Tool Condition Performance Monitoring, Evaluation and Analysis in a Modern Industrial Precision Manufacturing Environment.

By

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Declaration

This document is submitted to the Academic Council Committee of the Waterford Institute of Technology (WIT) in partial submission for completion of the Doctor of Philosophy Degree, PhD.

This statement serves as a declaration that the research and findings presented herein are all the author's own work and that this is a submission proposing the awarding of the Advanced Degree- Doctor of Philosophy.

Any work referenced within this document which is not the author's own will be clearly referenced. Additionally, work that has been published by the author will be declared in this document and included in the appendices

I, as the author, hereby declare that this submission is the author's own work and that, to the best of the author's knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other Advanced Degree, Ordinary degree or Diploma of the Institute or other Institute(s) of higher learning, except where due acknowledgment has been made in the text herein.

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Research title

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Acknowledgements

From an academic view I would like at the outset to acknowledge the support received from my supervisors at the Waterford Institute of Technology, Dr. Paul O'Leary and Dr. Ramesh Raghavendra. I have learned at the feet of the masters.

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On that theme, during this research the author has been extremely fortunate to interact through the FP7-REALISM project with many wonderful people within the CIRP (International Academy for Production Engineering) network. This research has resulted in publications and CIRP conference interactions with some of the global experts in the area of my research, and my learnings through this research were informed by you. Krzysztof Jemielniak, Roberto Teti, Kristian Martensen and all the co-authors on the scientific papers included in the appendices of this thesis- thanks so much for the opportunity to learn so much during our collaborations.

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You all just assumed that this was part of what I did for the past 9 years as you grew up and we grew together, and the accomplishment of this is testament to us as a family more than me as a person!

This is for you and is a thank you for all your support and encouragement.

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Abstract

This thesis presents research and evaluation of the various phenomena that potentially contain worthwhile information in the performance of machining operations. In particular what these phenomena can tell a computer-controlled machine, or the machine operator, about the degree of tool wear being experienced during the operation. Tool wear is an unavoidable element of machining operations and a variety of approaches have been investigated and implemented to delay the onset of wear, e.g. cutting fluid, tool coatings. However, there is currently no reliable system whereby tool wear itself can be monitored during the cutting operation; this information is only available at the end of the operation, through tool or work piece inspection and interrogation.

It was the intention of this research to determine which of the machining phenomena, or fusions of these phenomena, is likely to provide the most worthwhile information for such monitoring. All the data gathered during this research and presented in this thesis was from machines working in a commercial environment, carrying out typical live production cutting operations, thus providing data that could be worthwhile for modern industry.

While this work started as the author's own research into process monitoring of the machining process, it expanded into an FP7 funded project with the acronym "REALISM" Realism project (2015), with the author's organisation Schivo and WIT as the Lead Partners. This pan-European project formally commenced in Jan 2014 and had a 2-year duration, concluding at the end of 2015. REALISM's aim was to build and test a tool condition monitoring system and, based on that, to lay the groundwork for the future goal of optimizing tool usage and the tool change decision.

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Table 1 List of Acronyms and technical terms (Nomenclature)

Term	Explanation
CNC	Computer Numeric Controlled Machining
TW	Cutting tool wear
CTF	Catastrophic Tool Failure
TCM	Tool Condition Monitoring
Audible sound	Human perceptible pressure waves 2 KHz- 20 KHz
AE	Acoustic Emissions
V	Vibration
HMI	Human Machine Interface
ANN	Artificial Neural Network
FL	Fuzzy Logic

1 Introduction

The aim of this research is to determine if the physical, human detectible emissions from the CNC machining process can be captured using sensors to determine the state of the process in terms of the degradation of the cutting interface.

The objective of the research was to examine whether the physical emissions generated during the machining of material in cutting processes (subtractive manufacturing) can be used to determine the *in-situ* performance- and state of- the process.

In this era where the advent of the 4th industrial revolution (or Industry 4.0) is increasingly being propounded, the automated control of manufacturing processes is vital to the future of this industry. The reliance on human interpretation of the performance of all manufacturing processes needs to be removed from industry, and development of technological methodologies to replace human senses with machine systems to monitor processes is critical to the future efficiencies in making products.

The research outlined in this thesis aims to offer some enhancements to the state of the art and understanding in the field of monitoring the subtractive manufacturing process as applied to the metal removal process in machining.

The use of raw material machining and manipulation activities in manufacturing is not new, and has been employed by mankind since the early days of tool making, the genesis of which did not happen during the last industrial revolution, but rather earlier during the bronze and iron ages, and, in some respects, even earlier still in the realm of stone age man. Mankind has been using shaping and finishing processes for the manufacture of products for over 10,000 years and through the ages, the methods whereby the effectiveness of these processes have been evaluated have evolved along with the products developed and technologies used to develop them.

In the first instance the functionality of a product was the primary desired attribute. Early man knew through looking at his creation during manufacture if it was adopting the form that he had envisaged at the outset of his operation- and could modify his material manipulation method accordingly. Simple trials of the implement then confirmed the quality of the product (sharp, solid, etc. - basic desirable and functional attributes).

As mankind's ability to influence materials through the manipulation of their form became more advanced, the aesthetic appearance of the resultant product became important in the evaluation of the success of the manufacturing operation. The proposed creation, which was required principally to be effective in function, was also occasionally desired to be pleasing in appearance. In time, the aesthetics came to be an important evaluation criterion, as well as the overall functionality of the product.

The advent of the industrial revolution in the early to mid-18th century saw seismic shifts in mankind's ability to manufacture products- but also great shifts in the ability to control the processes used to make the products and huge improvements in the ability to control these processes. History has placed a lot of emphasis on the increased efficiency of manufacturing during this period, but it is also worth noting the advances that were made in process controls and the advent of standardisation of the outputs of these processes.

The second seismic jump in the development of predictable and repeatable material shaping processes came in the mid-20th century with the invention of the computer. Processes that previously involved material shaping through manual cutting and forming processes now became controllable through the use of Computer Numeric Control (CNC), which uses the Cartesian co-ordinate control system to determine the location and action of a cutting interface and to ensure the product's repeatability, and as a result the output from a process can become hugely predictable.

While the Cartesian Control system is an excellent method of determining where a physical unit is at a given moment in time (such as a mechanically controlled cutting interface) it cannot allow for variables within that interface- such as variations in the consistency of the material levels at the interface- i.e. tool wear in a cutting operation.

In modern precision engineering, tool wear affects the dimensional accuracy and surface finish of machined parts. Currently, errors associated with tool wear remain uncompensated for and are usually only detected at the end of the machine cycle, by which time the product may be scrap. The result of scrap generated from a poorly performing process is expensive in terms of material loss, labour costs, machine time, but also contributes to delays in customer lead-time delivery.

This research will consider a number of methodologies which could address this problem, by both providing real-time information on the performance of the CNC machining operation, through Tool Condition Monitoring (TCM), and also potentially enabling real-time correction to compensate for tool wear. This approach will also include investigating the feasibility of a sensor fusion system, whereby multiple sensor signals are combined to provide more accurate feedback on the performance of the machining operation. Such a solution could dramatically reduce unnecessary manufacturing cycles and scrap production, by defining tool offsets to allow for tool wear or by adjusting spindle speeds to correct cutting conditions, thus giving more predictable products.

This work uses sensors to gather physical data from CNC machining centres in a variety of configurations and in a variety of tool configurations and work piece materials. The phenomena being investigated are the audible sound, acoustic emissions (AE), vibrations and forces being generated at the actual cutting edge/work piece interface. An understanding of the physics of these phenomena, and the resultant use of this understanding, is the goal of the research.

A variety of signal collection, analysis and interpretation techniques, primarily controlled by LabVIEW, have been employed to provide meaningful information on the performance of the process. The development of a system to real-time monitor the machining process is the ultimate goal of the EU REALISM project.

There is then the further possibility that the research could eventually provide a platform for the future development of a feedback system, whereby the process performance information collected and interpreted by the performance monitoring system and be utilized to allow the operating system of the machining centre to adjust the process parameters, to bring the process back to centre of operational allowances. However, at the outset of the research, the evaluation of this goal will be left for the discussions and conclusions section of this document.

The primary research questions posed at the outset of this are whether it is possible to utilise the sensor configurations researched thus far, and available in the literature, in a normal production setting to provide meaningful information to either the operator or the CNC interface on the condition of the cutting operation in terms of both the onset of tool wear and also the potential for catastrophic tool failure.

Additionally, this research aims to evaluate the potential for the tool condition monitoring system to be successfully validated through accepted and proven validation methodologies employed in modern manufacturing.

A further element of the research intends to examine through interactive discussions with staff at the authors company how a live tool condition monitoring system would and could interact with the actual operators of the machinery, up to and including expert level programmers. The HMI concept presented herein was developed through the interaction with expert level programmers.

However, the critical question posed in this research is what physical phenomenon from the subtractive manufacturing or material removal processes can be harnessed and analysed in a real time production environment to determine the condition of the cutting process. As will be detailed in the literature review section there has been many years of research into a variety of physical phenomena from the cutting process and to varying degrees worth has been found in most, but all this experimentation had been undertaken in controlled environments.

The research presented in this document is unique in the sense that the majority of the work has been undertaken in real-life, normal production conditions and if the research proves successful it’s reasonable to believe that the systems and sensor configurations deployed could be quickly implemented into a normal production environment monitoring real production processes, with all the variables associated with real time and standard processes on a normal factory floor.

1.1 Scale of the CNC industry

The aim of this work is to solve a problem in the precision engineering industry relating to the monitoring of tool wear and the effects of tool wear on the generation of scrap.

Despite global economic uncertainty, the global market for CNC machines has remained strong, notwithstanding a dip at the start of the current economic downturn. Frost & Sullivan (2016) predicted that the European CNC marked will be €17.6 billion in 2018 and that the global market was predicted to be worth €75.3 billion. Competitiveness is vital to the machine manufacturers in this growing market and a monitoring system, such as that being investigated in this work, would give competitive advantage to any machine builder or user that adopted the technology. As a result, the technology is potentially very valuable and has attracted funding for research in private and public institutions.

A major reason for the sustained dominance in the CNC market by a small number of major CNC system suppliers, such as Mori-Seiki and Mazak, is that customers rarely switch suppliers, due to the investment in personnel training and the difficulty in moving applications from one machine to another. Reduction of training requirements and the simplification of user interfaces on these machines will result in an opening up of the market to smaller CNC manufacturers and increased competitiveness within the market.

The regions that are predicted to experience the largest growth in the machine tool industry over the next several years are South America and Asia according to HIS Technology trends (2015). Western Europe will continue to remain a dominant region, but the focus will remain on the high-performance machinery applications. In the period 2010-2014 it was expected that the emerging markets will expand beyond the low-valued machinery market. This in turn will place increased pressures on European manufacturers, increasing global competitiveness. As emerging markets continue to increase manufacturing competencies, it is vitally important that European manufacturers continue to increase their capabilities and to develop new technologies to maintain and grow their market share.

1.2 Outline of historic research efforts

As will be detailed in Chapter 2 there has been a lot of interest in developing a system for the monitoring of tool wear, with monitoring methodologies being proposed even before the 1970's. In addition to the advantage of giving information on when the tool is wearing, there is the extra advantage that monitoring the process used to manufacture something will also give reassurance that that process itself is stable and under control, and therefore the resultant product is also more likely to be stable and under control.

Industry and public funding agencies have, for many years, expressed an interest in research into this area, with a typical examples being –the Lazarus (1996) project, co-funded by the US Department of Defence and Allied Signal Aerospace, evaluating acoustic emissions in machining in the mid-90's, and, as far back as the late 60's, the structure of Polaris missile chambers were verified with AE, Lord Jr (1975).

Many inputs and outputs from the machining operation have been investigated as possible sources of information related to the effectiveness of the process. One of the early innovations for *in-situ* evaluation was the development by Renishaw of the touch-trigger probe in the early 1970's, which is now widely used in machine tools, to provide location and measurement information on both the tools and the work pieces, McMurtry (1986). There are ongoing attempts by the two largest CNC machining manufacturers to develop systems to feed back on the stability of the machine process. Yamazaki Mazak have developed a number of systems such as IBA (Intelligent Balance Analyser), ITS (Intelligent Thermal Shield), IPS (Intelligent Performance Spindle), IMS (Intelligent Maintenance Support) and AVC (Active Vibration Control). These systems are all useful for monitoring a specific element of the machine. However, there is no fusion of the information and, overall, a general machining performance status is not available. DMG Mori Seiki Co., a Japanese CNC machining manufacturer, has developed the Mori-Net system, which allows remote monitoring of the machine. However, the only real advantage of Mori's offering is that monitoring, which ordinarily takes place at the machine, can now be undertaken remotely, for example by the machine operator at home.

Other companies have developed systems, which enable some degree of monitoring of the performance of the machine. However, like the developments offered by the dominant CNC machine manufacturers, these do not have the resolution or analysis capability to give the required level of performance information. For example, the OMATIVE vibration control monitor system does indicate when there has been a change to the monitored state of the machine but will not provide any indication as to the cause or effect of the detected change. In research laboratories there has been extensive investigation of tool condition monitoring using the available signals and variables. Most commercially available systems apply "one process – one signal feature (SF)" strategies. Recently, more and more often, machine vision systems based on digital image processing (DIP) are applied for measurement of tool wear. Two approaches are taken in DIP: observation of the outline of a tool or observation of flank wear. Use of information on the state of tools from the camera, in conjunction with information from sensors: cutting forces, acoustic emission or vibration, can increase the effectiveness of any monitoring system. Moreover, the camera performs a direct measurement of the wear, whereas all other sensors perform implicit measurements, where likely wear is estimated from currently sensed parameters and previously acquired knowledge of the level of wear associated with particular levels of the sensed parameter. Despite many sensors and sensor techniques being available, it is generally acknowledged that reliable tool wear evaluation based on one signal feature (SF) is impossible, because the measured feature depends not only on the tool wear, but also on a variety of other process parameters, possibly of random nature. This can make the relationship between tool wear and measured values very complex, forcing the analysis to follow a statistical rather than strictly discrete prediction.

Suprock Technologies is one of the most recent additions to the market and have developed a shank holder which incorporates torque, vibration, and temperature sensors into it. However, this system experiences problems with wireless channel fading, due to the multiple propagation paths from the tip transmitter to the wireless receiver, and disruption of signal in the machining environment, particularly at high spindle speeds and is limited by its design to particular machining processes (rotating cutting and end-milling). This product also does not have an integrated artificial neural network and software designed to combine various sensory data into one simple graphical output and therefore requires significant operator knowledge to operate the system effectively, not alone in data interpretation, but also even in the positioning of the wireless receiver to reduce the risk of fading in the channel path.

1.3 Overview of current research

There are a number of research efforts that have completed in recent years, from small local academic projects to large funded projects (e.g. the European Seventh Framework Programme (FP7) funded ADACOM project (2013), IFACOM Project (2013), SOMMACT Project (2013) and the REALISM project (2015)). A flavour of the other research activities that have been and continue to be undertaken in this field will be outlined in a literature review in Chapter 2.

1.4 Benefits to industry

The benefits to industry of this research are simple- there is a clear commercial benefit in two respects, scrap reduction and process optimisation.

Globally, the CNC machining industry strives to achieve a scrap (non-conforming product that must be discarded) value of 2% of turnover. The reality is that this figure is nearer 5-7% in most companies. Tool wear accounts for in excess of 50% of the root cause of this scrap. The author obtained this information during an analysis undertaken over a 6-month period at his workplace, Schivo Precision, when in the position of quality manager. Based on turnover in the machine shop at that time of €5M, this represented unrecoverable losses (raw material, machine time & personnel time) of €250,000.

One of the unmeasurable costs within a CNC machining company is the cost of set up and determining that the process parameters are correct for the operation/material/machine/tooling. If a system were in place that indicated that the cutting conditions were optimised through interrogation of the physical emissions and intelligently communicated this to the machinist, then setup times could be greatly reduced. It is not unusual for the setup time for a batch of components to exceed the actual production time for that product.

1.5 Document layout

This work presents several machining emissions' measurements and their analysis for three different production machines working on different materials. In the initial work a test platform was developed to measure microphone recorded sound emissions, on the basis that experienced operators claim that they can recognise tool wear by listening to a machine. In subsequent work the machine emissions were expanded to include a wider acoustic spectrum, accelerometery and force. Work on a European funded project that arose out of this work, is also reported here.

This document is structured as follows:

- Chapter 2 provides a literature review of tool wear characterisation. It describes the fundamentals of direct and indirect measurements, as well as successful and unsuccessful efforts over the years. The move to multiple sensing of processes is described, as well as efforts to automate the analysis of the tool wear state, through the use of Artificial Intelligence (AI).
- Chapter 3 describes the test platforms developed during this work in Schivo; to select the sensor type and placement, data acquisition, analysis and decision-making. The placement of sensors proved to be a challenging problem, requiring a characterisation and complete understanding of the machining setup and process, and needed more than one attempt to achieve success. For each of these setups, the selection parameters are explained and justified, and a description is offered of the various problems encountered and solutions attempted. The design of a TCM human-machine interface is also considered here (published in Procedia CIRP). Finally, this chapter also presents the case for the development of a generic tool condition monitoring validation methodology, drawing on the author's experience of verifying and validating processes over many years.
- Chapter 4 details some case study work undertaken in tandem with the main body of work of this research into the Human Machine Interface and also into applying process validation techniques, commonly used in the medical devices sector, to this TCM system. Given that any tool condition monitoring system will require human interaction, the author felt it was important to consider how a human operator would interface with a system that could, potentially, be replacing the experienced machinist's intuition of the performance of the operation. Therefore some case studies and investigations were undertaken with the experienced machinists at the author's facility to best define the human machine interactions and

interfaces, including the process validation requirements that would be driven by the medical devices industry.

- Chapter 5 presents the measurements and data analysis; for each of the processes examined. The examination of the idea that experienced operators could identify end (or near end) of tool life was published in the *Wear* journal. Two experiments were performed successively on a 5-axes Röders machine, with the first providing little by way of useful results, but an extremely valuable lesson in sensor selection and sensor location. The second of the two experiments was then performed successfully, showing significant changes over a tool life, that could easily be used to characterise the process and indeed also to predict Catastrophic Tool Failure (CTF), which was tested even further in the follow-on EU funded REALISM project. The REALISM project has also yielded publications for the author on setup and analysis. These papers are included in the Appendices.
- Chapter 6 describes the contribution that the author believes this work has made to the state-of-the-art in the area of monitoring methods and techniques that can be employed to evaluate the performance of the CNC machining operation, without interfering with the process. The objective of the research, to determine what physical emissions from the machining process can be used to real time monitor the performance of the process, will be re-examined in this chapter.

In total, this research led to five publications, with the author's role recognised by being lead author in three of these papers (*Comparison and analysis of audible sound energy emissions during single point machining of HSTS with PVD TiCN cutter insert across full tool life*, published in the International Journal of Wear, *Automatic multiple sensor data acquisition system in a real-time production* *environment* and *Real time Monitoring of the CNC Process in a production environment- the data phase*, both published in Procedia CIRP), and as second author in the other two papers (*Human-Machine interface for Neural Network based Machine tool Process Monitoring,* also published in Procedia CIRP, and *Development of a generic tool condition monitoring validation Methodology,* presented at the International Manufacturing Conference), all of which are included in the Appendices.

2 Literature Review

2.1 Introduction

There has been a lot of research into the sensing, conditioning and analysis of process conditions during CNC machining. Some published works that deal with fundamental aspects of this topic include Fasano and Marmi (2006), in the area of mechanics, by Svrcek, Mahoney et al. (2006) in the most practical approach to process control, and there have also been several significant contributions to the state-of-the-art in the field, as will be discussed in this chapter.

Over the many years of research, many process variables have been tested to determine tool wear in real time, to provide the machine operator with accurate feedback. The variables examined can be broadly separated into direct and indirect measurements of tool wear. This research has focussed primarily on indirect measurements, including temperature, motor loadings, acoustic emissions, vibration, radioactive substrates remaining on material as a result of tool wear, etc. although a direct vision measurement was included in the EU-funded REALISM project, which derived directly from the early part of this research, but the test deployment included tool lengths of varying lengths, which ultimately proved too challenging for the camera's fixed focal length. Nonetheless, such direct measurement is very promising, has good accuracy and has proven successful in other deployments. Vision inspection systems are the most promising direct measurement method, where the tool is examined in situ using a bespoke camera system.

As this research is carried out in an industrial setting, the author draws from literature and work that has been undertaken on both an academic basis and on an industrial basis.

There are many indirect measurement approaches and the most important are considered in this chapter. Compared to direct methods, indirect methods are less accurate, but are also usually less complex to apply. This is a big advantage and is the reason indirect methods are so popular, and two of the most promising are the cutting force components and acoustic emissions, two parameters which offer good prospects for indirect measurements.

Increasingly, systems take outputs from multiple sensor types, which can be combined using sensor fusion, to improve the quality and robustness of the characterization of the process, tool, or machine.

2.2 State-of-the-art reviews in tool wear monitoring

Over many years, there has been a number of evaluations undertaken on the state-of-the-art of research internationally, including Micheletti (1976); Tlusty and Andrews (1983); Tönshoff, Wulfsberg et al. (1988); Byrne, Dornfeld et al. (1995), in a keynote paper, detailed the activities of the CIRP (International Academy for Production Engineering) Tool Condition Monitoring working group (TSC-3); Cho, Lee et al. (1999) gave an overview of the research being undertaken, however, only in Korea, into machining process monitoring; Kulianic and Sortino (2002); Byrne, Dornfeld et al. (2003) published another state-of-the-art paper within CIRP and at this point investigations were very active in the field; and finally, the most recent general evaluation was provided by Teti, Jemielniak et al. (2010) in their keynote paper submitted to the Annals of the CIRP.

Many of the process parameters being sensed are the same now as in the 1970s. What has changed dramatically in the intervening years is the computer processing power, memory storage and data acquisition speeds. If one accepts the prediction of Moore’s Law in terms of computing capacity doubling every 18 months, then it is easy to also accept that the available computing tools are dramatically different now to the ones that the early TCM pioneers had at their disposal.

In that light, the Teti, Jemielniak et al. (2010) keynote paper, being the most recent overview paper and issued more or less in the era when Big Data analysis is possible, offers the most relevant insight into the advantages and the limitations of the various methodologies that had been investigated. The sensed parameters are unlikely to change any more and, while the sensors may undergo further improvement, it is tempting to believe the state-of-the-art is now ripe for working TCM systems. For this reason, an area of particular interest to this researcher in that paper, although not part of the research presented in this thesis, was in the usage of artificial intelligence (in the form of Neural Network's and pattern matching) to interpret the data, and ultimately to use the data and the networks' understanding of this to make decisions.

Table 2 lists some key papers published in this space over the years of research. Some of these will be referred to again in this Literature Review to contextualise the work carried out as part of this thesis submission.

Table 2 Relevant publications/research papers on the subject.

Publication Title	Author	Date
Advanced monitoring of machining operations	Teti *et al*	2010
Application of acoustic emission for evaluation of tool wear in hard turning.	Šípek, Neslušan & Rosipal	2011
Real time monitoring of surface roughness by acoustic emissions in CNC turning.	Reddy & Reddy	2010
A critical analysis of effectiveness of acoustic emission signals to detect tool and workpiece malfunctions in milling operations	Marinescu & Axinte	2008
Application of AE and cutting force signals in tool condition monitoring in micro-milling	Jemelniak & Arrazola.	2008
Tool wear evaluation in drilling by acoustic emission	Gomez *et al*	2009
Investigation of acoustic emission and surface treatment to improve tool materials and metal forming process	Cao	2010
Cutting parameters analysis for the development of a milling process monitoring system based on audible sound energy	Rubio & Teti	2009
Acoustic emissions for tool wear identification	Dolinšek& Kopač	1999
Vibration analysis of cutting force in titanium alloy milling	Antoniali *et al*	2009
Tool condition monitoring in micro-milling based on hierarchical integration of signal measures.	Jemelniak, Bombinski & Aristimuno	2008
Fuzzy-logic control of cutting forces in CNC milling processes using motor currents as indirect force sensors	Kim & Jeon	2010
Sensor monitoring for cutting process optimisation of low machinability materials, machining on the cutting edge	Teti & Segreto	2008
Machinability assessment in turning of Nitinol through acceleration sensor monitoring	Segreto, Teti, Neugebauer, & Schmidt	2009
Sensor monitoring based optimisation during turning of titanium alloys	Teti, Segreto, Neugebauer, & Harzbecker	2008

2.3 Cutting Tool Condition

The cutting tool condition is the single most important factor between accepting a machined part, based on the accuracy and quality of the surface finish, or the scrapping of that part Teti, Jemielniak et al. (2010). The accuracy and quality of the surface finish expected is very high in some cases, with increasing customer expectation normal for some sectors. For example, for surgical products the cosmetic finish requirements was always high and continues to rise. This is also the case for the aerospace industry, where the accuracy demands on parts are consistently high (primarily to increase energy efficiency).

CNC technology has evolved to the point where, in some cases at least, finish tolerances of low single microns are now possible, which places a demand on the CNC operator and on the CNC manufacturing companies. This is all the more so, when the material being machined is challenging (Paro, 2004). A typical example in biomedical devices would be austenitic stainless steels and titanium (and its alloys), which have been widely used for biomaterials, such as artificial hip joints and dental implants and in the aerospace industry. A specific biomedical example that is very challenging is Ti–6Al–4V, one of the most often used biomaterials. It is well known for its poor machinability, due to its low thermal conductivity that causes high temperature on the tool face and strong chemical affinity with most tool materials, thereby leading to premature tool failure. Moreover, its inhomogeneous deformation makes the cutting force fluctuate and further aggravates tool-wear. In practice, the solution in industry to this challenging machinability is to limit the cutting speed to less than 60 m/min (Balkrishna R., 2011).

Another challenge is that as tool wear increases, the hardness of the material increases also due to the work hardening process while machining (Ulutan, 2011), (Fang, 2011).

The negative impact of tool wear is usually only detected at the end of the machine cycle. In most commercial deployments, errors associated with tool wear remain uncompensated for and once an error is spotted, the product is usually only of scrap value. For example, the author is an engineering manager at the Schivo CNC facility, where scrap at is estimated to be 2% of turnover and costs the company about €300,000 per year. Analysis of this figure has shown that over 50% of the scrap generated is attributed to worn or broken tooling.

If real time TCM were in place, then machining parameters could be adjusted to compensate for tool wear, tools could be replaced in proper time when they approach their tool life, and not prematurely (or posthumously) as they are now. Machines could also be scheduled for down-time and surface finish and dimensional stability would be increased.

2.4 Current Technology

Direct monitoring of the machining results (e.g. machined surface) is one of the traditional approaches to TCM. Another approach, which is widely applied, is the exchange of the tool after a predetermined machining time, which must be much smaller than the real tool life, to avoid machining with a blunt tool and thereby not assuring the desired product quality. Even more damaging is the possibility of catastrophic tool failure, which can happen when the tool wear is too high. TCM research is driven on by the need for higher quality, stimulated by growing demands for process automation and reduction of human supervision requirements.

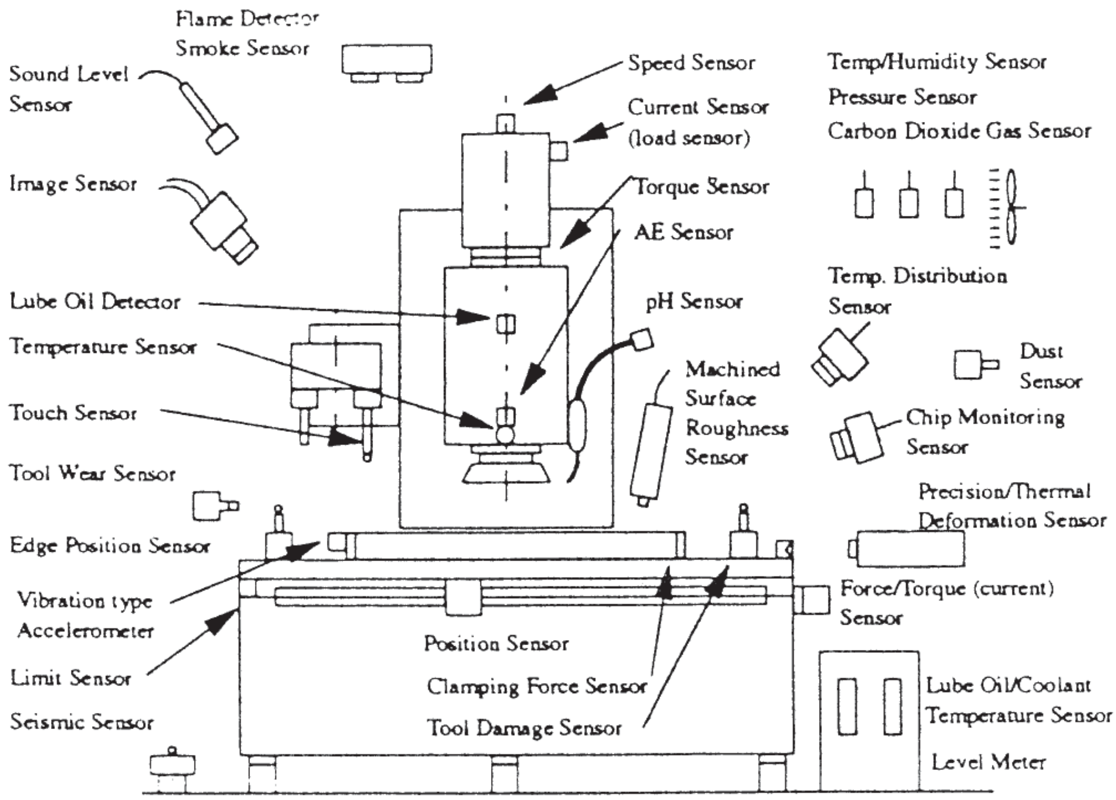


Figure 1 Illustration showing the various researched sensor systems

Figure 1 (Moriwaki, 1993) illustrates the many inputs and outputs from the machining operation that have been investigated as possible sources of information related to the effectiveness of the process. This illustration outlines many of the physical emissions from the CNC process that could be monitored and indeed have been evaluated through the years of research that will be discussed further in the literature review section of this document.

One of the early innovations in terms of *in-situ* evaluation was the development by Renishaw of the touch trigger probe in the early 1970's, which is now widely used in machine tools to provide location and measurement information on both the tools and the workpieces.

In terms of CNC machine development, there are ongoing attempts by the two largest CNC machining manufacturers to develop systems to offer feedback on machine process stability. Yamazaki Mazak have developed a number of systems such as IBA (Intelligent Balance Analyser), ITS (Intelligent thermal shield), IPS (Intelligent performance spindle), IMS (Intelligent Maintenance Support) and AVC (Active Vibration Control). These systems are all useful for monitoring a specific element of the machine. However, at the time of writing, there is no fusion of the information and, overall, a general machining performance status is not available. Mori-Seiki has developed the Mori-Net system, which allows remote monitoring of the machine. However, the only real advantage of Mori's offering is that monitoring that takes place at the machine can now be undertaken remotely. The Mori-Seiki Company presented their vision of next generation CNC machine technology at the 2015 CIRP winter meetings,

Other companies have developed systems which enable some degree of monitoring of the performance of the machine. However, like the developments offered by the big CNC machining manufacturers, these do not have the resolution to give the required level of performance information. For example, the OMAT vibration control monitor system does indicate when there has been a change to the monitored state of the machine, but will not provide any indication as to the cause or effect of the detected change. Inevitably it seems that it will improve, but most commercially available systems apply "one process – one signal feature (SF)" strategies.

Table 3 shows the current technologies available to industrial precision engineering firms and their associated limitations. Suprock Technologies is one of the more recent additions to the market and have developed a tool tip which incorporates torque, vibration, and temperature sensors into it. However, this system experiences problems with channel fading and disruption of signal in the machining environment, particularly at high spindle speeds and is limited by its design to particular machining processes (rotating cutting and end-milling). This product also does not have an integrated artificial neural network and software designed to combine various sensory data into one simple graphical output and also requires significant operator knowledge to operate the system effectively.

Table 3 Commercial products and their limitations.

Technology	Uses	Limitations
Probes	Quantify tool wear	Poor accuracy, not related to product quality, doesn't measure efficiency of process
Machine Vision	Position and speed determination	Processing lag time, poor accuracy, inability to determine surface roughness; doesn't measure process efficiency
Individual Sensors	Process efficiency	Not robust, Not accurate, limited capabilities, requires experience to analyse

In the laboratory, there has also been extensive investigation of tool condition monitoring. The most often used of the available signals and variables, are the cutting force components; acoustic emission (AE) and vibration (Cho, 2010), (Abellan-Nebot J.V., 2010).

Machine vision systems based on digital image processing (DIP) offer great promise, when applied for measurement of tool wear. Two approaches are taken in DIP: observation of the outline of a tool or observation of flank wear (Fadare D.A., 2009), (Shahabi H.H., 2009). Use of information on the state of tools from the camera in conjunction with information from sensors: cutting forces, acoustic emission or vibration, can increase the effectiveness of monitoring system (X, 2002).

Despite many sensors and sensor techniques available, it is generally acknowledged that reliable tool wear evaluation based on one signal feature (SF) is impossible, because the measured feature depends not only on the tool wear but also on variety of other process parameters of random nature. It makes the relationship between tool wear and measured values very complex and it has a statistical rather than strict, predictable nature.

2.4.1 Patented technology pertaining to TCM

To gain an understanding of the attempts that have been made to commercialize different methodologies or systems, the author decided that a review of successful patent applications relating to systems or devices that claim to monitor and measure tool breakage, would be of benefit.

Thomas, Lee et al. (1989) applied for a patent on a device, which used as its signal input, the cutting tool motor forces. A blunt tool has greater overall interaction with the work piece material, so motor forces tend to increase as a tool wears. The patent application proposed a system whereby continuous monitoring was employed on the ratio of one of spindle force or power, or low frequency vibration energy compared to high frequency vibration energy during the cutting process. The patent application does suggest some methodologies, such as motor power, that have since been found to be challenging in overall effectiveness in terms of their ability to provide useful, real-time information on the cutting tool condition. However, the patent application also saw great merit in the effectiveness of accelerometers.

Schweitzer and Perrin (2004) also patented the use of motor current as an indicator of the cutting performance. The basis of their device is the use of measurement of the active power being absorbed by the spindle motor and the comparison of this power to known power data for good cutting conditions, which had been detected, for example, during the first cutting operation of the tool. In theory, the application is feasible, assuming the motor information is valuable. However, (as discussed in the broader literature review) the use of motor power and currents can be challenging in monitoring the performance of the cutting tool, for example, due to transmission losses and excessive signal-to-noise ratios in the measured parameters. An application had been made by Howatt (1979) for a similar system, which again used a reference signal, detected during the first operation of the tool. This signal is assumed to be a known good set of information and compared that signal against the current signal being obtained from sensors providing information on the tool profile and cutting conditions. Again, the application goes into detail on the sensor signal analysis, but the main sensor application is an eddy current sensor, which would be unlikely to be accurate enough for today's high- precision applications.

The Howatt proposal also claimed improvements that its system would have over a previous patent filed by Hamilton, Gaudreau et al. (1978). Hamilton proposed the use of a distance comparison arrangement, where the degree of wear of the tool would be monitored using sensing device(s), to measure the distance to an area of the cutting surface of the tool and a non-cutting surface of the same tool. The logic being that as the tool wears, the distance to the cutting surface increases, while the distance to the non-cutting surface remain the same, in a manner similar to some of ultrasonic TCM research. The application details the electronics involved and it is particularly this element of the application that Howatt felt he had improved.

However, neither system would be sufficiently accurate for a modern application based on their platform technologies.

Thompson and Breuning (1986) proposed using a probe on the tool holder to probe the distance to the freshly cut metal, as an indication of tool wear. As the freshly cut metal surface comes closer to the probe, this is an indication that there is wear on the nose of the tool. The systems proposed for use, in order of preference were, air gauging, capacitance gauging, inductance gauging, optical and contact gauging. The measuring probe would be mounted just after the tool for the measurement of the distance to the cut metal surface. The obvious issue with this configuration is that their system is expected to perform distance measurements in an extremely harsh environment, where cutting fluid and swarf are interference factors. Their system provides some alleviation for this, by using a mean of the readings to determine the overall distance. However, overall their system would not produce the required accuracy and would not give more valuable information on the process, such as surface finish and chatter, which are both also caused by tool wear, but do not necessarily affect the depth of the tool cut.

A patent application, which employed the use of resistance to determine the wear of a tool, was successfully filed by Yellowley and Hosepyan (1991). Their system used a resistor applied directly to the tool, the resistance of which varied according to the level of wear being experienced by the tool. Overall, the patent application seemed speculative and lacking in detail and seemed to be an attempt to patent the use of resistance as a tool condition monitoring method rather than detailing the application. For example, the ideal location of the sensor was not identified, with multiple sites instead being suggested. Moreover, the benefit is further clouded by not specifying the cutting operation, as the application states that overall the invention relates broadly to the use of electrical resistance in tool condition monitoring.

A similarly vague (in this author's opinion) patent application was submitted by Ramamurthi (1993), which employed a plurality of sensors for monitoring of the tool condition. Their patent application is more concerned with the monitoring and understanding system that is being proposed, rather than the actual acquisition methods for the raw process data. In stating that, if suitable sensors were applied, theirs is a good initial expert system for the prediction of tool wear. While the application claims to be a system and method for the use of an expert system for tool life prediction and tool wear analysis, the actual patent claims relate more to the expert system than to the tool wear monitor method, in the opinion of this author.

More recently a system was developed, which was using work process data for the tools, rather than actual real-time condition information. The system, "Tool Sentinel" was patented by McDonnell and McDonnell (2006). Their system in essence used sensors to detect the machine cycles in which the tooling is being used and extrapolated a tool condition by comparing that data against the predicted tool life for that tool. The system can be used on multiple machines and with multiple tooling once all the prediction information has been entered for the tooling types and operation cycles. The obvious drawback is the fact that their system was theoretical rather than actually realised and would not detect issues such as unusual tool degradation (from a material fault in a tool or a workpiece material), or a catastrophic event (tool breakage). Another considerable drawback is the fact that the tool life is just an estimation and if the initial estimation of the tool life is conservative, then the system will declare a tool worn, when it may still have considerable cutting life left.

Overall the patents that have been applied for in relation to the area of tool wear and associated monitoring systems seem vague and many appear to be an attempt to get a patent on a particular tool condition monitoring methodology, while the validation of the system is not yet completed, and the fundamentals of the applied technology have not been practically proven.

Some of the most relevant patented technology in this field is summarised in **Table 4**.

Table 4 Patented technology pertaining to TCM.

Patent Name	Patent Number	Date Filed	Expired
Tool Wear and/or Breakage Control Device for a Machine Tool	US2004/0217873	6th Feb 2004	No
Production of Tool Wear Detector	4120196	25th Mar 1978	Yes
Apparatus for Directly Measuring Tool Wear	4176396	23rd Sep 1977	Yes
In-Process Cutting Tool Condition Compensation and Part Inspection	4620281	15th Feb 1984	Yes
Cutting Tool Wear Detection Apparatus and Method	4831365	5th Feb 1988	Yes
Tool Wear Detector	5000036	23rd Mar 1990	Yes
System and Method Utilizing a Real Time Expert System For Tool Life Prediction and Tool Wear Diagnosis	5251144	18th Apr 1991	Yes
Tool Wear Monitoring System	7010386	22nd Mar 2002	No

As can be seen from **Table 4** the majority of the patents pertaining to tool wear monitoring in machining applications is old technology and most of the patents which exist are expired. In this author's opinion, the technology that will likely be increasingly patented over the coming years will be for systems that will combine sensing with information from previous machining processes. The state-of-the-art for TCM will change most significantly in machine intelligence. Indeed, this was the most powerful IP identified by the author and European partners, from the very start of the EU FP7 REALISM project.

2.4.2 Review of EU funded research into TCM

There has been very strong EU research funding attracted to the area of TCM (apart from REALISM, which spun out of the early research for this thesis), as can be seen from the recently funded projects detailed in **Table 5**. There is a great appetite within the research community and CNC industry to develop systems to better monitor and control manufacturing systems, particularly those concerned with the cutting of metals. It has been recognised for some time that tighter controls are desirable within this industry to improve efficiency and therefore competitiveness.

Table 5 TCM EU funded research projects in recent years.

Project Title & Acronym	Reference No.	Key Partners	Date of Completion
ACCENT - Adaptive Control of Manufacturing Processes for a New Generation of Jet Engine Components	213855	UNINA, Rolls Royce	March 2012
Working on sensor-based system for analysis of nickel and titanium based alloys, when machined for large aerospace applications in jet engines. Much of the knowledge gained from this larger ACCENT project will feed into and enhance the concepts of this project.			
ADACOM - Adaptive control for metal cutting	214766	Trinity College Dublin, Daimler	Sep 2012
To develop a generic modular adaptive control platform that will allow metal cutting processes to respond to changing circumstances.			
COOLART - The art of cooling	268019	Institut fur Werfstofftechnik, Bremen	June 2016
Examined the effectiveness of the cutting process from the perspective of the effectiveness of the cutting fluids used in the machining process.			
AIMACS - Advanced Intelligent machine adaptive control Systems	260204	Stuttgart University, Audi	June 2013
To develop reliable techniques for monitoring machining parameters to allow increased optimisation of the machining process.			
TURNCOAT - Temperature sensor coatings for smart machine tools	262555	RWTH Aachen University, Sirrus	March 2013
To develop a machining tool with a wear resistant ceramic thin film temperature sensor for in-situ, continuous wireless monitoring of the tool temperature during the machining process.			
IFaCOM - Intelligent Fault Correction and self Optimizing Manufacturing systems	285489	UNINA	April 2015
To achieve near zero defect level of manufacturing for all kinds of manufacturing, with emphasis on production of high value parts, on large variety custom design manufacturing and on high performance products.			

As mentioned earlier, an excellent EU FP7 funded project (REALISM) spun out of this research. The author's early research, which will be detailed in further sections, led to the publication of a paper in the Wear journal- Downey, O'Leary & Raghavendra (2014)- and an industrial & academic collaboration was built for the two-year research project. This was the initial basis for contact with the EU partners, who made up REALISM.

2.5 General machine monitoring studies

As has been detailed in Section 0, there have been a number of high-level reviews of the state-of-the-art in machine tool monitoring. This is partly because of the huge efforts invested in TCM research and also partly because, being such a challenging and nuanced problem, solutions have been hard to come by and therefore many years have passed between the first and most recent state-of-the-art reviews. In addition to the state-of-the-art reviews, there have been many general studies on machine monitoring. O'Donnell, Young et al. (2001) gave a good overview of the direction that tool condition monitoring systems were headed, while prior to that a good review of the software methods was provided by Teti and Kumara (1997). More recently Möhring, Litwinski et al. (2010) provided an overview of how the process could be monitored using sensory elements within the machine tool.

In a related paper, Fan, Chen et al. (2012) outlined how it was possible to predict the degradation in accuracy within the machine tool through the use of mathematical predictions, coupled with knowledge of the wear characteristics of the machine over time as a result of tool wear. Girardin, Rémond et al. (2010) used sensors already fitted to the machine whose deployment was not intended by the manufacturer to monitor the process, for example energy consumption measurement, and with reasonable results. There has been a significant amount of further work on the use of artificial intelligence in the interpretation of the signals from various sensors, reported by Balazinski, Czogala et al. (2002), and recent years this area has increasingly seen the use of Artificial Neural Networks for the interpretation of the data, as discussed by Asiltürk and Çunkaş (2011) and Ghosh, Ravi et al. (2007). More recently, there has been good insights provided into the continuous development of general machine monitoring, such as that provided by Putz *et al* (2017)

2.6 Virtual machine tool studies

In recent years virtual machine tools have achieved some traction and it's worth mentioning this work here, as for the opportunity to develop crossovers between the virtual simulation of machines and the actual interrogation of machine tool wear. Altintas, Brecher et al. (2005) gave a good overview of the methodology that is used and applied when designing a virtual machine tool, and the paper also included a good state-of-the-art, which also included an overview of the use of Finite Element Analysis (FEA) in the structures of machine tools. This was further expanded on by Abdul Kadir, Xu et al. (2011), where a detailed technological review was provided.

2.7 Sensors for tool condition monitoring

Sensors for tool condition monitoring must fulfil various requirements. From their signals it should be possible to detect imminent tool breakage, tool wear and poor finishes in machining processes. To achieve this, tool monitoring devices must function as in-process systems in most cases. However, the environmental conditions in a machine tool are very tough and sensing process parameters is very demanding. Sensors for process monitoring must meet the following requirements:

- Accurately measure the sensed parameter and correctly convey that measurement the TCM processor.
- Cause no reduction in the static and dynamic stiffness of the machine tool.
- Cause no restriction of working space and cutting parameters.
- Should be wear- and maintenance-free, easily changed, and low cost.
- Be resistant to external influences, *e.g.* dirt/chips/fluid, mechanical, electromagnetic & thermal stress.
- Function independently of tool or workpiece.
- Display adequate metrological characteristics and afford reliable signal transmission.

Therefore, only a fraction of electronic sensors that are available on the market can meet these requirements to be suitable for tool condition monitoring. This research begins with isolated sensing of individual parameters and eventually examines the success of different sensor combinations, placed at different locations surrounding the tool workpiece interface. The aim of any sensor combination is to complement each other, as that their indirect measured parameters may not consistently reflect TCM status, may do so on a sufficiently consistent basis.

2.7.1 Intelligent Sensors

Generally, intelligent sensors have a much greater functionality than conventional sensors because they must respond to the special needs of the machine tool or process they are monitoring. An intelligent sensor may be best described as one driven based on *self-decision making* as opposed to *predetermined commands* (Jemielniak K. K., 2012). In addition to sensor feedback of the machining process the intelligent machine can utilize experience accumulated during past operations, accumulates knowledge through learning and can accommodate ambiguous inputs.

Intelligent sensors should be able to do some or all of the following:

- self-calibration
- signal processing
- decision making
- fusion ability
- learning capability.

Signal processing in this case means that the sensor has the capability to do feature extraction from the measurement vector, so that a data stream comes out of the sensor, not just the sensed signal. Decision making as part of the sensor system enables it to do such things itself not relying on the controller or other processors to do this. Sensor fusion describes the ability to combine or add the output of other sensors to provide a more robust decision on the process state. A very important aspect of the sensor is that it should be able to *learn* from past information using a neural network or other knowledge representation scheme, in order to continuously increase its reliability and robustness. An *intelligent sensor* is, thus, more or less a combination of conventional sensors, signal processing and feature extraction methods, as well as implementation strategies that are integrated in the sensor or sensor system (Jemielniak K. K., 2012).

2.7.2 Energy monitoring

In addition to the work that will be outlined around the research that continues into the efficiency of the cutting operation, it is worth mentioning the ongoing research into the energy efficiency of the CNC machine tools, as both areas of research can overlap, and in many cases the individuals undertaking the research into energy efficiency have interest in cutting performance, for example Mori, Fujishima et al. (2011), O'Driscoll and O'Donnell (2013) and Vijayaraghavan and Dornfeld (2010).

2.7.3 Visual & optical systems

Kurada and Bradley (1997) provided an early, good overall evaluation of the state-of-the-art of different sensing techniques. As a foundation for the discussion on vision sensor applications an overview of the basics of machine tool wearing is discussed, along with a general discussion on direct sensoring (proximity, vision) and indirect sensoring (force, vibration, AE).

The vision based tool condition monitoring systems comprises of three major components; illumination, cameras and image digitisation.

Two camera types are commonly used in vision tool condition monitoring. Vidicon cameras, which use an electron beam to provide image data onto a photosensitive surface, have been used, but have been found to suffer from image drift and geometric distortions. More recently CCD cameras have been employed in these types of systems, which offer high resolution and are also available in high speed format.

The image digitisation comprises of the following block sequence:

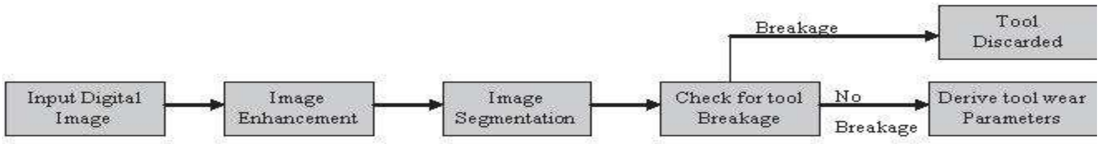


Figure 2 Block diagram of vision system for tool wear

The Kurada & Bradley (1997a) paper includes a state-of-the-art description on tool wear monitoring using vision systems. It discusses in broad terms the contribution made to the field, but makes no real claims as to the validity or worth of any of the various methods discussed. However, a second Kurada and Bradley (1997b) in a further detailed paper discussed in depth a specific application of vision systems in this area and discounted the general worth of the method.

Guisti *et al* (1987) proposed an in-cycle method to visually monitor the cutting face of a tool using two lighting configurations and one camera position to record wear from both the flank and rake faces. The images were segmented into 10-pixel wide strips and for each of the strips, the degree of wear was determined by comparing the average grey level for the worn and unworn regions of the tool. Although this approach was novel at that time and formed the basis in some respects for the more recent experimentation into the use of vision system examination, it was clearly constrained by the available technology.

Jeon & Kim (1988) illuminated the cutting tool tip with a 0.8mm beam diameter laser and captured the reflected pattern with a camera located perpendicularly to the flank face. A contour of the wear region of the tool was produced using a series of signal processing steps. The system was found to be accurate to within 0.1mm of the traditional tool microscope limits and was found to have very high processing speed of 1.7 seconds. the accuracy of 0.1mm is really not good enough for modern applications.

2.7.4 Ultrasonic analysis

There has also been considerable investigation into the use of ultrasonic analysis in TCM. The use of ultrasonic energy is not new in the field of machining. Ultrasonic energy has long been researched as a viable medium by which machining operations can be assisted. Studies and discussions into the use and viability of ultrasonic analysis in machining can be considered to have been begun in earnest by Wood and Loomis (1927), when their research considered the physical effects of high intensity sound. In the middle of the twentieth century, the modern era of research into the field of the use of in machining gained momentum with the work of Hartley (1956) and Neppiras (1964).

Through the years there were a number of advances in the field, all of which were based on the application of high energy and high frequency ultrasound waves at the cutting interface. Thoe, Aspinwall et al. (1998) provided a state-of-the-art review of the research into this area of machining, which made good observations in conclusion on the optimum conditions and configurations that would be required to achieve maximum efficiency from an ultrasonic machining process.

However, while the research and industrial development into the use of ultrasonically assisted machining was further pursued, the use of this energy for the monitoring of the performance of the cutting operation was also being researched.

In ultrasonic CNC research, there are two significant experimental attempts, by Hamm (2006) and also by Abu-Zahra and Nayfeh (1997), that have practically demonstrated that there is theoretical merit in the suggestion that ultrasonic analysis and monitoring of a cutting operation is viable.

The two practical investigations by Abu-Zahra and Nayfeh and by Hamm both demonstrated the merits of ultrasonic energy as a monitoring methodology, to determine tool wear in machining. However, both encountered similar experimental difficulties, in terms of transmission pathways and the overall practicality of the use of this medium.

A further discussion of the wider research, briefly touched on at the beginning of this section, which has been undertaken into ultrasonic applications at the cutting interface, would also demonstrate that researchers in this area have encountered similar difficulties in their research. However, the primary challenges and benefits have been teased out here, in covering the two papers and deeper analysis is outside the scope of this research.

2.7.5 Workpiece irradiation

The possibility of using radioactive materials was proposed by Cook & Subramanian (1978) whereby they coated the tool with radioactive material and analysed the degree of tool material evident on the surface of the work piece to evaluate the amount of work piece material that remained after the machining operation. The obvious hazard with this approach is the irradiation of the materials, and there was also wide variance in the experimental results. Overall this is a widely speculative approach with little practical application.

2.7.6 Acoustic emission

The acoustic emissions (AE) from a tool/workpiece interface are similar in nature to the vibration emissions. Both are energy release modes, where acoustic emissions are transient energy waves propagating at the surface of a solid- or through a liquid, while vibrations are energy waves propagating through a solid.

This section of the literature review treats only papers and research that discuss exclusively the use of vibration analysis. However, the author has chosen to review such literature separately, as there will be a discussion later in this document into the use of sensor fusion. Work will be outlined where vibration, AE and force are used together, which has been found to be a better use of multiple sensors, for example in Axinte, Gindy et al. (2004).

A general discussion of the theory of the use of acoustic emission in non-destructive evaluation was provided by Rao (1990). The author gives a detailed general explanation of the physics of acoustic emissions; particularly the use of acoustic emissions in catastrophic failure events, and the propagation of cracks and similar failure modes in materials.

The primary application of acoustic emission research is in the study of both plastic deformation and also crack initiation and propagation. At the time the Rao paper was published, the primary focus of acoustic emission applications was the testing and monitoring of structures and components, to detect and locate material flaws. The application of AE was emerging as a tool in fracture mechanics studies.

As an expansion of the initial discussion in the Rao paper, an explanation was entered into in a research project undertaken by Pathak and Murthy (1994) into acoustic emission studies for detection and monitoring incipient cracks in simulated aero engine mounts under fatigue.

The results obtained show, unsurprisingly, that there is a relationship between the propagation of cracks, the instance of crack face rubbing and the level of acoustic emission detected.

While the paper was a reasonably thorough treatment of the fundamentals of the science of acoustic emissions and provided an examination of a practical investigation into the worthiness of using AE for the monitoring of degradation of a material, by its own admission it was written at a time when the state-of-the-art of signal analysis was not sufficiently advanced. However, it can be seen as the research advanced with time that the use of AE became more and more sophisticated. Dolinšek and Kopač (1999) demonstrate that AE phenomena will usefully provide information on the degree of tool wear in the process. Later studies by Jemielniak (2000), Chiou and Liang (2000), Li (2002) and Jemielniak and Arrazola (2008) further demonstrated the worth of AE in this particular type pf process monitoring. Later in this document there is a section discussing multi-sensor deployment, and work has been done by Axinte, Natarajan et al. (2005) into the use of multiple AE sensors on the machine with very encouraging results.

Further work has been ongoing into the use of acoustic emission in machining such as that demonstrated by Albers *et al* (2017)

2.7.7 Vibration

The possibility of using an analysis of the vibrations within the machine structure to determine the performance has been investigated widely. As already mentioned there is also a good correlation between vibration and acoustic emission.

A general investigation, which provided a good examination of the structures of vibration signals within a tool condition monitoring environment, was undertaken by Alonso and Salgado (2008), where they used singular spectrum analysis (SSA) and cluster analysis to analyse the structure of the vibration signals that were detected during monitoring of cutting conditions.

In the experimental setup, two accelerometers were placed in the location of the tool, one measuring the vibration horizontally and the other measuring the vibrational displacement transversely. A wide range of conditions was tested, with six tools used with wear on the flank. Vibration signals were collected for three known wear states of the tools: sharp, usable and worn and it was demonstrated that there are significant differences in the accelerometer signals collected between the wear states of the tools. However, one obvious shortfall of this work is that the sensor deployments could only be undertaken within a strictly controlled laboratory environment and would not be practical in a real production environment.

Bhattacharyya *et al* (2005) undertook an investigation into vibration, as it relates to electrochemical machining during micromachining. Micromachining is defined literally as machining of dimensions that fall within dimensions of between 1 and 999 microns. In essence however, it is machining that is on a dimensional level that cannot be achieved by conventional means.

More recent work has been undertaken by Alonso and Salgado (2008) whereby analysis was undertaken of the vibration signals generated during normal machining, and this analysis demonstrated that there may be worthwhile information within the signals- although it is the belief of the author that the information generated further suggests that vibration is not sufficient as a standalone SF to monitor tool degradation. Additional insight into the use of vibration to monitor the state of a variety of machinery was provided by Dekys (2017) where vibratory analysis was examined as a method for monitoring the condition of machinery and also as a potential mode for the prediction of machinery faults.

2.7.8 Force

Force has for a long time been an area of interest within the research into tool wear. An earlier study by Jun, Burak Ozdoganlar et al. (2002) examined the feasibility of using a spindle deployed force sensor to monitor the performance of the machine, and therefore predict if the machine was experiencing undesirable operation. While this work was not directly looking only at tool wear, it concluded that the premise was fundamentally sound. Milfelner, Cus et al. (2005) provided an overview of the data acquisition system that was used in an application that used a force sensor for tool condition monitoring and the following year Teti, Jawahir et al. (2006) studied the chip formation in machining through monitoring of the cutting force signals.

Byrne and O'Donnell (2007) demonstrated the worth of force sensor monitoring in a drilling activity with an integrated sensor in the process. Most recently Denkena, Litwinski et al. (2014) showed the usefulness of the forces within the machine in experimentation that did not use a direct force sensor, but rather a force-sensitive axes slide within the machine to monitor the process.

The use of force sensing will be explored later in this thesis, and it will be demonstrated that force sensors have significant promise in monitoring the machining process. In addition to the application that will be presented in this work, ongoing research such as that by Sanchez (2017) and Yao (2018) continues to demonstrate the worth of this physical phenomenon for monitoring the cutting process.

2.7.9 Audible sound energy

To the author's surprise, at the outset of this research, there has not been a huge body or work undertaken to correlate the perceived ability of experienced machinists to "hear" the CNC machine process degrade through tool wear. When the author started reviewing the literature, Lazarus (1996) was one of the first works encountered pursuing this theme. In the Lazarus investigation, although the phenomenon is referred to as "acoustic emissions", which includes a large range of frequencies that are outside the frequency range of hearing for humans, it was in fact audible sound energy that was being assessed during the experiment. In any event the experimentation lacked a degree of sophistication, but ultimately concluded that humans can hear tools wear over time. Teti (1998) proved with a greater degree of sophistication that there clearly is a correlation between tool wear and the sound energy from a CNC machine in the 2-20kHz range. This was further demonstrated by the authors own paper in the Journal *Wear*, Downey, O′Leary et al. (2014). The big challenge faced by any investigation into audible sound energy is external interference from other noise sources, transmission paths & transmission media.

2.7.10 Temperature

It is commonly known that the CNC machining operation generates considerable temperature, both in the tool and the work piece, but in particular at the cutting zone. Hence the use of cutting fluids to try to control the temperature rises. There has been a number of studies investigating whether the temperature is a phenomenon worth monitoring within the machine, such as that undertaken by Ueda, Al Huda et al. (1999), whereby temperature measurement in the turning of hard steel was found to indicate temperature drift as the cutter degrades. Davies, Ueda et al. (2007) gave a more general overview of both the various strategies and experimental results from studies undertaken. Overall the monitoring of temperature in cutting is very tricky, particularly in normal production where cutting fluid is used both extensively and efficiently. An approach using a thermocouple was followed by Kerrigan, Thil et al. (2012) and this approach most effectively gets sensor data from the centre of the cutting zone.

The worth of temperature monitoring at the machining interface continues to be an area of significant interest to researchers such as that presented by Chen *et al* (2017) where the temperature at the cutting interface is proven to affect the formation of white layer and the subsequent onset of cutter wear.

2.7.11 Motor currents

Motor current has been proposed for quite some time as a means by which tool wear can be evaluated, with a good early proposal by Cuppini, D'Errico et al. (1990). In fact it should be noted that the majority of modern CNC machines are equipped with devices monitoring the energy being consumed by the main spindle motor.

The logic behind the monitoring of this is that as the tool blunts, the cutting operation becomes less efficient, therefore the spindle motor must work harder and consume more power. This premise can work where the cutting operation is very aggressive. However, in finer operations, such as finishing, the signal to noise ratio in the measured motor current, hides the change in energy consumption of the motor. René de Jesús, Gilberto et al. (2003) did propose the use of the drive current to detect a tool breakage, and this will work, but not quickly enough to prevent workpiece damage.

2.7.12 Multiple Sensor Monitoring

One piece of research that is very related to the author's is that of Axinte, Gindy et al. (2004), where a multiple sensor configuration (AE, force & vibration) is employed, with the view of improving the surface work piece quality, which is essentially the same as tool wear. It is of interest to this work as, later in this document, experimentation will be outlined, which fused these three sensors in a similar manner to Axinte et al. In another paper by the author - Downey, Bombiński et al. (2015)- an overview is given of a multiple sensor deployment on a production

CNC machine. Further good evidence of the worth of multiple sensor monitoring can be found in the work of Kang, Kim, and Kim (2001) and Duro et al., (n.d.)

2.8 Signal Processing

Signal processing methods and equipment have been widely deployed in other areas such as telecommunications, biomedical electronics, radar, etc. and has proven itself to be a powerful tool in many adverse environments.

The development of a robust and reliable tool condition monitoring system requires the application of the most meaningful TCM signal features (SFs), which best describe the tool wear (Jemielniak K., 2006). Therefore, the key issue in a TCM system is calculating a sufficient number of SFs related to tool and/or process conditions. There has been much work carried out on signal feature extraction of various different signals for various applications. Each of these signal feature extraction methods works, with varying success, with different sensor signals. Many of the various sensors used in tool condition monitoring (TCM) require individual feature extraction methods for optimal function. Feature extraction methods include; general purpose time domain features, acoustic emission time domain features, time series modelling, Principal Component Analysis, Singular Spectrum Analysis, Permutation Entropy (time domain), Fast Fourier transform, Wavelet transform and Hilbert–Huang transform (frequency and time–frequency domain). Each of these signal processing methods has advantages and disadvantages when used with different sensors and it is likely that for a multiple sensor configuration a number of these methods will need to be employed (Wang, 2007). It is impossible to predict in advance which SFs will be useful for tool and process condition monitoring in a particular application. Therefore, efficient methods to evaluate automatically their usability usually need to be applied. A robust TCM system should be able to combine signal feature extraction methods and use robust methods to process multiple sensors, without any intervention by, or even knowledge of, the machine tool operator.

Jemielniak and Otman (1998) gave an overview of signal conditioning techniques applied to raw acoustic emission data, and in a further paper Jemielniak, Bombiński et al. (2008) gave a deeper overview into the type of signal conditioning techniques that are essential in the conditioning of the huge amount of information that is now being offered as a result of both the increasing sophistication of the tool condition monitoring systems, but also the fact that the prevalent research for the past number of years has leaned toward sensor fusion, rather than rely on a single dataset.

2.9 Decision making support systems and paradigms

In monitoring and control activities for modern untended manufacturing systems, the role of cognitive computing methods employed in the implementation of intelligent sensors and sensorial systems is a fundamental one (Teti, 1997). A conspicuous number of schemes, techniques and paradigms have been used to develop decision making support systems functional, so that they can come to a conclusion on the machining process conditions, based on sensor signals data features. The cognitive paradigms most frequently employed for the purpose of sensor monitoring in machining, include neural networks, fuzzy logic, genetic algorithms and hybrid systems able to synergistically combine the capabilities of the various cognitive methods, are briefly reviewed here.

2.9.1 Neural networks

An artificial Neural Network (NN) is a computational model of the human brain that assumes that computation is distributed over several simple interconnected processing elements, called neurons or nodes, which operate in parallel. A NN provides a mapping, through which points in the input space are associated with corresponding points in an output space, on the basis of designated attribute values, of which class membership can be one. NN can capture domain knowledge from examples, do not archive knowledge in an explicit form such as rules or databases, can readily handle both continuous and discrete data, and have a good generalisation capability. NN can be employed as mapping devices, pattern classifiers or patterns completers.

Knowledge is built into a NN by training. Some NN can be trained by feeding them with typical input patterns and expected output patterns. The error between actual and expected outputs is used to modify the weight of the connections between neurons. This method is known as supervised training. Other NN are trained in an unsupervised mode, where only the input patterns are provided during training: the NN learns automatically to cluster them in groups with similar features.

2.9.2 Fuzzy logic

Fuzzy Logic (FL) has two different meanings. In a narrow sense, FL is a logical system, which is an extension of multivalued logic. But in a wider sense, which is in predominant use today, FL is almost synonymous with the theory of fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. A fuzzy set defines a mapping between elements in the input space (sometimes referred to as the universe of discourse) and values in the interval [0, 1]. A membership function is a curve that defines how each point in the input space is mapped to a membership value (degree of membership or truth degree) between 0 and 1. The processing core of a FL is based on a collection of IF-THEN rules, where the IF part is called the "antecedent" and the THEN part is called the "consequent". The application of a Fuzzy Decision Support System, (FDSS “Fuzzy Flou”) is utilised for tool wear estimation during turning using cutting force components measurements.

2.9.3 Other methods

Genetic Algorithms (GA) belong to a branch of computer science called “natural computation” where programmers, inspired by phenomena in the biological world, create models of these systems on a computer. This technique can solve complex problems, by imitating Darwinian theories of evolution on a computer. The first step in the use of a GA is building a computer model to represent a given problem. Interacting variables in the problem are first combined and encoded into a series of binary strings (rows of ones and zeros) to form numerical “chromosomes”. The computer randomly generates an entire “population” of these chromosomes and ranks them based on a “fitness function”, which determines how well they solve the problem.

GA are utilised to automatically construct a FL Knowledge Base (KB) from a set of experimental data on tool wear monitoring during turning without requiring any human expert intervention.

2.9.4 Hierarchical algorithms

In general, when a single NN is used for sensor monitoring of machining, several SFs are fed to the NN input nodes, while the process or tool conditions estimation is obtained at the NN output. However, the use of several SFs as input to a single NN requires a large number of experimental data that are usually not available if the monitoring system is supposed to be trained during the first tool life period and be ready for monitoring during the next ones (D’Addona, 2011), (Jemielniak K. B., 2008).

2.9.5 Sensor fusion technology

When measuring a particular variable, a single sensory source for that variable may not be able to meet all the required performance specifications. A solution to this problem is sensor fusion that combines sensory data from disparate sources, so that the resulting information is better than would be possible when these sources are used individually. The term “better” can mean more accurate, more complete, more dependable, more robust, or refer to the result of an emerging view, such as stereoscopic vision that calculates depth information by combining 2D images from two cameras at slightly different viewpoints. One can distinguish direct fusion, indirect fusion and fusion of the outputs of the former two. Direct fusion is the fusion of sensor data from a set of heterogeneous or homogeneous sensors, soft sensors, and history values of sensor data, while indirect fusion uses information sources like a priori knowledge about the environment and human input.

Over many years of research, many process variables have been tried to determine how tool wear in real time to provide the machine operator with accurate feedback. Early work focused on directly and easily measurable machine characteristics. It was subsequently realized that various other energy releases from the machining process can offer more valuable information about the process.

2.9.6 Belief network analysis & neural network control

As discussed earlier, the use of neural networks has increasingly become the analysis means of choice of the academic and research community. A neural network is a computing network that uses nodes to perform certain tasks, in a similar manner to that of the human brain. There is no central processing unit in the network, but rather a web of interconnected processing units, and this exponentially increases the available computing power and speed. The human neural network (our brains!) can take multiple sensory inputs, weight their importance in a situation, and come to a conclusion based on these multiple, varied information streams. The Artificial Neural Network (ANN) works in a similar manner and is ideally suited to the multiple sensor configuration that now seems the best solution for tool condition monitoring. It is based on multiple inputs and the architecture of a standard ANN shown in **Figure 3**, originally presented by Abu-Mahfouz I (2003).

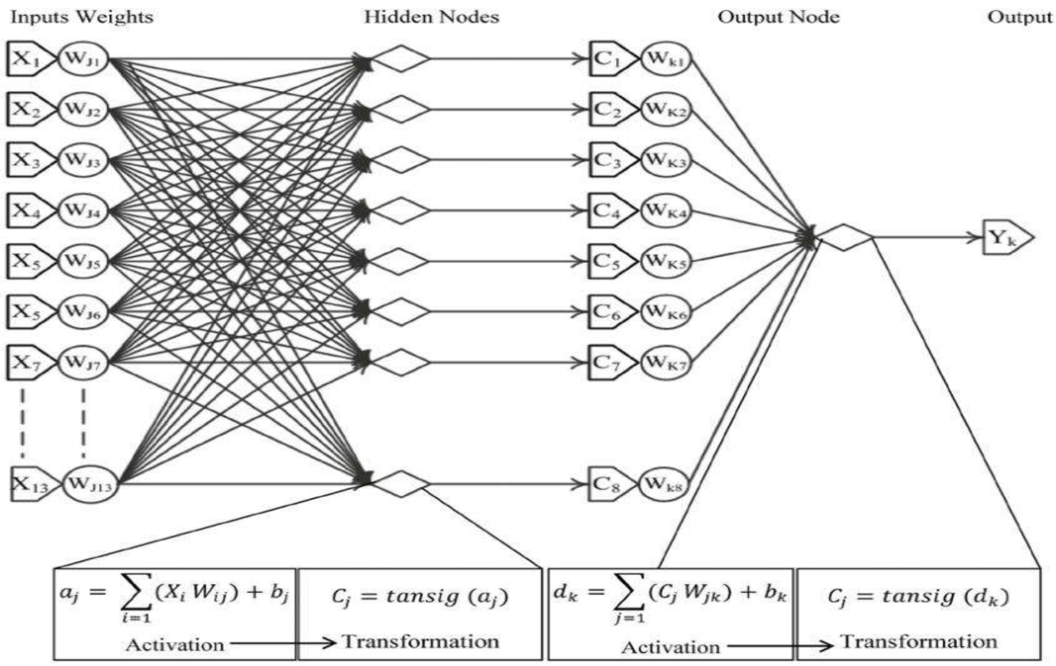


Figure 3 Architecture of a standard ANN

Ghosh, Ravi et al. (2007) outlined one of the earlier deployments of sensor fusion with an ANN with very encouraging results, finding that the ANN was able to be taught and learn as the process degrades. Asiltürk and Çunkaş (2011) and D'Addona, Segreto et al. (2011) further applied ANN to machining operations and demonstrated that the technology is capable of serious sensor interrogation. This author was a second author of a paper- Martensen, Downey *et al* (2015)- which reported on work undertaken with a number of machinists at the author's workplace, to determine the optimum human machine interface (HMI) for an effective ANN. An ANN was utilised in the later work presented in this thesis to attempt to evaluate the degree of tool wear exhibited. This was manually trained through the progressive wear of tools and feeding back the degree of tool wear detected to the system.

2.9.7 Summary of Literature & Patent review

As can be seen in the earlier sections, there has been a long desire to develop a system or methodology for the accurate monitoring and reporting on the performance of the CNC machining process. Many avenues have been explored and there is no phenomenon within or around the cutting process the viability of which has not been evaluated in detail. For the past number of years the conclusion has been reached that it is only a combination of the available phenomena (in a sensor fusion) coupled with sophisticated data mining and analysis techniques, that will result in accurate and reliable monitoring of this process. Neural networks, coupled with data from multiple sensors, are the technique that holds most promise at the moment. A neural network with input from multiple sensors mimics the cognitive ability of the human body, where the brain is the ANN, and sensors are the 5 senses. And we anecdotally know that experienced machine operators appear able to detect wearing tools through sound, vibration, touch and other variables. It is clear from the literature review that since the commencement of investigation into the potential to use physical phenomena from the CNC operation to interpret the performance of the operation 40 years ago the available technology has become so advanced that TCM systems are now inevitable. Early efforts as outlined earlier relied on piezo-electric sensors and analogue oscilloscopes as the sensor-interpretation circuit. Today we have extremely sophisticated sensors, deployed in fusion, with well-developed signal conditioning techniques. And this information is being interpreted by complex Neural Network computing systems.

In spite of previous technological shortfalls, for many years patents have been lodged outlining a tool condition monitoring system. As discussed earlier, these have proven largely speculative and without substance in terms of the key interpretative process that they will employ and have relied on vague descriptions of the hardware configuration. However, the key to intelligent tool condition monitoring systems now is in the sensor configuration (fusion) and subsequent signal interrogation.

It is this sensor fusion and the interrogation of the signals that this research intends to address. The experimentation that will be outlined in the coming pages will investigate the worth of each of the identified sensor sources against the next, across a number of machines, a number of cutting configurations, and a number of materials.

3 Outline of practical experimentation methodologies and techniques

3.1 Introduction

This research has undertaken a number of experiments through the installation of sensors on commercial CNC machines, all at Schivo Precision. Once the sensors were configured and installed a variety of cutting tests were undertaken to correlate the acquired sensor data with the degree of tool wear observed. The experimentation began with relatively straightforward operations and sensing, but then stepped up in intensity from the perspective of the machine type, and machining configuration. The work began with single point turning on a Harrison lathe, then on to a 5-axes Rx6 machining centre for two experiments and, finally, on to a Mazak Quick Turn Nexus 200 lathe, as part of the EU FP7 funded REALISM project.

The fundamental objective of this research was, as has been outlined, to examine the various physical phenomena that emit from the cutting process in order to gain an insight into which of those emissions could give an insight into the state of the process.

The author has from on the shop floor experience, knowledge that experienced machine operators can determine that a cutting process is degrading by listening to the cutting process or intuitively examining the vibration from the machine. This research intends to scientifically examine the basis for this anecdotal human interaction with the physical process.

The critical questions that will be posed in the following chapters surround the following research questions:

- Are there physical phenomenon that emit from the subtractive machining processes that can be detected intuitively by humans and examined and interpreted by the machine operators to allow non-automated examination of the condition of the cutting process in terms of tool wear and associated process degradation.
- Is it possible to use technological substitutes of the human senses; such as microphones, Acoustic emission sensors, Accelerometers & Force sensors to mimic the traditional and anecdotal claim that experienced operators can use the available range of human senses to detect a degrading process in a subtractive manufacturing operation.
- Further to examining if the emissions can be sensed by available physical sensors, as described in the previous point, is there a methodology through the use of software and machine learning that can mimic the processes used by the human operators to interpret the degree of change, or degradation, of the process and make informed decisions based on that perceived, tactile information.
- What can be learned, through the deployment of machine monitoring systems and the interrogation of the data from these systems, about the physical emissions from the processes and what these tactile phenomena are telling the experienced operator, and thus a system that uses technology to mimic both the physical senses of the operator and the cognitive capabilities that are claimed by very experienced people in machining companies across the world to be the core of the machine interpretation skillsets.

As will be outlined in the following pages, initially audible sound energy is examined, followed by vibration, acoustic emission and force within the machine structure.

3.2 Audible sound energy in single point turning- Harrison Lathe

An audible sound energy investigation into single point turning on a Harrison Lathe was the first investigation into TCM, in order to begin to understand the requirements and restrictions of a TCM system. As an early endeavour, it did not attempt to replicate a complete, robust TCM system and was also limited, in that the chosen Harrison Lathe (pictured in **Figure 4**) operation is much more straightforward for TCM than the later work described in this thesis. Furthermore, the data recorded was not analysed in real-time, but was post-processed and, even then, the analysis was performed selectively, having fully studied the data to find the most lucrative route to pursue.

Figure 4 Harrison Lathe used in 1st experiment

In terms of choice of sensed parameter, the author was interested in investigating experienced Schivo company operators' claims that they knew, from listening to a cutting operation, when a tool was nearing its end of life. Consequently, the sensed parameter in this investigation, was emissions in the audio range (actually, up to

22kHz, but in reality the operators' aural range is probably less than this, typically 2kHz to 18kHz). Therefore, a standard microphone was installed to sense the audio emissions, at the cutting interface in a single point turning operation. Two machining cycles were run back-to-back on the lathe, with identical cutting inserts and, for the full duration of the testing, the audible sound energy from the cutting process was recorded and stored for later analysis. During the cycles, the surface roughness of the work piece material was constantly measured to evaluate the surface quality, and therefore the degree of tool wear.

The experimental setup is shown in close-up, in the photographs in **Figure 5 – Figure 7.**

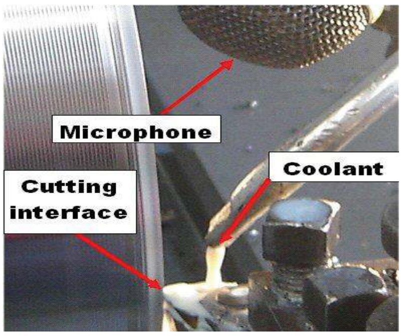


Figure 5 Microphone configuration

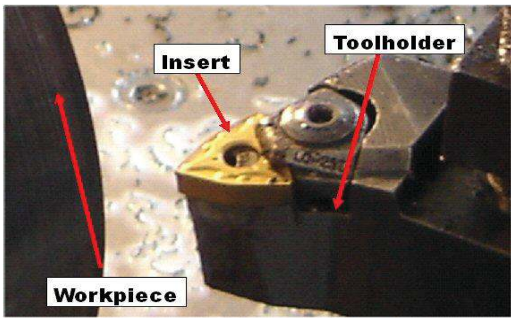


Figure 6 Detail of Insert/workpiece

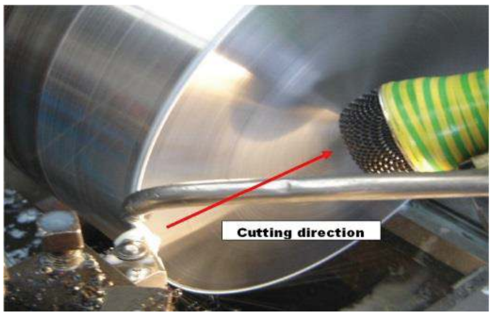


Figure 7 Direction of facing cut

The machining operational parameters are shown in **Table 6**:

Table 6 Machining operational settings

CNC Machine used	Harrison VM500 Lathe
Workpiece material	High speed tool steel
Cutting Tool	CNMG 120412 insert
Cutting fluid	Hocut HO80
Feed	120M/Minute
Speed	130 RPM
Cut depth	0.2mm

The above cutting conditions were chosen following discussions with one of the companies most experienced toolmakers and were considered optimum for the cutting process, tool insert employed, and material being machined. The sound energy emissions were detected using a Shure SM58 audio microphone connected to the Conexant high definition soundcard of a Toshiba Satellite laptop and recorded for later analysis using Audacity, an audio software package. The signal was band limited to 22kHz, which easily encompasses the audio range of Schivo operators, and therefore, to obey the Nyquist Sampling Theorem, the data was sampled at 44.1kHz. A typical time domain capture of the signal is shown in **Figure 8**.

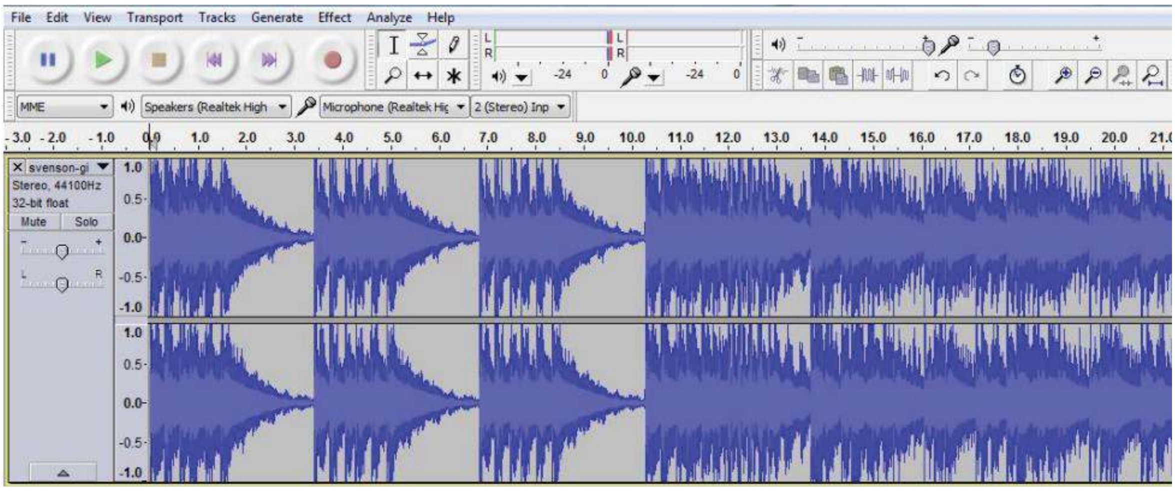


Figure 8 Typical time domain capture of the Harrison Lathe audio signal

At the end of the experimental cycles, two full sets of audio acoustic emissions' data had been recorded and were available for post-processing and analysis. The raw data was windowed using a Hanning Window, to keep spurious harmonics of the recorded frequencies low. A typical example of the frequency domain representation of one of the sampled, windowed audio signals is shown in **Figure 9**.

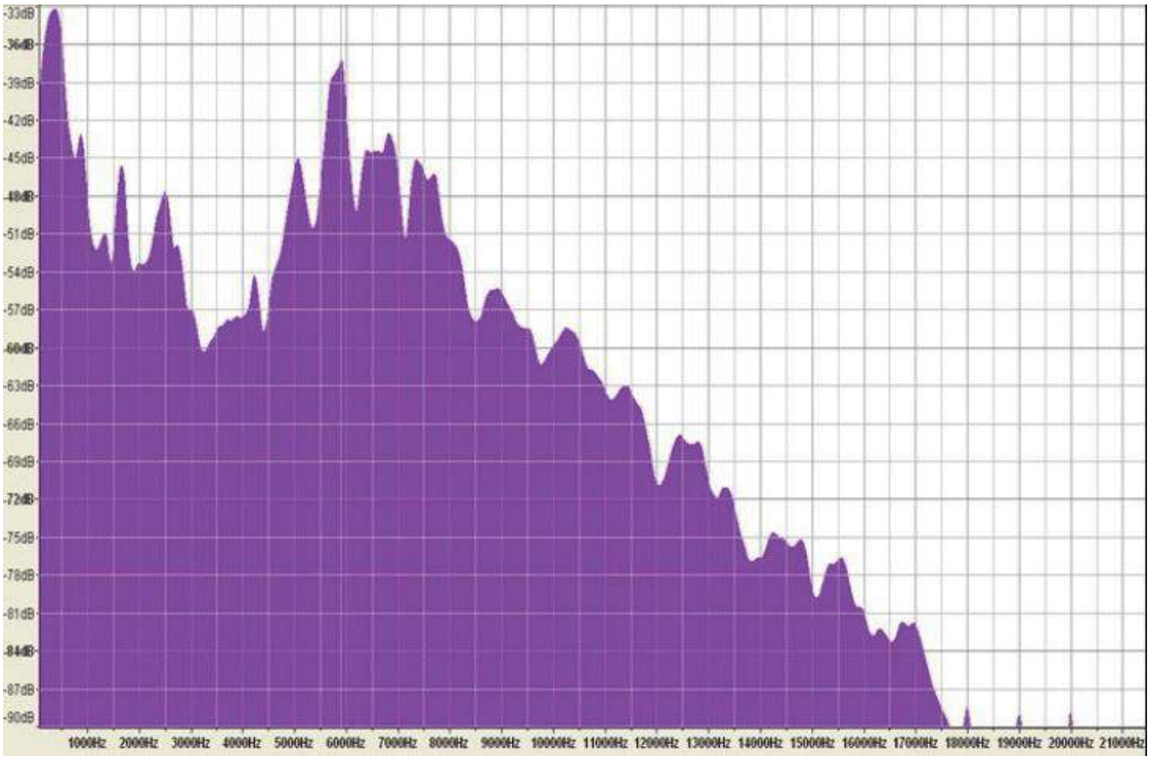


Figure 9 Frequency domain representation of a Harrison lathe audio signal

The machining configuration and settings described were used to machine material continuously, while recording the resultant microphone pickup on the PC. By repeatedly using a single point turning configuration the experiment is monitoring only the interaction of the same cutting edge type on the same material type. As mentioned earlier, the two full machining cycles were run back-to-back on the lathe, facing the billet, removing 0.2mm of material for each pass, with identical cutting inserts and, for the full duration of the testing. The total lengths of the two recorded data sets are shown in **Table 7**.

Table 7 Recorded Harrison Lathe audible acoustic emission data set durations

Cycle	Duration
Recording cycle 1, insert 1	1 hour, 33min, 42 seconds
Recording cycle 2, insert 2	1 hour, 29min, 10 seconds

At the end of the experimental cycles two full sets of acoustic emission data were available, having been stored on an external hard drive for later analysis. Both cutting inserts were marked up and retained, also for the later analysis.

While the experiment took place on Schivo's machine floor, for the duration of the experiment there were no other machining operations taking place in the vicinity, which might have added interfering acoustic components and compromise the signals being detected. To further confirm that any background acoustic energy was negligible to the sensor acquisition, the monitoring equipment was set to record background noise at the beginning and end of the experiment and the spectra were taken for these signals to confirm that their effect would be negligible.

The experiment was run with identical settings and configurations. For each experimental cycle, the only change was the replacement of the cutting tool insert with an identical unit. Throughout the experiment the surface finish obtained from the cutting operation up to that point, was monitored with a Mahr PocketSurf portable surface roughness meter. The surface tester was used to monitor the value of RA (roughness average) across the machined surface. RA was selected over Rmax or RZ, as this value is not as susceptible to skewing due to anomalous area detection during the measurement. The stroke length of the surface tester probe was set to 5mm and the readings were taken from the material *in situ* on the machine, to avoid disruption to the set-up.

The analysis of this data is presented in the next Chapter on Results and will consider the following questions:

(1) Is there a perceptible variation between the acoustic emission data from known good tool cutting conditions and the emission data where it is known that the tool is not cutting efficiently?

(2) Are there demonstrable correlations across a number of samples of acoustic emission spectra, across the range of the same tool cutting cycle, where the tool is known to be cutting effectively?

(3) Are there demonstrable correlations across a number of samples of acoustic emission spectra across the range where the tool is known to be worn and not cutting desirably?

(4) Is the data from the two experiments substantially similar, i.e. are the emission spectra for known good and known bad on both experimental cycles comparable in content?

It was determined to divide the cutting cycle into three simple phases of tool operation across the tool's life. Phase 1 is where the insert is cutting at maximum efficacy, due to the fact that since manufacture the tool cutting interface has experienced no stresses. This initial phase is expected to last no longer than one or two cutting passes. However, 20 passes were allowed during the analysis to allow for tool “wear-in” and thermal deformation. Phase 2 is where the cutting insert is experiencing normal operation. This is expected to be the longest, and naturally the most consistent in terms of performance, efficiency, temperature and audible acoustic emission. Phase 3 is where the cutting edge and supporting material of the insert is beginning to exhibit wear characteristics. The differences between the second and third phases of the insert’s operation and audible acoustic emissions that are released during these phases are those that are of interest to this research and formed the basis of a publication in the Journal *Wear*.

3.3 Audible sound energy and vibrations in 5-axes machining- Röders

The aim of this piece of research was to delve deeper into the requirements and restrictions of a TCM system on a commercial system, using the insights gained from the Harrison Lathe research. Once again, it did not attempt to replicate a complete, robust TCM system and was also limited to audible sound energy emissions, with vibration sensing now added as a sensed parameter. This endeavour is only slightly more complex than the earlier Harrison Lathe operation, with the addition of the extra sensor and the more difficult cutting process. Once again, the data recorded was not analysed in real-time, but was post-processed and, again, the analysis was performed selectively.

A further aim was to examine the audible sound energy emissions and vibration data emitted during the machining cycle, to determine whether there is a correlation between each of these phenomena and the wear of the tool. The experiment was undertaken across the full effective life of the tool in an unmanned, roughing, 5-axes operation.

In this operation, it is known from the outset that the cutting tool will be exhausted during the cycle but, in this case, it is sacrificial in nature in that the tool is used for roughing and any shortfall in the cutting performance of this tool will be corrected during the subsequent finishing operations on the workpiece. The machining cycle being monitored is the period in which a titanium billet (Ti-6Al-4V, which has been profiled on a lathe) is roughed in 5-axes to the desired geometry, prior to the finishing cutting operations.

The blank workpiece billet at the commencement of the machining operation is shown in **Figure 10**, and the resultant product at the end of both the roughing and finishing operations, which are run unmanned and uninterrupted, is displayed in **Figure 11**.

Figure 10 Blank workpiece billet

Figure 11 Finished product

The cutting configuration employed was multipoint tool geometry machining, in a roughing operation on a 5-axes Röders Rx6 machining centre. The main spindle column was stripped down and the two sensors (microphone for audio and accelerometer for vibrations) were mounted onto the main spindle housing, using high tension adhesive, as shown in **Figure 12**. Once completed the housings were fully re-assembled by Schivo maintenance personnel. The roughing operation is illustrated in **Figure 13**, and the resultant workpiece is shown in **Figure 14.**

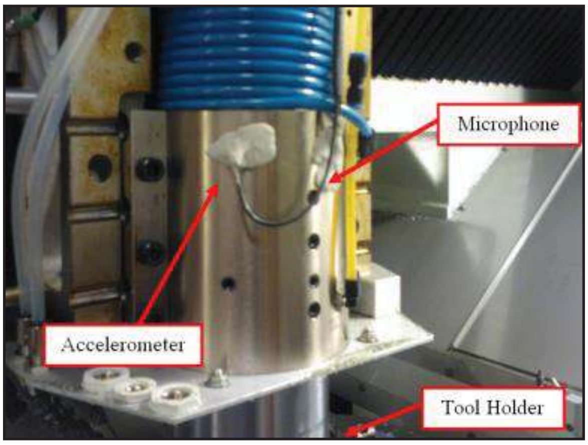


Figure 12 Sensor locations on machine spindle

Figure 13 Machining operation

Figure 14 Resultant workpiece

The accelerometer was connected to a PC (PC1), which had been fitted with a National Instruments DAQ (Data Acquisition unit) and LabVIEW software, to capture these sensor signals. The microphone was separately connected through a PicoLog datalogger to a second PC (PC2), which was dedicated just to capturing the data from this sensor. The computer configuration is shown in **Figure 15**.

Figure 15 Overview of PC & datalogger configuration

Two separate data acquisition systems were used in this experiment as PC1 was a dedicated PC that was seconded from the Engineering department of WIT and was configured with labview and the National Instruments Data Acquisition Card (DAC) that was used to compile the data from the microphone. In this instance the microphone used provided a digital output in terms of signal intensity, rather than the analog signal from a standard microphone used in the initial experimentation which has additional embedded information in the signal output. PC2 in **Figure 15** above was a PC that had dedicated software (Picolog) which took the information from the datalogger that had been acquired by the company for the experiment which acquired the vibration sensor data and data from two PIC sensors on the external machine housings.

The machining was undertaken, as outlined, in an unmanned configuration and the machining was commenced at the end of the day shift to run overnight. The principle parameters and equipment used are detailed in **Table 8** while the sensor settings and configurations are provided in **Table 9.**

Table 8 The 5-Axes machining operational settings

CNC Machine used	Röders RPX 500 DSC
Workpiece material	Titanium Ti-6Al-4v
Cutting Tool	M.A. Ford TuffCut XR 4 FL BN End Mill 6mm x13mm
Cutting Fluid	Hocut 870 synthetic, water soluble.
Feed	1530 MM/Min
Speed	10,800 RPM
Cut depth	0.5mm

Table 9 Sensor parameters

Data logger- audio signal (PC1)	PICO Tech PicoLog1212
Data logger- vibration sensors (PC2)	National instruments DAQ
Microphone (PC1)	Knowles EK-23024-C37
Accelerometer (PC2)	Knowles BU-23173-00
Piezoelectric sensors (PC2)	Farnell supplied standard piezo
Audio data acquisition software, PC1	PicoLog version 5.22.6
DAQ data acquisition software, PC2	Labview 2010, version 10.0.1 (32 bit)

The machine was monitored over two cutting trials and the durations of the measurements are given in **Table 10**.

Table 10 Recorded Röders 5-axes data set durations

Trial	Duration
Trial 1, 22 Oct 2013	3hr 15 minutes
Trial 2, 23 Oct 2013	3hr 12 minutes

This data analysis phase for this initial experimentation on the Röeders machine was inconclusive for a number of reasons (Such as sensor selection and location) and for that reason this experiment was re-run with a different sensor configuration**.** While the results are discussed in the next chapter, it is worth pointing out some of the reasons the author believes this experiment was not a success.

In reality, the experiment should have succeeded in analysing physical phenomenon on a machine, even in 5-axes configuration. Simply walking into the dedicated room that the machines are in at the beginning, and returning at the end of the cycle the author could clearly hear and feel the difference in the emissions from the machines. However the author believes a number of factors resulted in the data from all sensors being inconclusive, and will further outline this in the presentation and discussion of results in the next chapter.

3.4 Re-configuration and testing with the 5-axes Röders machining

The Röders machine presented an interesting and, in terms of other more complex work, valuable challenge. Although the first experiment's data was inconclusive as will be outlined in the discussion of results chapter, the insight gained on sensor selection and location was valuable.

The experiment was therefore re-run, but with a modified sensor configuration. Some experimental parameters remained the same. Again, the machine was monitored over two cutting trials, with a ballnose cutter being used for extended roughing of a titanium workpiece. The two trial durations are detailed in **Table 11.**

Table 11 Second experiment trial durations on the 5-axes Röders machining-

Trial	Duration
Trial 1, 21 Jan 2017	2hr 2 minutes
Trial 2, 22 Jan 2017	2hr 14 minutes

Again, the experiment was undertaken across a full tool life, where the tool was completely exhausted during the process. As this is a continuous process, it is not possible to measure the degree of tool wear at points during the process, but rather it is simply regarded as a binary condition, where the tool is cutting at its prime at the beginning and is completely exhausted at the end of the process, as per the photos in **Figure 16,** it is clear that the cutter was new at the commencement of the cycle and completely worn at the end of the machining cycle. This is the same machining strategy that was employed in the experiment outlined in the previous section, and in this 5 axes application this strategy is quite normal. The complex geometry of the component, coupled with the accuracy required, means that the primary material removal cycle- roughing- cannot be interrupted to evaluate the part. Hence a calculated evaluation I taken in terms of machining conditions to ensure that the tool will survive the full cycle, albeit completely exhausted toward the end of the cycle thus generating an extremely poor surface finish. This poor finish is then mitigated though the use of finishing cutting operations. The reason I chose this roughing operation in both this experiment and the previous was that although its not possible to measure the degree of wear across the cycle, it is known that the cutting interface is wearing extensively during this phase.

As the aim of the experimentation outlined in the various sections of this thesis is to evaluate the worth of the various physical phenomena emissions from the cutting process this roughing cycle the author believes this is a good method of comparing a known good cutting operation with that same operation in a known degraded condition. **Figure 16** demonstrates the degree to which cutter degradation occurs in this operation.

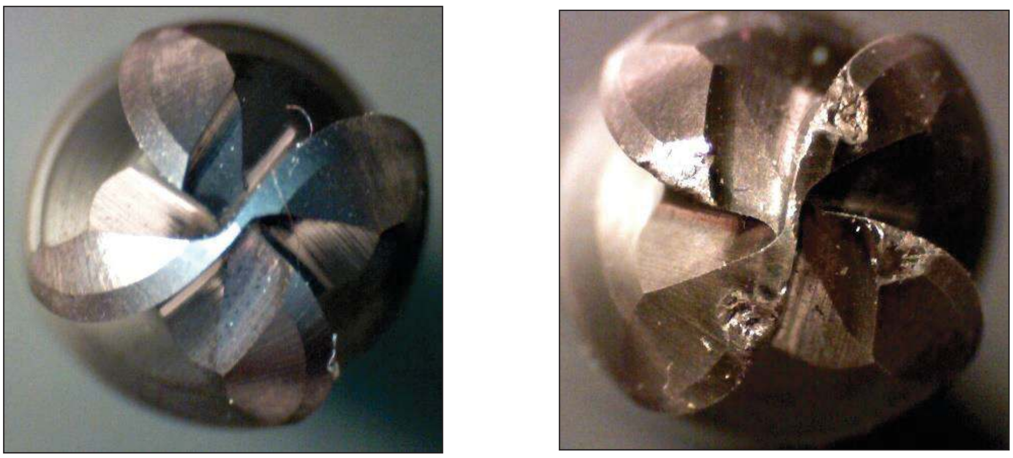


Figure 16 Photos of new and exhausted ballnose cutter X50 Magnification

In this experiment, the sensor configuration in table 12 was used. More consideration was given in this experiment to the sensor conditions, in terms of both location and fixation method. The accelerometer was bolted tight to the spindle housing and the microphone was hung freely at the top of the machine bay. This experiment, while using essentially the same sensing techniques used in the previous iteration was intended to build on the learnings from the failure of the previous experiment. While these failings will be discussed further during the results discussions in chapter 5, it was initially clear that errors were made in sensor location, sensor type, and sensor interrogation. Based on the success of the Harrison lathe experiment it was clear that the use of a digital system to capture sound was flawed this time hence the same audible sound energy capture method was used in this revised instance. Also, by affixing the Knowles microphone to the spindle the microphone was capturing some level of acoustic emission from the surface, and addition to sound energy causing potential destructive interference in the signals. In the previous experiment the accelerometer was affixed with an adhesive to the spindle housing, this time it was bolted and a coupling transmission media was used.

The sensor configuration employed in the 2nd 5-Axes machining experiment is outlined in **Table 12**, as is the data collection method.

Table 12 2^{nd} experiment sensor configuration on the 5-axes Röders

Sensor type	Description	Location	Data collection
Sound Energy	Shure SM58 Microphone	Top of machine bay	Audacity software
Vibration	Kistler 50g ceramic tri-axial shear accelerometer	Affixed to spindle housing	Picolog data logger and software

Figure 17 Approximate location of microphone

It was apparent at the commencement of the experiment that the audible sound energy being detected by the audacity software was of a far better quality than that detected during the previous attempts, described in Section 0. As, once again, the analysis is post-process and not in real time, it was not possible during the experimentation to determine definitively if this dataset was going to be of any more worth than the previous experiment.

3.5 Acoustic emission, vibration & force - Mazak Nexus lathe

This experiment was the most ambitious and detailed in this work and has led to four publications. This research was funded under EU FP7, as the REALISM project, with the author as the main industry partner and, through WIT's SEAM centre, also co-ordinating the project.

It is also the most comprehensive TCM research undertaken at Schivo and utilises the most sophisticated equipment. Three sensors were fitted to a Schivo Mazak Quick Turn Nexus 200 lathe and the experimental work was again undertaken in a normal production environment. The author led the Schivo input to the project and, also played a key role in the WIT input, including the selection of sensor deployment positions on the expensive, commercial machines. It was initially intended that a vision system would also be installed on the machine. However, this proved infeasible for a variety of reasons that will be outlined.

The sensors fitted to the machine were:

- Kistler 9017C force sensor with a Kistler 5073 charge amplifier
- Kistler 50g ceramic tri-axial shear accelerometer
- Kistler 50-400kHz piezoceramic acoustic emission (AE) root-mean-square (RMS) sensor with piezotron coupler

Figure 18 The Mazak Quick Turn Nexus 200

The general structure of the Tool and Process Condition Monitoring System is presented in **Figure 19**. In the cutting zone, there are many process variables (cutting forces, vibration, acoustic emission, noise, temperature, surface finish, *etc*.) influenced by tool and process condition. Signals acquired from the REALISM sensors (force, AE and accelerometer) were then subject to signal processing, the aim of which was the generation of useful signal features, correlated with tool or process condition. Signal features were then integrated into final diagnosis, which could be presented to the operator and/or sent to the numerical controller (NC), executing the appropriate action.

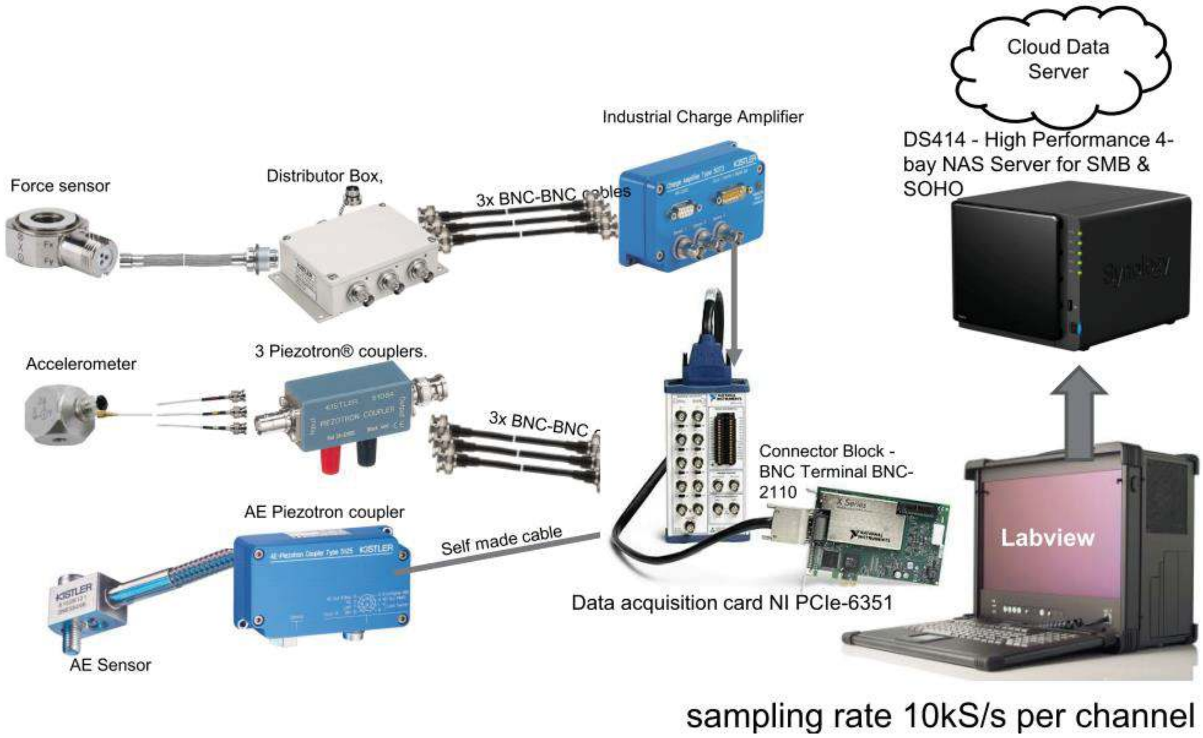


Figure 19 Outline of configurations for Mazak experiment

The signals from the sensors were conditioned appropriately (pre-amplifiers, low pass filters, with 2kHz cut-off frequencies), before being fed into a National Instruments DAQ (PCI-6351), for eventual feature extraction and analysis using a dedicated LabVIEW Virtual Instrument (VI), prepared by one of the EU partners. Ultimately, the diagnostic system should process the data in real-time. The low pass filter cut-off frequency of 2kHz was selected, as it was decided that the physical phenomena generated during machining (with the exception of AE) should be band-limited in frequency to 2 kHz. The applied sampling rate was 10kS/s per channel, which was a conservative over-sampling rate, to not alone obey Nyquist's Sampling Theorem, but also to offer finer frequency detail because of the over-sampling. Two different approaches are taken to determine tool wear from the sensor signal features extracted, one using the Wavelet Packet Transform; feeding a cognitive based Neural Networks (NN) system, and the other approach to detect Catastrophic Tool Failure, based on a simpler, statistical approach to sensor signal processing.

The overall circuit diagram for the monitoring system is shown in Figure 20 Monitoring system circuit diagram.

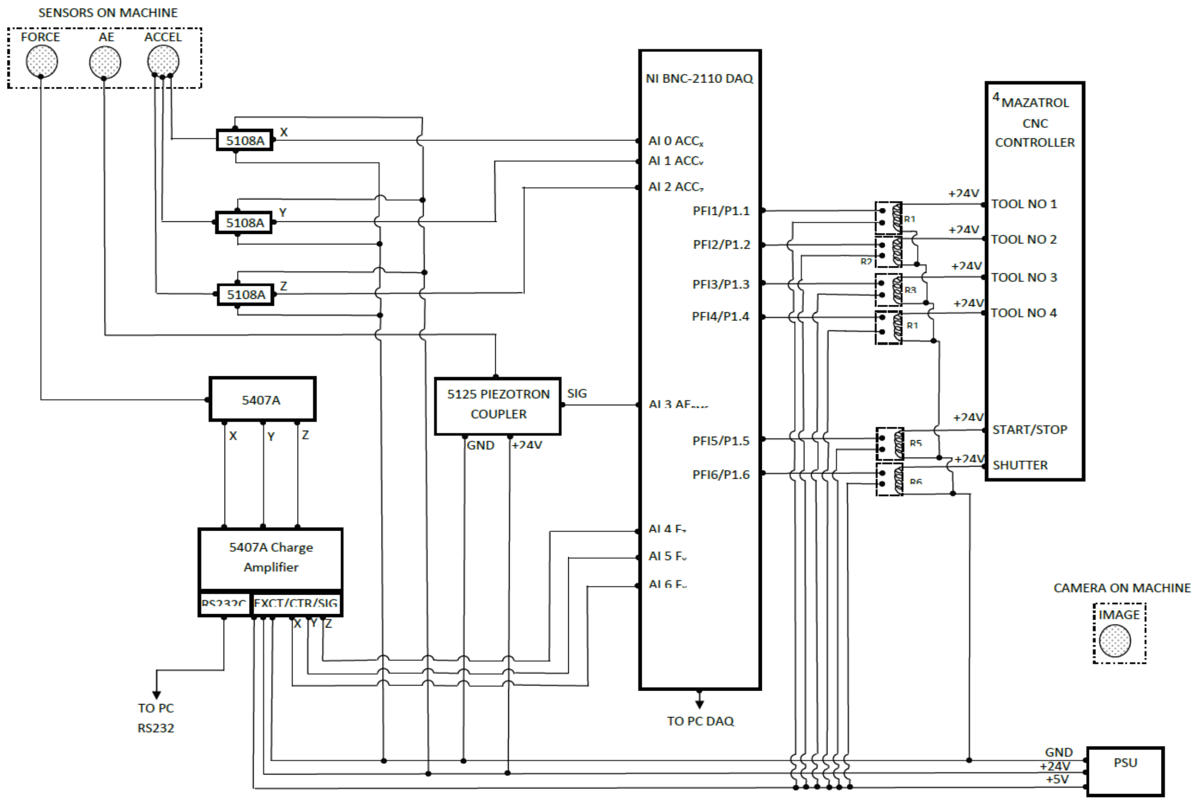


Figure 20 Monitoring system circuit diagram

The three sensors were all located on or in the turret of the lathe, as shown in **Figure 21**, where A is the force sensor, B is the accelerometer and C is the AE sensor. This is a challenging deployment, but because of the proximity to the cutting action, is more likely to be sensitive to the tool condition.

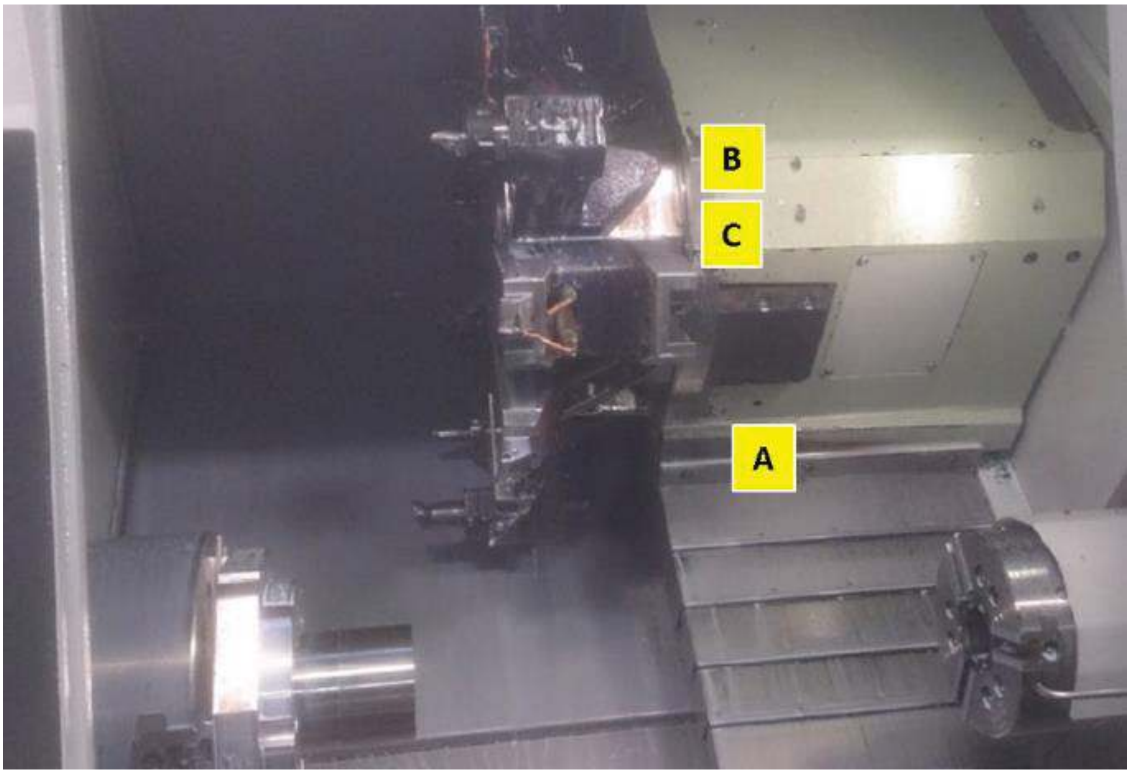


Figure 21 Sensor locations on the Nexus 200

The ideal locations for the accelerometer and the AE sensor are obviously as close to the cutting interface as possible, while also minimising, as much as possible, any crossing areas where transmission losses would be experienced. With that in mind both sensors were bolted firmly to the turret body, as shown in more detail in **Figure 22**.

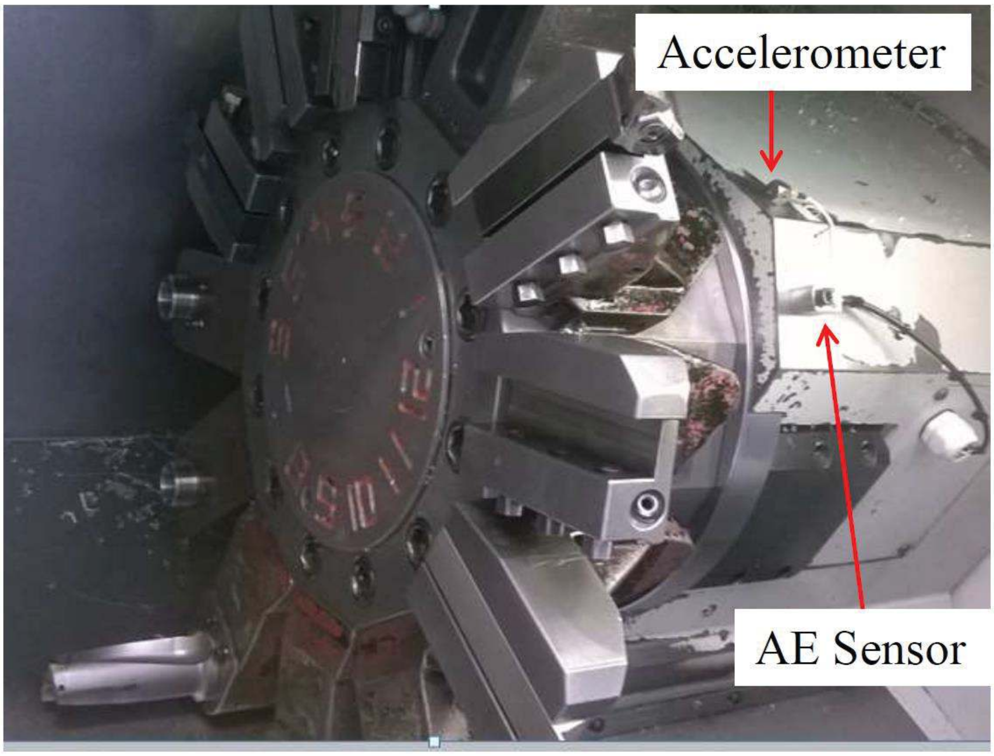


Figure 22 Accelerometer and AE sensors in relation to the Mazak tools

The ideal location for the force sensor is obviously in an area that experiences the greatest forces during the cutting cycles. One of these places is between the tool and the tool holder, but for obvious reasons this is not practical. The most practical place to put a sensor of this type is where the turret is bolted to the bed of the machine. However, the turret on the Mazak is on a slideway. A hole was therefore drilled into the bed of the machine, just below where the slideway rail itself is bolted to the bed as shown in **Figure 23**. The sensor was preloaded and using a shim system (made on one of Schivo's wire EDM machines) in the configuration shown in **Figure 24** the round hole (25mm) drilled through the machine casting sub-structure became two flat surfaces between which the force sensor and the preloading key could be deployed.

Figure 23 Force sensor location in relation to slideways and turret

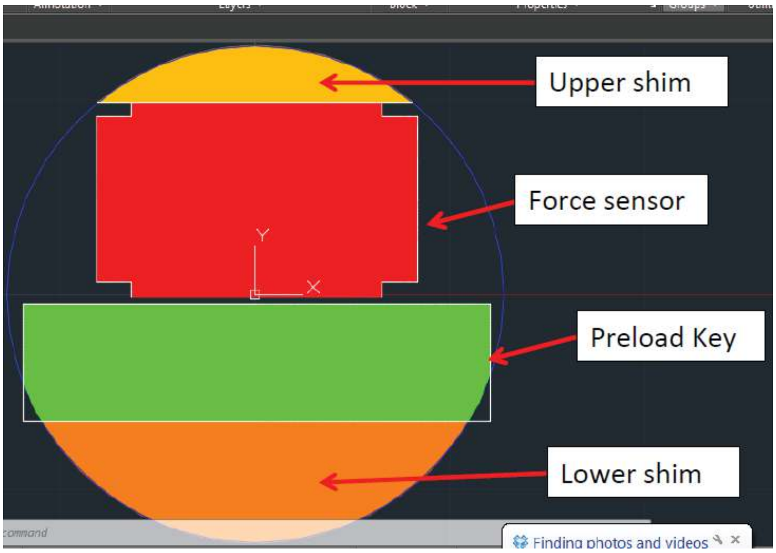


Figure 24 Sensor/preload key/shim configuration in drilled hole in casting

It was then possible to verify the signals from the sensors, as will be outlined in the Results chapter.

As mentioned earlier, it was the intention at the outset to include a vision system for the continuous evaluation of the tool wear in the machine after each operation. However, the proposed system was too bulky to fit into the machine, and it was felt that the system could be in danger of damage, in the event that a long tool indexed around onto the plane occupied by the camera.

This concern was verified when we physically tried to fit the vision system into the machine bay. It was clear that certain tools would indeed index into either the camera system or the lighting units. The use of the specific vision inspection system was at that time being verified in the labs of one of the project partners, Warsaw University of Technology, however the deployment of a system of this nature in a laboratory is far easier than deployment in a real time production environment, manufacturing standard production parts, which is the core intent of this authors research.

3.6 An overview of the role of the author in the REALISM project as it pertains to this research

As REALISM forms part of the research presented in this thesis, it is important to mention the roles taken by the author in that research project. A large body of work was carried out or overseen by the author on the machine shop floor in Schivo, during normal production hours to ensure the prevalence of factory floor real time conditions as opposed to laboratory environment conditions. Moreover, following the Schivo testing, some sensor signal data was also collected at another industrial partner, Tulino of Naples. In summary, on REALISM, the author had various responsibilities and contributions, including

- leading two work packages

    - Work Package 3, which involved the system development, deployment and implementation for sensor signal and sample material data collection and
    - Work Package 7, which focussed on the system validation and demonstration Validation of system robustness in representative process conditions and the testing of operator interface, all on the Schivo machine room floor;
- contributing significantly on other work packages, including
    - configuration of the sensor and data acquisition system, especially the type and precision of sensors required and their configuration;
    - signal processing and interpretation;
    - work in WIT on dimensional, surface and microstructural analysis on the worked samples to aid correlation of signal data to sample data;
    - the WIT work to integrate the working prototype, a complete system with both an operator interface and a machine feedback loop;
- acting as chair of the management board, which ran the REALISM consortium, and which comprised of one participant from each SME and each research centre;
- acting as chair of the REALISM Intellectual Property committee.

This research led to four publications, with the author's role recognised by being lead author in two of these papers (*Automatic multiple sensor data acquisition system in a real-time production environment* and *Real time Monitoring of the CNC Process in a production environment- the data phase*, both published in Procedia CIRP), and as second author in the other two papers (*Human-Machine interface for Neural Network based Machine tool Process Monitoring,* also published in Procedia, and *Development of a generic tool condition monitoring validation*

Methodology, presented at the International Manufacturing Conference), all of which are included in the Appendices.

4 HMI Case study at Schivo and system validation

4.1 Human-Machine interface case study with machine operators

One element of the REALISM project was to examine the human interactions with the CNC machinery, in addition to the physical sensing of the emissions from the process. This element of the project intended to analyse how the various roles within the organisation reacted to the human/machine interface and thus determine how this could be replicated or replaced with an artificial neural network type scenario.

While this element of the thesis is somewhat secondary to the main technical thrust of the research, it is an important consideration given the fact that the fundamental question is whether humans can intuitively sense degradation of the process through physical sensing.

With this in mind, a case study was undertaken through workshops with various personnel from the machining shop floor at the company and interviews were done with personnel at various levels within the organisation to examine peoples understanding and experience of their interactions with the machinery.

It was found that in the main Schivo CNC machine floor, tool wear is regarded as the dominant factor in unacceptable production. As discussed at length, it is believed anecdotally that experienced machine operators can detect the onset of tool wear in the process from the sound of the machine, or the vibration of the machine during the operation. Indeed, the author’s first publication on audio emissions tends to support this belief, as have other investigations into audible energy sensing. However, it has been found that there is no formal structure through which this decision making is reached, other than machine operator experience, which cannot be easily passed on. This section presents a case study, based on group interviews on key personnel at Schivo and the aim is to use the learning from the key personnel to develop a TCM human-machine interface, based on the insights gained from this case study.

The Schivo shop floor organisation can be broadly divided into 3 roles: maintenance, supervisors and operators. Supervisors are highly skilled and experienced, work mainly day shifts and decide the initial cutting parameters in many cases. They typically seek the process “sweet spots”, with minimum chatter and best tool usage based on their experience. The Operators work on a varied 3- or 4-shift pattern and are less experienced than supervisors but are typically qualified to alter cutting parameters when needed (such as excessive vibration, set offsets based on detected tool wear from product measurement) and replace the cutting tool edge or cutting tool. The supervisors and operators meet at the beginning of each shift, at the end of their shift, and also during the shift in an ad hoc manner. Operators inspect each part for conformance to geometric tolerances, with some measurements being 100%, and some are as few as each 15th part.

Statistical Process Control (SPC) is applied in some cases. Tool change is a function of the number of parts / cycles machined (for example: a change after 30 parts/cycles), detection of bad cutting conditions (mainly chatter) and/or out-of-tolerance inspection results.

While detection of tool wear, effective tool life utilization and decreased tooling and quality costs leading to reduced scrap are the primary aims of all TCM systems, Schivo would also like to become less dependent on the individual operator’s skills, and, by extension, to permit the use of less experienced operators without supervision.

In the course of the study, the operators were asked if they expected any negative effects from a monitoring system, and the general answer was no. Moreover, the organisation of supervisors and operators are expected to continue as before, regarding the control of the monitoring system parameters: Supervisors should be in charge of setting the monitoring control limits and control actions in the case of "out-of-control" signal, operators are not expected to have this authority- although they will be the first line of process control.

The best results in manufacturing system design are obtained by recognising the technical and the social systems involved, in the relationships between machines, between people and between machines and people. It is in this respect that the socio-technical perspective is not only important while designing the technical system, but equally important in establishing a platform for learning and knowledge creation. Looking first at the human-human relations; the roles with direct relations to the monitoring system can be divided into four roles. Successful operation of the process monitoring system depends on the communication between these roles.

The four roles defined during this phase of the research can be defined in the following hierarchy:

- Process Expert, or manufacturing engineer.
- Maintenance personnel
- Process and production Supervisor
- Machine Operator

The expert(s) would most likely be responsible for the design of the ANN system and the installation of the sensors, in addition to the initial training of personnel. (This would typically be a resource external to the company).

The Maintenance department is responsible for Machine tool (and other equipment) technical maintenance.

The supervisor is the cutting process expert, and is responsible for cutting process design including selection of cutting tools and cutting process parameters; spindle speed, feed rate, depths of cut etc. The supervisors will be responsible for the ANN machine learning each time a new product or a process change is introduced to the parameters of an existing product.

The operators are responsible for the daily operation of the CNC machine tool, such as changing tools, inspecting workpieces, etc. and have the closest hands-on experience on the monitoring system performance. Typically, the machine tool operator will be the “first line of defence” regarding maintenance, as well as key personnel to achieve innovations and continuous improvements.

Figure 25 from Martensen, Downey *et al (2016)* illustrates the main flow of interaction across the general roles. The upper and the lower part of the figure have different time-scales. While cutting process (re)design and ANN (re)learning will occur for each new product or process upgrade, the ANN systems re-design will preferably be rare.

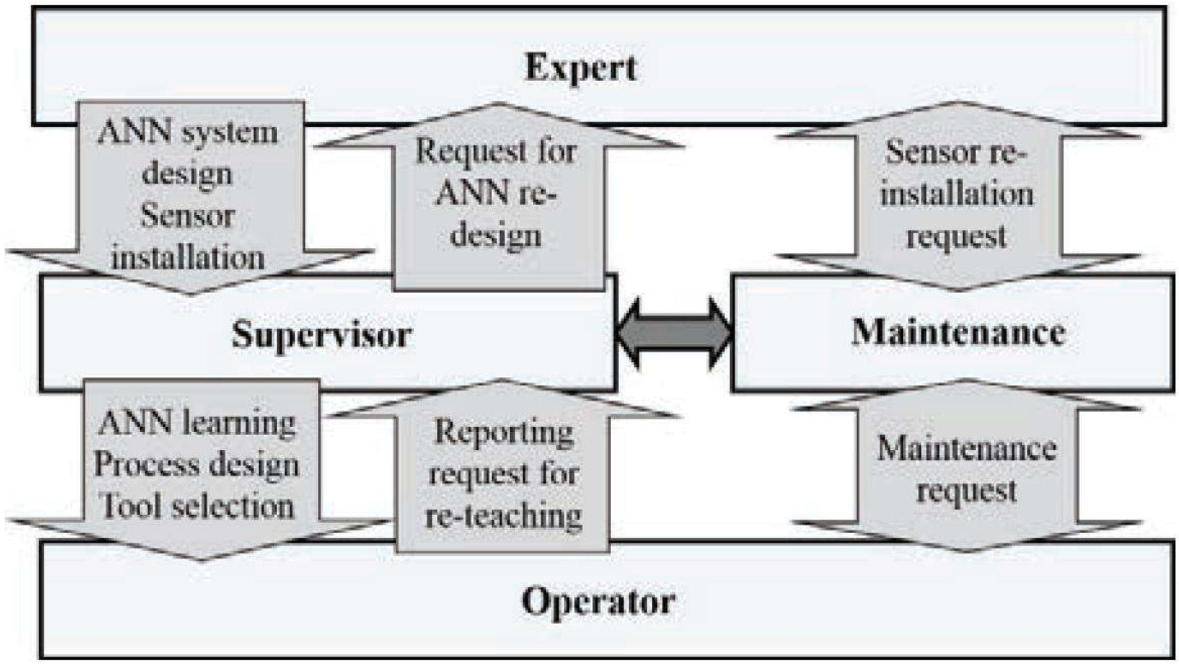


Figure 25 Interactions in an ANN-based TCM system

To comply to the needs of the different roles and the interactions between them the HMI could have the following features:

- Expert: The HMI facilitates the requirements of sensor installation, ANN design, and redesign, testing and diagnostics, as well as aiding the requirements of simple basic training of personnel. The expert might be the direct contact for an alarm event in the case of a sensor malfunction, etc.
- Maintenance: The HMI will mainly be around the output of statistics from the machine tool, vibration measurements, etc.
- Supervisor: The supervisor is required to complete the process and product data, as well as manage the ANN learning process. The HMI should also allow good communication with the operators, viewing shift/event logs.

- Operators: The operators need information on the tool condition from the HMI, and a signal /alarm regarding when to change the tool and a secondary alarm for CTF. Moreover, there should be inputs such as changing tool, workpiece changeover and any other events and anomalies worth reporting. The operator needs to communicate with the Supervisor(s) and other operators. It is an integral requirement of the system that the HMI should aid this.

The various roles and responsibilities are captured in Table 13.

Table 13 HMI roles and responsibilities

Role	HMI Input	HMI Output		HMI Com-muinication
		Push	Pull	
Expert	ANN design parameters	Sensor mal-function alarm	Performance reports	Basic trai-ning tutorials
Mainte-nance		Malfunc-tions alarm, requests from super-visors and operators	Sensor sta-tistics	Maintenance strategy
Supervisor	Process de-sign, tool selection, ANN ma-chine learn-ing parame-ters	Malfunction alarm	Shift reports, event logs, performance statistics	Tool change strategy
Operator	Tool change, product change(over) shift report, event log	Process and tool condi-tion, Change tool alarm, malfunction alarm	Performance statistics, shift reports, event logs (others and self)	Continious impro-vements

A final point is that a process monitoring system can be a tool for learning and knowledge creation. It is clear that the operator and the supervisor must be knowledgeable about the process and how different variables within the process interact, both in a practical and an abstract theoretical sense. Secondly they need to be able to make correct decisions based on analysis, knowledge, experience and skills. The interpretation ability learned through interaction with the process and the process monitoring system to decide, for example, that a tool needs to be replaced, is a single loop learning process.

A second desirable outcome would be for it to develop into a process of double loop learning, both about the process and also the monitoring system in itself. This would mean continuous improvements of the machining process and the process monitoring system requires an ability to analyse the process outputs and monitoring measurements over time. The HMI of the monitoring system should aid this analysis by making it possible to view the database of events and monitoring results. **Figure 26** illustrates how the human operator (in this case more or less all the roles mentioned previously) would interact with both the process monitoring system and the machining process, engaging a double loop learning from both. The HMI of the process monitoring system should aid this and allow the human operator to take an informed action to correct the process drift.

It should be noted at this stage that the development of the HMI and the work on the ANN and wavelet transform is at a concept stage during this research and would be intended for future work.

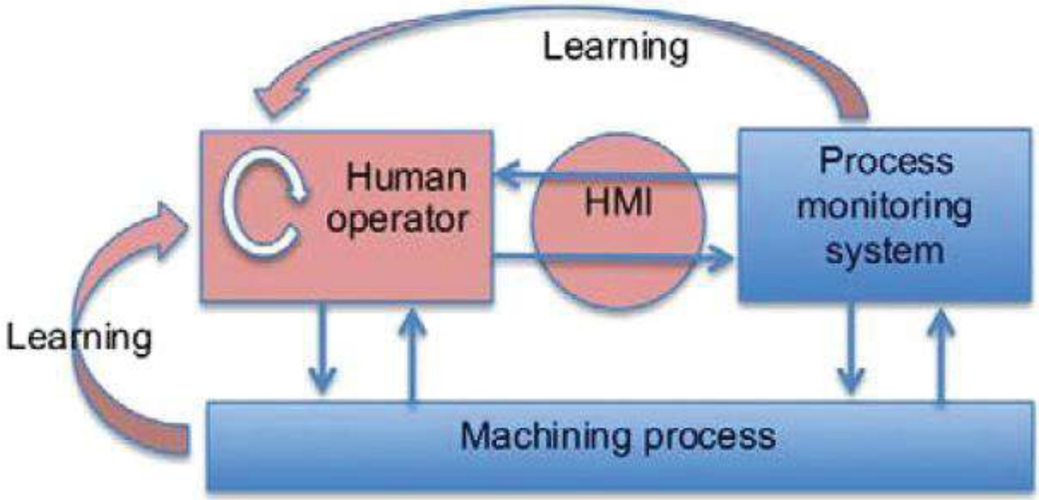


Figure 26 Control loop and knowledge creation loop

4.2 Development of a generic tool condition monitoring validation methodology

In further addition to the human machine interface research outlined in the previous section, a section of this project was devoted to the validation of the TCM system proposed.

Process validation is an ever increasingly important function within the development of manufacturing processes and operations, particularly within the high volume medical devices industry. Process validation allows examination of the stability of the process, thus resulting in statistical assurance that the process is under control rather than the traditional methods of continuous inspection. It is important that this is considered as part of a TCM system implementation.

The focus of this part of the research was on process validation design, qualification and ongoing monitoring phases and the associated regulatory requirements of Good Manufacturing Practices (GMP) validation. GMP's are enforced in different parts of world by different regulatory bodies; some of the more recognizable bodies would be U.S. Food and Drug Administration (FDA), the World Health Organization (WHO) and the European Union (EU). Validation is an essential part of GMP and the approach of bringing GMP validation techniques to Tool Condition Monitoring (TCM), in the medical devices industry, which relies heavily on validation, has received little attention in the literature. Validation involves identifying and testing all aspects of a process that could affect the final product quality/safety and demonstrating with a high degree of assurance that uniform product will be produced that meets the required quality specifications throughout the product lifecycle.

The Tool Condition Monitoring (TCM) system for this element of the research (as deployed during the REALISM project experimentation consists of a 3-axis force sensor, an acoustic emission sensor, 3-axis accelerometer, a data acquisition card, an industrial portable computer, custom Data Logging Software and custom Control Software, linked back to a Human Machine Interface (HMI). One of the unique elements of this system is the incorporation of a Case-Based Reasoning (CaBR) control system into the TCM, an area which has received little attention in literature.

Companies who pursue voluntary certification generally opt for certification to the baseline standard ISO 9001. This ISO 9001 standard and also the more specific standards of ISO 13485 (medical devices) and AS9100 (aerospace) standards all introduce the concepts of both validation and also verification, specifying that:

“The organization shall validate any processes for production and service provision, where the resulting output cannot be verified by subsequent monitoring or measurement”.

The ISO 9000:2005 standard provides definitions of such concepts and, specifically for this case, defines verification as “confirmation, through the provision of objective evidence, that specified requirements have been fulfilled” and validation as “confirmation, through the provision of objective evidence, that the requirements for a specific intended use or application have been fulfilled”.

In considering whether the output cannot be verified by subsequent monitoring or measurement, initially the prospect that the project may be classified as a special process was considered. Processes where the resulting output cannot be verified by subsequent monitoring or measurement are frequently referred to as “special processes”. ISO 9001:1994 in fact included the term “special process”, until it was superseded by the 2000 version of the standard. Thus ISO 9001:2008, clause 7.5.2, now refers to special processes as “processes requiring validation.” It’s important to note at this point that all special processes must be validated. Validation of special processes provides confidence that the process is fully understood and the output will achieve consistent results against the required specifications. In addition, within the aerospace industry, Nadcap accreditation is fast becoming a global requirement for suppliers using special processes. Nadcap accreditation is a contractual requirement, and not a mandatory AS/EN9100 requirement, and involves a stringent audit by PRIxx personnel.

Within the aerospace and oil and gas industries, 100% inspections are more frequently commonplace and sampling inspection is used less. Neither voluntary nor regulatory certification bodies offer any clear guidance on what verification actually means nor do they clearly define exactly what the term “verified” means. However, the most commonly accepted method of verification within the CNC industry is through 100% inspection. The standards stipulate that the organization shall only “validate any processes for production and service provision where the resulting output cannot be verified by subsequent monitoring or measurement”.

Verification can be thought of as a method of testing that provides assurance at a point in time that a product will do what it is intended to do without causing another problem. Validation on the other hand provides measurable evidence that over time the product will work properly suggests that in the medical devices industry process validation is generally seen as the endpoint of all validation activities, as illustrated in **Figure 27**.

Figure 27 Process Validation Funnel Diagram

Verification, through 100% inspection, is commonplace across the aerospace and the oil and gas industries. In the medical industry, this approach is usually not taken, but a lower rate of inspection, based on validations which use statistical analysis of the process.

The focus of this research has therefore been narrowed to the medical devices industry, which is mandated by Good Manufacturing Practices (GMP) and in which validation is a regulatory requirement.

The three most often referred to definitions of process validation are those presented by the European Agency for the Evaluation of Medicinal Products (EMEA), the US Food and Drug Administration (FDA) and the Pharmaceutical Inspection Co-operation Scheme (PIC/S) and that the three definitions are very similar, with the difference being that

“the FDA expresses a minor uncertainty of the concept, despite the efforts of validation, by stating that process validation only provides a high degree of (not absolute) assurance that the process will produce the intended product”.

Typically, validations are based on knowledge collected through process development activities or process experience over a period of time. Therefore, there is a body of knowledge about the process, generally in the form of statistical analysis. Verification on the other hand is completed at a point in time, i.e. Part A gets inspected followed by Part B, Part C etc. No knowledge of the process is gathered, other than the fact that each individual part passed or failed inspection. Without statistical knowledge of the process it can be difficult to have confidence in lower level statistical sampling and therefore the cost of 100% inspection needs to be absorbed into the manufacturing process. Another important point to mention is that 100% verification is also never 100% effective. For example, Juran (1935) estimated that 100% inspection was only 80% effective. However Sinclair (1979) demonstrated that not only was Juran correct in his statement that 100% inspection was not 100% effective, but even worse that he was optimistic with his estimation of 80% effectiveness. The aim of a TCM system development and deployment is to re-introduce the concept of 100% process confidence in place of validation.

In applying validation to TCM, several aspects are considered. The TCM consists of sensors, a data acquisition system, a computer, data logging software and custom control software linked back to a HMI. While systems may be rule- or knowledge-based in their decision making, here the control software incorporates a Case-Based Reasoning (CaBR) system, which requires the operator to initially teach the TCM by identifying when a pre-determined number of tools are worn. From this teaching, the TCM will compare the learned results against process conditions, gathered from the sensors, allowing the system to make decisions around the degree of tool wear present on the cutting tool.

Gupta et al (2011) proposed that “Validation of knowledge-based system has received great attention from researchers in the last several years”, that “however, the majority of the reported validation work to date has centred around rule-based systems” and that “published literature that deals with validation of Case-Based Reasoning (CaBR) systems is indeed scarce”. This will present challenges from a TCM validation perspective. Validation of the CaBR system shall establish whether an individual test case has been solved correctly through benchmarking against learned information acquired from operator expectation. Gupta suggest that this consists of determining two basic parameters, the Result Acceptability Criteria (RAC), and the System Validity Criteria (SVC). The RAC serves to determine whether an individual test case has been solved correctly by the CaBR system. It is the distance between the system solution and the benchmark standard.

The TCM has a direct impact on the quality of the product being produced, because if the TCM does not correctly interpret the process conditions there is a significant risk non-confirming product being produced or even of scrap.

The Global Harmonisation Task Force (GHTF) provides a decision tree which helps in the determination of whether a process should be validated or verified. Although a simple illustration, it provides an effective roadmap for identifying the decision as to whether to verify or validate by asking two questions: “Is the process output verifiable?” and “Is verification sufficient and cost effective?” The cost effectiveness verification is an extremely important consideration Snow et al suggests that “in many cases it may be more cost effective to validate the process upfront and to understand and control variation, thereby improving process capabilities, increasing yields and lowering scrap. This however is a business decision that needs to be taken early in the process development phase”.

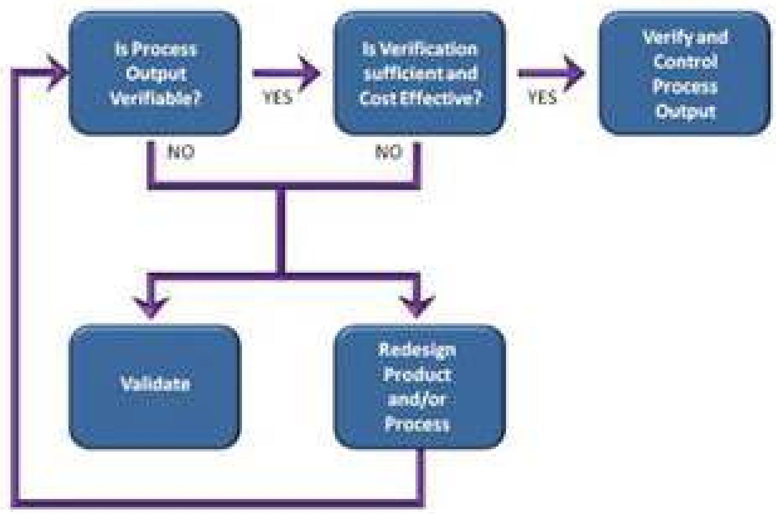


Figure 28 GHTF Process Validation Decision Tree

This research was published at the International Manufacturing Conference, with this author as second author on the paper. Inclusion of validation into the research is important from the perspective of ensuring that in the event that a tool condition monitoring system is employed, there is confidence that the system provides sufficiently robust controls over process stability, as is provided through the employment of a validation strategy.

5 Presentation of Results from Experiments

5.1 Introduction

This chapter outlines the results obtained from the experimentation activity detailed in the previous chapter. As in the previous chapter, each of the individual experiments is given a dedicated section where the sensor results are detailed, and analysis undertaken, to evaluate the success or otherwise of the experiment. As detailed in the previous section, there are a number of questions to be addressed during examination of the data collected during the experimentation phase of the research.

The experimentation phase of this research examined a variety of physical emissions from the machining operations, beginning with audible sound emissions on the Harrison lathe, then turning into a combination of audible sound energy and vibration in the initial 5-axes Röders examination, which as will be outlined in this chapter proved unsuccessful for various reasons that will be outlined.

The follow-up rerunning of this experiment bore more encouraging results, and the learnings gained from this are further expanded on in this chapter. The 2nd experiment in the Röders machine gave the author a valuable insight into the selection and locating of sensors and in many respects drove the success of the subsequent experimentation undertaken in the Mazak lathe studies.

Subsequent to this, this research was expanded during the REALISM project with the adoption of force sensing and enhanced and more technologically advanced acoustic emission and vibration sensors on the Mazak lathe in the experimentation that will also be examined in this section of the thesis.

It is the intention during the presentation of this chapter to outline to some degree how the research questions that have been posed earlier in this document have been considered during this overall research effort. As has been presented in earlier sections this research intended to investigate the potential that human detectible process emissions such as audible sound energy, vibration, force and Acoustic emissions could provide offer from the perspective of monitoring the subtractive manufacturing machining operation and thereby gleaning a real time insight into the performance and continual degradation of the operation to allow correction and mitigation against this continual, expected reduction in performance.

Additional to the known phenomena of continuous tool wear this research hoped to gain some insight into the phenomena of catastrophic tool failure experienced in the form of sudden edge breakage- resulting invariably in the complete destruction of certainly the tool, often the workpiece, and in extreme cases severe damage to the machine tool centre.

The research questions, as have been detailed, have focused on physical emissions that are generally anecdotally detectible by experienced machine operators in a machine shop, at the interface of the machine. The results that will be presented in the coming sections of this chapter examine the experiments that were undertaken in the previous section and attempt to analyse the data collected using software and technology to mimic what is believed to be the human operators intuitive examination of the equivalent data collected and analysed by them at the machining centres.

As will be described in the coming sections, while many of the experimental practices undertaken yielded positive results and even publishable outcomes, there were instances where the experimentation was unsuccessful. Encouragingly though, the unsuccessful experimental proved to be a good springboard to the next stage.

5.2 Audible sound energy in single point turning on a Harrison Lathe

As mentioned, at the conclusion of this experiment the cutting inserts were retained for later analysis. As can be seen in scanning electron microscope (SEM) images in **Figure 29** to **Figure 32**, both inserts exhibited considerable wear characteristics at the conclusion of the operations. The figures show the surface of the cutting interfaces on the inserts, before the commencement of the operations (fresh inserts, Figures 1 & 3) and after the extended cutting operations were completed (Figures 2 & 4). These images we obtained on an SEM and the approximate size of the images is 140 microns wide. The figures shown indicate the wear on the tool rake face.

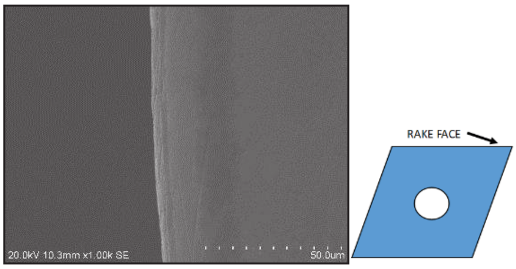


Figure 29 Unworn interface, Trial 1

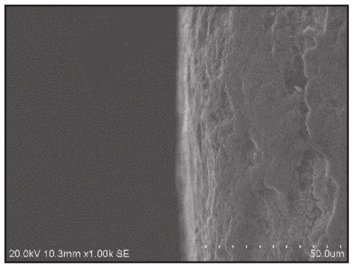


Figure 30 Worn interface, Trial 1

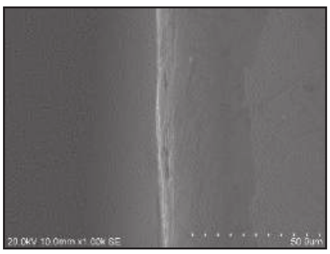


Figure 31 Unworn interface, Trial 2

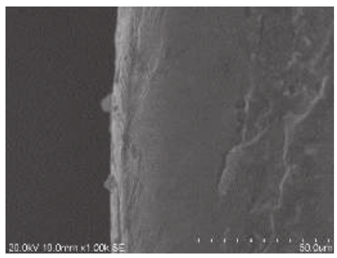


Figure 32 Worn interface, Trial 2

The analysis of the resultant data considered the following specific research questions:

- Is there a variation in the audible acoustic emission data from known good tool cutting conditions, to the emission data, where it is known that the tool is not cutting efficiently?
- Are there demonstrable correlations across a number of samples of audible acoustic emission spectra, across the range where the tool is known to be cutting effectively?
- Are there demonstrable correlations across a number of samples of audible acoustic emission spectra over the range where the tool is known to be worn and not cutting desirably?
- Are the data from the two experiments substantially similar, i.e. are the emission spectra for known good and known bad on both experimental cycles comparable in content.

A number of data sets were manually selected from the previously saved audible acoustic samples for spectral analysis. Manual selection was used in this case, but it will be apparent to the reader that this is a relatively easily automated process, although it has not been pursued in this work. For the purposes of the data analysis, it was considered that there are three phases of tool life during the full cutting operation and the first phase of the manual selection was based on these phases:

- New tool: No wear, no thermal excitation, essentially not yet “broken in”. This tool condition exists only at the commencement of cutting, and lasts for a few cutting passes;

- Normal tool condition: This is the longest phase of tool life, and is where the tool is at normal operating conditions;

- Worn tool: This is the phase where the tool has commenced the progressive wear phase and is no longer functioning desirably.

Table 14 illustrates where (in time) the samples were taken from the two experimental data sets, and how these relate to the expected phases of cutting performance

Table 14 Sample data set times and corresponding R_A values

Performance Phase	Experiment sample 1		Experiment sample 2		Sample Ref
	Sample Time	R_A	Sample Time	R_A	Number
Initial operation	47-57 sec	17µM	53-63 sec	22µM	1
	110-120 sec	24µM	130-140 sec	22µM	2
Normal operation	518-519 sec	22µM	572-582 sec	26µM	3
	713-723 sec	23µM	699-702 sec	27µM	4
	1119-1129 sec	27µM	1143-1153 sec	27µM	5
	1159-1169 sec	48µM	1166-1176 sec	36µM	6
Degraded Operation	4412-4422 sec	59µM	4374-4384 sec	50µM	7
	4415-4425 sec	84µM	4438-4448 sec	72µM	8
	4476-4486 sec	102µM	4518-4528 sec	90µM	9

It must be mentioned that, in a normal work setting, the recorded audible data can also include extraneous sources of audible energy from other actions or events on the factory floor. Many of these sources can be of short duration and should ideally not contribute to the analysis. While audio filters could be used, this would have risked excluding frequencies of interest to the wear analysis. This is one reason that relatively long, 10-second sample data sets of recorded sound were used for analysis, from each of the two experiment’s recordings. Longer data sets would have further reduced the impact of extraneous noise, but 10 seconds was reasoned to be of sufficient duration to reduce the impact on most, short-duration noise sources. This approach will not remove the impact of longer duration noise, but there do not appear to have been a sufficient number of these to impact the results.

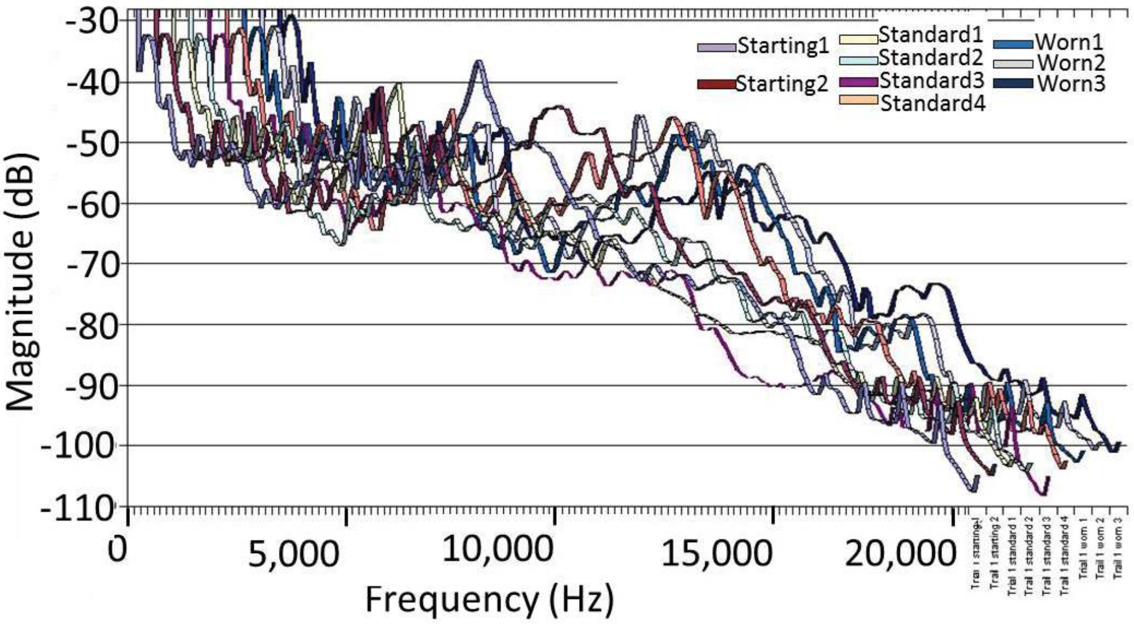


Figure 33 Sample 1, overall spectra

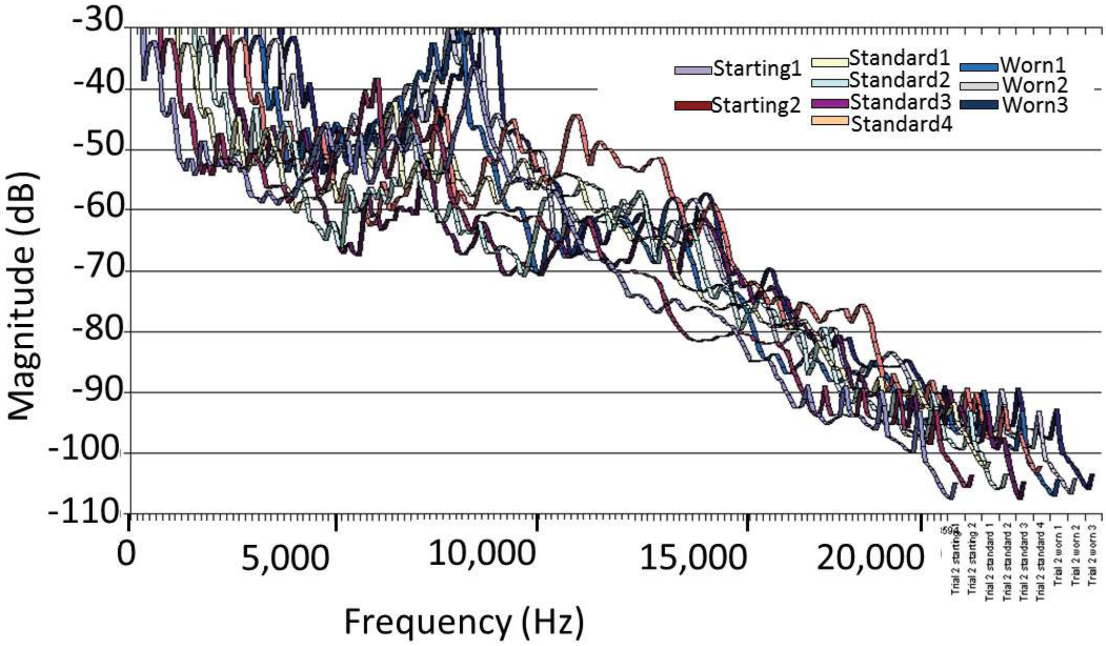


Figure 34 Sample 2, overall spectra

It is at this point that the second phase of manual selection was employed, to carefully consider the energy frequency regions of interest. It was noted through visual examination of the spectra, that there are significant changes to the energy content of frequencies in the region of 15kHz, for the recorded audio signals related to the inserts when in the worn phase, compared to the same region when the inserts are in good condition. A further examination of this region of the acoustic emission spectra for both data sets was then undertaken.

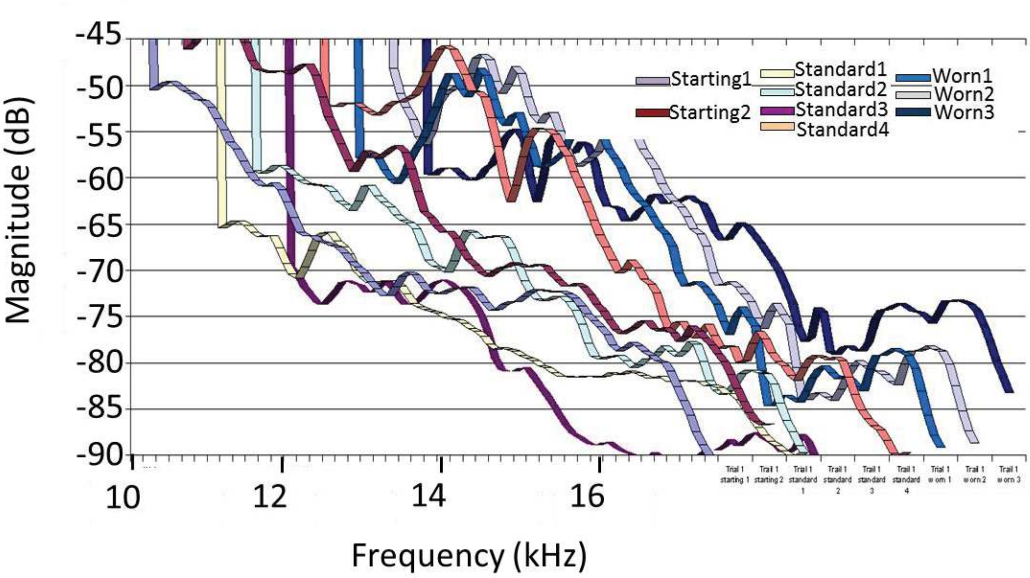


Figure 35 Trial 1, Spectral results for 10-18KHz

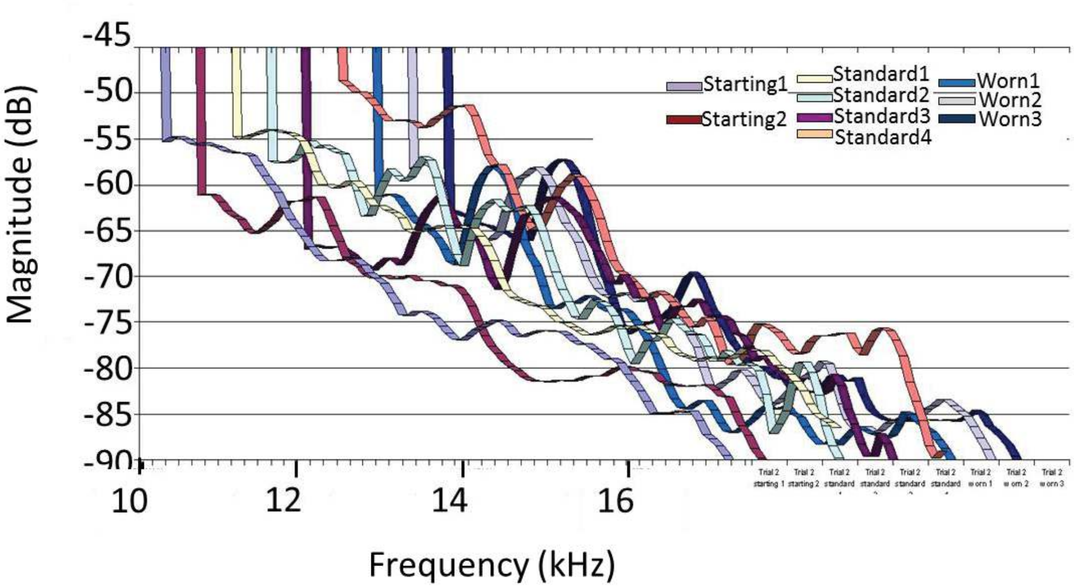
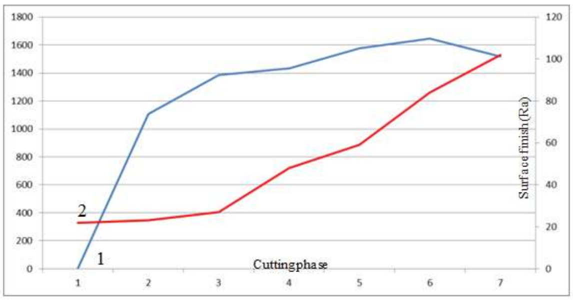


Figure 36 Trial 2, Spectral results for 10-18KHz

A simple aggregate spectral difference approach was applied to analyse frequency spectrum variations, by calculating the cumulative frequency domain amplitude differences between the start spectra and subsequent sample spectra. It was then possible to graph these differences from sample to sample, and plot the differences against the measured values of work piece surface finish, which allowed a correlation between the known degree of tool degradation and the differences between each adjacent audio sample, which gave the results for both Trials, shown in **Figure 37** and **Figure 38**. In both figures the red line is measured roughness and the blue line is spectral difference.



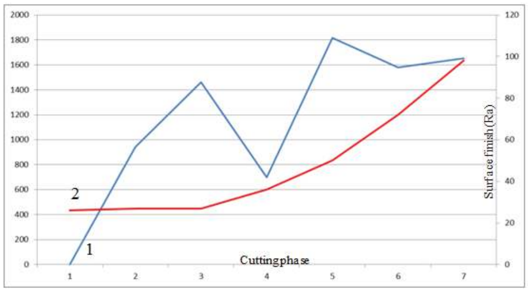


Figure 37 Spectral differences for samples against T1STD1

Figure 38 Spectral differences for samples against T2STD2

In the above figures, T1STD1 refers to the recording section taken at the start of experiment sample 1, while T2STD2 is the recording section taken at the start of experiment sample 2.

The experiment suggested that there is demonstrable relationship between the degree of tool wear, and measurable characteristics of the emitted sound energy from the process, which has been anecdotally known in the precision engineering industry, with experienced machinists appearing capable of discerning a good process from a bad one through the sound detected.

This finding is interesting for another reason. Not all operators can discern a wearing tool by listening to the cutting process. The reason for this may simply be hearing frequency range. For a healthy young person the hearing range extends up to 20kHz. However, this upper limit diminishes with age, with the rate and amount of diminution varying from person-to-person. For a middle-aged adult, the upper frequency limit for hearing is about 14kHz. It may be assumed therefore that not all operators can discern variations in the audible energy content of frequencies in the region of 15kHz.

4.3 Results from Röders 5-axes 1st experiment

This experiment was the first attempt to combine audio, accelerometer and vibration piezoelectric sensors and, although some useful experience was gained in logging multiple sensor signals and in analysis of the different kinds of resultant data, it was ultimately mainly a chastening lesson in careful sensor location selection.

It was known at the outset of this experiment that the tool would be significantly worn, as the machining cycle was roughing titanium and the resultant surface quality was unimportant, as the final finishing cycle would give the desired finish and accuracy. As can be seen in the photographs in **Figure 39** to **Figure 42**, the tool experienced considerable wear.

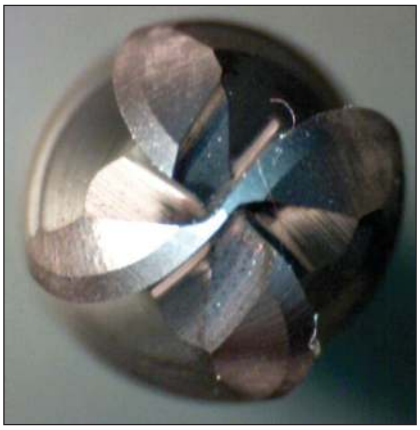


Figure 39 New tool- front view 50X

Figure 40 Worn tool- front view 50X

Figure 41 New tool- side view 50X

Figure 42 Worn tool- side view 50X

As the sensor signals comprised both real-time sound recordings and LabVIEW-acquired vibration data, there were two distinct data sets for analysis. However, unlike the previous experiment, the progressive degree of tool wear during the machining cycle was unknown, as the tool condition was only measurable at the start and finish.

A number of approaches were tried to glean valuable information from the data obtained, however it proved difficult to find any pattern in either the data from the microphone or the data recorded from the accelerometer.

Taking the audible recordings detected from the microphone and analysing them in the Audacity® software package, showed that the data quality was poor. The two piezoelectric sensors did not provide any useful data that could be correlated with the performance of the process. There was some potentially worthwhile information within the vibration data, but on its own it really didn’t amount for much.

Figure 43 is a screen shot of the sound energy data in *audacity*, and as can be seen although the machine is actively cutting in the period shown, the recorded data is quite flat, although the process audible energy was clearly varying, for anyone within earshot.

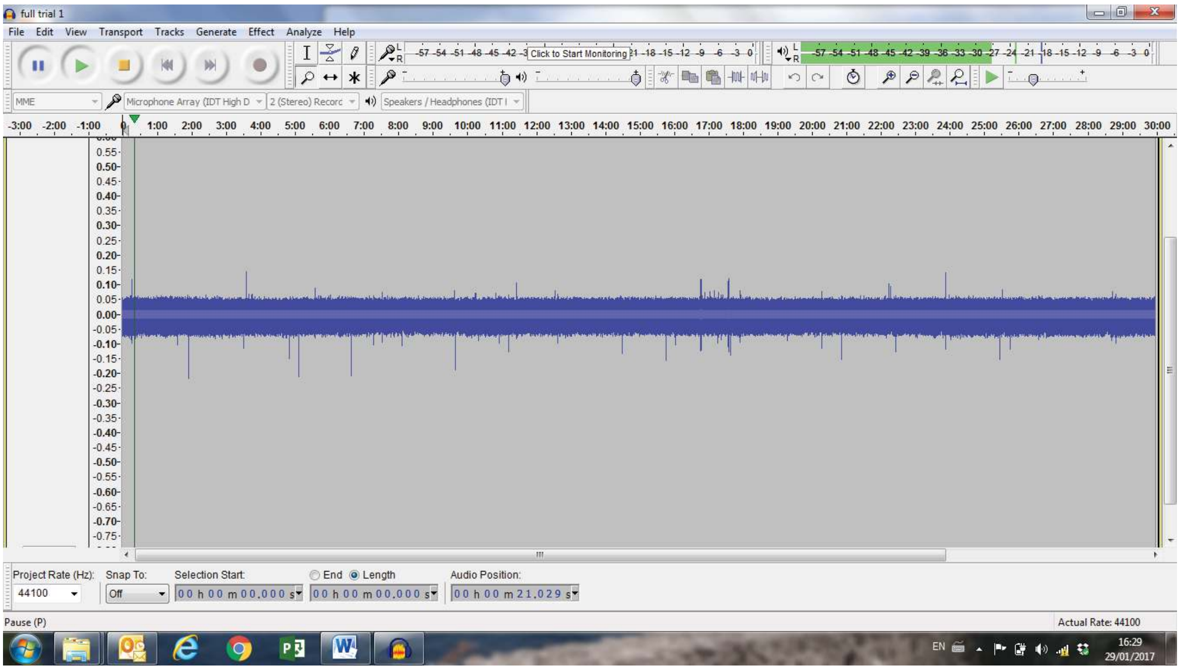


Figure 43 Sound energy from the Röders experiment

This is the type of data from the microphone that is observed at all periods of the machining cycle. Analysis of this data through spectral breakout and comparison between start (optimal cutting) middle (standard cutting) and end (worn cutting) showed no discernible differences.

The analysis parameters employed were a sampling rate of 44kHz, using a Hanning window function, and as can be seen from the below graph there is very little variability between the three signals when the spectral breakout is performed.

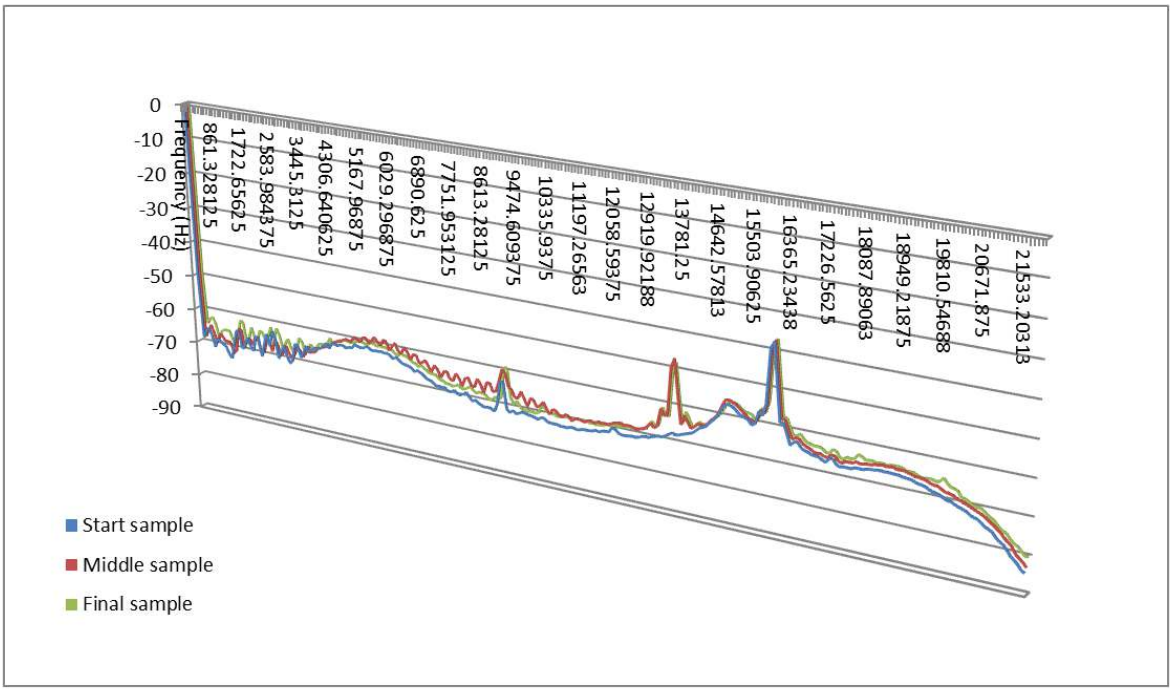


Figure 44 Spectral analysis of Röders' sound energy, start middle and end

The graph in **Figure 44** is intended as a basic demonstration of the lack of value of the sound energy emissions that were obtained during this experiment. Exhaustive attempts were made to glean useful information from the data, including identifying areas of the recording that exhibited some peak level of data, but ultimately it was not possible to find a pattern in the signals between known good cutting and known worn cutting.

The author believes that there may be a number of reasons for the poor quality audio data, but that the dominant reason was microphone location. This was the first of a number of lessons learned in terms of carefully choosing the location of sensors. Ultimately, the lessons learned proved of immense value to European partners in advising them when selecting the sensor positions on commercial machines, for the REALISM project.

In this particular case, there are a number of reasons that the microphone location was unsuitable. Affixing the microphone to the spindle body was good for proximity to the cutting energy emissions, but also exposed the microphone to the vibration of the spindle. Thus the microphone mechanism was detecting both air excitations (sound energy) and also surface vibrations. Therefore the audible energy had vibration data being misinterpreted as sound energy, in most instances saturating the microphone.

The signals from the three vibration sensors had, as detailed earlier, been collected separately using a National instruments DAQ and a bespoke LabVIEW VI. Analysis was also undertaken on these signals using LabVIEW Diadem software. Again, there was no discernible pattern detected from the accelerometer, and while a glimmer of pattern was detected from the two piezo vibration sensors it is now apparent that these sensors were fitted to areas of the machine that were very remote from the actual cutting interface. For future reference, such a deployment can be largely discounted as a viable indicator of tool wear, other than to mention that these sensor signals can be used to indicate the overall level of vibration experienced by the machine, as the tool becomes progressively worn.

A full data set recorded at 1000 points/sec on 3 sensors, Accelerometer, Vibration sensor 1 and Vibration sensor 2. Using LabVIEW DIAdem data analysis software a FFT (Fast Fourier Transform) was performed on 20 seconds of data every 30 minutes over the full process (which lasted for 3.5 hrs approximately). The FFTs were inspected to identify possible changes in energy content over the entire frequency range. The frequency ranges of interest were identified and peaks were then integrated to obtain a single scale value in order to determine the nature of change. The integral values were plotted for analysis. Each sensor data set was analysed and possible significant peak changes were found in the vibration sensors, while no discernible patterns could be identified in the accelerometer data.

It appears from the data that the vibration sensors 1 and 2 show an increase in terms of vibrational energy over time in the frequency range of 262 to 268 Hz (FFTs).

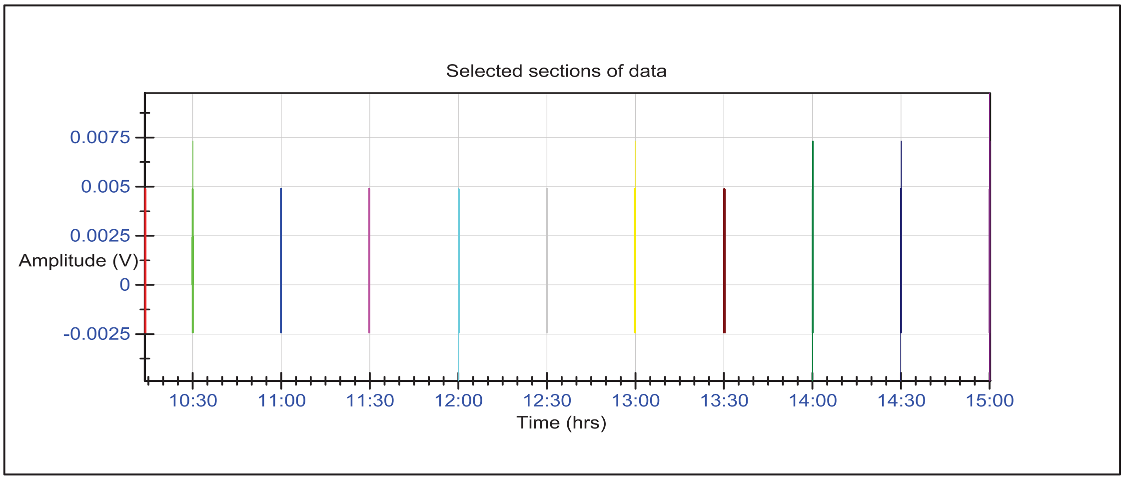


Figure 45 Selected sections of data signals

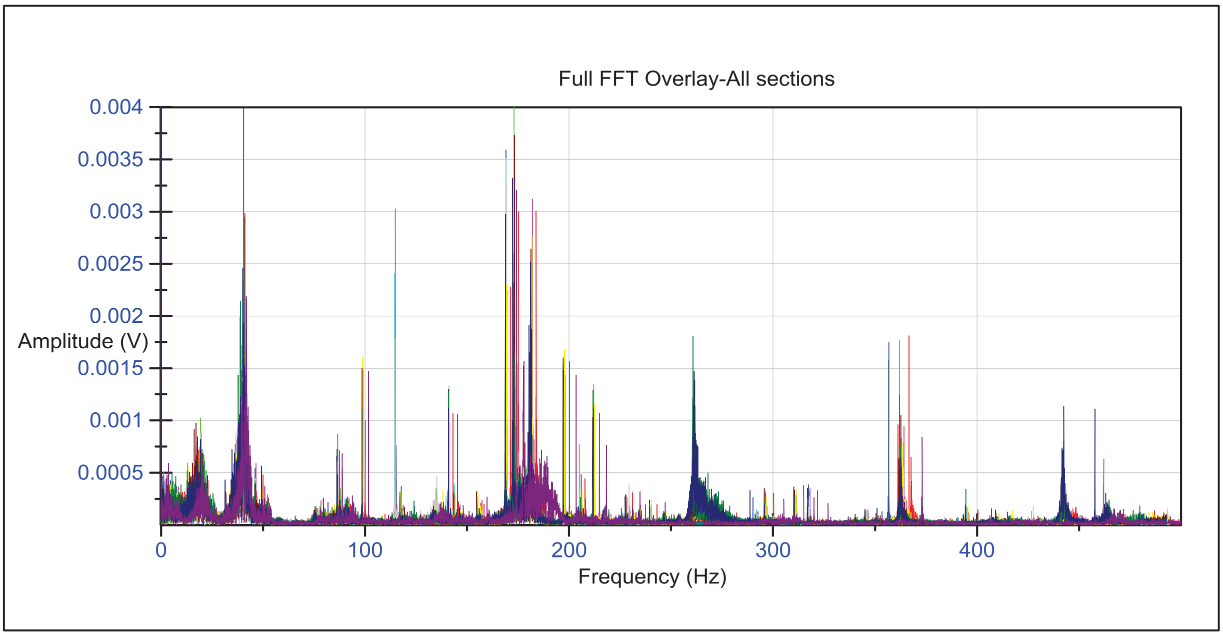


Figure 46 Full FFT spectrum overlay of all sections (vibration sensor 1).

Figure 46 shows the entire range of energy concentrations over the duration of the experience, as sensed by the vibration sensors. It is clear that over the acquisition period, the sensors do acquire a rich source of energy at distinct frequencies. The question of course then arises: if instead of integrating over all of the experiment time, instead discrete intervals, of relevance to the tool state, are analysed, then are the concentrations of energy the same and, even if so, are the ratios of each of the frequencies concentrations with respect to other frequencies changing in any useful way?

It is clear from **Figure 47** below that the individual frequency energy content does vary by cutting stage, for the recorded vibration signals. The graphs are indistinguishable in this form and are presented thus, simply to show the variation in energy in this frequency region for each of the recorded times. **Figure 48** presents a more easily understood interpretation of the energy.

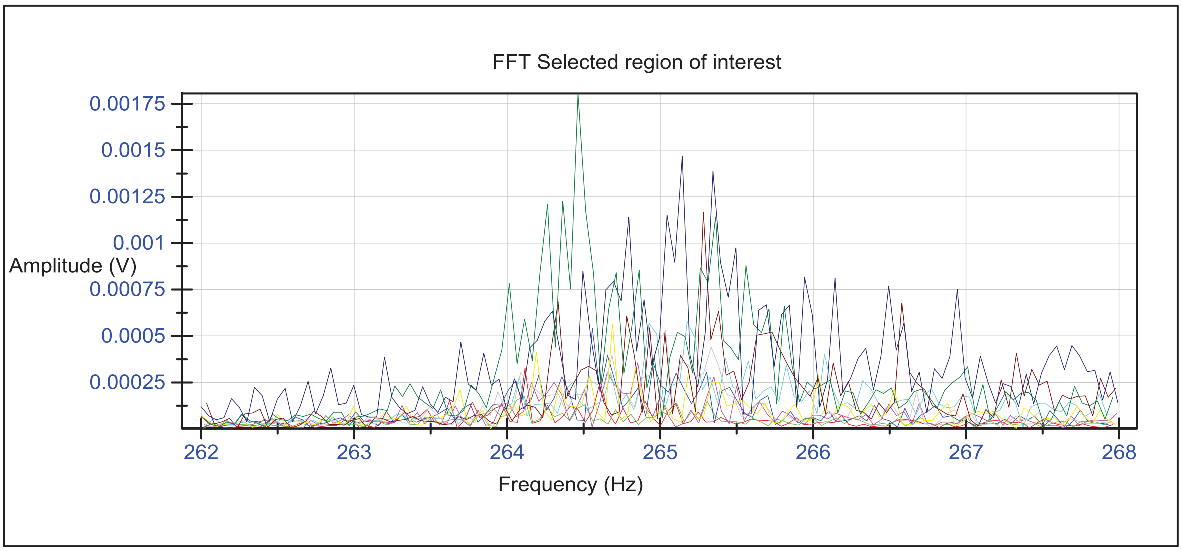


Figure 47 FFT selected region of interest (vibration sensor 1).

One of the most easily detected variations in any machining signal, as the tool wears, is the increase in energy going into implicit indicators of wear, such as vibration, sound, heat, etc. A quick examination of **Figure 48**, shows this is indeed the case for the first vibration sensor, where the total vibration energy (integration of the recorded curve in **Figure 47**) changes dramatically from time interval 7 onwards.

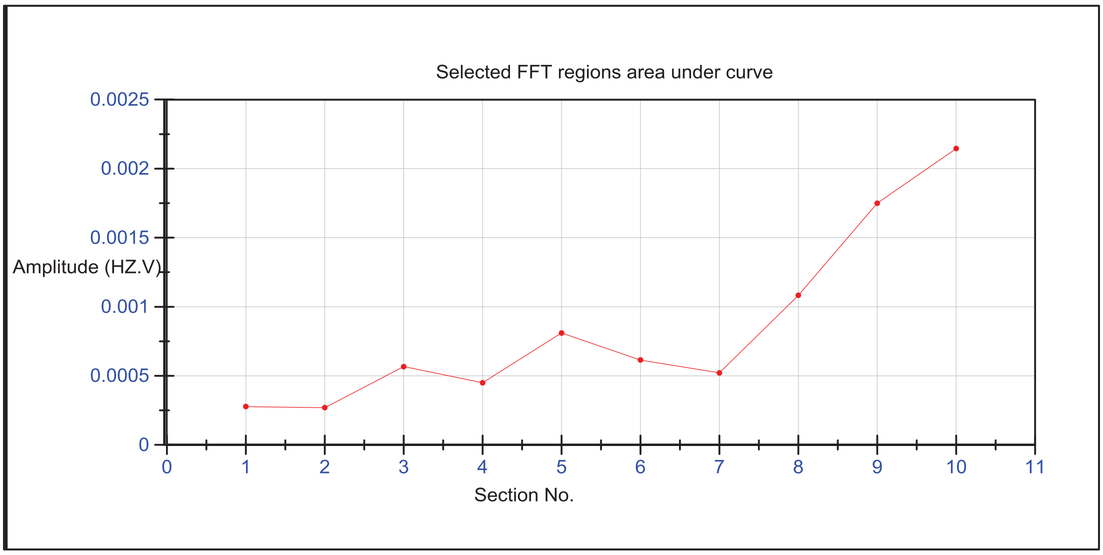


Figure 48 Integral values of each curve (vibration sensor 1).

In the above Figure 25 the section numbers on the x-axes refer to the samples taken at half hour intervals as presented in Figure 22 above. The second vibration sensor tends to confirm the analysis from the first, with a similar set of curves and integrated energy, shown in **Figure 49** and **Figure 50**. Once again in **Figure 49**, the graphs are indistinguishable in this form and are presented thus, simply to show the variation in energy in this frequency region for each of the recorded times. **Figure 50** presents a more easily understood interpretation of the energy.

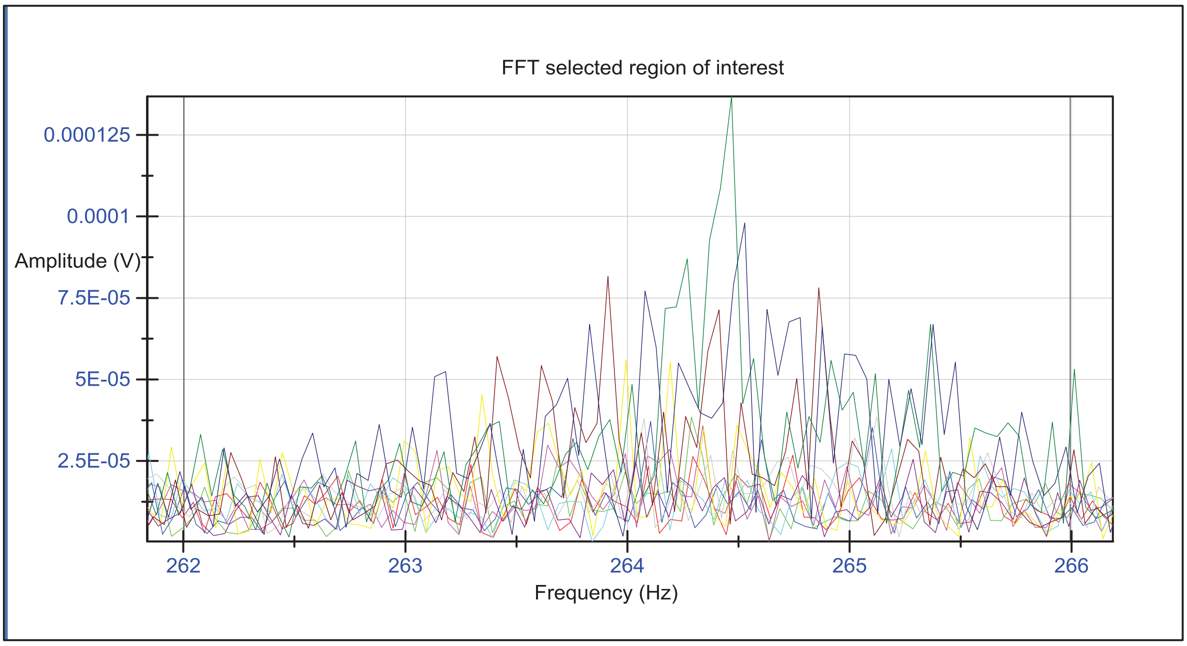


Figure 49 FFT selected region of interest (vibration sensor 2).

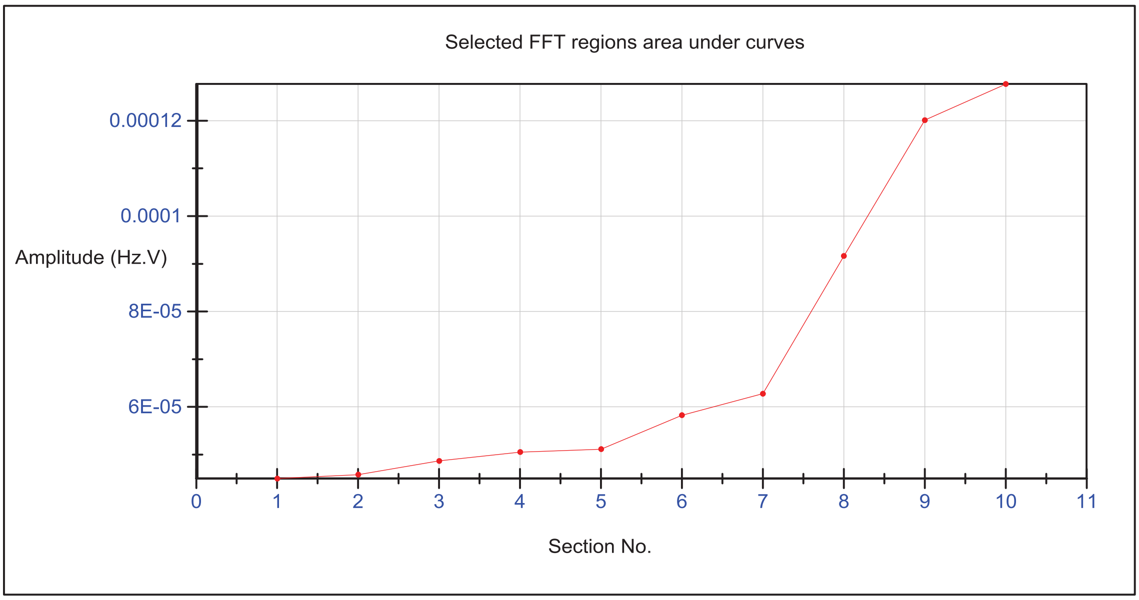


Figure 50 Integral values of each curve (vibration sensor 2).

On the basis of all the above presented data, it is safe to conclude that this sensor configuration did not work, as well as anticipated, although an apparent pattern was seen in the piezo vibration sensors. However, overall this is only a measure of the degree of vibration being experienced in the machine structure, as tool wear progresses and may not be a sufficiently accurate indication of the actual onset of cutting performance degradation.

5.4 The importance of sensor locations and installation methodology

The experience and insight gained from the first Röders' experiment proved to be of lasting benefit in this research. One of the biggest challenges encountered through the years of research into sensor monitoring of CNC machine operations, is the location of the sensing unit in relation to the physical emissions, and the method used to locate the sensor. The first experiment undertaken on the Röders machine served as a perfect representation of how the sensor locations and installations can make the difference between success and failure. In this instance the microphone was too far from the cutting interface and was picking up vibration from the main spindle body. Likewise, the accelerometer was not ideally mounted to the spindle body, and may even have been mounted in a manner to compromise the signal being detected, through a sensor loading error, where the sensor itself may have had an damping effect on the signal being detected.

In the earlier experiment on the Harrison lathe, the sensor location was ideal as it was separately mounted from the machine but was also extremely close to the cutting interface. This setup contributed greatly to the success of this experiment. However, in a normal production environment, it is not usually feasible for the sensor to be located in such close proximity to the cutting zone, because of issues such as cutting fluid interference, feed cable snarl-ups, etc.

Thus, the challenge from a sensor location and deployment perspective is to strike a balance between the sensitivity and robustness requirements of the sensor and the physical requirements of the system under test. This was a challenge that was encountered with each of the sensors deployments on factory floor machines during this research, and none more so than during the planning of the installation of the sensors on the Mazak lathe during the REALISM project. There was a lengthy discussion with the European partners, as to where each sensor and especially the embedded force sensor, should be located.

One of the European partners had a lot of experience working with force sensors and felt the best location was immediately under the turret slideway on the Mazak lathe machine body. Based on his experience and insight, the author believed that the action of the turret moving would skew the results and contaminate the data from the sensor and eventually persuaded the partners to embed the sensor into the main machine cast housing, where the data received gave an excellent insight into the forces within the machine at the onset of a catastrophic tool breakage condition, as will be presented later in this work.

In the next section of this chapter, it will be shown that the rerunning of the Röders experiment, with revised sensor configurations and locations- based on the learnings from the 1st iteration- clearly demonstrate the importance of using the correct sensors, in a carefully selected location, according to the criteria of best sensing, but minimal interference with the operation of the machine. While advanced data analysis and mining techniques are an excellent and advancing tool in this type of research, starting with high quality physical data is a most important aspect.

The success of sensor deployment can be further enhanced with some upfront consideration of the data-transmission path. For example, if audible sound energy is to be sensed, consideration should be given to any element of the transmission path that can be susceptible to noise, leading to contamination of all or some component of the sound signal. Or, for example, noise pickup through induced vibration can also add interference. Also, is the microphone deployed in a manner that allows the fundamental physics of the sensor work. The author believes that both these failure conditions were present in the initial Röders microphone deployment.

Similarly, there are transmission pathway considerations to be factored when deploying an acoustic emission sensor. In this case, a continuous physical connection must be maintained between the cutting interface and the sensor- this signal will be lost, if it is expected to travel through air or liquid, such as cutting fluid. Also, it is likely that the intensity of the transient elastic wave will decrease over longer transmission paths.

The location of a vibration sensor also requires considerable consideration during the design of the deployment and installation. This author made what was with hindsight a very fundamental error in locating the piezoelectric sensors internally to the machine panels. These panels are subject to general vibration that is caused by multiple machine activities that have no relationship to cutting performance or degradation.

A common sense review of transmission paths for physical phenomena is the best approach to good sensor locations. The two fundamental questions to be asked are: Is the location an area that will be subject to the phenomena being sensed from the cutting interface, and is there a potential for external, unrelated phenomena to interfere with the sensed signal or otherwise skew the data?

5.5 Results from 2nd Röders 5-axes experiment with sound energy and vibration

The results obtained from the microphone and accelerometer in the 2nd iteration of the 5-axes machining experiment were significantly improved than those seen during the first attempt, with better sensor locations and configurations in each case (the microphone was hung freely at the top of the machine bay, as shown in the photos in Chapter 3 and the accelerometer was bolted tight to the spindle housing).

As detailed in Section 0, the main reasons for failure of the first experiment was poor sensor configuration in terms of both the sensor type and the location and method of fixation. All of these issues were addressed and the lessons learned were of benefit later during the sensor deployment in the REALISM project on the Mazak lathe.

Once again, signal analysis was performed at a number of points from the two sets of data, captured using both the *picolog* and *audacity* software. The full datasets comprised of the following:

Table 15 Experimentation duration for the 2nd Röders 5-axes experiment

Trial	Duration
Trial 1, 21 Jan 2017	2hr 2 minutes
Trial 2, 22 Jan 2017	2hr 14 minutes

In this instance five snapshots were taken of data across the full tool life from the data, the snapshots represented 5 second durations, at the times indicated in **Table 16**, for both the sound energy and the vibration data.

Table 16 Sound and vibrations sample times on the 2nd Röders experiment

Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
3 Minutes	25 minutes	1h 20 minutes	1h 45 Minutes	2 h

As with previous sound energy analysis it was possible to undertake a spectral breakout of the data from both trials, this is shown in **Figure 51** and in **Figure 52**.

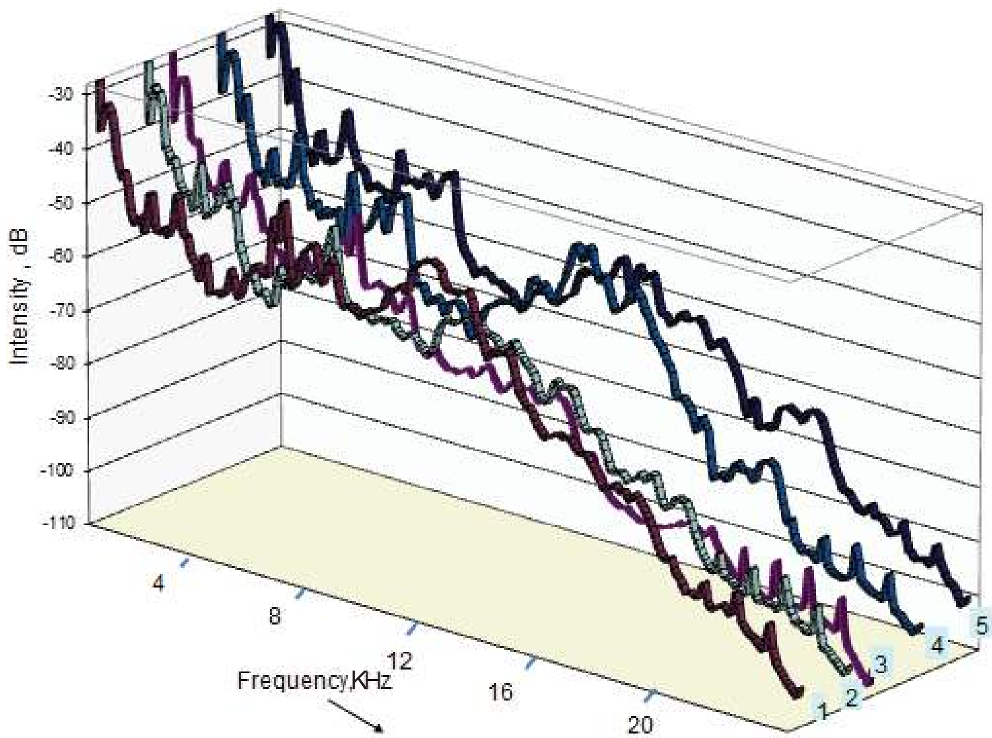


Figure 51 Spectral breakout, Trial 1

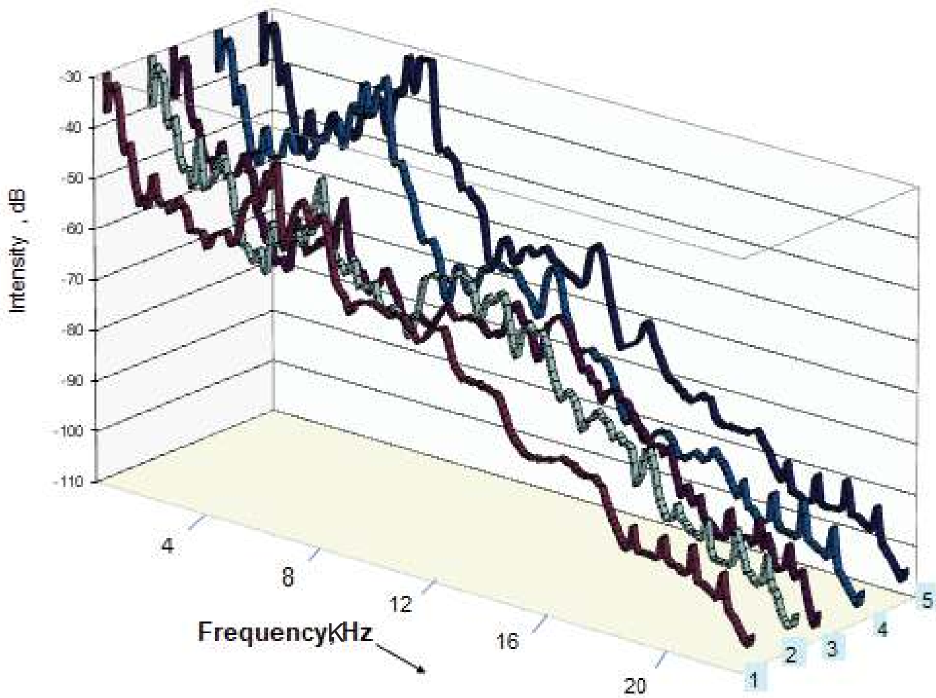


Figure 52 Spectral Breakout, Trial 2

It is clear even from visual inspection, that the energy changes quite a lot as the trials progress, with the most marked changes appearing in the range 8-18kHz. However, a less visible, but more useful change occurs for both trials in the 3-5.5kHz range. In the 8-18kHz region the change could be of use, where an intelligent system or operator is not looking exclusively for a simple pattern and is prepared to characterise the process variation in a more nuanced manner. In the 3-5.5kHz case however, the variation is easier to follow, as can be seen in **Figure 53** and **Figure 54**.

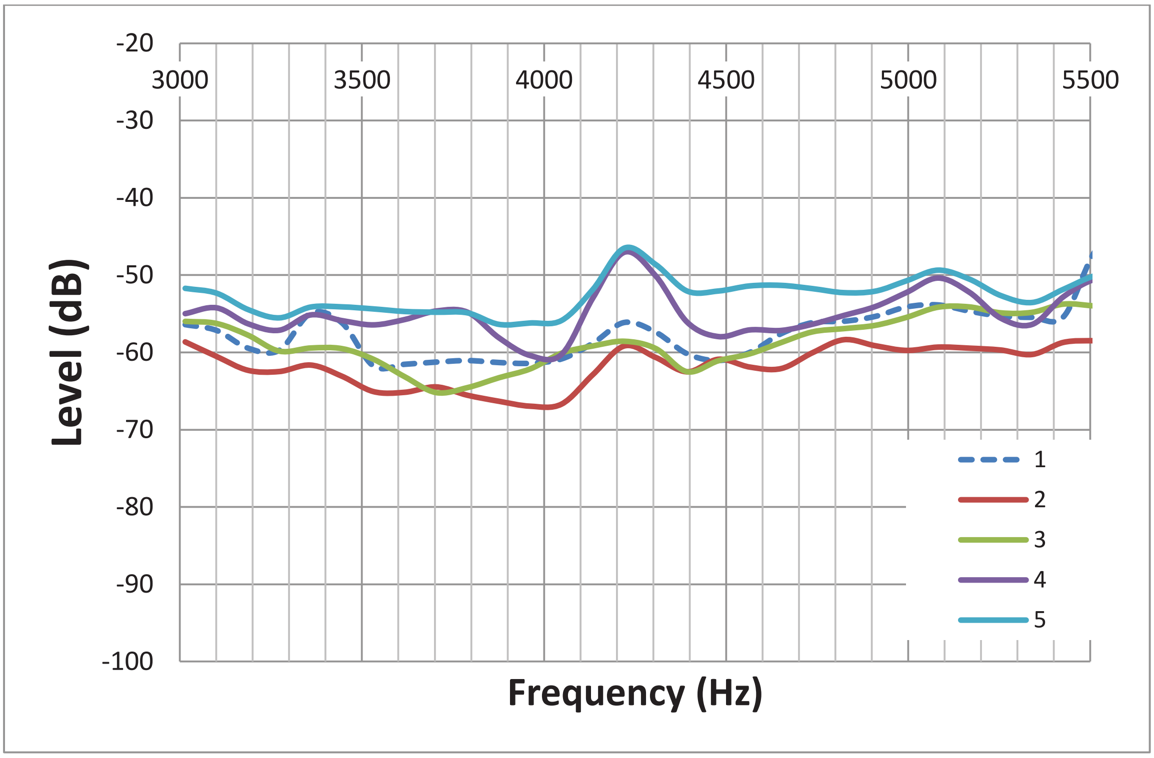


Figure 53 Trial 1 audio spectrum in the region 3-5.5kHz

Consider the graph shown in **Figure 53**, for example. In this 3-5.5kHz band, there is a reduction in the sound between the first sample and the second and third samples (the 25th minute and 1h 20th minute samples are quieter in this band than the initial 3rd minute sample). However, as the tool wears (samples 4 and 5, at 1h 45 minutes and at 2h), there is a marked increase in the energy in this frequency band. The same is the case for the second trial, shown in **Figure 54**.

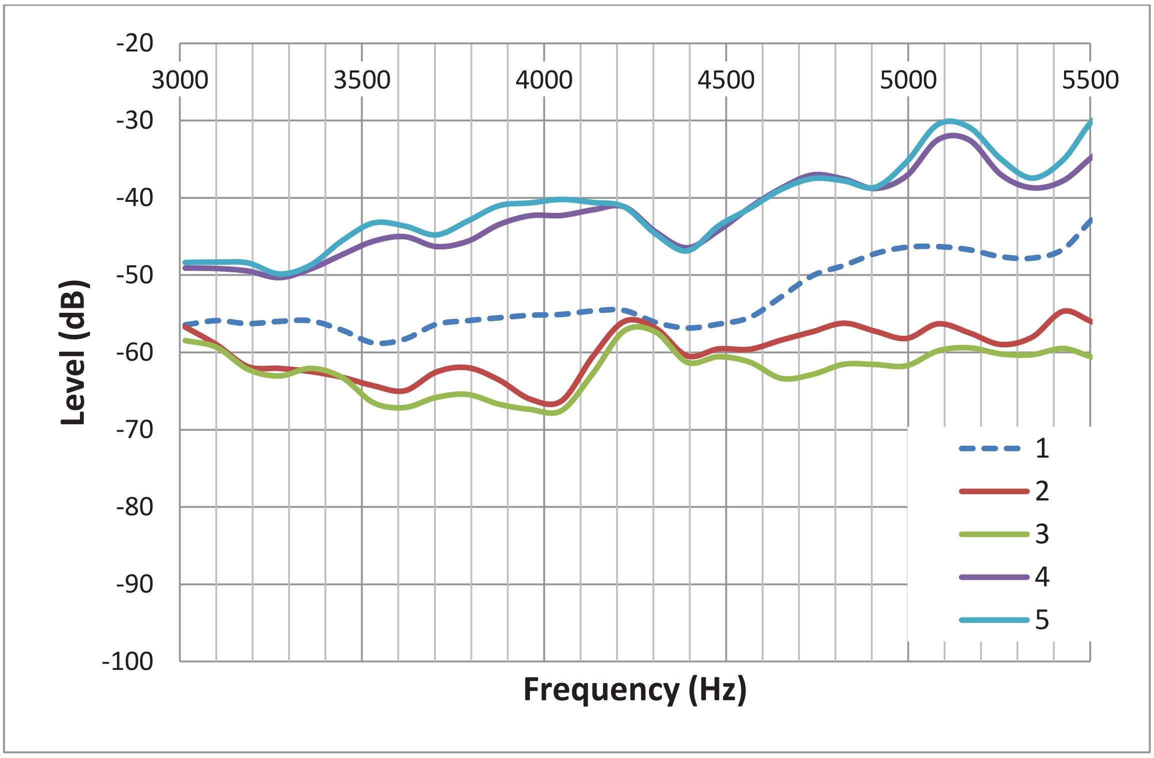


Figure 54 Trial 2 audio spectrum in the region 3-5.5kHz

In the case of the accelerometer measuring experimental vibrations, the time domain results across the 5 sampled points are shown in **Figure 55**. In this case, the variation in the average vibration between successive samples is plotted. This shows very little difference between successive samples, until the final worn sample (sample 5, after 2h), where the only change of any significance occurs. This simple analysis underlines the value of the accelerometer (and the measurement of machine vibrations) in anticipating the point when Catastrophic Tool Failure (CTF) will occur. This concept was explored in great detail in a subsequent experiment on a Mazak Nexus lathe, with European partners, and will be described in section 0.

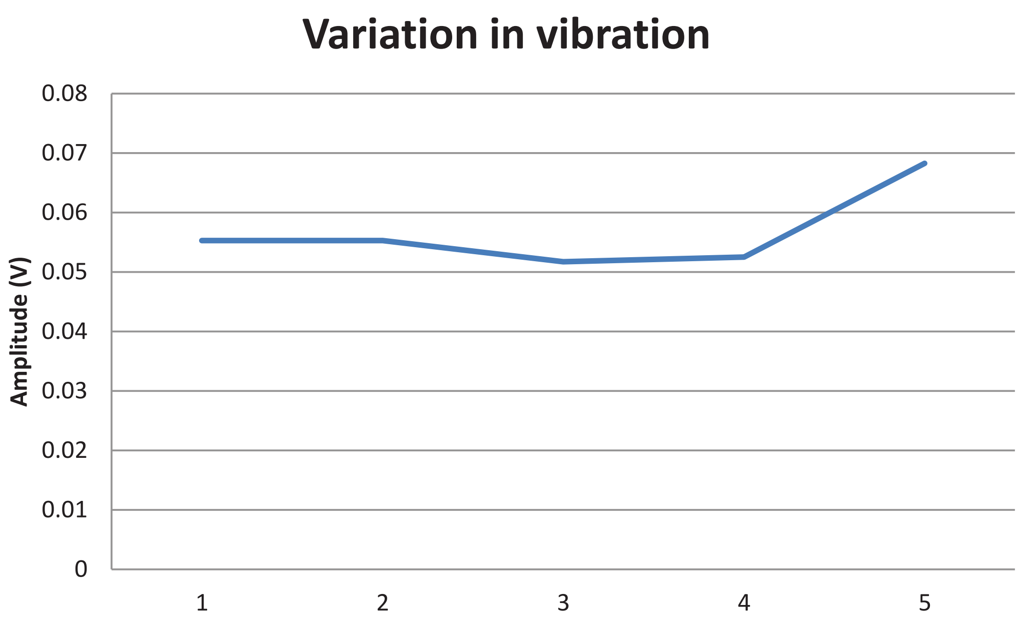


Figure 55 Progression of vibration sensor data

However, the true worth of the accelerometer data was found, once it had been transformed into its frequency domain equivalent. The data had been sampled at sampling periods of 1msec, so the sampling frequency was 1kHz. The first indication of the merit of transforming can be seen in **Figure 56**.

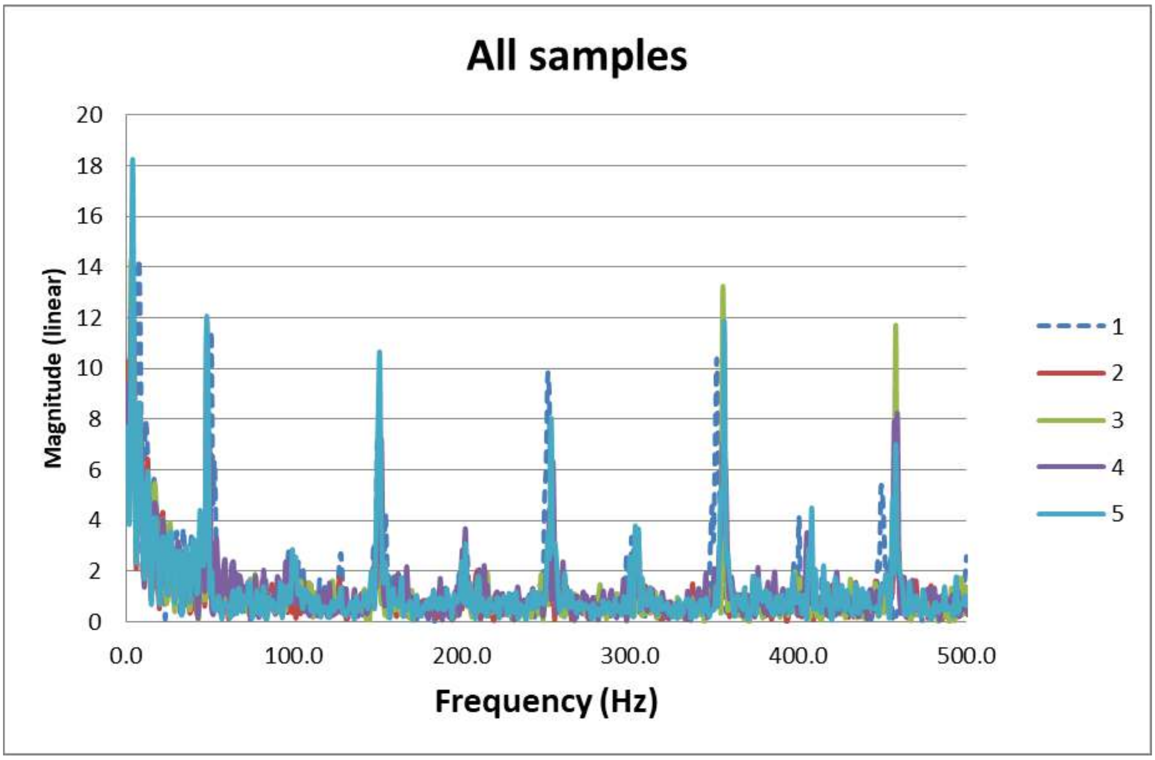


Figure 56 Frequency domain representation of all samples' vibration data

While it is difficult to distinguish differences between each of the samples from this graph, it is clear that the energy is concentrated in a small number of frequency bins. This makes analysis of the data and, in particular characterisation of the stages, a little more straightforward.

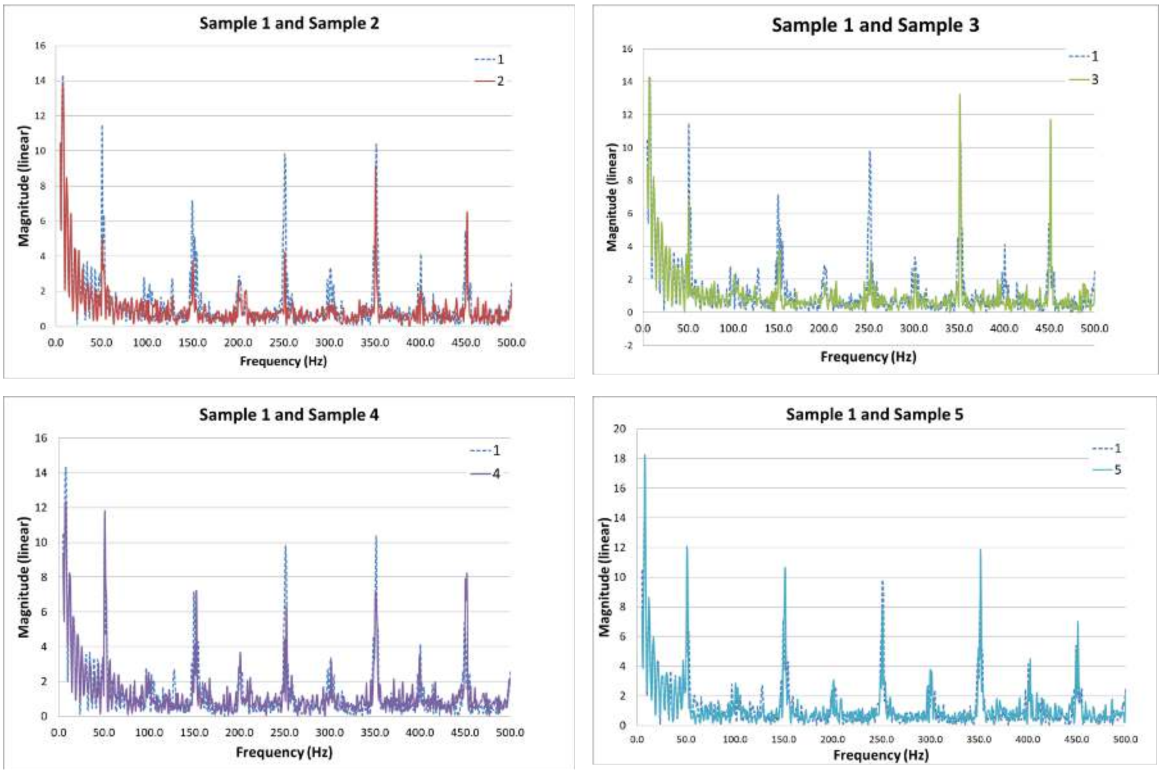


Figure 57 Frequency domain representation of all samples' vibration data

This is in marked contrast to the time domain data, where very little difference was noticed between the first 4 samples. Consider, for example, only one frequency bin, at approximately 250 Hz. Samples 2, 3, 4 and 5 have magnitudes of 42%, 35%, 63% and 100% of the magnitude at Sample 1. **Figure 58** highlights how the samples differ from the first sample (taken after 3 minutes). The second and third samples differ at higher frequencies (most visible at approximately 350 and 460Hz), whereas the fourth and final samples differ more at lower frequencies.

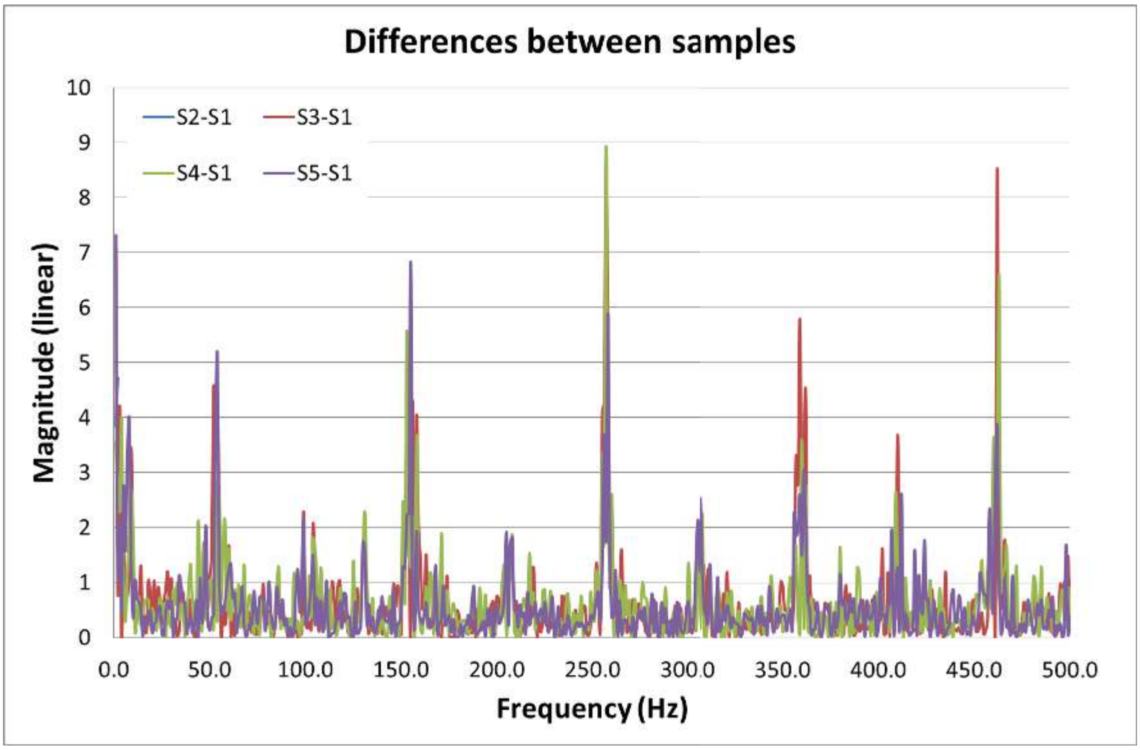


Figure 58 Frequency domain differences between samples' vibration data

The rerunning of this experiment provided a number of interesting insights into both why the initial experiment failed, but also built nicely on the initial experimentation undertaken on the Harrison lathe. This experiment, using a traditional microphone, appears to bear out the theory that audible sound energy is a good indicator of the degree to which a tool is wearing.

The results from the accelerometer also show drift, when the sensor is appropriately located and fixed, over the life of the tool.

The experimentation undertaken during both experiments on the Röders 5-axes configuration, as was known at the outset, would not allow comparison between some measure of the degree of tool wear (e.g. surface finish) and the sensor signals detected. However it was a good way of examining the sensor signal changes over the course of what is known to be an extended tool wearing cycle.

5.6 Results from Mazak Nexus lathe

Once the sensors on the Mazak lathe were confirmed operational, a number of preliminary cutting tests were then undertaken to verify the content of the signal data as detected by the LabVIEW VI.

The chuck was loaded with a billet of 316SS, with a starting diameter of 57mm and at a surface speed of 100m/min and a federate of 0.225mm/rev, took a number of passes at depths of 1-6mm with both a new and a worn Sandvik Carbide WNMG cutter.

Figure 59 shows the results obtained for the force sensor, for each of the axes.

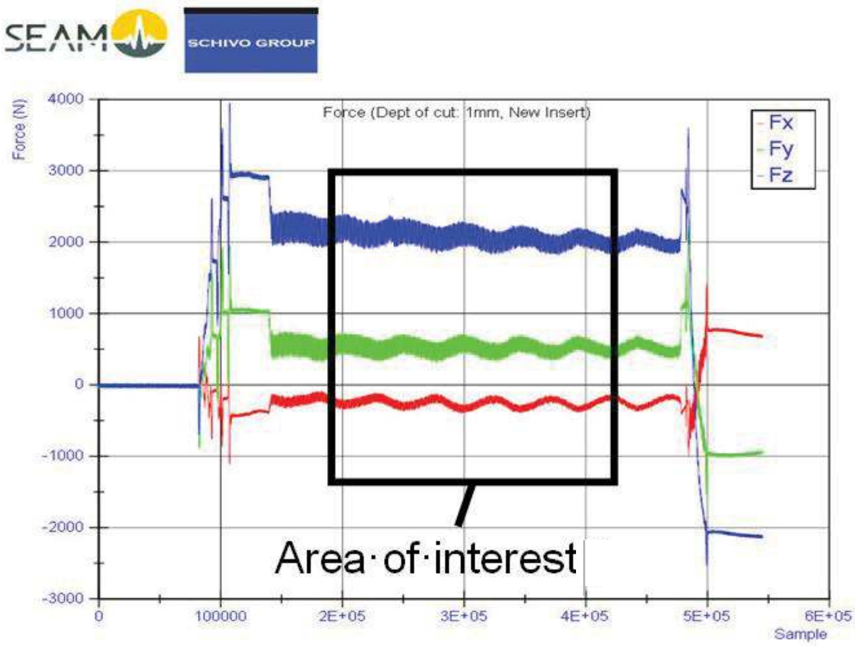


Figure 59 Force sensor results for each axis, 1mm cut, and area of interest

The graphs in **Figure 60** to **Figure 62**, for force in each of the sensors axes, show the forces experienced at various depths of cut for a new insert (red line), the worn insert (green line) and also force experienced in that axes, while no cutting is occurring (blue line). While it would be possible to use the no cutting line as a datum in the graphs from **Figure 60** to **Figure 66**, the author feels that the results are easily understood, so this was not done in this case.

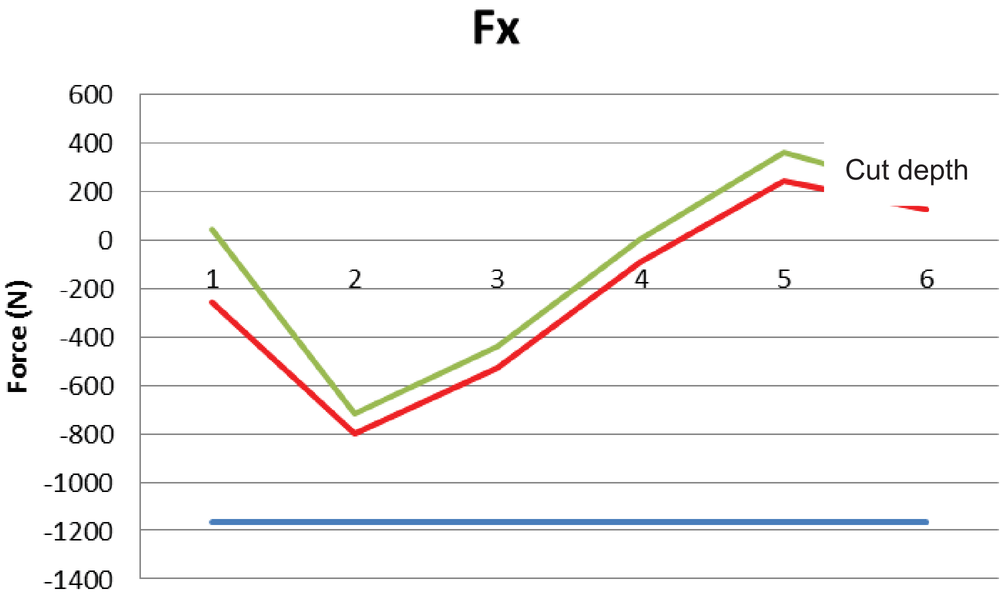


Figure 60 Sensor X-axes force for depths 1-6mm

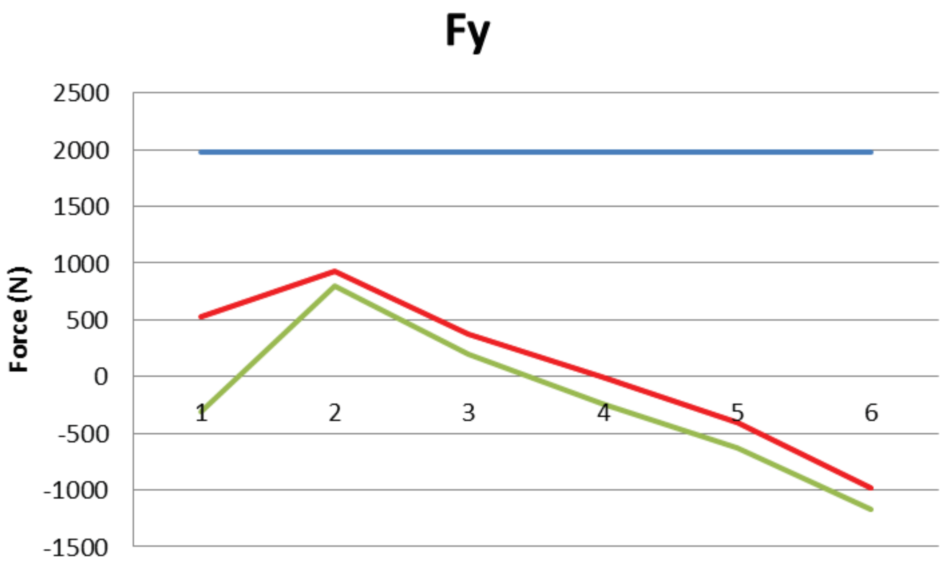


Figure 61 Sensor Y-axes force for depths 1-6mm

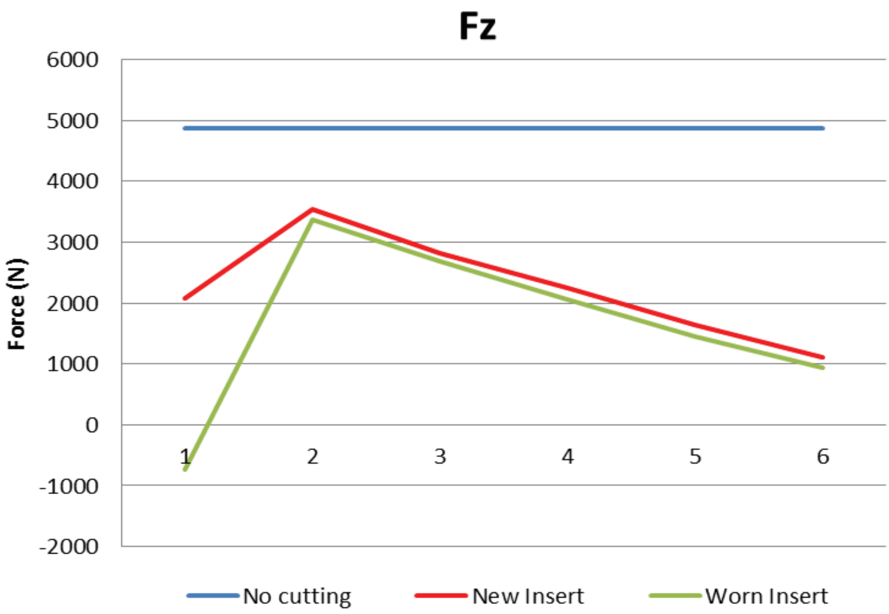


Figure 62 Sensor Z-axes force for depths 1-6mm

The graphs in **Figure 63** to **Figure 65** illustrate the measurements the accelerometer obtained for vibration in the three axes it monitored, and again the figures show the depth, while no cutting is again represented by the blue line.

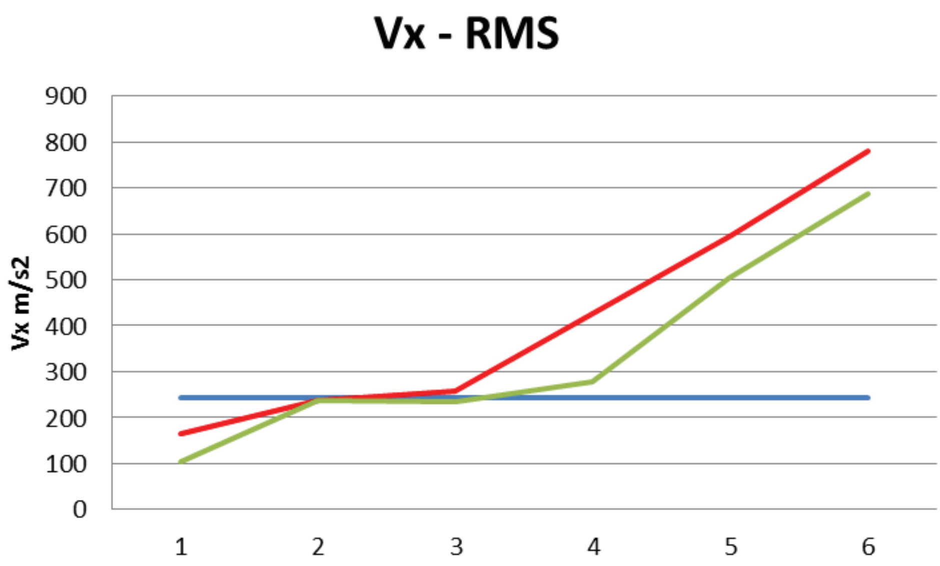


Figure 63 Sensor X-axes vibration for depths 1-6mm

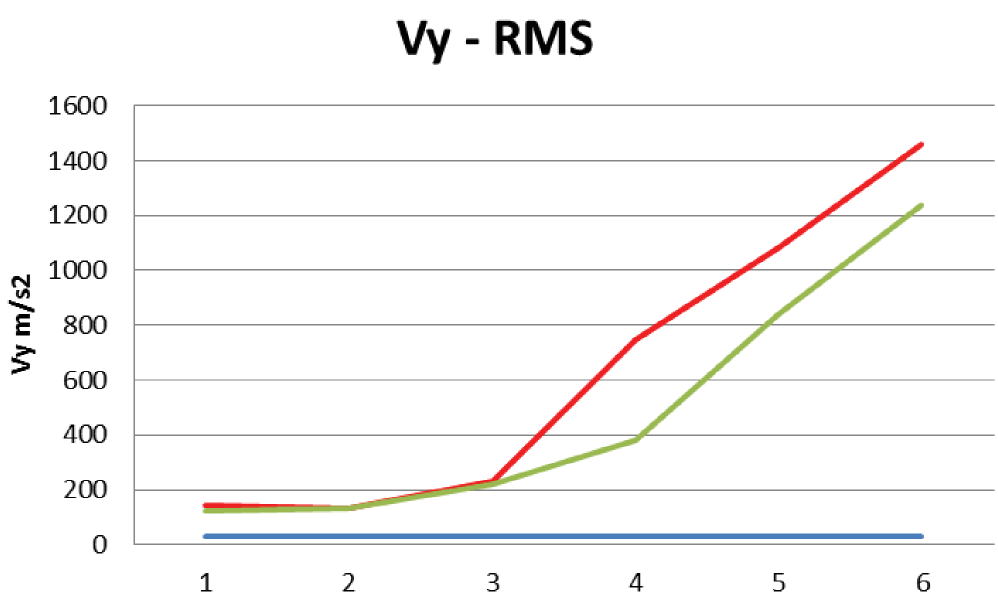


Figure 64 Sensor Y-axes vibration for depths 1-6mm

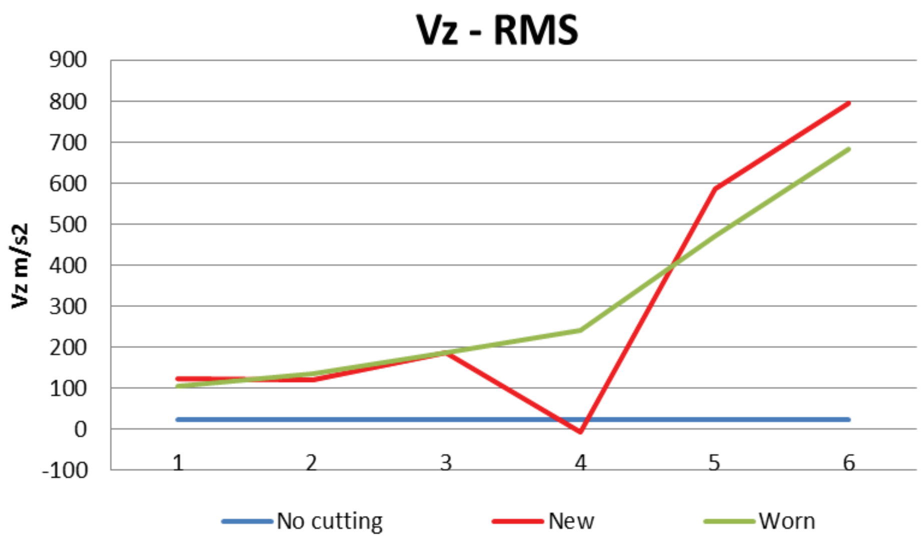


Figure 65 Sensor Z-axes vibration for depths 1-6mm

Finally, a comparison was undertaken of the readings achieved by the AE sensor for each of the facing passes and is shown in **Figure 66**, where no cutting is again represented by the blue line

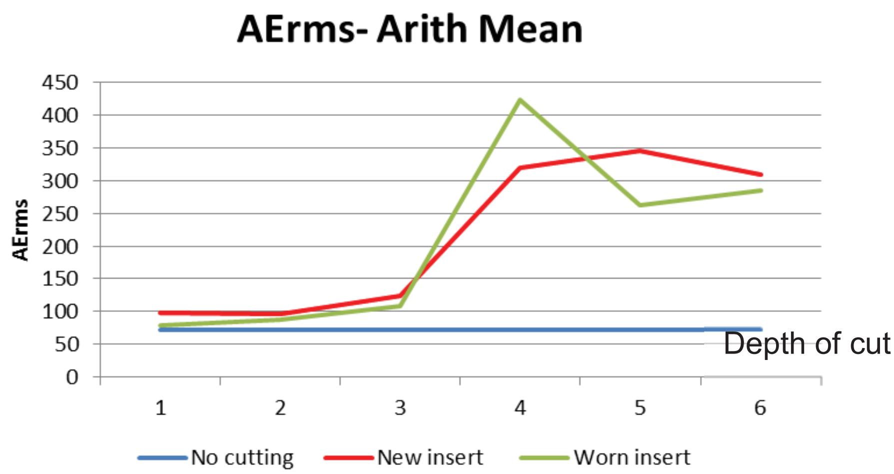


Figure 66 Comparison of the AE sensor readings for each of the facing passes

As is clear from the trial samples, there is good discrimination between the signals obtained for the worn and new cutters, and, as was to be expected, the strength of all three monitored phenomena increased with increasing cut depth.

After initial trials, the sensors continued to be analysed in normal production on this machine. Further machining trials yielded valuable information from the sensors that potentially can be used in providing predictions in advance of a catastrophic tool (CTF) failure. The CTF detection methodology uses a two-on-three logic, where if at least two or more cutting force components indicate CTF, then it is assumed to be true and sufficient to stop the process. In three trials subsequent to the initial experimentation the process experienced a catastrophic tool failure event (CTF).

The settings of the operations that yielded the CTF are detailed in Table 17:

Table 17 Parameters of cutting trials with CTF occurrence

Name	Workpiece start diameter (mm)	Depth of cut (mm)	Cut length (mm)	Feed rate (mm/rev)	Surface speed (Vc) (m/min)
CTF occurrence 1	113	5	149	0.4	260
CTF occurrence 2	72	4	149	0.3	195
CTF occurrence 3	100	4	149	0.3	195

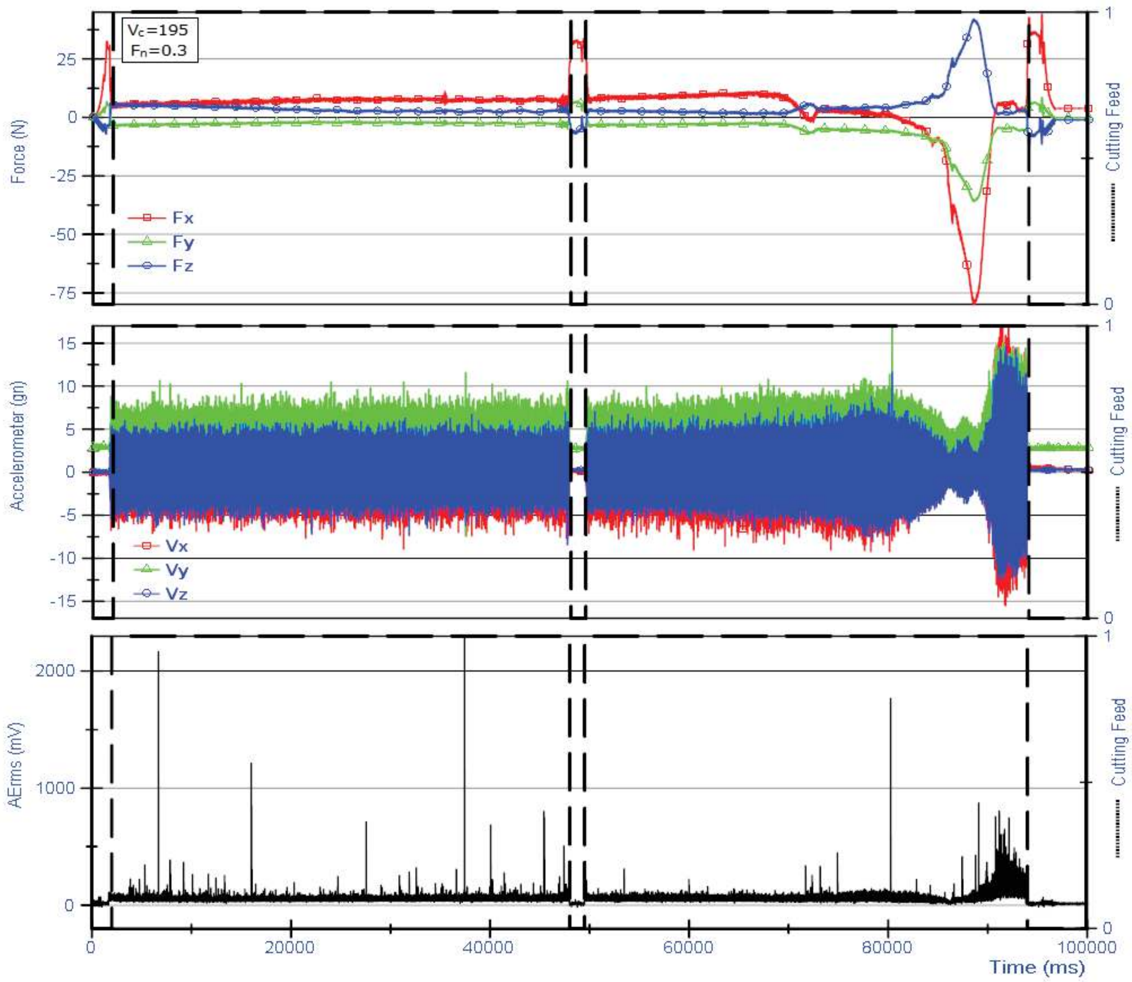


Figure 67 Sensor signals from CTF instance 1

As can be seen from **Figure 67**, there is an instance of catastrophic tool failure detected between 80s and 100s, where all sensors (Force, accelerometer and AE) exhibit significant changes in measured parameter energy levels. This is the end of a cutting pass that commenced around 50s, where the sensors are quiet, as the cutter indexes back to the start of the workpiece. However, it is worth noting that the CTF actually begins at around 70s where there is a signal feature seen on all sensors, although this is most easily seen on the three Force sensors or in the subsequently increased energy levels on the accelerometers. While the CTF event can be clearly seen in the signals from the force sensor and the accelerometer, it can be seen, but is less pronounced within the AE sensor signals.

The challenge, for an automated CTF system, is to automatically detect the changes at 70s. This is more straightforward with the force sensor, but, on the other hand cannot be as easily automatically detected in the sensor signals from the accelerometer or the AE sensor- where more complex analysis is required, or more time to make a decision, or both complexity and time are needed.

The experiment presented in **Figure 67**, was replicated a further 2 times, as will be presented in the following two figures. Again there is a catastrophic tool failure event, and a distinct signal feature is seen a couple of seconds in advance of this- of significant to note is the fact that in one of the subsequent repeats of this event the detected signal variation (known as a signal feature (SF) is detected on a previous machining pass, which indicates that this SF relates to a fundamental change to the cutter, rather than something specific to the particular cutting zone in operation.

This is illustrated in **Figure 68** & **Figure 69**.

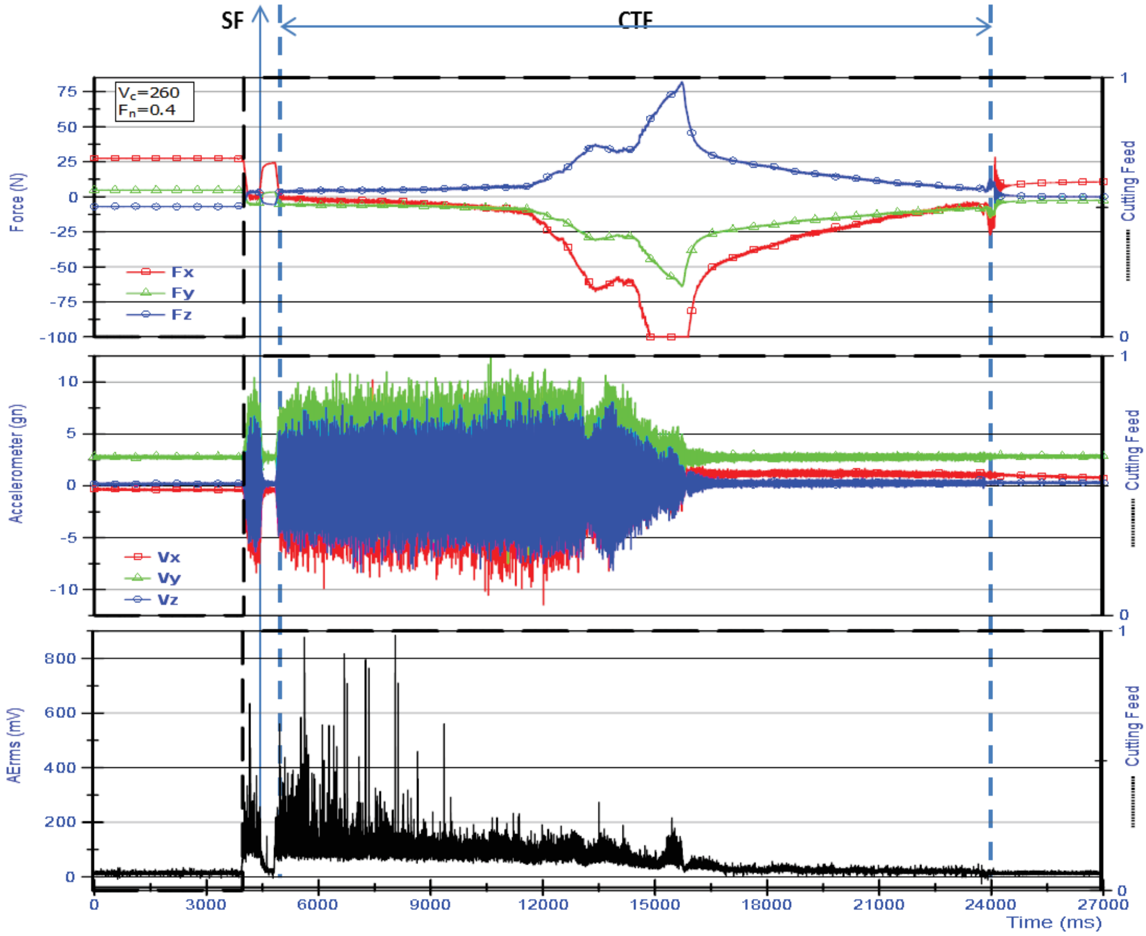


Figure 68 Sensor signals from CTF instance 2

In **Figure 68**, CTF can be seen at 12s, and the SF can be seen around 4.5s, in advance of the CTF event. The SF is clear across the three axes of the force sensor, most noticeable in the x-axes. In this instance of the experimentation it is unfortunate in some respects that the SF appears to almost coincide with the indexing of the tool back to the start of the workpiece, however elements of both events can be seen at around 4.5s on the x-axis of the graphs.

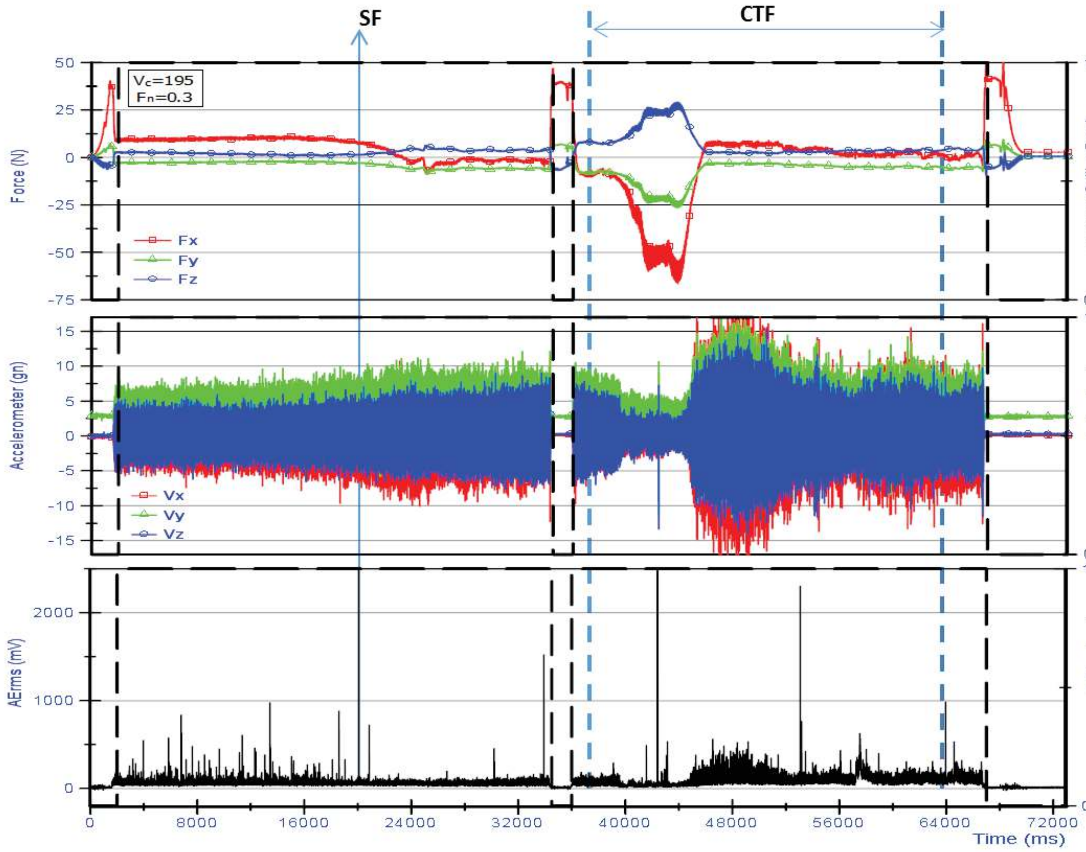


Figure 69 Sensor signals from CTF instance 3

Figure 69 shows the most interesting of the three trials in that the SF is actually detected during a previous cutting pass, therefore ruling out anything erroneous that is happening in the cutting pass during which the tool fails. It is clear from this that something fundamental is happing to the tool just in advance of the CTF event, and that this can be detected by the sensors. While predominantly detected by the force sensor, again there is some noticeable activity in the signals from the accelerometer (particularly in the z axes). However, in the AE sensor it will be necessary to mathematically evaluate the data behind the graphs, as there is no easily detectable SF in the time representation of the data.

Figure 70 shows, for reference, the axes within a CNC lathe, to clarify the results presented in the previous graphs detailing the incidence of CTF.

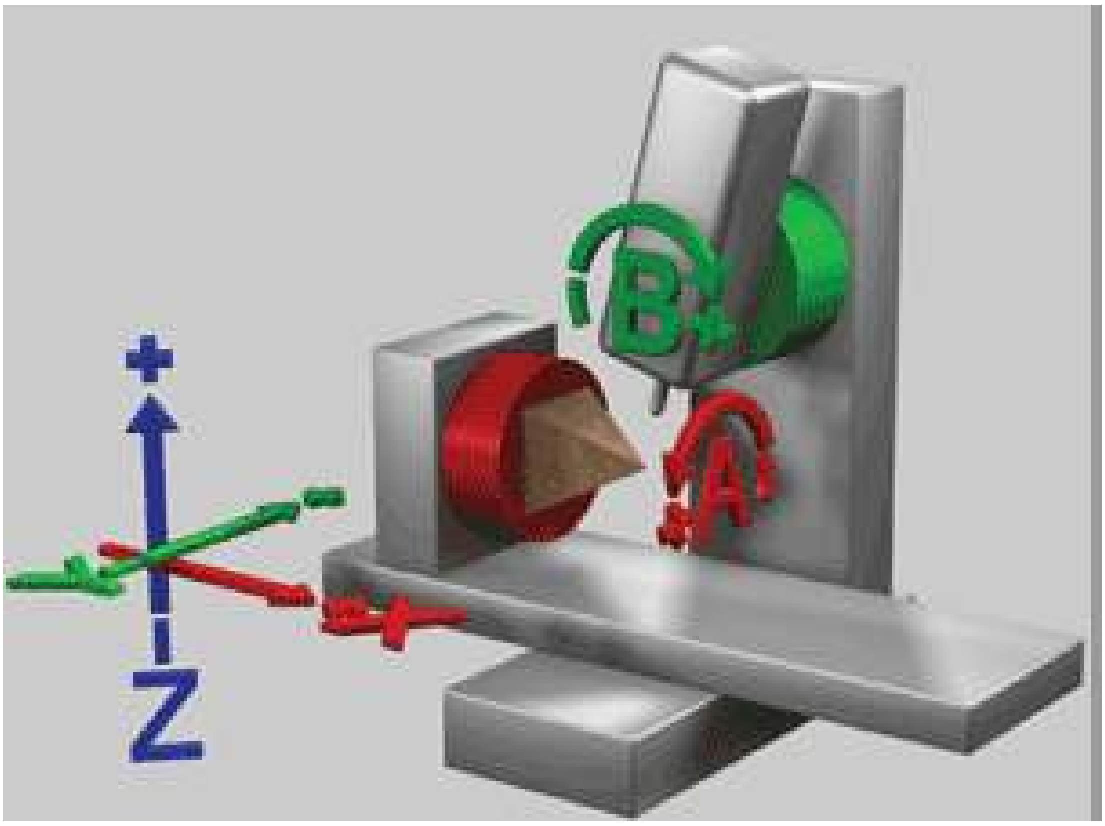


Figure 70 Illustration of axes in CNC turning

6 Conclusion

6.1 Overview

Tool condition monitoring has been an elusive challenge to engineers for many years, but increasingly the individual components of the challenge are being overcome, thanks to advances in the technology of sensors and of processors, memory and logging, in-camera systems and automated inspection, in automated decision-making, in integrating the TCM into the machine from the initial design outset and in absorbing the learning of many engineers over many years.

Direct tool measurement is challenging, but would be most accurate, where feasible. Indirect measurement, which has been the category of sensing used in this work, is well understood and once the variations in this implicit TCM approach are properly characterised, it can be relied upon for correct and timely decisions. However, the selection of and location of an implicit TCM sensor must be carefully done. In terms of selection, it is apparent from this work, that not all operations produce the same useful implicit information and that therefore no single implicit signal should be solely relied upon to perform TCM. For example, this means that two implicit sensor types is an insufficient number, in case neither indicates a wear condition. Therefore, a minimum of 3 sensor types should be used, to increase the likelihood of accuracy in the wear analysis.

In the case of Catastrophic Tool Failure, a similar argument holds. Implicit measurements are not guaranteed to always detect the problem. This simply means that CTF (or wear) does indeed lead to transfers of energy into other sensed parameters, but it would be unwise for an engineer to assume that, for every operation, each sensed parameter is guaranteed to see a change in energy levels.

An additional element of this research focussed on the fundamentals of the initial thesis, that *humans* could interpret the physical emissions from the machining process to determine whether the process was under control or was in a condition of degradation. The workshops undertaken with the staff on the machining floor examined the relationship between the people and the machines, and offer good insight into how this interaction can be maximised with the implementation of a fully validated tool condition monitoring system. Validation of a system of this nature has also shown to be key to ensuring that all the stakeholders have confidence that any deployed system is robust.

6.2 Tool condition monitoring results

This thesis presents a number of experimental approaches and a number of the approaches to a successful TCM system have been evaluated to determine their individual worth.

This research started as a result of the author's belief that the experienced CNC machinists at Schivo Precisions could determine the onset of tool wear for a cutting tool from the sound emanating from the machining centre. Anecdotal evidence at the time seemed to support this theory and on more than one occasion the author observed experienced machinists declaring a process to be undesirable based on the sound, and in some cases, based on the vibration within the machine.

This research commenced with an analysis of audible sound energy as the primary aim, and the results obtained during the experimentation undertaken on the Harrison lathe, as presented in the *Wear* paper, supported the theory. It is clear from the results that the fundamental, humanly observable sound energy from the machining process does indeed vary as the tool wears and the cutting process degrades. As this experiment focussed on the detectible range of human hearing, 0-20KHz, it is reasonable to conclude that the differences detected by the software across the phases of tool wear are differences that would also be detected by the human brain in the same manner, as long as the range of hearing included the region of change, which may not be the case for all operators, especially with their range of hearing typically shrinking with age.

The experiment that was undertaken on the Röders 5-axis machine should have produced similar results shown during the experiment on single point machining in turning on the Harrison lathe. In fact, within Schivo it was widely known that the sound energy emissions from the Röders machines at the commencement of the roughing cycle were hugely, and easily noticeably, different to the sound observed at the machines at the end of the machining cycle. However, the results obtained from the initial Röders experimentation were very disappointing, both from the microphone and the accelerometer, but were excellent lessons in the importance of both sensor selection and sensor deployment. The analysis of the results from the accelerometer and associated vibration sensors shows that the sensors locations were not ideal, but more importantly it is clear that the robustness of the fixation of the accelerometer to the main spindle body was not sufficient. To determine the level of vibration of a structure, the sensor must be inextricably affixed to the surface of the structure, and not allowed to vibrate on its own. In the event that a vibration sensor is allowed vibrate independently of the structure to which it is affixed, harmonics can occur that are completely independent of the vibration of interest. In the initial experimentation two piezo electric sensors were also deployed on the machine housings, at the tool changer and the pallet carousel. Interestingly the data received from these two instruments appeared to change across the tool life, with increasing signal amplitude as the tool became progressively worn. However, the author believes these are too remote and of too low a quality to be used in those positions longer term, as it would be very difficult to reliably relate this back to the precise onset of tool degradation.

With this in mind, the rerunning of the Röders experiment with the same experimental infrastructure for sound energy, as deployed during the *Wear* experiment was expected to similarly effective to the results obtained during the *Wear* experiment, and this proved to be the case. By expanding the analysis of the signals from the microphone the nature of the sound, in terms of frequency content, that the machinist is hearing that tells them all is not well. The second iteration of the Röders experimentation so closely mirrored the learnings, in terms of audible sound energy, from the initial single point turning experiment that it is reasonable to conclude that the reason that experienced machinists appear capable of determining the difference between a good cutting operation and a degraded cutting operation is change in the frequency components of the signals, in terms of their amplitudes.

It is for this reason that well-chosen digital signal processing of high-quality signals, feeding an appropriate machine intelligence system are important in the analysis of the TCM signals. Moreover, as demonstrated in the case study undertaken as part of this research, an extremely important consideration when designing such a complete TCM system for a human operator is the interface between the human and machine, and the architecture of the interface and how that will interact between the TCM physical systems and a human.

In tandem with the research into the use of audible acoustics and vibration, the experimentation detailed expanded the range of sensors, and therefore the range of physical emissions examined in the search for credible tool wear indicators. As has been mentioned in the literature review section, Acoustic Emissions, in the form of surface-borne transient elastic waves, has been the subject of considerable research down through the years, and eminent members of the REALISM consortium were big fans of this approach coming into the project. The author on the other hand was, and remains, unconvinced, given the success of the narrower bandwidth audio spectrum and indeed in the case of the REALISM work, the Acoustic Emissions' sensor was not as useful as the other sensors deployed. For example, the embedded force sensor was easily the most reliable sensor in predicating the onset of catastrophic tool failure, with the accelerometers also offering superior performance over the Acoustic Emissions sensor.

With the advent of the concept of industry 4,0, or the 4^{th} industrial revolution- the advent of the digital factory- the type of automated process monitoring that was investigated during this research is critical to the advancement of manufacturing technologies. While the increased adoption of additive manufacturing technologies is important, currently AM technologies cannot supply the types of products that subtractive manufacturing processes are currently employed for in terms of both accuracy and cost.

It is for this reason that for the coming years additive and subtractive processes will be used as complimentary technologies, and therefore the ability to apply closed loop digitisation and monitoring of these techniques is critical to the continuance of the industry 4.0 ethos.

6.3 Contribution to the state of the Art from this Research

This research has demonstrated the manner in which the audible sound energy emissions from the machining process are interrogated subconsciously by experienced machinists to glean information about the state of the process. This has been repeated across two distinct machining processes (single point turning and 5 axes milling) and the observed results, when applying the same methodology, all support the thesis that there is merit in the belief that humans can in fact discern the difference between a known good machining cycle and a degraded one.

The process emissions that were examined as part of this research were essentially audible sound, vibration, acoustic emissions (the audio spectrum extended to 100kHz) and vibration. The research demonstrated the worth of audible sound and, more importantly, was able to demonstrate *why* audible sound is a worthy means of evaluating the machining process.

6.4 Future Developments

The future realisation of automatic and human assisted tool condition monitoring depends upon a number of factors: the implementation of robust, accurate sensor monitoring systems that feed reliable data into a system, which itself is capable of carrying out appropriate signal processing, for signal feature extraction, and with enough machine processing power and memory resources, to use insights gained from previous processes, in arriving at a correct decision of the current and future tool wear.

Such future systems will be robust, reliable, intelligent and capable of communicating with skilled and semi-skilled operators. They will also be reconfigurable, capable of adapting for different metals and different processes. These systems will save time and money, and will produce a much more consistent finish over the tool life time. They will be successfully deployed in the production of small, precise and complex products, with applications in aerospace, biomedicine, transportation, even in MEMs and potentially nanotechnology devices. It can be seen from the work presented here, especially in the REALISM work, that modern sensor systems and the associated signal processing capabilities are increasingly capable of meeting these requirements. Moreover, the recent advances in machine algorithms, both offline and increasingly online (‘live’ decision-making) in other realms of engineering mean that the key pieces of this puzzle are rapidly becoming available.

Up to now, in spite of the many years of research and the availability of academic and industrial data, there has not been any great success in applying TCM on the shop floor or in commercially available tool and process conditions monitoring systems. However, it seems to this author that the stage is now finally set to see a change to the status quo.

After many years of research, the dawn of the TCM era is now upon us.

Appendix A – Presentations and Publications

A.1 Presentations list

Waterford Institute of Technology Research Day 2011,	Poster Presentation
SEAM Research centre industry day 2011,	Oral Presentation
Waterford Institute of Technology Research Day 2012,	Oral Presentation
9th CIRP ICME Conference, 2014	Poster Presentation
9th CIRP ICME Conference, 2014	Keynote Presentation
48th CIRP CMS Conference, 2015	Oral Presentation
48th CIRP CMS Conference, 2015	Poster Presentation

A.2 Publications list

1. Jonathan Downey, Paul O'Leary, Ramesh Raghavendra.
Comparison and analysis of audible sound energy emissions during single point machining of HSTS with PVD TiCN cutter insert across full tool life.
The International Journal of Wear, Issue 313 (2014), Pages 53-62.

2. Jonathan Downey, Sebastian Bombinski, Miroslaw Nejmen, Krzysztof Jemielniak.
Automatic multiple sensor data acquisition system in a real-time production environment.
Procedia CIRP, Volume 33 (2015), Pages 215-220.

3. Jonathan Downey, Denis O'Sullivan, Miroslaw Nejmen, Sebastian Bombinski, Paul O'Leary, Ramesh Raghavendra, Krzysztof Jemielniak
Real time monitoring of the CNC process in a production environment- the data collection and analysis phase.
Procedia CIRP, Volume 41 (2016), Pages 920-926.

4. Kristian Martensen, Jonathan Downey, Ivanna Baturynska
Human Machine interface for Artificial Neural Network based machine tool process monitoring.
Procedia CIRP, Volume 41 (2016), Pages 933-938.

5. Barry Ronan, Jonathan Downey, Liam O'Shea, Dr Paul O'Leary, Dr Denis O'Sullivan, Dr Ramesh Raghavendra.
Development of a generic tool condition monitoring validation methodology
Proceedings of the IMC Conference Belfast, 2015.

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