DRILL WEAR MONITORING using INSTANTANEOUS ANGULAR SPEED

A Comparison with Conventional Technologies used in Drill Monitoring Systems

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Abstract

Most drill wear monitoring research found in the literature is based on conventional vibration technologies. However, these conventional approaches still have not attracted real interest from manufacturers for multiples of reasons: some of these techniques are not practical and use complicated Tool Condition Monitoring (TCM) systems with less value in industry. In addition, they are also prone to give spurious drill deterioration warnings in industrial environments. Therefore, drills are normally replaced at estimated preset intervals, sometimes long before they are worn or by expertise judgment.

Two of the great problems in the implementation of these systems in drilling are: the poor signal-to-noise ratio and the lack of system-made sensors for drilling, as is prevalent in machining operations with straight edge cutters. In order to overcome the noise problems, many researchers recommend advanced and sophisticated signal processing while the work of Rehorn et al. (2005) advises the following possibilities to deal with the lack of commercial system-made sensors:

- Some research should be directed towards developing some form of instrumented tool for drill operations.
- Since the use of custom-made sensors is being ignored in drilling operations, effort should be focused on intelligent or innovative use of available sensor technology.

It is expected that the latter could minimize implementation problems and allows an optimal drill utilization rate by means of modern and smart sensors.

In addition to the accelerometer sensor commonly used in conventional methods, this work has considered two other sensor-based methods to monitor the drill wear indirectly. These methods entail the use of an instrumented drill with strain gauges to measure the torque and the use of an encoder to measure the Instantaneous Angular Speed (IAS). The signals from these sensors were analyzed using signal processing techniques such as, statistical parameters, Fast Fourier Transform (FFT), and a

preliminary Time-Frequency (TF) analysis. A preliminary investigation has revealed that the use of a Regression Analysis (RA) based on a higher order polynomial function can very well follow and give prognosis of the development of the monitored parameters.

The experimental investigation has revealed that all the above monitoring systems are sensitive to the deterioration of the drill condition. This work is however particularly concerned with the use of IAS on the spindle of the drill, compared to conventional monitoring systems for drill condition monitoring. This comparison reveals that the IAS approach can generate diagnostic information similar to vibration and torque measurements, without some of the instrumentation complications. This similitude seems to be logical, as it is well known that the increase of friction between the drill and work-piece due to wear increase the torque and consequently it should reduce or at least affect the spindle rotational speed.

However, the use of a drill instrumented with a strain gauge is not practical, because of the inconvenience it causes on production machines. By contrast, the IAS could be measured quite easily by means of an encoder, a tachometer or some other smart rotational speed sensors. Thus, one could take advantage of advanced techniques in digital time interval analysis applied to a carrier signal from a multiple pulse per revolution encoder on the rotating shaft, to improve the analysis of chain pulses. As it will be shown in this dissertation, the encoder resolution does not sensibly affect the analysis. Therefore, one can easily replace encoders by any smart transducers that have become more popular in rotating machinery. Consequently, a non-contact transducer for example could effectively be used in on-line drill condition monitoring such as the use of lasers or time passage encoder-based systems.

This work has gained from previous research performed in Tool Condition Monitoring TCM, and presents a sensor that is already available in the arsenal of sensors and could be an open door for a practical and reliable sensor in automated drilling.

In conclusion, this dissertation strives to answer the following question: Which one of these methods could challenge the need from manufacturers by monitoring and diagnosing drill condition in a practical and reliable manner? Past research has sufficiently proved the weakness of conventional technologies in industry despite good results in the laboratory. In addition, delayed diagnosis due to time-consuming data processing is not beneficial for automated drilling, especially when the drill wears rapidly at the end of its life. No advanced signal processing is required for the proposed technique, as satisfactory results are obtained using common time domain signal processing methods. The recommended monitoring choice will definitely depend on the sensor that is practical and reliable in industry.

Keywords: Condition monitoring, drill wear, vibrations, torque, instantaneous angular speed (IAS), encoder, time domain, frequency domain, time-frequency domain analysis, regression analysis

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Contents

List of symbols

Letters

M	Number of pulses
f_c	Clock frequency (cycles / sec)
N_c	Clock pulses
$x(t)$	Signal function of time
n	Number of measured points
t	Time (seconds)
T	Period (seconds)
X	Amplitude of $x(t)$
$X(j\Omega)$	Fourier transform of $x(t)$
f	Frequency (cycles / sec)
k	Number of discrete samples
T_m	Motor torque (N m)
P_m	Spindle motor power (Watts)
ω_m	Motor rotational speed (rad / sec)
ω	Instantaneous angular speed (rad / sec)
$\Delta\phi$	Variation of angular displacement (radians)
Δt	Time duration (seconds)

Acronyms

ADC	Analog Digital Converter
AE	Acoustic Emission
AMV	Absolute Mean Value
ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
BPN	Back Propagation Neural network

CET	Constant elapsed time
CF	Crest Factor
CP	Counting Pulses
DA	Data Acquisition
DFCA	Decision Fusion Center Algorithm
DFT	Discrete Fourier Transform
ET	Elapsed Time
FE	Frequency Energy
FFT	Fast Fourier Transform
FL	Fuzzy Logic
HMMs	Hidden Markov Models
IAS	Instantaneous Angular Speed
NNs	Neural Networks
PSD	Power Spectral Density
RA	Regression Analysis
RAMV	Ratio of the Absolute Mean Value
RBES	Rule Based Expected Systems
RCE	Restricted Coulomb Energy
RMS	Root Mean Square
RPM	Rotations per Minute
SEM	Scanning Electron Microscopy
STFT	Short Time Fourier Transform
TCM	Tool Condition Monitoring
TF	Time Frequency
TFD	Time Frequency Distribution
TFR	Time Frequency Representation
TIM	Time Interval Measurements

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CHAPTER 1: INTRODUCTION AND LITERATURE

1.1 Introduction

Machining operations such as turning, drilling, boring, milling and grinding are material removal processes. Some of these processes, such as drilling, have been used for thousands of years, and are today still widely used in industrial environments (Krar and Oswald, 1977). Machining remains very important in the manufacturing environment, and in terms of income it ranks number one, as the cost of machining amounts to more than 15% of the value of all manufactured products in industrialized countries (Trent and Wright, 2000). Drilling is one of the most common machining processes and generates more income than any of the other processes individually. It is estimated that 40% of all metal removal operations in aerospace are by drilling (Ertunc and Loparo, 2000).

Drilling is simply defined as a metal removal process for producing holes in components. The process involves feeding a revolving cutting tool along its axis of rotation into a stationary work-piece. A circular hole is therefore generated in the work-piece (Armarego and Brown, 1969).

The state-of-the-art clearly indicates that one of the most important problems encountered during industrial drilling operations, is the detection of sudden failures and continuous determination of the drill wear condition. This detection could prevent damage to the work-piece and avoid unnecessary shutdown time due to replacement of a failed drill. In large industrial applications where hundreds or even thousands of drills operate in series, defect drills would be detected when output work-pieces or assembly parts are appearing with poor quality (Joshua, 1996). Once more, this will normally result in downtime. This is also critical in the economics of drilling operations. It is therefore necessary to improve the monitoring of the drill tool utilization at its optimal rate to be cost effective.

Most on-line monitoring systems are based on conventional vibration monitoring technologies. They normally use force, torque, current signals, power, and vibration sensors to assess the tool condition. But none of these sensors have provided a definitive answer to the manufacturing industry's need for more comprehensive automatic control. These sensors used for on-line monitoring systems also suffer from a lack of manufacturers' interest for industrial implementation, because they are not practical to implement even if possibly reliable with good indication of tool wear. The situation becomes worse for drilling operations, as one cannot continuously instrument drills without excessive financial expense. In turning operations for instance, it is economic to instrument tool holders when changing only the tool. However, such holder design (custom-made sensor) still has to find its way into drilling operations. The instrumentation of the chuck was unfortunately not successful in terms of signal response discrimination and wear development.

Added to that it is also clear from laboratory experience, just how complex the drilling process is and how inaccurate the estimation of the life and wear of a drill is. The reasons for this being the following:

- Wear is not a continuous process and leads to a stochastic behavior of the drill life.
- The non-homogeneities and variances in material affect the life of the drill.
- During a continuous drilling process, the temperature changes influence the drill wear while during an intermittent drilling process this temperature effect becomes dependent on the downtime between consecutive drilling operations.
- Different types of drill wear can be measured using a direct method but for indirect methods, it is not easy to correlate the measured wear to a specific sensor signal.

In such conditions, how can one predict or avoid a sudden drill failure in a very large scale drilling operation? The general trend in drilling operations is to replace the drill at estimated preset intervals. But even in this case, there is no way one can predict, avoid or even detect a sudden failure. Consequently, research in the field of drill condition monitoring is still opened to find a simple solution that is attractive to industry and automatically monitor drilling operations.

Much effort has been devoted to the implementation of an intelligent signal analysis through neural network (NN) tools in order to separate the unwanted information from the useful, for easy detection of a worn tool. However, it seems that really successful on-line drill monitoring will most likely involve intelligent transducers that could very easily be integrated with instrumented drill tool devices. This could justify the present investigation of the IAS parameter as a monitoring tool in comparison to conventional parameters such as torque and vibration measurements.

From the literature (Jantunen, 2002), it is clear and very logical to monitor forces in a cutting process in order to follow the development of cutting tool wear, because cutting forces increase as tool wear increases. This is due to the increase of friction between tool and work-piece. But the logical consequence of the friction increase is the reduction of the spindle speed while the cutting force or torque should increase. And bearing in mind the simple relationship between torque and angular speed (power = torque × angular speed), it is however surprising that so little has been done to explore the use of the IAS of the spindle as one of the monitoring parameters available in the arsenal of TCM methods. During the drilling operations, the increase of friction between the drill and the work-piece is attenuated by the re-sharpening of the drill edge during the revolving of the cutting drill. This process could delay to some extent the deterioration of the drill condition as well as it could change the elapsed time period of the drill revolution. This could be verified with the outlier points of the drill output signals. However, at the end of the drill life the effect of a dull drill is visible on both the machine feeding and high levels of vibration of the system. Nevertheless, with all the advanced technologies in rotating machines where small changes in rotational speed can be identified, there should be reason to be more optimistic.

Conceptually the IAS could be measured quite easily by means of an encoder, while it can also be shown that it provides diagnostic information comparable to information provided by the direct measurement of torque on an instrumented drill shank. Vibration measurements are merely used here for the purpose of comparison with the proposed measurands. Hence, this research provides comparative results of wear monitoring between strain gauged-based torque measurements via telemetry, vibration measurements, and the encoder-based method of IAS measurement. The comparative results illustrate the effectiveness of the encoder sensor as a possible, likely accurate and practical reliable transducer in drilling.

The state-of-the-art of sensors and signal processing methodologies used for the drill TCM in this work can be summarized as follows:

First, the use of strain gauge-based torque measurements via real time telemetry is considered. The results show that strain gauge measurements produce output signals that are sensitive to the drill wear and offer good correlation with the drill condition. However, the implementation of this concept for drill wear monitoring implies a significant instrumentation load and the inconvenience of attaching strain gauges to each rotating drill bit to be used.

Secondly, the use of an encoder-based system to assess the IAS is considered. The encoder-based system uses a fixed angular encoding device that rotates with the shaft such as a gear or an optical rotary encoder. A transducer is then used to sense the passage of each encoder segment with respect to a reference point as the shaft rotates (Resor et al., 2004). The principle of this method is the use of the digital time interval measurements (TIM) of pulse train output signals from an encoder to calculate the IAS. The TIM investigation is also based on the principle that the elapsed time (ET) between two pulses during the rotational speed is dependent on the deterioration of the drill condition. The results show good correlation between the pulse output and the drill condition and the method seems less complicated to implement despite the high cost of the encoder. However, non-contacting transducers that have become more popular in rotating machinery applications are feasible as a means of monitoring the drill condition.

For instance, the optical tracking of a zebra stick can also give a chain of pulses as output signal, carrying the same information as an encoder.

Thirdly, the use of accelerometers for vibration measurements is one of the conventional technologies used in TCM. The tested results also show good correlation between the output signal and the drill condition. Unfortunately, accelerometers seldom find favor in industrial drilling environments. The advantages and disadvantages of vibration measurements are discussed later in this study.

Various papers published different analysis methods using conventional measurements, despite the highly non-stationary and transient events encountered during drilling operations. Most of these analyses are based on the assumption that drill signals are stationary. In the time domain, statistical parameters are calculated but do not yield a robust on-line drill wear detection method for the workshop environment. Many researchers recommend advanced signal processing to overcome the poor signal-to-noise ratio of the workshop. Another very popular method used in signal analysis is spectral analysis via fast Fourier transform (FFT) that decomposes the time series signal into its frequency components. Spectral analysis can provide information about the frequency components but does not give any information about their temporal localization. Hence, some focus must be emphasized on time frequency distributions (TFDs) that compensate for the lack of time localization.

In conclusion, the main aim with this research is to consider the feasibility of using IAS as a reliable and practical way of drill wear monitoring for possible implementation in the context of automated large-scale manufacturing. This work is intended to offer a useful contribution to drill wear monitoring compared to the traditional analysis schemes. If the monitoring of the time period changes between encoder pulses for sharp and worn drills is successful, then it would become possible to implement a system that can quickly and automatically monitor the IAS and send out an alert when an incipient mechanical failure is detected by means of the time period changes. This decision-making of drill condition could be applied using the following signal processing methodologies: statistical parameters, frequency content (FC) of IAS signal and differentiation of time frequency representation (TFR) structures. The results have shown that the use of a high order polynomial regression on both statistical parameters and computed power spectral density (PSD) to mimic drill wear development, proved to be well suited to the monitoring of parameters that follow drill life trends. The measurement of IAS has the advantage of monitoring and control of the drill condition in real time as it relies only on the time period changes between pulses. Thus, one can take advantage of new technologies and the large number of recent publications on IAS to improve the sensor reliability.

1.2 Importance of drill wear monitoring

Drill condition monitoring is considered important for the following reasons (Jantunen, 2006):

- Drill changes are presently based on conservative estimates of drill life, which do not take into account sudden failures. Not only does this lead to wastage of useful drills, but also leads to an unnecessarily high number of changes. Consequently valuable production time is lost.
- The optimal drill life cannot be fully realized without efficient methods for drill wear monitoring because of variations in drill life. This factor is not economically very important as far as the cost of a single drill is concerned, but nevertheless becomes economically meaningful when the cost of the entire production process is concerned.
- Drill wear influences the quality of the surface finish and the dimensions of the parts that are manufactured. This also requires some means of automatic tool condition monitoring.

Hence, cost effective unmanned production therefore becomes possible in practice if there is a reliable method available for drill wear monitoring and drill failure detection.

1.3 Approach and research objectives

Due to the complexity of the cutting process in drilling operations, it is usually not possible to obtain a full mathematical description of the relevant dynamic process, in order to predict the drill condition. Therefore the approach followed in this work is basically to find suitable and indirect monitoring methods to determine drill wear. The direct method is illustrated by means of scanning electron microscopy (SEM) photographs which serve to interpret particular phenomena observed during the post processing of signals.

On-line direct measurement is not feasible because of the obstruction of view between the drill, the work-piece and the chips. Generally, direct methods such as visual inspection, computer vision or direct determination of the tool wear, have not yet proven to be attractive neither economically nor technically but are still used in industrial practice, specifically in aerospace. In this work, a sample of drill bit wear was directly measured by SEM analysis to illustrate different types of wear met in drilling operations.

In automated operations where manufacturers always strive to reduce operating costs while trying to improve product quality and meeting customer satisfaction, one of the principal methods used to determine the tool wear is the indirect measurement of phenomena related to tool wear. Measurements that can continuously monitor the process and indirectly indicate the level of the tool wear include cutting force, torque, temperature, vibration, spindle motor power, feed motor power, strains and spindle speed.

Indirect methods are also required in this project to develop a drill tool system for practical monitoring. They consist of identifying the best and practical sensor signal technologies considering vibration measurements, strain gauge-based torque measurements via real time telemetry, and the IAS of the spindle via an optical encoder-based system.

Features are extracted through the use of conventional signal processing methods such as the statistical parameters in the time domain, FFTs in the frequency domain and spectrograms in the time-frequency (TF) domain. Due to the stochastic behavior of drilling operations, regression analysis (RA) will be recommended not only because of its success in mimicking drill wear development but also because of disparities encountered in the representation of data. Therefore, it seems logical to monitor the trend of features and parameters in drilling operations rather than the absolute values.

Further study could make use of the above features to develop automatic diagnostic methods based on the application of fuzzy logic (FL) or neural network (NN) environment for the decision making required to discriminate the drill tool condition.

1.4 Literature survey

This literature survey presents a review of the state-of-the-art in the field of drill wear monitoring. The survey focuses on and evaluates methods used by other researchers, with a spotlight on sensors and signal processing methodologies used for TCM: trends in the sensor-based methods, how they measure and assess drill wear, and the decision making based on different diagnostic methods.

Drill wear monitoring found in the literature can be classified into two categories as follows:

- Direct method: an off-line system of drill monitoring consisting of a visual inspection, through computer vision or determination of drill wear by means of an optical measurement such as a magnifier measurement.
- Indirect method: it is generally an on-line drill wear monitoring system. It consists of monitoring indirect measurements of phenomena related to drill wear. In other words an off-line monitoring is usually first performed and the measured drill wear is then correlated to the measured signals.

Direct methods are usually used to understand and visualize different modes of wear when a drill is worn. In aerospace for instance, a visual inspection is often used to assess the drill condition. However, due to the high complexity and unreliability of models that could describe drill wear, indirect methods are rather widely used for on-line monitoring and automatic drill processes. They are suitable for preventing, sudden failure or incipient mechanical failure, and fracture or breakage failure.

1.4.1 Drill wear

Different types of drill wear can be observed on a drill during the cutting operation as described in paragraph 2.3.4, but most researchers prefer to measure drill wear at the corners of the cutting lips of the drill after cutting a specified number of holes. It seems to be an easy and reliable way of measuring compared to the other types of wear. In most of the published papers found in the drill wear survey; researchers have fixed the standard parameter of a severely worn drill at 0.3mm. However, none of the referred researches provided details of how and at which frequency wear was measured or according to what criteria should the drill be removed for different measurements. Others measured the changes in diameter (tolerances) of the holes drilled instead of the corner wear or analyzed the image of the drill tool surface. Indeed, the idea behind this is that a drill that has been subjected to corner wear should affect both the hole diameter dimension and the contact surfaces between the drill and the work-piece.

A general survey of how drills wear is reported in the following paragraphs together with different drill wear criteria, depending on the researchers:

Ertunc and Loparo (2000) proposed a direct method to measure the drill wear when the worn area on the drill cutting lip (edge) is obtained after drilling a certain number of holes. One can either remove the drill from the machine, or install a measuring device on the machine to analyze the image of the tool surface. The characterization of the drill wear and the assessment of its condition are done by means of the changes in the intensity of the light. Indeed, when the drill wears the deformation of its external surface is affecting the light reflectivity. They also observed different types of drill wear and concluded that the maximum wear occurs at the corners of the cutting lips at the location of the highest cutting speed. Therefore outer corner wear was selected as the criterion. Liu et al. (2000) have also used this method but the flank wear was chosen because of the high reflectivity of the worn drill area.

Flank wear has also found favor with many other researchers as a valid criterion in the determination of drill wear. Li and Tso (1999) artificially induced amounts of flank wear as a standard for evaluating drill wear condition. Panda et al. (2006) predict flank wear on drills without providing much detail on wear measurements and methods used. Kim, Ahn, Kim and Takata (2002) also induced artificial flank wear in their study of drill wear estimation, based on spindle motor power. But the method was only marginally successful, because the correlation between the motor current and the tool wear or breakage was not completely understood. However, the evaluation tests have shown that the proposed method was useful as a real time estimator of drill wear. Liu et al. (2000) identified the existence of two main regions of tool wear in a cutting tool, as flank wear on the tool flank face and crater wear on the tool rake face. But in their paper, they focus on corner wear instead of flank and crater wear, to predict drill bit condition. Corner wear seems to be easy to measure and drill life is also characterized strongly by corner wear on the drill.

Some published works consider the quality of the finished surface and the hole diameter (tolerance) as criteria for drill wear. Atlas et al. (1996) for instance, cite an experiment where drill wear appears to be determined by measuring the diameter of the hole drilled.

Everson and Cheraghi (1999) consider that the drill point, the chipping at the lip areas and the point geometry variation are beyond control during drilling operations because they cannot be detected unless the hole cut by the drill bit is manually inspected. In their results of acoustic emission (AE) correlation to the quality of the hole diameter, they showed that the AE energy and the root mean square (RMS) of the AE signal are correlated to the lip height variation, under a wide variety of conditions. Indeed, the drill bit relative lip height has a significant influence on the diameter of the hole.

Finally, some other researchers have preferred to consider different types of drill wear altogether. In their experiments El-Wardany et al. (1996) induced different types of wear artificially and found that failure of a drill occurs in one of two modes: fracture or chipping and excessive wear. They followed up drill wear while drilling of holes were in progress, starting from plastic deformation on the drill flank as well as the wear of the chisel edge. They concluded that accelerated wear occurred only on the chisel edge and on the margin of the drill. Abu-Mahfouz (2003) artificially induced five different drill wear conditions for prediction and classification of drill bit wear. He found that flank wear is a good indication of the drill condition and has been used to indicate the severity of drill wear. Typically, the failure of a drill occurs due to excessive wear on the flank, chisel wear, crater wear, outer corner wear, and fracture or chipping of the cutting lip or edge.

In conclusion, the above drill wear survey clearly illustrates that there is no formal procedure or a predominant drill wear mode that could lead to a standard metric for drill wear. Drills normally wear in different ways when drilling under normal cutting conditions or when wear is accelerated. It seems that corner drill wear predominates during accelerated conditions, while the fracture of the lip edges would predominate during normal cutting conditions. Note that the major weakness of these methods is that the different types of wear have been artificially induced only for the identification of the wear with the signal changes. The reason for that could lie in the following statement: most effective and reliable methods for tool wear monitoring are so slow in practice so that they are not suitable for the detection of sudden failures (Jantunen, 2002).

1.4.2 Measuring methods

In drilling operations, TCM measurements can be classified in four principal categories according to the publication of Rehorn et al. (2005):

- Force measurements: torque, drift force and feed force.
- Vibration and sound
- Acoustic and ultrasonic vibration
- Spindle motor and feed drive current

A statistical study from their work has shown that 70% of measured signals are force measurements, 14.8% are vibration and sound measurements, 7.4% are acoustic and ultrasonic vibration measurements, and 3.7% are spindle motor and feed drive current measurements. It is clearly shown how preponderant the use of force measurements is. The above categories of signals used for TCM in drilling operations have been reviewed as follows:

The first category uses force measurements such as torque, feed or thrust force, and drift force. It relies on the change of the force magnitude as the drill wears down. The practice of measuring cutting forces is common in machining operations, but the use of torque is almost unique to drilling. The literature certified that force measurements have been very popular and successful monitoring methods in laboratory tests, but are still not widely used in the production environment. Unfortunately, most of the related transducers used are still inconvenient in practice for robust and reliable wear detection. In their review papers, Rehorn et al. (2005) and Jantunen (2002) report on researchers who successfully tested force measurements in the laboratory. Most of them concluded that thrust force and torque are the best indicators of the drill tool condition. Dynamometers are the most popular sensors used but seem to have an adverse influence on the measured vibration depending on their placement on fixtures. El-Wardany et al. (1996) listed another transducer used to measure the torque based on the measurement of eddy currents to detect fracture by means of the dynamic components of the signal. The technique is also suitable for static measurement. It was found useful for both wear and failure monitoring (Jantunen, 2002). Care should be taken to ensure that a close tolerance is obtained in the work-piece hardness to avoid spurious behavior of thrust force and torque. This method that was patented in Germany has been successfully applied on drills of 10 mm diameter.

The second category uses vibration measurements: It comprises the characterization of the drill bit with the change of magnitude or frequency contained in the vibration signals, to identify sharp or worn drill conditions. Accelerometers are commonly used to measure vibration. They offer many advantages and are simple to install. However, vibration is not popular in drilling operations due to the excessive noise generated during the cutting process. The frequency responses realized on the drill itself and on the work-piece display many modes of vibration, without considering the spindle rotational frequency and other vibration modes from machine accessories. It is clear that as the drill cuts, mechanical vibration modes of the drill, work-piece and machine are excited. That is why divergent opinions are found in the literature on the use of vibration measurements. Jantunen (2006) for instance, tested different sensors and his results show that vibration, sound and AE measurements are more reliable for tool wear monitoring than the most commonly used forces. El-Wardany et al. (1996) used vibration measurements to extract features such as kurtosis and cepstrum that are sensitive to drill wear and breakage but insensitive to the cutting conditions and sensor location. The results seemed to be effective and robust for the proposed monitoring features, but they concluded that additional research is required to develop practical vibration monitoring techniques which are sensitive to tool conditions and relatively insensitive to cutting conditions, sensor location, etc. Abu-Mahfouz (2003) also used vibration data to extract features in both the time and frequency domains to produce a TCM system that will lead to more efficient and economical drilling tool usage. His results strongly suggest that vibration signals have tremendous promise for TCM and manufacturing process diagnostics. Overall, vibration measurements have been positively tested in drilling but with quite a limitation. Most of them rely more on the advanced and sophisticated processing of signals than on the measurement methods.

The third category uses acoustic emission (AE) and ultrasonic vibration: this category comprises mechanical vibration measurements in frequency ranges above 20 kHz. There is very little information in the literature regarding the use of AE and ultrasonic vibration in drilling. Due to the inconvenience of mounting the transducers, this category is also not used in practice even though it has been reported that AE is reliable for tool breakage monitoring (Jantunen, 2006). AE was reported to be approximately 33% successful when used to monitor drill failure in the paper of El-Wardany et al. (1996). Everson et al. (1999) illustrated the application of AE in the precision of the hole drilled. They managed to correlate the diameter of a hole drilled with an AE signal measurement parameter. The results of the study show a correlation between the AE energy and the root mean square (rms) with the lip height variations under a wide variety of conditions.

The fourth category uses the spindle motor and feed drive current measurements: in general the spindle current varies with the torque, while the feed drive current varies with the penetration of the drill. They also rely on the change of the force magnitude and power as the drill wears. This momentum method has been rarely examined and bearing in mind the simple relationship between power, torque and angular speed, it seems logical that the increase of torque due to friction should in principle affect the other parameters. Ertunc and Leparo (2000) used a commercial power cell that could measure the spindle or servo power by sensing the change in the instantaneous power fed into a machine or a process. Kim et al. (2002) measured the spindle motor power despite recognizing that the cutting force measurements using a dynamometer is more accurate, it is more suitable for laboratory applications than for real production. They used a mathematical model of torque acting on the lip edge, on the chisel edge region and on the margin edge region of a drill and then correlated this to the motor input power and the motor rotational speed by the following relation:

$$T_m = \frac{P_w}{\omega_m} \qquad 1.1$$

where T_m is motor torque, ω_m is the motor rotational speed and P_w is the spindle motor power. This monitoring of power requires measurement of the spindle armature current and the voltage as well as the measurement of the average spindle speed in order to calculate the corresponding torque. Here the knowledge of the torque under the no load condition is required and is subtracted from the total torque calculated. This example illustrates how it is more complicated to measure the torque than the current of the spindle. Experimental results have shown that current measurements could effectively be used for tool breakage detection. The measurement results were almost constant during the entire drill life-time until the drill totally failed. This system could afford damage to at least one work-piece because of drill failure. Routio et al. (1995) also analyzed the electrical currents of the spindle motor to determine the spindle power and the feed power. Once again, spindle current and power have proven to be effective in the determination of drill life-time.

1.4.3 Diagnostic methods

Jantunen (2002) documents different diagnostic methods used in drilling operations for decision-making:

- Rule Based Expert Systems (RBES)
- Fuzzy Logic (FL)
- Regression analysis (RA)
- Neural networks (NNs)

The RBES is the simplest method of diagnosis for TCM. It uses predefined limits as an indication of a tool failure or a worn tool. El-Wardany et al. (1995) used a feature known as the instantaneous Ratio of the Absolute Mean Value ($RAMV_i$) as threshold for controlled identification of the vibration signal. The ability of the monitoring features to detect drill wear and breakage was verified experimentally and the results confirmed its effectiveness and robustness. It is calculated as follows:

$$RAMV_i = \frac{AMV_i}{AMV_b} \qquad 1.2$$

where AMV_b represents a baseline instantaneous absolute mean value calculated at the start of the drilling process, and AMV_i is the current absolute mean value calculated at the i-th revolution of the spindle.

$$AMV_{i \vee b} = \frac{1}{N}\sum_{i=1}^{N} | x_i | \qquad 1.3$$

where x_i is the instantaneous amplitude of the vibration signal, and the subscript $i \vee b$ means i or b.

FL uses a similar system of predefined limits, but with the difference that the limits are not exactly defined and they are in this case usually overlapping. Jantunen (2006) achieved a simulation model to develop an automated diagnostic method based on a simplified FL method. Liu and Tso (1999) established models based on the relationship between the current signals and the cutting parameters under different tool wear states with a partial experimental design and regression analysis. And then they finally used a fuzzy classification method with success.

Regression is often more effective to be able to follow the trend in the monitored signals and parameters than just to look at the absolute value by using the RA for example. This method has been successfully used by Jantunen (2006) in his PhD thesis. He developed higher order polynomial regression functions with a limited number of terms to mimic drill wear development and monitoring parameters that follow this trend. A great advantage of regression is that it solves the problem of how to save large volumes of measured data for a number of tools. Very little has been found in drilling literature about regression techniques as a tool for condition monitoring. This technique seems very useful for the detection of breakage and not for the determination of wear.

The use of artificial NNs can be seen as an attempt to automate the process of writing the diagnostic rules i.e. if a sufficient amount of good data exists; it will be possible to train a net that could be capable of diagnosing the tool condition. Depending on the NN architecture, one can be able to distinguish between a worn drill and a usable one, on-line with almost 100% reliability. In this category of diagnosis, one can distinguish:

- A self-organizing neural network has been used in the development of a diagnostic system based on the use of feed force and torque together with the fast Fourier transform (FFT). This approach is regarded as a promising empirical modeler.
- The restricted Coulomb energy (RCE) network is a parallel NN modeled after the human learning and classification process. The RCE network correctly recognized normal and tool failure cases with a rate of more than 90% accuracy.
- Adaptive resonance networks have been tested for the detection of severe micro-drill damage just before a complete tip breakage occurs. According to adaptive resonance theory (ART), adaptive resonance occurs when the input to a network and the feedback expectancies match.

NNs have found favor in TCM research in the machining operation field. The list of published papers is countless. In drilling operations, Liu et al. (1998) experimented with the back propagation neural network (BPNN) for the on-line detection of drill wear. They achieved almost 100% reliability, even when changing the experimental conditions such as drill size, feed rate and spindle speed. They concluded the robustness of the method for the on-line drill wear detection systems and hence these systems can be used in very complex production environments, such as flexible manufacturing systems. Panda et al. (2006) also experimented with the BPNN to predict drill bit flank wear. They found the NN performance satisfactory when validated with experimental results. Ertunc and Loparo (2001) proposed two methods using hidden Markov models (HHMs), as well as several other methods that directly use force and power data to establish the health of a drilling tool to avoid catastrophic failure of the drill. In order to increase the reliability of these methods, a decision fusion center algorithm (DFCA) is proposed which combined the outputs of the individual methods to make a global decision about the wear status of the drill. Experimental results demonstrate the effectiveness of the proposed monitoring methods and the DFCA. Brophy et al. (2002) used two stage NNs to detect anomalies in the drilling process using data from a real manufacturing process in order to avoid false alarms when transporting laboratory conditions to the production environment. The network has been used to classify drilling operations as normal or abnormal. Abu-Mahfouz (2003) used a multiple layer neural network successfully for twist drill wear detection and classification. He found that the NN performance is sensitive to the type of input data. The results demonstrate the effectiveness and robustness of using vibration signals in supervised NNs for drill wear detection and classification. Huyser-Honig and Hingwe (2003) proposed what they called the most promising method that they were currently using, involving HMMs in a LabVIEW program. But they also recognized the advantage of using NNs that are often good at solving complex problems for conventional technologies.

1.5 Scope of the work

Based on the information presented in the above drill wear survey, it is clear that the use of cutting forces and vibrations in drill TCM has attracted most researchers in drilling, while the use of drive and spindle power has to date received less interest. This lack of interest is somewhat surprising bearing in mind the relationship between power, torque, and angular speed. If the effects of drill wear increase friction between the drill tool and the work-piece, it can be expected that the monitored forces and rotational speed will also change as the drill gradually wears. In the same manner, a non-engaged drill is expected to rotate faster than a sharp drill that is engaged, a worn engaged drill is expected to rotate slower than a sharp engaged drill. Accordingly, this dissertation will essentially investigate the use of IAS as an indirect monitoring parameter compared to other parameters such as vibration and torque, used in drill TCM.

During experiments, conventional accelerometers have been used for vibration measurement while new measuring methods were also used to measure the torque and the IAS. This was respectively done using a strain-based torque measurement via telemetry and an encoder-based IAS measurement method.

However, direct drill wear monitoring methods by means of SEM photographs were used in order to illustrate that wear, fracture and chipping are typical failure modes found in drilling operations. Their impact on the required quality of drilled holes is not negligible, specifically in the aerospace environment. Direct methods of monitoring these modes of failure are conversely not recommended for high volume production, even if applicable for experimental purposes. Extending these operations to large-scale production environments could be very expensive if appropriate measures are not taken.

The literature reviewed in the paper of Rehorn et al. (2005), illustrated that currently available sensors are adequate to extract significant information from drilling processes, but present many limitations in practice. Having identified the weaknesses of these conventional sensors, the route forward should be improvements based on TCM trends research. Hence, faced with the lack of custom-made sensors for drilling, this dissertation will focus on the use of the IAS via an encoder-based sensor that represents an alternative and practical sensor. The measurement of torque via a strain gauge-based sensor will serve as the comparison. If the test is successful, a non-contact sensor that could yield the same results could replace the encoder sensor or some other spindle current measurement device. This development approach will conduct a series of drill investigations in order to identify the sensitivity of the spindle rotational speed to drill wear compared to the successful torque and vibration measurements.

No new signal analysis is needed at this stage; commonly used signal analysis techniques are applied. But the highly non-stationary and transient events encountered in drilling would necessitate the use of time-frequency methods to investigate its effectiveness in terms of identifying wear and breakage. Spectrogram analysis would therefore be advised to the measured signals. The convergence of TF results lead to recommendations for future research based on the actual results observed.

We have reason to believe that the use of the encoder-based sensor and the use of RA could overcome some of the obstacles encountered in drilling that might be the cause of unsuccessful implementation of TCM in real production environments.

1.6 Document overview

The dissertation is divided into six chapters of which the contents are described below:

Chapter one describes the objectives of the present work and evaluates an overview of the literature in the area of drilling TCM. It also outlines the goal of the current work in light of the literature survey.

Chapter two presents the general terminology on drill bits, and reviews the mechanics of the drilling process and different aspects of tool wear.

Chapter three reviews the theoretical steps used in TCM: sensors, measuring methods, signal analysis and feature extraction, and decision-making.

Chapter four describes the all-experimental set-up and the features of the research experiments.

Chapter five presents and comments on the results of the drilling operations tests. Signals from drill experiments are analyzed using traditional processing techniques and a representation of the IAS signals in the TF domain by means of a spectrogram is provided.

Chapter 6 concludes the work and proposes recommendations for future research.

CHAPTER 2: GEOMETRY AND DRILL WEAR

2.1 Drill geometry

A drill may be divided into three sections: the shank, the body, and the point (Krar and Oswald, 1997). The geometrical characteristics of a typical drill are shown in figure 2.1 for the shank and the body and in figure 2.2 for the other drill parameters.

a) Shank

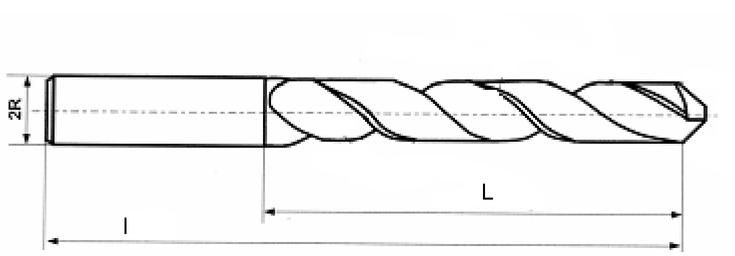
The shank is the end of the drill, which fits into the holding device that rotates the drill. The drill shanks may be straight for drill diameters up to 12.7mm or tapered for drill diameters over 12.7mm. The torque and thrust forces applied by the machines are transmitted to the drill point through this shank.

b) Body

The drill body extends between the point and the shank. The body contains the flutes, margin, body clearance and web, each of which affects the cutting action of the drill. The body needs to be stiff enough to transmit the torque and thrust to the point.

c) Point

The point is the entire cone-shaped cutting end of the drill. The shape and condition of the drill point are very important, since they determine the efficiency of the cutting action of the drill. The point as described in figure 2.2 consists of the chisel edge, lips or cutting edges, lip clearance and the heel.



L : Body
l - L: Shank
R : Drill radius

Figure 2.1: Drill geometry (Altintas, 2000)

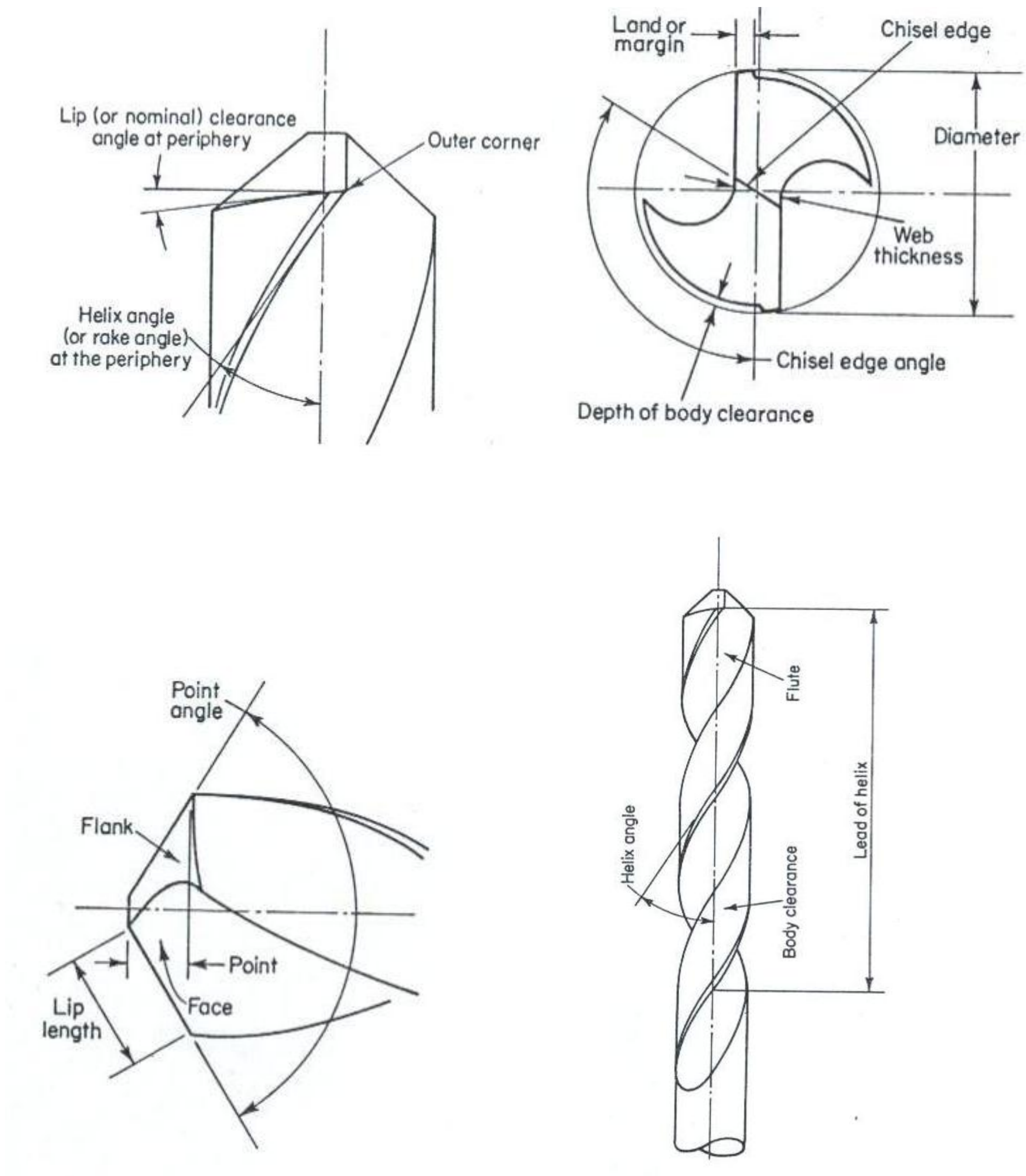


Figure 2.2: Drill characteristics (Armarego and Brown, 1969)

2.2 Mechanics of drilling process

Drilling is a complex three dimensional material removal operation. Drill geometry differs significantly from turning and face milling that can operate with orthogonal and oblique cutters. Relatively little work has been done on the mechanics of drilling using the mechanics of orthogonal or oblique cutting models. The general approach has been to investigate the drill geometry applied forces with respect to the important variables for single-point tools and hence qualitatively describe the drilling results in terms of the theories of orthogonal and oblique cutting. But in this work we will focus on the forces of interest during drilling operations: the thrust force used to push the drill into the work material along the axis of rotation, the torque applied to the drill as well as the spindle drive speed. Based on the book of Altintas (2000) and a paper published by Kim et al. (2002), the mechanics of the drill may be analyzed separately as follows: forces applied to the chisel, the cutting lip and the margin edge region forces. Hence the total thrust and torque forces exerted on the drill are found by summing the contributions of the chisel, lip and margin forces. Margin forces are defined as the contact friction arising between the margin edge and the machined hole due to wandering phenomena caused by unbalanced cutting forces, traverse deformation of the drill and other factors.

2.3 Drill wear

2.3.1 Introduction

Cutting tools should be used only while their edges produce parts within the specified surface finish and dimensional tolerance. When the quality of the cutting edges is lost due to wear or breakage, the tool reaches its limit and must be replaced by a new one (Altintas, 2000). Tool wear is a result of physical (mechanical), thermal and chemical interactions between the cutting tool and work-piece, that remove small parts of material from the cutting tool. Altintas (2000) defines tool wear simply as a gradual loss of tool material at the work piece material and tool contacts; while tool breakage is defined as the loss of a major portion of the tool wedge, which terminates the total cutting ability of the tool. From the above definitions it follows that the cutting conditions, the tool material and the work-piece will largely influence these interactions.

2.3.2 Tool failure mechanisms

There are several types of tool wear mechanisms (Altintas, 2000; Armarego and Brown, 1969):

- Abrasion wear results from friction between the tool flank and the work piece, and from the action of sliding chips in the shear zone. This wear depends on the parts' hardness, strength properties and the geometry of the two mating surfaces, which also dictate appropriate machining speeds.
- Adhesion wear is based on the concept of the formation of welded junctions and the subsequent destruction of these junctions. When the destruction is due to shearing below the interface, a wear particle is transferred. In most cases, the soft metal of the work-piece is rubbed on the harder rotating surface of the drill.
- Diffusion wear is a process of atomic transfer at contacting asperities occurring at high temperatures. One can see that the diffusion may be classified as part of the abrasion and also under certain circumstances as part of the adhesion, because it occurs in the adhesion of contacting asperities.
- Fatigue wear is due to a fluctuating stress from compressive to tensile in the material below a surface. This change in sign of the stress as an asperity passes a given point can cause fatigue failure of the material below the surface.

Any of these mechanisms may dominate the process, depending on the machining application and composition of the machined material.

2.3.3 Acceptable wear

Premature tooling failures due to adhesion, diffusion or fatigue factors may be minimized by careful analysis of work-piece materials and operating parameters, as well as proper shop and tool preparation practices. Acceptable tool wear should be a gradual, predictable degradation from normal abrasion.

2.3.4 Drill failure modes

Tools wear by a process of attrition on both the rake and the clearance face and, at times, by chipping of the cutting edge (Armarego and Brown, 1969). The wear rate is greater near the cutting edge than further down the clearance face and also at very high speeds. The general classifications of the various types of drill wear modes for large drills are:

- Outer corner wear: due to high friction (rubbing) and impact forces between the drill and the hole machined wall. In other words, it is due to a hard or abrasive skin on the work material.
- Flank wear or wear land formation: the clearance face is usually worn to form an approximately flat surface extending back from the cutting edge.
- Margin wear: also due to the impact of tool skin hardness on the work material.
- Crater wear on the rake face of one cutting edge: normally due to high temperature conditions along the rake surface.
- Chisel edge wear: normally occurs due to the very high shear stresses in the flow zone of the tool work-piece interface acting at high temperatures, which causes erosion of the chisel edge.
- Chipping at lip: removal of relatively large discrete particles of tool material.

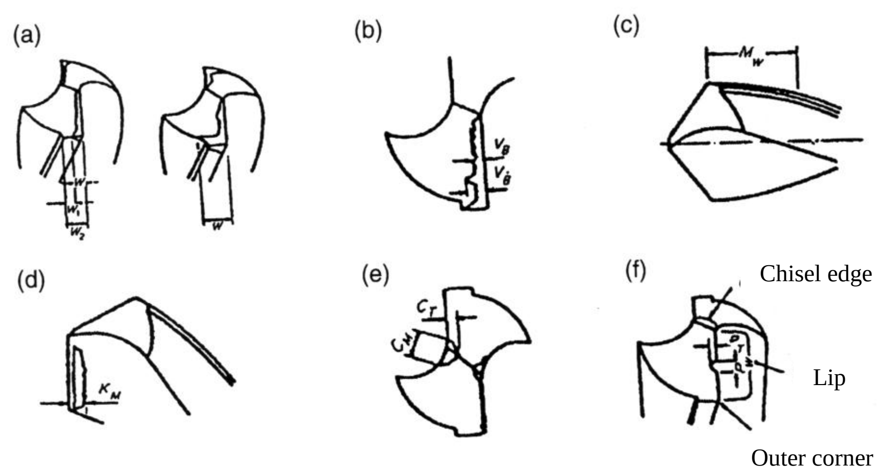


Figure 2.3: Types of drill wear modes and length: (a) outer corner wear, (b) flank wear, (c) margin wear, (d) crater wear, (e) chisel edge wear, (f) chipping at lip (Ayesh et al., 2002)

All these types of wear affect the performance of the cutting in various ways; specifically the cutting forces are normally increased by wear of the tool.

2.3.5 Drill wear stages

The general trend of a curve depicting different stages of drill wear states as function of drill life is given in figure 2.4:

- First stage: Initial stage of wear.
- Second stage: Slight wear or regular stage of wear.
- Third stage: Moderate wear or micro breakage stage of wear.
- Fourth stage: Severe wear or fast wear stage.
- Fifth stage: Worn-out or tool breakage.

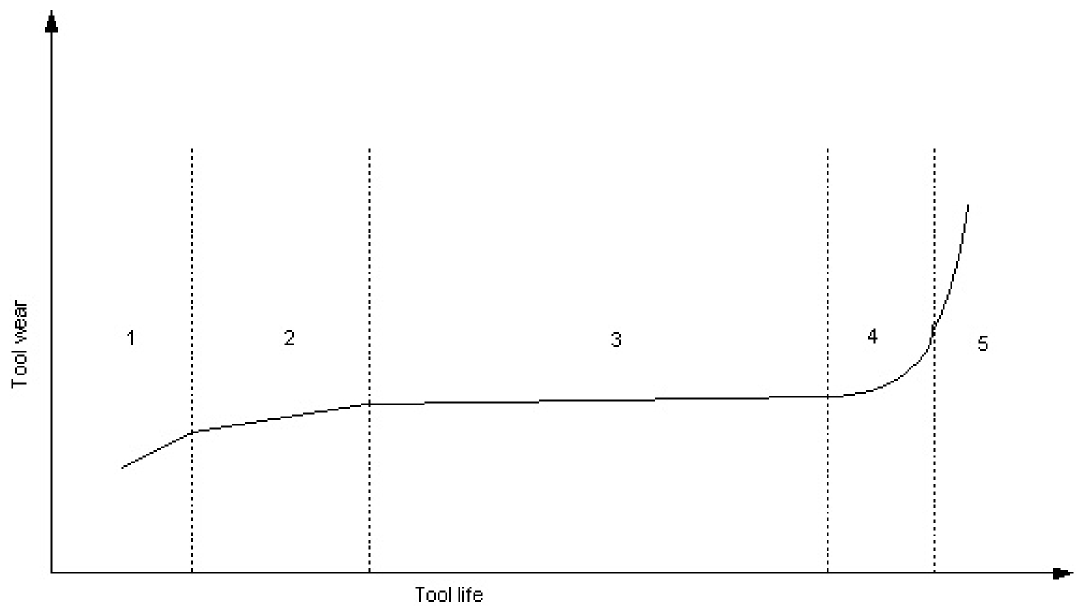


Figure 2.4: Drill wear states function of tool life (Ayesh et al., 2002)

2.3.6 Machining and tool life

The concept of drill wear in drilling operations could not be separated from machining and tool life concepts and vice versa. It is therefore important to elaborate somewhat on these concepts.

The *machinability* refers in general to the work-piece material, and it is simply defined as the ease with which a material can be machined (Trent, 1977). Hence, a material is said to have a good machinability if it can be characterized by the following criteria:

- Tool wear is low or the tool life is long.
- The surface finish produced is good.
- The cutting forces are low.
- Furthermore, the ease of chip disposal and good dimensional accuracy is also considered important. Here the chip shape also influences the clearance of the chips from around the tool under standardized cutting conditions.

Still these parameters are subject to numerous variables such as tool material and geometry, cutting conditions, and so forth. It is therefore not surprising that the term machinability is a difficult concept to describe in quantitative terms (Armerego and Brown, 1969).

The expression *tool life* refers to the cutting tool. It represents the useful life of a tool, expressed as the time (or other units such as the number of components produced) from the start of a cut to some end point defined by a failure criterion. The tool life between tool re-sharpening or a replacement can be specified as the total time to failure or the number of components produced to failure (Armerego and Brown, 1969).

High cutting forces may cause complete failure, or shock loads that produce a fracture extending from the rake face to the clearance face. This condition is aggravated by discontinuous chip formation, interrupted cutting conditions, crater and wear land formation and poor tool design. Complete failure may also be caused by excessive cutting temperature, which soften the tool in the cutting region and allow it to flow plastically under the action of the cutting forces. It is thus seen that tool failure is related to tool wear and the conditions of the finished component. Various tool failures have been used to determine tool life and the tool life values determined will depend on the criteria used such as chipping wear, crater wear, a combination of wear land and crater wear, tool wear volume, limiting surface-finish and component size criteria as well as the force criteria.

The variables affecting tool life may be listed as (Armerego and Brown, 1969):

- The cutting conditions: speed, feed and depth of cut, etc.
- The tool geometry.
- The tool material.
- The work material, and
- The cutting fluid.

The paper of Scheffer and Heyns (2004) provides the reasons for the variation of tool life in the case of TCM:

- Fluctuations or in-homogeneities in the work-piece and drill tool composition.
- The raise of temperature due to the increase in the number of drilled holes.
- The variation of time periods allowed for cooling down the drill between different runs that also influences the temperature effect.
- Other reasons can be found in the drill bit geometry during cutting operation taking into account the excess rate in the cutting speed.

2.4 Mathematical modeling of wear

Mathematical models are very useful to study tool wear. Most models attempt to predict variables such as the cutting forces (thrust and torque) in the case of the drilling machine. These models are functions of cutting parameters (drill size, feed rate, spindle speed, drill wear) so that one can examine their effects on cutting forces for drill wear detection. Three types of models are generally used in machining operations: analytical, computational and empirical models. Analytical models are very complex and have not found application in TCM, while computational approaches are applicable to certain machining operations only. However, empirical models generated from experimental data are widely used.

An empirical model can be drawn from the correlation between the cutting parameters at the optimal drilling conditions. For example, one of the most popular equations that are widely used in machining is the well known Taylor equation that is based on experimental work. He demonstrated that the tool life varies with the cutting speed as follows:

$$VT^n = C_t \tag{2.1}$$

where T is the tool life in minutes, V is the cutting speed, n represents a constant at the conditions tested and C_t is a constant parameter dependent on the variables. This Taylor equation can be extended to include the cutting conditions, the temperature, the tool geometry, work-piece hardness and many other machining parameters that are defined in the literature. A review of the most commonly used Taylor tool life equations can be found in the work of Scheffer and Heyns (2003).

Tool life predictions based on these Taylor equations are however inconsistent in some cases, while others provide good approximations in certain ranges. Noori-Khajavi and Komanduri (1995) for example, made a rough estimation of drill life using Taylor's tool life equation at the recommended speed. They concluded that it would take thousands of holes for one drill bit to wear completely if the recommended cutting speed and feed were used. A preliminary set of laboratory tests done for this dissertation, at the recommended speed confirmed these assertions. Hence, in order to accelerate the wear in this investigation, the drilling life was estimated to be only hundred or less drilled holes when the drilling cutting speed was set to more than 130% of the recommended speed.

Analytical or theoretical models found in the literature estimate cutting forces such as the thrust force used to push the drill into the work-piece, or the torque applied to the drill and spindle drive. However, these complex models were developed for sharp drills and do not furnish any correlation with the deterioration of the drill condition. Consequently, their application in drill condition monitoring is not feasible, also because of the difficulty to ascertain certain parameters in the mathematical equations.

It seems that numerical approaches such as the Finite Element Method (FEM) and other types of computational simulations predicting important variables such as cutting forces, temperature, pressure, chip flow angles etc., still have to find application in drilling operations.

CHAPTER 3: TOOL WEAR MONITORING

3.1 Introduction

The essential goal of effective monitoring in most manufacturing processes is the achievement of improved and cost effective product quality. In other words, the tool should be used at its optimal capability before its replacement. Thus it is fundamental to find the best approach for the development of an appropriate monitoring system for any specific set-up. Scheffer (2002) published an overview of process monitoring in the area of manufacturing. Traditionally the steps required in the design of a TCM process, are depicted as in figure 3.1. This scheme has been successfully implemented in turning production development.

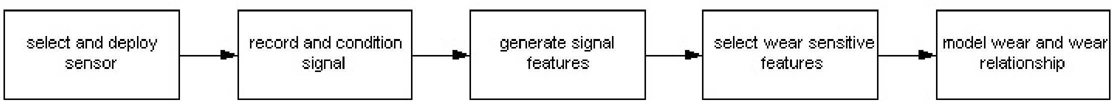


Figure 3.1: Tool Condition Monitoring steps

3.2 Sensor selection

Scheffer (2002) reviewed a variety of available sensors for process monitoring. The most commonly used are force, power, vibration and acoustic emission sensors. He included other sensors as tabulated in table 3.1.

Table 3.1: Sensor-assisted TCM (Scheffer, 2002)

Flame detector	ph sensor	Smoke sensor
Sound level sensor	Level meter	Image sensor
Lubrication oil detector	Accelerometer (vibration)	Temperature sensor
Touch sensor	Seismic sensor	Tool wear sensor
Edge position sensor	Humidity sensor	Tool damage sensor
Limit sensor	Gas sensor	Current sensor
Clamping force sensor	Chip monitoring sensor	Pressure sensor
Speed sensor	Dust sensor	Torque sensor
Thermal deformation sensor	Temperature distribution sensor	AE sensor
Coolant temperature sensor	Surface roughness sensor	Encoder-based sensor

These sensors and many more have found some application in the manufacturing industry where they are used for various monitoring objectives. Applications of TCM in industry however depend mostly on robust and reliable sensor measured signals of the above measurands. As far as drilling machines are concerned, the majority of researchers investigating TCM have usually used cutting force measurements to indirectly indicate the level of tool wear (Brophy et al., 2002) as well as an analysis of the vibration signals. Their results have not met unanimity on the best signals to select between forces and vibration but rather confirmed that the choice of the correct transducer is critical to the monitoring of the system operation in order to sense the desired information and not the noise. However, both methods are still faced with limitations in industrial implementation.

To overcome these constraints to successful and practical implementation, new investigations in the sensors field are needed. Rehorn et al. (2006) have shown the importance of using newly-designed or custom-made sensors in drilling as it is prevalent for those machining operations with straight edged cutters. Hence, research must be directed towards an instrumented tool for these operations or effort focused on the use of intelligent and available sensors in the arsenal of existing technology sensors. Despite its advantages and disadvantages, the encoder-based sensor could present a starting point for another orientation in drill sensor technology.

3.2.1 Strain gauge-based sensor

Strain gauges are widely used in manufacturing to measure specific loading conditions due to some form of complex loading. The loading conditions could cause simultaneous bending, torsion and axial loads. In most applications, strain gauges use wire connections for measurements that are not suitable in the case of rotating tools. A wireless system, such as radio telemetry, was therefore necessary for acquiring the signal. In fact, in order to diagnose the torque measurements, strain gauge sensors were bonded to a drill bit with superglue adhesive. The results have shown that this is a reliable way of acquiring torque data without excessive noise.

Telemetry is a process by which an object's response characteristics, such as thrust force and torque are measured, and the results are transmitted to a distant station, where they are displayed, recorded and analyzed (http://www.telemetry web, 2004). The use of telemetry in machining processes could present several advantages for rotating machinery, such as drilling operations:

- The latest development in sensor technology is to develop wireless systems that can achieve high sampling rates across multiple channels.
- Integrated sensor systems can handle noisy input data.

However, telemetry can still not be used for monitoring the torque in the actual manufacturing processes, because of the inconvenience and the cost to instrument each drill bit with strain gauge sensors.

3.2.2 Encoder-based sensor

Encoders are widely used in manufacturing to measure the velocity on rotating machines. In general, they generate a signal representing the relationship between the angular displacement of the shaft of a rotating machine and the time. A transducer is then used to sense the passage of each encoder segment with respect to a reference point as the shaft rotates (Resor et al., 2004). The transducers could rely on the Hall Effect, fiberoptic reflective light intensity, magnetic pick-up, or even inductive and capacitive sensing, laser encoding, etc. Regardless of the sensing used, the output is a pulse train type signal in which the passage times vary as a function of the shaft rotation and the torsional oscillation. The encoder selection is usually based on factors such as resolution, cost, environmental suitability and sensor mounting convenience (Li et al., 2005). But the installation convenience is considered to be the most important factor influencing the selection of encoders in on-line monitoring. The installation of sensors may be by contact or non-contact, depending on the sensing technique. The contact sensor as used in this work requires a skilful installation to minimize eccentricity and misalignment while a non-contact measurement results in very high reliability, long mechanical life, high tolerance for axial movement and a good solution for electrically isolated applications (Li et al., 2005).

3.2.3 Sensor requirement for tool

Sensors used for tool wear monitoring and TCM in general should be robust, easy to install, and must meet certain requirements such as (Scheffer, 2003):

- Measurement as close to the machining point as possible.
- No reduction in the static and dynamic stiffness of the machine tool.
- No restriction of working space and cutting parameters.
- Wear and maintenance free, easy to replace and cost-effective.
- Resistant to dirt, chips and mechanical, electromagnetic and thermal influences.
- Function independent of tool and work-piece.
- Adequate metrological characteristics.
- Reliable signal transmission, e.g. from rotating to fixed machine components.

3.3 Measuring methods

The measurands in drilling processes could be classified as follows:

3.3.1 Cutting forces

Torque, drift force (lateral force affecting the work piece), feed force (thrust force), and strain measurements are all measures of cutting forces. The increase in the cutting forces as tool wear increases, also affects the dynamic and static force components that increase with tool wear due to friction effects. Figure 3.2 depicts the difference between the static and dynamic components of the cutting force. Measuring cutting forces during drilling processes requires special instrumentation such as a dynamometer that in most cases needs special mounting fixtures, a strain gauge using the real time telemetry, plates and rings, measurement of displacement, etc.

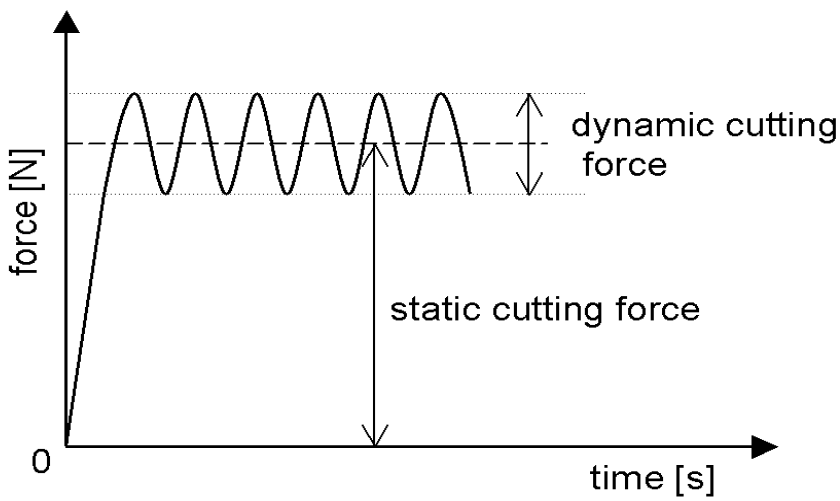


Figure 3.2: Static and dynamic forces (Scheffer, 2002)

3.3.2 Vibration and sound

In general, the vibration measurement technique uses accelerometers which are very suitable for wear monitoring because they offer the following advantages: no effect on stiffness and damping properties of the drilling system; can be mounted close to the cutting action, independent of tool or work-piece; when properly shielded have good resistance to coolants, chips, electromagnetic or thermal influences; are easily replaceable and are very cost-effective. However, during cutting processes, accelerometers are very sensitive to noise in workshop environments.

The most basic vibration monitoring technique is to measure the overall vibration level over a broad band of frequencies. And one of the problems encountered when monitoring the tool life with accelerometers, is the identification of the frequency range that is influenced by tool wear, since machining processes comprise many factors that produce vibrations that are not related to tool wear. It would seem that the frequency range sensitive to tool wear depends on the specific machining operation, and must be determined experimentally because a global range that would satisfy all machining operations does not exist (Scheffer, 2003). However, in the specific case of a drilling machine, some authors advise picking a range around the spindle rotation speed.

Sound measurements are based on airborne transmission of the mechanical vibration of the machine tool, tool holder and the tool itself. Sound measurements, although very easy to perform, have not been widely used, probably because they are affected by background noise to an even greater extent than vibration measurements (Jantunen, 2006). However, in some cases, operators rely on what they hear to define whether the tool is worn or not.

3.3.3 Acoustic emission and ultrasonic vibration

The applicability of acoustic emission (AE) and ultrasonic vibration (UE) measurements for tool failure and tool wear detection, in drilling operations has been studied. It has been found that the AE suffers from severe attenuation and distortion caused by the environment while the low frequency signal used for UE analysis does not. Although these methods offer the advantage of remote transducer placement, they are unfortunately much more sensitive to machine and tooling variations. It has been reported that ultrasonic vibrations are especially suitable for drill breakage for instance. Unfortunately, their sensor methods are usually more expensive than most industrial accelerometers or dynamometers.

3.3.4 Spindle motor and feed drive current

Spindle motor current is in principle a measure of the motor torque. But since the direct torque measurement is more complicated than measuring the spindle motor current, the measurement of current has been widely investigated and used. Similarly, the feed drive current corresponds to the measuring of the thrust force (Jantunen, 2002). Both methods are closely related to the cutting forces except that they use a long measuring chain where other factors might also influence the signals. They simply indicate how much power is used in the cutting processes and also provide information about the dynamics of cutting through analysis of the current signal frequency content. But it is fair to claim that direct torque is a more sensitive way to measure than is the spindle motor current, since the torque sensor is located close to the cutting tool and the dynamic of the electrical motor does not influence it to the same extent as it influences the current measurement.

3.3.5 IAS-based encoder

Feasible acquisition methods for IAS measurement are based on the measurement of the time duration of every single pulse. Based on the above mechanism of data acquisition (DA), the measurement of angular speed can be categorized into two broad groups: timer/counter-based methods and analog-to-digital converter (ADC)-based methods. The first method treats the signal from an angular transducer as a pulse train. The pulse train is used to start and stop the timer/counter. The second method treats an angular speed as an ordinary analogue signal (Li et al., 2005).

3.3.5.1 Timer/counter-based methods

This method dominated the development of angular speed measurement techniques. It is conceptually measuring either an elapsed time (ET) between successive pulses or counting pulses (CP) during a prescribed period of time. The following are some representative methods used (Li et al., 2005):

- Measurement of ET between successive pulses
- Counting of pulses (CP) during the prescribed period

- The combined method using both ET and CP
- The constant elapsed time (CET) method based on both pulse counting and period measurement
- Double buffered method based on both pulse and interval measurement of speed pulses. Unlike the CET method, having varying time durations for measurement cycles, the buffered method uses a fixed length of measurement cycle.
- Pure software based method: makes maximum use of computer capacity, no additional hardware is required.

In condition monitoring and fault diagnostic applications, it is often useful to determine the angular speed at a specific angular displacement, from the angular speed signal, and this for only a small fraction of a revolution. Hence, under such conditions the CP technique is appropriate to provide an average speed over multiple pulses but inappropriate for the measurement of IAS. As IAS is necessary for condition monitoring applications, the ET of a single pulse has to be measured in order to ensure the instantaneous speed measurement.

3.3.5.2 ADC-based methods

This category of angular speed measurement method has attracted little interest from researchers in the area of condition monitoring and control. Here are two representative methods (Li et al., 2005):

- Direct ADC method: this method treats an angular speed signal as an ordinary analogue signal and extracts angular speed from the logged data using an efficient signal processing technique.
- Frequency-to-voltage (F/V) converter-based method: This method converts the frequency of an angular signal into a voltage signal using an F/V conversion circuit. The voltage amplitude is proportional to the input frequency. The voltage signal is then acquired using an ADC system. As the frequency of the angular signal is proportional to the angular speed, the acquired data from the ADC will give the angular speed.

Li et al. (2005) consider the measurement of angular speed as a generic issue in a variety of applications in the area of monitoring and control of rotary machinery, and find applications in the timing of automotive engines, measurement of torsional vibrations, fault detection on diesel engines, etc. Note that the word *instantaneous* refers to the angular displacement and the time duration. Hence, the measurement of IAS is realized in the following difference form:

$$\omega = \frac{\Delta\phi}{\Delta t} \qquad 3.1$$

where $\Delta\phi$ is angular displacement and Δt is the corresponding time duration.

As mentioned above, the speed variations during a revolution need to be known in condition monitoring and fault diagnosis applications. Considering the measurement principle of IAS shown on figure 3.3, the IAS (rev/min) can be calculated by:

$$n = \frac{60\, f_c}{N_c M} \qquad 3.2$$

where M is the number of pulses or evenly spaced divisions of a pulse train with $\frac{2\pi}{M}[rad]$ corresponding to one unit of angular displacement. The IAS is calculated by measuring the ET for the corresponding unit of angular displacement with f_c being the clock frequency and N_c the number of clock pulses. By means of an accurate shaft encoder resolution, the monitoring of the IAS using the variation or the changes of ET between two pulses is feasible.

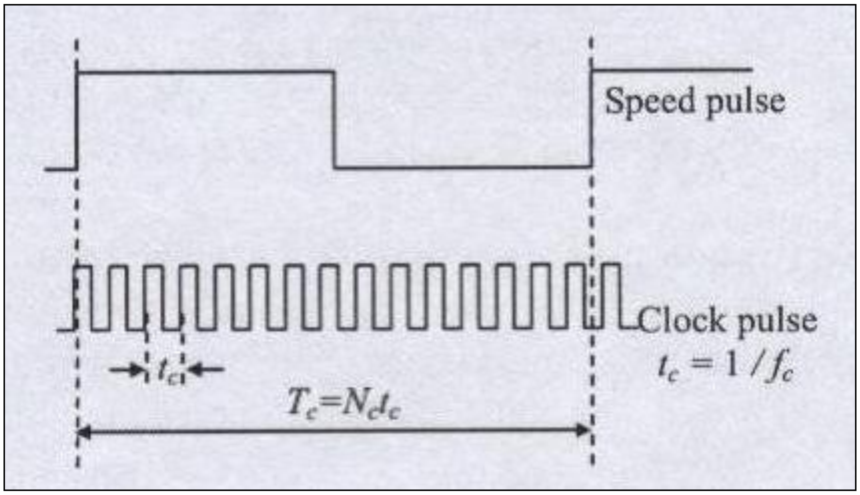


Figure 3.3: Measurement principle of IAS (Li et al., 2005)

3.4 Signal analysis

3.4.1 Introduction

The primary function of signal analysis could be described as the pickup of meaningful information out of the mass of information. Therefore, for the best performance of the monitoring system, only those features which show a high sensitivity to tool wear and low sensitivity to process parameters should be utilized. Various signal analysis techniques have been used in the context of drill wear. And it is not a concern of this work to discuss the best techniques to be used. The focus will be on the usually common analysis techniques by means of measured signals. But it has been shown that drilling signals present important stochastic features. It may therefore be expected that the drill wear evolution should well be monitored by following statistical trend features due to the disparities of data. Note that the drill's wear progresses rapidly towards the end of the drill life as it was shown in figure 2.4. Hence, the choice of signal analysis technique should be in accordance with the cost effective technique that could quickly detect the failure and the end of drill life. In the following discussion, we define the most important signal analysis methods used for drill wear and drill failure monitoring. These methods have been widely and successfully used in conventional technologies and their suitability for use with the IAS signal will be determined in this work. Preliminary TF analysis has been added in order to test the effectiveness of the IAS signal response to the identification of drill failure.

3.4.2 Time domain analysis

In principle, the time domain raw data of machining signals are not very informative as such, as they contain the combined energy of signals and noise. Hence, the evaluation of changes by measuring only the amplitude of these signals could be biased. That is why a number of statistical parameters are used for the computation, assuming that the signals are random and have a probabilistic distribution. In addition to the use of $RAMV_i$, Rehorn et al. (2005) reported the successful use of time domain signal analysis for drilling by means of statistical methods. From those parameters, one can name the following: the mean, the rms, the crest factor, standard deviation, variance, and kurtosis. These parameters are typical features used in time domain analysis and are defined as follows (Rao, 1995) for discrete samples:

Signal average: The signal average or mean value of a discrete function $x(n)$ over an interval T is the average value of the signal measurements in the drilling process.

$$\bar{x} = \frac{1}{N}\sum_{n=0}^{N-1} x(n) \qquad 3.3$$

Peak: The peak value of the signal is defined as half the difference between the maximum and minimum:

$$peak = \frac{1}{2}(\max(x(n)) - \min(x(n))) \qquad 3.4$$

Root mean square (RMS): The RMS value of the signal is the normalized second statistical moment of the signal. It is defined as:

$$RMS = \left(\frac{1}{N}\sum_{n=0}^{N-1}(x(n) - \bar{x})^2\right)^{\frac{1}{2}} \qquad 3.5$$

Variance: The variance is the mean square deviation about the mean defined as

$$Variance = \frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\bar{x})^2 \qquad 3.6$$

Crest factor: The crest factor is defined as the ratio of the peak value to the RMS of the signal.

$$CrestFactor = \frac{peak}{RMS} \qquad 3.7$$

Kurtosis: The kurtosis is the normalized fourth statistical moment of the signal.

$$Kurtosis = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\bar{x})^4}{(RMS)^4} \qquad 3.8$$

3.4.3 Frequency domain analysis

Spectral (or frequency) analysis is a term used to describe the analysis of the frequency domain representation of a signal. It consists of the conversion of a time domain representation of a signal into a frequency domain representation. This can be achieved by the widely used discrete Fourier transform (DFT) of digitized data, which is used to generate the power spectral density (PSD) function. It provides a means to determine the frequency content of a measured signal. Assuming that wear influences the frequency content of the signal, the DFT then gives an inside view of the process through the power spectrum. It is a more powerful tool to get rid of noise and disturbances than statistical parameters. This analysis approach is being widely used in drilling operations on vibration, torque, drift force, and feed force signals (Jantunen, 2002) to detect drill failure. It has been observed that the magnitudes of PSD at all frequencies increase proportionally with an increase in drill wear. Therefore, the area under the PSD plots also change consequently. It is also reported that other techniques of analysis such as autocorrelation and cepstrum analysis work well in drilling and milling operations.

3.4.4 Time frequency domain analysis

The spectral analysis defined above can give information about the frequency components, but it does not give any indication about their temporal localization. Hence, in order to compensate for the lack of time localization, the time frequency distribution (TFD) has been introduced. A TFD is defined as a transform that maps a 1-D signal onto a 2-D time-frequency map. It describes how the spectral content of the data evolves with time. As such, TFDs are natural tools for the analysis, synthesis, interpretation and processing of non-stationary signals (Swami et al., 2001).

Conventional spectrum analysis in drilling operations assumes that the signals, which are analyzed, are random and stationary. But some researchers have found that highly non-stationary and transient events are important in drilling operations (Atlas et al., 1996). Therefore, the use of the frequency spectrum in drilling operation signals could be unsuitable. Add to that, the frequency response obtained from the IAS signal has confirmed the non-linear characteristics of drilling signals. To overcome this misuse of the spectrum, time frequency analysis has been designed specifically to work on non-stationary signals and is useful for extracting valuable information from manufacturing and machine monitoring sensor signals (Atlas et al., 1996). Unfortunately, there has been a severe lack of research interest in TF methods in all machining operations to identify wear and breakage failure (Rehorn et al., 2005).

There are several types of TF analysis, but the most common TF processing methods found in TCM are the time frequency representation (TFR) and wavelet analysis. Apparently, the Short Time Fourier Transform (STFT) and the S-transform has not been used in the analysis of machining data. Rehorn et al. (2005) propose a prudent focus on the use of the S-transform in order to perform feature extraction for TCM applications, as it has been used successfully to analyze a variety of transient signals in many fields.

3.4.4.1 Time frequency representation

Both long- and short-term changes in manufacturing and monitoring signals commonly represent the most important aspects of the signals. Atlas et al. (1996) refer to the changing portions of the signals as the time-varying signals. It is the frequency content of these time-varying signals that conveys the most meaningful features. Thus representations, which can show the changes in frequency content with time, can also furnish a rich representation of vibration, torque and IAS signals. In general, a TFR comprises the spectrogram and the minimum cross entropy (MCE).

A *spectrogram* is a TFR found from the STFT. A simple code from the Signal Processing Toolbox in Matlab exists for the representation of spectrogram analysis.

An *MCE* is a class of TFRs, which satisfy the following three fundamental properties: the positivity, a time marginal's properties, and a frequency marginal's properties. Details about spectrogram and MCE formula can be found in the paper published by Atlas et al (1996).

3.4.4.2 Wavelet analysis

Wavelet analysis is widely used in TCM application and has become well known as a useful tool for various signal-processing applications. The wavelet analysis is a time frequency function which decomposes the information of a signal f(t) into various components or constituent parts called levels that can be reconstructed to the original signals. There has been limited works done on wavelet analysis in drilling operations. It has been proposed from these works that wavelets could be combined with ANNs to provide self-learning and adjusting (Rehorn et al., 2005). It has even been argued that wavelets are favored over FFTs because of their variable resolution and they allow the simplification of the representation and modeling of the thrust force.

3.5 Decision making

Decisions on tool condition can be made in different ways: analysis of the time domain signature, comparison of a signal feature to a predefined threshold, trending features, the use of ANNs, fuzzy logic, pattern recognition algorithms, Hidden Markov Models and so forth. In general, the focus of the above diagnostic tools may be classified in the following three general techniques of decision approach (Stander, 2003):

- Decision based on an absolute threshold being exceeded.
- Decision based on a trend.
- Artificial neural networks.

3.5.1 Absolute thresholds

This method of diagnosis in a monitoring system uses a predefined threshold as an indication of tool failure or a worn tool. It is the basis of Rule Based Expert Systems (RBES), and comprises the detection of a sensor level beyond a fixed acceptability level. Caution should be taken when working with predefined thresholds, because they can vary according to the machine to be monitored, with the ambient conditions, the support structure, etc. Fixed limits should be used as a guide and never used on its own to predict fault detection.

3.5.2 Trend analysis

Trend analysis is the detection of a change in sensor level with time, and this, relies on the detection of significant differences from previous levels. As a rise or a drop in the value of the monitor does not necessarily indicate a fault, it could be interesting to analyze a trend in the rate at which values are changing, rather than the change in the absolute value when the change in the slope is consistent.

3.5.3 Artificial neural networks

This method has been applied widely in detection and pattern classification in various areas of manufacturing such as drill wear. Conceptually it is a multidimensional curve fitting process, which relates a certain output to a certain input. Some reasons for using ANN in drilling operations include: the method has been successful at rates varying between 85% and 100% (Rehorn et al., 2005), and the method has shown great potential of learning features to be used for drill TCM. The most widely tested NN approach is the so-called multilayer perception (MLP).

CHAPTER 4: EXPERIMENTAL SET-UP

4.1 Set-up

Figure 4.1 schematically illustrates the experimental set-up used in this drill wear investigation. Drilling experiments were performed on a three-axis MITCO milling machine, equipped with an automatic feeding rate system for all samples of drilled holes. A detailed description of the hardware and details of the equipment used are given in table 4.1. In order to hold and keep the work-piece tightened, a vice was mounted on the milling machine bed with the ability to move in three orthogonal directions.

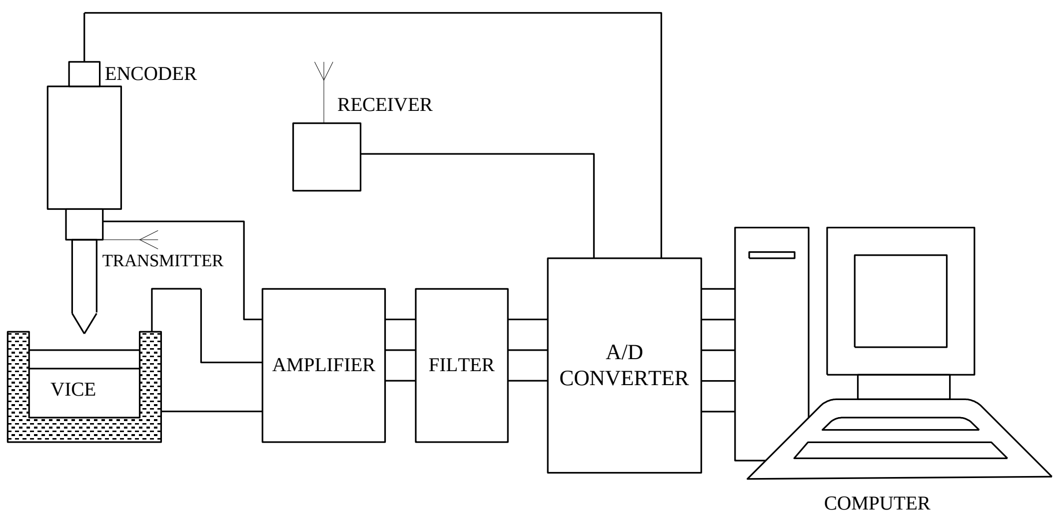


Figure 4.1: Schematic diagram of experimental set-up.

For all experiments, a 10 mm drill bit was used to cut 16 mm deep holes in a mild steel work-piece material, at the recommended operating parameters except for the case where 3, 6, 8, and 12 mm drill bits were used in order to test to what extent the results obtained from a 10 mm drill could be generalized. The thrust cutting force and the torque are the major sources of excitation and are the most commonly monitored variables in drilling operations. They could be measured respectively by means of vibration measurements and strain gauges. Hence, accelerometers were used to measure vibration signals in the axial direction (thrust force) and in the transverse direction (for the drift force), while strain gauges were used for the measure of torque via telemetry. To test the sensitivity of acceleration as a measurand to detect wear, accelerometers were attached both on the spindle house and on the work-piece vice. But as the accelerometers mounted on the work-piece vice have shown the best results, they were therefore retained for the remaining results presented through this work.

Table 4.1: Specifications of equipment

Types	**Specifications**
Drilling machine	Three axis milling machine, MITCO model
Sensors	Accelerometers: SN 11552 model 627A01 (Az1) (on spindle); SN 12250 model E327A01 (Ay) (on spindle); SN 33989 model 352C68 (Az2) (on the vice) Strain gauges: KFG-2-120-D2-11 Shaft encoder: HENGSTLER 0523 RI-58-0/1024K – 42 RH (5VDC)
Amplifiers	PCB Piezotronics model 482A22, ICP sensor signal conditioner
Filters	Accelerometer signals: 4^{th} order Chebyshev type with –3 dB roll-off at 4350 Hz Encoder signal: set to allow 250 Hz frequency response
Telemetry system	Torque Track 9000 AII – Digital technology (Binsfeld Eng Inc.)
Data Acquisition	National Instruments A/D card PCI – 6110E: 5 MS/s, 12-Bit, simultaneous – Sampling Multifunction Pentium 4 PC, MATLAB 12a
Work-piece material	Mild steel (~200 HBN) 80×180 mm with 16 mm of thickness

A shaft encoder HENGSTLER 0523 model, mounted at the top of the milling machine shaft was used to measure the changes in the IAS. The output from the encoder is a chain of 1024 pulses per revolution.

The signals from the accelerometers were amplified by means of an ICP sensor signal conditioner and then passed through an analogue filter designed with the Filter Lab Low Pass Program to avoid aliasing. The torque signal from the strain gauge is passing through a telemetry system with incorporated internal amplification and filtering: A Display device Output/RF Level evaluates the radio signal strength while the RD9000 filter can be set either to activate a 10 Hz low-pass filter or 250 Hz full frequency response. The later set-up filter was used for the purpose of these experiments.

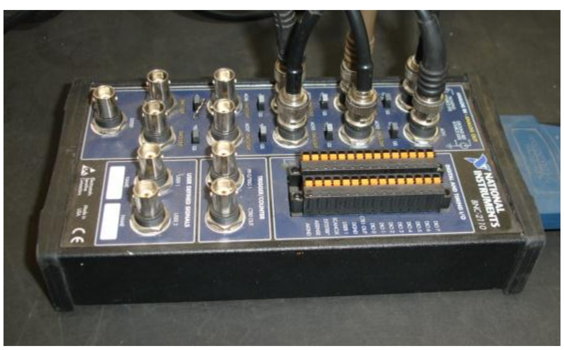
All the signals were sampled using a DA board. The DA channels could not accept different sampling rates per channel, hence the highest sampling rate, which is the signal from the shaft encoder, determined the choice of sampling rate. The sampling rate from the shaft encoder signal is calculated as follows:

$$f_{\max} = \frac{870 rev}{\min} \times \frac{1 \min}{60 \sec} \times \frac{1024 cycles}{rev} = 14848 \frac{cycles}{rev} \approx 15 kHz \qquad 4.1$$

Hence, in order to get an accurate signal of chain pulses in the time domain, the experimental data should be sampled at least ten times the calculated frequency. That is equal to 150 kHz. But as smaller drills have to be tested at high speed above 870 rev per min, the sampling frequency was therefore set up at 200 kHz per channel. All the data were saved on the hard disk of the computer for further processing and analysis.

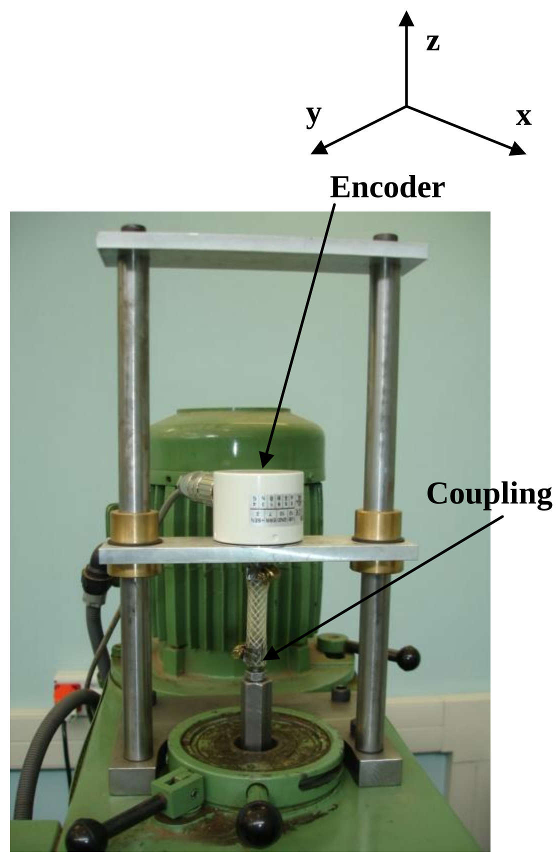
Photographs of the experimental set-up are shown on the following pages. Figures 4.2 and 4.3 respectively depict the electronic equipment used during experiments and the DA ADC plug. The telemetry system receiver is shown in figure 4.4 while figure 4.5 illustrates the drill bit which has been instrumented with strain gauges, the battery, the telemetry transmitter, as well as the work-piece on the vice. A photograph of the milling machine and accessories used for drilling operations can be seen in figure 4.6 while figures 4.7 and 4.8 present photographs of different sensors: accelerometers mounted on the vice and the encoder-based sensor joined at the top of milling shaft by means of a flexible coupling.

Figure 4.2: Instrumentation set-up



Figures 4.3 and 4.4: ADC plug and Telemetry receiver

Figure 4.5 and 4.6: Instrumented drill with telemetry transmitter and milling machine equipment



Figures 4.7 and 4.8: Mounted sensors used

4.2 Test procedure

The experiments consisted of drilling holes in a mild steel work-piece material under dry cutting conditions. The experiments have been done on the same basis, e.g. one size drill bit for all samples except for the sizes mentioned under point 4.1, and the other parameters were fixed as recommended in the Machining Data Handbook (MD Center, 1972).

In tool life tests, it is generally found that an increase in either the speed or the feed rate above the recommended level may cause a decrease in tool life. Noori-Khajari (1994) made a rough estimation to calculate the drill life using Taylor's tool life equation, at the recommended cutting speed. He found an average tool life of 4240 holes while the drill tool life was reduced to only 30 holes when the cutting speed was doubled. Also from the laboratory experiments, it is clearly shown that, when drilling at the recommended feed rate and cutting speed, one set of experiments using a specific drill will last longer before a completely worn drill is achieved. Consequently, large capacity memory must be available in order to store the huge amount of unnecessary data. Needless to say that, during normal cutting conditions, signal magnitudes from the drilling operations are almost constant until the drill starts to wear. Hence, the strategy used to decrease the experimental time and the amount of data to be stored, was to increase the cutting speed by 1.35 according to the available speed on the milling machine.

4.2.1 Machining parameters

Based on the above considerations, the machining parameters were fixed as shown in table 4.2. A relatively high cutting speed of 870 rpm instead of the recommended speed of 600 rpm and a feed rate of 0.13 mm/rev were used to drill holes in the mild steel. The choice of the cutting speed further depended not only on the drill size, but also on the available speed settings on the milling machine. Indeed, sometimes in industrial practice one cannot achieve the recommended value of a cutting speed on a specific type of drilling machine and would select the closest one. Hence, the cutting speed was maintained at the same level, except for the experiments where 3, 4, 6, and 12 mm drill bits were used.

Table 4.2: Cutting parameters

Cutting parameters	**Specifications**
Drill tool	High Steel Speed (HSS)
Spindle speed	870 (rpm)
Feed rate	0.13 (mm/rev)
Depth of holes	10 mm
Cooling	None

4.2.2 Sensor issues

One of the issues to be solved in order to be successful in on-line TCM is the convenience with which one could install the sensors described in table 4.1 for the acquisition of signals. In the following, a description of sensors used is provided with the correlated issues due to their installation.

Two accelerometers were stud-mounted on the milling machine bed vice in the Y- and Z-directions, while the third accelerometer was stud mounted on the structure supporting the spindle in the Y- direction. Theoretically this mode of mounting is the best and does not present any problem if well mounted perpendicularly to the surface.

For the measurement of the torque, KFG-2-120-D2-11 strain gauges were used. The active length of these gauges is 2mm but the packaging extends them to around 7mm. With these dimensions, it is not easy to stick two sets of strain gauges on a 10mm drill bit. The procedure required skilful installation of strain gauges. This entailed: treatment of attachment surfaces, mark attachment position, cement the gauge with appropriate cement, press and cure, check the resistance and insulation, connect lead wires with a solder and then connect to the telemetry transmitter in full bridge configuration. After the strain gauges have been installed, a tape was applied to shield the delicate strain gauges from cutting shavings. Care was taken at each stage to prevent useless measurements due to the release of strain gauges from the drill bit surface. Overall, the telemetry transmitter and its battery had to be fixed on the drill tool and being replaced with the drill tool changes or when the battery was flat.

The measurements of the IAS were done via the encoder-based methods. The RI-58-0/1024K – 42 RH encoder used also needed careful installation to minimise eccentricity and misalignment with the shaft. Hence, a flexible coupling was carefully used to connect the encoder to the shaft at the top of the milling machine. Appropriate software was written in MATLAB changing the chain of pulses signal in rotational per minute speed based on the pulses' time periods.

The above issues clearly demonstrate how inconvenient and tedious the use of strain gauge sensor was in the telemetry system and its consequence in the data acquisition. The encoder system used requires a high sampling rate with the consequence of a huge amount of data to be stored.

4.2.3 Calibration and channel set-up

The calibrations for the channels used are shown on table 4.3. Acceleration and encoder calibrations are fixed and readable on the sensor devices, while the strain calibration was performed according to guidelines provided by the manufacturer. The torque calibration was done considering the drill as round shaft with glued strain gauges in full bridge configuration, and according to the following procedures:

The given equations define the relationship between the input signal to the BT9000 transmitter (typically from the strain gauges) and the full-scale output voltage of the Torque Track RD9000 system. The calculations are based on geometry parameters of the drill (drill diameter), sensor parameters (gauge factor) and transmitter gain setting. Hence, the torque signal is calibrated as follows:

Step 1: Calculate full scale torque, T_{FS} that corresponds to the maximum system output of 10 V.

$$T_{FS}(Nm) = \frac{(V_{FS})\times(\pi)\times(E)\times(4)\times(D_o^4 - D_i^4)}{(V_{EXC})\times(GF)\times(N)\times(16000)\times(1+\upsilon)\times(G_{XMT})\times(D_o)} \qquad 4.2$$

where E = 206.8 × 10^3 N/mm^2 and the following characteristics are used for the HSS drill bit:

- D_o (drill diameter measured) = 10 mm
- GF (gauge factor from gauge package) = 2.03
- G_{XMT} (BT9000 gain based on jumpers) = 2000
- V_{FS} = 10 V; V_{EXC} = 5 V; N (Number of active gauges) = 4 and D_i = 0 for solid shafts

$$T_{FS} = \frac{(10)\times(\pi)\times(206.8\times10^3)\times(4)\times(10^4)}{(5)\times(2.03)\times(4)\times(160000)\times(1+0.3)\times(2000)\times(10)} = 15.386Nm$$

Hence, the 10 V read at the RD9000 output corresponds to 15.386 Nm or 153.86 Nm/V.

Step 2: Trim the full scale output

The above full scale output voltage of the RD9000 should be trimmed so that the voltage output corresponds to an even round number torque level. For that, calculate the trimmed voltage value (V_{TRIM}) that corresponds to the round number (trimmed) torque level (T_{TRIM}). Note that T_{TRIM} must be greater than T_{FS} calculated above.

$$V_{TRIM} = \frac{(T_{FS})\times(V_{FS})}{T_{TRIM}} \qquad 4.3$$

Hence, $V_{TRIM} = \frac{(15.386)\times(10)}{20} = 7.693V$

- Step 3: Adjust the full scale output to equal V_{TRIM} on the RD9000 to 7.693 V.

The system is now calibrated so that 20 Nm equals 10 V and the gain of the system is therefore 2 Nm/V.

The complete channel set-up is well summarized in the table 4.3 and a set of measured variables per drill is shown in table 4.4.

Table 4.3: Channels set-up

Channel	Sensor	Calibration	Gain	Sampling rate	Test description
1	Az	104 mV/g	94.33	200 kHz	Thrust acc.
2	Ay (on vice)	102 mV/g	96.18	200 kHz	Drift acc.
3	Encoder	1024 pls/rev	1	200 kHz	IAS
4	Ay (spindle)	102 mV/g	96.18	200 kHz	Drift acc.
5	Strain	20 Nm/10V	2	200 kHz	Torque

The drill bits identification and typical measured variables during experiments are shown in table 4.4. When using 10mm drill, all variables were measured except for drills with diameter less or more than 10mm where only acceleration and IAS were measured.

Table 4.4: Variables measured

Definitions	Exp1	Exp2	Exp3	Exp4	Exp5	Exp6	Exp7	Exp8	Exp9	Exp10	Exp11
Drill Name	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
Diameter(mm)	10	10	10	12	8	8	6	6	4	3	3
Speed (RPM)	870	870	870	650	870	870	1247	1247	2347	2347	2347
Acceleration	×	×	×	×	×	×	×	×	×	×	×
Torque	×	×	×								
IAS	×	×	×	×	×	×	×	×	×	×	×

4.3 Measurement

When starting a drilling operation, the drill cuts metal and removes chips from the hole. The initial chips are in the form of short spirals and as the temperature increases, the chips increasingly come out sticking to the drill, assuming a helical form. It is therefore evident that the temperature and the formation of chips are major disturbances during data acquisition of measured signals. Hence, to avoid corrupted measurements and disturbances because of excessive chips emerging from the hole, a manual trigger was used to start the data recording for an overall period of five seconds. Data was acquired as soon as the drill reached essentially steady conditions. In practice the influence of the emerging chips on the vibration measurements, was minimized by triggering as soon as the point of the drill bit completely penetrated the work piece.

Figure 4.9 shows the scheme of data acquisition followed during the entire set of experiments.

Process → Trigger manually → Start recording → Record for 10 sec. → Save recorded signals

Figure 4.9: Scheme of data acquisition

4.3.1 Frequency response for work-piece and drill

The drill itself always has many modes of vibration, in both torsional and transverse directions that range from audible frequencies to more than 50 kHz (Atlas et al., 1996). Experimental modal analysis was performed on the tool and the work-piece system, and the modal parameters were estimated from the measured frequency response functions. Table 4.5 identifies the main natural frequencies of the work-piece and drill tool system obtained by impact testing. The beam drill and work-piece were excited by means of a hammer and the response was obtained using an accelerometer. The signals were processed through a Diagnostic Instruments PL202 analyzer that gave the natural frequencies shown in table 4.5. These results were compared to the FFT spectra of the drill and work-piece system measured during drilling operations. The results shown in chapter 5 illustrate significant modes in the spectra in the frequency band of 0-5000 Hz with the following distinct frequency bands 0-1000 Hz, around 2000 Hz, and 3000-4800 Hz. These frequencies are similar to the ones in table 4.5. The non periodic nature of the cutting process in drilling is quite evident from the broad band nature of the FFT spectra. It is expected to track the variations of the spectral modes with the increase of drill wear. In general, the tracking of these frequencies is a tedious job in an environment with many disturbances.

Table 4.5: Frequency responses for work-piece and drill system

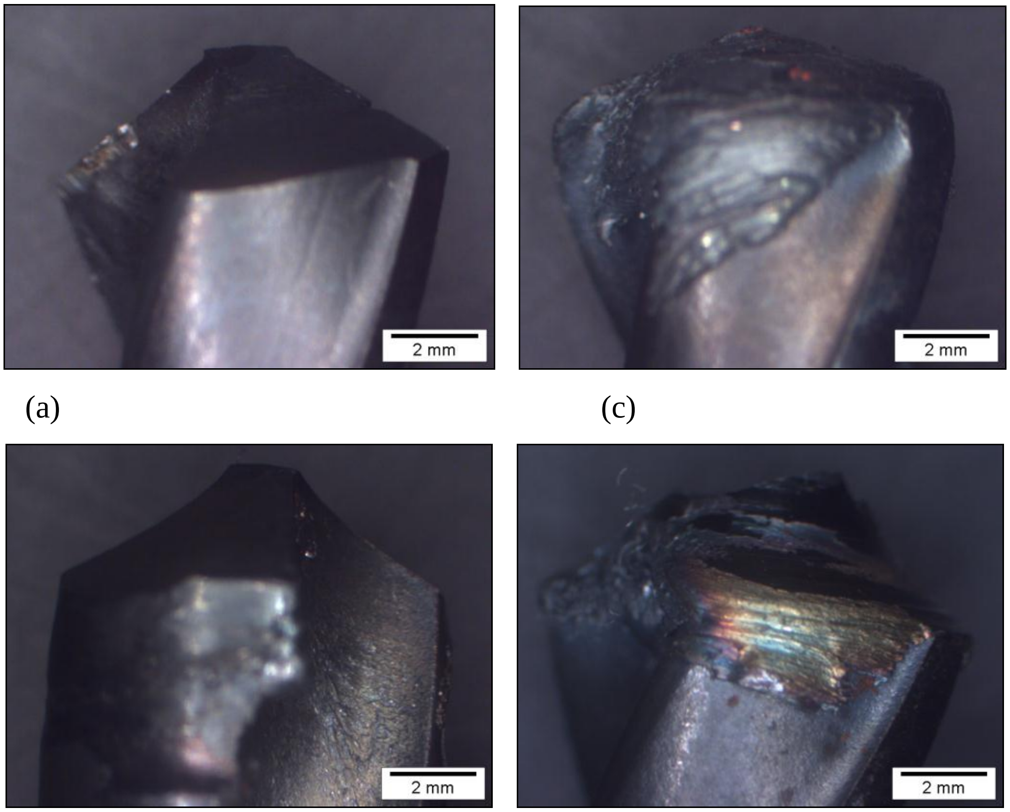
	Range of Natural frequencies (Hz)
Work-piece and vice	800-1700, 2500-3500 and 4000-4800
Drill tool	400-1250 and 2230-3500

CHAPTER 5: RESULTS and DISCUSSION

5.1 Drill wear progression

Drill life varies widely due to the complexity and the stochastic behavior of drilling operations. For instance, an uninterrupted drilling operation associated with high cutting forces produces excessive drill wear, while an intermittent operation at the recommended drilling parameters induces slow and gradual wear. In general, it is the attrition process on both the rake and clearance face that stimulates an increase of the cutting temperature. This could lead to a process of diffusion or exothermic oxidation that could also damage the drill catastrophically as shown in figure 5.1 (c) and (d). The most important is to identify drilling process parameters that do not generate chip light emission and can produce several holes with moderate drill tool wear as shown in figure 5.1 (a) and (b).

Based on the above considerations, it is clear that the dominant drill wear pattern depends on the drilling operation conditions and cutting parameters. When drilling at the recommended cutting parameters, fracture or lip edge chipping is the predominant wear mechanism as shown in figure 5.1 (a) and (b). In contrast, the SEM photographs in figures 5.1 (c) and (d), illustrate plastic deformation and diffusion as the dominant wear mechanism for cases where the recommended cutting speed was exceeded by more than 1.35%. The damage in figure 5.1 (c) and (d) is an illustration of uninterrupted drilling without sufficient cooling time between operations and where the chip light emission was extensive. This was an important indication of very high chip temperature due to excessive rubbing between the drill bit and the work-piece. In this case, the corner wear was rapidly accelerated, the cutting edges disappeared and the drill tips rounded.



(a) (c)

(b) (d)

Figure 5.1: SEM micrographs image of worn point drills: (a) fracture or chipping on the drill lips; (b) Typical outer corner wear; (c) Point drill diffusion; and (d) Corner wear and diffusion of drill lips

In general, the wear mechanisms of the drill shown in figure 5.1 (a) can be explained as follows: drill wear begins by the fracture or chipping of one side of the lip edge. This is followed by a certain unbalance in the forces due to the change in the drill geometry that accelerates the wear from the fracture point to the chisel and through the flank. Normally, when lip fracture initiates, the measured signal magnitude suddenly jumps to a higher level. Similarly the same phenomenon of magnitude jump has been observed after the fracture of the second lip edge. It was therefore concluded that, when operating at the recommended cutting speed, outer corner wear was moderate; crater wear was definitely visible probably due to the temperature effects while flank and chisel wear could also be clearly identified. SEM photos of the drill point in figure 5.1 (a) have been taken to explicitly illustrate different modes of wear as shown in figure 5.2. Of concern are chipping or fracture at the lip edge, flank wear, chisel edge wear and crater wear. Some of these wear patterns have been microscopically measured. If 0.3 *mm* is considered as a standard value for a worn tool, figure 5.2 (a) for instance, shows that the area of the fracture lip is larger than 0.04 mm^2 and could therefore be considered a worn tool. Flank wear in figure 5.2 (b), was also measured and was approximately 0.5 *mm*, larger than the standard value for a worn tool. The chisel wear shown in figure 5.2 (c) is completely worn with a fracture line initiating in the center. The crater wear observed in figure 5.2 (d) is also of sufficient magnitude to be concerned about the attrition of new phases due to the temperature increase.

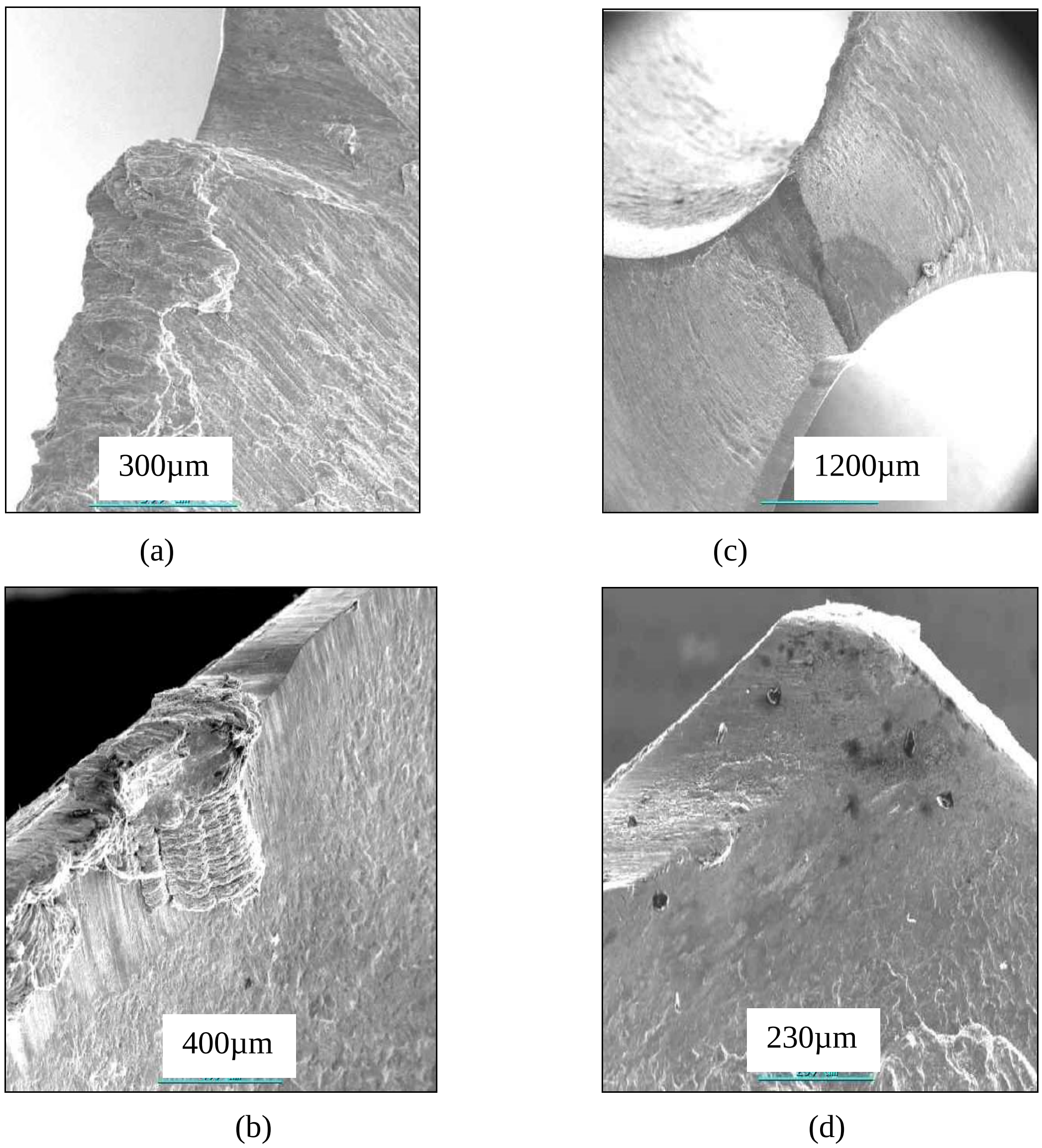


Figure 5.2: SEM photographs of different wear mechanisms: (a) Chipping or fracture at lip; (b) Flank wear; (c) Chisel edge wear; (d) Crater wear.

5.2 Signal Processing techniques

5.2.1 Sensor signal characteristics

Typical time response histories of signals measured while drilling a hole are illustrated in figure 5.3. The thrust and drift vibrations are time domain signals monitored respectively in the X- and Y- directions. The raw IAS signal from the 1024 pulse encoder has a distinctive and almost constant period. The strain measurement illustrates the measured dynamic cutting torque.

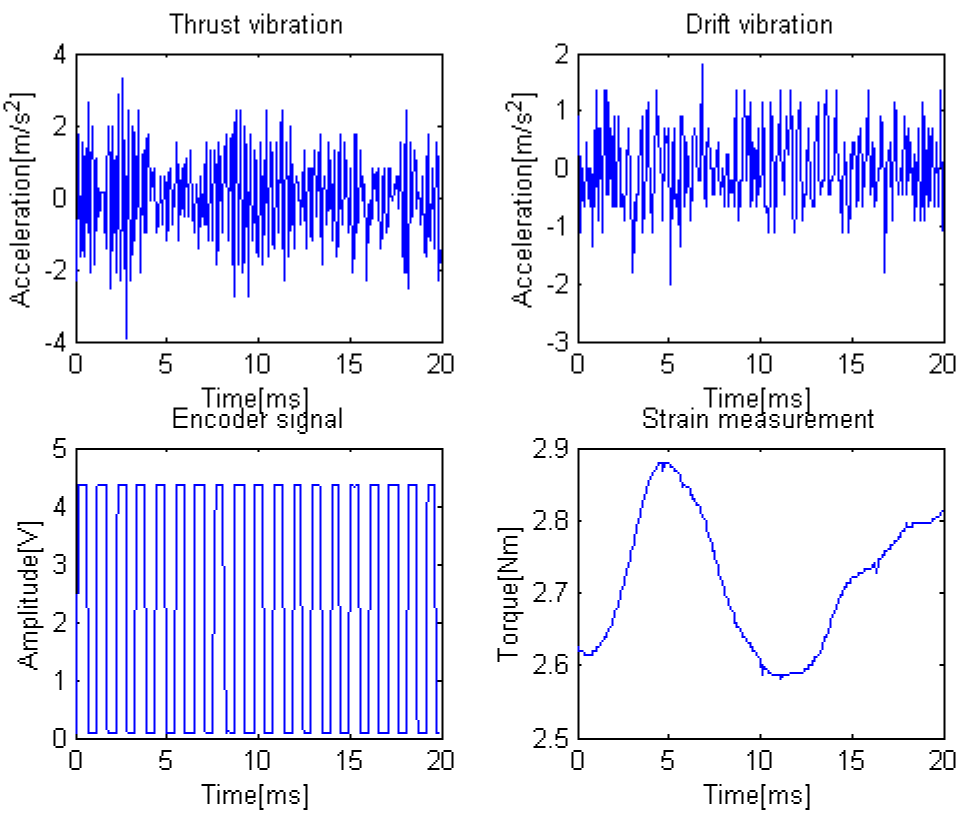


Figure 5.3: A typical sample of raw signals for all the measured channels

Figures 5.4 and 5.5 compare typical patterns and levels of signals in all the channels measured during drilling experiments comprising a sharp and a worn drill bit. The comparison clearly shows the effects of drill deterioration on the measured signals based on the following assumptions:

- The fluctuation of the speed due to mechanical effects in rotors and gears is negligible

- The electric supply fluctuations are negligible
- The changes observed in the measured responses signals are caused by the deterioration of the drill tool.

The pattern and magnitude of measured signals differ between a sharp and a worn drill bit. Compared with conventional technologies which show an increase of signal magnitude as a sharp drill bit wears, the IAS signal magnitude clearly illustrates a decreasing trend. Indeed, the thrust force and the torque, being major excitation sources in drilling, respectively influence the thrust vibration and the drift vibration. It can be seen from vibration signals measured from a worn drill bit that both cutting forces cause high levels of transient vibrations (spikes). These levels are fairly high in the axial direction compared to the transverse direction. This could be explained by the fact that the cutting force acting from the drill chisel on the work-piece is predominant compared to the transverse cutting force. With the progression of drill wear as shown on figures 5.4 and 5.5, the vibration signal amplitude increases from 5 m/s^2 for a sharp drill to more than 45 m/s^2 for a worn drill. At the stage when the drill bit is completely worn or broken, the signals are characterized by repeated spikes. These spikes were also observable during experiments by the sound caused by the milling machine feeding on the work-piece and its vibration. Therefore results must be interpreted with caution as it is known that these vibration signals are usually related not only to the dynamics of the cutting system, but also to the machine components. Consequently, the magnitude of torque signals determined via strain measurement also increases with the deterioration of the drill bit. In this instance, the torque increases from an average value of 2 Nm for a sharp drill to more than 5 Nm for a worn drill. Contrary to the above signals, the IAS signal also displayed changes due to the deterioration of the drill, but with the difference that the IAS magnitude trend is now in the opposite direction, i.e. decreasing from a sharp drill to a worn drill. This could be explained by the fact that the increase in friction between the drill and the work-piece is obviously affecting the magnitude of the IAS signal with the progression in drill wear. In fact, figures 5.4 and 5.5 clearly illustrate that the IAS average shifts from roughly 940 rpm for a sharp drill to 930 rpm for a worn drill. The speed changes are small compared to the overall spindle rotation speed.

In conclusion, the results of the investigation have shown how sensitive the measured signals on all the channels are to the deterioration of the drill bit.

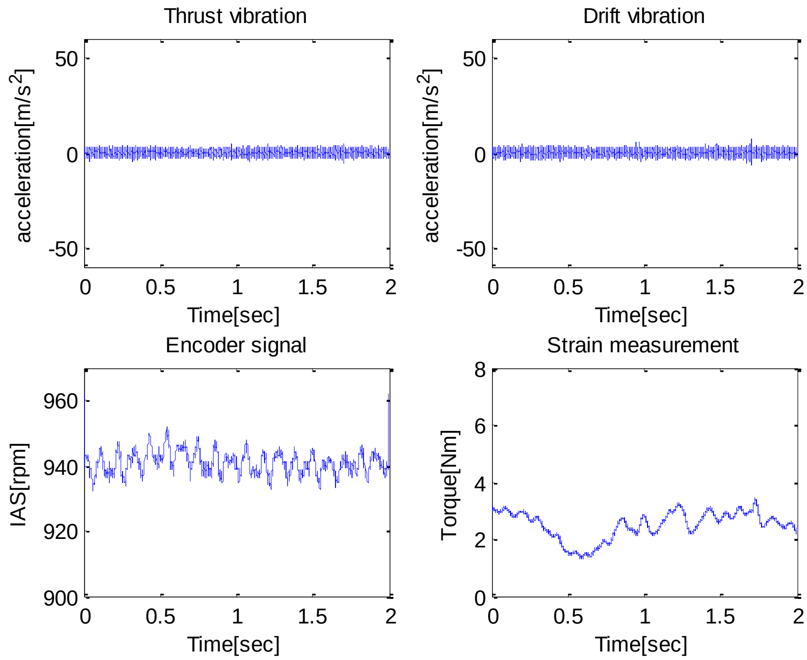


Figure 5.4: Typical characteristic signals for a sharp drill

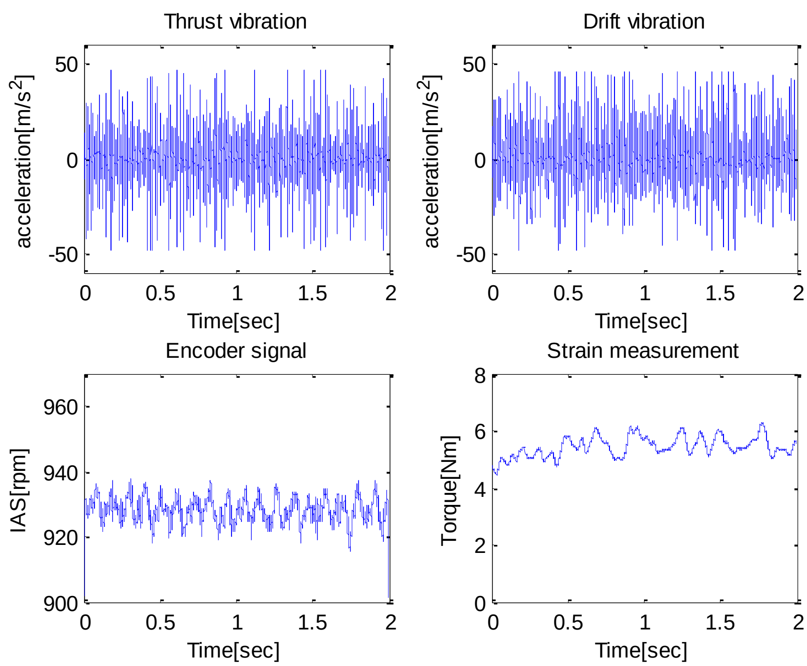


Figure 5.5: Typical characteristic signals for a worn drill

5.2.2 Sensor signal time domain analysis

5.2.2.1 Drill wear rates

The sensor signal characteristics have shown that the pattern and levels of measured signals are changing and increases from a sharp drill to a worn drill. Therefore, the simple calculation of the rms value will follow the same trend. Past research in conventional technologies, as well as the direct torque measurement on an instrumented drill shank presented in this work, has arrived at the same conclusion (Jantunen, 2002). Bearing in mind the simple relationship between torque and angular speed (power = torque × angular speed), it is no surprise to see the IAS results showing the inverse trend. This is interesting in the sense that the IAS could also provide diagnostic information comparable to conventional technologies with the possible advantage of using simple, accurate and reliable sensors.

Before presenting the drill wear results from the measured signals using the rms value calculation, some remarks have to be made about the acquisition of data. During the course of experiments as said in paragraph 4.2.2, apart from taking vibration measurements, the strain measurement and the encoder signal presented some issues. The telemetry set-up using strain gauges on a small 10 mm drill bit and a non constant power battery have led to many corrupted measured signals that lead to the restriction of samples to be presented. In addition the high sampling rate due to the high encoder resolution led to the problem of saving huge amounts of measured data. All these issues have made the utilization of all four channels at the same time difficult. However, in the following discussion, results of three samples with acceptable results are provided. Other results by means of 8 drill bits as shown in table 4.4 could be found in section 5.4 where the measured responses from the 4 channels are not grouped together because of data storage space issues. In this instance, only the IAS was measured to check the reliability of the findings.

D1, D2 and D3 drill samples shown in figures 5.6 and 5.7 respectively illustrate the relationship between the rms value of thrust and drift vibrations, as well as the torque and the angular speed against the number of drilled holes. This relationship is then used to determine the likely rates of useful drill life. Each sample of drill has been used to drill holes in work-pieces until it was worn. The results of the investigation confirmed what other researchers have stated, that the rates of drill wear are unpredictable and the drill life varies as does the measured parameter values. The tested drills have shown different drill life from one case to another. Different reasons can be found to explain these variations in drill life as mentioned in paragraph 2.3.6. Consequently, one can neither determine the drill tool life using a mathematical model based on Taylor equations, nor develop a dynamic based model to predict tool life with repeatable results. The failure to develop a prediction model for drilling with repeatable results is probably an indication of the need for an effective on-line TCM. Likely, the results have shown good correlation between time response signals for the drills tested (drill wear) and drill tool life. The RMS value of measured signals illustrates small changes during normal cutting until drill failure at the end of drill life. Compared with both conventional vibrations or with the torque measurement, the IAS seems to be more directly related to machine dynamics with less measurement complexity.

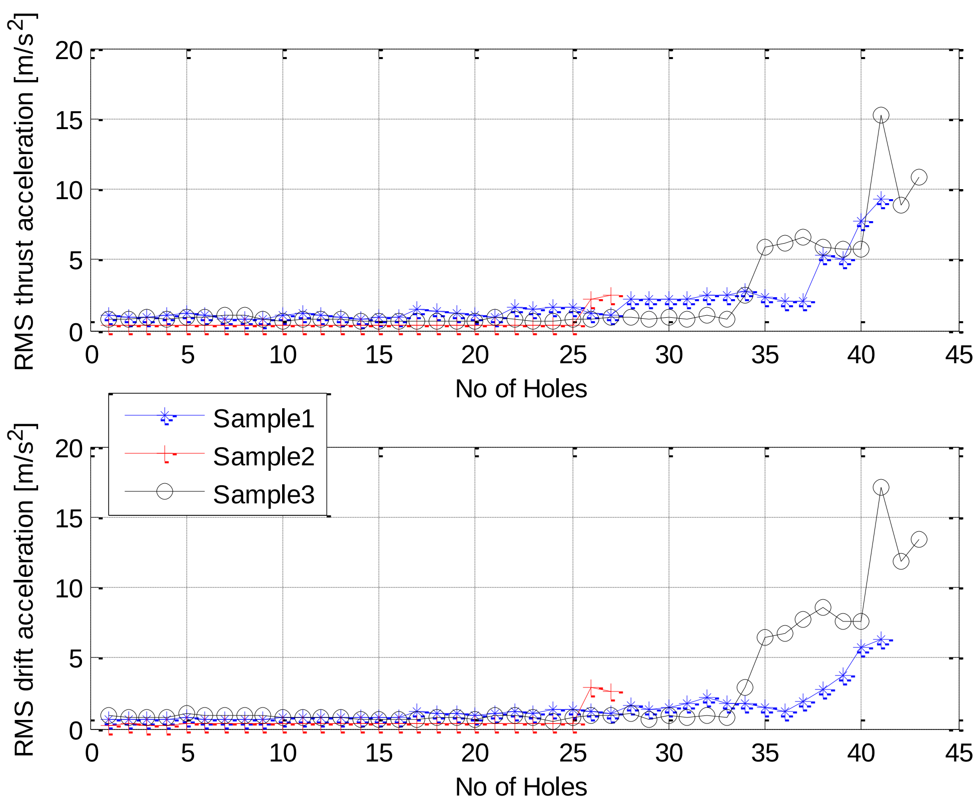


Figure 5.6: Different rates of drill wear using vibrations measurements

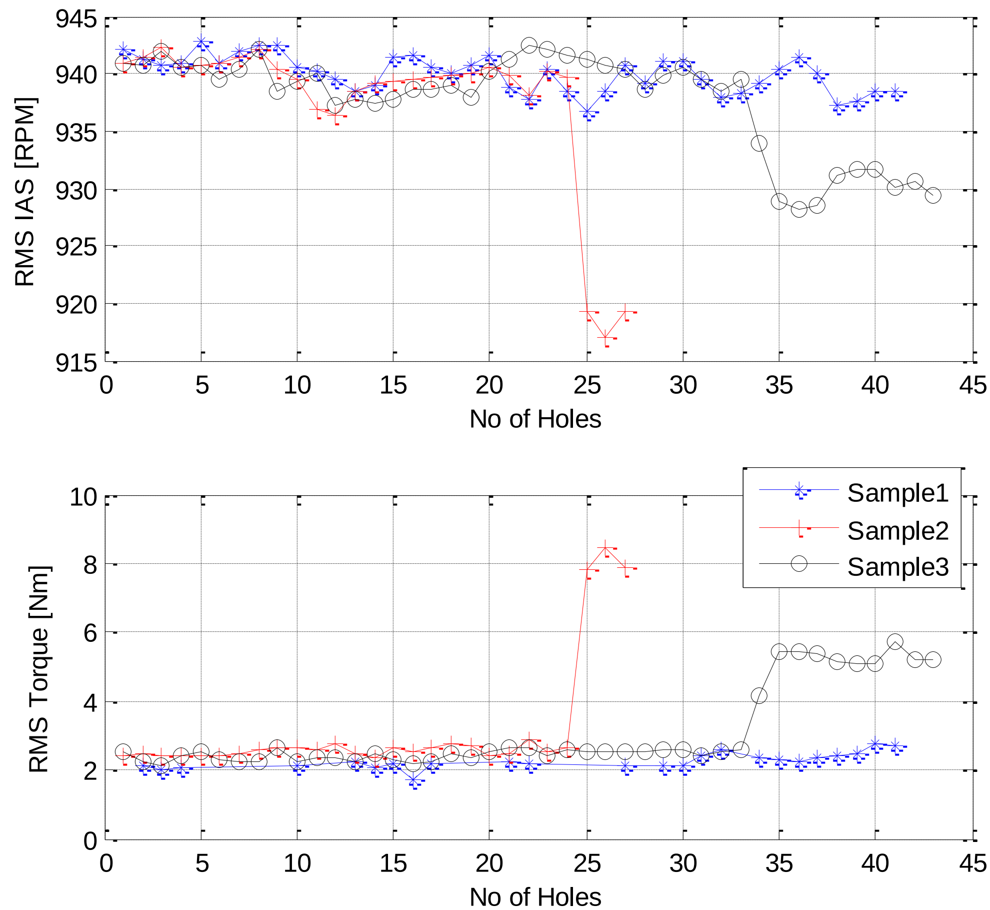


Figure 5.7: Different rates of drill wear using IAS signal and Torque signal

If the IAS can provide diagnostic information on drill condition comparable to conventional methods, it is therefore possible to relate the drill wear to the IAS. This is the reason for comparing the torque measurement with the IAS in the following paragraph.

Note that the torque curves above closely follow the general trend of curves depicting the different drill wear stages previously shown in figure 2.4: initial stage of wear, slight wear or regular stage of wear, moderate wear or micro breakage stage of wear, severe wear or fast wear stage and worn-out or tool breakage. At the same time, the IAS curves seem to mirror the trend of drill wear stages. It is clearly demonstrated that the IAS curve trend decreases as a function of drill life. At the beginning of drilling operations, there is a reduction of the IAS, showing that the drill bit begins to wear as soon as the drilling operation starts. Therefore a steady period follows where the drill is moderately worn. At the end of its life, the drill wears at an accelerated rate with an increase in friction between the tool and work-piece and the IAS also decreases consequently. These results merely demonstrate that the friction increases torque and diminishes the angular speed. What could then be their impact on the mechanical power as a product of the two? This is considered in section 5.2.2.4.

Hence from the RMS torque and IAS values presented in figure 5.7, one can clearly see that the IAS curves obtained are essentially mirror images of the torque curves. And superimposing these curves on the same graph, the general trend in drill wear development could be as shown in figure 5.8.

However, it can be noticed that the trend of these curves are accelerated at the end of drill life and seems to be useful for the detection of the breakage drill failure. The on-line monitoring in this case could not avoid the possibility of scrapping parts or damaging the work-piece.

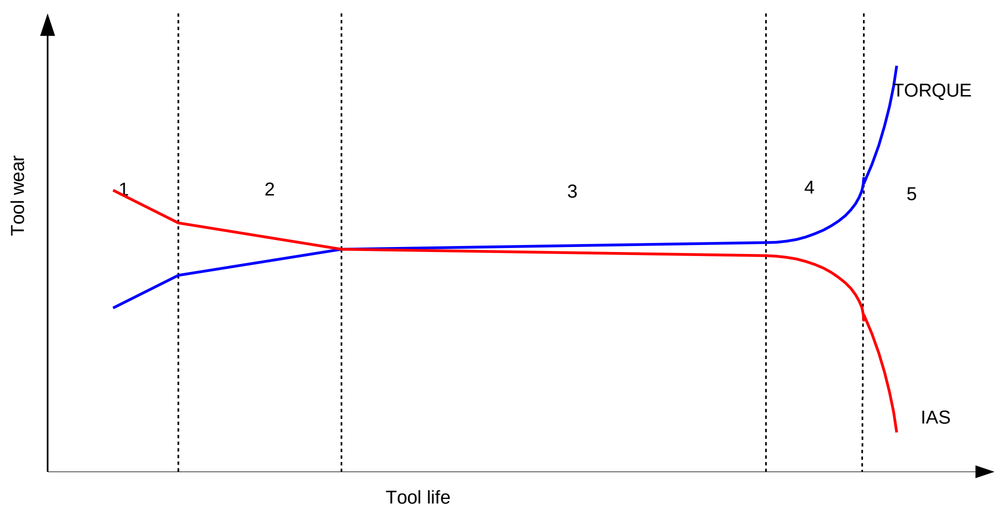


Figure 5.8: Drill wear stages function of drill life using torque and IAS trends

5.2.2.2 Statistical parameter features

When comparing the characterization of signals of a sharp drill and a worn drill, the rms feature appears to be an obvious choice feature. But other signal metrics based on the time domain waveform can also be used to evaluate the patterns and levels of different measured signals. They are the peak value, the crest factor and the kurtosis. The mean value was not meaningful on some channels and was therefore not used. Although the kurtosis of a signal is often used for similar reasons as the crest factor, it was also taken into consideration for confirmation of crest factor results. As far as drilling operations are concerned, the peakiness of a signal would not be a realistic feature indication due not only to the stochastic drill behavior, but also because the peak level is not an averaging statistical value. Any spurious data caused by stochastic phenomena or noise could have a significant effect on the peak level. Therefore, one could not expect better results with derivative factors such as crest factor and kurtosis. The rms value that find favor in the computation is largely used but the choice of sample length or a broad band of frequencies sensibly influenced the results.

Figures 5.9 to 5.12 and figures in appendices 1 and 2 show typical examples of the statistical parameters for drills D1, D2 and D3. They all display curves with similar trends for different signal metrics considered. Features were extracted from thrust and drift vibrations, IAS and torque signals. The peak value, the rms value, the crest factor and the kurtosis were calculated and plotted as a function of the number of drilled holes. Contrary to the crest factor and kurtosis, the peak and rms values seem to be well correlated with the wear and seem to serve as good indicators of damage. The evolution of the computed peak and rms signals as functions of the number of drilled holes remains almost constant during the normal cutting until the drill failed at the 25th hole and then starts to increase significantly for all the signals except for the rms of the IAS that decreases. Indeed, both the rms and peak graphs present a smooth change during normal cutting that could be explained by a progressive deterioration of drill condition. At the end of drill life, the peak graphs present sharply increased changes while it is attenuated for the rms graphs. When comparing the two features in the presence of transient signals (spikes) specifically when the drill is worn, the spikes exhibit high peak value while the rms averages the peaks out.

Unfortunately, crest factor and kurtosis results are not consistent and this was experienced for different samples tested.

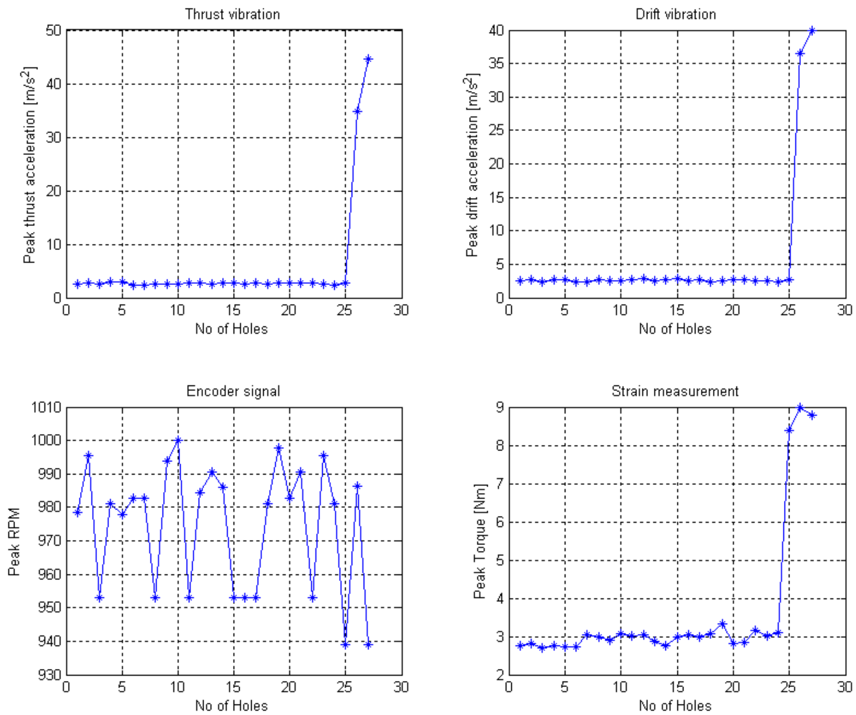


Figure 5.9: Peak value of sensor signals for each hole

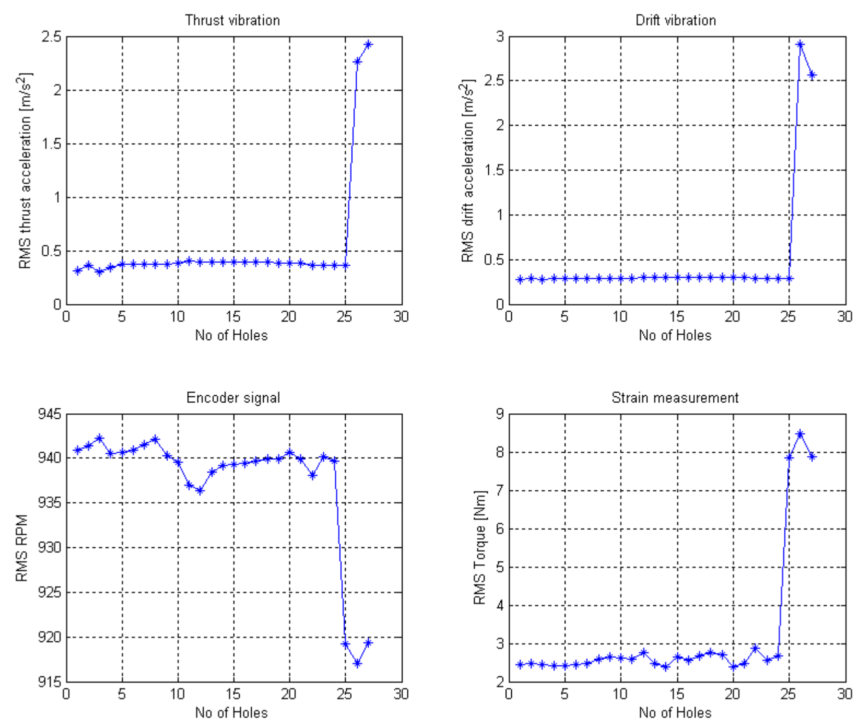


Figure 5.10: RMS value of sensor signals for each hole

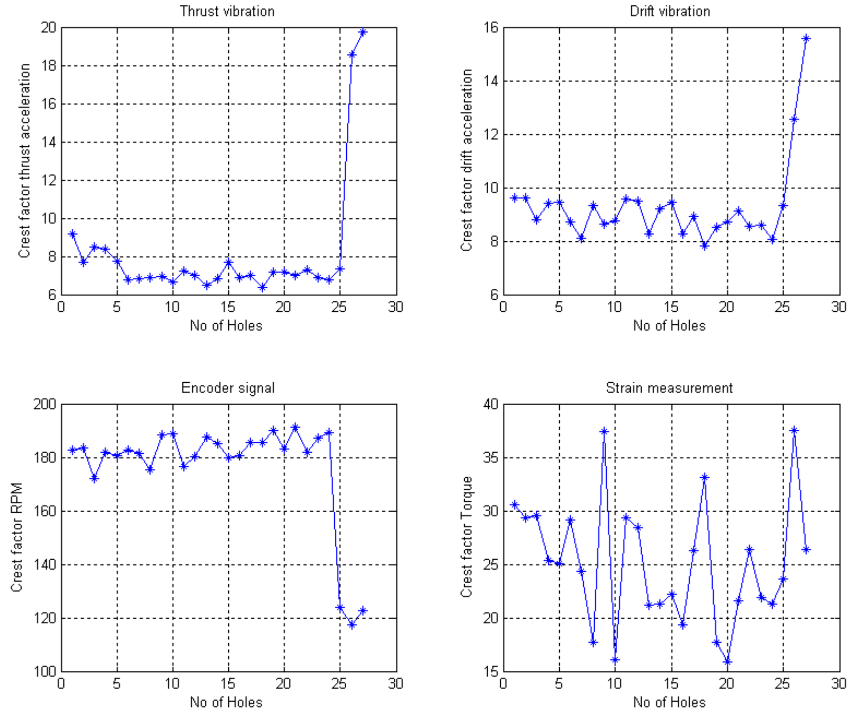


Figure 5.11: Crest factor of sensor signals for each hole

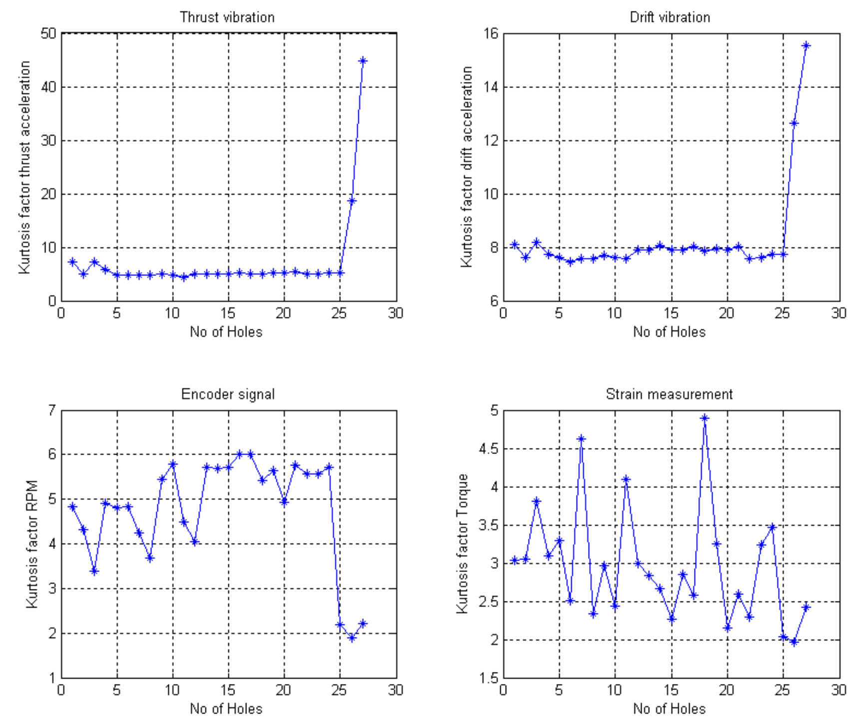


Figure 5.12: Kurtosis value of sensor signals for each hole

To summarize the discussion on the time domain signal metrics: good correlation between the drill tool condition and the peak value as well as the rms value has been observed for the signals on all four channels. The trend of curve is that the computed values remain quasi constant during the normal cutting period and starts to increase or decrease rapidly at the end of the drill life. The rms feature could therefore be very useful for sending a warning signal at the end of drill life or drill failure detection. However, the peak value is prone to give a false alert during drilling operations because of the high level of transient vibrations (spikes) when the drill is worn while the spikes are largely attenuated by the averaging procedure in the calculation of the rms.

5.2.2.3 Torque against IAS drill wear rates

The results from drill wear rate have clearly shown that both conventional and IAS measurements could provide comparable diagnostic information. The analysis of normalized torque and IAS shown in figure 5.13 based on drills D2 and D3 clearly shows that the percentage torque changes due to the deterioration of the drill are more significant than the IAS changes. These changes are of the order of 65% for measured torque while they are less than 2.5% for the measured IAS. This high percentage change of torque is largely demonstrated by the existing published paper reviews which successfully demonstrate the merit of conventional technologies in TCM based on force measured signals and its corresponding sensors used. While this success is undoubtedly evident in researches performed in laboratories, it however seems that this TCM approach has the effect of obscuring its failure in the application on unmanned machining in drilling operations. Thus, one of the essential problems to overcome should be the development of effective and reliable sensor systems to monitor the drilling process that could facilitate automatic corrective action in unmanned machining area. Decades of past research using conventional technologies in drilling have also failed to respond to the need of such sensor systems for a flexible manufacturing industry that could comprehensively be controlled by an automated system. Hence, as a response to newly designed sensors in drilling, the present encoder- and strain-based methods are compared as an addition to conventional sensor-based methods.

As discussed earlier, the IAS measured via an encoder-based sensor has proven that it could be correlated to the drill wear as it is the case for the measured torque via a strain- based sensor. Despite it being less sensitive compared to the torque due to small variation of periods between sharp and dull drill pulses, it however should not be an issue to assess pulse period small changes when considering progress in new technologies where digital analysis can differentiate decimal between small fractional changes. Indeed, different researches have illustrated not only the benefits of IAS measurement in rotating machines as an important TCM parameter but have also demonstrated that it could be measured accurately using a high resolution. For instance, Li et al. (2005) and Gu et al. (2006) advised that high resolution encoders are effective and accurate in the discrimination of small changes specifically in the frequency domain. Their results demonstrate that the measurement of the IAS outperforms conventional vibration analysis in the diagnosis of incipient faults such as motor bar defects and shaft misalignment. These results were also confirmed by the work of Fyfe and Munck (1997) where higher sampling rates on keyphasor and data signals resulted in improved accuracy in spectral results by improving the measurement of the keyphasor pulse period. If the problem could be to which extent the small changes must be correlated to drill wear, the results shown in figure 5.13 seem to be well correlated for both sensors used. This is a very important feature in the development of an instrumented tool as it is used in other machining operations using straight edged cutters. In fact, in rotary machines, non-contact measurements can be implemented by using a keyphasor or so-called zebra strips (Resor et al., 2004 and Fyfe and Munck, 1997) that could be attached as a band around the spindle shaft. Such a sensor is cost effective and unlike existing conventional sensor technologies, it seems not only flexible to implement but could also be used as custom-made sensors.

In conclusion of this section, the investigation demonstrates that it is also normal to monitor the IAS in the same manner as the conventional monitoring technologies monitor the forces or vibrations. In addition, it reveals that the encoder-based sensor presents a great potential as a flexible sensor in a production environment. Based on the comparison of the above results, it could be argued that the monitoring of the IAS as a means of monitoring the drill bit condition is feasible in the same way as it is for the force to change with drill wear. The detection of the small change in IAS level with time is monitored by means of a high resolution encoder or high sampling rates on keyphasor that measure accurately the rotational speed. The results presented in section 5.4.1 seem to be in favor of the above conclusion as the 1024 high resolution encoder measures more accurately the IAS than one pulse per revolution.

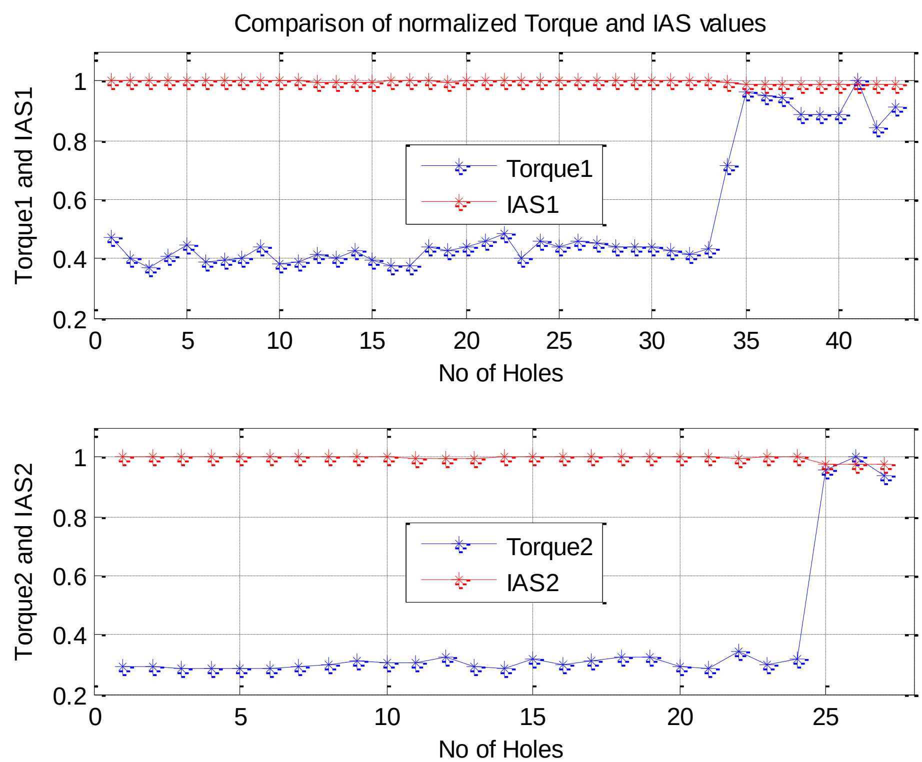


Figure 5.13: Comparison of torque and IAS normalized values for two drill samples

5.2.2.4 The mechanical power

The mechanical power expressed in Watt as the product of torque (Nm) and angular speed (rad/s) has been calculated from the respective rms values obtained previously. The results are shown in figure 5.14 where the average mechanical power is plotted against the number of holes for drills D1, D2 and D3 respectively. As expected, the power follows the same trend as the torque graph. The power remains more or less constant around 200 Watt until the drill fails when it starts to increase significantly to reach approximately 280, 500 to 800 Watt. Note that the changes in power are of the same order as for the torque around 65%. Note that the milling machine has a power specification of 2 CV or Horsepower (1472 Watt).

These results confirm the magnitude changes obtained with the normalized rms torque and IAS data presented above and also provide similar diagnostic information comparable to the estimated power based on spindle power (Kim et al., 2002). They have proposed an analytical estimation of drill wear based on spindle motor power integrating a drill wear torque model. Unfortunately, this method was more suitable to the laboratory than to real time because of the use of dynamometer to measure the cutting force but could well support the spindle motor power estimation in real time.

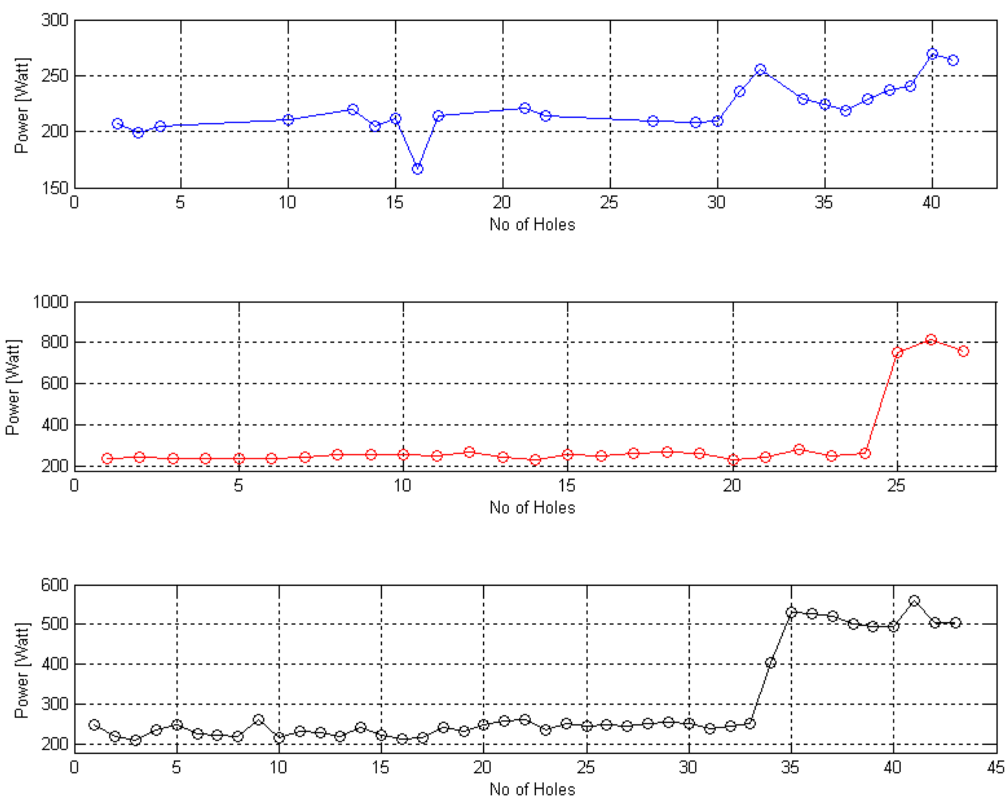


Figure 5.14: Computed power from torque and IAS RMS values against the number of holes for drills D1, D2 and D3 respectively

5.2.3 Sensor signal frequency domain analysis

5.2.3.1 Signal frequency responses

After the time domain analysis, the measured signals were further analyzed in the frequency domain to determine their frequency contents and their localization. The frequency domain analysis used in conventional technology schemes generally consist of the spectral evaluation related to the dynamics of the cutting system. In general, spectra are derived from FFT applied to measured signals in the frequency ranges of interest. Note that FFTs are extensively used in the treatment of random vibration problems for the purposes of physical interpretation of measured data (Heyns, 2003). When applied on measured signals, the results of frequency responses illustrate the frequency content of the signals. The dominant frequencies observed on the spectra are often related to a particular machine component or process in the system and can thus aid in determining the severity of the signal.

Based on the above explanation, FFT was applied to the measured signals and the resulted frequency responses are shown in figures 5.15 to 5.24 where distinct features that support the drill wear monitoring can be extracted through different frequency bands. To discriminate the sharp and the worn drills in conventional technologies, it is expected that the measured signal magnitude of the worn drill will increase sharply just before its failure. Consequently, it is expected that the measured IAS signal of the worn drill will decrease due to additional friction. Hence two measurements were taken for each of the three drills at the beginning and the end of their lives for comparison of the magnitude. The corresponding frequency responses are plotted in figures 5.15 to 5.24 beside the measured time domain signals to illustrate the magnitude changes in both time and frequency domains. The broad band nature of dominant frequencies observed on the vibration spectra in the frequency domain analysis clearly illustrates the aperiodic nature of the drilling process. It can be seen from a comparison of the sharp and worn frequency response results that as the drill tool wears and the instability in the worn signal appears, the magnitudes of monitored parameters increase at the excited frequencies. This is in accordance with conventional vibration monitoring strategies that rely on the response amplitude difference between a sharp drill and a worn drill. As expected, the amplitude of worn drill parameters is generally greater than the amplitude of sharp drills except for the IAS which reduces as the drill condition deteriorates. The results also show that the frequency bands of interest are as defined in section 4.3.1 for all the measured signals; dominant frequencies of the measured vibration signals are observed in the ranges of 10-1500, 2000-3000 and 3800-5000 Hz. Almost 14 Hz and 5 Hz frequencies of the measured IAS and torque signals correspond respectively to the rotational frequency of the spindle and to the frequency of the telemetry signal transmission.

For all the measured signals, the changes observed in the frequency responses related to the drill bit condition are well illustrated in the RA developed in section 5.3 where the evolution of the drill condition (drill wear) is shown by plotting the polynomial regression of the frequency content (FC) of each measured signal as a function of drill life.

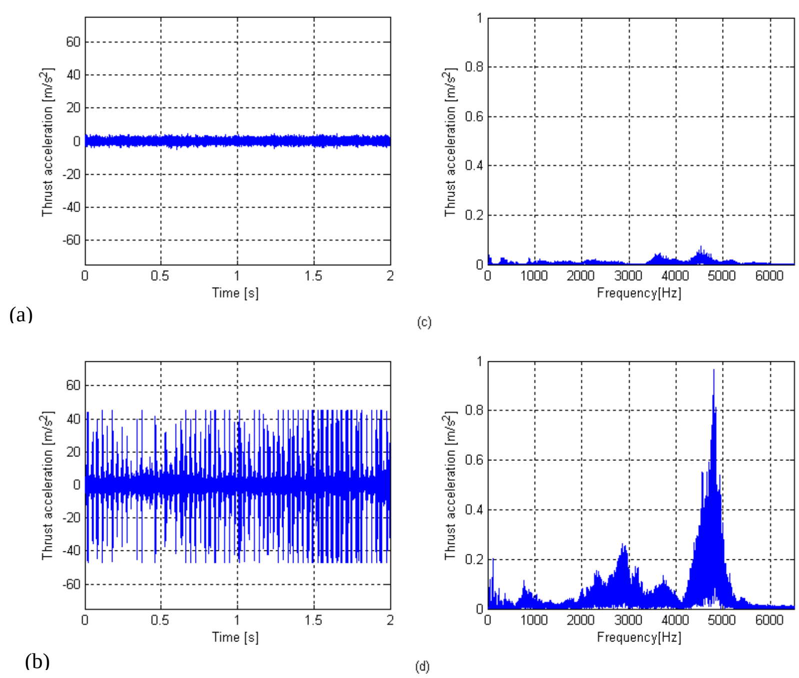


Figure 5.15: Drill D1 Thrust acceleration using 2nd and 39th holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

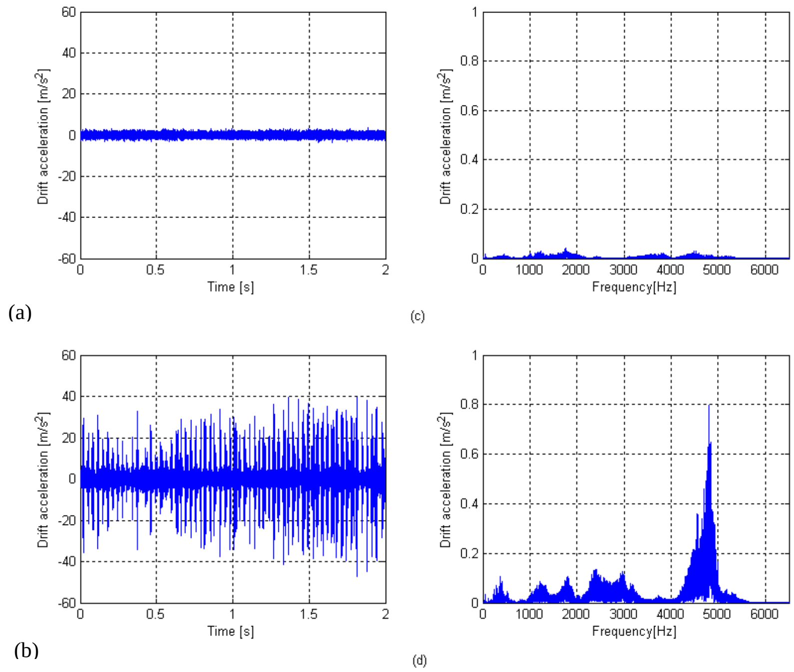


Figure 5.16: Drill D1 Drift acceleration using 2nd and 39th holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

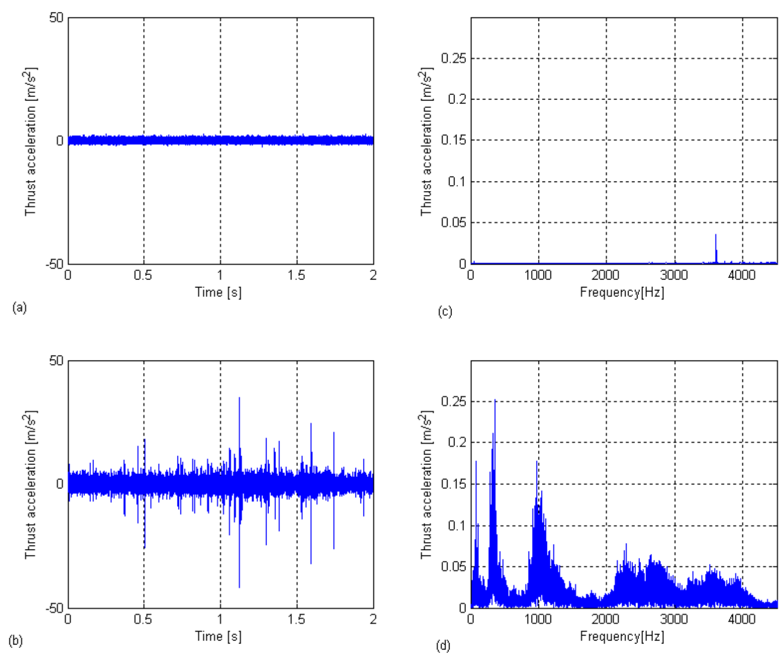


Figure 5.17: Drill D2 Thrust acceleration using 2nd and 26th holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

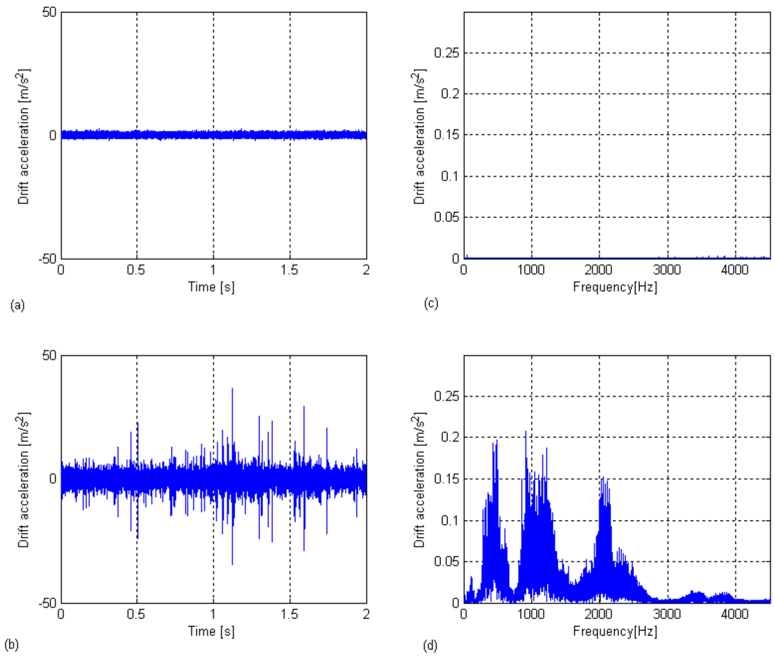


Figure 5.18: Drill D2 Drift acceleration using 2nd and 26th holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

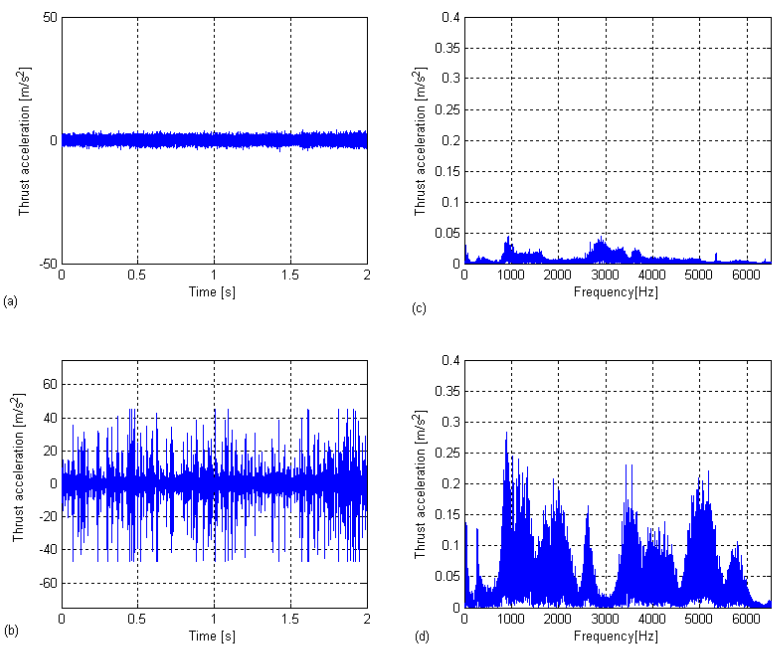


Figure 5.19: Drill D3 Thrust acceleration using 2nd and 41st holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

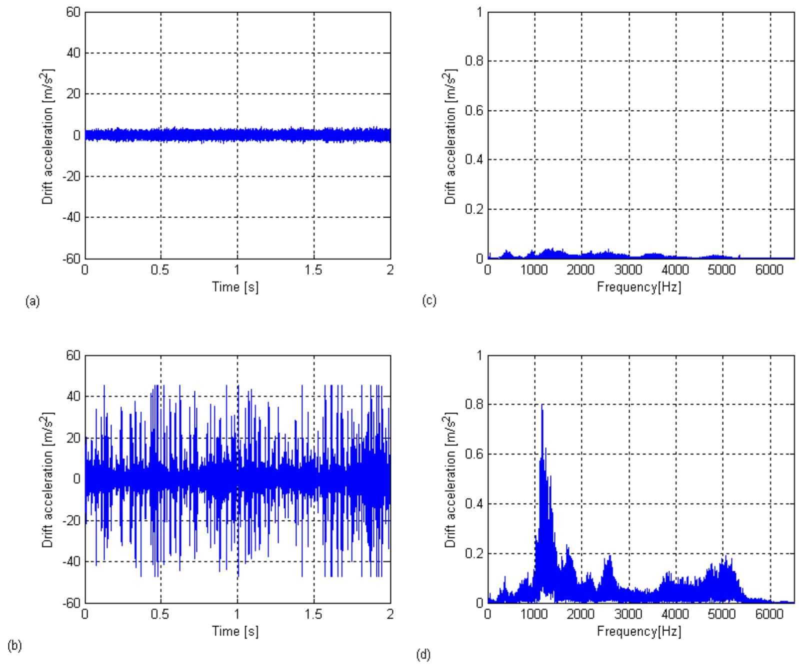


Figure 5.20: Drill D3 Drift acceleration using 2nd and 41st holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

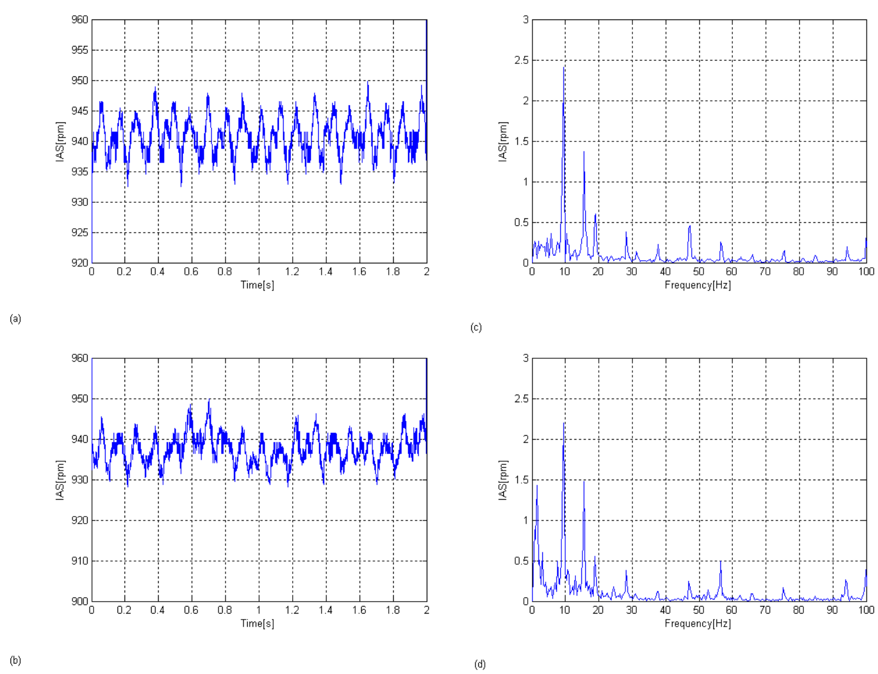


Figure 5.21: Drill D1 IAS using 2nd and 39th holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

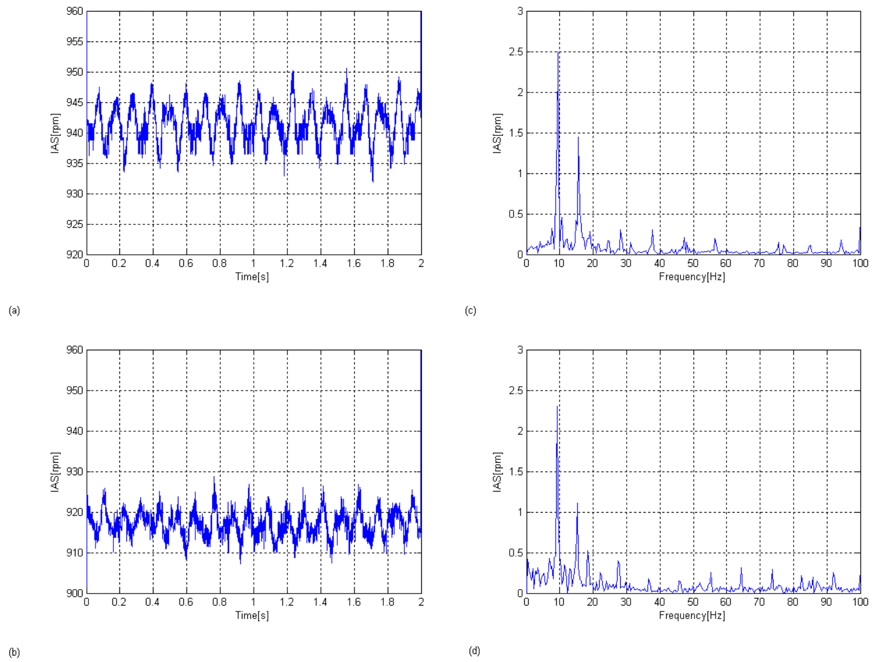


Figure 5.22: Drill D2 IAS using 2nd and 26th holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

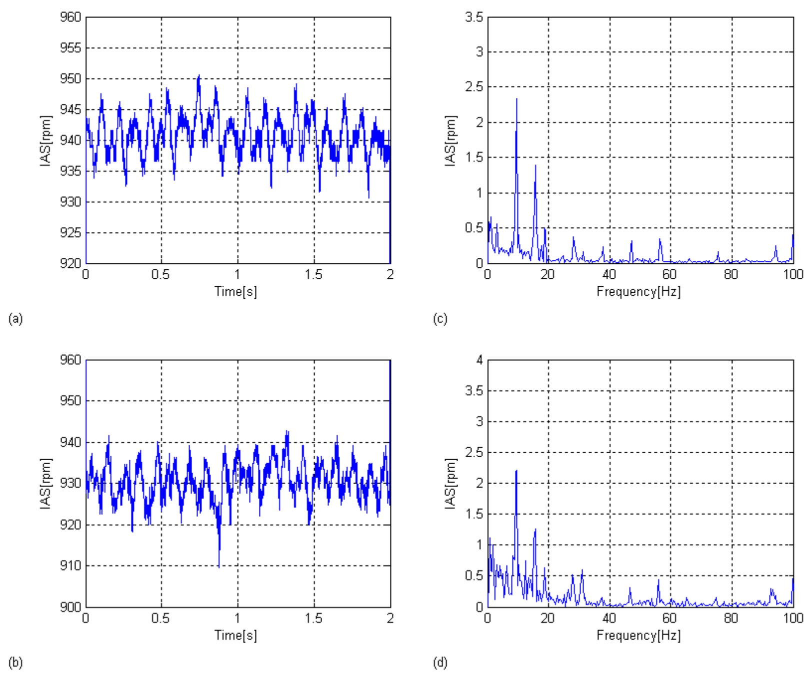


Figure 5.23: Drill D3 IAS using 2nd and 41st holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

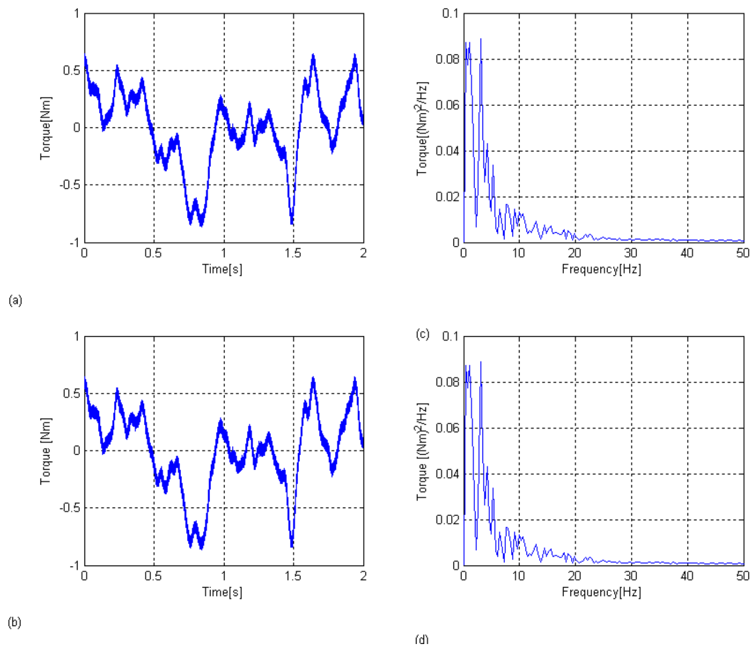


Figure 5.24: Drill D1 Torque using 2^{nd} and 39^{th} holes: (a) Time domain response (sharp drill); (b) Time domain response (worn drill); (c) Freq. domain response (sharp drill); (d) Freq. domain response (worn drill).

The above analysis of frequency responses was done on measured signals for drills D1, D2 and D3, except for the torque measurements where the results of one drill are shown. The reason is that the torque signals, although dynamic, were measured at lower frequencies and are therefore without great significance in the frequency domain. Indeed, the torque signals from the strain measurements were not sufficiently stationary and periodic for frequency domain analysis but useful and meaningful in time domain analysis.

5.2.3.2 Spectral analysis

The results obtained in section 5.2.3.1 from the frequency responses compared two measurements from a sharp drill signal to a worn drill signal. In the following spectral analysis, the spectral evaluation related to the dynamics of the drilling of holes is illustrated by plotting on a single graph the ensemble of spectra of each drill used. Hence, data from drilling operations were used to create three dimensional waterfall plots that show the frequencies and magnitude of PSD extracted from the measured signals. A PSD was then performed on every measured signal recorded from the drilled hole by means of drills D1, D2 and D3 until their failure. The PSD observations are quite similar not only in the time domain but also to what the literature on drilling operations has provided. No noticeable change in spectral magnitude could be observed during normal drilling until the drill ceases to produce the required hole quality, passing from a usable to a worn state. If at that stage it has been observed that the signal magnitude in the time domain suddenly increased, the results in the frequency domain also exhibited the same behavior. Thus the frequency content changes in accordance with the deterioration of the drill by increasing in magnitude when excessive damage occurs at the final stage. In the case of drill vibrations for instance, these FC localizations are comparable to the frequency responses shown in Table 4.5 and in section 5.2.3.1.

To monitor excited frequencies observed in the above range of frequency responses, reliable features contained in vibration, IAS and torque signal measurements were used by means of waterfall plots where PSD magnitude are shown versus frequency and the number of drilled holes.

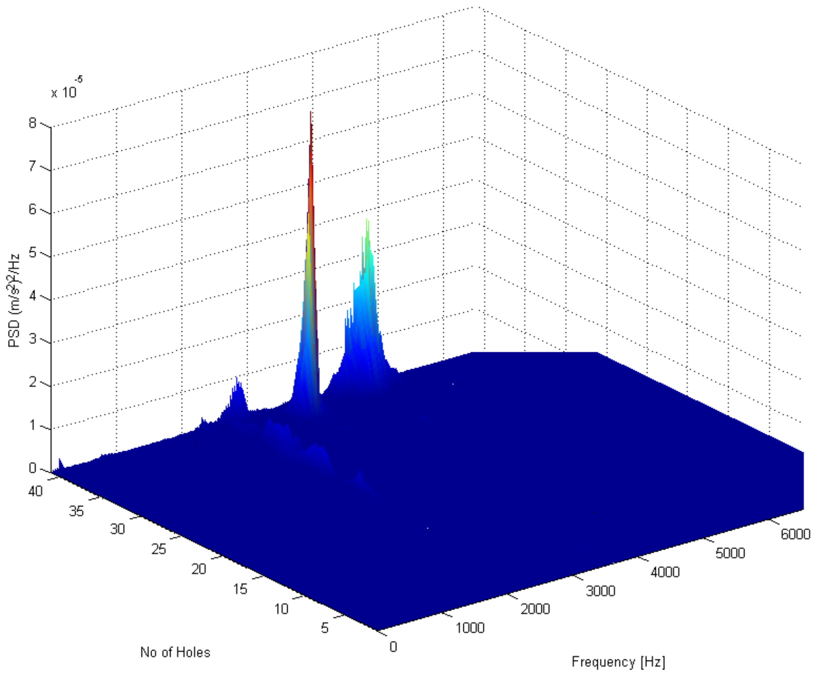
A. Vibration Spectral Analysis in thrust and drift directions

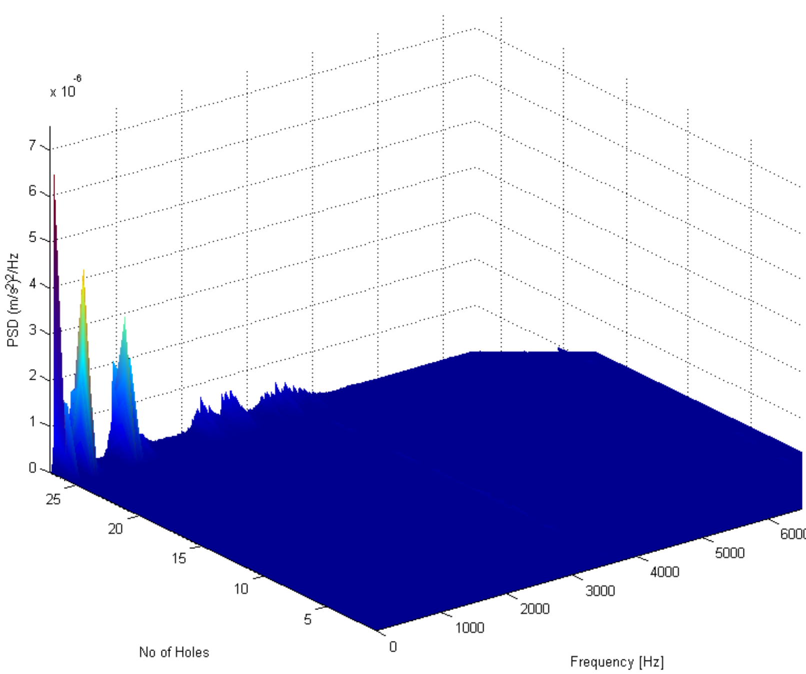
Figures 5.25 and 5.26 show three dimensional waterfall spectral maps extracted from drills D1, D2, and D3 for vibration measurements in the thrust and drift directions respectively. These waterfall plots show the PSD magnitude changes as a function of frequency and the number of drilled holes. Indeed, the plots illustrate that the PSD amplitude remains quite small during normal drilling operations and suddenly increases at the end of drill life. The plots also show that the drill has many vibration modes in both the thrust and drift direction as it seems that excited frequencies are not the same for each drill. In general, the excited frequencies are comprised of the range of modal parameters estimated in the frequency responses analysis. The spectral analysis results from vibration signals were therefore plotted in the range of 0.0–6.5 kHz, the region comprising the excited frequencies. It can be seen that the excited frequencies are not the same for the three drills tested. This could find explanation in the work of El-Wardany (1995) where he has established a correlation between the PSD of vibration signals and different types of wear (chisel, outer corner, flank and margin). Nevertheless, it is beyond the scope of this work to correlate the type of wear to specific spectral energy or to estimate the sensitivity of vibration signals to different wear types. But the findings have sufficiently shown that there is a correlation between the increases in amplitude of excited frequencies with the progress of wear. This is illustrated by the FC changes depending of the severity of the wear.

A.1 Spectral analysis in the thrust direction

Figure 5.25 shows a three dimensional waterfall plots that illustrate the spectral density of vibration signals measured in the thrust direction for drills D1, D2, and D3 respectively. The spectra show that the FC increase significantly at the end of drill life where the spectral energy is high in the frequency bands of 3800-5000 Hz for drill D1, 10-1500 Hz for drill D2, and both 10-1500 and 2000-3000 Hz for drill D3. Indeed, these frequency bands show distinctive features that can support discrimination between a sharp and a worn drill. These frequency bands will be used in the further study in decision making by means of RA. Note that the failure of the drills does not excite the same frequencies. As said before, there should be a correlation between different types of wear and the spectral behavior of the vibration signal that lead to different excitation.

Not only have the findings sufficiently shown that the amplitudes of excited frequencies are most likely to increase with the progress of wear but also show the rapid progression of the spectral amplitude at the end of the drill life with a rate change of more than 800% in some frequency regions. It can be concluded that the FC changes depend on the severity of the wear.


x 10^-5
PSD (m/s²)²/Hz
8
7
6
5
4
3
2
1
0
40
35
30
25
20
15
10
5
0
No of Holes
1000
2000
3000
4000
5000
6000
Frequency [Hz]


x 10^-6
PSD (m/s²)²/Hz
7
6
5
4
3
2
1
0
25
20
15
10
5
0
No of Holes
1000
2000
3000
4000
5000
6000
Frequency [Hz]

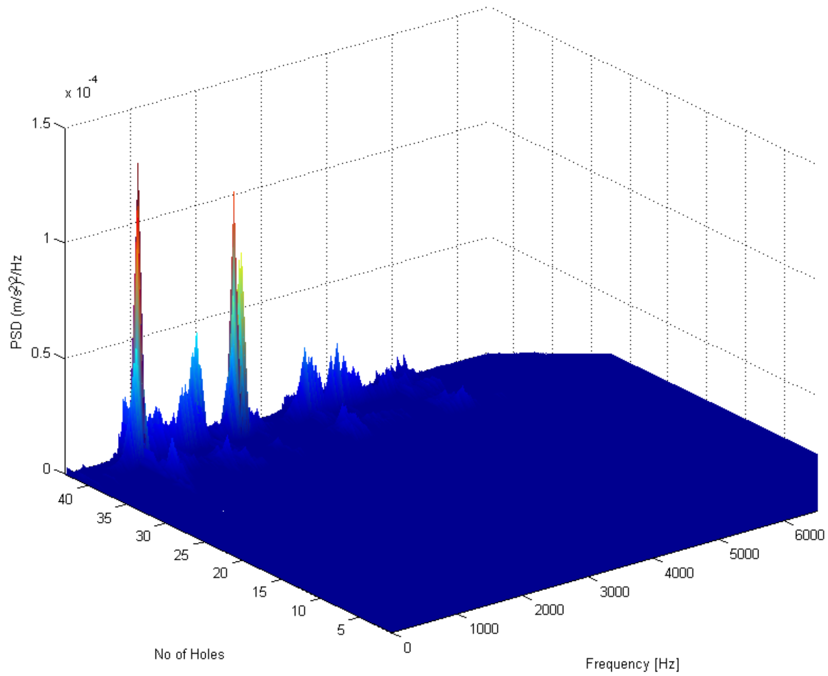
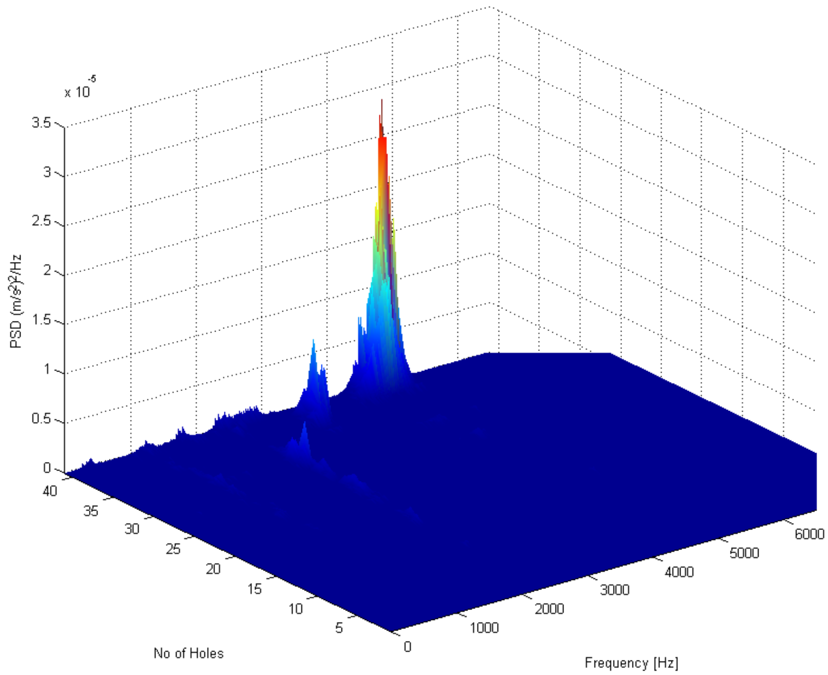


Figure 5.25: Waterfall plots – PSDs of vibration measurements in the thrust direction for D1, D2 and D3 respectively

A.2 Spectral analysis in the drift direction

Figure 5.26 shows three dimensional waterfall plots that illustrate the spectral density of vibration signals measured in the drift direction for drills D1, D2, and D3 respectively. Once more the spectra show that the FC increase significantly at the end of drill life where the spectral energy is high in the frequency bands of 3800-5000 Hz for drill D1, 10-2000 for drill D2, and 1000-3000 Hz for drill D3. These frequency bands are practically similar to the ones found in the thrust direction and can also support the discrimination between a sharp and a worn drill.

As discussed above, the excited frequencies in the drift direction increase with drill wear. In some cases, disturbances (data failure, chip effects, machine components, chatter, etc.) could probably affect the gradual increase of the PSD. In general the observed chatter was an indication of drill tool wear and was a source of high spikes vibrations at the end of drill life. Nevertheless, the general trend on different spectra is the FC magnitude changes are very low during normal drilling until drill failure at the end of its life.


x 10^-5
3.5
3
2.5
2
1.5
1
0.5
0
PSD (m/s^2)^2/Hz
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35
30
25
20
15
10
5
No of Holes
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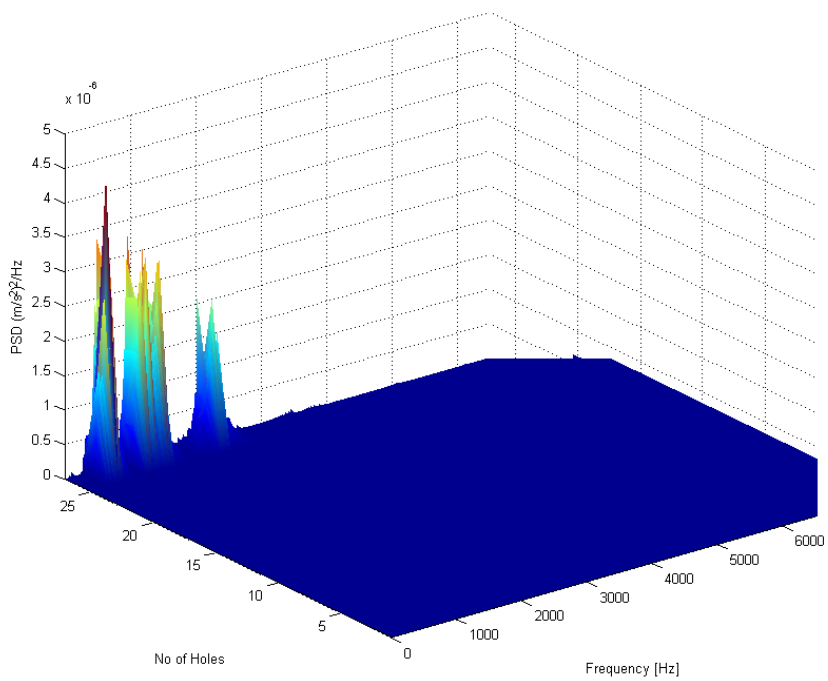
1000
2000
3000
4000
5000
6000
Frequency [Hz]


x 10^-6
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4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
PSD (m/s^2)^2/Hz
25
20
15
10
5
No of Holes
0
1000
2000
3000
4000
5000
6000
Frequency [Hz]

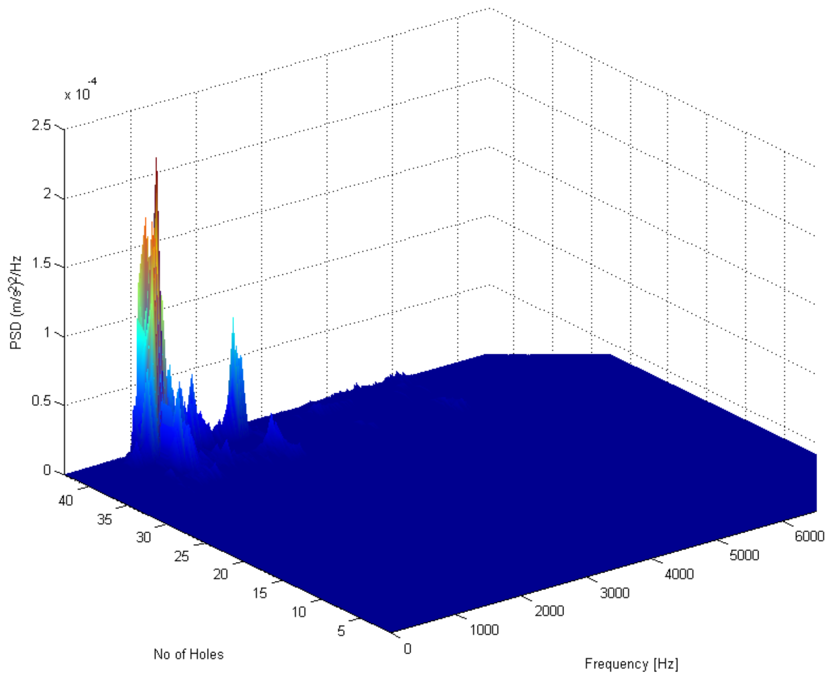


Figure 5.26: Waterfall plots – PSDs of vibration measurements in the drift direction for D1, D2 and D3 respectively

B. IAS spectral analysis

Figure 5.27 shows three dimensional waterfall plots that illustrate the spectral density of the angular speed signals measured at two different speeds, 1350 RPM (for drills D10 and D7) and 870 RPM (for D5 and D2). These plots illustrate the presence of the rotational speed frequency at the running speeds around 22.5 Hz and 14.5 Hz. It is difficult to visualize the change of the spectral amplitudes through these plots. The main reason could probably be found in the small changes of the speed from a sharp drill to a worn drill. Compared to the results from the frequency responses using FFT in two dimensions, the IAS three dimensional waterfall plots seem not to present distinctive and evident features that could clearly support the classification of the drill condition. Note the first two plots present a fixed or residual frequency around 12 Hz beside the main rotational frequency of 22.5 Hz. If that fixed frequency is related to any vibration caused by the machine, it is explained through the paper of Groover et al. (2005) that it will remain at that fixed order regardless of the changes in the running speed.

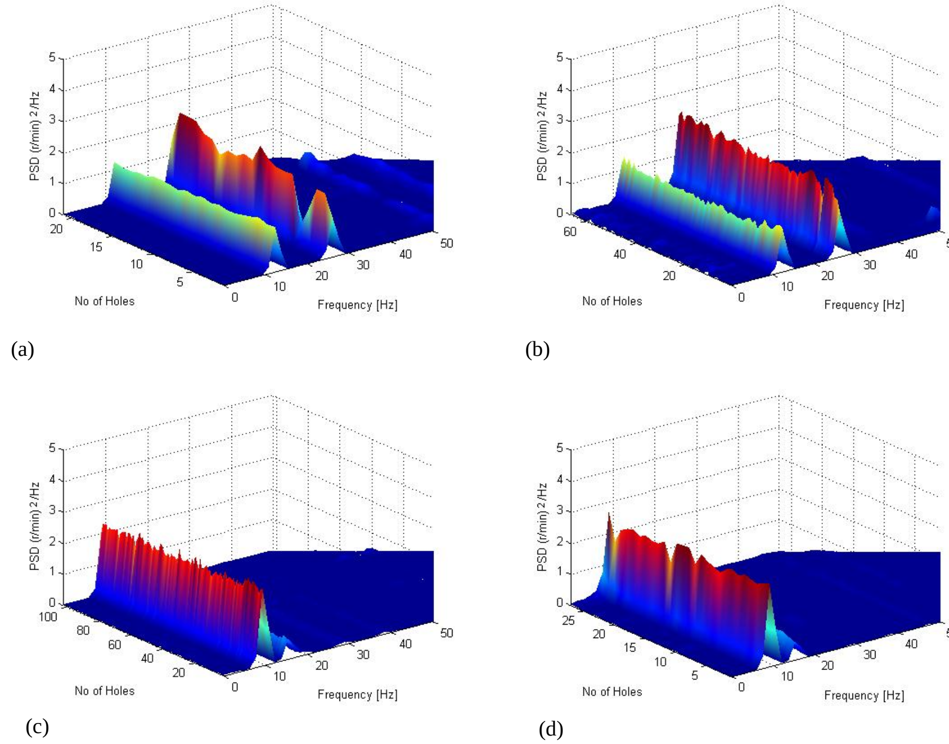
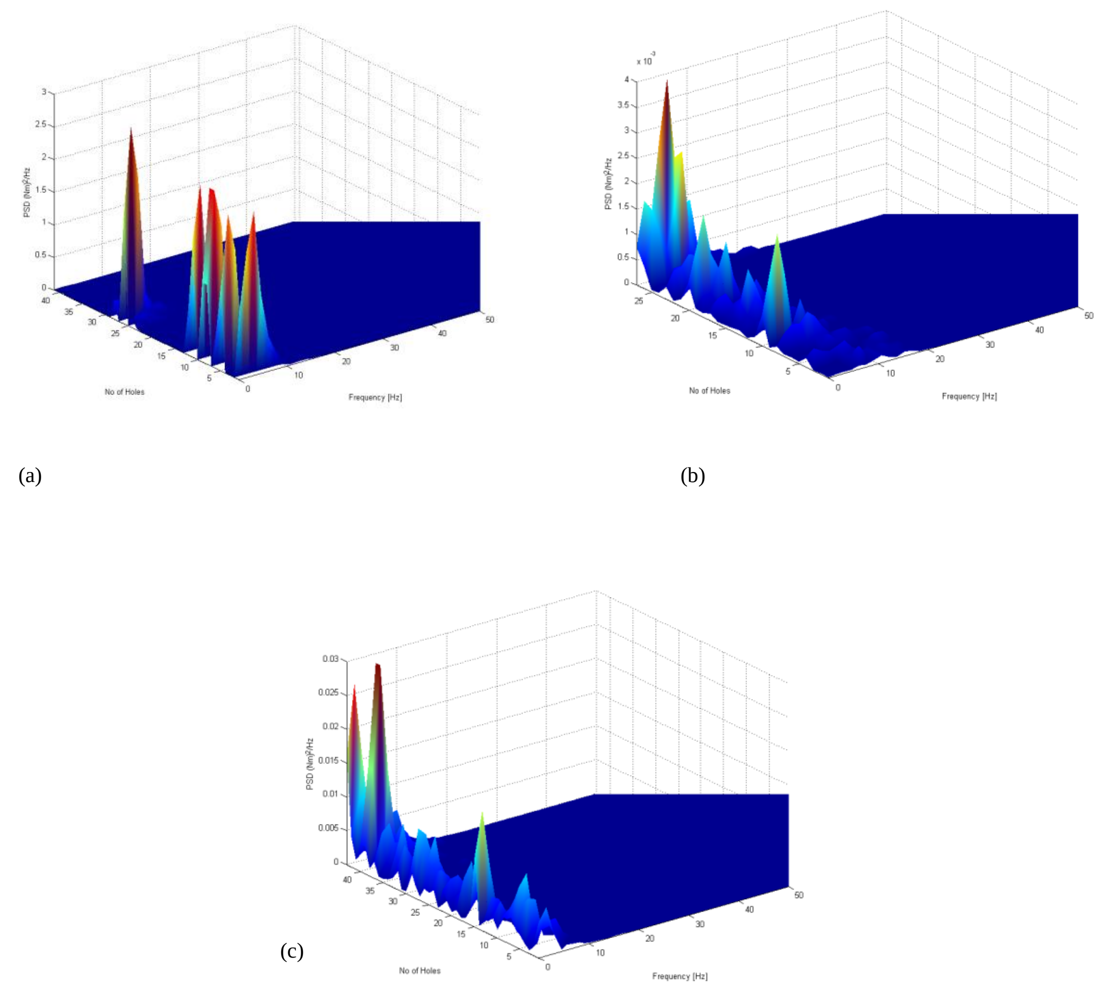


Figure 5.27: Waterfall plots of IAS measurements during drilling at (a) 1250 RPM for D10 (3mm) and (b) D7 (6mm), (c) 870 RPM for D5 (8mm) and (d) D2 (10mm)

C. Strain spectral analysis

Figure 5.28 shows three dimensional waterfall spectral maps extracted from drills D1, D2, and D3 for the torque strain measurements. These waterfall plots show the PSD magnitude changes as a function of frequency and number of drilled holes. Indeed, the plots confirm the frequency response results observed in section 5.2.3.1 that the measured strain signal is transmitted via telemetry at low frequency that is around 5 Hz. Frequency at which the signal was observed and nothing could be seen then after. The waterfall plots also reveal minor changes in spectral amplitudes during the normal cutting and then sensibly increase at the end of the drill life except for the first drill where measurements were probably affected by the multiple disturbances encountered during that measurement. Note that within 250 Hz frequency band of the telemetry, the FC in the strain signal was given by the frequency at which the telemetry radio was transmitted that is 5 Hz. The corresponding torque is calculated using the appropriate calibration as shown in chapter 4. Once more, the findings have illustrated a correlation between the amplitudes of telemetry transmission frequency increasing with the progress of drill wear.



(a) (b) (c)

Figure 5.28: Waterfall plots – PSDs of strain measurements (torque) for (a) D1, (b) D2 and (c) D3

5.2.4 Sensor signal time frequency domain analysis

The signal processing will be concluded with a brief analysis in the time frequency domain. The above spectral analyses have revealed information about the frequency contents in measured signals. In the time frequency domain, these signals are analyzed using 3-D waterfall plots to determine not only the FC, but also to indicate the frequency temporal localization. The time spectral map waterfalls shown in figures 5.29 to 5.31 illustrate the spectral evolution of each measured signal with respect to time. Note that these representations in the conventional spectrum are based on assumption that signals which are analyzed are random and stationary. Indeed, the time spectral map results reveal that the drilling signals have lost to some degree their highly non stationary and transient behavior to present a certain periodicity. Consequently one could observe that there is a certain convergence in the distribution of the PSD of measured signals, to specific frequencies that have been excited during the drilling operations. In the case of drill D1 for instance, the convergence of the PSD distribution around 4500 Hz in the frequency band of 3800-5000 Hz is very well illustrated where the FC magnitude is increasing with time for both thrust and drift signals. At the same time the PSD magnitudes of no excited frequencies were very low and almost constant. The same trend is noted in the other measured vibration signals except for the cases where many frequencies were excited in the same regions. In fact, drills D2 and D3 have exhibited different convergence of the PSD distribution in different band regions comprising 10-1500, 1500-2500, and 3800-5000 Hz in both thrust and drift direction.

The analysis in the time frequency domain using the PSD changes with respect to time was also applied on the signals from measured IAS and torque signals. All these spectral map waterfall plots illustrated a convergence of the PSD distribution respectively at the rotational spindle speed and at the frequency corresponding to the telemetry radio transmission of the signal. These frequencies are respectively around 14.5 Hz and 5 Hz. Despite their convergence at these specific frequencies, the IAS and torque time spectral map did not illustrate a decreasing or an increasing trend of the FC with respect to time, probably for multiple reasons: short period of data acquisition, disturbances encountered in strain measurements, non-conformity in the stationary and periodicity of strain signals, minor changes between the angular speed of a sharp drill and a worn drill, etc.

The waterfall plots shown in figures 5.29 to 5.31 illustrate the time spectral maps of signals measured respectively on drills D1, D2 and D3 in the four channels: thrust and drift vibrations, IAS and torque measurements. The ranges of excited frequencies are similar to the frequency responses studied in section 5.2.3 and will be used to identify the FC range of interest and then band pass filtered the measured signals during the RA.

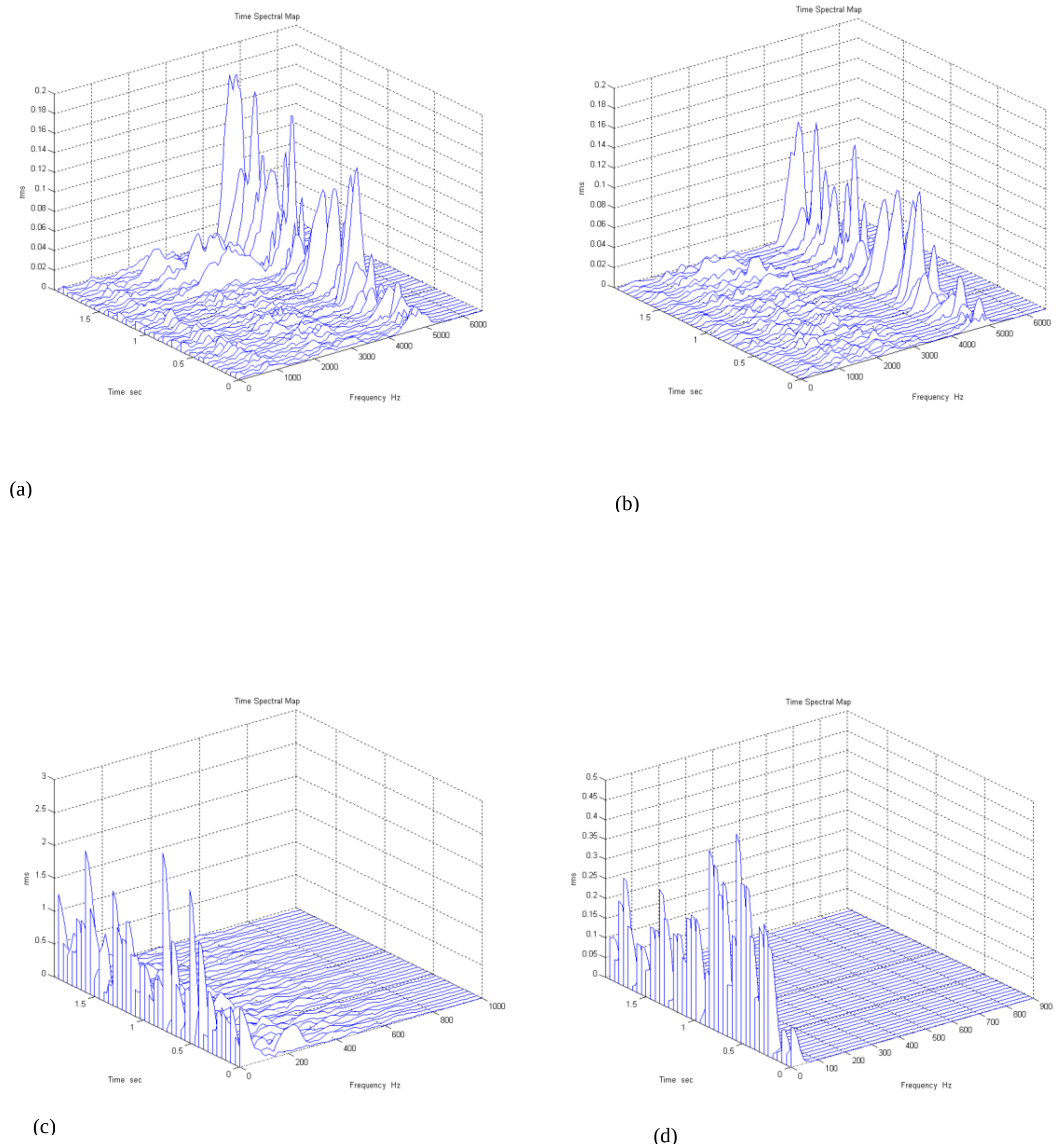


Figure 5.29: Time Spectral Map Waterfall for drill D1 – (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

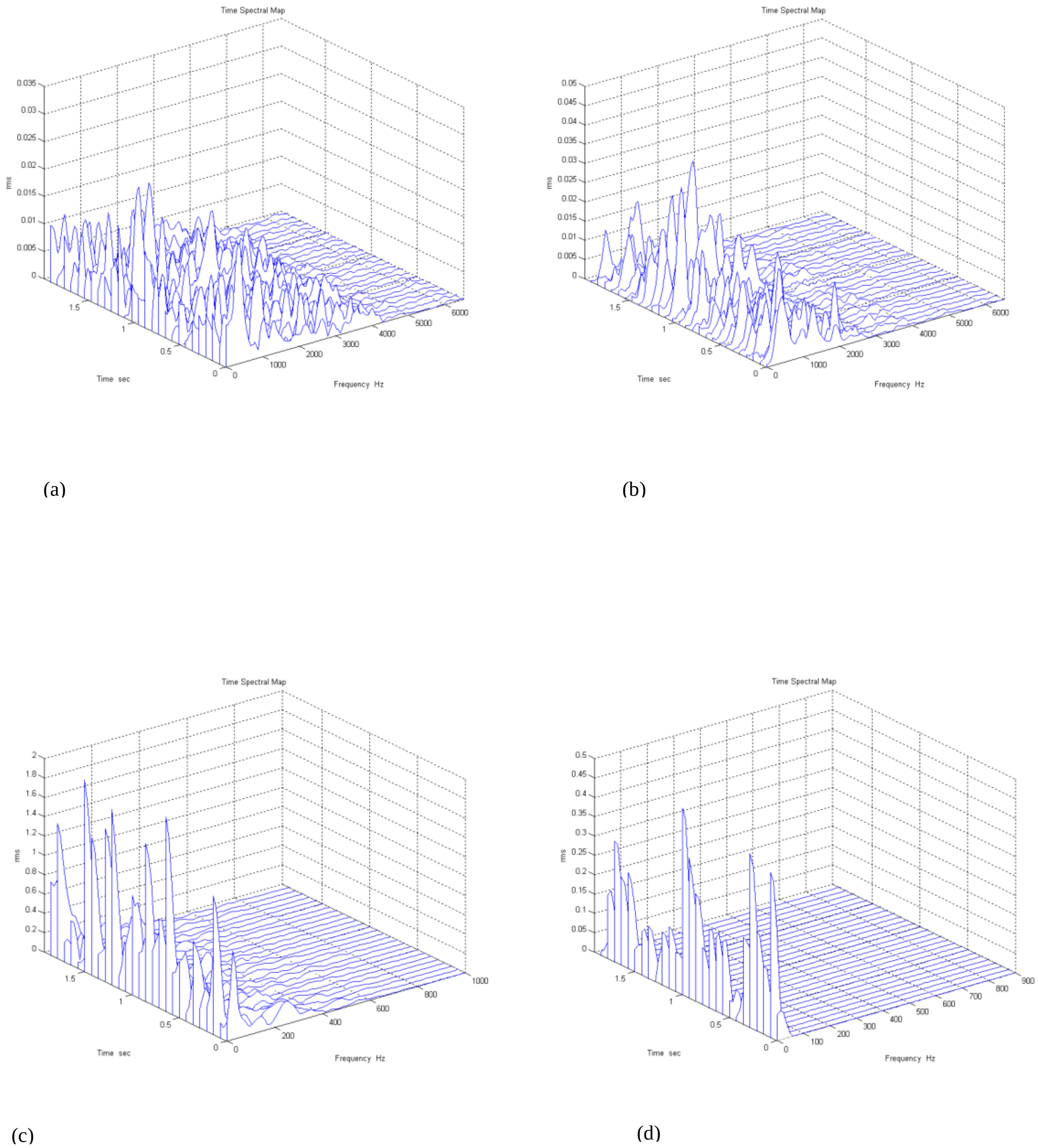
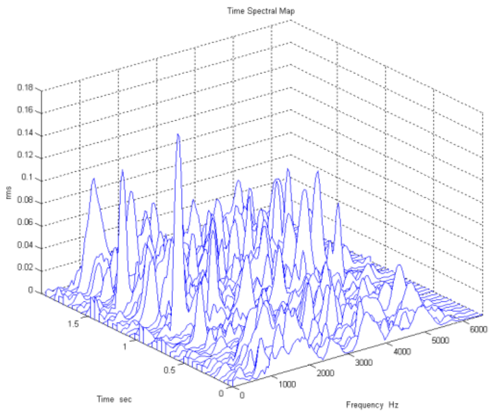
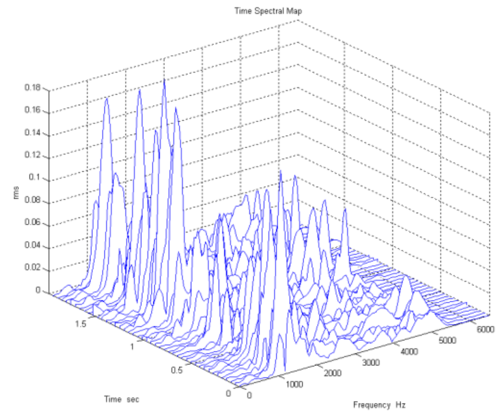


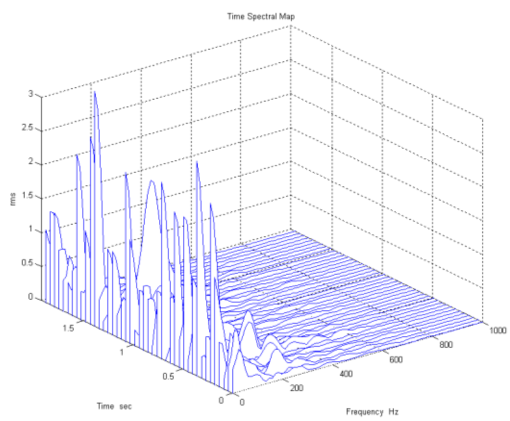
Figure 5.30: Time Spectral Map Waterfall for drill D2 – (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque



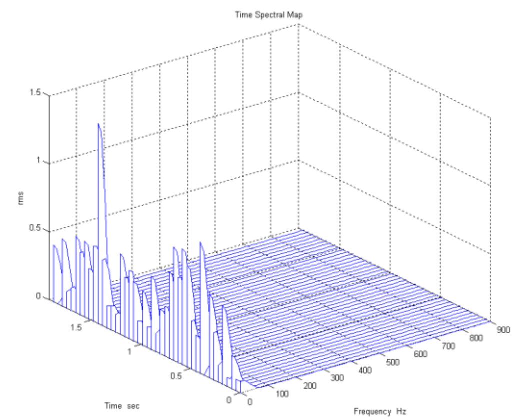
(a)



(b)



(c)



(d)

Figure 5.31: Time Spectral Map Waterfall for drill D3 – (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

5.3 Decision making – Regression analysis

The relationships between analyzed signals and drill wear form the basis of the present diagnosis system. The state-of-art technology in drilling operations has not yet revealed a published model or numerical approach to model the drill wear for a multiple of reasons discussed previously: drill geometry, dynamics and material properties of the tool, non-uniform hardness of the work-piece material or the cutting parts, etc. Drill life is still not predictable and it varies from one operation to another. However, based on a number of studies, Jantunen (2006a) arrived at some interesting conclusions that could make it sensible to monitor a number of parameters such as the rms-value or an amplitude value at a specific frequency if an FTT has been used. This useful technique was applied at the slow development of the drill wear process but which is rapidly increasing at the end of the drill life.

Indeed, it is about developing a tool using a higher order regression function that can quite well mimic the development of analyzed signals (vibrations, IAS and torque) resulting from the drill wear. The approach of making a decision on drill condition using a high order regression function is similar to the trend analysis studied in section 3.5.2 where the drill is considered worn when the rate of change from the previous sensor level with time is significantly consistent. This RA technique is used on the assumption that the wear progression is moderate and/or slow during normal drilling operations and severe at the end of drill life. When applied on such wear progression, the regression function results illustrated a quick and fast response when using polynomial functions of the sixth and ninth order while the second- and third- order functions reacted very slowly. Since there is a lot of variation from test to test in the monitored parameters, the FL was then used to automatically classify these monitored parameters.

Some of the advantages of using higher order polynomial regression function over the use of the average method are its ability for quick fault detection at the end of drill life and mostly it also reduces the variation of noisy data from statistical parameters calculated in time domain by smoothing sudden individual peaks and keeps the trend of the analyzed parameter. To some extent it mimics the shape of the wear development enabling prognosis of the development of the monitored signal with a minimal risk of damaging parts. When compared with conventional monitoring methods that use time consuming processes analyzing large amounts data, RA makes the analyzed signal stable and there is no need to store large amounts of data but only a summary of terms need to be saved for each analyzed parameter.

Based on the above assumptions from the literature that support the current experimental data which also reveal that wear progression is moderate during normal drilling and severe at the end of drill life, a trial and error RA method using MATLAB code has been tested on the experimental test data to assess the wear rate. Results are presented in the time and frequency domains. The RA was preferred to the use of moving average or the exponential function not only for its ability of smoothing time series data but also because it seems to react quickly to change the monitored parameter, specifically at the end of the drill life.

5.3.1 Regression analysis in time domain

The prognosis based on the regression analysis does not provide the drill life duration but could allow a quick response after the rate of signal change has reached a certain percentage of the normal cutting rate. This could be a sufficient indication of the drill condition. At this stage, one cannot avoid a defect of at least one part as the change often occurs quickly at the end of drill life.

The results in figures 5.32 to 5.34 for drills D1, D2 and D3 are based on the rms value of each drilled hole signal calculated in time domain analysis and plotted against the number of holes that lead to drill failure. These results show that the RA function in the time domain has a high capability of mimicking with success the development of drill wear via the monitored parameter such as rms value from thrust and drift vibrations, as well as from IAS and torque measurements. The RA also has the capability of reacting quickly enough at the end of drill life as the rate of the signal changes is big enough. This quick response of the high order regression function at the end of drill life happens as soon as the rate of change from the previous sensor level reaches about 800%, 3%, and 35-65% for the vibration, encoder and torque signals respectively. This is a significant change for each case even if the vibrations seem to be more sensitive than the others. In modern life where the time subdivision is more accurate, the change in rotation speed of 3% could be large enough to be detected and therefore the decision on the monitored parameter being effective. However the drawback of such a quick response in the presence of noisy data is that it could lead to another quick response and then provide unreliable indications.

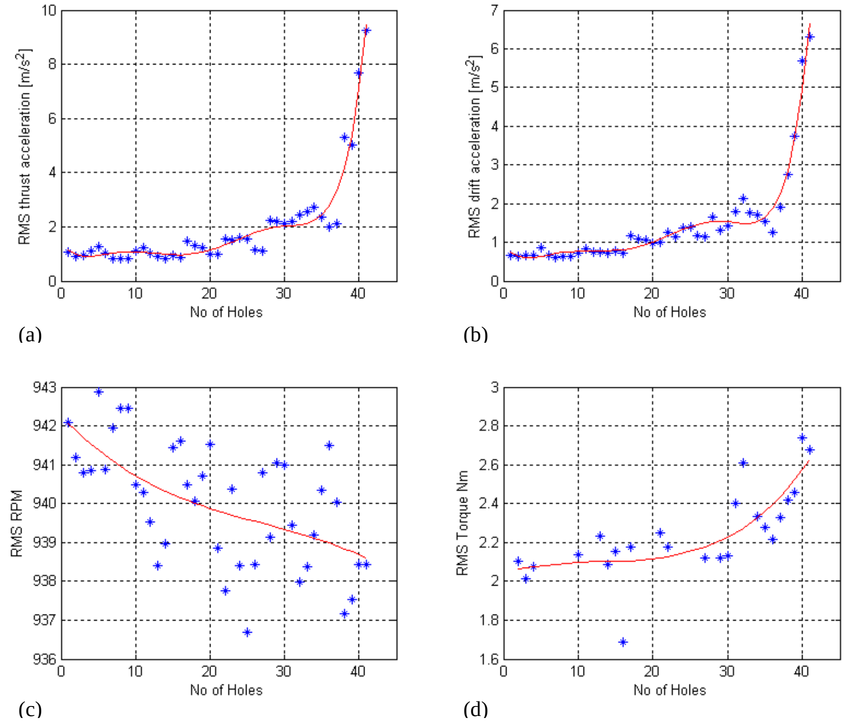


Figure 5.32: Time Domain Polynomial regression for Drill 1: (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

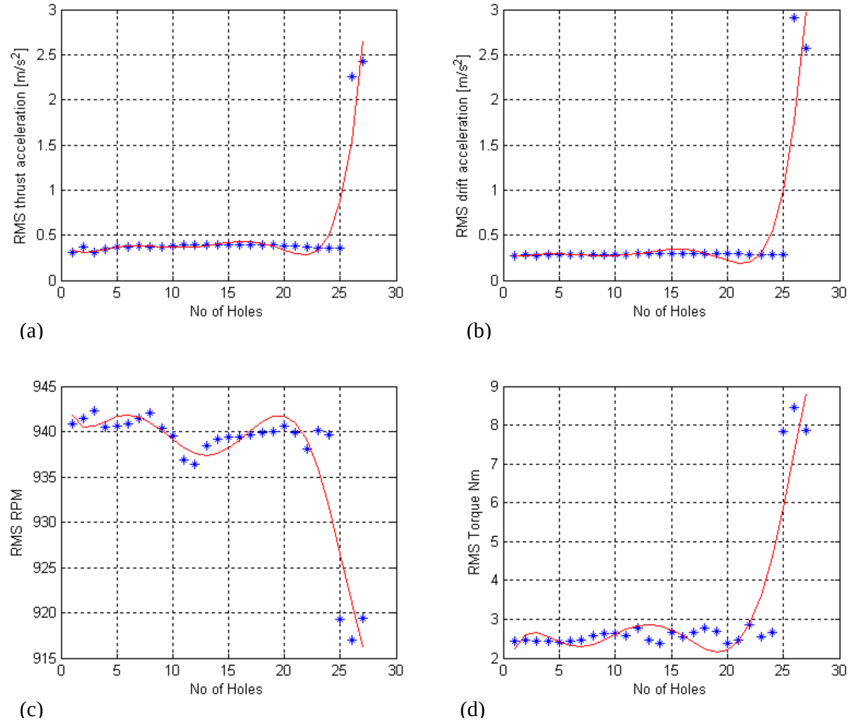


Figure 5.33: Time Domain Polynomial regression for Drill 2: (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

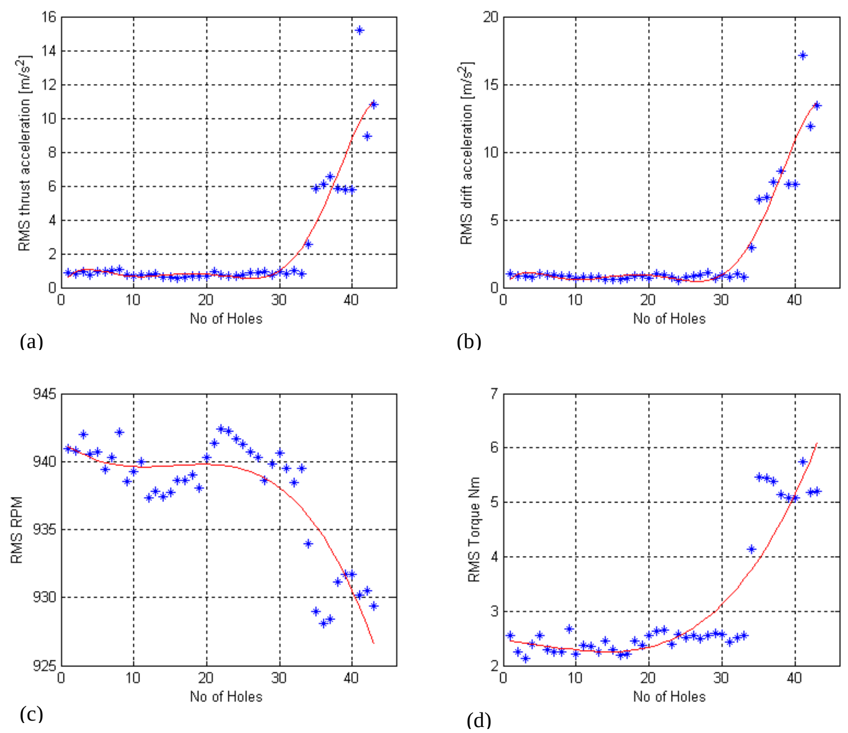


Figure 5.34: Time Domain Polynomial regression for Drill 3: (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

5.3.2 Regression analysis in frequency domain

Based on the frequency responses and the spectral analysis performed in frequency domain analysis, the maximum spectral amplitude value was calculated in different band regions of the excited frequencies that show distinctive features that could support the drill wear monitoring. In the case of vibration signals, the band regions that were more sensitive to drill wear are 3800-5000 Hz for drill D1, 2000-3000 Hz for drill D2 and 10-1500 Hz for drill D3. While the IAS and torque frequencies of interest were unchanged and the calculation of FFT maximum was performed respectively in the 8-20 Hz and 0-10 Hz band regions. As discussed in section 5.2.3.2, it is evident that drills are not failing in the same way and therefore the vibration excited band frequencies are not repeatable in each case while the rotational and the telemetry transmission band frequencies would remain the same. The correlation between the frequency and the type of wear is not part of this dissertation. These calculated maximum values were then used for the prognosis of wear development by means of a higher order function regression.

The results are presented in figures 5.35 to 5.37 for drills D1, D2, and D3 showing the RA function applied to the maximum values of the calculated FFT. The results revealed that the RA function applied in the frequency domain can mimic the development of the monitored parameters such as the maximum spectral amplitude calculated from measured thrust and drift vibration signals, as well as from measured IAS and torque signals. As it was been demonstrated in the time domain, the high order regression function in the frequency domain also has the capability of reacting quickly enough at the end of drill life. This quick response of the high order regression function at the end of drill life happens as soon as the rate of change from the previous sensor level reaches about 800%, 3%, and 35-65% for the vibration, encoder and torque signals respectively. This is a significant change for each case with the regression on the vibrations being more sensitive than the others. Once more this trend of the regression function presents the risk of damaging at least one part as it is increasing quickly at the end of the drill life.

A mathematical model being ignored with drilling operations presenting different drill lives, the RA analysis function held great promise in decision making. It can provide not only the smooth trend of drill wear development but also the rate at which values are changing minimizing the effect of disparities that arise when considered for instance the absolute values that are prone to send spur alarms. However, one could not avoid cautioning the reader about the effectiveness of the findings, specifically the application of the RA on the IAS where a study in greater depth is recommended. Indeed, the calculated IAS presents some disparities in the data so that the application of a high order polynomial function on such noisy data would tend to become unstable. The fact that the drill rotates in continuous contact with the work-piece wearing and reshaping the cutting edges, this cutting process lead to both the reduction and the increase of the angular speed and therefore affects the duration of the period between pulses. Thus, it appears that the use of the RA is not really the problem but it is the nature of the IAS data that could cause problem. Nevertheless, the present results demonstrate a good correlation between the RA analysis and the drill life and can enrich the literature in the search of an effective and reliably sensor systems in unmanned drill tool wear monitoring.

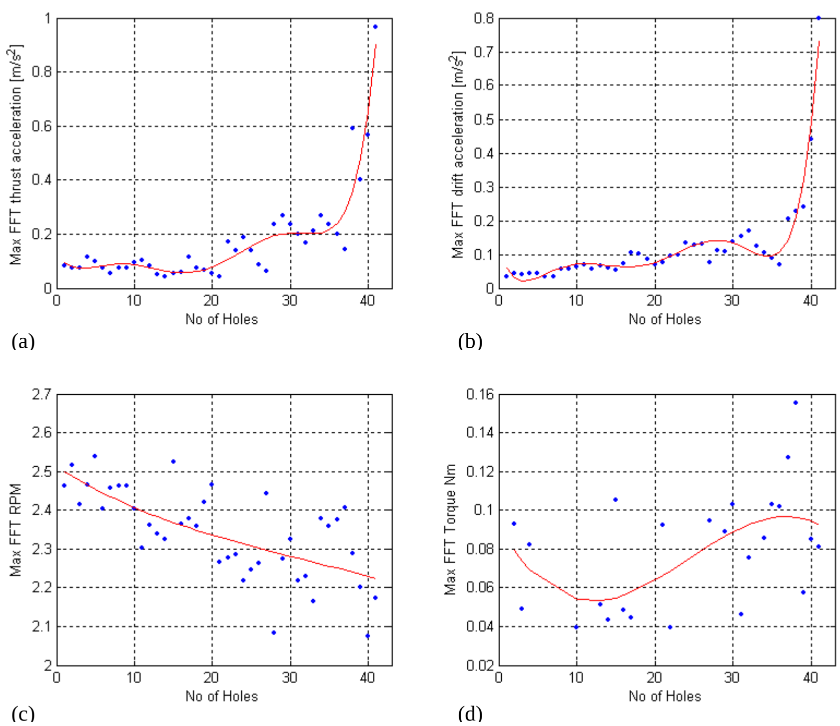


Figure 5.35: Frequency Domain Polynomial regression for Drill 1: (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

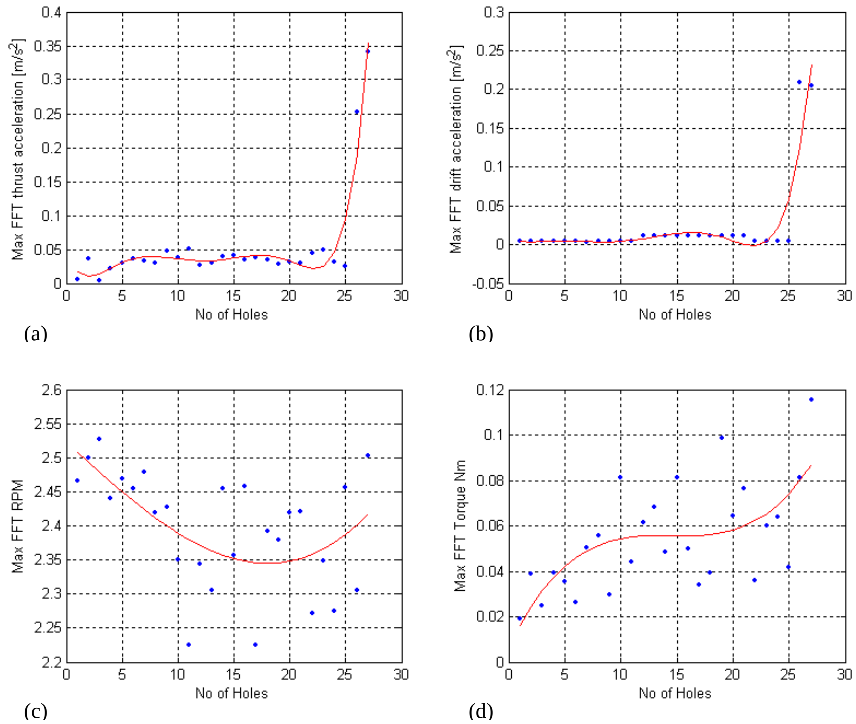


Figure 5.36: Frequency Domain Polynomial regression for Drill 2: (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

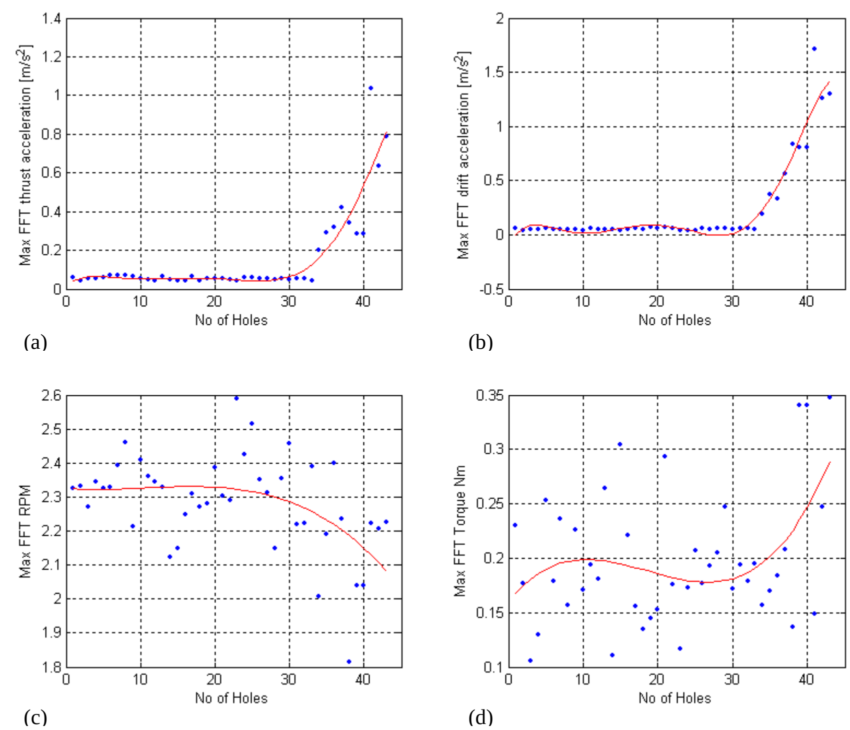


Figure 5.37: Frequency Domain Polynomial regression for Drill 3: (a) Thrust Acceleration; (b) Drift Acceleration; (c) IAS; (d) Torque

5.4 Reliability of the Encoder Results

The signal analysis and the decision making by means of the regression analysis have demonstrated the usefulness of an encoder for IAS monitoring as it can provide similar diagnostic information comparable to conventional signal analysis that characterized vibration and torque features related to drill wear. The popular trends developed in TCM to date in both sensors and signal processing methodologies widely follow conventional technologies. However, their potential weaknesses are well known in flexible manufacturing. Therefore the development of effective and reliable sensor systems is essential to achieve full potential of unmanned machining operations. Similar to the sensing of the tool shank without contact proposed in the paper of Vilcek and Poskocilova (2008), the encoder-based sensor is probably another step in the development of some form of instrumented tool to overcome the lack of custom-made sensors in drilling. Between the sensing methodologies developed in this work, the encoder presents the advantage of ease of installation, not encumbering and seems very practical to be used in real time for monitoring purposes. For this reason, additional drill bits with different diameter sizes were tested to investigate the reliability of the encoder based sensor and examine to what extent the results obtained based on 10 mm diameter drill were valid. Before that, the encoder resolution is herein investigated to find the simplest and practical way of using the encoder. If for instance one pulse resolution suffices to give successful results, then the opportunity of using a cheaper encoder sensor will be greater. Probably the IAS measurement could be reduced cost effectively to a simple angular speed by also increasing the sampling frequency for the accuracy of the measurement.

5.4.1 Encoder resolution

The resolution of the encoder was tested both by re-sampling the 1024 pulses per revolution signal to one pulse per revolution. Drills were tested using only two channels with output signals respectively of one and 1024 pulses per revolution at the sampling rate of 200 000 Hz. The goal is to show if there is any significant difference in the results when analyzing signals with two different resolutions. The success of results could mean that a keyphasor represents an alternative sensing method to the shaft encoder based signals. A keyphasor will probably be preferable to the encoder because in the on-line monitoring for instance, one cannot afford to instrument hundreds or thousands of drills in series with shaft encoders. Needless to say, this is expensive and not economical for the process. The re-sampling results are shown on figures 5.38 to 5.40 where the rms value of IAS from both channels were computed and plotted against the number of drilled holes for drills D2, D3, D4, D5, D9, and D10. The results reveal that the calculated angular speeds are quasi similar in both channels for 8mm, 10mm and 12 mm size drills while the results for small drills (3mm and 4mm) seem to present some minor disparities. Nevertheless, the drill size is not the sole factor that could justify the high speed obtained with the high resolution (1024 pulses) encoder. As discussed in section 3.3.5.1 the measurement of the IAS is based on the measurement of either an elapsed time between successive pulses or counting pulses during a prescribed period of time. In this case the ET method was used and taking in account 1024 pulses per revolution rather than one seems to give a precise and accurate estimation of the angular speed. This assumption seems to be demonstrated for 1024 pulses where a small fraction of a revolution could provide an indication of the instantaneous speed while a complete revolution is required for a pulse per revolution to estimate the necessary ET to estimate the speed. The results show that the estimation of the IAS in both channels is quite the same for drills turning at low RPM and illustrate minor difference for drills operating at high speed where the accuracy is given by the high resolution of the number of pulses.

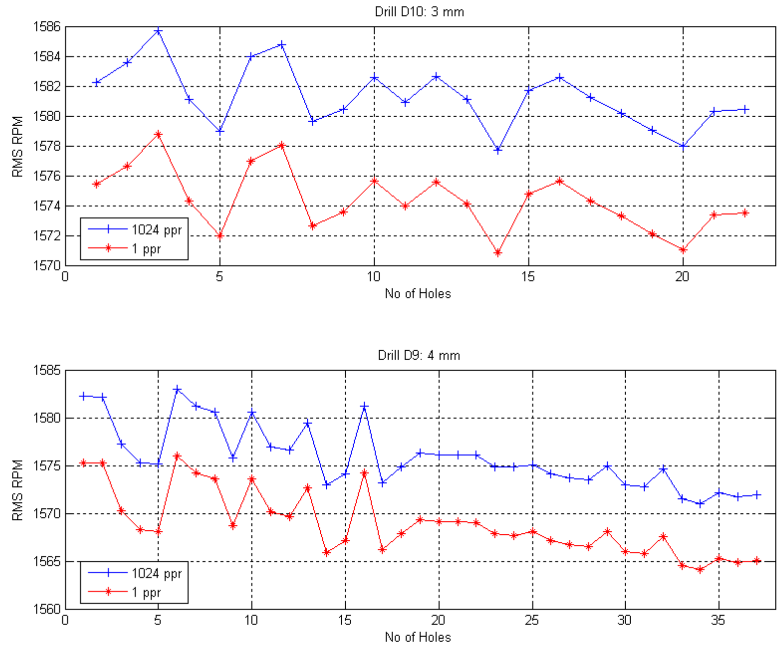


Figure 5.38: RMS value of IAS in RPM for D9 (4mm) and D10 (3mm) drills respectively for 1024 and 1 pulses per rev.

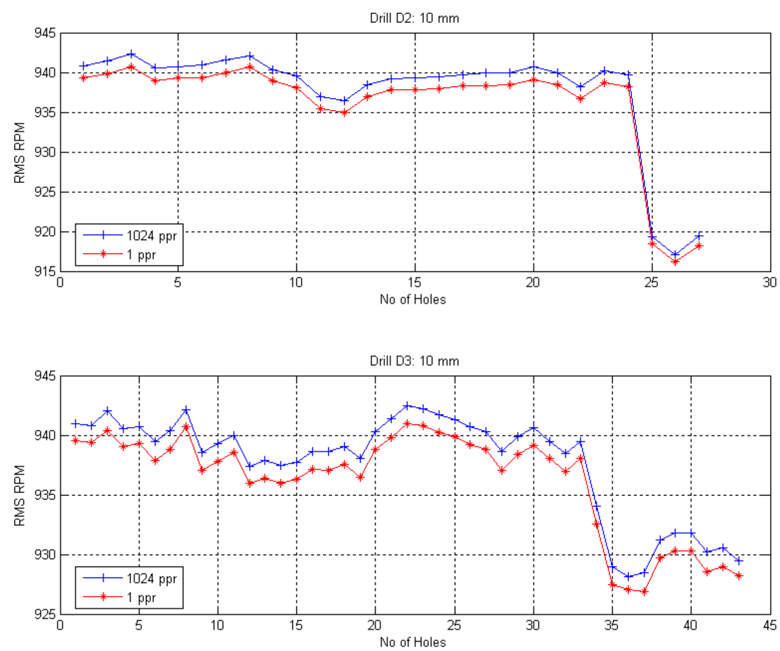


Figure 5.39: RMS value of IAS in RPM for D2 (10mm) and D3 (10mm) drills respectively for 1024 and 1 pulses per rev.

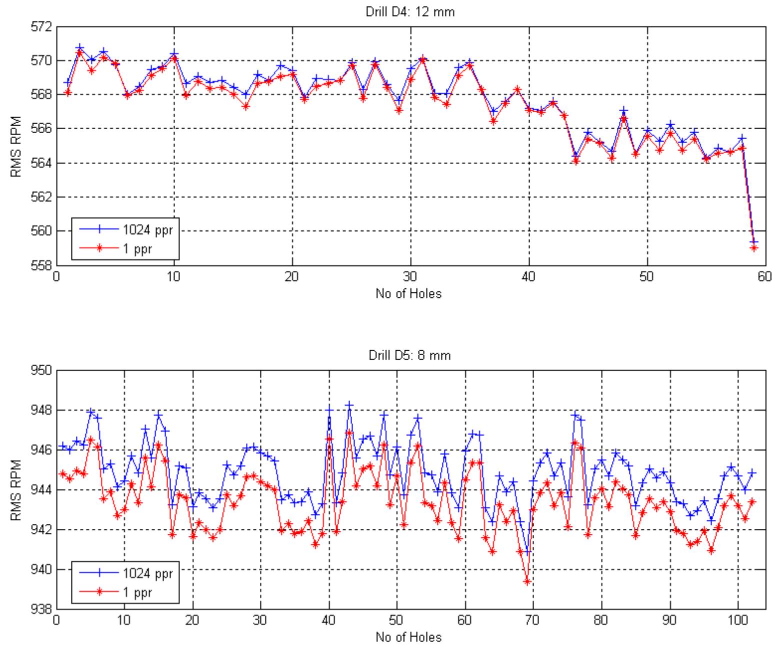


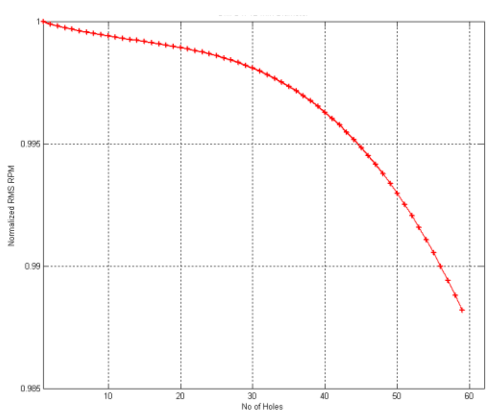
Figure 5.40: RMS value of IAS in RPM for D4 (12mm) and D5 (8mm) drills respectively for 1024 and 1 pulses per rev.

Therefore if the decision making should be based only on the detection of a change in sensor magnitude feature level with time where the detection of a significant change rate in sensor level is a major criterion, the above results have shown that the encoder resolution does not significantly impact the results. It can be concluded that one keyphasor could represent a positive alternative sensing method to the multi pulses shaft encoder based signals in the same manner Vilcek and Poskocilova (2008) used a distance sensor without contact to measure the deflection of the drill in a plane normal to the drill axis. The drawback of this sensing method is the reduction of the IAS measurement to a single pulse per revolution. However, the results show that the rate of change in sensor level with time is consistent in both cases even if the accuracy was achieved with the IAS measurement by means of the multi pulses encoder based sensor.

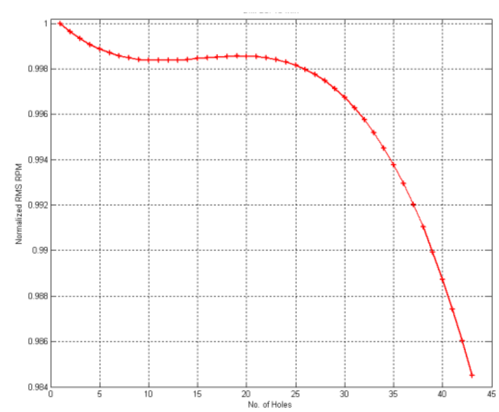
5.4.2 Drill wear rate using IAS drills' different size

Results presented when considering a 10 mm diameter drill have shown that IAS signals can provide similar diagnostic information comparable to conventional technologies. In this section, an investigation was made to establish the effectiveness of generalizing the above results to a range of drill sizes. Specifically for smaller size drills where fracture and breakage are typical failure modes encountered. For that, polynomial RA analysis was applied on the rms value of IAS signals measured for different size drills. Comparisons are based on the normalized rms values as the rotational spindle speed changes with the drill size. The results are shown on figure 5.41 using respectively the following drill sizes: 12mm, 10mm, 8mm, 6mm, 4mm and 3mm. From these curves, it seems that drills with greater sizes fit well into the pattern of conventional drill wear stages while small size drills do not. Indeed, small drills have a short drill life and in general fail due to breakage and not wear. Similar to drill wear stages of angular speed obtained on 10 mm drills, the curves in figure 5.41 illustrate a decreasing trend of the IAS with time and also show that the life of drills differ from drill to drill. Specifically, when drilling continuously small drills are subject to fracture failure and fail in a short life time. Consequently, drill wear stages resume in descendant slope curves missing the quasi constant normal drilling stage. At the end, these results reinforce the assumption of using the IAS as a recommended feature to monitor the drill condition.

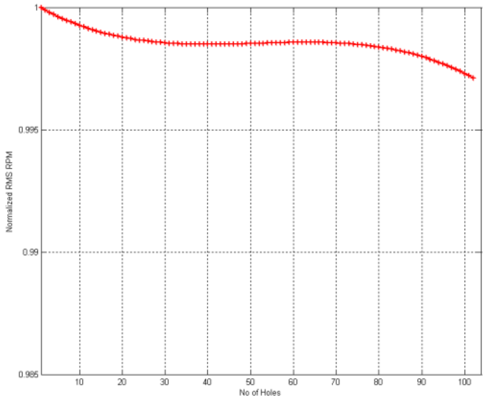
Drill D4: 12 mm



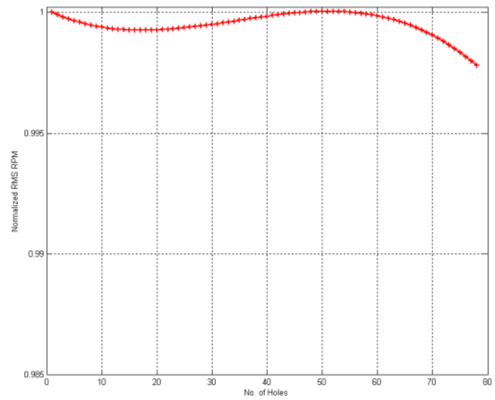
Drill D3: 10 mm



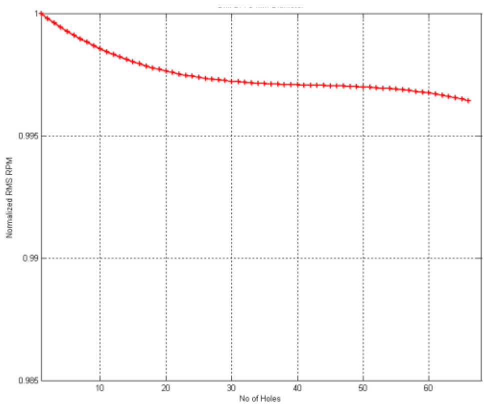
Drill D6: 8 mm



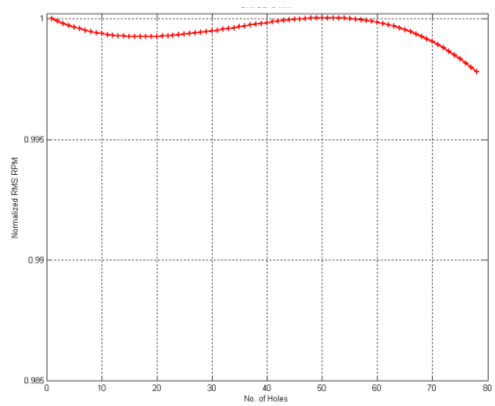
Drill D5: 8 mm



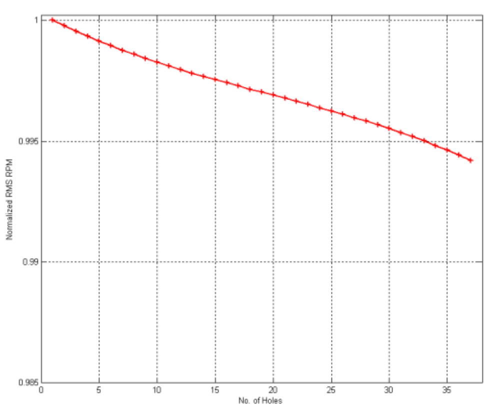
Drill D7: 6 mm



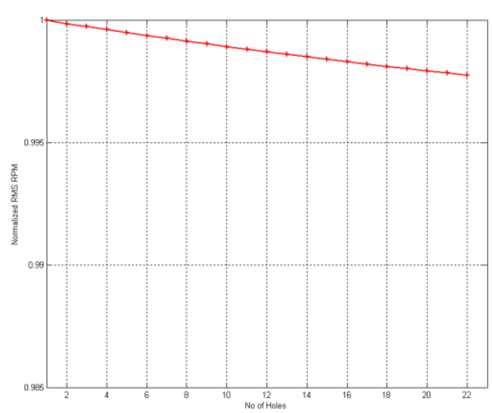
Drill D8: 6 mm



Drill D9: 4 mm



Drill D10: 3 mm



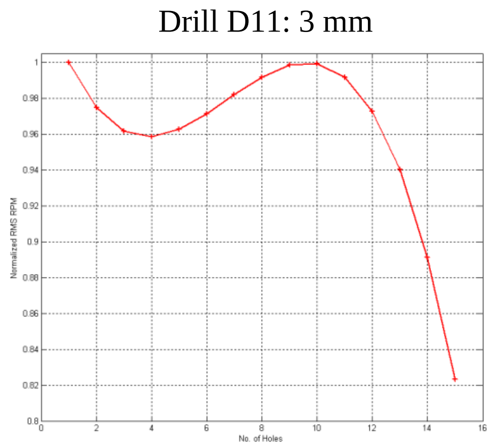


Figure 5.41: Normalized IAS trends for different drill sizes: 12mm, 10mm, 8mm, 6mm, 4mm and 3mm

CHAPTER 6: CONCLUSIONS

6.1 Conclusion

The suitability of the drilling process from an industrial perspective is predominantly linked to the economic gain in terms of cost reduction, prevention of downtime, prevention of tool damage, and the improvement of both quality and production. In order to achieve these goals, an effective and high performance TCM that integrates intelligent and innovative sensor technologies, comprehensive signal processing and powerful tools for decision making is recommended. Under such conditions, there is always great potential to improve the cutting drill tool utilization to its optimal rate.

In this work, a comprehensive cutting test procedure was carried out with drills of different sizes using an encoder based sensor that could challenge the lack of interest in conventional technology sensors in industry; and that has been largely successful in the laboratory. Conventional sensors are considered more expensive and complicated monitoring systems to implement in industry and therefore have less value. In contrast this work considers the encoder as the simplest type of sensor with great diversity potential in industry. Hence, vibration based accelerometer sensors and torque based strain sensors were compared against the use of IAS based encoder sensors to assess the drill condition.

Based on the test results, it has been observed that all the sensors used could provide similar diagnostic information related to drill wear. This good correlation between sensors and drill wear, specifically in the case of the encoder based sensor, is considered to have significant potential response to the lack of custom made drilling sensors. Considering that the angular speed measurement is based on the ET period of successive pulses, one could take advantage of recent advanced techniques in rotating machines that accurately measure the time subdivision to improve the measurement of the angular speed. In this context, the more accurate the angular speed measurement is;

the better will its impact be on the improvement in drill utilization rate and therefore its use at the optimal rate.

If the encoder presents advantages of being practical, easy to install and not encumbering, additional test results have also proven that a keyphasor could represent a better alternative as an effective and flexible sensor in the automated industrial environment.

Different analysis techniques were considered with minor discussions on the benefits and disadvantages of the techniques used. The rms statistical parameter was not only consistent but was also used based on the sensor signal characteristics which show patterns and levels of measured signals changing with the drill condition. Indeed, all the quantities measured could follow the drill wear stages and could provide information that discriminate the drill condition in the time domain. The FFT is an averaging method and when applied to already average measurements, it was without surprise to see good results in the frequency domain as well.

Based on the above successful analysis techniques, one could conclude that the decision making trend on drill condition, based on either the averaging or the exponential smoothing methods, seems to be appropriate to the present tested data. However the RA was in contrast used on the one hand because the method was found well suited with the experimental data and on the other hand, it was found more appropriate to be used in the unmanned cutting environment for an automatic diagnostic approach. Hence, a trial and error based on the polynomial regression was used and the results have shown good correlation with drill wear. In fact and unlike averaging and exponential methods, it was found that the RA well mimics the shape of wear development and could be used to give prognosis of drill failure with a minimum risk of work-piece damage. The method has the advantages of smoothing time series data, filters unwanted variation of the measured parameters and thus provides a prognosis of the forthcoming trend of the monitored parameters. The major drawback of the RA remains its instability in the presence of noisy data.

6.2 Recommendations for future work

At present, no significant research has been found in the literature dealing with the measurement of the angular speed in the field of drilling operations except few examples like the real time drill wear estimation based on the spindle motor power (Kim et al., 2002). However one can find huge number of recent publications of assessing the IAS using digital time interval techniques. In fact, they are based on the time duration of every simple pulse of the signal chain pulses. In this work a high order encoder resolution was chosen with the aim of improving the angular speed measurement. However it is also known that a high sampling rate could as well improve the measurement with less encoder resolution. Indeed, the comparison between the two test results was promising with a better accuracy when using a high encoder resolution. A wider investigation that could focus on both one pulse per revolution and a high sampling rate is therefore recommended to ensure the same accuracy and repeatability in both cases.

This work has added another approach of sensing drill wear that works using laboratory data. In normal production where external disturbances influence measured signals, conventional technology based sensors were found unsuccessful and one can even predict a failure diagnosis in such environment. The encoder seems to be flexible and less sensitive to external disturbances; a wider testing approach in industry is also suggested including an automatic diagnosis approach such as the FL. In this context, the higher order polynomial regression was not only useful in decision making but could also be used as features in FL to diagnostic and predict automatically the drill condition. The incorporation of those features in a state-of- art as the ANNs would find favor in on-line and automated monitoring system for the classification of the drill condition.

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APPENDIX A1: Statistical parameters for D1

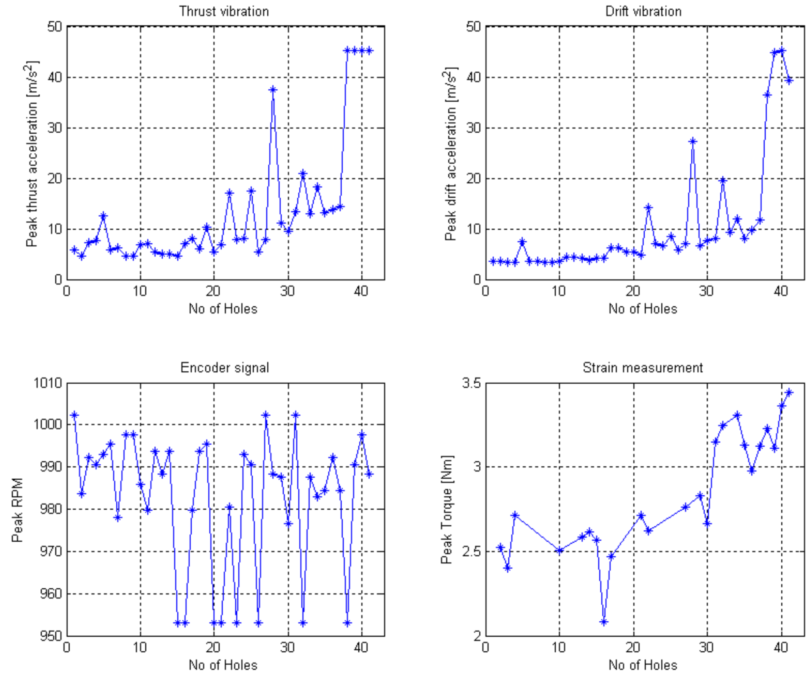

Figure A.1.1: Peak value of sensor signals for each hole

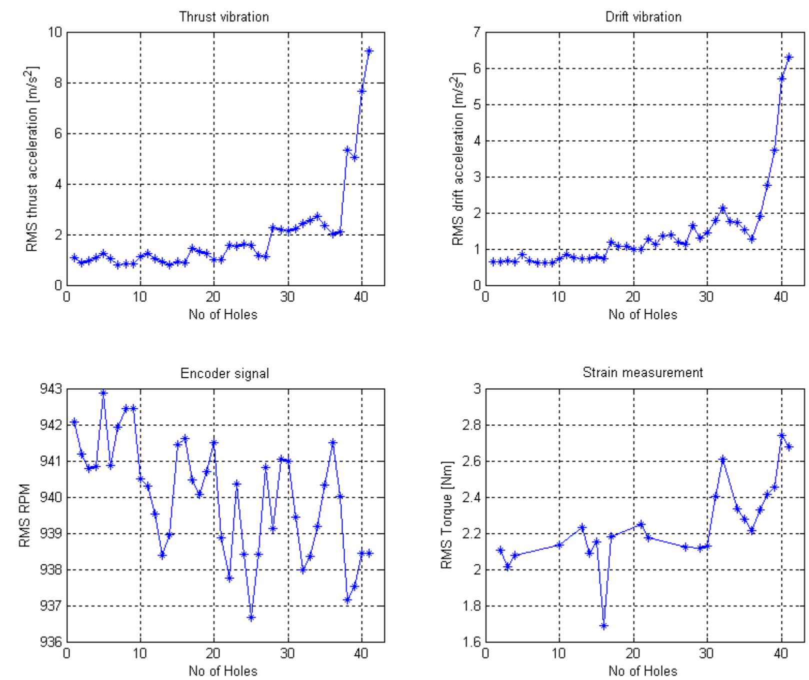

Figure A.1.2: RMS value of sensor signals for each hole

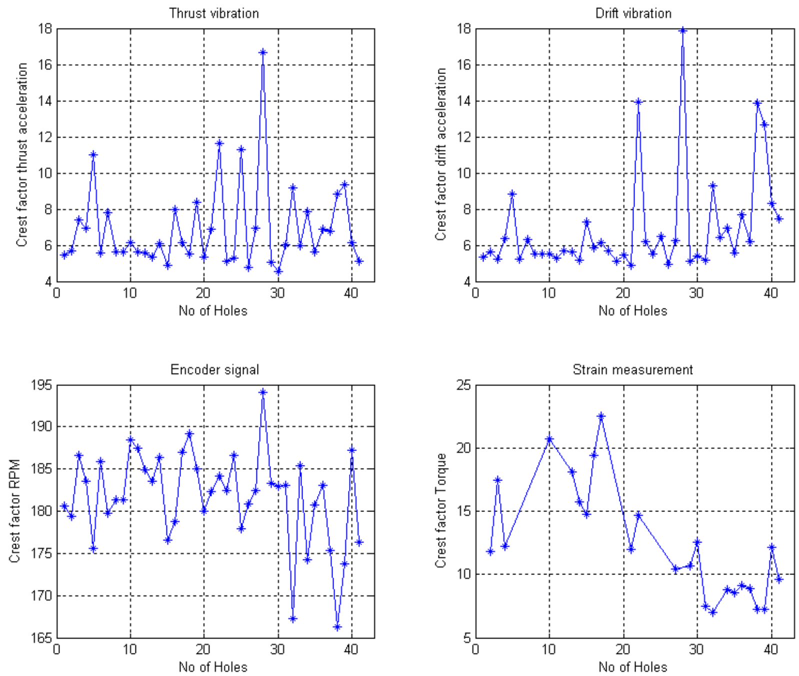

Figure A.1.3: Crest factor of sensor signals for each hole

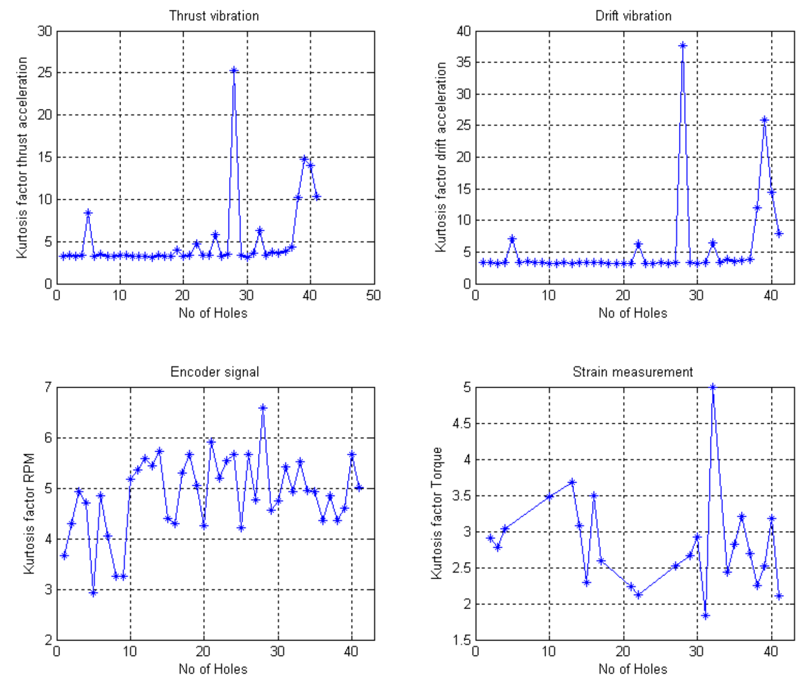

Figure A.1.4: Kurtosis value of sensor signals for each hole

APPENDIX A2: Statistical parameters for D3

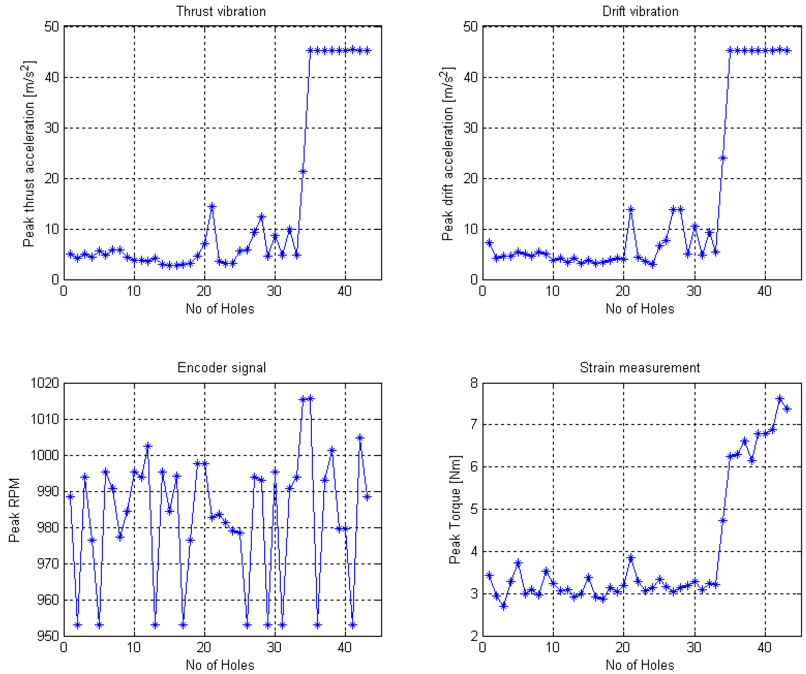

Figure A.2.1: Peak value of sensor signals for each hole

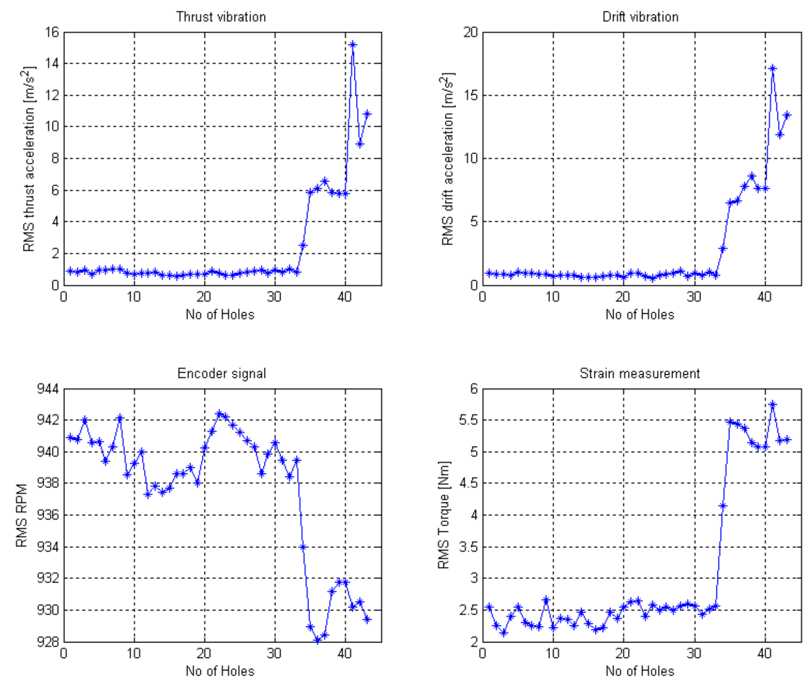

Figure A.2.2: RMS value of sensor signals for each hole

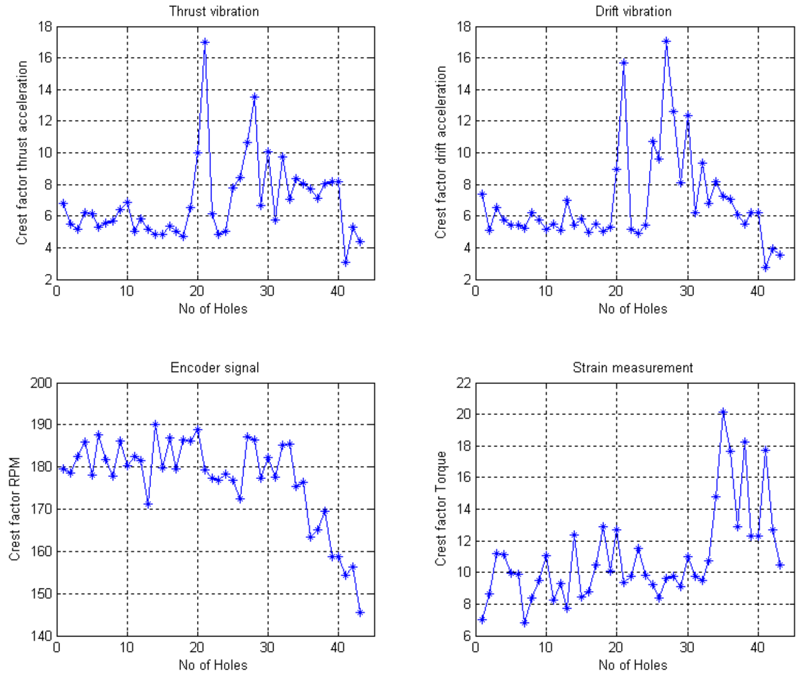

Figure A.2.3: Crest factor of sensor signals for each hole

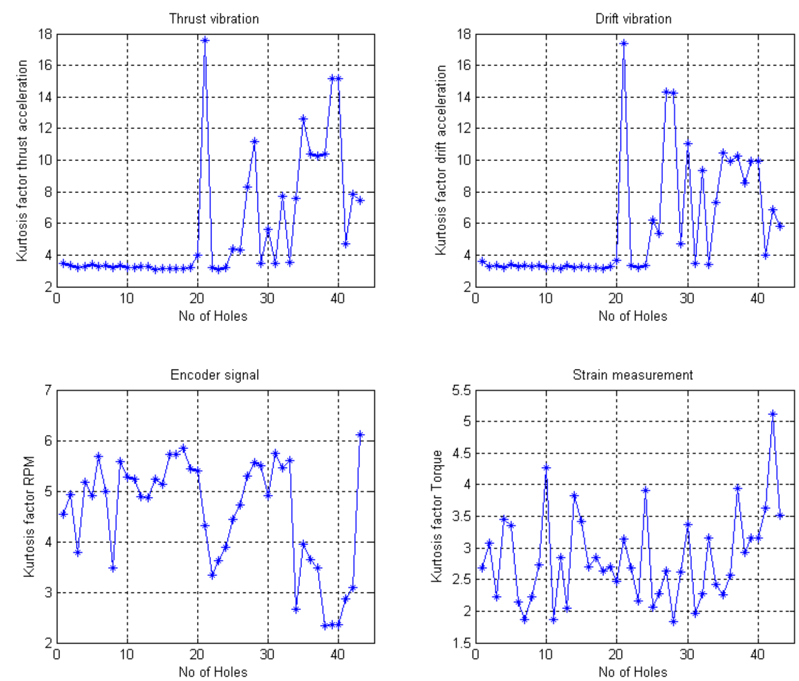

Figure A.2.4: Kurtosis value of sensor signals for each hole