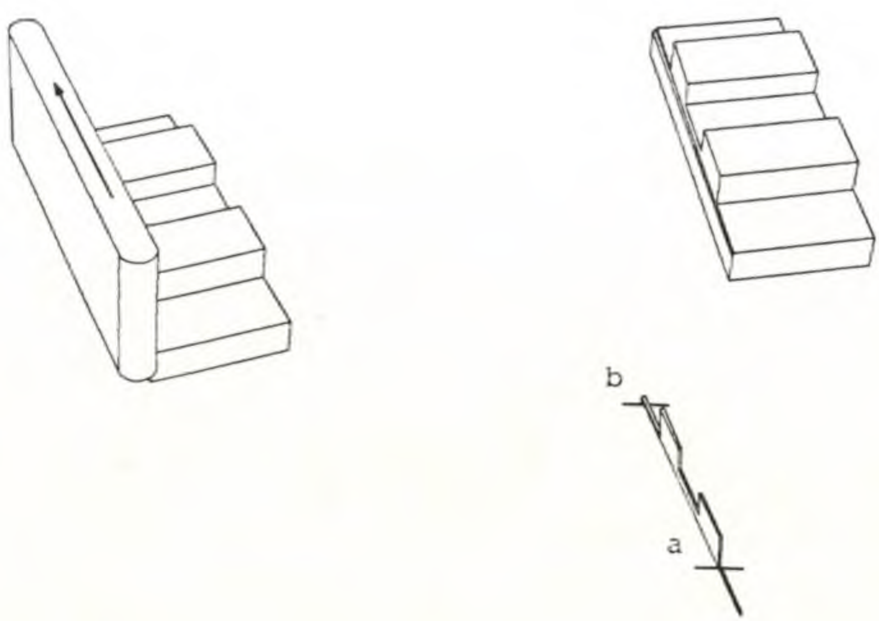


Fig. 5.15 Cutting Experiment

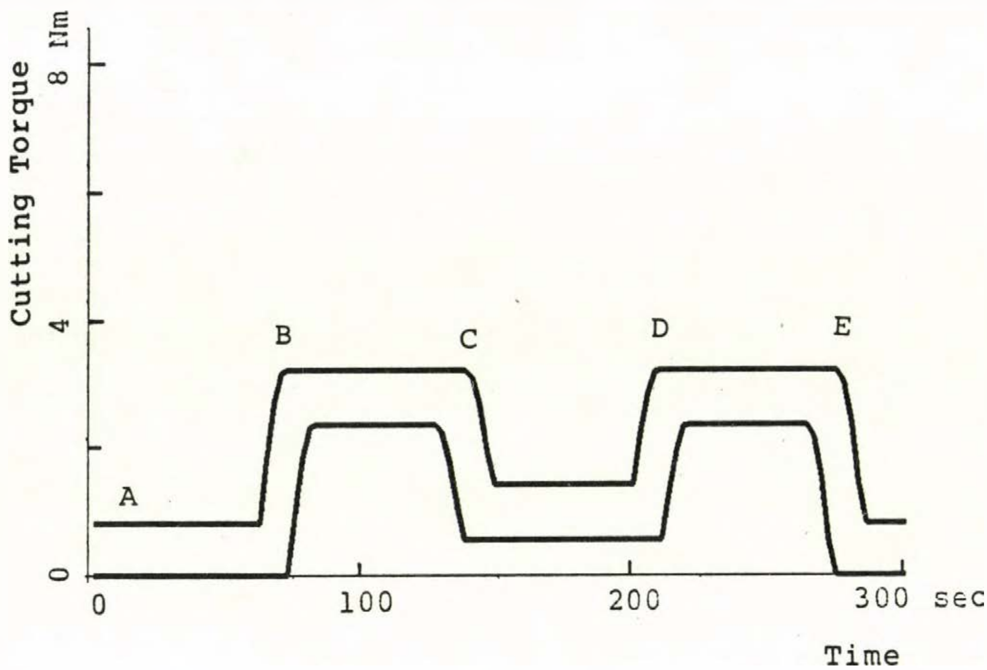


Fig. 5.16 Calculated Tolerance

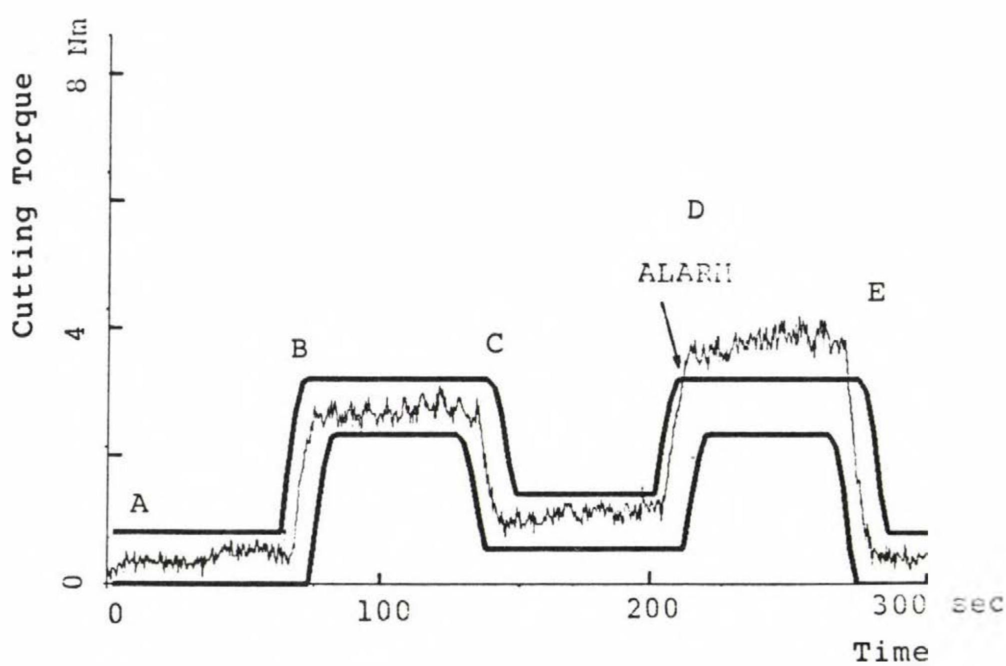


Fig. 5.17 Cutting Experiment

detect the breakages. The threshold is calculated from the residual. The algorithm clearly indicates the breakage, while normal events, such as beginning and end of cutting, do not cause false alarm.

The comprehensive monitoring method detects the troubles in machining by comparing the measured cutting torque with a preliminarily calculated reference, i.e. it uses preliminary information about the cutting process. It can detect any failure causing a deviation of the cutting torque from its estimated value. An upper and a lower limit is calculated from the estimated cutting torque, and the actual data is always checked whether it is within the limits. Upon detection of a data being out of the limits an alarm signal is generated. Both magnitude and timing tolerance is considered for the cutting torque when calculating the upper and lower limits.

The two methods were implemented in a 16 bit microcomputer. The application experiments clearly indicated that the solution is feasible, i.e. application of digital computing methods can be used for failure detection, and the methods proposed here allow real time application because the computing speed is high enough.

CHAPTER 6

CONCLUSION

The work presented methods for monitoring the machining operation via spindle motor current. In order to verify the methods first the cutting torque - spindle motor current transfer function was determined. Based on the results of transfer function determination two ways for monitoring the cutting process were described. The first one is a stand alone method, the second one uses preliminary information, the estimated cutting torque pattern, about the process. The methods were implemented into a 16 bit microcomputer.

In determining the cutting torque - spindle motor current transfer function the following main results were obtained:

- There is a strong correlation between cutting torque and spindle motor current in the time domain.
- The correspondence in the frequency domain is also very good, the transfer function is constant in the 0 - 16 Hz interval.
- The strong correspondence enables a monitoring method based on spindle motor current measurement.

CHAPTER 6

In monitoring the face milling process by using a stand alone system, the following results were achieved:

- Even a small brekage on the cutting edge of the tool causes detectable changes in the spindle motor current.
- The breakages in many cases initiated other problems, such as intensive tool wear or additional breakages, which had serious consequences later.
- The method of constructing a model of the cutting process and detect the significant discrepancies between model and process proved to be applicable to detect abnormal events.
- The abnormal events were detectable in this way, when the signal from the failed part was mixed with signals coming from normally operating parts, thus it enabled common sensoring for all the cutting edges.
- For modelling the cutting process the autoregressive model was adequate. The advantage of easy model equations and the possibility of recursive estimation proved to be very useful in this application.
- The change in the cutting process due to tool breakage was detected as a spike in the residual.
- The data involved in the autoregressive model had to include at least one whole revolution of the tool, and better results were obtained when the data included about two entire revolution. Further increase in the number of data involved did not result in further improvement in the detection ability of the method.
- In case of a six tooth face mill cutter twelve data from

every revolution was sufficient to detect the breakage of a cutting edge. This means, that the minimum model order was about 24.

- When determining the model order by using theoretical criteria, some subjective judgement was also necessary.
- The detection method proved to be very tolerant to the value of observation noise variance in the estimation procedure. Values within a very wide range (from about 0.02 % to about 2 % of the signal mean) gave almost identically good detection signal. This feature is very important, as measurement of the observation noise variance may meet with difficulties in practical cases.
- The estimation algorithm needed careful initialization of the parameters. In initialization a succesful method was to set all the varibles at zero, except for the estimation covariance, which was taken as unit matrix.

The cutting torque estimation system developed indicated the following:

- Cutting torque calculation can be based on a geometric modelling system. By dividing the tool path into discrete intervals the time series of material segments removed in cutting can be obtained with a reasonable amount of calculation.
- Using the NC part program for the description of tool movements had the advantage of providing additional, technological data about the cutting process.
- Technological information about the cutting process

obtained from the NC part program and the data base of a CAD - CAM system can provide the necessary technological data for torque calculations. The information of the NC part program, as spindle speed and feed rate, had to be combined with other technological parameters, as tool type and workpiece material.

- The cutting torque can be calculated as a linear combination of the volume of material removed and the tool workpiece contact surface area. The empirical equation proposed here proved to describe the cutting torque in face and end milling well under various cutting conditions.
- The agreement in magnitude between measured cutting torque and estimate was very good, even when machining a cast workpiece with geometrical inaccuracies within a few millimeters.
- The agreement in timing was also very good, when machining a workpiece of accurate size. The agreement was lower but acceptable when machining a cast surface with geometrical inaccuracies within a few millimeters.
- Verification of the NC part program can be performed by examining the outcome of geometrical cutting simulation. The tool model removing the material from the workpiece model finally results in the model of the finished workpiece, and its shape and size can be checked.
- The estimated cutting torque can be used for optimization of the cutting conditions. The cutting parameters can be set to provide a minimum manufacturing

time while not exceeding the maximum torque permitted for tool and machine tool.

The implementation of autoregressive modelling method into a 16 bit microcomputer gave the following results:

- The autoregressive modelling of cutting processes can be implemented into a microcomputer, the memory and input - output resources are sufficient.
- Using a fast calculation algorithm to update the AR model allowed already a real time application of the microcomputer implementation.
- The adaptive method calculating a moving threshold from the residual and comparing the actual value to this moving threshold was succesfully tested, and breakages were detected in this way.
- The adaptive method proved to be able to distinguish the beginning and end of cutting or a change in the depth of cut from breakages, i.e. slow changes in the cutting process did not cause false alarm.
- The residual's variance calculated from a few data repetitively was a reliable basis of the moving threshold calculations.
- The detection results in off line and on line experiments were satisfactory.

The comprehensive monitoring of the cutting process performed by a 16 bit microcomputer indicated that:

- Troubles in the machining operation can be detected by comparing the measured cutting torque to a preliminary estimate.

- Tolerances were necessary to compensate the geometrical inaccuracies of the workpiece and fixtures.
- Tolerances were required both in magnitude and timing.
- An error, when the way of machining slightly differed from the prescribed one, was successfully detected by using this method.
- The simplicity of the algorithm enabled the application of a slow computer language (BASIC) for real time application.

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