Force Prediction in End Milling Using Artificial Neural Nets Augmented by Acoustic Emission

Abstract

End milling is one of the most extensively used machining operations generally in modern machine shops and particularly on CNC machining centers. Cutting force magnitudes have enormous influence on the performance measures of end milling such as tool wear, tool edge chipping, tool breakage, work-piece dimensional accuracy. Hence it is of significant economic importance to be able to predict cutting forces under varying cutting conditions prevailing on the shop floor. The traditional approach of relying on analytical and computational models has generally failed to develop the ability to predict cutting forces under shop floor conditions.

Much research effort world-wide has been directed in recent years into developing intelligent manufacturing systems who can monitor themselves, anticipate problems that would be encountered on the next workpiece, and take necessary precautions. Developments in artificial intelligence (AI) have been particularly useful in this context. Amongst AI techniques, learning based on artificial neural nets (ANN) has been found to be particularly useful.

Development of new sensing and sensor fusion techniques have also contributed to progress towards developing intelligent manufacturingf systems. Amongst the sensors, acoustic emission sensing has been found to be particularly suitable for monitoring machining operations. There is evidence that the true mean square value of AE has a significant positive correlation with the energy expended in the deformation and friction zones in machining.

It also appears that the learning effectiveness of ANN can be improved by augmenting the net with real-time sensory information. However, notwithstanding the significant effort put into applying ANN and AE to end milling, little work has so far been done towards applying ANN and AE for predicting cutting forces in end milling.

In view of the above considerations, this project has attempted to predict cutting forces in end milling using ANNs augmented by acoustic emission information. To this end, cutting forces have been measured for a given cutter-work material-cutting speed-feed rate combination in a range of radial and axial depths of cut using a three-component milling dynamometer. Simultaneously, the true measn square values of acoustic emission was measured using well known acoustic emission sensor placed in the vicinity of the cutting zone. Next, using a well known commercially available software called Qnet, back propagation networks (BPNs) were trained to learn randomly selected subsets of the measured data. In these learning exercises, the input array was restricted to the cutting conditions: cutting speed, feedrate, axial depth of cut, radial depth of cut. The network architectures, momentum parameters, the numbers of back propagation cycles, etc. were fine tuned to obtain the best possible results. The results showed that the force prediction ability of the network could not be better than about 3%. Hence, in the next phase, the input arrays were augmented with the

corresponding measured values of the true mean square of acoustic emission. It was found that the learning ability improved signifiicantly to below 1%.

The present project has demonstrated that it is possible to have satisfactory force prediction accuracy with neural nets augmented by AE sensing. However, this should only be considered as a preliminary finding. Further work covering a much wider range of cutting situations and exploring more refined AE signal processing and ANN strategies is needed before the full benefit of the approach can be realized.

Acknowledgment

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I have to thanks for my girl friend, Renee. She give support to me when I feel sorry to my project and my supervisor.

Contents

Chapter 1
Introduction

1.1 The input-output view of a machining operation

This project aims to predict the cutting force magnitudes in end milling. Cutting forces may be considered as a subset of the performance outputs from a machining operation [Armarego, 1996]. This section briefly summarises the input-output views of a machining operation as outlined by them and subsequently refined in [Venuvinod, 1997].

Figure 1.1 shows the Input output view of a machining operation. Inputs are any parameters which determine the behaviour of the process. Outputs are any variables or parameters which result from the particular behaviour of the process. In this figure, {I}, {P} and {O} are stated clearly. The direct relationship among {I}, {O} and {P} are as shown in Figure 1.1. {I} is the input parameter set, after any machining process {P}, the input set are converted into output set {O}. For instance, wood is transformed into paper by a manufacturing process. Then wood is one of the {I}, {P} is the mentioned manufacturing process and {O} is the output data concerning the process behaviour which is of importance to the process designer.

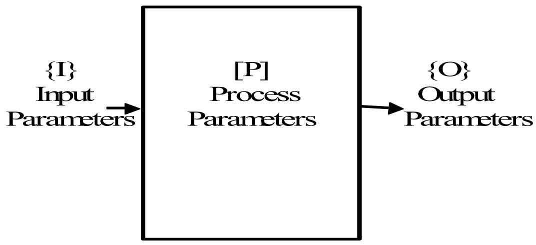

Figure 1.1 The input-out view of a machining operation [Armarego, 1996]

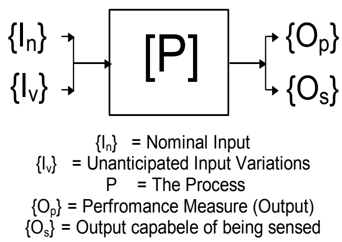

Figure 1.2 The classification of process inputs and outputs [Venuvinod, 1997]

There are two kinds of inputs to a model as shown in Figure 1.2: one is the nominal input array while the other is the array of unanticipated inputs. Both of them are inputs to a process. The difference is that, in a nominal input set, all the information is known and the associated parameters under our control. However, in the cases of $\{I_v\}$, the information might not be known or can not be controlled. For instance, when we set the cutting speed of a turning machine at a certain value, it is possible to keep the speed in an acceptable range. This means the cutting speed is under our control. Another example is by taking the transformation of wood into paper. The nominal input is the properties of the raw material, wood. If there exists some impurity in the wood and can not be found out before any manufacturing process has taken place, the output “paper” may not be in the desired form and may have to be rejected. The impurity will then become the “unexpected” input to the transformation process. Similarly, a process planner may be excepted to have a tempered structure steel after a machining process. However, it is possible that there exist some martensitic structure steel in the batch of workpieces. Such unexpected input is not under our control and it will be grouped as $\{I_v\}$.

A partial list of the common input parameters to machining operations is given below [Armarego, 1996]:

- Work Material Properties
  - Mechanical (elastic and plastic)
  - Thermal
  - Fracture
  - Wear

- Tool Material Properties
  - Mechanical (Hardness, etc.)
  - Thermal
  - Fracture
  - Wear, Diffusion, etc.
  - Coatings

- Tool Geometry
  - ISO 3002/1
  - Chip Former Features

- Cutting Conditions
  - Cutting Speed
  - Feed (rate)
  - Depth of Cut
  - Radial Depth of Cut
  - status of dry or wet

With regard to model output, it contains the basic machining performance information. Armarego *et al* have argued that there is a need to quantitatively predict the performance output [Armarego, 1996].

According to Venuvinod [Venuvinod, 1997], it is more useful to sub-divide the output array from a process into two subsets. One is performance output $\{O_p\}$ while the other is sensory output $\{O_s\}$. $\{O_p\}$can determines the efficiency and effectiveness of the process, while $\{O_s\}$ contains variables that can be measured or sensed in real time. There is a possibility of overlap of the output. That means one can put the output into either $\{O_p\}$ or $\{O_s\}$.

A partial list of $\{O_p\}$ according to [Armarego, 1996] is given below:

- Chip Formation Geometry
  - Chip Thickness, Length and Width
  - Chip/Tool Contact Length
- Cutting Forces
  - 3 forces, torque and thrust, etc.
  - Cutting Power
- Cutting Temperatures
  - Mean Rake, Mean Flank, etc.
  - Temperature Field(s)
- Tool Wear and Life
  - Flank Wear Parameters
  - Crater Wear Parameters
  - Groove Wear Parameters
  - Tool Fracture
  - Tool Life (Taylor Constant, Index, etc.)
  - Failure Modes (Entry, Exit Failures, etc.)
- Surface Finish and Integrity
  - Surface Roughness and Topology
  - Residual Stresses
  - Surface Hardening
  - Surface Damage
- Component Dimensional Accuracy/Errors
  - Cutting Vibrations and Chatter
- Chip Form for Chip Control
  - Classification according to Spaans, etc.

- Burr Features
    - Entry Burr
    - Exit Burr

A partial list of $\{O_s\}$ is as follows:

- Cutting forces using dynamomter
- Acoustic Emission using AE sensors
- Cutting Temperature using calorimeters, thermocouples, thermal paints, infrared radiation camera, etc.
- Tool Wear using AE, vision system, cutting force signals, noise, vibration, etc.
- Tool breakage using AE, cutting force, vibration, noice, induction coil, vibration, etc.
- Chip clogging using AE, Cutting force, vibration, accelleration signals.
- Power consumption

It is interesting to note that, many of the members in $\{O_s\}$ family can be measured by using Acoustic Emission. The relationship between $\{O_p\}$ and $\{O_s\}$ often is that, $\{O_p\}$ can not be directly measured. However, by measuring the sensory subset $\{O_s\}$, it might be possible to predict $\{O_p\}$.

1.1 The importance of being able to predict cutting forces

Owing to increasing competitive pressures, most machining industries continue to face the problem of achieving cost savings. The cost of a product includes many elements such as the cost of materials, the cost of equipment, the cost of tooling, the cost of the manufacturing processes, and the cost of rework.

An ability to predict tool breakage can lead to significant reductions in manufacturing costs. One method used in detecting tool breakage is in-process monitoring of cutting force or torque. A sudden change in the force amplitude indicates the tool breakage. A large increase in the cutting force can lead to tool breakage. Gradual tool wear often leads to a gradual, albeit small, increase in the cutting force. Further, an increase in cutting force, in turn, indicates an increase in power consumption. Hence, cutting temperatures can be expected to rise thus leading to more rapid tool wear. It is therefore clear that an ability to predict cutting forces will facilitate the avoidance of tool breakage and tool wear in industrial practice.

The magnitude of the cutting force can also have a direct effect on the work-piece accuracy. Elements of the machine tool - fixture- work-piece - tool (MFWT) system deflect under the action of the cutting forces. This leads to deviations of the relative path of the tool tip from the surface being machined from the programmed path. Consequently, there would be significant dimensional errors on the machined part. The traditional answer to this problem is increased inspection and rejecting the parts which are outside the permitted tolerance zones. However, this approach invariably leads to increased costs of inspection and re-work. The modern answer to this problem is compensation - correcting the CNC program to compensate for the errors arising from the deflections of the MFWT system (and other errors such as the kinematics and thermally induced errors inherent in the machine tools). Several research projects are currently in progress at the City University of Hong Kong aimed at developing such error compensation systems. However, a pre-requisite to the success of such work is the ability to predict the magnitudes of cutting forces from given sets of process input conditions.

To measure cutting force, the traditional approach is directly measure the cutting force during cutting. However, it is not practical to have a dynamometer located in a shop floor. The measuring device is far more expensive compare to a AE sensor. A dynamometer costs approximately $300,000 while a milling machine only costs $100,000 and AE sensor worth $10,000. It is ten times of a dynamometer against a sensor. Both the sensor and the dynamometer are hi-tech material. They have to be take care under any operation. Therefore, the installation of a dynamometer is not valuable.

1.3 Current state of force prediction through modeling

According to [Venuvinod, 1997], there always exists a network of cause-effect relationships within a process, and by analysing these relationships in terms natural laws, it should is possible to predict the output {O_p} quantitatively. ‘generality” and “accuracy” are the two vital critical point of a model. “generality” is the capability in transporting the model under different conditions. It is great to know that if there is an existing model which can be used for a variety of process. Even the perfect model is not available. And “accuracy” is the effectiveness and efficiency of a process. The greater the “generality” and “accuracy” of a model, the greater is the usefulness of the model.

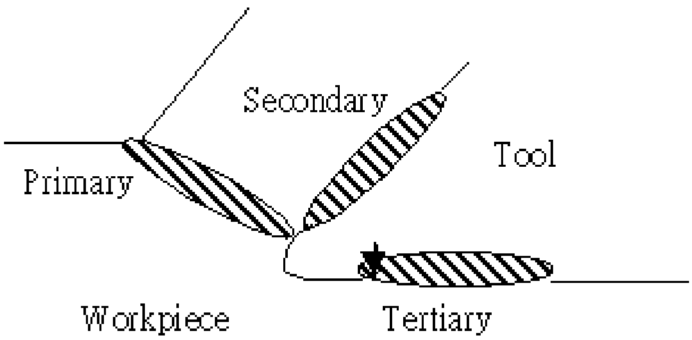

Figure 1.3 The three shear planes of metal cutting

The literature on analytical modeling is too vast to be comprehensively reviewed here. Hence, discussion will be limited to shear plane based models. Analytical modeling started with Merchant 1944 model for single edge orthogonal cutting [Merchant, 1944]. The assumptions include sharp cutting edge, the admissibility of the approximation of a shear plane, the constancy of chip-tool friction angle, and the constancy of the shear flow stress on the shear plane. The first assumption means that the parasitic rubbing and plowing forces in the vicinity of the cutting edge cannot be predicted. The implication of the second assumption is that the theory is applicable only when the shear zone is thin. This approximation is valid only for less work hardening materials and at high cutting speeds. Another problem is that the model requires the chip thickness or the shear angle to be known a priori. The first was Merchant's own solution which provided the upper bound to the shear angle and hence to the lower bound of cutting force. Subsequently, many other (approximately 52 according to Lindstrom) shear angle solutions have been developed [e.g. Lee, 19??]. However, none has been found to be universally applicable or robust enough.

Merchant's approach has been extended to single edge oblique cutting [e.g. Shaw, 19??, Armarego, 19??, Zorev, 19??]. In terms of the ability predict forces, these models suffer from the same set of limitations as the single edge models. In addition, there is the problem of predicting the chip flow angle. Stabler has developed a simple equation stating that the chip flow angle is equal to the cutting edge inclination angle [Stabler, 19??]. But this, at best, is a very course approximation.

More recently, much activity has taken place in extending the shear plane models to a variety of practical machining operations for cutting force prediction. The more notable in this regard is the work being done by Armarego and et al at University of Melbourne to systematically extend the theory to other operations. In this continuing effort, Armarego *et al* try to predict cutting forces in different operations from a common machining database derived from single edge orthogonal cutting and containing information on the shear angle, chip-tool friction, shear flow stress on the shear plane and the chip flow angle[e.g. Armarego, 19??, 19??, 19??].

In recent years there has been much activity with regard to the development of computational models.Amongst the computational approaches, finite element modeling (FEM) has been particularly popular. However, a major problem with all computational approaches has been that they require a priori knowledge of the stress-strain-strain rate-temperature relationship of the work material. Such information is very difficult to obtain since it is difficult to simulate the extreme strains and strain rates prevailing during cutting in actual material tests in practice. Another problem is that these models require a quantitative criterion for chip separation and a knowledge of the progression of chip-tool friction as one progresses from transient to steady state cutting. As a result, as recently observed in a CIRP report [Childs], computational models are still unable to quantitatively predict cutting force magnitudes - the error is often of the order of 100%.

A further complication in predicting cutting force is the presence of the built-up edge under a range of cutting conditions. While this phenomenon has been extensively studied experimentally, there are no analytical models either to predict the existence of built-up-edge or take into account its influence on the cutting forces.

Although modelling has provided us with a deep understanding of the machining process, currently available models suffer from many limitations. For instance, many of the performance outputs can not still be predicted and the model performance against the two basics criteria, "generality" and "accuracy" , is still far from being satisfactory. One major drawback is the requirement for massive machining databases, MDB, which consists of the appropriate magnitudes of the various variables and parameters used in the model for the specific machining process (see Figure 1.3). The database provides the machining coefficient for the machining process. However, the process of determination of these parametrs, variables or coefficients itself requires extensive and expensive off-line experimentation, X_{off}. Owing to this requirement of massive experiments, the manufacturing cost will be greater. This is not an efficienct approach.

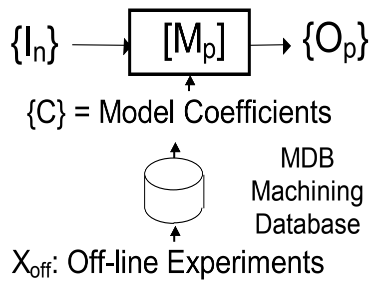

Figure 1.3 Prediction based on modelling supported by machining database

As noted recently in [Venuvinod, 1996], a problem with all the analytical approaches summarised above is that these machining databases, of necessity have to be static. In particular they cannot anticipate the myriad real time factors that influence cutting force magnitudes. These disturbing or unknown factors include the presence and size of built-up-edge, unanticipated variations in work material properties (grain size, phase dispersion, hard scales, etc. — all of which influence cutting forces, minute variations in the sharpness of the cutting edge, the presence of lubricating films on the tool faces, and so on. Thus, while these models appear to have been validated against limited experimental data, they are unlikely to be robust enough to be applicable in the highly variable CNC machining environment.

1.4 Force prediction through learning

Force prediction using modelling approach has been discussed in the previous sections. However, modelling always involves a sets of equations which is only applicable in limited cutting conditions. It becomes less capable to the modern rapid growing industries. A new approach, “learning”, is introduced which simulate the capability of a human brain. The learning approach is believed availible with “no limitation”. The general archeture of a learning system as shown in Figure 1.4 is proposed by Veninoud.

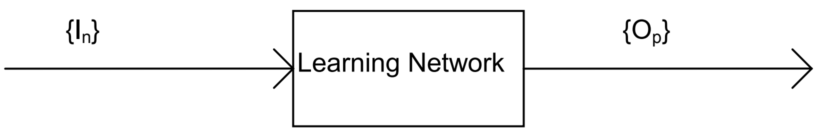

Figure 1.4 A view of Learning Network

The steps of learning is as simple. The inputs array which can cause the desired output array is feed into the learning network, an array which known as Weighting is kept changing until the generated output is similar to the desired output. The greater similarity of the generated output to the desired output, the greater accuracy with the learning network. Unlike the modeling approach, LN, or ANN, is an implicit model which the contains inside the network and the processing method are all unknown to user.

ANN can be classified as supervised or unsupervised. The former one will have desired output while the later haven't. These two networks will be used for different purpose. However, both of them operates similarly. There are two learning stages for different kinds of ANN, training and testing. The training stages requires input to the network and desire output together alter the weighting in the network. Weight is the spilit of the network. The training cycle is repeated until testing stages give out satificaty accuracy.

1.5 Augmenting learning with sensing

The basic ability of a learning network can be improved by adding a sensory input as the nominal input array based on the idea of Veninoud[ ]. The general drawback of traditional approach of modelling is from the large size MDB. To generate a rather reliable MDB, a large sum of expensive off-line experiments is required. This will greatly increase the manufacturing cost. At the same time, the modelling method with MDB can not due with inherent variable input. Such input may always happen in the realistic shop floor operation.

As shown in Figure 1.2, there always exist an output together with $\{O_p\}$, say $\{O_s\}$. These output is the result of model Mp and must contains much information compared with the various input. The main critical point is how to fully utilise the hidden information of the sensory output. To use a sensing output as one row of the input array is one of the answer and this new approach has brought success to Venioud's experiment about compensation for workpiece dimensional errors in turning.

1.6 The end milling operation

1.6.1 A typical feature of the milling process is that the rotating tool (the milliig cutter) has a number of cutting edges each of which works over only part of its rotary path and travels over the remainder without cutting. The machine tool designer must always bear in mind the implications of these conditions, which concern the pulsations of the cutting forces; the vibrations of tool, workpiece and machine; the quality of the surface produced;, etc. The axis of rotation of the milling cutter remains usually stationary and the feed movement is carried out by the work-piece.

When the cutting edges are arranged on the circumference of the milling cutter, the process is called Peripheral Milling, whereas when they are arragned on the cutter face, the process is called Face Milling.

As each tooth or insert of a milling cutter enters the workpiece, it is subjected to a mechanical shock load. The magnitude of this load depends upon the workpiece material, cutter position, operating conditions, and cutter geometry. Cutting forces in milling are cyclical, being roughly proportional at any position. Heat generated in the milling operation is also roughly proportional to the undeformed chip thicknes and cutting forces. Rapid changes in generated heat place a severe strain upon the cutter material and can lead to thermal cracking.

1.6.2 Up and Down Milling

If the rotation of the milling cutter cutter is such that the tangential cutting force is generally opposed to the direction of workpiece feed and the axis of the cutter does not intersect the workpiece, the undeformend chip thickness constantly increases during the cut. This is called up milling or sometimes conventional milling. If the rotation of the cutter is such that the tangential cutting force is generally in the same direction as the workpiece feed and the cutter axis does not intersect the workpiece, the undeformed chip thickness constantly decreases during the cut. This is called down milling , also known as climb milling. Up and down milling exist in their pure forms only when the cutter spindle center-line does not intersect the workpiece. In such cases, each tooth executes up milling action in one part of the cut and down milling in rest of the cut.erations, either up milling or down milling may be selected by proper selection of the direction of the machine table feed, cutter position, and direction of cutter rotation. However, this condition is not satisfied in all slotting and side milling operations, and some face milling and end milling situations.

One of the significant differences between up and down milling lies in the direction of the cutting forces generated. In up milling, the tangential force opposes the thrust force which is the force attempting to push an individual tooth or insert out of the cut. As a result, the feed force must be high for the cut to be made.

1.6.3 Chip Formation in Milling

The basic process of chip formation in milling is the same as for all other metal cutting operations — a wedge- shaped cutting tool engages the workpiece to remove a layer of material in the form of a chip. Chip formation in milling differs from single-point metal cutting in several aspects. Practically every millng operation consists of an interrupted cut, with each tooth or insert generally in the cut less than half the total machining time per cutter revolution. While the tooth or insert is in the cut, the thickness of the chip being formed constantly changes because of the dual motion — cutter rotation and work-piece feed which is characteristic of the milling process.

1.6.4 Versatility of End Milling Cutters

End mills are the most common and widely used type of milling cutter. These versatile tools are also available in more standard styles, shapes, and sizes than any other milling cutter. Major applications include facing, slotting, profiling, plunge cutting and diesinking and cavity cutting. Because their versatility, they are the most extensively used milling cutters on CNC machining centres.

1.6.5 End Milling Operation Inputs

The normal input array, $\{I_n\}$, to an end milling operations are (see Fig. ?):

- cutting speed / RPM
- axial depth of cut / a_a
- radial depth of cut / a_r
- feed rate / f

1.6.6 End Milling Operation Outputs — Performance Measures, $\{I_p\}$

A partial list of $(I_p\}$ for end milling is: power consumption, Longitudinal feed force (F_l), transverse feed force (F_t), thrust force (F_n), mean torque experienced by the cutter, mean cutting temperature, mean flank wear and/or wear rate, tool edge chipping, tool fracture, roughness of the machined surface, chatter. The present project is mainly concerned with predicting the three force components F_x, F_y, and F_z.

1.7 Objectives of the present work

It is useful now to define the basic objectives of the current project. The following observations derived from a review of the literature have led to the specific objectives listed in the next paragraph:

- End milling is one of the most extensively used machining operations generally in modern machine shops and particularly on CNC machining centres.
- Cutting force magnitudes have enormous influence on the performance measures, $\{O_p\}$, of end milling such as tool wear, tool edge chipping, tool breakage, work-piece dimensional accuracy. Hence it is of significant economic importance to be able to predict cutting forces under varying cutting conditions prevailing on the shop floor.
- The traditional approach of relying on analytical and computational models has generally failed to provide satisfactory prediction of cutting forces.
- Much research effort world-wide has been directed in recent years into developing intelligent manufacturing systems who can monitor themselves, anticipate problems that would be encountered on the next workpiece, and take necessary precautions. Developments in Artificial Intelligence (AI) have been particularly useful in this context. Amongst AI techniques, learning based on Artificial Neural Nets (ANN) has been found to be particularly useful.
- Development of new sensing and sensor fusion techniques have also contributed to progress towards developing intelligent manufacturing systems. Amongst the sensors, acoustic emission sensing has been found to be particularly suitable for monitoring machining operations. There is evidence that the true mean square

value of AE has a significant positive correlation with the energy expended in the deformation and friction zones in machining.

- It appears that the learning effectiveness of ANN can be improved by augmenting the net with real-time sensory information.
- Notwithstanding the significant effort put into applying ANN and AE to end milling, little work has so far been done towards applying ANN and AE for predicting cutting forces in end milling.

The following are the objectives of the work described in this dissertation:

- Measure cutting force in end milling under a variety of cutting conditions
- Investigate the effectiveness of BPN in learning to predict end milling forces
- Implement a system for measuring AE from end milling
- Investigate the effectiveness of augmenting the BPN with the TMS values of AE

Chapter 2

Literature Review

2.1 Cutting force models for end milling

The need to quickly predict tool failure in milling process is the need to modern industries. To monitor the cutting force during milling process is one of the approach to achieve the goal. Many survey and research has been done on the mentioned area, also with milling[Adolfsson, 1996] [Alauddin, 1996] [Altintas, 1992] [Tama, 1996] [Altintas, 1989][Ryabov, 1996] [Altintas, 1988] [Ber, 1988][Tam, 1987][Devor, 1980], Computer based modelling is now becoming widely used[Armarego, 1993][Armarego, 1991] [Altintas, 1991] [Deshpande, 1990] [Armarego, 1985][Whitfield, 1976]. In this paper, emphasis is paid on the multi-point cutting process- end milling process. The process is far more complicated compare to the single point cutting process. The end milling process is a helical one which consists with three components: tangential force, axial force and radial force[Armarego, 1970]. The forces are generated during the entrance and exit of the tool into the workpiece. There has already developed many models to predict, control and monitor milling force[Rober, 1996][Bayoumi, 1994][Tai, 1995]. However, no exact one is the most powerful.

2.2 Sensor for machining

Sensing has been clearly defined as the measurement and monitoring of the generating output of machining, tool condition monitoring, force prediction, etc [Takatsuto, 1994][Lee, 1988][Bischoff, 1987][Suzuki, 1985][Moriwaki, 1984] [Suzuki, 1983][Micheletti, 1976][Zakaria, 1973]. The signal collected will then be analysis with a signal processing algorithm. A system known as “smart sensor” system is proposed[Santochi, 1996][Kuo, 1994][Guinea ,1991]. The proposed system has been described in the previous chapter in detail. The general purpose of introducing sensory control in the field of machining is to give immediate response when there is any detectable alarm[Li, 1993] [Jiri Tlusty, 1988]. Also, the sensor must be smart enough to distinguish between unwanted noise and failure event. It becomes the great aspect in searching for the best threshold level under varying cutting condition.

The sensor itself also must have a portable capability. It means that the sensor can be installed in a wide range of machining operation. Also it must have the reliability and maintainability. The reliability of a sensor comes with the control system which set the threshold level to the sensor and the ability in separating the noise. The maintainability of the device can greatly reduce the installing and maintaining cost. In the modern industry, the sensors are always comes with a shielding in order to reduce the effect of interpreting noise. Also, they always have a housing accompanied so as to minimise the accidental breakage.

Therefore, sensor system is widely used for the advantage of providing fast response with is critical in modern manufacturing.

2.3 Acoustic emission sensing for machining operations

Research of Acoustic Emission has been started by Dornfeld and Kannatey-Asibu regarding to orthogonal cutting[Blum, 1990][Heiple,1994]. And later on the study is extended to the topic of obilque cutting. There are many documents talking about the influence of three cutting parameters, cutting speed, depth of cut and width of cut on AE RMS. There is only one model stating the general relationship of these three cutting parameters to tool failure, tool wear, etc. The literature claimed that the AE RMS should increase as the cutting parameters increase for the reason of their indirect effect on shear angle.

In process monitoring for tool conditioning, material behavior, cutting force generation, detection of thermal condition have become the wide interest of the modern industries. Many researches have been carried out to find out the best approach to satisfies the interest [Yen, 1986][Blum, 1988][Lan, 1985][Tse, 1985][Kannateyasibu, 1981][Kannateyasibu, 1980] . However, no certain approach is believe to be the absolute answer to the interest. Over the last decade, Acoustic Emission has been analyzed in detail under different machining conditions. Now there is no doubt in using Acoustic Emission as it brings lots of information content that is not easily to be found out and noticed by any other means of sensing[ ]. Acoustic Emission, in short, is the transient wave released from the plastic deformation zone during metal removing process. It shows changes when there is tool wear, too breakage, built up edge, etc. Several technique of analyzing AE have been developed. Two examples of the technique are time domain analysis and frequency domain analysis by Fast Fourier Transform function. And these two techniques are widely used in many researches. The AE generated always in the order of 0.1 to 1 MHz range[ ]. It requires a sensor with high frequency response. Basic Acoustic Emission will be discussed in Chapter 3 detailly with the sensor employed.

2.4 Acoustic emission sensing for end milling operations

In this section, a detail discussion of one paper will be proposed. The most important paper which gives me the motivation of the this project is by Man Liu and Steven Y. Liang. The title of the paper is Monitoring of Peripheral Milling Using Acoustic Emission. The document stressed that there is no document clearly analysis the relationship of feedrate, depth of cut, and acoustic emission.

In order to make comparison between the two experiment data, it is recommended to use the same apparatus, operating under the same working condition. However it is not possible for different shop floor layout. Maximum similarity is required. In Man Liu's paper, he used AE TMS as the characteristic parameter of AE signal. The primary definition of TMS will be clearly stated in the later chapter. In his preliminary experiment, the vertical distance between AE sensor and the cutting zone has found great influence on the AE TMS. The greater the distance, the weaker the AE TMS. However, he doesn't explained the principle behind in detail. And, the observation will be confirmed by later experiment with explaination as soon as possible.

Also, he has used the resultant force at all without any statement. However, the reason of using resultant can be explained in later chapter after my experiment. He has made modifaction of the sampled data by introducing a transfer function which will make the sampled data more smoother for measurement.

He has made some assumption on the experiment, that's all the AE energy are coming from the tool/workpiece interfaces, the deformation energy from the cutting zone, the rubbing energy from tool/workpiece interfaces. And he assumes no AE energy is related the chip breaking and formation. And based on this assumption, he generates a set of equations.
It should now first define zone AB and CD. The following figures will illustrate the location of the zone

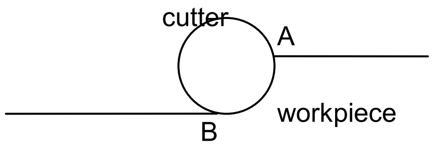

Figure 2.2 cutting zone AB

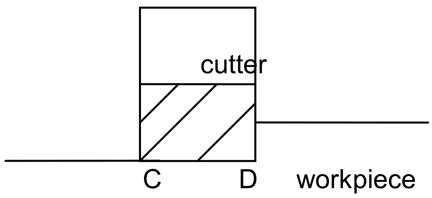

Figure 2.3 Rubbing zone CD

It is clearly noticed from the figures that AB is the perperheral cutting zone while CD is the rubbing zone. Now, I would like to discuss these equations in detail. The first equation he used is

$$TMS = C_1\ (E_{AB}^{AE} + E_{CD}^{AE})$$

where E_{CD}^{AE} is the energy from rubbing zone CD

E_{AB}^{AE} is the energy from cutting zone AB

C_1 is a proportional constant

Based on this equation and the observation after his testing, he generates two equation which are simple linear equation in the format of y=mx + c showing the general relationship between axial depth of cut - AE TMS and radial depth of cut - AE TMS.

According to the energy conservation equation, there will be machanical energy which converts into other from of energy in cutting, so there is only a portion of energy which will finally detected by AE sensor. However, the main problem is that he first assume the " total energy" but not concern the energy from different zones individually. For more generality, I would like to setup another energy equation.

$$TMS = (C_2 E_{AB}^{AE} + C_3 E_{CD}^{AE}) \text{------------------}$$

where C_2 and C_3 are proportional coefficient of zone AB and CD

For graphs from Mr. Liu, not all the cutting x - axis value are the same. For example, the radial depth of cut from the three different cutting parameters doesn't have the same x - axis value, it seens that only linear portion are shown. There is no explaination of these distortion.

Mr. Liu has developed two equations based on his experimental data regarding to the radial and axial depth of cut. Both of them are liner polynomial equation with two leading coefficient. However, he doesn't provide a good representation of the coefficient. In another work, it is to do lots of off-line experimental to draw a MDB which is only for the coefficient. Furthermore, he only has experiments on two kinds of material and working under several cutting conditions. It is not enough to draw conclusion for the AE generation with the effect of different cutting parameters.

2.5 Learning using ANN in machining

With the idea of "smart sensor", an Artificial Neural Network computer based software is widely used in many on-line monitoring and tool failure detecting projects[Javed, 1996][Lung, 1995][Zilouchian, 1995][Kamarthi, 1994][leopold, 1994][Kurapati, 1992]. The main purpose is the "rapid replacement of flexible human workers who have high quality sensory interpretative abilities"[ ]. The system then have the ability to make decision itself, just like what a human worker does. The technique used is pattern recognition technique, which is the common way of thinking of a human. There are two kinds of ANN, supervised and unsupervised. The general classification of the ANN is based on the training procedures. Supervised network operates with an array of desired output, while unsupervised learning network works without desired output. However, all the other procedures are similar. The main architecture of the ANN is described in Chapter 4.

Chapter 3
Acoustic Emission (AE): Theoretical Background

(Note: There are many excellent books on AE. The following discussion is largely compiled from information available in [?].)

3 .1 Development of AE

During the past 40 years, extensive developments in non destructive testing (NDT) have taken place- The traditional methods based on ultrasonics, readiography, eddy currents and penetrants have especially benefited from advances in instrumentation. Techniques based on different physical phenomena such as exoelectron emission, holography, thermography, and nuclear magnetic resonance have shown promise of eventual evoluton as practical NDT methods. Acoustic emission (AE) which deals with the very high fequency (i.e. way beyond the capacity of the human ear) noises made when materials deform or fracture is a technique based on entirely new concepts which has progressed to a practical NDT.

AE can be used in the laboratory as a research tool or to assure safety. Studies of Barkhausen noise, the martensitic transformation, corrosion, etc fall in the former category. Use in the petrochemical or allied industries, for weld monitoring, for testing reinforced plastic installations or machined parts are examples of the latter classification. AE can be used with many different materiils and in many different ways.

3.2 The nature of AE

Most materials emit AE during deformation. In any situation involving the redistribution of energy at least some energy will be available as AE — and corrosion, transformation is included along with deformation and fracture. If there is no materail change, there will be no redistribution of energy and there will be no AE. AE activity only appears as the result of physical activity or change. Furthermore AE occurs at the same time as the physical activity occurs. Using modern scientific instrumentation a detectable amount of energy is produced as the result of most activities.

3.3 **Theory of AE**

3.3.1 Sources of AE

Source identification is necessary so that the behavior of the materail can be predicted and in order that a meaningful approach can be made to modelling sources. As well , information about unwanted (extraneous) sources is also needed, to assist in the positive identification of damage related AE in real situations.

3.3.2 True Mean Square (TMS) Values

Root mean square (RMS) measurements are often made with an instrument called a true RMS meter. However, most of the indicators display to some extent frequency and wave shape. Commmercial equipment often provide an RMS capability and the makers have gone to a great deal of trouble to ensure that frequency effects are minimized. The value of RMS measurements lies in their ability to differentiate between large and small signals. Thus it is common to use ring down and RMS measurements in conjunction. For those unable to afford an RMS meter a high speed rectifier gives similar answers.

The energy associated with an AE event is dependent variously on the source sensor distance, frquency effects, differing attenuation of different wave types and it is hard to build suitable instrumentation. Furthermore it is difficult to see how a sensible answer can be obtained from a heavily conditioned signal. Nonetheless it is considered by some workers to be the most important of the single figure indicators.

The first attempts at energy measurement were by Beattie and Jaramillo [?], who put together a device suitable for laboratory use. Shortly after Beattie compared various techniques for energy analysis — showing how RMS and energy values are related and stressing the need for broad-band measurements, Duncan showed that the area under the envelope of the signal was related to the energy of the signal and that it was true even for a band-pass limited situation [?]. However his idea of band-pass limitation was sufficient to cover in excess of the normally used AE range, say, from 10 kHz to 2.2 MHz. He compared his results with a RMS voltmeter and decided that energy could be obtained from squaring the RMS signal.The squared value is termed as True Mean Square (TMS).

3.4 AE Sensors

The sensors (transducers) first used in AE research were PZT (lead zirconium titanate) accelerometers chosen to have the highest sensitivity consistent with a high frequency response. In the interests of simplicity and greater sensitivity the backing mass was soon discarded, leading to a design which was to remain essentially the same to the present time.

The ideal transducer should be small, highly sensitive to a specified parameter, easy to couple to the workpiece, cheap and easy to construct. In addition, it should exhibit its high sensitivity over a wide frequency range whilst maintaining a linear response, and it should have a simple dependence on a single parameter such as displacement normal to a surface. Such sensors are not presently available and the imperfections of existing devices should be noted and understood.

Sensors based on the use of PZT material are cheap to produce and robust in use but their characteristics are far from ideal. The few types of presently available transducers having better characteristics are really only suitable for laboratory usage.

The sensing element usually comprises a single disc of PZT poled in the thickness direction which when unclamped will possesses a well-defined natural frequency largely dependent on thickness. The flat surfaces are covered with a conducting material. e.g. silver for the reason of electrical connection. To ensure ease of handling, the element is enclosed in a conducting, metallic, non-magnetic cylindrical case and generally a plug is attached. One surface of the silvered disc is glued to the inside bottom of the case and a lead is attached, using conductive cement, to the other surface of the disc. With available pressure sensitive adhesives, sufficient ohmic contact is readily made between disc surface and plate; in any case separation distances are small and capacitative compling is likely to be adequate in many situations. Invariably the cable between transducer and preamplifier is kept short. It is of shielded coaxial material with the shielding connected to an earth point — often quite simply via the connector to the equipment earth point. This gives a certain amount of protection against EMI (electro-magnetic interference). Added protection is obtained from an insulation wear plate, attached to the bottom of the case, which helps to prevent the formation of earth loops.

Problems with low signal/noise ratios can be addressed by filtering and by using resonant sensors. A PZT sensor is naturally resonant but the various modes of vibration of the disc are extensively cross-coupled; thus the sensor does not have a simple response curve but one which comprises a dominant peaks.

Some transducers have been made from laminar material of an irregular shape in an attempt to improve frequency response. An interesting practical technique known *as* inductive tuning involves connecting a small inductance across the terminals of the transducer as close as possible to the sensing element. Resonant peaks can be enhanced and shifted by varying the value of the inductance. Naturally the technique is sensitive to lead capacitance and is best suited to permanent transducer installations.

Adding protection against EMI is sometimes obtained by using a high common mode rejection capability of the differential amplifier

Sensors can be selected base on the following criteria.

- Availability: Sensor costs are not negligible and a complete range of sensors is not normally available for immediate use. Hence, it should take the availability into account.
- Sensitivity: Estimates can always be made of the expected AE activity but in general the most sensitive sensor will be chosen which has the best frequency response, the smallest size. Also the sensitivity should be kept constant over the chosen frequency band.
- Frequency response: Waves propagating in structures which approximate to plates or shells can often be characterised in terms of mode and frequency; a sensor can be chosen to work or avoid a particular frequency. It is possible to choose a sensor having maximum sensitivity to AE and minimum sensitivity to background noise.
- Size: It is possible to minimise the timing error in location measurement by shortening the distance between the active contact area of the sensor and work-piece.

3.5 Calibration of AE Sensors

3.5.1 Calibration is defined as the correlation of readings of an instrument with a standard. This was especially troublesome until suitable simulated sources of AE were developed.

Calibration of a sensor is carried out by the operator. Nelson Hsu [Hsu, 19?] invented the lead pencil break as a suitable simulated source of AE. A simple jig has been developed which ensures that a constant angle and length of lead is maintained. A lead pencil is often used and the most suitable lead appears to be 0.5mm diameter 2H material. It is possible to measure the initial load applied to the lead and this is often done in laboratory situations. Triggering of apparatus by the fracture is also possible by making resistance measurements.

3.5.2 Calibration procedures

Calibration means the measurement of output given a known input. Calibration procedures may vary depend on the chosen calibration method. Providing a suitable known AE input presents problems because information is still lacking about the nature and size of the AE event at its source and about its distortion as it propagates through a structure. As will the importance of specimen dependence is not always will understood. In the past, reciprocity techniques for calibration of transducers have always been highly attractive on paper but difficult to apply.

At least two needs can be identified. First need is to specify the performance of a transducer and second is to relate signal output of an installed sensor to the AE event at its source. There is also the need to choose calibration parameters. Clearly the effects of propagation and coupling can be eliminated.

3.6 Some uses of AE

AE has been used to detect collapse of bubbles in the blood stream, to measure hydrogen content by evaluating embattlement, to quantifies atmospheric smog by monitoring crack growth changes in given material, to measure previously attained maximum pressures by utilising the Kaiser effect and equipment is available for the detection debris left behind during the manufacture of jet engines. Vibro-acoustic emission is a recent Rolls-Royce development which is fully described by its title — signals are produced when components are vibrated. AE has been used to study chip formation during the machining of metals and appears to have possibilities for use in process control. A model has been developed which allows the mode of chip formation, the chip-tool contact length, the tool-flank wear to be identified or measured.

Although forces, power consumption, temperature are readily measured in the laboratory it seems difficult to make these measurements in an industrial situation. AE count rate and RMS measurements have been used to identify changes in plastic deformation in the shear zone at the tip of the cutting tool which is understood to be the principal source of AE. AE has been found to increase with feed and cutting speed and is sensitive to the depth of cut . It was observed that AE activity changed dramatically as the tool wore which is in contrast to metals. It is because the chip changed in shape from short discontinuous to long continuous. AE has been used to characterise hardboard but the attenuation is very high and signals can only be detected close to the sensor. The distance should be within about 6cm .

Chapter 4

Backpropagation (BPN) Networks: Theoretical Background

(Note: The contents of this chapter have been significantly influenced by [?, ?, and. ?])

4.1 Introduction to artificial neural nets (ANN)

A human brain continually receives input signals from many sources and processes them to create the appropriate output response. Our brains have billions of neurons that interconnect to create elaborate "Neural networks". These networks execute the millions of necessary functions needed to sustain normal life. For some years now, researchers have been developing models, both in hardware and in software, that mimic a brain's cerebral activity in an effort to produce an ultimate form of artificial intelligence. Many theoretical models (or paradigms), dating as far back as the 1950's, have been developed. Most have had limited real-world application potential, and thus, neural networks have remained in relative obscurity for decades. The backpropagation paradigm, however, is largely responsible for changing this trend. It is an extremely effective learning tool that can be applied to a wide variety of problems. Backpropagation related paradigms require supervised training. This means they must be taught using a set of training data where known solutions are supplied.

4.2 The basic structure of backpropagation nets (BPN)

4.2.1 Backpropagation type neural networks process information in interconnecting processing elements (often termed neurons, units or nodes — we will use "nodes"). These nodes are organized into groups termed layers. There are three distinct types of layers in a backpropagation neural network: the input layer, the hidden layer(s) and the output layer. A network consists of one input layer, one or more hidden layers and one output layer. Connections exist between the nodes of adjacent layers to relay the output signals from one layer to the next. Fully connected networks occur when all nodes in each layer receive connections from all nodes in each preceding layer. Information enters a network through the nodes of the input layer. The input layer nodes are unique in that their sole purpose is to distribute the input information to the next processing layer (i.e., the first hidden layer). The hidden and output layer nodes process all incoming signals by applying factors to them (termed weights). Each layer also has an additional element called a bias node. Bias nodes simply output a bias signal to the nodes of the current layer. All inputs to a node are weighted, combined and then processed through a transfer function that controls the strength of the signal relayed through the node's output connections. A nodes operation is shown below. The transfer function serves to normalise a node's output signal strength between 0 and 1.

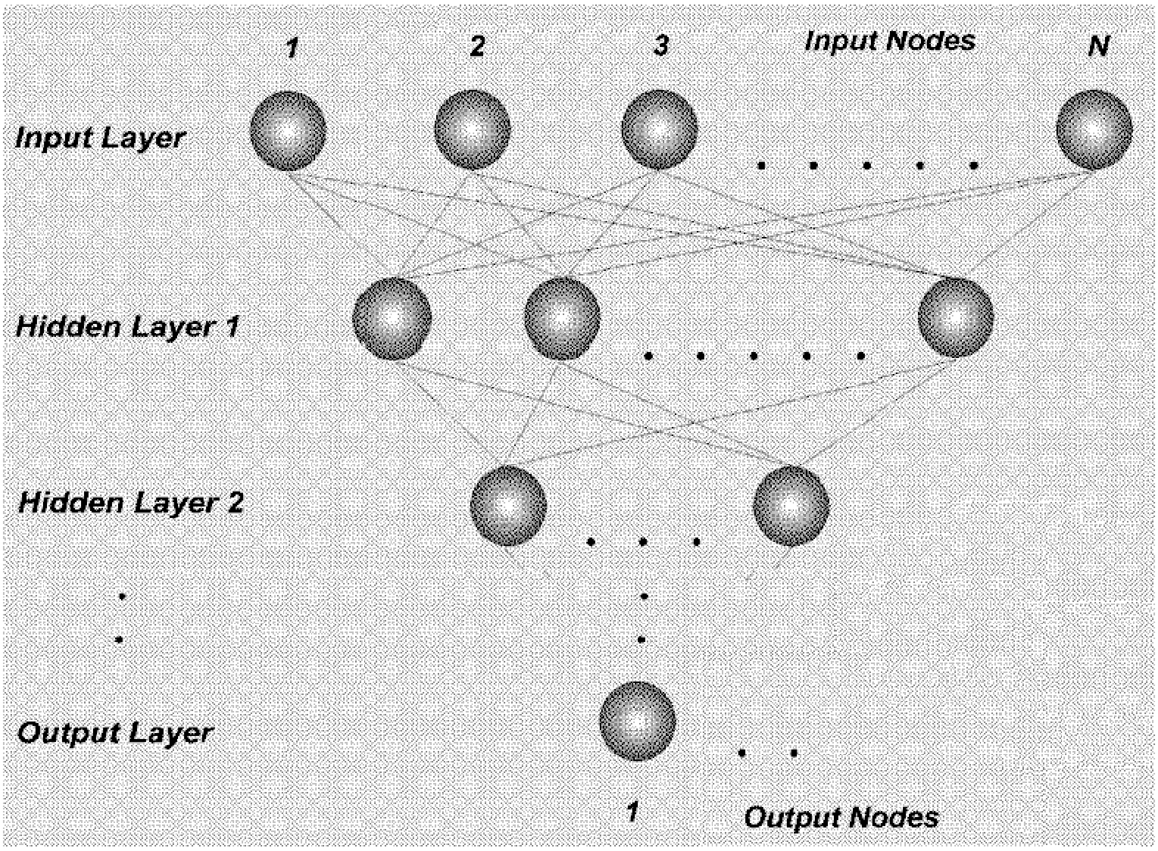

Figure 4.1 The back propagation network [?]

4.2.1 Input and output layers

The input layer of a neural network has the sole purpose of distributing input data values to the first hidden layer. The number of nodes in the input layer will be equal to the number of input data values in the model.

4.2.2 Hidden processing layers

Choosing the number of hidden layers and the number of hidden nodes in each layer is not so trivial. The construction of the hidden processing structure of the network is arbitrary. While there is normally a large envelope of hidden layer constructions that yield like results, the importance of selecting an adequate hidden structure should not be underestimated. Many factors play a part in determining what the optimal configuration should be. These factors include the quantity of training patterns, the number of input and output nodes and the relationships between the input and output data.. It may often be tempting to construct a network with many hidden layers and processing units--falling into "the bigger the brain the better the model" trap. This philosophy can easily result in a poorly performing model. When a network's hidden processing structure is too large and complex for the model being developed, the network may tend to memorise input and output sets rather than learn relationships between them. Such a network may train well but test poorly when presented with inputs outside the training set. In addition, network training time will significantly increase when a network is unnecessarily large and complex.. Generally, it is best to start with simple network designs that use relatively few hidden layers and processing nodes. If the degree of learning is not sufficient, or certain trends and relationships cannot be grasped, the network complexity can be increased in an attempt to improve learning. A plausible starting point for the loan application model would be to use 2 hidden layers with 3 to 4 nodes per layer. If this design does not train sufficiently, the size and complexity of the hidden structure can be increased.

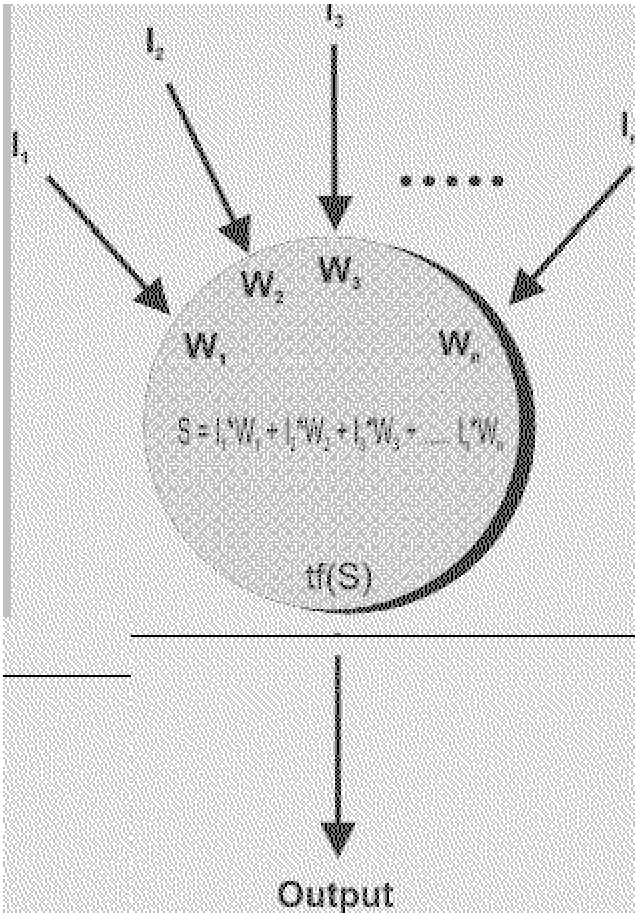

Figure 4.2 Input-output view of BPN node

It has been demonstrated theoretically that for a given network design with multiple hidden layers, there will always exist a design with a single hidden layer that will learn at an equivalent level. However, in practice, it is usually better to employ multiple hidden layers for solving complex problems. To adequately model a complex problem, a single hidden layer design may require a substantial increase in the number of hidden nodes compared to a 3, 4 or 5 hidden layer construction. In simple terms, a single hidden layer design with 10 nodes may not learn and perform as well as a network with two hidden layers containing 5 nodes each. Multi-hidden layer networks tend to grasp complex concepts more easily than networks with one layer. One reason for this is that the multi-hidden layer construction creates an increased cross-factoring of information and relationships. Thus, a network's learning ability is controlled by both the total number of hidden layers and the total number of hidden nodes.

4.2.3 Network connections

Another network design consideration concerns how to control the network's connections. Input information can be channelled and processed in a localised area of the network. "Pass-through" nodes can be constructed that receive only one input connection from the preceding layer and pass that information down to the next layer. This has the effect of creating connections that skip a layer. While the connection editor gives the modular almost unlimited flexibility in designing a network, the fact is that the vast majority of designs work best fully connected.

4.2.4 Transfer functions

A node's transfer functions serves the purpose of controlling the output signal strength for the node (except for the input layer which uses the inputs themselves). These functions set the output signal strength between 0.0 and 1.0. The input to the transfer function is the dot product of all the node's input signals and the node's weight vector.

This sigmoid function is the most widely used function for backpropagation neural networks. The sigmoid function is represented by the mathematical relationship.1/(1+e-x). The sigmoid function acts as an output gate that can be opened (1) or closed (0). Since the function is continuous, it also possible for the gate to be partially opened (i.e. somewhere between 0 and 1). Models incorporating sigmoid transfer functions often help generalised learning characteristics and yield models with improved accuracy. Use of sigmoid transfer functions can also lead to longer training times.

The Gaussian transfer function significantly alters the learning dynamics of a neural network model. Where the sigmoid function acts as a gate (opened, closed or somewhere in-between) for a node's output response, the Gaussian function acts like a probabilistic output controller. Like the sigmoid function, the output response is normalised between 0 and 1, but the Gaussian transfer function is more likely to produce the "in-between state" It would be far less likely, for example, for the node's output gate to be fully opened (i.e. an output of 1). Given a set of inputs to a node, the output will normally be some type of partial response. That is the output gate will open partially. Gaussian based networks tend to learn quicker than sigmoid counterparts, but can be prone to memorisation.

The hyperbolic function counterparts to the sigmoid and gaussian functions are the hyperbolic tangent and hyperbolic secant functions. The hyperbolic tangent is similar to the sigmoid but can exhibit different learning dynamics during training. It can accelerate learning for some models and also have an impact on predictive accuracy. Experimenting with transfer functions for each individual model is the only conclusive method to determine if any of the non-sigmoid transfer functions will offer both good learning and accuracy characteristics.

For most modeling tasks, the sigmoid function should at least be a baseline model to measure results. A general rule of thumb is that the sigmoid will produce the most accurate model; but be slower learning. If you intend to frequently train similar models and training speed is critical, different combinations of transfer functions, including hybrid networks, are worth investigating to find faster training models that exhibit acceptable accuracy.

4.3 Programming versus training

Traditional programming techniques requires that someone create an algorithm. While for some problems designing the sequence of instructions is stragihtforward, for many real-world problems it is very difficult to create an algorithm. Imagine trying to write a program that could recognise a person's face. There are many variations that would have to be taken into account. For instance, is the person smiling or frowning?

Neural networks, in contrast to being programmed, are trained. This means that examples are presented to the network, and the network adjusts itself by some learning rule (based on how correct the response is to the desired response). Therefore, you feed plenty of representative examples to a neural network.

4.4 Neural networks versus expert systems

Neural networks, expert systems and fuzzy logic collectively make up the field of artificial intelligence. However, they differ significantly from each other, as well as from traditional programming. Expert system differ from traditional programming in that the knowledge base is separated from the means of processing the knowledge(the inference engine). This allows additional knowledge to be added to the system without reprogramming.

This technique requires that an expert knowledgeable in the relevant area be available, so that rules can be created to encode knowledge. An example of a rule might be "if there is a large amount of facial hair around the mouth, ten the person is a male." Confidence factors are often added to rules, such as "if there are earnings hanging from the ear, the terson is a female- confidence 85%."

When developing neural network solutions to a problem, neither the knowledge nor the explicit rules for processing the knowledge are coded by the programmer. Instead, the neural network learns the rules for processing the knowledge. This is done by adjusting the weight values in a highly connected network based on the example data. You can think of a neural network as a very general model that is parameized by the adjustable weights. Therefore, you don't need access to an expert in the relevant knowledge domain to develop a neural network (although such an expert may be essential in selecting and preparing the data that is presented to the network).

An interesting point is that expert systems can tell you how they arrived at a particular answer, but neural networks can't always do that. For the same reason that the complexity of the problem prevents experts form telling you exactly how they arrived at an answer, this information may not be easily available from a neural network.

4.5 Neural networks versus statistics

A knowledge of statistics is excellent preparation for appreciating the power and flexibility of neural networks. In statistic, one must often make many assumptions about the data, and must sometimes limit the analysis to a certain number of possible interactions. By contrast from a practical point of view, neural networks are basically "non-parametric," although in theory one can think of a neural network as being parametized by its weights. In addition, more terms can be examined for interaction by a neural network, since the network will, we expect, place its emphasis on those inputs that help to predict the output. By allowing more data to be analysed at the same time, more complex and subtle input interactions are possible. It should be stressed that statistics can be helpful in understanding the data, which can lead to developing a better neural network model.

Chapter 5
Experiments and Observations

5.1 The equipment used

5.1.1 The milling machine

The milling machine used in this experiment is a vertical milling machine which is commonly installed in the shop floor. The bed can also by fed in the x, y, and z axes manually or automatically by setting the feed rate. Most milling machines are equipped with power feed for one or more axes. Power feed is smoother than manual feed and, therefore, can produce a better surface finish. Power feed also reduces operator fatigue on long cuts. On some machines, the power feed is controlled by a forward reverse lever and a speed control knob.

5.1.2 The dynamometer

The three component dynamometers Types 9265 is piezoelectric transducers for measuring the three orthogonal components of a force. The dynamometers have high rigidity and therefore high natural frequency. The high resolution enables small dynamic changes of large forces to be measured. For each of the three force components a proportional electrical charge is generated dynamometer. These charges are converted into analogue DC voltages in the topped charge amplifiers. These voltages can then be recorded, displayed or processed as required. There is drift in z channel, why? It is advisable either to connect the dynamometer to the coolant circuit of the machine tool, or to start measuring the cutting force only when there is no longer drift in the z channel. The dynamometer is a precision instrument. Its inherent accuracy can be exploited and maintained only if it is fitted and handled with due care. Any failure fixture will introduce internal stress which may even make damage on the device.

5.1.3 The AE transducer

The AE sensor used was a piezo-electric sensor form Kistler with a wide bandwidth of about 1 MHz. The sensor has high and low pass filters and a resonant frequency of 100 –

900kHz. A review of literature showed that, in metalcutting, most of the work with AE has been done in the frequency range of 100 –500kHz . In this range, it is fairly safe to trust the sensor dynamics without worrying about the AE signals being easily contaminated with lower frequency machine harmonics. The CRO used in the experiments was HP 54602A with upper limit of frequency of 150 MHz.

The technical data of the equipment are listed as below.

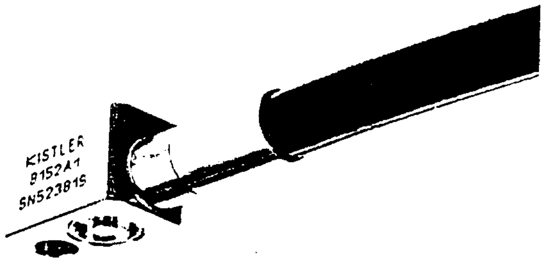

Figure 5.1 A View of the AE sensor

5.2 Force measurement

Force measurement is carried out at the same time when AE TMS is recorded. The calibration procedure should be completed before any measurement is undertaken. Because the measurement process involved three devices, the dynamometer, the charge amplitude and the plotter. The calibration of there device is very important. The procedures in calibration are listed in the user manual of that machine. The general steps in the force measurement are stated below.

Step 1- Connect the dynamometer to the amplifier. Connect the amplifier to the plotter. Make sure all the connections are correct.

Step 2 - Adjust the position and the scale factor of each pointer so as the full scale deflection of the point will not exceed the margin. The recommended scale factor for end milling is stated below.

F_x - 200mV

F_y - 200mV

F_z - 50mV

Step 3 - before starting the cutting process, turn the paper motor on, otherwise the paper will not move and the measured cutting force will only “vibrate” within a line.

Step 4 - after the cutting process has finished, turn off the motor for not to waste graphic paper.

Step 5 - repeat step 3 to 4 until all the trail testes has been completed.

Step 6 - tear out the graphic paper and start the measurement by using a ruler and a calculator.

Step 7 - draw a line at the mid point approximately as Figure shown below.

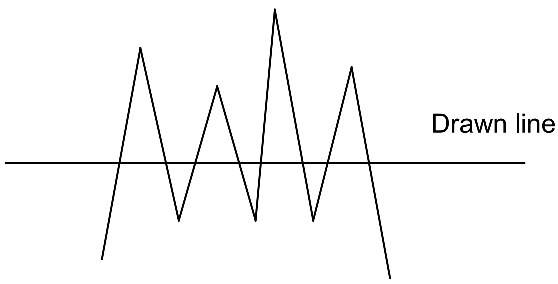

Figure 5.2 Force measurement

Step 8 - measure the distance between the base line and the drawn line. The Base line is the line when there is no cutting.

Step 9 - Calculate the cutting force by submitting the measured distance into the equation

$$\frac{M}{25} * S * 5000$$

where M is the measured distance

S is the scale factor

Step 10 - tablized the cutting force with AE TMS for each trial.

5.3 Calibration of the AE transducer and signal processing system

Before conducting the experiments, the involved equipment was be carefully prepared so that the effect of noise and other uncertainties can be minimized. Noise can come from the measuring equipment, the amplifier, the milling machine and/or the surroundings. Also, periodic calibration of AE sensor is very important. One needs to make sure that one is indeed measuring AE form the phenomena being studied and not from some extraneous source.

The AE measuring device was first to be calibrated in order to elimination of the effect of AE noise, to fine tune the setting so as to obtain the best measurement and to calibrate the HP oscilloscope to ensure that the measurement was exactly what was intended. Background noises in the laboratory premises are mostly electric pulses which are propagated and get mixed with the AE measuring system. These could be burst signals having the same frequency content as acoustic signals emitted from the test material, and the amplitude is often comparable to the acoustic signals. Therefore, it is usually impossible to eliminate the effect by setting the frequency bandwidth and the threshold level. The only noise elimination method then is through shielding and averaging.

The Hugh-Nielsen test was used for calibration.

Step 1 - Prepare 5 to 10 2H pencils ,a pencil sharpener, a steel bar with a tapped hope on it. The hole was used to attach the sensor on to the plastic. The cross on the surface represents the point where 0.5mm 2H pencil tips were broken for calibration purpose. The break action was taken at an angle of 30 and the tip length was 1mm.

Figure 5. A view of the steel bar for calibration

Step 2 - screw the sensor onto the surface of the bar. The clamping force should not be very large. Otherwise, the sensitive sensor will be damaged.

Step 3 - connect the CRO is a plotter. Turn on the CRO and wait for it warm up.

Step 4 - adjust the frequency resonant range within 1 MHz, the volt / unit to 1 V and the time base to 20 ms. Set the trigger level for about 100mV to prevent the effect of noise. The trigger level, time base and volt / unit can be changed throughout the experiment depends on the situation.

Step 5 - slowly put the pencil tip in the surface of the steel bar. The distance between the active point and the sensor is 2 cm. Push the pencil downward quickly so that the tip will break immediately.

Step 6 - output the screen to the plotter

Step 7 - repeat step1 - 6 with another sharpened pencil

5.4 AE TMS measurement

There are two parts in these testes which greatly involved human error. One is the AE TMS measurement and the other is force measurement. The instruction of AE TMS measurement is listed below.

Step 1 - Connect the CRO to the sensor. Care must be taken on the connecting cable.

Step 2 - Turn on the CRO and input the settings which are obtained during calibration stage. However, the time base, volt / unit can be changed during the cutting for a full scale display. Remember to set the probe to 100.

Step 3 - screw the transducer on the workpiece

Step 4 - Start the cutting process with different cutting material and cutting parameter. Start recording the V_{rms} value on the screen. This will be the average volt of the input signal and is the AE RMS.

Step 5 - To obtain the TMS, just simply take square of AE RMS.

Step 6 - Tablized the AE TMS with the force measured.

Step 7 - Repeat step 3 to 6 with different workpiece and cutting parameters.

The general human error is coming from the RMS reading. The RMS value displayed on the screen keep changing during the cutting. To minimise the reading error, the RMS value during the cutting should be recorded down and eventually take the average of the recorded values. Set the calculated as the ultimate AE RMS.

5.5 The experimental conditions

5.5.1 Work materials

The work materials used are the most common

5.5.2 End mills

The most frequently used tool on a vertical milling machine is the end mill. End mills are made in either a right-hand or a lift-hand cut. By viewing the cutter from the cutting end, the two kinds of cutters can be identified. In this experiment, a right-hand cutter which rotates counterclockwise is chosen. The helix of the flutes can also be left or right hand. Figure are the different views of the single end, four flute, right hand end mill used in these experiments.

Figure 5.

A right hand helix flute angles downward to the right when viewed form the side. Four flutes end mills may have either center cutting teeth or a gashed or center drilled end. End mills with center drilled or gashed ends cannot be used to plunge cut their own starting holes.

5.5.3 Cutting conditions

The cutting conditions in these shop floor experiment are similar to the experiments carried out before. No coolant is used during metal removal processes even it is recommended for most cutting processes.

5.6 Experiments with different work materials

The steps of these testes are the same with section 5.7 except to keep the cutting conditions constant but different work materials. There are totally five materials available, mild steel, steel 4140, soft aluminium, aluminium 6061 and brass.

The steps are listed below.

Step 1 - prepare the different workpieces with good machined surface.

Step 2 - set the required cutting parameter, feedrate, cutting speed, axial depth of cut and radial depth of cut before cutting.

Step 3 - clamp the workpiece into the dynamometer and attached the transducer on to the workpiece surface.

Step 4 - start the cutting process, at the same time record down the AE TMS and cutting force.

Step 5 - unclamp the workpiece from the base.

Step 6 - Repeat step 3 - 5 with different work materials.

The setting of cutting parameter is tablized below.

Cutting speed/ RPM	feed rate /mm/min	depth of cut /mm	radial depth of cut /mm	lubricant
450	189	2	10	no

Table 5.

And all the testes are under the same cutting parameter.

5.7 Experiments with different cutting conditions

The only material for these experiments is mild steel. The steps of due with different cutting conditions are similar in Section 5.6.

Chapter 6
Training and testing BPNs for force prediction

6.1 BPN software used

The neural modeling system used in this project is known as Qnet V2.7. It executes in 32 bit protected mode of CPU. Networks sizes is only limited by the size of computer system's memories and hard disk capacity. It offers a capability of designing an advaned backpropagation neural networks just by several easy steps. The training data and testing data are grouped in the format of ASCII file or any data file output from MS Excel. The most benefit it offers is that one can integrate the source code into his application after he found that the designed network gives out best accuracy.
The general system requirements are listed below.

- 386,486 or Pentium or higher CPU
- Windows 95
- VGA or higher graphics adapter
- 4 Mbytes of system memory
- Minimum 2 Mbytes of free hard disk space for installation

6.2 Learning using only the cutting conditions as inputs

In this training cycle, only cutting condition parameters are involved, depth of cut a_a, radial depth of cut a_r, feed rate f, and cutting speed RPM. The architure of the BPN is shown as below.

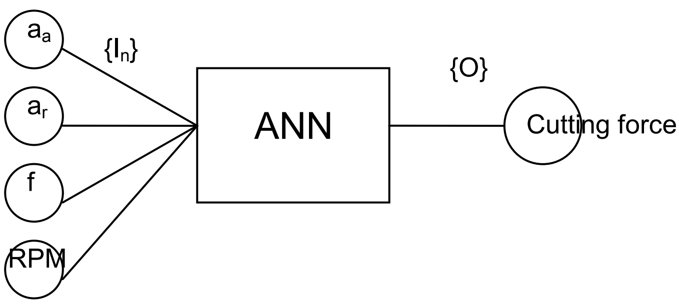

Figure 6.1 Four inputs ANN

The general training procedure and testing procedure are as described in Chapter 4.
The summaries of the procedure are listed in steps below.

Step 1- obtained the data sets from the shop floor experiment. Prepare and verify the data for reliability by plotting the data into graphs and take out the unstanding point.

Step 2 - divided the data set into two groups, one as training cases, and the other as testing cases. The ratio of training to testing is approximately 4 to 1. As there are only 180 sets data, it is best to put 140 sets into training group and the remaining into testing group. It has to be stressed that the data for the two groups should be selected randomly.

Step 3 - start to input the data into the ANN with different parameters according to the sequence from the following table.

Trail	cycle	momentum	hidden layer	hidden nodes
1	10000	0.8	1	2
2	5000	0.8	1	2
3	1000	0.8	1	2
4	500	0.8	1	2
5	10000	1	1	2
6	10000	0.5	1	2
7	10000	0.1	1	2
8	10000	0.01	1	2
9	10000	0.8	2	2
10	10000	0.8	3	2
11	10000	0.8	4	2
12	10000	0.8	1	5
13	10000	0.8	1	8
14	10000	0.8	1	10

Table 6.1 Parameter for different trials

Step 4 - save the networks for each trail for later testing process. Eg. The filename can be taken as the trail no. of easy retrieval.

Step 5 - After training processes have been completed. It should now start the testing processes. Input the testing cases into the trained network for each combination, and record down the accuracy.

There is another experiment which combines the data from the paper by Lin[ ] The procedures are same as above except this time more cases are used. There are 34 cases and it will be divided proportionally into 4 to 1.

6.3 Learning when the inputs array is augmented by AE TMS

The ANN is used to predict cutting force in this section. The advantage of using a sensor input as an input array has been discussed in the above chapter. The architecture of the ANN is sketched as below.

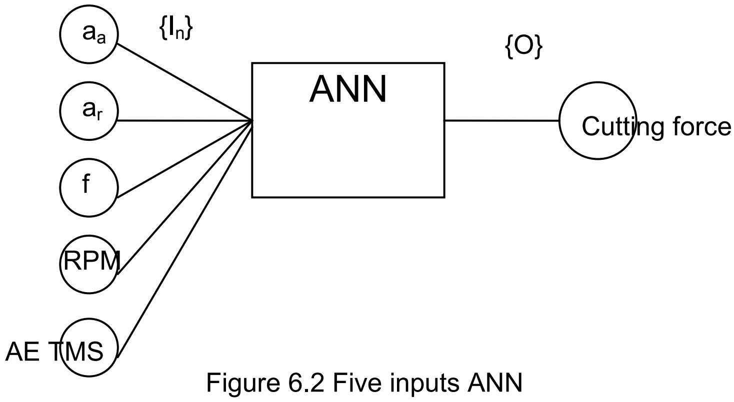

Figure 6.2 Five inputs ANN

The steps of training and testing cycle are absolutely the same with section 6.2. The only difference is the larger input array.

Chapter 7
Results and Discussion

7.1 AE TMS magnitudes for different work materials

The AE TMS tested with 5 kinds of materials are plotted as a histogram for easy comparasion.

	Brass	Steel 4140	Aluminium 6160	mild steel	soft aluminium
TMS /V	40	9.6	6	2	1.2

Table 7.1 AE TMS of different materials

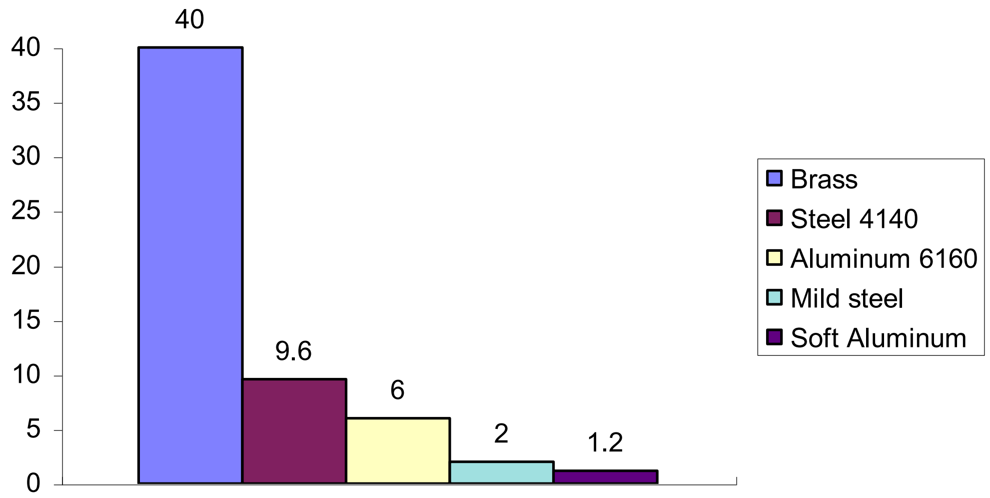

Figure 7.1 Histogram of AE TMS against different materials

All the testes are carried out under the same cutting condition stated as below.

And the cutting tool is used as the previous four flute end mill. It is interesting to see that, brass has the highest AE TMS within the five chosen material. There is an extra hardness test which is used to verify the five materials hardness.

	Brass	Steel 4140	Aluminium 6160	Mild Steel	Soft Aluminium
Hardness/ HRB	78	105.3	57.4	89	-
Force/ N	2000	2400	900	2000	1000

Table 7.2 Hardness and cutting force of the chosen material

From the hardness table, it is shown that the steel 4140 has the highest hardness. The harder the material, the more force required for cutting. The only exception is happened for Soft Aluminium. The hardness test of the material is unknown because it is much softer even out of the hardness test range. The measuring machine shows negative sign which is meaningless. The high force for cutting soft aluminium is not because of its hardness, but for its stickiness. The material adheres on the cutting tool like a cream. This explains why it requires larger force than the others.

Another observation is that, even steel 4140 is the hardest., it generates less AE energy compared to Brass, which is far more softer than it. And the same observation is happened with aluminium 6061 and Mild Steel. These can be conclude that, the AE TMS has no immediate relationship with material hardness.

The side observation is that, only mild steel and steel 4140 emit smoke. These is because of the energy is generated into heat energy and temperature thus increases. At the same time there is some oil inside the steel. Together with the influence of high temperature, the oil becomes vaporised. That is the reason of only steel will give out smoke.

7.2 Effectiveness of BPN when the input array is restricted to cutting conditions alone

The data obtained in shop floor experiment will be feed into a backpropagation neural network. Some modification will be first make on the input cases. Some data will mixed with the experimental data in order to increase the reliability of the old one. The tables below are the training result of the mixed data. The main focus are paid on the change of momentum, no of hidden layer, no. of hidden nodes and training cycle.

F_x	F_y	F_z	F_r
8	8.2	9.5	6.9

Table 7.3 Training accuracy vs different cutting force (without AE)
(Cycle=10000, momentum=0.8, Hidden layer=1, Hidden nodes=2)

In this test, F_x, F_y, F_z and F_r are all introduced. The difference among this four force to the training accuracy are recorded and compared. It is obsively seen that Fr will give the best accuracy. This is may be the reason why Liu use resultant force in his experiment. There is no empirical explanation to why Fr give better accuracy. It’s just the result.

	Training cycle			
	500	1000	5000	10000
F_r	13.5	13.4	13.5	8

Table 7.4 Training cycle vs F_r (momentum=0.8,
Hidden layer=1, Hidden nodes=2)

	momentum				
	1	0.8	0.5	0.1	0.01
F_r	13.4	8	11	13.16	12.144

Table 7.5 Momentum vs F_r (Cycle=10000, Hidden layer=1, Hidden nodes=2)

	hidden layer			
	1	2	3	4
F_r	8	10.5	12.2	9.6

Table 7.6 Hidden layer vs F_r (Cycle=10000, momentum=0.8, Hidden nodes=2)

	hidden nodes			
	2	5	8	10
F_r	9.5	8	10.2	11

Table 7.7 hidden nodes vs F_r (Cycle=10000, momentum=0.8, Hidden layer=1)

It is obviously that only increase of training cycle and no. of hidden layers will not improve the performance. And the improvement can be very large, from above 8% down to less than 1.5% when using Fr instead of Fx.

However, the accuracy of the system doesn’t show good improvement by the change of no. of units and the momentum. According to the literature, the smaller the momentum, the greater accuracy of the ANN. However it is not the case in this experiment. The optimize choice of the learning setting is:

Momentum	Training Cycle	hidden layer	Hidden nodes
0.8	10000	1	5

Table 7.8 The setting for a good ANN

And when accompanied with the use of AE sensory input, the accuracy can be very high. It has to be recognized that the ANN training accuracy is maximized by chance. It has to be training and training again with different learning setting until the RMS level is accepted. In this experience, the accepted level is 3%. All the RMS value above this threshold value will be considered as failure, and another training will be arranged with different training settings.

7.3 Effectiveness of BPN when the input array is augmented with AE TMS

The input array this time has one more member, AE TMS, which is the sensory input from the milling process. The accuracy of augmented ANN is tablized below.

F_x	F_y	F_z	F_r
1.1	1.05	2.01	0.7

Table 7.9 Training accuracy with differnet cutting force (with AE)

	Training cycle			
	500	1000	5000	10000
F_r	5.2	5.5	6.5	0.7

Table 7.10 Training cycle vs F_r (momentum=0.8, Hidden layer=1, Hidden nodes=2)

	momentum				
	1	0.8	0.5	0.1	0.01
F_r	6.5	0.7	7.8	5.2	9.2

Table 7.11 Momentum vs F_r (Cycle=10000, Hidden layer=1, Hidden nodes=2)

	hidden layer			
	1	2	3	4
F_r	0.7	1.03	2.1	1.05

Table 7.12 Hidden layer vs F_r (Cycle=10000, momentum=0.8, Hidden nodes=2)

	hidden nodes			
	2	5	8	10
F_r	1.01	0.9	1.05	1.06

Table 7.13 hidden nodes vs F_r (Cycle=10000, momentum=0.8, Hidden layer=1)

The training and testing process shows similar trends to that without AE. However, The results are sound good, within 3% level.

7.4 General observations

During the shop floor experiment, it is noticed from the CRO reading that there are some peaks occurring at the tool entrance and exit in TMS. During the cutting process, only continuous variation of the signal level, fast or slow, is observed. The fast and slow graphs were directly depended on the time constant of AE signal. Such observation will be paid attention on the future development.

For the ANN, the relationship between input or size of input array should be kept as simple as possible. The more complex the network input, the more hidden nodes are needed. This will increase the response time also. And this is prohibited as fast deterministic power is a “must” in shop floor. It is observed that the larger the training cycle, the accuracy increase gradually. And , as Fr is mainly depended on F_x, improvement on F_x is reflected to Fr. Say, when the training cycle is 10000, both accuracy of F_x and Fr is improved to a great amount.

Also, the worst situation is that the learning network is fallen into a local minimum. There is only one way to prevent it. By changing the momentum, and keep on trying until a global minimum is found. However, there is no guarantee a global minimum can be located. However, it is observed that the best momentum for the training and testing cycle is as the same as that recommended by the software manufacturer.

Another problem associate with the training process is the suitable time to "stop" the training. The reason for stopping training is very complicated. There is to phenomena happen to a network, one s convergence and the other is divergence. When the error in the input-output network is approaching zero, it is convergence. When the calculated error increase subsequently, it is divergence. For small sets of input cases, it is far more difficult to determent the stopping point. The general relationship of a input-output network can not be found out as easy. However, for a larger set of training cases, the network will suffer from "memorize" the training pattern rather than to "learn" the pattern. The network becomes less able to due with the input signal.

There is no general role in determining the splitting of the data. According to the literature, the learning count meets the most suitable point around 10000. However, one of the following learning process will involve different no. of learn counts which may shows the different accuracy with different learning count.

In the past experiment, the experimental data are recorded and often reliability testes on the data, 180 sets training cases were chosen and the sets were splitted into two group, say 140 and 40 while the former one is for training purpose and the later one is for testing purpose. The grouped data are then rearranged randomly by a computer in order to minimize the "memories" effort of the network.

The beautiful data from Mr. Liu has been mixed with my own experimental data to see whether there is any improvement. Only data with similar cutting condition and end mill are used. The observation is that there is no great different to the final result. The reason might be the small size of data from Liu which doesn’t give any influence on my own result.

Chapter 8
Conclusion

8.1 Conclusions

The above testes confirmed that the prediction of cutting force can be best implemented by adding a sensing input, AE TMS which is a output from the cutting operation.

Sound result on using AE
extra work on differnet material

The literature had clearly state that the AE measurement is greatly influenced by the tool wear, tool geometry and the speed of cutting. The first experiment by Dornfeld and Kannatey were about the correlation between AE signal and the cutting process conditions. However, the studied experiments were mostly based on the single point cutting, such as turning. In this study, the focus is paid on the relationship of AE RMS value and the varies cutting parameter under multipoint cutting process. Theoretically, the AE RMS and the three cutting components should increase with the increase in cutting speed, axial and radial depth of cut due to the larger area of shear zone, and tool/chip interfaces. However, the experimental data don't follow the theory well. And this contradiction always happened in my experiments.

To the experience, there is one assumption that should be take into account. As AE is emitted as a burst wave. If the distance between sensing point and the source deeps changing, there will be some effect to the AE intensity measured. In the experimental setup, the sensor is attached on the workpiece rather than on the tool side. As the tool feed forward, the displacement of the source will cause distortion on the target AE, and as the distance is longer. The probability of detecting noise increase. Therefore, a multi-sensor system is recommended. We can assume the cutting zone as a single point source, and the AE emission is the summation of all the individual emissions in the zone. The wave emerges in all direction., and eventually they come into the sensor. If we arrange the sensors with equal distance from the source, it can be predicted that the detected voltage should be equal. There are two proposed system and will be explained clearly in next section.

The Huhg - Nicken pencil broken test was implemented successfully. As mentioned in literature, the test was found to be fairly repeatable. It is recommended that any user of AE most qualitatively re-calibration the sensor at regular intervals by using this test.

Drawback in AE approach is represented by the dependence of the response on cutting conditions. It is require to find out the information content of AE on any cutting condition. However, it is not yet clear what information content an AE signal has. By "information content", we mean the amount of understanding of the cutting phenomenon the AE signal provided. This project was not success as one of the hidden aims of this project is to show how much can the AE related to the end milling. In contrast, force signals are much better understand. The reason is that, for each process there are well developed models relating the input conditions and cutting state to the forces. It requires further research to investigate the "information content" of the AE.

After the model of AE is well developed as that of force model. It can be used to replace the measuring of cutting force in most industries. The result will be better system to reduce manufacturing cost. According to the literature, up milling progress different result as that give out in down milling. And the investigation of up milling is left for further experiment. Also, only mild steel is used for the reason of commonly usage in the production shop and the easy availability in the laboratory.

After the experiment, even the data of cutting forces and AE TMS doesn't show linear correlation, the result obtained by ANN gives out surprise. By adding a sensory input to the ANN, the accuracy gradually increase, from around 8% to under 1%. Base on this sound result, the work will be carried out on future work.

8.2 Suggestions for future work

In the following experience, it is desirable to find out the information content of the AE during metalcutting. It has to be determined the effect of a various range of workpiece material, and repeat the past experiences with more changing parameter. The experience is carried out under specific condition, with specific material, tools and cutting condition. The result sounds good. The work will be extended to a wide range of cutting condition, work material and tools.

Also, a multisensor system mentioned earlier should be introduced to minimize the effect of noise.

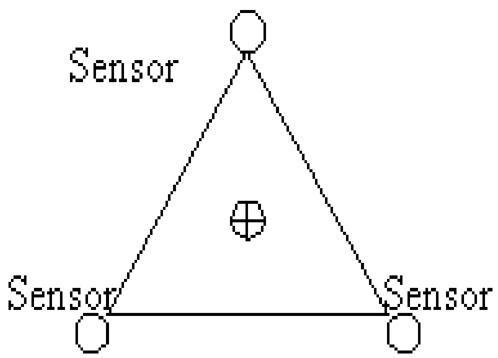

Figure 8.1 3 sensors in equal distance triangle

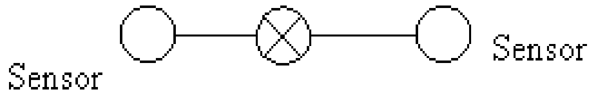

Figure 8.2 2 sensors system in equal distance

where $\otimes$ is the single point source

Another purpose of the proposed system is to overcome the effect of moving source. IN the early days of AE, before the computer-based data logger was available, manufacturers quickly developed extensive multi-transducer equipment based on existing strain gauge systems.

The reason of introducing the mentioned system is to overcome the effect by moving sourecs. As the sensor is directly located on the workpiece instead on the tool, the deformation zone which is the "only" source of AE emittion keeps on moving. The moving speed of the sources depends on the table feed rate. As AE is propagated in wave form, themovement is sources will result in variation in AE amplitude. BY untroducing this multisensory technique, the influence of the displaycement will be minimize. The system works with three sensors and formed a trangle arrangement.

Reference

[Armarego, 1996 Armarego, E.J.A., Jawahir, I.S., Ostafiev, V.A., and Venuvinod, Patri K., "Modeling of Machining Operations," paper presented to the Working Group on Modeling of Machining Operations, STC C, CIRP General Assembly, Part II, Como, Italy, August 1996.

[Venuvinod, 1996 Venuvinod, Patri, K., "Prediction augmentation through reinforcing interactions amogst modeling, sensing, and learning," paper presented to the Working Group on Modeling of Machining Operations, STC C, CIRP General Assembly, Part II, Tianjin, China, August 1997.

Non destructive testing handbook, vol 5

[Adolfsson, 1996] Adolfsson, C.M. "Muti-toothe cutting processes: models and methods for cutting force analysis (milling, bandsawing),"
Lunds U. (Sweden) ,Vol1, no. 24, 1996

[Akbari, 1993] Akbari, J., Saito, Y., Hanaoka, T., " Detection of cutting mode during scratching of ceramics using acoustic-emission, " paper presented to Working Group on Modeling of Machining Operations, STC C, CIRP General Assembly, Part II, Tianjin, China, August 1993.

[Alauddin, 1996] Alauddin, M., El Baradie, M.A., Hashmi, M.S.J., "End-milling machinability of Inconel 718, " paper presented to Proc. I. Mech. Engrs, J. Eng. Manuf., vol 210, 1996

[Alauddin, 1996] Alauddin, M., El Baradie, M.A., Hashmi, M.S.J., "Modelling of cutting force in end milling Inconel 718, " paper presented to 12th Int. Conf. Comp. Aided Prodn. Eng. Cookeville, 1996

[Altintas, 1987] Altintas, Y., Yellowley, I., Tlusty, J., "The identification of radial width and axial depth of cut in peripheral milling, " paper presented to Int. J. Mach. Tools Manuf., vol 27, no. 3, p357-365, 1987

[Altintas, 1988] Altintas, Y., Yellowley, I., Tlusty, J., "The detection of tool breakage in milling operations, " paper presented to Trans. ASME. J. of Eng. for Industry, vol 110, p271-277, Nov 1988

[Altintas, 1988] Altintas, Y., "In-process detection of tool breakages using time series monitoring of cutting forces, " paper presented to Int. J. Mach. Tools Manuf., vol 28, no. 2, p157 - 172, 1988

[Altintas, 1989] Altintas, Y., Yellowley, I., "In-Process Detection of Tool Failure in Milling Using Cutting Force Models, " paper presented to Trans. ASME, J. of Eng. for Industry, vol 111, p149 - 157, 1989

[Altintas, 1991] Altintas, Y., Spence, A., "End milling force algorithms for CAD systems

Annals CIRP

40
1
31
34
1991

[Altintas, 1992] Altintas, Y., "Prediction of cutting forces and tool breakage in milling form feed drive current measurements
Trans. ASME. J. of Eng. for Industry
114

386

392
Nov
1992

[Andeasen, 1993] Andeasen, J.L., De Chiffre, L., "Automatic chipbreaking detection in turning by frequency analysis of cutting force
Annals CIRP

42
1
45
48
1993

[Andreev, 1974] Andreev, V.N., Gaduky,, "How vibrations affect the life of high speed end mills
0
0
0
16
0

1974

[Aoyama, 1987] Aoyama, H., Kishinami, T., Saito, K., "Study on a throw away tool equipped with a sensor to detect flank wear
Bull. JSPE

21
3
203
208
Sep
1987

[Armarego, 1963] Armarego, E.J.A., Brown, R.H., "The Influence of Rake Angles on the Forces in Machining
Machine Shop and Metal Working
1963

[Armarego, 1970] Armarego, E.J.A., Uthaichaya, M., "A Mechanics of Cutting Approach for Force Prediction in Turning Operations
J. Engg. Prod.
0
0
0
1
0
1970

[Armarego, 1970] Armarego, E.J.A., Epp, C.J., "An Investigation of Zero Helix Peripheral Up-Milling
Int. J. Mach. Tool Des. Res.
0
10
0
273
0

1970

Armarego, E.J.A. Armarego, E.J.A., Whitfield, R.C., "Computer Based Modelling of Popular

1985 Machining Operations for Forces and Power Prediction
Annals of CIRP, 34/1
0
34
0
65
69
1985

[Armarego, 1991] Armarego, E.J.A., Smith, A.J.R., Karri, V., "Mechanics of Cutting Model for Simulated Oblique Rotary Tool Cutting Processes
J. of Materials Proc. Tech.
Elsevier
0
28
0
3
14
1991

[Armarego, 1991] Armarego, E.J.A., Deshpande, N.P., "Computerized End-Milling Force Predictions with Cutting Modles Allowing for Eccentricity and Cutter Deflections
Annals of CIRP, 40/1
0
40
0
25
29
1991

[Armarego, 1993] Armarego, E.J.A., Deshpande, N.P., "Force Prediction Models and CAD/CAM Software for Helical Tooth Milling Processes. I. Basic Approach and Cutting Analysis
Int. J. Prod. Res.
0
31
0

1991
2009
1993

[Armarego, 1993] Armarego, E.J.A., Deshpande, N.P., "Force Prediction Models and CAD/CAM Software for Helical Tooth Milling Processes. III. End Milling Operations, " paper presented to Int. J. Prod. Res.
0
32
0
1715
1738
1993

[Armarego, 1993] Armarego, E.J.A., , Karri, V., Smith, A.J.R., "Computer-Aided Predictive Models for Fundamental Rotary Tool Cutting Processes, " paper presented to Annals of CIRP, 42/1
0
42
0
49
54
1993

[Armarego, 1994] Armarego, E.J.A., Karri, V., Smith, A.J.R., "Fundamental Studies of Driven and Self-Propelled Rotary Tool Cutting Process - II Experimantal Investigation, " paper presented to Int. J. Mach. Tools Manufact.
0
34
0
803
815

1994

Armarego, E.J.A. 1996 Armarego, E.J.A., Wang, J., "Prediction of Forces, Torque and Power in Face Milling Operations, " paper presented to Proc. 4th Int. Conf. Adv. Manuf. Sys.

TeUdine, Italy
0
0
0
0
0
Sep
1996

[Arsecularatne, 1996] Arsecularatne, J.A., Fowle, R.F., Mathew, P., "Prediction of cutting forces and built-up edge formation conditions in machining with oblique nose radius tools, " paper presented to Proc. I. Mech. Engrs.
210
457
469
1996

[Balazinski, 1994] Balazinski, M., Ennajimi, E., , "Influence of feed variation on tool wear when milling stainless steel 17-4Ph, " paper presented to Trans. ASME. J. of Eng. for Industry,
116

516
520
Nov
1994

[Bayoumi, 1994] Bayoumi, A.E., Yucasen, G., Kendall, L.A., "An analytical mechanistic cutting force model for milling operations: a theory and methodology
Trans. ASME. J. of Eng. for Industry
116

324
330
Aug
1994

[Bayoumi, 1994] Bayoumi, A.E., Yucesan, G., Hutton, D.V., "On the closed form mechanistic

modeling of milling: specific cutting energy, torque, and power
J. Materials Eng. and Performance
3

151
158
Feb
1994

[Ber, 1988] Ber, A., Rotberg, J., Zomback, S., "Method of Cutting Force Evaluation of End Mills
Annals of CIRP, 37/1
0
37
37
1988

[Bischoff, 1987] Bischoff, B., Hallan, M., Moser, T., Shi, T.
Ramalingam, S., "Real time tool condition sensing: Part I - Modeling for a physically based approach and experimental results
ASME Winter annual Meeting
Boston
Dec 1987

[Blum, 1988] Blum, T., Suzuki, I., Inasaki, I., , "Development of a condition monitoring system for cutting tools using an acoustic emission sensor, " paper presented to Bull. JSPE

22
4
301
308
Dec
1988

[Blum, 1990] Blum, T., Inasaki, I., , "A study on acoustic emission from the orthogonal cutting process, " paper presented to Trans. ASME. J. of Eng. for Industry

112

203
211
Aug, 1990

[Boston, 1932] Boston, O.W., Kraus, C.E., "Elements of Milling, " paper presented to Trans. ASME
0
0
0
71
0
1932

[Boston, 1934] Boston, O.W., Kraus, C.E., "Elements of Milling, Part 2, " paper presented to Trans. ASME
0
0
0
355
0
1934

[Boston, 1937] Boston, O.W., Gilbert, W.W., Kaiser, K.B., "Power and Forces in Milling SAE-3150 Steel with Helical Mills
Proc. ASME
0
59
0
545
0
1937

[Bregger, 1979] Bregger, K.D., "On-line tool wear sensing for turning operations

Purdue U.

1
133
1979

[Brown, 1975] Brown, R.H., Luong, H.S., "Some new observations of the deformed zone in orthogonal cutting of mild steel
Metals Technology
2
2

1975

[Bruzzone, 1995] Bruzzone, A.A., Lonardo, P.M., Melkas, J., "Tool wear monitoring through the neural network classification of diffraction images
ATTI del II Convegno
0
0
0
343
352
Sep
1995

[Budak, 1992] Budak, E., Altintas, Y.,
Flexible milling force model for improved surface error predictions
Eng. Systems Des. and Anal. Conf.
Istanbul

Jun
1992

[Budak, 1994] Budak, E., Altintas, Y., Armarego, E.J.A.
Prediction of Milling Force Coefficients From Orthogonal Cutting Data
Trans. ASME, J. of Eng. for Industry

0
0
0
0
0

1994

] Bukkapatnam, S.T.S., Lakhtakia, A., Kumara, S.R.T.
Analysis of sensor signals shows turning on a lathe exhibits low dimensional chaos
Physical Review E
52
3
2375
2387
1995

[Carolan, 1996] Carolan, T.A., Hand, D.P., Barton, J.S.
Assessment of tool wear in milling using acoustic emission detected by a fibre-optic interferometer
Trans. ASME J. Mauf. Sci. Eng.
118

428
433
Aug
1996

[Chakraborty, 1958] Chakraborty, A.N.,
To Invetsigate the Vertical Force at Different Depths of Cuts, Speeds, Feeds and Rake Angles in Turning Mild steel
ME Thesis
Jadavpur University

1958

[Chen, 1992] Chen, P.,
Cutting temperature and forces in machining of high-performance materials with self-propelled rotary tool
JSME Int. J.
35
1
180
185
Mar
1992

[Choi, 1990] Choi, G.H., Dornfeld, D.
Analytical Predictions of Rotary Cutting Processes
Trans. North Amer. Manuf. Res. Inst./SME
0
0
0
146
0
1990

[Choi, 1990] Choi, G.S., " Monitoring and control of machining process using neural networks, " paper presented to U. of California, Berkeley,1990

[Choudhury, 1995] Choudhury, S.K., Ramesh, S., "Online tool wear sensing and compensation in turning, " paper presented to J. Materials Proc. Tech., vol49, no.3, P.247-254, 1995

[Chow, 1984] Chow, J.G., "Sensor development and on-line monitoring and the determination of temperature distributions in machining, " paper presented to Carnegie-Mellon U., p1-168, 1984

[Chryssolouris, 1995] Chryssolouris, G. "Sensor synthesis: A perscpective, " paper presented to CIRP/VDI Conf. Monit. Machng & Frmng Pr., VDI Berichte 1179, p335-346, 1995

[Colbaugh, 1995] Colbaugh, R., Glass, K. "Real-time tool wear estimation using recurrent neural networks, " paper presented to 10th IEEE Int. Symp. Intelligent Control
Las Cruces, Aug 1995

[Colgan, 1994] Colgan, J., Chin, H., Danai, K.
On-line tool breakage detection in turning: a multi-sensor method

Trans. ASME. J. of Eng. for Industry
116

117
123
Feb
1994

[Colwell, 1971] Colwell, L.V., "Methods of sensing the rate of tool-wear
Annals CIRP

19
1
647
651
1971

[Cook, 1980] Cook, N.H.
Tool wear sensor
Wear

62
563
567
1980

[Cook, 1980] Cook, N.H., "Tool wear sensors
Wear

62
49
57
1980

[Crawford, 1953] Crawford, S.H., Merchant, M.E., "Influence of Higher Rake Angles on Performance in Milling, " paper presented to Trans. ASME, 1953

[Das, 1996] Das, S., Chattopadhyay, A.B., Murthy, A.S.R., "Force parameters for on-line tool wear estimation: a neural network approach, “ paper presented to Neural Networks, p1639-1645, Dec 1996

[Das, 1997] Das, S., Bandyopadhyay, P.P., Chattopadhyay, A.B., "Neural-network-based tool wear monitoring in turning medium-carbon steel using a coated carbide tool, “ paper presented to J. Materials Proc. Tech., no.63, p187-192,1997

[Diei, 1984] Diei, E.N., Dornfeld, D.W., "Acoustic emission sensing of tool wear in peripheral milling, “ paper presented to ASME Winter Annual Meeting, New Orleans, Dec 1984

[Diei, 1985] Diei, E.N., "Investigation into the milling process using acoustic emission signal analysis (cutting process, tool wear, tool fracture, chipping, sliding contact)
PhD Thesis
U. of California
Berkeley

1
151
1985

[Diei, 1987] Diei, E.N., Dornfeld, D.A., "Acoustic emission sensing of tool wear in face milling
Trans. ASME. J. of Eng. for Industry
109

234
240
Aug
1987

[Diei, 1987] Diei, E.N., Dornfeld, D.A., "Acoustic emission sensing of tool wear in face milling.
Trans. ASME. J. of Eng. for Industry
109
3
234
240

1987

[Diei, 1987] Diei, E.N., Dornfeld, D.A., "A model of tool fracture generated acoustic emission

during machining
Trans. ASME. J. of Eng. for Industry
109

227
233
Aug
1987

[Diei, 1987] Diei, E.N., Dornfeld, D.A., "Acoustic emission from the face milling process - the effects of process variables
Trans. ASME. J. of Eng. for Industry
109

92
99
May
1987

[Dong, 1994] Dong, W.P., Au, Y.H.J., Mardapittas, A., "Characteristics of acoustic-emission in drilling, " paper presented to Tribology Int., vol 27, no3, p169-170, 1994

[Dornfeld, 1980] Dornfeld, D.A., "Acoustic emission and metalworking - Survey of potential and examiples of applications, " paper presented to 8th NAMRC, SME, p207-213, May 1980

[Dornfeld, 1980] Dornfeld, D.A., Kennatiyasibu, E., "Acoustic-emission during orthogonal metal cutting
Int. J. Mech. Sci.
22
5
285

296
1980

[Dornfeld, 1981] Dornfeld, D.A., "Investigation of machining and cutting tool wear using acoustic emission
AF/DARPA Rev. Progr. Quant. NDE
Plenum Press

4475
483
Aug
1981

[Dornfeld, 1981] Dornfeld, D.A., "Investigation of machining and cutting tool wear and chatter using acoustic emission
AF/DARPA Rev. Progr. Quant. NDE

475
483
Aug
1981

[Dornfeld, 1983] Dornfeld, D.A., "Investigation of metal cutting and forming fundamentals and control using acoustic emission
10th NSF Conf. Prodn. Res. Tech.
NSF, USA

Mar
1983

[Dornfeld, 1984] Dornfeld, D.A., Pan, C.S., "Chip form detection using acoustic emission
11the NAMRC

386
389
1984

[Dornfeld, 1984] Dornfeld, D.A., Pan, C.S., "Study of continuous/discontinuous chip formation using acoustic emission signal analysis
ASM Metals Cogr.
Am. Soc. of Metals

1984

[Dornfeld, 1985] Dornfeld, D.A., "Acoustic emission monitoring and analysis of manufacturing processes
12fh NSF Conf. Prodn. Res. and Tech.

1985

[Dornfeld, 1985] Dornfeld, D.A., "Role of acoustic emission in manufacturing process monitoring
13th NAMRC
SME, NAMRI
Berkeley

69
74
May
1985

[Dornfeld, 1986] Dornfeld, D.A., "Acoustic emission process monitoring for untended manufacturing, " paper presented to Jap/US Symp. Flexible Automation, Osaka, p831-836,Jul 1986

[Dornfeld, 1987] Dornfeld, D.A., Rangwala, S., "Integration of sensors via neural networks for detection of tool wear states , " paper presented to ASME Winter Annual Meeting, vol25, p109-120, 1987

[Dornfeld, 1989] Dornfeld, D.A., "Monitoring of the machining process by means of acoustic emission sensors , " paper presented to Symp. on Acoustic Emission, Charlotte, Mar 1989

[Egorov, 1986] Egorov, S.N., Prima, V.I., "Cutting forces in end milling , " paper presented to Soviet Eng. Res., vol6, p12-82, Dec 1986

[El Gomayel, 1986] El Gomayel, J.I., Bregger, K.D., "On-line tool wear sensing for turning operations, " paper presented to Trans. ASME. J. of Eng. for Industry, no. 108, p44-47, Feb 1986

[Emel, 1989] Emel, E., Kannateyasibu, E. Jr., "Acoustic emission and force sensor fusion for monitoring the cutting process, " paper presented to Int. J. Mech. Sci., vol31, no.11, p795-809, 1989

[Emel, 1991] Emel, E., "Tool wear detection by neural network based acoustic emission sensing, " paper presented to ASME Winter Annual Meeting, Atlanta, Dec 1991

[Emel, 1991] Emel, E., Kannatiyasibu, E., "Acoustic-emission monitoring of the cutting process - negating the influence of varying conditions, " paper presented to J.

Eng. Matls. Tech., vol113, no.4, p456-464, 1991

[Ezugwu, 1995] Ezugwu, E.O., Arthur, S.J., Hines, E.L., "Tool-wear prediction using artificial neural networks, “ paper presented to J. Materials Proc. Tech., vol49, no3, p255-264, 1995

[Fu, 1992] Fu, J.J.C., "Tool wear monitoring in face milling by integration of static and dynamic signals using neural networks (static signals)
PhD Thesis
Lehigh U.

1
184
1992

[Gee, 1984] Gee, D., Patterson, R.L., Zielaskiewicz, S.M., "Automatic detection of cutting tool failure, “ paper presented to 2nd Biennial Int. Mach. Tool Tech. Conf. Rosemont, IL.,Sep 1984

[Giusti, 1979] Giusti, F., Santochi, M., "Development of a fibre optic sensor for in process measurement of tool flank wear, “ paper presented to 20th MTDR Conf., Birmingham, p351-359,Sep 1979

[Giusti, 1984] Giusti, F., Santochi, M., Tantussi, G., "A flexible tool wear sensor for NC lathes, “ paper presented to Annals CIRP, p229-232, 1984

[Giusti, 1987] Giusti, F., Santochi, M., Tantussi, G., "On-line sensing of flank and crater wear of cutting tools, “ paper presented to Annals CIRP, vol36, no1, p41-44,1987

[Govekar, 1994] Govekar, E., Grabec, I.
Self-organizing neural network application to drill wear classification
Trans. ASME. J. of Eng. for Industry
116

233
238
May
1994

[Guinea, 1991] Guinea, D., Ruiz, A., BArrios, L.J. “Multi-sensor integration -- an automatic feature selection and state identification methodology for tool wear estimation, “ paper presented to Computers in Industry, p121-130, Nov 1991

[Haber, 1996] Haber, R., Alique, J.R., Salvador, P., “Fuzzy supervisory control of end milling process, “ paper presented to Information Sciences, vol89, no1, p95-106, Feb 1996

[Heiple, 1994] Heiple, C.R., Carpenter, S.H., Armentrout, D.L., "Acoustic emission from single point machining: source mechanisms and signal changes with tool wear
Materials Evaluation
52
590
596
May
1994

[Huang, 1996] Huang, S.J., Chiou, K.-C., "Application of neural networks in self-tuning constant force control
Int. J. Mach. Tools Manuf.
36
1
17
31
Jan
1996

[Hutton, 1990] Hutton, D.V., Yu, Q.H., , "On the effects of a built-up edge on acoustic emission in metal cutting
Trans. ASME. J. of Eng. for Industry
112

184
189
May
1990

[Inasaki, 1981] Inasaki, I., Yonetsu, S., "In-process detection of cutting tool damage by acoustic emission measurement
22nd M.T.D.R. Conf.

261
268
1981

[Inasaki, 1988] Inasaki, I., Blum, T., Suzuki, I., Sato, M., "Practical mounting device for an acoustic emission sensor for the failure detection of multipoint cutting tools, " paper presented to USA/Jap. Symp Flexible Automation, Minneapolis, p1017-1024, Jul 1988

[Iwata, 1977] Iwata, K., Moriwaki, T., "An application of acoustic emission to in-process sensing of tool wear
Annals CIRP

26
1
21
26
1977

[Javed, 1996] Javed, M.A., Hope, A.D., Littlefair, G.
Rao, B.K.N., "On-line tool condition monitoring using artificial neural networks
Non-Destructive Testing and Cond. Monit.
38
5
351
354
May
1996

[Jin, 1994] Jin, W.L., Venuvinod, P.K., Wang, X., "An optical fibre sensor based cutting force measuring device, " paper presented to Int. J. Mach. Tool Des. And Res., vol35, no. 6, p877-883, 1994

[Kakino, 1980] Kakino, Y., "In-process detection of tool breakage by monitoring acoustic emission, " paper presented to Int. Conf. Cutting Tool Materials,Fort Mitchell, KY, p29-43, Sep 1980

[Kakino, 1983] Kakino, Y., ujiwara, A., Hashitani, M.
Yamada, T., "In-process detection of thermal crack of cutting-tool by making use of acoustic-emission
Bull. JSPE

17
4
241
246

1983

[Kamarthi, 1994] Kamarthi, S.V., "On-line flank wear estimation in turning using multi-sensor fusion and neural networks, " paper presented to Pennsylvania State U. University Park, 1994

[Kannateyasibu, 1980] Kannateyasibu, E., , "Investigation of the metal cutting process using acoustic emission signal analysis, " paper presented to U. of California, Berkeley, p1-154, 1980

[Kannateyasibu, 1981] Kannateyasibu, E., Dornfeld, D.A., "Quantitative relationships for acoustic emission from orthogonal metal cutting, " paper presented to Trans. ASME. J. of Eng. for Industry, vol103, no. 3, p330-340, 1981

[Kannateyasibu, 1982] Kannateyasibu, E., Dornfeld, D.A., "A study of tool wear using statistical analysis of metal cutting acoustic emission, " paper presented to Wear, vol76, no.2, p247-261, 1982

[Ko, 1994] Ko, T.J., Cho, D.W., "Cutting state monitoring in milling by a neural network

34

5

659

676

Jul

1994

[Kojima, 1986] Kojima, K., Inasaki, I., Miyako, R., "Monitoring of turning process with acoustic emission signals, " paper presented to Nippon Kikai Gakkai Ronbunshu, vol52, no.474,p799-805, Feb 1986

[Kuo, 1994] Kuo, R.J., "Multi-sensor integration for intelligent control of machining through artificial neural networks and fuzzy modelling, " paper presented to Pennsylvania State U., p1-181, 1994

[Kurapati, 1992] Kurapati, V., "Tool wear monitoring using artificial neural networks, " paper presented to Florida atlantic U., p1-143, 1992

[Lan, 1982] Lan, M.S., Dornfeld, D.A., "Experimental studies of tool wear via acoustic emission analysis, " paper presented to 10th NAMRC, SME, May 1982

[Lan, 1983] Lan, M.S., "Investigation of tool wear, fracture and chip formation in metal cutting using acoustic emission, " paper presented to U. of California, Berkeley, 1993

[Lan, 1985] Lan, M.S., Naerheim, Y., "Application of acoustic emission monitoring in machining, " paper presented to 13th NAMRI, p310-313, 1985

[Lan, 1986] Lan, M.S., Dornfeld, D.A., "Acoustic emission and machining - process analysis and control, " paper presented to Advanced Manufacturing Processes, Marcel

Dekker, New York, 1986

[Lee, 1988] Lee, L.C., Lee, K.S., "In-process tool failure sensing in automated machining systems, " paper presented to IES J., vol28, no. 4, p10-15, Oct 1988

[Lee, 1985] Lee, M.Y., Wildes, D.G., Hayashi, S.R., "Characterisation of acoustic-emission sources in metal-cutting processes, " paper presented to J. of Metals, 1985

[Leem, 1995] Leem, C.S., Dornfeld, D.A., Dreyfus, S.E., "A customised neural network for sensor fusion in on-line monitoring of cutting tool wear, " paper presented to Trans. ASME. J. of Eng. for Industry, vol117, p152-159, May 1985

[Leem, 1996] Leem, C.S., Dornfeld, D.A., "Design and implementation of sensor based tool-wear monitoring systems, " paper presented to Mech. Systems &Signal Processing, vol 10, no.4, p439-458, Jul 1996

[Leopold, 1994] Leopold, J., "Neural network application in machining investigations, " paper presented to ICAMT , Johor Baru, Aug 1994

[Li, 1993] Li, C.J., Li, S.Y., "A new sensor for real-time milling tool condition monitoring, " paper presented to J. Dynamic Sys., Measurement and Control, vol115, no. 2. P285-290, Jun 1993

[Liang, 1987] Liang, S.Y., Dornfeld, D.A., "Detection of cutting tool wear using adaptive time series modeling of acoustic emission signal, " paper presented to ASME Winter Annual Meeting,ASME, Boston, p27-38, Dec 1987

[Liang, 1989] Liang, S.Y., Dornfeld, D.A., "Tool wear detection using time series analysis of acoustic emission
Trans. ASME. J. of Eng. for Industry
111
199
205
Aug
1989

[Liu, 1990] Liu, M., Liang, S.Y., "Monitoring of peripheral milling using acoustic emission
Trans. NAMRI/SME
120
127
1990

[Luong, 1995] Luong, L.H.S., Spedding, T.A., "A neural-network system for predicting machining behavior
J. Materials Proc. Tech.

52
3
585
591
1995

[McBride, 1993] McBride, R., Carolan, T.A., Barton, J.S., "Detection of acoustic emission in cutting processes by fibre optic interferometry
Measurement Sci. Tech.
4
1122
1128
Oct
1993

[Micheletti, 1976] Micheletti, G.F., Koenig, W., Victor, H., "In process tool wear sensors for cutting operations
Annals CIRP
25
483
496
1976

[Moriwaki, 1980] Moriwaki, T., , "Detection of cutting tool fracture by acoustic emission measurement
Annals CIRP
29
1
35
40
1980

[Moriwaki, 1983] Moriwaki, T., "Application of acoustic-emission measurement to sensing of wear and breakage of cutting tool

Bull. JSPE

17
3
154
1983

[Moriwaki, 1984] Moriwaki, T., "Sensing and prediction of cutting tool failure
Bull. JSPE

18
2
90
96
Jun
1984

[Moriwaki, 1991] Moriwaki, T., Hino, R.
Application of neural network to AE signal processing for automatic detection of cutting tool life
J. JSPE

57
7
1259
1264
Jul
1991

[Naerheim, 1983] Naerheim, Y., Arora, A., "In-process monitoring of machining using acoustic emission
Rev. of QNDE
Santa Cruz, CA.

753
762

1983

[Nakamura, 1985] Nakamura, S., Oshikawa, T., Futamata, I., "Design and signal processing of six-axis force sensor
Robotics Research (book chapter)
MIT Press
Boston

75
81
1985

[Nayfeh, 1993] Nayfeh, T.H., "A direct on-line ultrasonic sensing method to determine tool and process conditions during turning operations (tool condition, ultrasonic sensing)
PhD Thesis
Virginia Polytechnic Inst. and State U.
1
129
1993

[Noto La Diega, 1980] Noto La Diega, S., Passannanti, A., "A linear force model for orthogonal cutting, " paper presented to V Congr. AIMETA, 1980

[Oraby, 1990] Oraby, S.E., "High capacity compact three-component cutting force sensor, " paper presented to Int. J. Mach. Tools Manuf., vol 30, p549-554, 1990

[Quinlan, 1987] Quinlan, J.C., "New tool-wear sensors aid adaptive machining, " paper presented to Tooling Production, vol 53, p41-43, Dec 1987

[Ramalingam, 1988] Ramalingam, S., Shi, T., Frohrib, D.A., "Acoustic emission sensing with an intelligent insert and tool fracture detection in multi-tooth milling, " paper presented to 16th NAMRI, p245-255, 1988

[Raman, Shivqkumar1989 Raman, Shivqkumar, "Coupled sensing for tool wear modelling, " paper presented to The Pennsylvania State U., 1989

[Rangwala, 1990] Rangwala, S., Dornfeld, D., "Sensor integration using neural networks for intelligent tool condition monitoring, " paper presented to Trans. ASME. J. of Eng. for Industry, vol112, p219-228, Aug 1990

[Rangwala, 1989] Rangwala, S.S., Dornfeld, D.A., "Learning and optimization of machining operations using computing abilities of neural netwrorks, " paper presented to IEEE Trans. Sys., Man and Cybernetics, vol 19, no2, p299-314, Mar 1989

[Rice, 1993] Rice, J.A., Wu, S.M., "On the feasibility of catastrophic cutting tool failure prediction via acoustic emission analysis, " paper presented to Trans. ASME. J.

of Eng. for Industry, vol115, p390-397, Nov 1993

[Roget, 1988] Roget, J., Souquet, P., Gsib, N., "Application of acoustic emission to the automatic monitoring of tool condition during machining
Materials Evaluation
46
225
229
Feb
1988

[Romashev, 1989] Romashev, A.N., Sakharov, G.N., "Sensor tool for monitoring tool state during turning, " paper presented to Soviet Eng. Res., vol9, no. 7, p111-113, 1989

[Rutelli, 1988] Rutelli, G., Cuppini, D., "Development of wear sensor for tool management system
. Eng. Materials and Tech.
110
59
62
Jan
1988

[Ryabov, 1996] Ryabov, O.Mori, K.Kasashima, N., "An in-process direct monitoring method for milling tool failures using a laser sensor, " paper presented to Annals CIRP, vo;.45, no. 1, p97-100, 1986
45
1
97
100
1996

[Sabberwal, 1960] Sabberwal, A.J.P., " An improved three-dimensional milling force dynamometer, " paper presented to Engineering, May, 1960

[Sampath, 1986] Sampath, A.Vajpayee, S., "On-line tool wear prediction using acoustic emission
12th All India M.T.D.R. Conf.
Tata McGraw-Hill

Delhi

269

272

Dec

1986

[Sanjanwala, 1990] Sanjanwala, A.Choudhury, S.K.Jain, V.K., "On-line tool wear sensing and compensation during turning operation

Precision Eng.

12

2

81

84

Apr

1990

[Santochi, 1996] Santochi, M.Dini, G.Tantussi, G.

, " sensor-integrated tool for cutting force monitoring

Annals CIRP

46

1

49

52

1996

[Schmenk, 1984] Schmenk, M.J., "Acoustic emission and the mechanics of metal cutting

ASME Winter Annual Meeting

New Orleans

95

106

Dec

1984

[Shi, 1988] Shi, T.Ramalingam, S.Frohrib, D.A., "Tool fracture detection in the sub-

millisecond time frame using machining iserts with integral sensors
USA/Jap. Symp. Flexible Automation
Minneapolis

1025
1033
Jul
1988

[Shinno, 1997] Shinno, H.Hashizumz, H.Sata, H., "In-process monitoring method for machining environment based on simultaneous phenomena sensing
Annals CIRP

46
1
53
56
1997

[Shirashe, 1996] Shirashe, K.Altintas, Y., "Force and surface generation mechanism with variable pitch helical end mills
Int. J. Mach. Tools & Manuf.
36
5
567
584

1996

[Stephenson, 1985] Stephenson, D.A., "Computer prediction of the mechanical outputs of three-dimensional turning and drilling
PhD Thesis
U. of Wisconsin

1
359
1985

[Subramanian, 1977] Subramanian, K.Cook, N.H., "Sensing of Drill Wear and Prediction of Tool Life
Trans. ASME, J. of Eng. for Industry
0
0
0
295
0
May
1977

[Sunil, 1990] Sunil, E.V.T.Kumara, S.R.T., "Machine condition monitoring for automation using neural networks
ASME Winter Annual Meeting
Dallas
1990

[Sutherland, 1986] Sutherland, J.W.DeVor, R.E., "Improved method for cutting force and surface error prediction in flexible end milling systems
ASME Winter Annual Meeting
Anaheim
Dec
1986

[Suzuki, 1983] Suzuki, H., "Design of a tool wear sensor and development of adaptive control optimization for turning operations
PhD Thesis
Michigan Technological U.
1
147
May
1983

[Suzuki, 1985] Suzuki, H.Weinmann, K.J., "An on-line tool wear sensor for straight turning operations, " paper presented to Trans. ASME. J. of Eng. for Industry, vol107, p397-399, Nov 1985

[Tai, 1994] Tai, C.C.Fuh, K.H., "Predictive force model in ball-end milling including eccentricity effects, " paper presented to Int. J. Mach. Tools Manuf., vol34, no.7, p959-979, Oct 1994

[Tai, 1995] Tai, C.C.Fuh, K.H., "Prediction of cutting forces in the ball-end milling process, " paper presented to J. Materials Proc. Tech., vol54, no. 1, p286-301, Oct 1995

[Tai, 1995] Tai, C.C.Fuh, K.H., "Model for Cutting Forces Prediction in Ball-End Milling, " paper presented to Int. J. Mach. Tools Manfact., p511-534, 1995

[Takatsuto, 1994] Takatsuto, M.Takada, N.Kato, K., "Judgement of tool life in drilling using acoustic-emission, " paper presented to JSME Int. J. Series C, vol. 37. No. 1, p224-229, 1994

[Takeyama, 1968] Takeyama, H., Doi, Y., Mitsuoka, T., "Sensors of tool life for optimization of machining, " paper presented to J. Mech. Lab. Japan, vol 14, no. 2, p45-59, 1968

[Tan, 1994] Tan, P., "A Study of Predictive Models for Forces and Computer Geometric Errors in End Milling and Slotting, " paper presented to The University of Melbourne, 1994

[Tanaka, 1992] Tanaka, C., Nakao, T., Nishino, Y., Takahashi, A., "Detection of wear degree of cutting-tool by acoustic emission signal, " paper presented to Mokuzai Gakkaishi, vol38, no. 9, p 841-846, 1992

[Tansel, 1991] Tansel, I.N., McLaughlin, C., "Identification of tool breakage with time series analysis in milling, " paper presented to ASME Winter Annual Meeting, Atlanta, Dec 1991

[Tansel, 1992] Tansel, I.N., "Modelling of 3-D cutting dynamics with neural networks, " paper presented to Int. J. Mach. Tools & Manuf., vol32, no. 6, p829-853, Dec 1992

Tansel, I.N. 1997 Tansel, I.N., Trujillo, M.E., Bao, W.Y., "Detection of tool breakage in micro-end milling operations by monitoring acoustic emission, " paper presented to 27th NAMRC U. of Nebraska-Lincoln, May 1997

[Tarn, 1987] Tarn, J.H., Tomizuka, M., "On-line monitoring of tool and cutting conditions in milling

Boston

Dec

1987

[Tarng, 1993] Tarng, Y.S., Lee, B.Y., "A sensor for the detection of tool breakage in NC milling

J. Materials Proc. Tech.

36
3
259
272
1993

[Tarng, 1993] Tarng, Y.S., Cheng, S.T., "Fuzzy control of feed rate in end milling operations
Int. J. Mach. Tools & Manuf.
33
4
643
650
Aug
1993

Tarng, Y.S.
1995
Tarng, Y.S., Wang, T.C., Chen, W.N., "Use of neural networks in predicting turning forces
J. Materials Proc. Tech.
47
273
289
1995

[Tarng, 1995] Tarng, Y.S., Wang, T.C., Chen, W.N., "The use of neural networks in predicting turning forces
J. Materials Processing Tech.
47
3
273
289
Jan
1995

[Tarng, 1996] Tarng, Y.S., Chen, M.C., Liu, H.S., "Detection of tool failure in end milling
J. Materials Proc. Tech.
57
1
55

61
1996

[Teti, 1989] Teti, R., "Tool wear monitoring through acoustic emission
Annals CIRP
0
38
1
99
102
1989

[Teti, 1992] Teti, R., La Commare, U., "Cutting conditions and work material state identification through acoustic emission methods
Annals CIRP
41
1
89
92
1992

[Teti, 1993] Teti, R., "Sensor signal frequency analysis for metal cutting process monitoring
1st AITEM Conf.
Ancona, Italy
0
0
0
55
64
Sep
1993

[Thangaraj, 1985] Thangaraj, A., "Computer-assisted monitoring of drill wear and prediction of drill failure
PhD Thesis

Carnegie-Mellon, U.

1
130
1985

[Thangaraj, 1987] Thangaraj, A., Wright, P.K., "Drill wear sensing and failure prediction for unended machining
Int. Conf. Manuf. Syst. Tech of Future
Cambridge, MA

429
435
Jun
1987

[Tlusty, 1983] Tlusty, J., Andrews, G.C., "A critical review of sensors for unmanned machining
Annals CIRP

32
2
563
572
1983

[Toenshoff, 1988] Toenshoff, H.K., Wulfsberg, J.P., Kals, H.J.J., Luttervelt, van C.A., "Development and trends in monitoring and control of machining processes
Annals CIRP
0
37
2
611
622
1988

[Tomizuka, 1983] Tomizuka, M., Oh, J.H., Dornfeld, D.A., "Model reference adaptive control of the milling process, " paper presented to Control of Manuf. Proc. and Robotic Sys.

ASME. New York, 1983

[Tse, 1985] Tse, M.K., Briggs, J.C., "In-process tool wear sensing by acoustic emission, " paper presented to 11th World Conf. Non-Destructive Testing, Las Vegas, p70 - 77, Nov 1985

[Uehara, 1984] Uehara, K., Kanda, Y., "Identification of chip formation mechanism through acoustic emission measurements, " paper presented to Annals CIRP, vol33 no.1, p71-74, 1984

[Victor, 1980] Victor, H., "Computer-aided measurement of cutting force applied to the wear of an end milling cutter, " paper presented to Wear, vol62, no.1, p185-195, 1980

[Wang, 1991] Wang, J.-J., Liang, S.Y., Book, W.J., "Analysis of milling forces via angular convolution, " paper presented to ASME Winter Ann. Meeting, Atlanta, Dec 1991

[Wang, 1994] Wang, J.-J., Liang, S.Y., Book, W.J., "Convolution analysis of milling force pulsation, " paper presented to Trans. ASME. J. of Eng. for Industry, vol116, p17-25, Feb 1994

[Watanabe, 1986] Watanabe, T., "Model-based approach to adaptive control optimization of milling, " paper presented to J. Dyn. Sys., Meas. and Control, ASME vol108, no.1, p56-64, Mar 1986

[Whitfield, 1976] Whitfield, R.C., Armarego, E.J.A., "Predictive Milling Force Models For CAD/CAM System, " paper presented to 3rd Int. Conf. on Manuf. Engg. Inst. Engrs. Australia, Newcastle, 1976

Xu, Q. 1994 Xu, Q., Krishnamurthy, K., Lu, W., "Neural network controller for force control in end milling operations, " paper presented to Int. Mech. Eng. Cong. and Exposition, Chicago, Nov 1994

[Xu, 1994] Xu, Q., Krishnamurthy, K., McMillin, B., "Identification of cutting force in end milling operations using recurrent neural networks, " paper presented to IEEE Int. Conf. Neural Networks, Orlando, Jun 1994

[Yanushevsky, 1990] Yanushevsky, R., Minis, I.. "Optimal control of cutting force in metal cutting operations, " paper presented to Am. Control Conf., San Diego, May 1990

[Yee, 1986] Yee, K.D., Blomquist, D., Dornfeld, D.A., "An acoustic emission chip-form monitor for single point turning, " paper presented to 26th Int. MTDR Conf. Manchester, Sep 1986

[Yellowley, 1986] Yellowley, I., "Observations of the Mean Values of Forces, Torque and Specific Power in the Peripheral Milling Process
Int. J. Mach. Tool Des. Res.

0
25
0
337
346

1985

[Yellowley, 1993] Yellowley, I., Lai, C.T., "The use of force ratios in the tracking of tool wear in turning, “ paper presented to Trans. ASME. J. of Eng. for Industry, vol115,p370-372, Aug 1993

[Yen, 1984] Yen, D.W., "A new approach and a remote sensing technique for adaptive control machining (semi-analytical FEM, metal cutting, inverse solution) , “ paper presented to Carnegie-Mellon U., 1984

[Yen, 1986] Yen, D.W., Wright, P.K., "Remote temperature sensing technique for estimating the cutting interface temperature distribution, “ paper presented to Trans. ASME. J. of Eng. for Industry, vol108, no. 4,p252-263, Nov 1986

[Young, 1994] Young, H.-T., Mathew, P., Oxley, P.L.B., "Prediction of cutting forces in face milling, “ paper presented to Int. J. Mach. Tools Manuf., vol34, no.6,p771-783,Aug 1994

[Young, 1990] Young, H.T., "Experimental analysis of milling force pulsation, “ paper presented to J. Chinese Scoc. Mech. Engrs., vol11, no4, p368-375,Aug 1990

[Yucesan, 1992] Yucesan, G., "Modelling of cutting forces for milling operations, “ paper presented to Washington State U., 1992

[Zakaria, 1973] Zakaria, A.A., "On-line tool wear sensing for the adaptive control of metal cutting processes, “ paper presented to Purdue U., p1-248, 1973

[Zhang, 1993] Zhang, B., "Tool condition monitoring in turning using optical sensors, “ paper presented to U. of Windsor (Canada), p1-148, 1993

[Zilouchian, A.1 995] Zilouchian, A., Masory, O., "Neural network controller for turning operation of a metal cutting process, “ paper presented to Am. Control Conf.Seattle, Jun 1995