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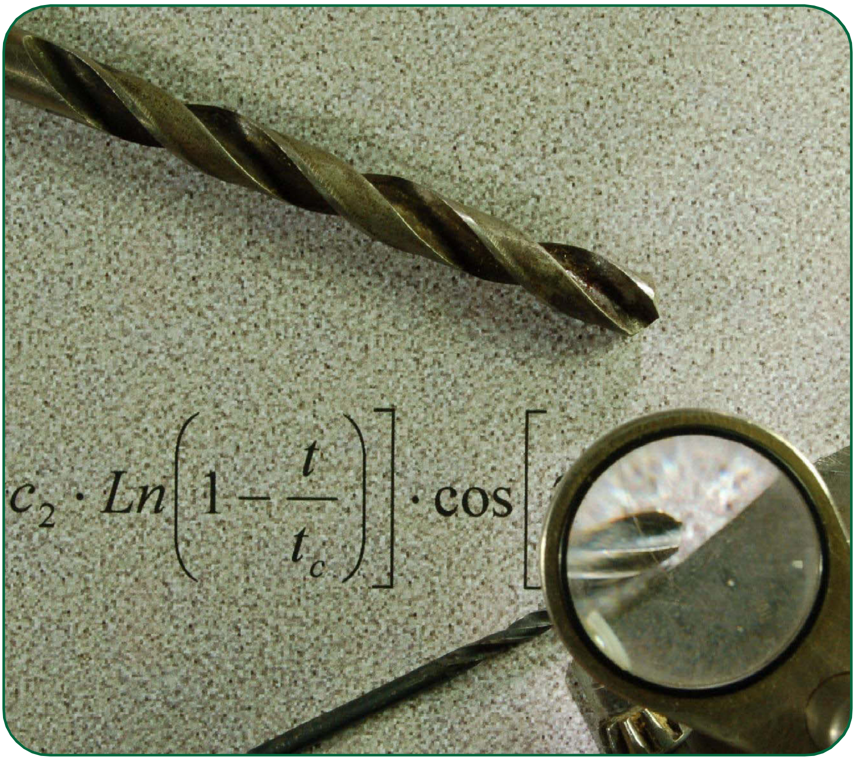

Erkki Jantunen

Indirect multisignal monitoring and diagnosis of drill wear

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Erkki Jantunen

VTT Industrial Systems

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Abstract

A machine tool utilisation rate can be improved by an advanced condition monitoring system using modern sensor and signal processing techniques. A drilling test and analysis program for indirect tool wear measurement forms the basis of this thesis. For monitoring the drill wear a number of monitoring methods such as vibration, acoustic emission, sound, spindle power and axial force were tested. The signals were analysed in the time domain using statistical methods such as root mean square (rms) value and maximum. The signals were further analysed using Fast Fourier Transform (FFT) to determine their frequency contents. The effectiveness of the best sensors and analysis methods for predicting the remaining lifetime of a tool in use has been defined. The results show that vibration, sound and acoustic emission measurements are more reliable for tool wear monitoring than the most commonly used measurements of power consumption, current and force. The relationships between analysed signals and tool wear form a basis for the diagnosis system. Higher order polynomial regression functions with a limited number of terms have been developed and used to mimic drill wear development and monitoring parameters that follow this trend. Regression analysis solves the problem of how to save measuring data for a number of tools so as to follow the trend of the measuring signal; it also makes it possible to give a prognosis of the remaining lifetime of the drill. A simplified dynamic model has been developed to gain a better understanding of why certain monitoring methods work better than others. The simulation model also serves the testing of the developed automatic diagnostic method, which is based on the use of simplified fuzzy logic. The simplified fuzzy approach makes it possible to combine a number of measuring parameters and thus improves the reliability of diagnosis. In order to facilitate the handling of varying drilling conditions and work piece materials, the use of neural networks has been introduced in the developed approach. The scientific contribution of the thesis can be summarised as the development of an automatically adaptive diagnostic tool for drill wear detection. The new

approach is based on the use of simplified fuzzy logic and higher order polynomial regression analysis, and it relies on monitoring methods that have been tested in this thesis. The diagnosis program does not require a lot of memory or processing power and consequently is capable of handling a great number of tools in a machining centre.

Preface

This research was carried out at the Technical Research Centre of Finland (VTT) during 1994–2005. Publications I and III are linked to the Predictive Intelligent Machine and Machining Monitoring Sensors (Pimms), BRST-CT98-5429 project. Publications II and V are part of the FMS Maint System, EUREKA MAINE EU 744 project. Publications IV, VI and VII relate to Multiple Intelligent Diagnostics for Machinery (MindMan), and Publication VIII to On-Line Multi-Sensor Diagnostic Analysis for Maintenance using Neural Networks (Neural Maine), EUREKA Project EU 1250. These projects have been funded by the EU, the National Technology Agency of Finland (Tekes), Finnish industry and the Technical Research Centre of Finland. The financial support is gratefully acknowledged.

Professor Mauri Airila, whom I would like to thank for his advice and support, supervised this thesis. I would also like to thank Professor Kenneth Holmberg for his advice and encouragement.

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A great number of researchers, whose names are acknowledged in the papers that form part of this thesis, were involved in the above projects and influenced this work, for which I wish to express my gratitude. Special thanks are due to Mr. Harri Jokinen for the discussions and planning, Mr. Antti Poikonen for installing the measuring system and programming the data acquisition program, Mrs. Natalia Siren for programming the fuzzy logic and regression analysis functions, and Mrs. Adelaide Lönnberg for checking the English language of the thesis.

Finally I would like to thank my wife Sinikka and our children Taru, Arto and Eero for their patience and support.

December 8th, 2005

Erkki Jantunen

Contents

Appendices I, II, III and VII of this publication are not included in the PDF version. Please order the printed version to get the complete publication (http://www.vtt.fi/publications/index.jsp)

List of symbols

Letters

$c_{1\ldots10}$	constants
a	regression coefficient
b	regression coefficient
b_l	defines the relation between the increasing part and the stable part of the thrust force when drilling one hole
c	damping, regression coefficient
ClassMean	mean value of class
d	constant
e	exponent in regression analysis
E	Young’s modulus
f	exponent in regression analysis, feed
f_0	natural frequency of the drill
f_n	natural frequency for bending
F_0	force at the natural vibration frequency of the drill
F_{dh}	shape function that takes into account the unstable features of drilling a hole
F_{dp}	drilling process force
ϕ_{ge}	angular geometrical error due to tolerance in manufacturing
F_{nrpm}	force that takes into account the harmonic components of the drilling speed
F_{rnd}	random force (noise)
$F_{rpm1,rpm2}$	forces that take into account geometrical differences in cutting lips
ϕ_{wd}	difference in wear of the two cutting lips of the drill
F_x	horizontal drill force
g	exponent in regression analysis
h	influence of wear
H_B	Brinell hardness
HighHigh	higher limit of class
HighLow	high limit after which the class descends from unity
i	class index, counter for hole number, index in regression analysis
I	moment of inertia
j	size of class
k	shape of class, stiffness
K_n	coefficient that depends on the vibration mode
l	length of the drill

LowHigh	lower limit where class reaches unity
LowLow	lower limit of class
m	mass
μ	mean value
n	number of samples, order of harmonic component
p	factor used for emphasising the most recent data in regression analysis
q	constant that defines how much weight old data is given in regression analysis
ρ	density
σ	standard deviation
S	cross-sectional area
t	time
t_c	total lifetime of the drill
t_d	time it takes to drill one hole
ω	angular speed of rotation
x	coordinate axis
y	monitored parameter

Acronyms

AD	analogue to digital conversion
AE	acoustic emission
ARMA	autoregressive moving average
ART	adaptive resonance theory
FEM	finite element method
FFT	fast Fourier transform
FLVQ	fuzzy learning vector quantization
HMM	hidden Markov model
HOS	higher order spectrum
HSS	high speed steel
LVQ	learning vector quantization
MARSE	measured area under the rectified signal envelope
PC	personal computer
PSD	power spectral density
RAMV	ratio of the absolute mean value
RCE	restricted Coulomb energy
rms	root mean square

List of publications

This dissertation consists of a summary and eight appended publications I-VIII.

Publication I	Jantunen, E. 2002. A Summary of Methods Applied to Tool Condition Monitoring in Drilling. International Journal of Machine Tools and Manufacture, Vol. 42, pp. 997–1010. ISSN 0890-6955
Publication II	Jantunen, E. & Jokinen, H. 1996. Automated On-Line Diagnosis of Cutting Tool Condition. International Journal of Flexible Automation and Integrated Manufacturing, 4 (3 & 4), pp. 273–287. ISSN 1064-6345
Publication III	Jantunen, E. 2001. The Applicability of Various Indirect Monitoring Methods to Tool Condition Monitoring in Drilling. International Journal of Comadem, Vol. 7, No. 3, July 2004, pp. 24–31. ISSN 1363-7681 (also published in COMADEM 01. September 4–6, Manchester, UK, ISBN 0 08 0440363)
Publication IV	Jantunen, E. 2004. Dynamic Effects Influencing Drill Wear Monitoring. Proceedings of the MFPT 58th Meeting, Ed. H.C. Pusey, S.C. Pusey & W.R. Hobbs, April 25–30, Virginia Beach, USA. Pp. 51–60.
Publication V	Jantunen, E., Jokinen, H. & Milne, R. 1996. Flexible Expert System for Automated On-Line Diagnosis of Tool Condition. Proceedings of a Joint Conference, Technology Showcase, Integrated Monitoring, Diagnostics & Failure Prevention, MFPT 50th Meeting, Joint Oil Analysis Program Technical Support Center, University of Wales, Ed. H.C. Pusey & S.C. Pusey, Mobile, Alabama, USA, April 22–26. Pp. 259–268.

Publication VI Jantunen, E. 2003. Prognosis of Wear Progress Based on Regression Analysis of Condition Monitoring Parameters. Finnish Journal of Tribology, Vol. 22/2003, 4, pp. 3–15. ISSN 0780-2285 (also published in COMADEM 03 August 27–29, Växjö, Sweden. ISBN 91-7636-376-7)

Publication VII Jantunen, E. 2006. Diagnosis of Tool Wear Based on Regression Analysis and Fuzzy Logic. IMA Journal of Management Mathematics, Vol. 17, No 1, January, pp. 47–60. ISSN 1471-6798

Publication VIII Jantunen, E. 2000 Flexible Hierarchical Neuro-Fuzzy System for Prognosis. Proceedings of COMADEM 2000, 13th International Congress on Condition Monitoring and Diagnostic Engineering Management. Ed. H.C. Pusey & Raj B.K.N. Rao, December 3–8, Houston, USA. Pp. 699–708. ISBN 0-9635450-2-7

Author’s contribution

The author was responsible for the monitoring methods, signal analysis and simulation program approach in publication II. In publication V the author was responsible for the fault tree and symptom tree database definition and the definition of data acquisition, signal analysis, regression analysis and simulation module.

1. Introduction

1.1 Background and motivation

Tool wear and failure monitoring has aroused interest among many researchers and research organisations. The background and motivation for this interest is that tool condition monitoring is considered important for the following reasons:

- Cost effective unmanned production is only possible in practise if there is a reliable method available for tool wear monitoring and breakage detection. For example, based on a recent study it has been claimed that in machining centres tool maintenance and tool monitoring cause most of the stoppages during unmanned operation [Kuhmonen 1997].
- Tool wear influences the quality of the surface finish and the dimensions of the parts manufactured. The quality of the surface finish and the dimensions are linked to the above mentioned unmanned operation, i.e. if this is not monitored or the quantity of tool wear is not monitored, the unmanned machining might lead to poor quality.
- The economical tool life cannot be fully benefited from without efficient methods for tool wear monitoring because of the variation in tool life. This factor is not economically as important as the above two during drilling as far as the cost of tools is considered, but nevertheless economically meaningful when the costs of production are studied in detail.
- Where sudden tool failures are to be avoided, tool changes need to be made based on conservative estimates of tool life. This does not take into account sudden failures and at the same time leads to an unnecessarily high number of tool changes, because the full tool life is not benefited from and valuable production time is therefore lost.

1.2 Research question

In order to overcome the challenges described in the previous chapter, condition monitoring and diagnosis of tool wear is needed. This then leads to the research question: *How can the wear of the cutting tools of a machine tool be monitored* *and diagnosed in a practical and reliable manner?* Tool wear monitoring is difficult because so many factors affect the signals collected, i.e. tool type, cutting depth, cutting speed, feed rate and work piece material. Also in a cutting process many factors can cause distortion in the measured signals, e.g. cutting fluid, changes in the environment, chip formation which is a very dynamic process, and the material and geometry which are not necessarily homogeneous. In addition to the technical boundary conditions described above, the developed solution has to be easy and fast to configure for different environments, since otherwise it would not be used. The solution also needs to rely only on a limited number of transducers of an acceptable price level, so that the solution can be economically extremely well justified. If it is not clear that it will save money, industry will not make the investment. Also, in the end a diagnostic system has to be so easy to use that no special skills are required for taking it into use and interpreting the results.

1.3 Objectives of the research

The main goal of this thesis is to develop tools for practical monitoring and diagnosis of drill wear. For this purpose a number of sub-goals have to be fulfilled. It is necessary to discover which indirect monitoring methods are best for drill wear. It is also necessary to identify which signal analysis techniques work best for this purpose. For practical reasons the diagnosis has to be made automatic, which leads to the use of artificial intelligence and search for a suitable approach. In addition the diagnosis has to be reliable, i.e. the use of a number of signals is tested in order to be able to handle noise in the measurement signals. For practical reasons the automatic diagnosis approach has to be easy to configure in various environments. Due to the large number of tools in an industrial environment, there is a need to develop an approach for handling the great amount of data collected. A method for handling the varying process conditions also needs to be developed. Finally the goal is to be able to predict or make a prognosis of the remaining life time of the drill in order to enable uninterrupted unmanned use of machining tools.

1.4 Contents of the thesis

The thesis is divided into seven further chapters as follows:

Chapter 2 reviews the current state-of-the-art study of drill wear monitoring and diagnosis. Commonly used indirect monitoring methods are described. The most common signal analysis techniques are presented. Following these the diagnosis methods commonly used for drill wear monitoring are discussed.

Chapter 3 describes the test and measuring arrangement together with the test program.

Chapter 4 summarises the results of laboratory tests done with various measuring methods and signal analysis techniques. This chapter also attempts to explain why some measuring signals are better than others and, similarly, why some analysis techniques work better than others.

Chapter 5 presents an extremely simplified dynamic model of the drill and the drilling forces and especially how wear influences these forces. The model is used for artificially producing vibration data. The model provides further understanding about the reasons why certain measuring signals together with certain analysis techniques work better than other methods.

Chapter 6 discusses two possible approaches to automating the diagnosis of drill wear by flexible expert systems. Methods of automatic adjustment of the diagnosis of the tool condition are given special emphasis, as well as how the reliability of the diagnosis can be improved by combining a number of analysed parameters. Also are covered the practical aspects of data management in an industrial environment.

Chapter 7 discusses the findings of the thesis in different areas, i.e. the measuring methods, signal analysis techniques and the diagnosis based on artificial intelligence techniques.

Chapter 8 concludes this thesis and provides some suggestions for future research.

1.5 Scope of the research

The thesis covers all commonly used indirect monitoring methods such as drilling force and vibration, and tries to provide an understanding of which of these methods work best in drill wear monitoring. The direct tool wear monitoring methods that measure tool wear as such are not studied here. The reason is that although many attempts have been made to develop such monitoring methods, they still seem to be too complicated and costly for practical purposes. Similarly the work covers commonly used signal analysis techniques in condition monitoring, and tries to establish their suitability for drill wear monitoring. Neither new measuring nor signal analysis techniques are developed. However, problems related to the noise of measuring signals and the influence of cutting parameters are given a lot of consideration. Also a lot of emphasis is given to the consideration of how the drill wear monitoring and diagnosis can be made easy or automatic in practice even though there are so many factors that influence the monitoring, i.e. cutting process parameters such as drill size, drilling speed and feed and also the influence of the work piece material. For this purpose regression analysis techniques are studied together with fuzzy logic and the hierarchical structure of the diagnostic program.

Although tool wear monitoring in principle has similar challenges for a number of tool types and it could be argued that the same approach could be used, this work concentrates only on drilling, which is the most widely used machining method and which has some specific features that tend to make it more difficult to monitor. These challenges are e.g. the discontinuous nature of the drilling process, the great variation in tool size, the difficulties in positioning the measuring sensors and the complexities of modelling the drilling process.

The actual drilling process and drill wear as a physical phenomenon are not covered in this work, i.e. only the indirect monitoring signals are studied. Similarly the developed simulation model does not try to model the drilling forces in such a way that these could be used for the machining process. Instead, it merely tries to mimic the features of the measuring signals based on some characteristics of the drilling process.

The aim of the developed approach is not to differentiate between types of drill wear such as chisel, corner, crater, flank and land wear. The purpose is simply to detect whether the drill starts to get so worn that is should be changed. In addition tool breakage, which is the typical failure mode of smaller size drills, is not covered.

1.6 Scientific contribution of the thesis

The scientific contribution of the thesis can be summarised as the development of an automatically adaptive diagnostic tool for drill wear detection. The new approach is based on the use of simplified fuzzy logic and higher order polynomial regression analysis, and it relies on monitoring methods that have been tested in this thesis. The diagnosis program does not require a lot of memory or processing power and is thus capable of handling a great number of tools in a machining centre. The work consists of:

- Extensive testing of monitoring methods and signal analysis techniques. Evaluation of the best combination of monitoring methods and signal analysis techniques for drill wear monitoring.
- A simplified simulation model has been developed which can be used to produce data with features similar to real data, thus the model helps to understand why certain analysis techniques work and others do not. Especially the importance of natural vibration modes of drills and the influence of drill size on these becomes apparent with the model. This model can be used in the definition, training and testing of an automatic diagnostic tool based on artificial intelligence.
- The development of higher order polynomial regression functions with a limited number of terms which can be used for filtering the monitoring signals, i.e. they remove individual peaks from the measuring signals. The regression functions also reduce the amount of data that needs to be saved, i.e. only the summary terms of the regression functions need to be saved in order to be able to follow the trend of the monitoring signals.
- The introduction of a term into the regression functions, which controls the amount of emphasis that older data is given, compared to the current data. This feature makes the regression function fast enough to react to the rapidly developing increase of monitoring signals at the end of the

drill life. It also enables to some extent the feature that monitoring signals can adapt to changes in cutting parameters or to a change of work piece material.

- The regression functions can be used to give a prognosis of the remaining lifetime of the drill at the end of the drill life. In theory, this kind of prognosis could in fact be done fairly early assuming constant cutting conditions and homogeneity of the work piece material. However, in practice the warning of the end of the drill's lifetime is given in terms of a few percent of the total lifetime prior to the final end.
- The development of an automatic diagnosis method based on the use of multiple signals and a simplified fuzzy logic approach.
- The use of hierarchy in the diagnostic approach in order to make it possible to combine signals and parameters from a number of sources, such as the tool wear monitoring parameters and cutting process parameters.

2. Drill wear monitoring

Successful tool wear monitoring requires that a number of technical tasks are understood and handled. The wear process must be understood in order to be able to use proper monitoring signals and signal analysis techniques. Diagnostic methods that can analyse the state of the tool automatically must also be understood. Because of the complexity of the problem many different types of approaches have been developed and tested. There exist a few good summaries and reviews of what has been published in the technical literature in this field, such as those by e.g. Rehorn et al. [2004] and Byrne et al. [1995]. Dimla et al. [1997] give a review of neural network solutions and include information about the sensor signals used. In an older review, Cook [1980a] lists both direct and indirect methods that have been used for tool wear monitoring and provides literature references. Also the somewhat older review by Tlusty & Andrews [1983] focuses on sensors used in unmanned machining. Li & Mathew [1990] give a good summary of wear and failure monitoring techniques that have been used in turning, which is the most widely studied machining process as regards tool condition monitoring [Jantunen 2001]; it is probably the easiest to monitor because the work piece rotates rather than the tool. There is also a database [Teti 1995] of references related to tool condition monitoring, which inspired the compilation of the database reported by Jantunen [2001]. Publication I gives a more thorough summary and publication III discusses the benefits of various measuring signals and signal analysis techniques. Drill wear is also covered in publication VII.

2.1 Drill wear

Tool wear, and especially drill wear, is a rather complicated phenomenon. Drilling operations differ significantly from turning and face milling for several reasons [Rehorn et al. 2004]. The major difference is the fact that drilling is a complex three-dimensional material removal operation, unlike the relatively simple cases of orthogonal and oblique cutting. Drills have vastly different geometries compared with turning and face milling tools. They are usually much longer than a turning cutter and have far less cross-sectional area than a face milling cutter. Drilling operations are different in that they require the full immersion of the tool, rather than operating on the periphery or surface as is the case in face milling and end milling. Altogether seven different types of drill wear can be recognised [Kanai & Kanda 1978]: outer corner wear, flank wear (actually two types), margin wear, crater wear, chisel edge wear and chipping at the lip. Because of adhering material many of these wear types are in practice difficult to measure; therefore the outer corner wear has been used as a measure of drill wear since it can be easily and reliably measured [Kanai & Kanda 1978]. It is not within the scope of this work to try to measure directly or to increase the understanding of what happens when a drill gets worn. Instead, it is recognised that in principle drill wear is an accelerating process that takes place at the outer margin of the flutes of the drill due to intimate contact and elevated temperatures at the tool work piece contact [Thangaraj & Wright 1988]. Thangaraj & Wright [1988] explain that there is a period of initial wear, then a period of moderate wear and in the third phase a period of excessive wear. Due to production variations, a new drill is typically slightly asymmetric. Accordingly, the two corners of the drill point wear gradually while the maximum wear alternates from one cutting edge to the other. This alternating process continues until both lips have zero clearance at the margin. The drill then adheres to the work piece and breaks if the cutting process is not stopped in time. In addition, chip flow creates significant friction between the cutter and the work piece inside the drill hole. These frictional forces can significantly change the dynamics of the system and they can cause the cutter to break [Rehorn et al. 2004]. Drills, like other cutters, can fail due to either breakage or excessive wear. Based on tests it has been determined that drills of a diameter less than 3 mm tend to fail by fracture, while larger tools will fail through excessive wear [Thangaraj & Wright 1988]. In tests reported in the literature there is often great variation in the wear development of the tested drills, as in the tests with 160 drills reported by Kanai & Kanda [1978].

Drill wear is a highly complex phenomenon, and in the published literature no model exists that could describe it well enough to form a basis for drill wear monitoring. There are studies that describe the principles of tool wear in machining, such as those reported by Zhang et al. [2001] or Bhattacharyya & Ham [1969] who develop an approach to model flank wear. This model discusses the influence of various wear modes (adhesion, abrasion) and the influence of temperature but it does not look at the dynamics. It should be noted that this type of study usually concentrates on turning, which is a much more stable process than drilling. Material has been published on how to evaluate the lifetime of a tool, for example by Cook [1980b]. There are models that can be used to calculate the drilling forces, e.g. in the work by Williams [1974] or Watson [1985a, 1985b, 1985c, 1985d] for the estimation of static force components. In the references the geometry of the drill is taken into account sector by sector and a computer program to calculate the feed and the torque is presented. Liu [1987] presents a model to calculate the thrust and torque of multifacet drills as a function of drill geometry based on the summation of terms calculated for a number of segments. Chandrasekharan [1996] takes into account the drill geometry and his model is capable of predicting the drilling forces in the different phases of drilling a hole (tool entry, cutting lips only, entire drill). Also the rotational effects can be modelled. Following the principles shown by Chandrasekharan [1996], Yang et al. [2002] introduce dynamics into their model. Many of the references studied in this thesis show how important the dynamics are in drilling and how the dynamic response increases as a consequence of drill wear. Rotberg et al. [1990] show the most important vibration modes. They suggest that the spikes in vibration monitoring of drills are generated when the drill tends to stick in the work piece for a very short instant (stick slip) and as a consequence the drill tends to unwind. In this phenomenon both torsional and compressive stresses are included. As the twist increases, the drill releases and continues cutting and hence the impulsive nature of vibration is introduced. It is suggested that this phenomenon becomes increasingly severe as wear develops.

2.2 Monitoring methods

A great variety of monitoring methods have been used and tested for tool wear monitoring. In principle there are two possible approaches, i.e. direct and indirect methods. Direct methods measure tool wear directly, which means that these methods actually measure tool wear as such. Unfortunately these direct methods that can be based on visual inspection or computer vision etc. have not become economically or technically advanced enough for use in industry, therefore they are not studied here. Instead of wear, indirect monitoring methods measure something else which must be a function of wear. Publication I gives a summary of indirect monitoring methods that have been applied to tool condition monitoring in drilling. The following chapters give a brief description of the most widely used monitoring methods and try to explain why these methods can be expected to work. A brief description is given of the most commonly used measuring methods, signal analysis techniques and fault diagnosis approaches.

2.2.1 Torque, drift force and feed force

Measuring of cutting forces is very popular in all types of cutting processes. In the summary given in publication I the measurement of feed force is the most popular method used in drill wear monitoring tests. The second most popular method is to monitor torque. It is logical to monitor the cutting forces since they increase as a function of wear as reported e.g. by Lin & Ting [1995], Pan et al. [1993] and Subramanian & Cook [1977]. In theory, drift force would not work in the case of twist drills with two cutting lips, since these two cancel the influence of each other and the forces are in equilibrium and thus no indication of drill wear should be seen. However, due to production tolerances the cutting lips are not exactly identical and a drill is slightly asymmetrical. Therefore, it only wears at one lip until the height of both lips is equal [Barker et al. 1993, Braun et al. 1982, El-Wardany et al. 1996]. The second lip, which is now sharper, starts to cut and this process of alternating the cutting lip continues until neither lip has any more clearance at the margin. Although the measurement of cutting forces has been a very popular and successful monitoring method in laboratory tests, there is a drawback related to their use in normal production. The measurement of cutting forces is not easily arranged between the tool, tool holder and spindle. A force or torque transducer is relatively big and possibly makes the change of tools more complicated.

Aatola et al. [1994] gain the best indication of drill wear with feed force and torque measurements, but at the same time they suggest that the big and heavy force and torque transducer used in the tests might have had an adverse influence on the measured vibration. Another option is to make the measurement of drilling forces from the other direction, i.e. below the table where the work piece is positioned. Unfortunately this kind of measurement chain is somewhat longer so that the forces are measured further away from the drill.

Von Nedeß & Himburg [1986] show the dynamic effects including the influence of the machine tool and the machining process on drilling and their influence on the feed force and torque. They point out that the drill wear causes a much higher increase of the dynamic components compared to the increase of the static forces. König & Christoffel [1980] have reached a very similar conclusion, i.e. the dynamic components of thrust force and especially torque are considered good indicators of drill wear. In the same reference torque is also considered good in indicating the risk of tool fracture, whereas thrust force is considered to indicate the actual tool breakage better when it has already happened. Also Christoffel & Jung [1981] explain how drill wear can be monitored indirectly with the dynamic components of thrust force and torque. They also explain the self-exciting nature of the dynamics. Brinksmeier [1990] points out the importance of being able to measure the dynamic changes of torque signal in order to monitor drill wear and fracture. For measuring the higher frequency content in a torque signal, a new sensor based on eddy current technology is introduced. However, the tested version of the new sensor is relatively big and not suitable for monitoring drills with a smaller diameter. Brinksmeier [1990] predicts that the size of the sensor can be reduced, enabling a wider size range of drills to be monitored.

Li et al. [1992] verify that the dynamic components of feed force and torque give a clearer indication of tool wear than an increase in the average level. In this case an attempt is also made to define the rules of how different wear modes (chisel, flank and corner) can be distinguished from each other together with the capability of detecting tool breakage. The dynamic influence in thrust force and torque is also emphasised by König & Christoffel [1982]. With a drill diameter of 8 mm they demonstrate how big the change is in the spectrum of thrust force at a frequency of 1050 Hz. It is also pointed out how great the difference is in the roundness and shape of the drilled hole of a sharp drill and a worn drill, the difference being linked to the radial vibration of the drill.

McPhee et al. [1995] emphasise to the frequency content of the drilling power measured using a dynamometer. The drills in question are coated. It is noted and measured in the study that the dynamometer has a remarkable influence on the vibration response of a drill. In that study the most interesting frequencies with a 6 mm diameter drill are around 800 Hz which is related to the dynamics of the dynamometer, and around 2250 Hz which is considered to be linked to the drill. It is concluded that frequency analysis may assist in distinguishing between jamming and failure.

Lenz et al. [1978] have studied the influence of wear on drift forces. In their study, however, the feed force and torque do not give a similar indication. The results seem to support the idea that during drilling, the cutting moves from one lip to another as discussed previously.

2.2.2 Vibration and sound

Vibration is the most widely used measuring method in condition monitoring of rotating machinery. However, it has not been as popular in drill wear monitoring, possibly due to the amount of noise in a typical cutting process. Vibration measurement is easily arranged, since an accelerometer can easily be installed close to the spindle bearing and no modifications of the machine tools or the work piece fixture are needed [El-Wardany et al. 1996]. There is no effect on stiffness and damping properties of the drilling system and the sensor can also be mounted on the table close to the cutting action [Abu-Mahfouz 2005]. Abu-Mahfouz [2005] points out that accelerometers, when properly shielded, have good resistance against coolants, chips, electromagnetic and thermal influences. It is logical to expect vibration measurements to react to tool wear, because if in a dynamic system such as the machine tool the cutting forces increase, the dynamic response will also increase. As explained in the previous chapter, the drift forces can be used for monitoring drill wear, and these forces are also the cause of increasing vibration as a function of wear. Unfortunately there are a number of drawbacks related to vibration monitoring. Besides the influence of tool wear, the vibration signal is influenced by the work piece material, cutting conditions and machine tool structure.

Abu-Mahfouz [2003] has used vibration measurement to detect drill wear and also to differentiate between different types of wear, i.e. chisel, crater, flank, edge and outer corner wear. Narayanan et al. [1994] concentrate the diagnosis of drill bit wear on higher frequencies around 10 kHz. From their results it seems clear that the best indication of drill bit wear is seen at these frequencies. However, the geometrical details of the tool and tool holder are not reported and there is no explanation of the reasons why these frequencies are the best for drill bit wear monitoring. Also Barker et al. [1993] used vibration acceleration for monitoring the wear of drill bits, which were for drilling holes into electronic circuits.

Similarly to vibration, also sound can be used for drill wear monitoring. Mechanical vibration of the machine tool, tool holder and tool is partly transferred to airborne vibration, i.e. sound. Consequently the same information observed from vibration signals can be obtained from sound measurements recorded with a microphone. Sound measurements, although very easy to perform, have not been widely used, probably because they are affected by noise to an even greater extent than vibration measurements. In the tests covering a number of monitoring methods reported in publication II, vibration monitoring was the most effective method.

2.2.3 Acoustic emission and ultrasonic vibration

In addition to mechanical vibration up to 20 kHz, a higher frequency range has been used for monitoring drill wear. Vibration measurements in the frequency range 20–80 kHz are in the literature called ultrasonic vibration [Hayashi et al. 1988]. The use of ultrasonic vibration has been justified by pointing out that at lower frequencies structural vibrations are dominant, and that higher frequencies suffer from the joints commonly found in machine tools; thus ultrasonic vibrations are especially suitable for e.g. drill breakage detection. There are a few other studies, such as those by Kutzner & Schehl [1988], König et al. [1992] and Schehl [1991], which describe the results with ultrasonic vibration measurements, but the technique has not been widely used. It should also be noted that in these studies the emphasis is on such a low frequency range (most of the information was obtained at frequencies below 60 kHz) that although König et al. [1992] and Schehl [1991] describe it as acoustic emission, some others would call it ultrasonic vibration.

It is interesting to note that results reported with drills with very small diameters from 1 to 3 mm are good with this technique. König et al. [1992] point out that with such small drills the spindle current does not work, cutting forces do not give as good an indication as acoustic emission, and especially with the smallest drill diameters it is not possible to predict the upcoming tool breakage; acoustic emission does, however, give some indication even with such small drills. In another study [König et al. 1989] the same research team recommends the use of the frequency range 5–40 kHz.

König et al. [1992] discuss the advantages of using acoustic emission in monitoring drill wear, especially that of small drills. However, their signal analysis technique of a band passing the signal in the frequency range 1–5 kHz actually means that this kind of measurement is normally defined as mechanical vibration, although the used sensor is capable of measuring higher frequencies up to those defined as acoustic emission. Waschkies et al. [1994] suggest the use of an average value of acoustic emission measured in a wide frequency range of 0.1–1 MHz for drill wear monitoring.

2.2.4 Spindle motor and feed drive current

Spindle motor current is in principle related to measuring torque, although the measuring chain is longer. Similarly, measuring the feed drive current can be considered identical to measuring thrust force, although again through a longer measuring chain. Since they are so easy to measure, both the spindle motor current and feed drive current have been used relatively widely in test, e.g. by Adamczyk [1998], Li [1999], Ramamurthi & Hough [1993] and Routio & Säynätjoki [1995]. Li [1999] reports good results with spindle current and feed force current monitoring of breakage of small drills. The tested drills have a diameter of 1–4.5 mm, i.e. they are so small that the breakage is the typical failure mode [Thangaraj & Wright 1988].

Ramamurthi & Hough [1993] use the spindle motor current and feed motor current for tool wear detection with good results. In this case these signals are used together with thrust force measurement, which is used to predict tool failure. One of the purposes of their study was actually to test whether the current sensor would be sufficient for drill wear monitoring, since it is cheaper and easier to use than other measuring methods. From this it is concluded that if wear is not diagnosed then tool failure is predicted or vice versa, i.e. in this case the combination of two measuring techniques improves the reliability of the diagnosis.

Kim et al. [2002] predict the flank wear of a twist drill based on measured spindle motor power. The developed theory starts from the model reported by Williams [1974]. The cutting torque is divided into three components, i.e. lip, chisel and margin components. Of these only the lip component depends on the flank wear of the drill. This dependency is shown to be remarkable. In the tests the accuracy of predicting the drill wear for a drill with a 4 mm diameter was 0.02 mm for flank wear, whereas the flank wear criterion requiring drill replacement was 0.18 mm. Because of the structure of the model, also the effect of the feed rate change can be handled.

Adamczyk [1998] emphasises to the disengagement phase of the drilling process. In this phase both the feed drive current and spindle current were highly correlated with the flank, corner and margin wear of a drill with a 10 mm diameter. In fact the correlation was higher with current measurements than with acceleration measurements. The results reported by Routio & Säynätjoki [1995] on the use of spindle power for drill wear monitoring are not encouraging.

2.3 Signal analysis techniques

Various signal analysis techniques have been used in the context of drill wear monitoring. It is very important what kind of signal analysis technique is used. In principle the signal analysis tries to identify the meaningful part of the signal that is giving an indication of wear, and to remove the noise, i.e. parts of the signal that do not contain or show a wear-related trend. The used signal analysis method should be quick to perform, because during drilling the wear progresses very rapidly towards the end of the tool life, as explained in Chapter 2.1 of this thesis. In a case where drill wear is monitored in a machine tool where a great number of tools might be used, the amount of data that needs to be saved in relation to signal analysis is of some importance. Thus if a lot of information needs to be saved in order to follow the trend in parameters calculated with the signal analysis as a function of wear, the hardware must have sufficient data storage capability. The following chapters give a short introduction to the most important signal analysis methods and how they have been used in the reported literature. Publication I gives a more thorough presentation of the current use of various signal analysis methods in drill wear monitoring.

2.3.1 Time domain signal

The time domain signal is the first thing that is seen when a measurement is performed. Typically today the measurement is performed using a computer with an AD card or with some measuring equipment that performs the AD conversion. Already at this stage the frequency at which data is gathered influences the result, i.e. if data is gathered at a lower frequency than what the transducers can measure, this actually means that information at high frequencies is not properly treated. It is not practical to save the raw time data for long periods of time and for a number of tools. Typically some statistical parameters are calculated from the time domain raw data, and these parameters are then saved and used for diagnosis of tool wear. When calculating the statistical parameters the choice of sample length influences the results. The root mean square (rms), arithmetic mean, standard deviation and kurtosis are examples of time domain statistical parameters. Formulae for calculating these parameters are found in a number of books, e.g. that by Press et al. [2002] which also gives the computer code in C++ to calculate the most typically used parameters.

Noori-Khajavi [1992], Noori-Khajavi & Komanduri [1993] and Noori-Khajavi & Komanduri [1995a] used mean value and variance with force and torque transducers. In these tests no correlation with drill wear was found in the time domain. Lin & Ting [1995] have used average values of thrust force and torque. The test material was used for developing a model to calculate the force and torque as a function of drill feed, diameter and wear. The authors conclude that the models can be used for wear estimation. Liu & Anantharaman [1994] used average, peak, rms values and the area of thrust and torque with success. Radhakrishnan & Wu [1981] used mean, peak and standard deviation values of thrust force and torque signals. In these tests the standard deviation, which in practice is the same as the rms value, proved to be the best indicator of wear.

Thangaraj & Wright [1988] calculated the mean, standard deviation and maximum values of thrust force sampled at a low frequency of 40 Hz for each hole. With this kind of approach the maximum value gives the best indication of wear. The results with mean, minimum and maximum values of cutting forces reported by Valikhani & Chandrashekhar [1987] are not promising. The statistical parameters were measured for each hole. It is noted that the fluctuation of forces increases with drill wear, which could give grounds for drill wear monitoring. Tansel et al. [1992] report good results in monitoring the breakage of micro-size drills using average and standard deviation values of thrust force. In this case the statistical parameters were studied in four different segments of drilling a hole. Ramamurthi & Hough [1993] used a number of statistical parameters in connection with spindle and feed motor current together with thrust force. The statistical parameters are the rms value (spindle motor current), mean value (thrust force) and rms value of the high pass filtered signal (feed force current) together with a parameter that indicates the increase in each of these as a function of drilling time/wear.

Schehl [1991] used band pass filtered rms values of acoustic emission with success. König et al. [1992] suggest the use of band pass filtering of acoustic emission together with the use of a rectifier. The technique has the advantage that in this way acoustic emission signal can be gathered at a relatively low frequency, which makes the measuring and analysis equipment much cheaper. Routio & Säynätjoki [1995] have used maximal stable values of feed force, torque, spindle and feed drive current. In these tests the indication of wear and tool failure was observed very late because the analysed signals were almost constant until they rose very dramatically in the last hole. El-Wardany et al. [1996] use the kurtosis value, which is an indicator of peakedness of the signal, together with a new parameter called ratio of the absolute mean value, for analysing vibration for drill wear and failure monitoring successfully. Kutzner & Schehl [1988] suggest the use of a band passed high frequency vibration signal for monitoring small diameter drills. The basic idea is that the rotational natural frequency should lie in this frequency range.

2.3.2 Fast Fourier transform

Fast Fourier transform (FFT) is a means to determine the frequency content of a measured signal. The principles of FFT can be found e.g. in a book written by Randall [1977]. Basically, the idea of looking at the frequency content of a measured signal is based on the concept that at some frequencies wear influences the signal more than at some others; thus FFT serves as a means to eliminate meaningless information and emphasise more meaningful information instead. Braun et al. [1982] discuss the effectiveness of using FFT in the development of a trend index for sound signal monitoring together with the use of an enveloping technique. El-Wardany et al. [1996] use FFT to calculate the power spectrum and also cepstrum. The power spectrum is used for monitoring the drill wear of large drills with a drill diameter of 6 mm. The cepstrum with statistical parameters explained in the previous chapter, are used for detecting the tool breakage of smaller size drills with a drill diameter of 3 mm.

Valikhani & Chandrashekhar [1987] have, alongside the statistical functions explained earlier, also used the power spectrum successfully to monitor tool wear based on the drift force. However, they indicate that the amount of test material is limited and suggest further testing. Govekar & Grabec [1994] used a relatively small number of points, 256 in the time domain instead of the typical 2048, for FFT when measuring torque and feed force. The reason for this choice is apparently the use of neural networks (self organising map) as the following diagnostic tool in the approach.

Noori-Khajavi [1992], Noori-Khajavi & Komanduri [1993] and Noori-Khajavi & Komanduri [1995a] report that use of the power spectral density (PSD) function gave better results in drill wear monitoring than the statistical parameters described in the previous chapter. The PSD function was calculated for thrust force, torque and strain measurement in two horizontal directions. In this case relatively low frequencies from 50 Hz to 300 Hz gave the best results. No individual frequencies were considered; instead the change of area under the PSD plots was used. Barker et al. [1993] tested higher order spectral (HOS) functions calculated for vibration for drill wear detection, and compared these with the normal power spectrum approach. With the tested material the HOS approach gave a higher detection rate of drill wear, although at the same time the false alarm rate also increased.

2.3.3 Other analysis techniques

Envelope detection is one method of signal analysis that has become popular especially in rolling bearing fault detection. Envelope detection is a means of looking at the signal energy contents in a certain frequency range. Typically this range is rather high, i.e. of the order of 10 kHz, and the idea is that by using band pass filtering it is possible to concentrate on the information in this range. Braun et al. [1982]] and Braun & Lentz [1986] suggest the use of envelope detection or a somewhat further developed signal analysis technique which can pick up the information at higher frequencies for drill wear monitoring using sound signal measurements. Hayashi et al. [1988] used envelope detection of high frequency vibration (20 kHz – 80 kHz) together with a statistical parameter called the clipped running mean, i.e. a running mean from which some higher peaks that pass a certain threshold value have been clipped away. Together with this parameter, the number of occurrences of values that are higher or lower than certain limits that have been calculated in relation to the clipped running mean are followed. These then give an indication of tool breakage.

Drilling a hole is not a stable process in that the measured signals vary from the beginning to the end of drilling a hole. Quadro & Branco [1997] recognise five stages and two of these are considered best for monitoring drill wear using acoustic emission. In this study acoustic emission is studied using the measured area under the rectified signal envelope (MARSE). One approach that can be used in signal analysis is autoregressive modelling. Radhakrishnan & Wu [1981] use the autoregressive moving average (ARMA) model for modelling the thrust force and surface waviness. The approach is suggested for use in on-line monitoring of drill wear.

Wavelet transform is another method that can be used to extract meaningful information from the measured time signal. The principles of wavelet analysis can be found e.g. in a book written by Newland [1993]. When compared to FFT, which only gives information in the frequency domain, or the time domain parameters, which only contain information in the time domain, a wavelet can be considered to include both of them, i.e. information in the time-frequency domain. Li [1999] used wavelet transform for drill breakage detection based on AC servo motor current measurements of all four axis motors. The drill size in the tests was small, from 1 mm to 4.5 mm in diameter. However, the diagnosis was passive, i.e. there was no warning prior to actual breakage. Tansel et al. [1993] used wavelets to diagnose a severely damaged micro drill from a new one. The monitored signal was thrust force. Again there is no indication whether a warning was obtained prior to the drill being severely damaged. Hiebert & Chinnam [2000] used wavelets to analyse the thrust force and the torque. Some of the wavelet parameters were used as input into a neural network, which aimed to diagnose the degradation of drill bits. The reliability of the method is discussed and it is noted that since many degradation signals increase in slope as they approach failure, the accuracy of failure predictions should increase when approaching the critical limit.

Abu-Mahfouz [2003] combines and also compares, in the case of a vibration acceleration signal, the effectiveness of statistical time domain parameters such as mean, variance, skewness and kurtosis, together with parameters calculated using discrete harmonic wavelet transform and the eight highest peaks calculated with the Burg power spectral density function. In the approach, different types of wear can be detected and in that study the parameters calculated with the wavelet transform proved to be superior compared to the other methods.

2.4 Fault diagnosis systems

Today machining processes are usually automatic and unmanned. However, various types of problems or faults in the process necessitate manual intervention. Tool wear and breakage is one of the factors that prohibit fully automatic production in three shifts. If tool wear and breakage monitoring is used, in practice it needs to be automatic, i.e. the system used for tool monitoring needs to be able to diagnose the condition of the tool automatically, which means that some sort of artificial intelligence is involved.

Tönshoff et al. [1988] define the components that are needed in a tool wear monitoring system: sensor, signal conditioning, model and strategy. The three first components are covered in the previous chapters. Strategy means that different actions are taken based on the monitored signals. A monitoring system only gives an indication or alarm if the signals reach a certain level. A diagnostic system tries to find a functional or causal relation between the failures in machining and their origin. Adaptive control systems automatically adapt machining conditions according to a given strategy. Tönshoff et al. [1988] also point out the advantages and challenges of multi-sensor systems, and how they bring more information. At the same time the importance of building multi-model systems is explained. It is claimed that the use of more sensors and models results in a more reliable and more flexible supervising process and increases the feasibility of better control.

Ertunc et al. [2001] employed Hidden Markov Models (HMM), which have successfully been used in speech recognition, for drill wear detection based on thrust force and torque. In the approach three different stages of the tool were recognised, i.e. sharp, workable and dull. It is suggested that different models should be defined for different cutting conditions since these influence the results. In addition to the HMM approach, Ertunc & Oysu [2004] tested a so-called phase plane method. They report that one of the benefits of this approach is its simplicity, since the thrust force is plotted as a function of the torque, and if the tool is in a normal condition the plotted results stay within a predefined rectangle. The authors state that even though the method is very simple, it does give satisfactory criteria for monitoring tool wear.

Liu et al. [2000] report the results of using a polynomial network for predicting corner wear in drilling operations. The input parameters are cutting speed, feed rate, drill diameter, torque and thrust force. The development of a polynomial network is rather straightforward, but it means that the network is first trained with suitable data. Liu et al. [2000] had 27 training cases and eight test cases. It is concluded that the use of thrust force gives a more reliable indication than the use of torque. The difference between the predicted corner wear and measured corner wear was less than 10% with the test data.

2.4.1 Predefined limits / rule based systems

The simplest way to automate the diagnosis of tool condition is to use predefined limits for the measured signals and parameters calculated from those signals. This means that if a parameter value exceeds the limit given to it, the tool is considered worn. The approach can be made more reliable by combining the information from various sensors and/or calculating a number of parameters of these signals. This information can be combined with the information from the cutting process parameters, e.g. using the so-called rule based approach in building rules, i.e. the knowledge base, so that a number of conditions need to be fulfilled simultaneously. One example could be that if the drill diameter is more than 4 mm and less than 5 mm and the drilling speed is … and … etc then …. Erdélyi & Sántha [1986] describe the principles of this kind of approach in general for a production cell. Publication V addresses the principles of this type of approach in greater detail for tool wear monitoring.

The use of sophisticated analysis methods can be seen as one attempt to make the use of predefined limits more reliable and possibly more general. If the parameter that is used to detect tool wear is insensitive to other factors, such as the cutting speed, it is easier to build rules that define the condition of the tool. This highlights one drawback of the rule based approach. If many different types of tools are used in the machine tool, it might be very laborious to build a rule based expert system that can detect tool wear and warn of the upcoming breakage. However, the rules might also be very simple for each machining state/tool and one way to define the limits is simply to define them manually for each tool type.

Another possibility to make the definition of limits more general is to use trending, which means that the parameter values are saved when the tool is in good condition and the limits are defined at the beginning for the relation of the current measurement to the measured value. For example, Thangaraj & Wright [1988] use the gradient of the thrust force and state that the proposed control system does not require considerable tuning for operation under a wide range of cutting conditions. Another example is given by El-Wardany et al. [1996], who perform the more sophisticated analysis only when a certain parameter reaches a predefined value compared to the initial value. Also Lechler [1988] discusses the definition of limit values and how they can be used for tool wear and fracture monitoring with various force and strain based sensors. They point out how important it is for the personnel to have sufficient training.

Adamczyk [1998] suggests a relatively simple combination of rules based on standard deviation values of the feed drive and spindle current for the stable and transient phase of drilling. Basically, if a simple condition is fulfilled in both conditions the drill is considered worn. Adamczyk [1998] shows a simple procedure for combining information from three different sensors (two current and one accelerometer). Takata et al. [1986] present some results with the pattern recognition technique, which is based on speech recognition. The signal measured and analysed with a sound sensor forms a 16 x 16 time/frequency pattern which can be used for defining the cutting state and detecting a broken tool. Tönshoff et al. [1988] describe the principles of building a rule based approach that relies on the information from three different types of sensor: force, temperature and vibration.

Li et al. [1992] use a simple rule set based on the relationship between the current value and the average value of feed force, torque and their dynamic components. One of the advantages of the approach is that there is no need for training or definition of the limits; instead they are calculated for each of the monitored tools. The rule set can also distinguish between various types of drill wear. However, the approach has been developed based on only four tested drills, which unfortunately raises the question of how general the results actually are.

2.4.2 Fuzzy logic

The rules in rule based systems are usually crisp but they can also be fuzzy, i.e. not exact. The principles of fuzzy logic can be found e.g. in a book by Rao & Rao [1993]. Li & Wu [1988] categorise drill wear into four fuzzy classes: initial, small, normal and severe. In this approach fuzzy limits are defined based on an algorithm used for clustering thrust force and torque data. When the data is analysed, the result is not crisp but shows membership to each of the four classes. The approach works, although only two test cases are shown. In the approach, only the parameters (rms value) related to thrust and torque are used and a so-called c-mean algorithm is used for defining the relationship between the tool conditions and the measured parameters. Du et al. [1995] describe the c-mean algorithm in a more general form together with other possible approaches to linking together the measured parameter values and state of the tool. Xiaoli & Zhejun [1998] used this kind of approach for monitoring tool wear during boring. The monitored seven parameters in this case were from wideband AE measurements which had been treated using wavelet transform. The seven parameters were actually a set chosen from 16 frequency bands. The authors conclude that the proposed approach can give a high success rate over a wide range of cutting conditions.

Du et al. [1995] justify the use of fuzzy classification by claiming that for dealing with uncertainties inherent in the metal cutting processes, fuzzy systems offer the advantage of providing systematic means for describing the relationship between tool condition and various process signatures. Fuzzy logic can also be used in connection with neural networks for pre-processing input data into the network and/or post-processing the output of the network [Rao & Rao 1993].

Li & Tso [1999] develop regression models for spindle motor current and feed motor current as a function of cutting variables, i.e. cutting speed, feed rate and drill diameter, for various flank wear states. Using fuzzy classification it is then possible with the test data to predict the membership in three different wear states. The number of definition cases for development of the regression functions is 12. In this set eight cutting speeds are used together with five feed rates and three drill diameters. The number of test cases is also 12. The result is considered good since the grade of membership function associated with the relevant flank wear states is always close to unity. However, although the results in the paper are considered good, the relatively small number of test cases compared to the number of input parameters raises some questions about the generalised nature of the methodology.

Li et al. [2000] used fuzzy logic together with neural networks. In this case drill wear is monitored using vibration acceleration. The rms value in five separate frequency bands between 0 and 2500 Hz are used as input features. Drill wear is categorised in five different classes: initial wear, normal wear, acceptable wear, severe wear and failure. It is concluded that a fuzzy relationship between the tool condition and monitoring may be identified by using a fuzzy neural network. However, the recognition rate for initial wear is reported to be 52% and for severe wear 68%. Drill failure and air cutting have been recognised at a rate of 100%.

2.4.3 Neural networks

Neural networks have become very popular in industry because of their classification and optimisation capabilities [Dimla et al. 1997]. Neural networks can be seen as an attempt to automate the process of building a diagnostic system. In principle neural networks can be trained to model non-linear dependencies of manufacturing process parameters and parameters which indicate tool wear and failure. The principles of neural networks can be found e.g. in a book by Rao & Rao [1993]. Dimla et al. [1997] critically examine 37 approaches that have been tried with different types of neural networks in order to diagnose tool wear and breakage in various types of machining processes. The success rate is tabulated based on references. Some of the main conclusions by Dimla et al. [1997] are: The most widely tested neural network approach is a so-called multilayer perception (MLP) network. MLP networks are particularly suitable for high-speed real time applications. In many cases more than one feature has been extracted from one sensor and this is criticised as not really being a multi-sensor approach. Although most of the references claim to be on-line solutions they actually seem to be off-line networks, which have not been tested in a real production environment. In most cases the data has been sampled using only one set of cutting conditions. A tool condition monitoring system needs to be able to handle various cutting conditions.

Liu & Ko [1990] built a simple network comprising two input features and one output. Drill wear was classified into five categories. The inputs were peak to peak acceleration and the percentage increase of the thrust force. They concluded that an on-line recognition level of over 85% can be reached. The limited number of tests did not include variation of cutting process parameters. The same data was used to develop a two-category linear classifier for drill wear detection in studies by Liu [1987] and Liu & Wu [1990]. In this case a success rate greater than 90% is reported for drill wear monitoring in one drilling process condition.

Liu & Anantharaman [1994] tested the influence of the number of hidden layers. In the cases tested the number of input features was nine based on thrust force, torque and one process parameter. It is concluded that artificial neural networks can distinguish between a worn and a usable drill with 100% reliability and also accurately distinguish the average flank wear even under different drilling conditions. However, the authors have not included documented material of the variation of cutting conditions. They compare different versions of the number of neurons in the hidden layer and also a modified version with adaptive activation-function slopes. This modified neural network is reported to converge to a solution much faster than a conventional feedforward network.

Liu et al. [1998] introduced the influence of drill size, feed rate and spindle speed together with the same thrust force and torque parameters used earlier in the neural network solution. They report that the network can reach up to 100% reliability for on-line detection of drill wear states and that it is feasible to recognise the drill wear states on-line even if the drill size, feed rate and spindle speed have changed. However, it should be noted that there was no variation of the work piece material and that the total number of tests was seven, in which five different drill sizes, six feed rates and five spindle speeds were used, which would suggest that the number of test cases was rather small compared to the number of influencing parameters.

Noori-Khajavi [1992], Noori-Khajavi & Komanduri [1993] and Noori-Khajavi & Komanduri [1995b] use neural networks for sensor signal integration. This is done based on torque, feed and drift force signals. Noori-Khajavi [1992] shows that it is not advantageous to integrate information from these because they are equally good and contain the same information of drill wear. Govekar & Grabec [1994] use a self-organising neural network. Torque and feed force spectra are further treated so that the low frequency information below 200 Hz is left out and the information at higher frequencies is combined into 30 representative bands. They conclude that the approach is promising. The effect of cutting process parameters is not covered.

Tansel et al. [1992] tested a different kind of neural network called a restricted coulomb energy (RCE) network for drill wear diagnosis in micro drilling. The theory of RCE network is explained in their report. The drilling of each hole is divided into four segments and the average and standard deviation of feed force is used as the input features, i.e. altogether eight inputs. The RCE network recognized tool failure with an accuracy of over 90%. The processing parameters were not varied, although it is pointed out that the feed force varied a lot from test to test. The same test data as in the previous reference has been tested in connection with another type of neural network based on adaptive resonance theory (ART) [Tansel et al. 1993]. In this case the input features were calculated using wavelet transform of the feed force. The approach was tested with two network structures, one with 22 input features and the other with six. The approach with a higher number of input features gave a better indication, only one error in 61 cases, but was slower. Again there was no variation of process parameters.

Tsao [2002] tested two types of neural network solution for flank wear prediction of a coated drill based on maximum values of thrust force and torque. The two neural network methods were radial basis function network (RBFN) and a modified RBFN called adaptive RBFN (ARBFN). With a training set of 18 cases and a set of nine test cases good results were obtained. In the prediction the maximum drill wear error was only 0.4% which is a remarkable result. It should be noted that together with the variation of spindle speed and feed rate, also the drill coating deposition was varied. One thing that is clearly noticeable in the measured data is that the results are very consistent, i.e. the relation between the maximum thrust force and torque with the drill wear is very similar in all three cases for all the varied input parameter combinations, which would indicate that possibly very simple methods could give good results with the measured data.

Fu & Ling [2002] have developed a very basic neural network for the detection of breakage of micro drills. The solution is based on torque signal together with such parameters as the drill diameter, feed and spindle speed. The maximum and average values of torque were used. The approach works with very small drills but is passive in the sense that detection is made only after drill breakage has occurred, which is much easier than making a prognosis of breakage beforehand. There are benefits related to this late detection, although not as remarkable as in the case of prognosis.

Brophy et al. [2002] report the results of a project in which the network developed was based on input from a spindle power signal. In this case a network was developed to detect abnormalities in drilling. The spindle power was treated in the first stage with principal component analysis (PCA) to get the input features for the neural network. After a training phase of 3 weeks the neural network was tested in real production for 3 months. The authors report that the network draws similar conclusions to those of an experienced operator.

Abu-Mahfouz [2003] used a multiple layer neural network to detect drill wear and to differentiate between different types of wear such as chisel, crater, flank, edge and outer corner wear based on a vibration acceleration signal. From acceleration signal statistical time domain parameters together with wavelet based parameters and parameters of Burg power spectral density function were calculated. In the study, different types of architectures of the neural network were tested and also the process parameters, i.e. speed and feed, were varied. The reported results are promising. The percentage of correct predictions was around 80 to 90 when differentiating between the various artificially introduced wear types, and 100 when detecting drill wear. Based on the same measured signal and analysed parameters as described above Abu-Mahfouz [2005] reports the results of two other neural network approaches, namely learning vector quantization (LVQ) and fuzzy learning vector quantification (FLVQ), in detecting drill flank wear. Again the reported results are good with success rates of 86% with LQV and 88.8% with FLVQ. Also in this case the process parameters are varied. The test material was based on drilling tests in dry conditions covering the total tool life [Abu-Mahfouz 2005].

3. Machining tests

The complete test and measuring set-up and the test program are described in detail in publication II. In this chapter the main characteristics of the set-up and the drilling program are described briefly.

3.1 Test set-up

A horizontal-type machining centre was used in the drilling tests for tool condition monitoring. The main specification of the machining centre is shown in Table 1.

Table 1. Specification of the machining centre in the tests.

Machine tool	Niigata EN40B	Spindle nose	NT No. 40 for BT
Control unit	Fanuc 11 MA	Number of tools	30 tools
Controlled axis	4 axis (X, Y, Z, and B)	Spindle speed	15–6000 $^{1}/_{min}$
Table size	400 x 400 mm	Main motor power	11/7.5 kW

3.2 Test program

The twist drill sizes investigated in the tests were: diameter 3.3 mm, 5.0 mm, 6.8 mm, 8.5 mm and 10.2 mm. The drill material was HSS and the work piece material was Fe52. The total number of tested drills was 26. A description of the drilling parameters and monitoring methods is given in publication II.

3.3 Measuring arrangement

In the drilling tests the tested measuring methods included vibration, sound, acoustic emission (200 kHz and 800 kHz centre frequencies and also 100–1000 kHz frequency range), spindle power and current, z-servo current, force measured from guideways, feed force and torque with a dynamometer and 3-axis table dynamometer. In the tests the measuring signals were recorded with a 14 channel instrument tape recorder and analysed afterwards in the laboratory. The measuring configuration was varied during the measurements due to the limitations of the tape recorder, i.e. the number of channels used (12) was not sufficient for recording all the possible signals simultaneously. A more thorough description with a graphical presentation of the measuring arrangement is given in publication II.

4. Signal analysis

A detailed description of the signal analysis methods and results is given in publication II. Some results are also shown in publications III, VI and VII. Due to the great amount of test data, an automatic analysis program for PC was used. The data recorded with an instrument data recorder was analysed overnight with a PC equipped with an AD card. A mathematical programming toolbox MatLab was used for the signal analysis. The signal analysis was done both in the time domain (statistical parameters) and in the frequency domain (FFT analyses). Prior to the signal analysis the data was cleaned of irrelevant signals, i.e. data recorded during rapid movements of the tool prior to actual drilling. Regression analysis was used to rank the different methods used in the tests.

4.1 Statistical analyses

For all of the recorded measuring signals (12 sensors), except for the tachometer pulse used for recording the running speed of the tool, altogether eight statistical parameters in the time domain were calculated. These were: arithmetic mean, root mean square (rms), mean deviation, standard deviation, skewness, kurtosis, maximum and minimum. All of these time domain parameters are easy and fast to calculate [e.g. Press et al. 2002]. Usually they contain the whole frequency content of the measured signals and are therefore rather sensitive to noise, i.e. there is a lot of variation in the measured values. In the case of vibration signals, low-pass filtering was also tested to improve them. In drill wear monitoring the best results with statistical parameters were obtained with the root mean square and mean deviation of low-pass filtered horizontal vibration (cf. publication II). Figure 1 shows an example of the analysed root mean square value of a low-pass filtered horizontal vibration signal in drill wear monitoring.

4.2 FFT analyses

Fast Fourier transform (FFT) was used in the case of dynamic monitoring signals (vibration, force/torque, spindle motor power and sound) that were expected to contain frequency dependant information. A sample and hold card was used together with the normal AD card in order to analyse data simultaneously from four channels. A MatLab mathematical package was used for programming the tested functions. FFT based functions including autocorrelation, spectrum, 1/3 octave spectrum, 1/1 octave spectrum, cepstrum and liftered spectrum were tested for one signal at a time. For simultaneous analysis of more than one signal at a time, the tested functions were frequency response, coherence, coherent output power, cross-correlation, signal to noise ratio, Scot and multi-signal frequency response and partial coherence. In the signal analysis a Hanning window [Randall 1977] was used, as well as time and spectrum domain averaging. In order to save space, normally only the 20 highest amplitudes of each function were saved together with the corresponding frequency. As seen from the tabulated lists in publication II, it makes little difference whether the analysis is based on one or more signals. Due to the large number of analysis functions and analysed parameters, a procedure based on regression analysis was developed for further analysis of FFT based functions in order to define which of the measuring signals and analysis functions could be expected to work best for diagnosing drill wear. Of all the functions analysed with FFT the best results in drill wear monitoring were obtained with a horizontal vibration spectrum.

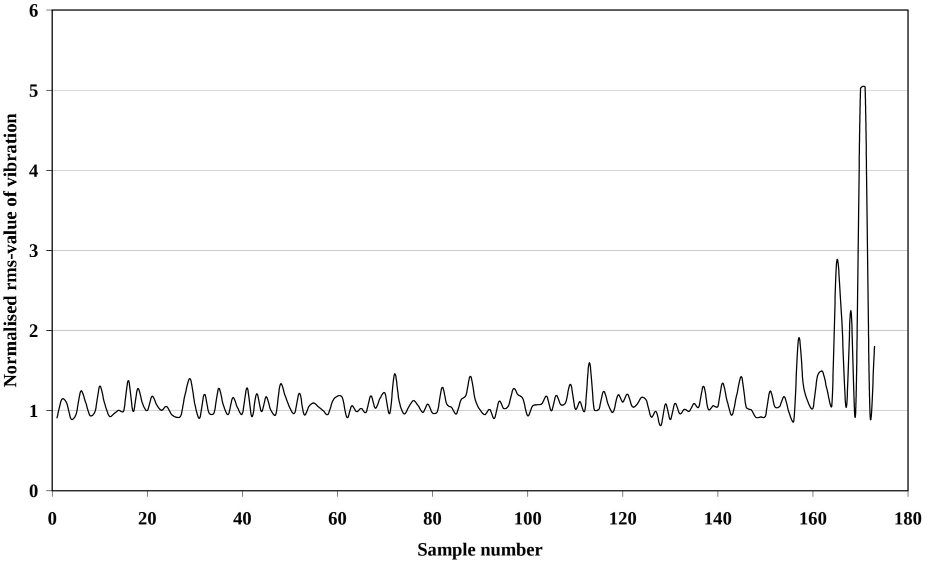

Figure 1. Normalised rms value of vibration (perpendicular to drill axis) for a 10.2 mm twist drill.

4.3 Regression analyses

In order to define which analysis functions work best for drill wear monitoring, regression analysis was used for parameters calculated using both statistical and FFT based signal analysis methods. The four regression analysis functions (1st, 2nd and 3rd order polynomials and a logarithmic function based on the idea developed and reported by Jantunen & Poikonen [1993]) used to rank the signal analysis results are described in publication II. The idea behind the ranking of monitoring parameters was that the coefficient of determination calculated in the regression analysis could be used to define the ranking order of the measuring signals, analysis functions and parameters. Of all the measured signals the best results were gained with horizontal vibration. However, it can be said that the difference is not big and other measuring signals such as sound, force and acoustic emission also worked well. A more detailed discussion of the applicability of various monitoring methods is given in publication III. In publication II the conclusion is that for practical purposes it could be beneficial to use more than one measuring method in order to get rid of false alarms.

The development of a higher order polynomial regression function with a limited number of terms is described in detail in publications VI and VII. The principle of why a regression analysis technique can be expected to help in monitoring and diagnosis of drill wear is explained in detail in publication VI. Basically the idea is simply to mimic the development of the wear curve, which in the case of tools typically develops exponentially towards the end of the tool life. A higher order polynomial regression function with a limited number of terms is defined in its general form by the following equation:

$$y(t) = a \cdot t^{e} + b \cdot t^{f} + c \cdot t^{g} + d \tag{1}$$

where y(t) is the monitored parameter as a function of time. The parameter can be either a statistical time domain parameter such as root mean square (rms) value or an amplitude value at a specific frequency if FFT has been used. In the equation a, b and c are regression coefficients and t is time. The exponents e, f and g define the degree of the function and there is also a constant d in the function. With a proper choice of exponents e, f and g Equation 1 can also be used to define the 1st, 2nd and 3rd order polynomials (with the 3rd order d also becomes a regression coefficient). As shown in publication VI Equation 1 also mimics quite closely the behaviour of the logarithmic regression function, with the difference that with Equation 1 the total lifetime of the drill does not need to be known. The principles of the solution for regression coefficients can be found e.g. in the book by Milton & Arnold [1995].

For emphasising the most recent data, a factor to be used when calculating the summary terms in regression analysis is introduced:

$$p_i = q^{(n-i)} \tag{2}$$

where n is the current total number of samples, i is the index in the calculation of the summary terms, and q is a constant that defines how much weight the earlier terms are given when all the terms in the calculation of the summary terms are multiplied by p. The most important reason for the introduction of factor q is that regression analysis functions tend to become very stable, i.e. they do not react to current data very rapidly if they have been used for some time with similar data. This lack of response is contradictory to what was presented in chapter 2 concerning the rapid development of wear towards the end of the tool life, hence the introduction of factor q is needed.

Figure 2 shows the same data as in Figure 1, analysed using a higher order polynomial regression function with the following parameter values: e = 9, f = 6, g = 3, d =1 and q = 0.99.

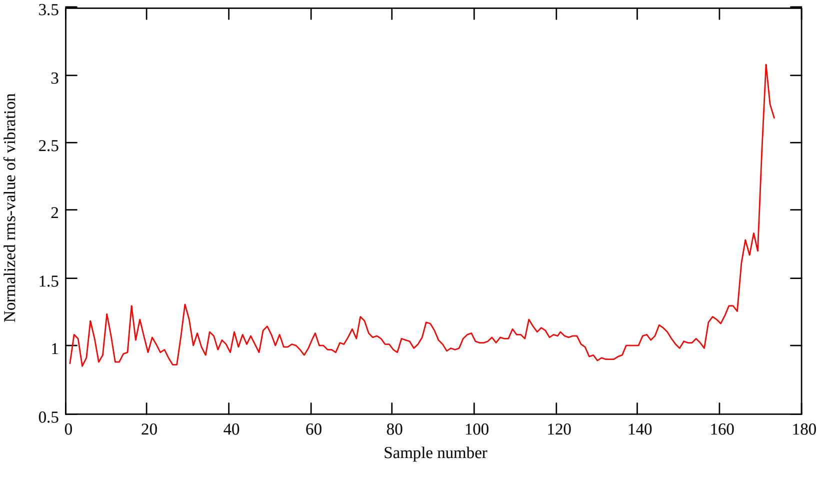

Figure 2. Normalised rms value of vibration (perpendicular to drill axis) for a 10.2 mm twist drill analysed using a higher order polynomial regression function.

5. Simulation model

The development of artificial drilling forces that are influenced by drill wear and a simplified dynamic model that can be used for producing vibration simulation data are described in detail in publication IV. The purpose of developing this simple model was to get a better understanding of the dynamics that influence the drilling process, especially what could happen when a drill is worn. The simulated signals can be used in the testing and training of automatic diagnosis tools. The drilling force model is not supposed to predict the absolute level of drilling forces correctly, consequently it is not of use in the adjustment of machining processes.

5.1 Drilling force model

The artificial drilling force model was developed for calculation of the horizontal drilling force, i.e. the force perpendicular to the axis of the drill. This is also known as the drift force. In principle it should be zero when there are two cutting lips in a drill, since these cancel the influence of each other. However, for a number of reasons the force is not zero in practise, as discussed in chapter 2 of this thesis. As explained in chapter 2, Yang et al. [2002] have treated the dynamics and especially the horizontal vibration of a drill due to the imbalance of forces in their model, which gave the idea for the development of the following simplified model, which is described in more detail in publication IV.

The developed model tries to introduce excitation forces perpendicular to the drill axis at frequencies which might be seen in reality, and also a term is introduced which is a function of drill wear. The simplified horizontal force is calculated according to the following formula:

$$F_x(t) = F_{rpm1}(t) + F_{rpm2}(t) + F_{nrpm}(t) + F_{rnd}(t) + F_0(t) \tag{3}$$

The first two terms in the formula, F_{rpm1} and F_{rpm2}, try to take into account the possible geometrical differences between the two cutting lips and are defined as follows:

$$F_{rpm1}(t) = F_{dp}(t) \cdot \left[c_1 - c_2 \cdot Ln\left(1 - \frac{t}{t_c}\right)\right] \cdot \cos\left[2 \cdot \pi \cdot \omega \cdot t + \phi_{ge} + \phi_{wd} \cdot \sin\left(\omega \frac{t}{c_3}\right)\right] \tag{4}$$

$$F_{rpm2}(t) = F_{dp}(t) \cdot \left[c_1 - c_2 \cdot Ln\left(1 - \frac{t}{t_c}\right)\right] \cdot \cos\left\{ 2 \cdot \pi \cdot \omega \cdot t + \pi \cdot \left[1 + \phi_{wd} \cdot \sin\left(\omega \frac{t}{c_4}\right)\right]\right\} \quad (5)$$

where c1 … c4 are constants, t_c is the total lifetime of the drill, ω is the angular speed of rotation, ϕ_{ge} is the angular geometrical error due to the tolerance in manufacturing the drills, ϕ_{wd} is the difference in wear of the two cutting lips of the drill and F_{dp} is a drilling process force that scales the size of the forces and is defined as follows:

$$F_{dp}(t) = c_5 \cdot H_B \cdot f \cdot F_{dh}(t) \quad (6)$$

where c_5 is a constant, H_B is the Brinell hardness of the work piece material and f is the feed per revolution. The influence of the work piece hardness and the feed follows the statistical model presented by Subramanian & Cook [1977]. However, two terms that take into account the influence of the geometry and wear have been left out since the model described here does not try to predict the cutting forces. It should be noted that the statistical model [Subramanian & Cook 1977] deals with torque and thrust force and the model in this study deals with the horizontal drilling force, which can be estimated to be a function of the thrust and torque [e.g. Yang et al. 2002].

Here the term F_{dh} takes into account the unstable nature of the drilling process, i.e. in the beginning the forces increase when a hole is started, reaching a stable level when the cutting lips of the drill have fully reached the work piece material. F_{dh} is defined as follows:

$$F_{dh}(t) = \frac{t - i \cdot t_d}{\frac{t_d}{b_1}} \qquad \text{if} \qquad i \cdot t_d \le t < i \cdot t_d + \frac{t_d}{b_1} \quad (7)$$

$$F_{dh}(t) = 1 \qquad \text{if} \qquad i \cdot t_d + \frac{t_d}{b_1} \le t \le i \cdot t_d + t_d \quad (8)$$

where t is time, i is a counter for the hole number, t_d is the time it takes to drill one hole and b_1 is a coefficient that defines the relation between the increasing part and the stable part of the thrust force.

The term F_{nrpm} is supposed to describe a number of harmonic components that are multiples of the drilling speed and that can originate from such sources as the bearings and the electric motors of the machine tool in question:

$$F_{nrpm}(t) = \sum_{n=3}^{11} \left\{ F_{dp}(t) \cdot \left[\frac{c_6}{n} - \frac{c_7}{n} \cdot Ln\left(1 - \frac{t}{t_c}\right) \right] \cdot \cos(n \cdot 2 \cdot \pi \cdot \omega \cdot t) \right\} \tag{9}$$

where c6 and c7 are constants, n defines the order of the harmonic component, $F_{dp}(t)$, ω and t_c as defined above.

In order to make the simulation produce signals that also contain random noise, the term F_{rnd} is introduced:

$$F_{rnd}(t) = rnd(c_8) - \frac{c_8}{2} \tag{10}$$

where c_8 is a constant and rnd denotes the MathCad program function [Mathsoft 2002] that produces an equally distributed random number between 0 and c_8.

One phenomenon that can quite clearly be seen and understood is the influence of vibration on the drilling forces, i.e. since the drill is vibrating perpendicular to its axis the drilling forces are also a function of this. The phenomenon can be seen, for example, in the paper by Yang et al. [2002]. The influence of vibration at the natural frequency of the drill is taken into account by the term F_0.

$$F_o(t) = \cos(2 \cdot \pi \cdot f_o \cdot t) \cdot F_{dp}(t) \cdot \left[c_9 - c_{10} \cdot Ln\left(1 - \frac{t}{t_c}\right) \right] \tag{11}$$

where c_9 and c_{10} are constants, t_c is the total tool lifetime, F_{dp} is the drilling force as defined above, and f_o is the first natural frequency of the drill and tool holder calculated using the following formula [Thomson 1972]:

$$f_o = \frac{1}{2 \cdot \pi} \cdot \sqrt{\frac{k}{m}} \tag{12}$$

where m is the mass of the drill and tool holder, and k is the stiffness of the structure. Assuming the drill is a straight round bar that is fixed at one end, the formulae for calculating the natural bending and torsional frequencies can be found e.g. in the book by Young [1989]. For bending, the formula for natural frequency can be written in the following way:

$$f_n = \frac{K_n}{2 \cdot \pi} \sqrt{\frac{E \cdot I}{\rho \cdot S \cdot l^4}} \tag{13}$$

where K_n is a coefficient that depends on the vibration mode, E is Young's modulus, I is the moment of inertia, ρ is the density of the material, S is the cross-sectional area and l is the length of the drill. Making assumptions about the effective diameter and length of a drill, the influence of the drill diameter on the natural frequency can be calculated according to Equation 13. Figure 3 shows the approximate frequency of the first and second bending modes together with the first rotational natural frequency of a drill as a function of drill diameter. As Figure 3 shows, there is a strong dependency of the drill diameter, i.e. the smaller the drill diameter is the higher is the natural frequency. The calculation formula for the natural frequency of the torsional vibration mode is also found in the book by Young [1989]. It should be noted that the torsional natural frequencies are quite a lot higher (more than 10 times) than those of the lowest bending modes.

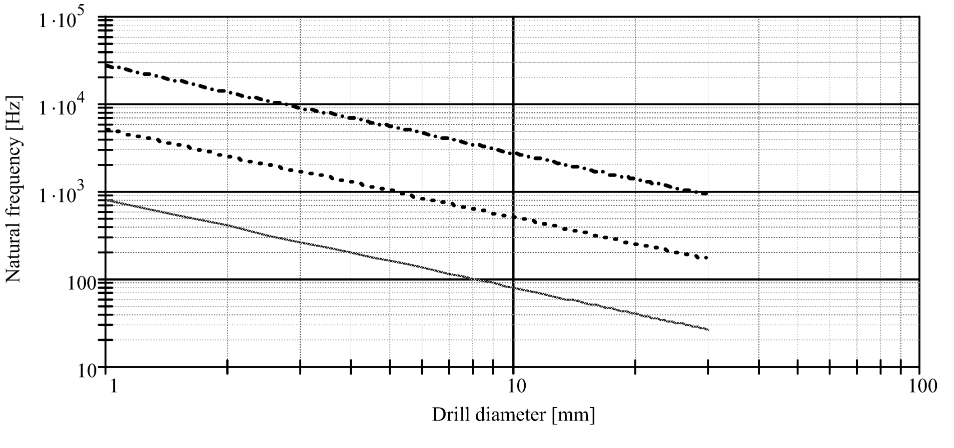

Figure 3. Approximate frequency of the first (lowest line) and second (intermediate line) natural bending vibration modes together with the first (highest line) rotational natural frequency of a drill as a function of drill diameter.

All of the terms described above, except for the random force, are described to some degree as functions of a term, which could be called the wear influence shown in the following formula:

$$h = Ln\left(1 - \frac{t}{t_c}\right) \tag{14}$$

where t is the time and t_c is the total lifetime of the drill. All the terms except for the random term in equation 3 are scaled by a term that takes into account the Brinell hardness of the work piece and the feed of the drill. The influence of drilling separate holes is also included in these terms, i.e. when a new hole is started the forces start from zero again except for the random term.

It is quite apparent in the above development of the simplified simulation model that the model is not a physical one that could correctly predict the horizontal forces in a drilling process. There are many constants in the formulae which were chosen by trial and error when judging the predictions. However, the model can easily be used for producing test data for the development of a diagnostic approach for the automatic diagnosis of drill wear. Based on literature references the model includes terms that could be expected to influence the drilling process but their size as such and relation to each other has no justification through testing.

5.2 Dynamic model

The simplified dynamic model has been developed following the principles presented by Yang et al. [2002]. In the model it is assumed that the tool and tool holder can be modelled as a beam that is rigidly supported at one end and that the excitation force influences at the other end. In their approach Yang et al. [2002] performed the study with two degrees of freedom, i.e. with two differential equations which gave the basis for the iterative calculation of the excitation force. In the present study a model with only one degree of freedom is used and the excitation force is assumed to take into account the influence of the rotating route that the drill travels in the hole during the drilling process. The following basic differential equation describes the dynamic model [Thomson 1972 and Yang et al. 2002]:

$$m \cdot x'' + c \cdot x' + k \cdot x = F_x(t) \tag{15}$$

where m is the mass of the vibrating tool and tool holder, c is the damping, k is the stiffness, and $F_x(t)$ is the dynamic horizontal drilling force as defined in the previous chapter.

Figure 4 shows an example of the calculated vibration acceleration response, together with the excitation force for holes two, three and four. Figure 5 shows the corresponding acceleration response together with the excitation force for the last three holes when the drill was defined as having broken right after the 60th hole. In the examples the following values of input parameters have been used: c = 1.21 Ns/m, c_1 = 20, c_2 = 400, c_3 = 2, c_4 = 1.7, c_5 = 1, c_6 = 0.04, c_7 = 0.08, c_8 = 0.5, c_9 = 0.02, c_{10} = 0.04, b_1 = 4, f = 0.2 mm/rev, f_o = 84.539 Hz, k = 395 N/mm, m = 1.4 kg, t_c = 240.001 s, t_d = 4 s, ϕ_{ge} = 0.00013 rad, ϕ_{dw} = 0.00027 rad and ω = 10 rad/s. The mass, damping and stiffness in this example are the same as in the example given by Yang et al. [2002]. The calculated standard deviation of the vibration acceleration during the simulated drilling of the last hole is about seven times that during the drilling of the first holes.

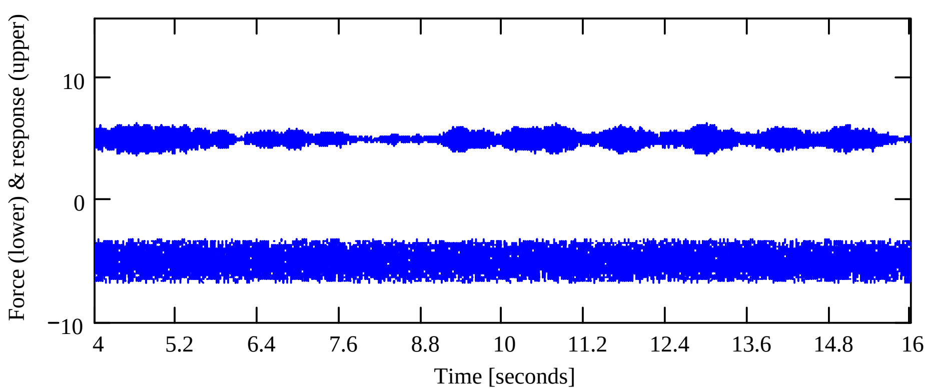

Figure 4. Excitation force (lower curve) and vibration response (upper curve) for holes two, three and four.

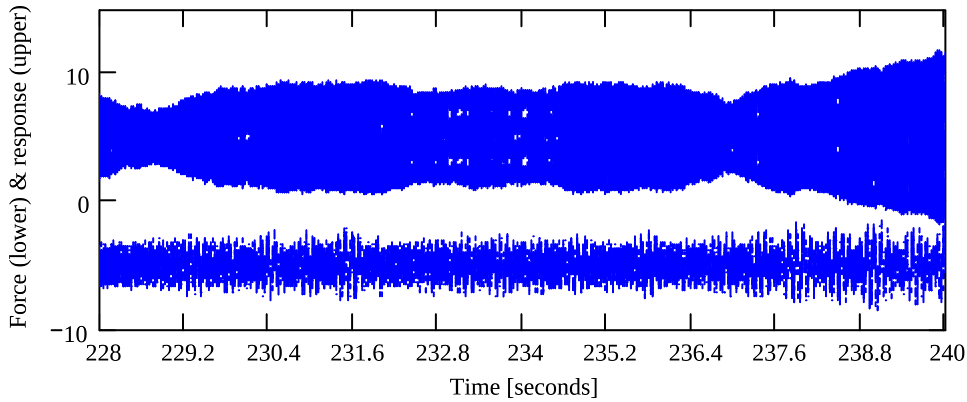

Figure 5. Excitation force (lower curve) and vibration response (upper curve) for the last three holes.

6. Diagnosis of tool wear

In order to enable the unmanned use of machine tools and flexible manufacturing systems, the diagnosis of tool wear needs to be made automatic. In practice this means that some kind of artificial intelligence is needed. Also important is easy configuration for a range of machine tools. The principles of an expert system based approach are described in detail in publication V. The advantages of regression analysis are discussed in publication VI. In publication VII, regression analysis techniques are combined with fuzzy logic. The possibilities of a hierarchical neuro-fuzzy approach that combines information from various sources are described in publication VIII.

6.1 Expert system

Assuming that the diagnosis of drill wear can be based on diagnostic rules such as: “If the amplitude of some parameter increases beyond a predefined limit the drill is worn,” it is possible to build rule based expert systems that can be used for the diagnosis of drill wear. The main practical problem with this kind of an approach is the time it takes to describe all the rules. For example, if there is variation in the measuring signals and parameters used for diagnosing wear, a lot of work is needed to redefine the expert system for the specific case it will be used in, or if a generic system is developed it will be very complicated. In the developed approach the basic idea is to use a fault tree database interface program for defining the faults to be monitored, such as drill wear, and describe the corresponding condition monitoring methods (symptoms) using a symptom tree database interface program. After defining the fault and corresponding symptoms that can be used to diagnose the fault, the user starts a rule synthesiser program. The rule synthesiser translates the contents of the fault and the symptom databases into an expert system rule code for the computer performing the monitoring task. In this automatic code writing process, the rule synthesiser takes one page at a time from the symptom tree and from it writes a module onto the expert system code. The procedure is shown in Figure 6.

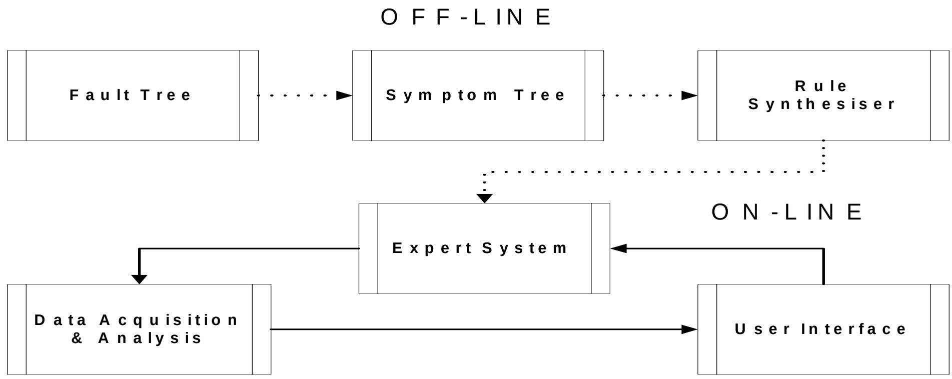

Figure 6. Principles of the new approach to expert system rule generation.

6.1.1 Fault tree

In the fault tree user interface window and the corresponding table of the database, the machine tool is defined by a chain of subcomponents. The approach is general, i.e. it can handle various types of faults and also various types of rotating machinery. In the case of drill wear, the subcomponent chain is defined as follows: component = machine tool, subcomponent = spindle, subsubcomponent = tool holder, subsubsubcomponent = drill. For this chain 18 different types of fault can be defined, e.g. such as worn out. Since the fault tree is part of a database, all the typical features of a relational database program such as find, copy etc. are available.

6.1.2 Symptom tree

In the following step of building an expert system for each of the faults, a symptom tree database definition is performed. The definition of symptoms that define a fault include the following: status of the machine tool (power on, hydraulics on etc.), machining information (spindle rotating, machining etc.) and condition monitoring information (signal, sensor, time criticality, analysis method, averaging, alarm limit etc.). The definitions include all the necessary information for defining the data collection through an AD card and also all the necessary information for performing signal analysis using a collection of mathematical subroutines. When FFT is used to calculate e.g. the power spectrum or other analysis functions, only the so-called cursor values, i.e. the 20 highest peaks of the analysed functions, are saved to keep the size of the database reasonable. Again all the features of a typical relational database are available. Since the above definitions are done for each tool type included in the wear monitoring program, the editing functions are important to make the amount of work manageable.

6.1.3 Rule synthesiser

The idea of the rule synthesiser is to automate the laborious writing of expert rules for different types of machine tools using a variety of tools. In principle, all the necessary information is saved in the fault and symptom tree database tables. The rule synthesiser takes the information from the symptom tree database table and automatically generates the computer program code containing the needed expert system rules. The rule synthesiser works by processing each rule specification in the symptom tree database, then breaking each rule into several function calls. The rule synthesiser also builds the links between these function calls in a logical order so that the data can go through the steps of data acquisition, signal processing, feature extraction and testing against the specified limits. In addition, the rule synthesiser automatically combines rules into groups corresponding to each fault defined in the fault tree, e.g. all the rules needed to detect a worn-out drill of a specific size e.g. 10.2 mm.

6.1.4 Fault manager

The purpose of the fault manager module is to combine the information based on various sensors and analysis functions into the final conclusion. Typically in a cutting process there are a number of changes taking place in the measured signals. These can be due to changes in the cutting parameters or variation in the work piece material etc. In order to handle this it is suggested that a number of measuring signals and analysis functions are used. The rule synthesiser can build the rules for each of these features used in the expert tool. Development of the analysed features with time is saved using regression analysis techniques, thus only the summary terms of the regression functions need to be saved. The fault manager then follows these features and their reliability based on the coefficient of determination of the regression analysis functions, and calculates the sum of the coefficients of determination of those analysis functions that have triggered the predefined threshold limit. The final conclusion of whether a tool is worn is then based on comparison of the sum of coefficients of determination.

6.2 Fuzzy classifier

Fuzzy classification is one possible way to automate the diagnosis of tool wear as described in chapter 2 of this thesis. The development of the approach of using simplified fuzzy classification following the principles shown by Rao & Rao [1993] in the diagnosis of drill wear is explained in publication VII. The idea is that in the beginning, when a tool is in good condition, some of the early data is used for defining the fuzzy classification limits for the analysed parameters of the monitored signals. In the developed approach the number of classes has been limited to eight, class two meaning that the tool is in good condition and class eight that it is completely worn. Class one has been reserved for lower values of the monitored parameter, which possibly mean that the cutting conditions are different from those when the limits were defined.

The classes are defined using the mean and standard deviation of the measured signal. These statistical parameters are typically used when so-called health indexes are calculated [Williams et al. 1994] or alarm limits are defined in condition monitoring standards such as the PSK 5705 Standard [2004]. In the developed approach the classes are defined using the following definitions: The mean value of each class (class index i = 1..8) is defined according to the following formula:

$$ClassMean_i = (i-2)\cdot j\cdot\sigma + \mu \tag{16}$$

where j is a coefficient defining the size of the classes, k is a coefficient that defines the shape of the classes, and μ is the mean value and σ the standard deviation of the first measured parameters. The upper and lower limits of the classes are defined as follows:

$$LowLow_i = ClassMean_i - j\cdot(1+k)\cdot\sigma/2 \tag{17}$$

$$LowHigh_i = ClassMean_i - j \cdot (1-k) \cdot \sigma / 2 \tag{18}$$

$$HighLow_i = ClassMean_i + j \cdot (1-k) \cdot \sigma / 2 \tag{19}$$

$$HighHigh_i = ClassMean_i + j \cdot (1+k) \cdot \sigma / 2 \tag{20}$$

Figure 7 shows an example of fuzzy classification of the rms value of vibration. In this example the basic signal is the same as that used in the analysis of data in Figure 1 and Figure 2. In the example, the 20 first values analysed have been used for defining the mean and standard deviation in the above equations. The values used are j = 1 and k = 0.5.

The results of fuzzy classification can be used as input for a neural network as shown in the following chapter. The use of fuzzy logic in pre-processing the input data for a neural network follows the principles presented by Rao & Rao [1993].

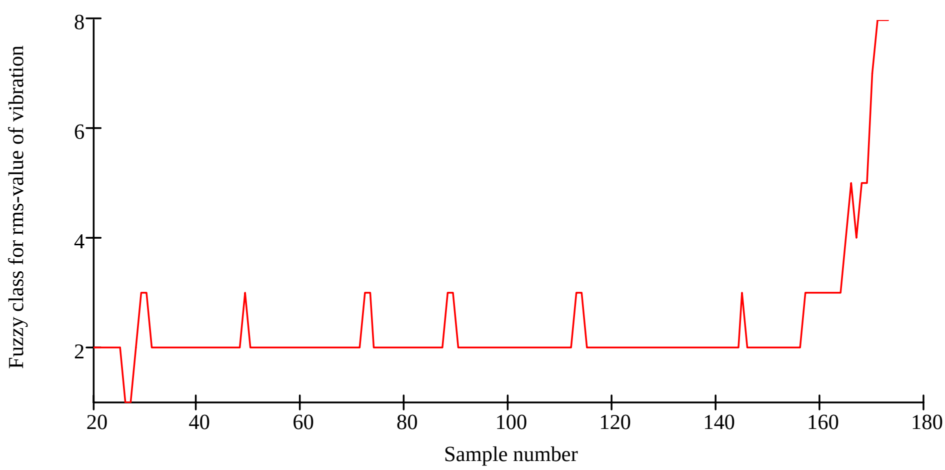

Figure 7. A result of fuzzy classification of the rms value of vibration.

6.3 Hierarchy

Publication VIII describes the principles of building a flexible hierarchical neuro-fuzzy system for prognosis. The basic idea is simply to use a hierarchy, i.e. to build a bigger and a more complicated model using sub-models, as seen in Figure 8. In the most simplified level a higher level conclusion is drawn based on a number of monitoring parameters analysed. In this approach the maximum number of parameters in a sub-model is limited to eight, i.e. the conclusion at the lowest level is based on eight parameters. The choice of eight as the maximum is based on numerical and logical reasons. It is relatively easy to handle models of this size and eight is a multiple of two, which can be handled with three bits. At sub-model level the idea is to define the condition of the monitored tool or, more generally, the condition of a machinery part.

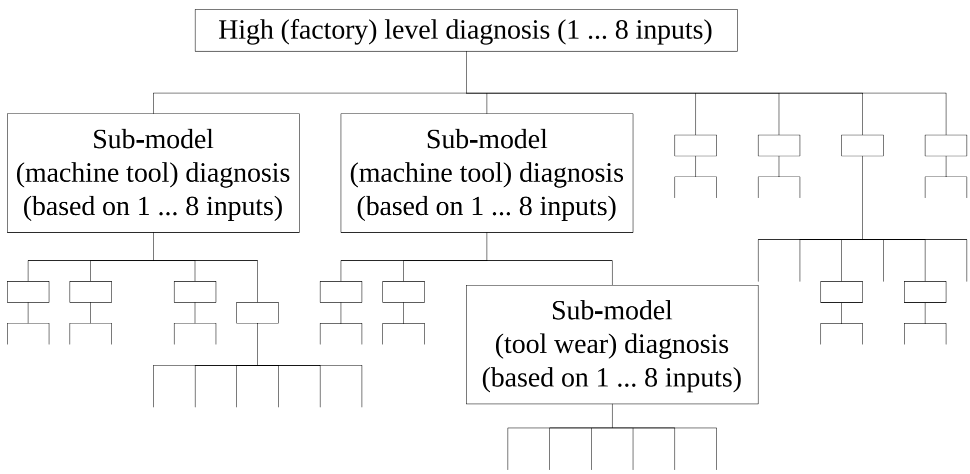

Figure 8. Structure of the hierarchical neuro-fuzzy system.

Table 2 shows the principal idea of the hierarchical approach. In case of drill wear monitoring, typically two measuring signals such as vibration and acoustic emission could be used. If four statistical parameters are calculated from these two signals, this actually fills the lowest level sub-model and should be the basis for defining that the drill is worn. At any level of the hierarchical approach the decision making process is similar, since at the maximum there are always eight inputs and only one output representing the conclusion. In the case of drill wear monitoring, it is important also to be able to define when drilling is taking place so that the signal analysis is only carried out when it is relevant to do so. In the case of flexible manufacturing systems, the hierarchical model could be used in such a way that various tool types could have various sub-models and also the condition of the machine tool could be followed using some sub-models dedicated to various types of relevant wear models, such as spindle bearings and tool changers etc. However, this is beyond the scope of this thesis.

Table 2. Principles of the hierarchical approach.

Model level	**Fault**	**Parameters to handle**	**Technique for classification**	**Technique for conclusion**
Low level (linked to wear of component which can be monitored)	E.g. drill wear (bearing fault etc.)	Parameters analysed from monitoring signals	Fuzzy logic based on values of mean and standard deviation, allows manual interpretation	Simple logic: highest wins, if two signals indicate, etc., Could be neural net if statistical data for training
Machine level(s), possible to handle various process states, different tool types etc.	Machine needs maintenance, tool change etc.	Conclusion from lower level	Values from lower level	Usually logical, corresponds to rule based approach
High level (factory level)	Production can be followed (are there any faults)	Conclusion from lower level	Values from lower level	Usually logical

7. Discussion

7.1 Measured signals and signal analysis

In the reported tests and in the available literature, which is covered in chapter 2 of this thesis, there is a lot of variation in how well different measuring signals and analysis techniques have worked. This is due to the wide variety of factors influencing the results. The size of drills and the work material together with the drilling process parameters influence the measured signals. For example, it is easy to understand that the smaller the drill, the smaller the forces and the higher the frequencies are at which one could expect the greatest variation to take place. This tendency can be well understood in the light of dynamic simulation. The natural frequencies of a drill and the drill holder increase with a decrease in the diameter of the drill. This then actually means that a combination of measuring and signal analysis techniques that works well with a certain size of drills does not work as well with others.

Feed force and torque have been used a lot in laboratory tests with drills and some good results have been reported. However, it is difficult to measure forces at very high frequencies and this is one reason why good results with small drills have been reported with measuring techniques such as high frequency (ultrasonic) vibration measurements capable of sensing these higher frequencies. Also when smaller drills are used this influences the analysis techniques that should be used. These should be simple and quick enough to react to the quick changes and they should not be too demanding on the analysis equipment. As a consequence, measuring motor currents works better with large drill diameters because the drilling forces are higher; their portion of the total signal is then higher and also the measuring chain might be able to react quickly enough, but when the drill sizes are smaller the opposite is true.

The results reported in publications II and III apply to drills of moderate size, i.e. about 5 mm and more in diameter for the reasons stated above. The measuring equipment and signal analysis techniques that have been used with dynamic signals such as force, vibration and sound cover the frequencies of interest, i.e. rotational frequency and the lowest natural frequencies of the tested drills. However, already the somewhat more complex analysis based on FFT was occasionally rather slow with the equipment being used to analyse the test signals. It could be claimed that although the amplitudes at certain frequencies gave a better indication of drill wear, there is a risk that since the drills in these tests (as in many tests reported in the literature) wear very quickly at the end of their life, this phenomenon could be missed between analysis rounds.

In the literature even more complicated approaches than FFT, such as autoregressive modelling [Radhakrishnan & Wu 1981], are suggested for diagnosing drill wear. It would seem that this kind of method is not very generic, i.e. the models work for one specific drill size and work piece material, but they would need to be trained for new combinations and this would be very time consuming and laborious, even though it would apparently work in a fixed case.

Publication II lists the best measuring and analysis functions for drill wear monitoring. Vibration, acoustic emission, sound and some of the force measuring techniques were the best methods. Publication III shows good examples of vibration, acoustic emission and sound measurements analysed in the time domain. All of these measuring techniques can be considered acceptable for on-line use in a real production environment, in the sense that the necessary sensors can be mounted relatively easily to a typical machine tool and they do not influence the production. In publication II, statistical time domain parameters such as root mean square, mean deviation and maximum were listed as the best in drilling tests. However, as explained above, especially the drill size has a great influence on what would be the optimum measuring arrangement and signal analysis technique, thus the results shown in this thesis should not be over-generalized. To overcome the challenges brought about by drill size, it is suggested that the smaller the drills are, the higher the frequencies should be that are included in the measuring and analysis chain. Also, since the proportion of signals from the drill decreases with decreasing drill size, it raises the question of how close to the drill the sensors should be able to measure. In other words, the closer to the drill the sensors can measure, the higher the proportion of the drill signal is of all the signals that the sensor can measure. In order to overcome this problem of low signal levels with smaller drills more sophisticated signals analysis might be needed than is the case with medium and bigger size drills which introduce higher signal levels from drilling.

The higher order statistical parameters such as kurtosis and skewness were especially sensitive to variation in the tests, therefore they were not as good as the above-mentioned parameters. It is logical that the minimum value is not a very good parameter for drill wear monitoring, because the lowest values in the measuring signals resulted from some disturbance in the measuring procedure.

7.2 Simulation model

In theory, assuming the static drilling forces can be calculated as explained in chapter 2, and knowing how the cutting forces introduce wear into the drill, and also knowing how the drill dynamics influence the cutting forces and vice versa, it would be possible to build a dynamic drill wear model. This kind of model would also need to have probabilistic features in order to introduce differences between the cutting lips, which is one of the important factors that influence the vibration response of a worn drill. As stated earlier, this type of model does not seem to exist today and the simulation studies presented in publication IV are very far removed from this kind of approach.

The approach suggested in publication IV and covered briefly in chapter 5 of this thesis simply tries to show and test the possible influence of various artificial dynamic loads, which would increase with a similar trend to that seen in laboratory tests, and then to hide this trend behind noise and see how the used analysis functions work in this type of scenario. The model presented by Yang et al. [2002] is much cleverer in the way it calculates real forces and torque, taking into account the dynamic influence caused by the fact that drills do not drill straight but vibrate and consequently move from one edge to the other. However, the model only vibrates if it is given an initial push from equilibrium, and the only dynamic influence taken into account is then vibration due to the natural vibration modes of the drill and the unstable forces introduced by this vibration. In publication IV a number of dynamic excitation forces are introduced into the model; these are not derived from laboratory tests or theory, but are the results of a trial and error approach in the sense that with a suitable combination of parameters and logically chosen excitation forces, the final result resembles that seen in the tests when vibration is considered. It is also important to remember that the influence of wear has been introduced into the excitation forces as a function of the term defined by Equation 14, and consequently this term defines the influence of wear throughout the simulation model. The simulation is also very limited in the sense that it could be expected that different types of wear, e.g. chisel, corner, flank and margin wear, introduce different kinds of vibration spectra [El-Wardany et al. 1996], but this is not covered at all in the model.

It should also be remembered that when the simulation model described in chapter 5 and publication IV is limited to the first radial vibration mode, Rotberg et al. [1990] point out on the basis of measurements that the most important vibration mode in drill wear monitoring is the torsional vibration mode coupled with the axial vibration mode. The natural frequencies of these vibration modes are higher than for the radial modes. Also when studying the drilling process it is somewhat unclear how much support the drilled hole actually gives in a radial direction when there is no support in the torsional direction. However, in principle the situation seems to be similar for all of the vibration modes. Wear introduces higher dynamic loads and consequently the vibration increases at the first natural modes (the second mode in a radial direction might be more easily excited than the first, due to the supporting effect of the hole) in all possible directions. This means that the behaviour could be expected to be similar in all directions, and in fact in reality all of these vibration modes are combined. Although the calculation procedure is similar, it becomes more demanding the higher the natural frequencies are, and in this sense the modelling in the radial direction is easiest to perform. Again the findings presented by Rotberg et al. [1990] point out how far from reality the simulation described in chapter 5 really is, although it is claimed that the principles and the trends could be similar in reality as are the indications in measured parameters.

It should be noted that the simplified simulation shown in publication IV with MathCad [Mathsoft 2002] takes about an order of magnitude longer than the wear process of a typical twist drill because of the high frequency range. It could be deduced that the introduction of a real drill geometry by performing the calculation over a number of sections would multiply the calculation effort by hundreds if not thousands.

With this kind of simplified model, with a one-degree-of-freedom model the vibration at the natural frequency is very dominant. However, this tendency of some frequencies to dominate the spectrum is similar to what was measured in the reported tests, and in some cases this phenomenon is used in signal analysis using band pass filtering [e.g. Kutzner & Schehl 1988]. It could also be claimed that the simulation model supports the idea that the measuring technique and analysis function used should be able to handle the frequency range where the torsional and radial natural frequencies of a drill installed in a drill holder lie. This simulation model supports what was said in the previous chapter about the influence of drill size. With small drill diameters the frequency range goes beyond the capabilities of normal vibration measuring equipment, i.e. the frequencies for a drill with a 1 mm diameter might be of the order of 25 kHz [Kutzner & Schehl 1988]. The simulation model also supports what has been claimed about the best statistical indicators of tool wear, but this proof should be treated as uncertain because the input, i.e. forces introduced into the model, certainly have an affect what the produced signal looks like.

7.3 Regression analysis

As pointed out in chapter 2 there are a number of problems related to automatic diagnosis of tool wear in practice. The measured signals are noisy because of the nature of the cutting process and there may be sharp peaks in the signal, which may not indicate anything. The absolute values of the analysis parameters are usually not meaningful because there is so much variation due to the variation in tool size, the cutting parameters, work piece material etc. Instead it is important to notice the trend in the parameters analysed. However, this could mean that a lot of information would need to be saved. The use of the higher order polynomial regression function with a limited number of terms as described in chapter 4 and in more detail in publications VI and VII provides a solution to the problems described above: The higher order polynomial regression function smoothens sudden individual peaks and picks up the trend in the analysed parameter. Since the regression function mimics the shape of wear development, the function can also be used to give a prognosis of the upcoming tool failure. When regression functions are used, the trend in a signal is saved. One of the benefits of regression functions is that in order to save the information they contain, only a very limited number (nine) of summary terms need to be saved.

There are also possible drawbacks related to regression functions. One is that they may be slow to react to changes if a stable situation has continued for a long time. In the proposed approach, the idea behind introducing a weighting term is to solve this problem and keep regression functions quick enough to respond. Another factor that influences this is the order of the function, and for this reason the use of relatively high order functions is suggested. A drawback of higher order polynomial functions is that they may behave in very strange ways, i.e. they tend to become unstable with noisy data. The use of a limited number of terms helps in this respect because with this limitation the functions actually behave like a third order function, with the difference that now the changes can take place more rapidly.

It could be argued that higher order polynomial regression functions tend to increase the relative error. However, this is not really linked to the higher order polynomial functions but rather to the nature of the problem. Wear tends to develop very quickly towards the end of the tool life so there is no way of avoiding this, i.e. any prediction technique/function would suffer from the same problem of the relative error increasing. The use of the weighting function, i.e. that the current data is emphasized at the cost of older data, provides some help in this respect and makes the prognosis more reliable than if all the data had equal weight. Introduction of the weighting function can in some cases also make it possible for the approach to adapt to small changes caused by a change of cutting parameters. However, this is something that should be tested more thoroughly. The polynomial regression function does filter out some of the unwanted variation of the measured parameters, i.e. short peaks due to noise in the signals, and in this way makes the analysis more robust which is important in a machining environment. Naturally, if smoothing of the time-series data had been the sole target of the data manipulation, a much more simplified function would have been available, such as that described by Williams et al. [1994]. Their study gives examples of the use of moving average or exponential smoothing in condition monitoring. The biggest difference between the approach suggested in this thesis and those very simple methods is that the simple methods do not give a prognosis of the forthcoming trend of the monitored parameter. Due to this restriction, simple smoothing techniques do not react as quickly to changes of the monitored parameter.

The results of publications VI and VII suggest that relatively high values of the parameters of the regression function such as $e = 9$, $f = 6$ and $g = 3$ give good results. Typically q can have a value of e.g. 0.99 if the process is stable with frequent measurements. The lower the value is, the more the last measurements are emphasized. In fact, using lower exponent values such as $e = 3$, $f = 2$ and g =1 together with a lower value of q = 0.9 would give a result quite close to that obtained with the higher exponent values mentioned earlier. However, if there is enough data the higher values result in a regression function that more closely resembles the wear function described in publications VI and VII.

Certainly, instead of the higher order polynomial regression function quite a number of other functions could also be tested. One of the simplest possible solutions would be the exponential function. In simple format this kind of function also includes three unknowns, i.e. the exponent, a parameter used to multiply the exponent term, and a coefficient. Based on the definition an exponent function could be rather sensitive and possibly not as well suited to prognosticating as the polynomial regression function. However, it has not been within the scope of this thesis to widely compare different possible regression functions. It is accepted at this stage that the polynomial function is suitable for the defined task and it is left to further studies to suggest and compare other possible functions.

7.4 Expert system

There are a number of advantages in building an expert system as suggested in chapter 6.1 of this thesis. It is not necessary to write a lot of expert system code manually that could handle a huge number of tools. It is easy to make changes or add information thanks to the practical user interface. Unfortunately there are also disadvantages in this approach. The amount of work is still relatively high and demanding, i.e. the user must know what to do and how to define limits for the various signals, and this need for professional manpower makes the whole approach unpractical for everyday use. In addition the size of the final program will be extensive, but this is not possibly so meaningful today because of the improvement of processing power.

7.5 Fuzzy classification

The simplified fuzzy classification has been introduced into the approach in order to make diagnosis of tool wear automatic. The same approach can be applied using both fuzzy limits and crisp limits. In both cases the conclusion can be shown in eight classes and it can be argued whether the simplified use of fuzzy limits actually brings any benefits. One argument is that in reality the limits are fuzzy, and thus the use of fuzzy limits is closer to reality. Another argument is that the use of fuzzy limits could make the following step more robust if neural nets were used. The reason for this is that the use of fuzzy limits brings some variation to the inputs of the neural net.

The diagnosis examples shown in Publication VII are based on the use of two measuring signals, i.e. vibration and acoustic emission, and the final conclusion of drill wear is in most cases based on the simple rule that at least two parameters must give an indication of drill wear. In publication VII different parameter values and principles in making the final conclusion are tested. The conclusion is that relying on more than one statistical parameter makes the diagnosis more stable, and that conservative values (small values of j) should be preferred when the fuzzy limits are defined. The use of small values of j actually means that the upcoming tool failure is seen too early rather than too late. It should be noted that there is a remarkable difference in using fuzzy classification in such a simplified manner as was done in publication VII, compared to that shown e.g. in the paper by Du et al. [1995]. The more sophisticated (normal) way of using fuzzy limits could reveal a much improved connection between the various parameters and improve the reliability of the conclusion. However, the problem is that this relationship would have to be trained prior to the use of the approach, which again is a very severe limitation if an automatic approach is the final goal.

7.6 Automatic diagnosis

Many of the approaches that have been developed for tool wear diagnosis and are reported in the literature rely on training and a definition phase in order to work properly. This is also true for the rule based approach described in chapter 6.1 of this thesis. In normal production, the need for training and the definition phase might be very problematic if a great number of tools are used in different machining conditions with varying work piece materials. The following development phase based on the use of regression analysis techniques and fuzzy logic does not suffer from this as much. A number of parameters have to be defined, but when this has been done for the production environment these could be kept the same for a number of tools, and the definition of limits for diagnosing tool wear should take place automatically. There are also limitations to the suggested approach. The first measurements are used for defining the limits, and if the tool fails during that period the diagnosis system does not provide any help. This restriction does not apply in cases where the tool type and cutting parameters are kept constant, i.e. there is historical information of similar cases and thus the same limits can be used that were defined earlier and have proved to work.

Naturally, significant questions related to the suggested approach remain open. Although the approach works with laboratory data from medium and large size drills, does it really work in real life in normal production where the environment is much more demanding? There are external disturbances influencing the signals and there is variation in the work piece materials etc. Is the approach really so easy to define that it attracts users? Will there be too many mistakes in the diagnosis, so that users do not rely on the system? The only way to get answers to the above is to test the system in real production. This has not been done to date, but hopefully the opportunity will come to test and gain experience of the capabilities of the suggested approach in real production.

8. Conclusion

There exists a great potential to improve the machine tool utilisation rate with an advanced condition monitoring system using modern sensor and signal processing techniques. A comprehensive cutting test procedure was carried out with drills. Based on the tests, different measuring methods and analysis techniques together with their benefits and disadvantages have been discussed. Especially vibration measurements and methods that are closely related to it, i.e. sound and acoustic emission, seem to be potential and practical methods that could be recommended for everyday use in production. The importance of natural vibration modes of the drill and tool holder is apparent in the light of tests and the simplified simulation carried out. The use of higher order polynomial regression analysis functions with a limited number of terms is suggested for filtering the measured data and saving it in a compact form, which is especially beneficial when the number of monitored tools is high. An automatic diagnosis approach has been developed based on simplified fuzzy logic. The approach can be linked to a wider context, e.g. monitoring a complete machine tool through the proposed hierarchical structure. However, even though the results with laboratory data are promising, there are no test results from a real production environment. It should also be noted that the current results apply to medium and large size drills, and unfortunately the diagnosis of wear and breakage of small size drills is more demanding. The proposed approach is unable to detect what kind of wear is taking place, i.e. it does not differentiate chisel, corner, crater, flank or land wear from each other.

Based on the research reported in this thesis and the above conclusions, some suggestions can be made for further work:

- First of all, wider testing of the developed approach both in the laboratory and in the industry is suggested. In these tests the benefits of the higher order regression analysis function could be tested more thoroughly, including mathematical optimisation of the order of the function and the emphasis of current data, i.e. the variation of parameter q. These tests could also include testing of the whole automatic diagnosis approach in the prediction of the remaining lifetime of the tool. Furthermore, the tests might also help to widen the scope of the approach so that it could also be used for monitoring small size drills.

- One further step in gaining a better understanding of drill wear monitoring could be the development of a real physical wear model for drill wear. This could include the statistical treatment of material variation both in the drill and in the work piece, leading to a natural variation of the wear of the cutting lips. The model could also aim to differentiate between various wear types. This kind of model would probably have to be built using the finite element method (FEM) for modelling. However, it should be noted that even the very simplified model presented in this thesis could be used more widely in the development of automatic tool wear monitoring, diagnosis and prognosis.
- Assuming that all the above-mentioned testing gave positive results, one further task that would then have to be carried out is the development of an automatic tool monitoring information database for practical and easy handling of the numerous tools in a real production environment.
- Further work could also be done in testing the same approach in diagnosing and predicting the condition of machinery components suffering from a similar type of exponentially increasing wear, such as rolling bearings. Although the first version of the hardware capable of performing all the tasks presented in this thesis has been built, a further version could be developed that would include a better capability of signal amplification and filtering and improved automatic adjustment of parameters.

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Indirect multisignal monitoring and diagnosis of drill wear

Abstract
A machine tool utilisation rate can be improved by an advanced condition monitoring system using modern sensor and signal processing techniques. A drilling test and analysis program for indirect tool wear measurement forms the basis of this thesis. For monitoring the drill wear a number of monitoring methods such as vibration, acoustic emission, sound, spindle power and axial force were tested. The signals were analysed in the time domain using statistical methods such as root mean square (rms) value and maximum. The signals were further analysed using Fast Fourier Transform (FFT) to determine their frequency contents. The effectiveness of the best sensors and analysis methods for predicting the remaining lifetime of a tool in use has been defined. The results show that vibration, sound and acoustic emission measurements are more reliable for tool wear monitoring than the most commonly used measurements of power consumption, current and force. The relationships between analysed signals and tool wear form a basis for the diagnosis system. Higher order polynomial regression functions with a limited number of terms have been developed and used to mimic drill wear development and monitoring parameters that follow this trend. Regression analysis solves the problem of how to save measuring data for a number of tools so as to follow the trend of the measuring signal; it also makes it possible to give a prognosis of the remaining lifetime of the drill. A simplified dynamic model has been developed to gain a better understanding of why certain monitoring methods work better than others. The simulation model also serves the testing of the developed automatic diagnostic method, which is based on the use of simplified fuzzy logic. The simplified fuzzy approach makes it possible to combine a number of measuring parameters and thus improves the reliability of diagnosis. In order to facilitate the handling of varying drilling conditions and work piece materials, the use of neural networks has been introduced in the developed approach. The scientific contribution of the thesis can be summarised as the development of an automatically adaptive diagnostic tool for drill wear detection. The new approach is based on the use of simplified fuzzy logic and higher order polynomial regression analysis, and it relies on monitoring methods that have been tested in this thesis. The diagnosis program does not require a lot of memory or processing power and consequently is capable of handling a great number of tools in a machining centre.

Keywords
drill wear, condition monitoring, signal analysis, polynomial regression analysis, fuzzy logic, diagnosis

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Erkki Jantunen

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