Distributed Embedded System with Internet/GSM Connectivity for Intelligent e-Monitoring of Machine Tools

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A thesis submitted in candidature for the degree of Doctor of Philosophy of the Cardiff University.

August 2006

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Acknowledgements

Praise be to GOD ALMIGHTY, my creator and sustainer, who made me capable enough to complete this thesis.

I am also thankful to:

My supervisors, Dr. Roger I. Grosvenor and Mr. Paul Prickett for their knowledge, expert guidance and patience whilst assisting me throughout the degree.

Mr. Qaisar Ahsan, Mr. R.A. Siddiqui and Mr. R. Nawaz who were always with me whenever I needed help in the course of this degree. Dr. Alun Jennings' technical guidance is also acknowledged.

Mr. R. Leach for his help in carrying out the experimentation work on the machine tool while designing and developing the system.

My whole family, especially my wife Hina and my son Amer in whose presence I always found the life in its best ***colours***.

My Great friends KingRajori, Syed Muhammad Asghar Shah, Joji and Mani who always remained a source of motivation.

Ministry of Science & Technology, Govt. of Pakistan for their financial support, without which I would not have been able to engage this course.

SUMMARY

Machining is one of the most important operations in many industrial environments. To prosper in today's competitive industrial world any machining system should be able to deliver the highest possible quality at the lowest possible costs, with very high reliability and flexibility. To fulfil these requirements the idea of e-Monitoring an industrial process was introduced by the Intelligent Process Monitoring and Management (IPMM) Centre at Cardiff University. It has considerable potential applications in industrial systems to not only monitor the health of the machines but also for data management and presentation for future decision making.

The research presented in this thesis considers the evolution of two different low complexity signal analysis techniques which can be used for e-Monitoring the health of the cutters used in milling machine tools. The researched techniques are based in the time and frequency domains. The frequency domain analysis technique is based on the idea of using switched capacitor filters and microcontrollers to monitor the frequencies of interest in existing machine tool signals (spindle load and speed) thus avoiding the need for external sensors. The results of frequency domain analysis are used to assess the health of the cutter. The time domain analysis technique uses the same signals to analyse any variations within a tool rotation period and relate these to the health of the cutter. The results are integrated before final decision making which helps in reducing false alarms.

The thesis goes on to logically describe the design and development of an on-line microcontroller based distributed intelligent e-Monitoring system for a milling machine tool model Kondia B500, using the proposed signal analysis techniques. Some additional features such as internet and GSM connectivity have also been added to the designed system. The designed system was interfaced to the machine tool and tested for its reliability which was found to be competitive with many other very expensive systems. The designed system can be fitted into a machine tool at the manufacturing stage or it could be interfaced to an existing machine tool for automatically detecting a tooth breakage.

Dedication

To Amer and Hina - the colours of my life.

CONTENTS

ACRONYMS

ADC	Analogue to Digital Converter
AE	Acoustic Emission
AEWMA	Adaptive Exponentially Weighted Moving Average
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ART	Adaptive Resonance Theory
ASIC	Application Specific Integrated Circuit
ASPS	Automated Sensory and Signal Selection System
CAN	Controller Area Network
CT	Communication Time
DAC	Digital to Analogue Converter
DAQ	Data Acquisition
DCE	Data Communication Equipment
DNS	Domain Name Server
DOC	Depth of Cut
DSC	Digital Signal Controller
DSP	Digital Signal Processing
DTE	Data Terminal Equipment
EMI	Electromagnetic Interference
EWMA	Exponentially Weighted Moving Average
FAC	Fuzzy Adaptive Controller
FAM	Fuzzy Associative Memory
FEN	Front End Node
FET	Field Effect Transistor
FFT	Fast Fourier Transform
FIFO	First In First Out
FIR	Finite Impulse Response
FNIP	Fuzzy-Nets-In-Process
FPGA	Field Programmable Gate Array
FRF	Frequency Response Function

FSC	Fuzzy Search Classifier
FTP	File Transfer Protocol
FVBE	Force Variation Based Encoding
GA	Genetic Algorithm
GDP	Gross Domestic Product
GSM	Global System for Mobile communications
GTM	Genetic Tool Monitor
HSP	Hardware Signal Processing
HTTP	Hyper Text Transfer Protocol
IC	Integrated Circuit
IE	Internet Explorer
IF	Intermediate Frequency
IIR	Infinite Impulse Response
IP	Internet Protocol
IPS	Internet Protocol Suite
ISR	Interrupt Service Routine
LAN	Local Area Network
LCL	Lower Control Limit
LM	Load of Machine
M2M	Machine to Machine/Man to Machine
MA	Moving Average
MAC	Media Access Control
MAF	Moving Average Filtering
MIPS	Million Instruction per Second
MLP	Multi Layer Perceptron
MOS	Metal Oxide Semiconductor
MOSFET	Metal Oxide Semiconductor Field Effect Transistor
OEE	Overall Equipment Effectiveness
OS	Operating System
PCB	Printed Circuit Board
PDU	Packet Data Unit
PFT	Parallel Filtering Technique
PHY	Physical Layer
PIC	Peripheral Interface Controller

PLC	Programmable Logic Controller
PT	Processing Time
PWM	Pulse Width Modulation
RAM	Random Access Memory
RAN	Resource Allocation Network
RCE	Restricted Coulomb Energy
RMS	Root Mean Square
SABE	Segmental Average Based Encoding
SFT	Sweeping Filter Technique
SIM	Subscriber Identity Module
SIMM	Single Inline Memory Module
SM	Speed of Machine
SMTP	Simple Mail Transfer Protocol
SoC	System on Chip
SOC	System Operation Console
SPC	Statistical Process Control
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
TCMS	Tool Condition Monitoring System
TCP	Transmission Control Protocol
TINI	Tiny Internet Interface
TPMT	Tooth Period Modelling Technique
TREE	Tooth/Tool Rotation Energy Estimation
TWEM	Tool Wear Estimation Method
UCL	Upper Control Limit
VCO	Voltage Controller Oscillator
WSSR	Weighted Sum Squared Residuals
WT	Wavelet Transform
WT-NN	Wavelet Transformation and Neural Networks

NOMENCLATURE

F_c	Cutting Force
F_{clk}	Clock Frequency
F_f	Feed Force
f_o	Centre Frequency (Hz)
F_s	Sampling Rate
H_{OBP}	Gain
i	Current
KΩ	Kilo Ohm
Lf	Last Frequency
LM	Load of Machine
M	Order of the Moving Average Filter
MΩ	Mega Ohm
Ps	True Power Consumption
Q	Quality Factor
R	Resistance
Sumi	Current value of SUM in the buffer
Vali	Current Data Value in the buffer
Δf	Frequency Resolution
Δq	Charge Transferred per unit time
Δt	Sampling Period
ωo	Centre Frequency (radians/second)

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CHAPTER 1

INTRODUCTION

The advancements in technology in the current era have been at an enormous pace. It is now possible for researchers to explore techniques and methods for the design and development of global systems with capabilities of relevance to a wide range of applications. In today's system integration era, the importance of systems engineering research applications is increasing constantly. In general, systems engineering can be defined as "the application of engineering in finding solutions to a complete problem in its full environment by the systematic use of different engineering tools in the context of the lifetime use of the system". Alternatively, it may also be defined as "a management technology where the technology is the result of, and represents a totality of the technique and its application with regards to use of scientific knowledge for the enhancement of systems" [1.1]. This concept emphasises the need for using as many engineering approaches and tools as required in order to achieve the best possible solution to an existing problem.

The manufacturing industry plays a key role in any country's economic growth and continued well being. A major portion of the Gross Domestic Product (GDP) of any country is linked directly or indirectly to this industry. Manufacturing plays a key role in keeping the job market healthy and has a strong positive or negative implication on many other related industries. The impacts of strength variations within the manufacturing industry in the context of the overall economy of any country are enormous.

The manufacturing industry's technological growth rate has been very high. Consequent to the demands arising associated with increasing overall productivity the manufacturing industries are now paying more attention to the monitoring of industrial processes. The recent technology advancements have also been a major driving force behind increased process automation in every field in general and within the manufacturing sector in particular. Global competition is responsible in compelling most manufacturers to improve plant machinery and processes to stay competitive. These trends are shaping new dynamics in the global automation market. Here "automation" can be defined as "the process of making machines self-acting or self-moving and the technique of making a device, machine, process or procedure more fully automatic thus reducing the need for human intervention" [1.2]. As part of this manufacturing companies have a need to track and improve their process and plant productivity and performance through real-time monitoring and management systems. These industries have to adopt this approach in order to increase their productivity and quality to remain competitive in the market.

Embedded systems are a key player in making automation more efficient, reliable and cost effective. An embedded system may be defined as "a special-purpose computer system, which is completely encapsulated by the device it controls. It has specific requirements and performs pre-defined tasks, unlike a general-purpose personal computer" [1.3]. These characteristics are not the only factors which are making embedded systems more and more popular. There are other positive aspects behind the growth of their application rate. For example in most of today's applications, the space for controlling or monitoring hardware is a major issue. The embedded systems require much less space as compared to a PC if these can effectively be used to perform the same task.

The need for monitoring systems which can be used for different processes and attached resources is being increasingly recognised. Monitoring systems for manufacturing processes and machines are becoming almost a requirement. These can be either integrated monitoring systems or distributed monitoring systems or a combination of both. The combination of integrated and distributed monitoring systems using the available communication infrastructure makes it possible to reach effective, more reliable and accurate decisions in less time. These systems open up the current states of the process to concerned engineers, managers and technicians. This is the area where embedded systems if used to their best potential can deliver excellent results. Although the use of embedded systems in control applications has been established for some time their use for monitoring systems has been very restricted, despite their advantages.

Metal cutting forms a major part of the manufacturing industry. There are many types of machines used for metal cutting. One of the most important types of machines is a milling machine. Milling is normally defined as the process of machining flat, curved, or irregular surfaces by feeding the workpiece against a rotating cutter containing a number of cutting edges. The health of a milling tool in use by any milling machine directly affects the quality and finish of the part and the productivity and power consumption of the machine. The condition of the tool is thus very important for producing high quality products. There has been a large body of research around the world for developing an effective tool condition monitoring system. Despite this effort no truly practical solution has been developed; the search goes on. The demand for such systems is very high. It is supported by the fact that manufacture and use of machine tools has been subject to changing patterns over a number of years. In particular the survival of UK machine tool manufactures has been under great threat [1.4]. This is due to the fact that they have been subjected to strong competition from machine tools designed with many added features from overseas. Therefore research into these additional capabilities such as the monitoring of the cutting tools and their implementation are important.

1.1 Aims and Objectives

- The research presented in this thesis is aimed at developing tool condition monitoring techniques using both time and frequency domain analysis.
- These methods are combined in an integrated monitoring technique.
- It also investigates the deployment of embedded systems within machine tools for implementing these techniques.
- It goes on to explore the use of embedded systems for improved data analysis and for the effective transfer of data using the Ethernet, and mobile messaging services to relay the information to the concerned users. Embedded systems have been used in this work to their best potential in order to achieve all of these features in the designed and implemented monitoring system. The resulting tools are shown to provide a low cost yet effective e-Monitoring solution with excellent capabilities for tool condition monitoring.

1.2 Thesis Structure

The thesis is organised into the following chapters.

Chapter 2 discusses the major motivations behind this research. The needs and demands of the modern manufacturing industry are identified, their economic trends are explored and a holistic view about the requirements and roles of e-Monitoring systems for such applications is presented. This narrows down to the requirements for Tool Condition Monitoring Systems (TCMS) for milling machines to provide a focus on the main objectives of the research.

Chapter 3 presents a review of techniques, methods and systems researched in the past. The different aspects and techniques related to TCMS in terms of data acquisition, data analysis, decision making and its presentation/communication to end user are explored. It goes on to explore the merits and demerits of different systems with a view to providing comparative analysis for their best possible application.

Embedded system technology in terms of the requirements of the researched system's design, cost, effectiveness and availability is reviewed in Chapter 4. It further explores the technologies used in general and their specific attributes in particular. The PIC18F458 microcontroller is explained in detail along with Tiny Internet Interface (TINI) system for Ethernet connectivity and uWeb Lite embedded system for providing real time GSM connectivity using mobile phones. It also includes a brief audit of the machine (Machine Tool Kondia B500) used for system implementation and testing.

The low complexity frequency domain signal analysis techniques known as "Sweeping Filter Frequency Analysis" and "Parallel Filtering for Signal Analysis" are discussed in Chapter 5. The supporting hardware and software are discussed in complete detail. The real time results of these techniques are presented. It is worth noting that for both techniques spindle load and spindle speed signals have been used as the source of information thus eliminating the need for using any additional sensors.

Chapter 6 explains a reliable time domain signal analysis technique called "Tooth/Tool Rotation Energy Estimation (TREE)" and its role within the designed machine tool condition monitoring system. It includes the description of the designed hardware as well as the software used in the implementation of the technique. Real time results of different tests are presented and analysed. The effectiveness of the supporting hardware technology in terms of system requirements is analysed and discussed. It also explores the features of the supporting technology used in terms of the designed system requirements.

Chapter 7 presents a complete structure of the integrated system implementation as an effective and complete e-Monitoring solution in the context of a true embedded solution for machine tool condition monitoring. It also presents the design and implementation of additional features in the system including; Ethernet connectivity and the system's capability of supporting a GSM mode M2M (Machine to Machine, Machine to Man) connectivity. The benefits achieved as a result of these extra features are explored and discussed.

Chapter 8 presents the overall communication architecture of the system. The data and result communication between tiers one and two of the system are discussed. It also describes the internet and GSM connectivity of the proposed system.

Chapter 9 presents a critical assessment of the research work. It contains the description of the overall characteristics of the subsystems in terms of today's TCMS requirements. It also describes hypothesis, demonstrates precision, thoroughness, contribution, and comparisons. The designed system's architecture in terms of its effectiveness is analysed. The comparative analysis of previously designed systems and techniques with respect to this particular research area is presented and the needs for future work are identified and discussed.

Chapter 10 presents the important conclusions drawn from this research. These conclusions are drawn based on the results obtained from the complete implementation of both time and frequency domain analysis techniques on designed system hardware with supporting software.

In the course of this research a thorough review has been carried out outlining effective techniques of data analysis, design and implementation of supporting system for a cost effective, efficient and reliable TCMS. However it is accepted that the complexity of the problem does not allow solving all the relevant issues. Therefore this research is presented as a contribution to the overall area of machine tool condition monitoring systems. The keywords "author" and "researcher" have been used to refer to the writer of this thesis.

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CHAPTER 2

RESEARCH MOTIVATION

The search for improvements in Electronics and IT system design has been constant and the results have been enormous. The resulting developments have been a source of motivation for researchers in many different fields, including manufacturing. In this area work has included the use of Intelligent Process Monitoring and Management Systems for improving product quality and achieving process reliability. The reliability and productivity of industrial systems and machines is directly linked to their failure rate, failure detection time and their associated repair times. All of these factors contribute to the downtime of the machines.

The contribution made by improvements in reducing machine downtime may be illustrated using an approach known as Overall Equipment Effectiveness (OEE). The OEE of any system/machine is dependent upon three factors:-

OEE = System Availability Rate *x* Performance Rate *x* Quality Rate

The system availability rate measures any machine system's availability as a whole within the context of a manufacturing industry. It includes setup losses and downtimes due to failures. The performance rate accounts for overall performance of the system/machine in terms of its efficiency. The quality rate as obvious from the name is related to quality related losses. The OEE of many computer integrated manufacturing systems has been lower than expected [2.1].

The improvement of OEE for a manufacturing system is dependent upon improvements in all of its constituent components. If a catastrophic failure occurs and goes unnoticed due to the absence of an effective monitoring system, it will not only affect the quality of the product but will require additional set up costs once it has been detected. Since both

of these factors are components of the overall OEE of the system the importance of an effective TCMS can not be over emphasised.
One of the major motivations behind this research was to design a low cost yet effective tool condition monitoring system. The above presented facts make a strong case for monitoring the tool condition dynamically during a cutting process. Although there has been a great deal of research aimed at the development of an effective tool condition monitoring system no definitive solution has been designed and implemented. There have been various techniques and technologies developed, implemented and tested but mostly for academic research purposes. Different factors responsible for this situation can be identified as follows.

One of the major factors behind industrial organisations' reluctance in adopting machine Tool Condition Monitoring Systems (TCMS) is their overall cost as compared to their performance. In this context there are two different techniques used for data acquisition for TCMS: direct sensing and indirect sensing. In indirect sensing, the existing sources of information from a machine tool are used whereas in direct sensing additional sensors need to be deployed to acquire the required information. Although there has been research on indirect sensing using existing signals from the machine tool to supply information to TCMS the results have up to this time not been as effective as the systems designed by using additional sensors. However the overall cost of direct sensing is significantly higher and the use and placement of the sensors restricts the freedom of operation of machines thus reducing its overall effectiveness. For example the use of a dynamometer (a popular technique for data acquisition and analysis in designing TCMS) requires the purchase of the dynamometer (normally costing around £10,000) and its supporting equipment, Data Acquisition Card (costing around £600-900) and a PC (costing around £500-£600) in addition to expensive software. To further illustrate the cost and performance issues of TCMS design, consider the findings of Al-Habaibeh and Gindy [2.2] who analysed the subject by using 15 sensory signals and considering the effectiveness of 23 different signal processing and feature extraction systems. These researchers suggested that the cheapest system costs around £3900 with an accuracy of around 80%, where as a system of accuracy around 91% costs around £19,000. This factor has limited the take up of TCMS in industry. Therefore the improvement of the cost effectiveness of such monitoring systems remained another motivation behind this research effort. The data analysis and management costs are in addition to the system cost in conventional condition monitoring systems. Therefore for a cost effective system the design and management costs need to be as low as possible. To meet these demands and overcome these limitations the work reported here using embedded direct sensing was undertaken. It was taken as a challenge to research data analysis techniques which can be implemented on resource limited 8-bit microcontrollers and still have the capabilities to detect tool breakage in real time. The data analysis techniques should not be mathematically very complex as some of the microcontroller resources need to be used for real time data communication using the CAN bus. The approach of real time data analysis was adopted to avoid unnecessary storage of data. All these factors were taken into consideration to meet the demands in designing a low cost yet effective TCMS.

The reliability and performance of existing TCMS is another major issue which affects their use. Reliability is assessed in terms of a system's capabilities to detect faults effectively as well as generating the minimum possible false alarms. The generation of false alarms reduces the system's availability rate whereas undetected faults affect performance and quality rate. Therefore a monitoring system with a very high reliability rate plays an important role in improving the OEE of manufacturing systems. The improvement of the reliability of tool monitoring system was taken as another challenge and the technique of integrating results from time domain to frequency domain and vice versa was used.

Flexibility of the designed TCMS is another important requirement. This normally refers to the ability of any system to be used for a different application which has changed parameters. The absence of this basic attribute in most of the designed systems is one of the major reasons behind industrial managers' reluctance towards accepting TCMS for implementation. To meet these needs any designed system using existing machine signals should have the capacity to deal with different signals in different scenarios thus providing more flexibility. This research focussed on designing a system which does not need any changes in the overall hardware infrastructure of the system to achieve the desired flexibility.

The efficient and timely communication of data to concerned individuals is a primary requirement of an effective and reliable TCMS. Real time decision making capability is an important characteristic of such systems. The data processing, communication and data presentation in an accurate and desired format was taken as another challenge in the course of this research. The designed monitoring system is capable of either analysing the data or transferring it to a more powerful system for further analysis if required. It can take immediate decisions and act accordingly to initiate the generation of an alarm and transfer the information about this event to concerned persons e.g. engineer/manger/technician in all the required details and formats.

Taking all these challenges as a combined source of motivation for this research it was identified that a low cost yet reliable, flexible, reusable and effective TCMS was required to increase the OEE of machines in manufacturing industries. This research proposes that the latest technological trends and breakthroughs can be used to implement new techniques in the design and implementation of such a TCMS. The following paragraphs describe this research's aims and outlines procedures to effectively tackle all of the challenges in the design and implementation of such a system.

The advantages of using existing machine tool signals to remove the requirement of using additional sensors for information retrieval have been identified above. In this research spindle speed and spindle load signals have been used as sources of information for analysis and decision making. The system uses two different data analysis techniques; one each for time and frequency domain analysis of the acquired signals before decision making. The results of each technique are integrated before reaching a final decision which increases the reliability of the system. These techniques are efficient enough to be used for designing a reliable TCMS yet simple enough to be implemented on 8-bit microcontrollers.

The integration of monitoring systems within the actual machining systems is an ideal scenario. The monitoring system needs to be fitted into the actual system it is monitoring and still be able to communicate with the rest of the world. The designed system uses a Tiny Internet Interface (TINI) not only to act as a second tier in the overall system architecture but also to transfer data over the internet as and when required. The normal role of a second tier in the system is to provide some additional analysis and storage support to the first tier in case it is required when abnormalities are observed.

In the context of larger manufacturing set ups the communication of brief summaries about the productivity, OEE and current status of different sections/machines may be important to different individuals involved in decision making. The research presented suggests the addition of GSM capabilities to our monitoring systems. In this way M2M connectivity can be achieved and rapid actions made possible.

The reusability of such systems can be achieved by using microcontroller based technology at the heart of such designs. Attempts have been made by the researcher to keep the software programming efficient enough so that changing machine parameters e.g. spindle speed and number of teeth in the cutter are automatically detected and any dependent variable is adjusted accordingly by the system itself.

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CHAPTER 3

LITERATURE SURVEY

3.1 Introduction

This chapter provides a comprehensive review of the machine tool condition monitoring systems and methodologies developed for CNC milling machines. Milling is one of the most important machining processes. To achieve unmanned machining, the demand for a reliable and cost effective Tool Condition Monitoring System (TCMS) has grown. This has led to extensive research into this area. A TCMS is essentially an information flow and processing system in which the information source selection and acquisition, information processing and refinement, and decision-making based on the refined information are integrated [3.1]. Any comprehensive machine tool condition monitoring system can generally be sub-divided into three major sub-systems (methods) namely:-

a. Data retrieval and acquisition from the machine.
b. Data refinement and processing (feature extraction).
c. Final decision making.

Each of these sub-systems is discussed in necessary detail in the following paragraphs.

TCMS techniques are generally sub-divided into two main categories namely: direct monitoring techniques and indirect monitoring techniques [3.2]. Figure-3.1 represents the major data retrieval options when designing such a monitoring application [3.3]. The direct monitoring techniques deal with the actual direct sensing of the health of the tool. Examples of these are the use of optical sensors, proximity sensors and touch trigger probes. The major practical problem with direct sensing is that since the cutting area is normally inaccessible, the on-line TCMS development is very complicated. The indirect monitoring techniques rely on the data retrieved by other sources which may involve the deployment of additional sensors or the use of machine signals for information retrieval before final decision making by correlating the information obtained to the tool health.

Examples include the use of a dynamometer for force signals, Acoustic Emission (AE) sensors and using the machine's current or power signals.

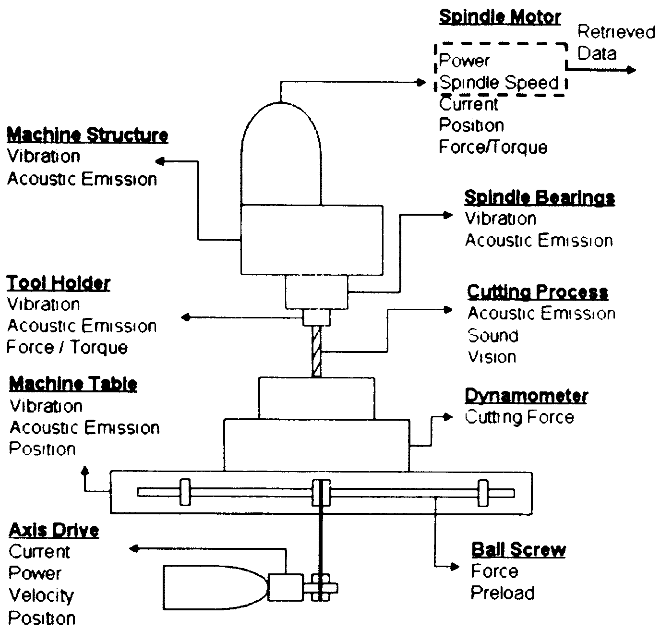

Figure-3.1, Possible Information Sources [adapted from 3.3]

The major requirement for the reliability of such designs is to ensure the calibration of the measured signals with the actual process parameters before making final decisions. The cutting conditions including spindle speed, feed rate and depth of cut affect the acquired signals and therefore there exists a strong requirement for calibration before setting alarm levels.

Figure-3.2 represents a selection of the possible data refinement and processing options drawn from review of different research papers whereas Figure-3.3 illustrates some of the basic routes to final decision making about the health of the tool. The dashed rectangles in each of these figures represents the route adopted for this research.

Figure-3.4 gives an understanding of different conditions and parameters which affect cutting tool life. Despite the requirement for more precise practical calibration, the majority of the research methods use indirect sensing techniques [3.4,3.5] because of their stated advantages over direct sensing.

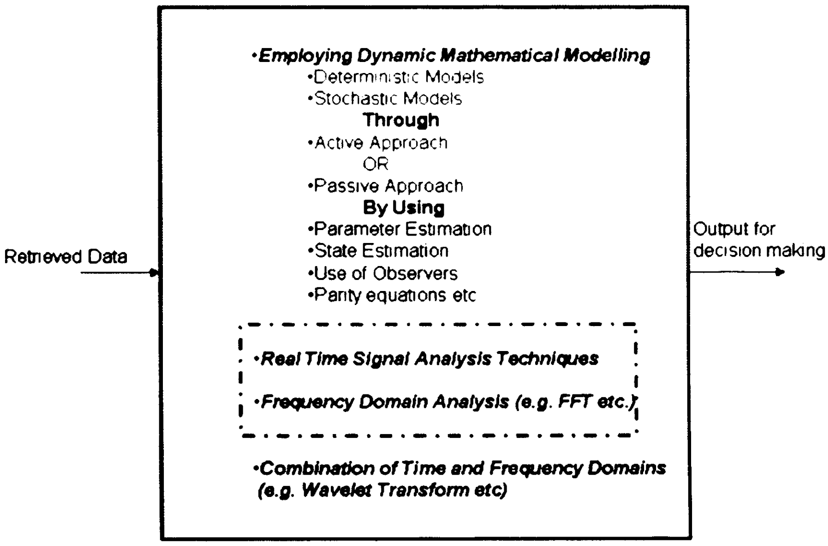

Figure-3.2, Feature Extraction /data processing options

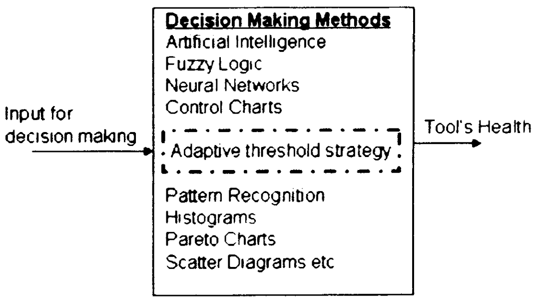

Figure-3.3, Decision making options

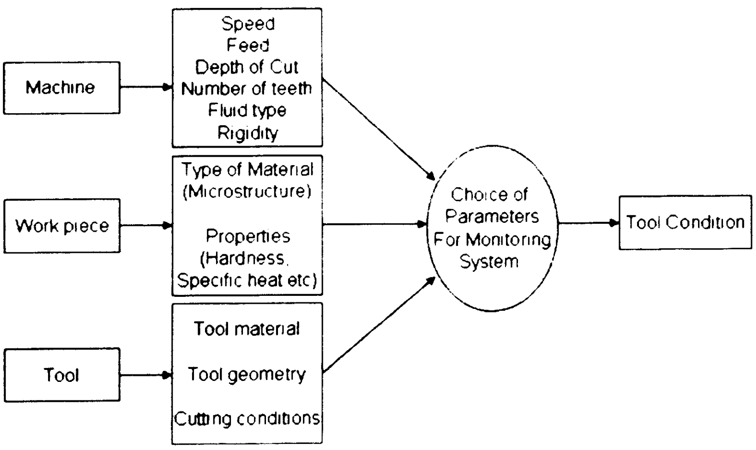

Figure-3.4, Factors influencing tool life

The practical ability and success rate of any TCMS relies on two basic elements: first, the number and type of sensors used and second, the associated signal processing and simplification methods utilised to extract the necessary important information from machining signals [3.2]. The first element involves expensive hardware which influences the cost of the system, whereas the second element affects the efficiency and the speed of the system. It is worth noting that there exists a balance between the above mentioned two elements; as the number of sensors used for better information retrieval and higher reliability increases so does the overall cost of the system. It is therefore imperative for researchers to take all these parameters into consideration. It is also necessary for any TCMS to be reliable and safe, highly automated and fast in response generation. The overall objective is to design a TCMS with high efficiency, short development time and with a reduced number of sensors. This basically includes the selection of sensors and associated signal processing methods which provide the minimum classification error of process faults. The aim of the research being reported here has been to develop a TCMS which is based on existing machine signals thus producing a low cost yet effective monitoring solution.

The following review of research is divided into three main sections. The approaches taken to Sensor Selection and the associated Data Acquisition processes are discussed in Section 3.2. Signal Processing and Feature Extraction techniques are then considered in Section 3.3. The use of these elements as inputs in the assessment of Process Condition and hence in Decision Making is considered in Section 3.4. This approach is taken to allow the consideration of the development of an optimum milling process monitoring system, which exhibits the most effective attributes of the systems being reviewed.

3.2 Sensor Options and Data Acquisition.

As mentioned in the previous section, TCMS can be designed by using additional sensors or can rely upon existing machine tool signals or use a combination of both. This section deals with the reported literature related to the first part of a TCMS design namely; sensor and non-sensor based data acquisition systems. Any data acquisition system for a machine tool condition monitoring system needs to collect data from different applicable sources at the correct time and under the correct conditions [3.6]. Different additional sensors which have been used in the past for designing such a system and the levels of research associated with them are shown in Figure-3.5 [3.7].

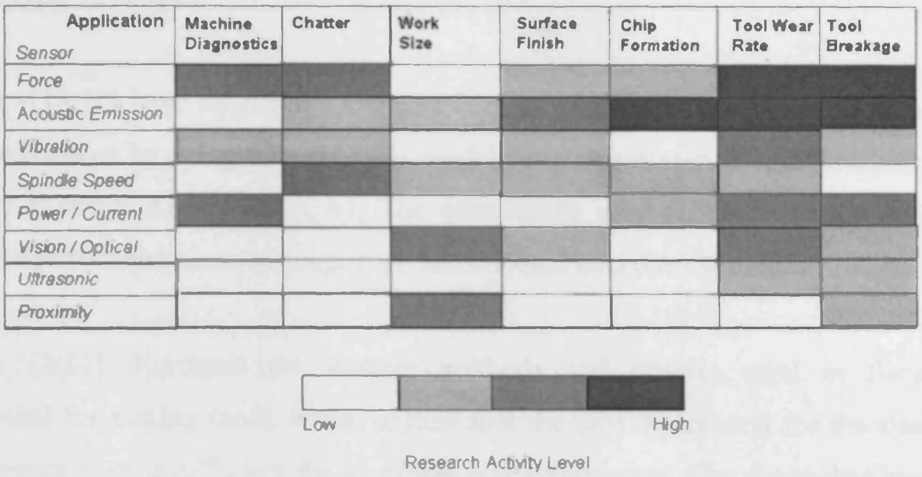

Figure-3.5, Sensors and their applications in TCMS applications [adapted from 3.7]

The review of research presented here starts by examining approaches where sensors are used to acquire process related information.

3.2.1 Cutting Force Signals

Cutting force has received a great level of attention from researchers. Both the static and dynamic components of cutting force contain information about the state of chip formation and the cutting tool [3.8]. Dynamometers are the most commonly used force sensors for the machine tool condition monitoring. A dynamometer typically consists of four three-component force sensors fitted between a base plate and a top plate. Each sensor contains three pairs of quartz plates, one sensitive to pressure in the Z direction and the other two responding to shear in the X and Y direction respectively. The following researchers have based their work on dynamometer measurements. The main aim of these methods is the identification and/or detection of tool wear.

Kuljanic and Sortino [3.9] have proposed a Tool Wear Estimation Method (TWEM) for face milling based on the analysis of force signal variations. They used a Kistler 9123C rotating type dynamometer to acquire the force signal. The dynamometer signals were stored in a PC using a data acquisition board. The effects of three different cutting parameters namely; cutting speed, feed per tooth and depth of cut were analysed. The feature extraction approach used by them is explained in Section 3.3.2 (in line with overall review structure).

Tansel et al [3.10] have proposed a Genetic Tool Monitor (GTM) to identify problems in milling operations by using an analytical model for micro-end-milling operations and an associated Genetic Algorithm (GA). The researchers used the components of cutting force in the horizontal plane to support process related decision making.

Astakhov [3.11] discussed the current methods and criteria used in flank wear measurement for cutting tools. It was argued that the existing criteria for the flank wear measurements were insufficient for its proper characterization. The researcher has shown a correlation between the work required by the cutting system and the flank wear which is independent of the particular cutting regime, cutting time and other parameters of the cutting process. The experimental data obtained using a dynamometer showed that the influence of cutting speed on the contact characteristics between the flank-workpiece can not be generalised as it differs considerably from material to material. Astakhov suggests that minimum tool wear occurs at optimum cutting speed and the apparent friction coefficient reaches its lowest value at this speed. This supports the selection of the most appropriate cutting speed for different materials for minimum wear.

Zhu et al [3.12] reported a model based monitoring and fault diagnosis methodology for free form surface machining. They have proposed a threshold based fault detection method using the cutting force signal. They have used the National Instruments™ Labview software system for further processing details of which are reported in Section 3.3.1 of this chapter.

Sarhan et al [3.13] reported the interrelationship between cutting force variations and cutting tool wear in end milling operations in terms of magnitudes of the frequency harmonics of the cutting force signals. The researchers have designed and manufactured a high sensitivity strain gauge dynamometer to be used in measuring the cutting force signal. The dynamometer was calibrated in both static and dynamic ranges. The acquired data was amplified and converted to digital format using an A/D card and passed to a PC for further processing and decision making.

Two different encoding methods to estimate tool wear from the cutting force signal data were reported by Tansel et al [3.14, 3.15] using a back-propagation neural network. The methods used were force variation based encoding and the segmental average based encoding. Force signals were digitised and stored simultaneously, using digital oscilloscopes and a PC for further processing and decision making about the health of the tool. They have reported that there is a relationship between cutting force and tool usage and claim it is possible to estimate tool wear from the characteristics of cutting force. They have produced a large body of research in this area [3.16-3.20] aimed at developing more accurate and robust systems.

Alauddin et al [3.21] have reported the effects of variations in cutting speed, feed rate and axial depth of cut on the cutting forces in end milling operations. They used a table type three-component piezoelectric transducer for force signal acquisition. The acquisition of average cutting force data was performed using an A/D card and a PC. These researchers advocated the idea that cutting forces decrease as the cutting speed increases. They also reported that cutting forces increase for an increase in feed rate as well as in the axial depth of cut.

Charbonnaud et al [3.22] have reported the design and validation of a monitored robust force control strategy for achieving an improvement in the quality of face milling operations. They suggested that for an industrial implementation mean force could be used to regulate the cutting process for higher quality manufacturing. Moreover, maximum force level should be taken into account in the monitoring application for controller switching. The milling action was modelled and a force controller implemented using a Kistler dynamometer.

Lin and Yang [3.23] have reported a force signal based model for wear monitoring in face milling operations. They suggested that a relationship between the flank wear and average cutting force coefficients can be used to estimate tool wear. The relationship has been drawn from the data obtained from a series of experiments which show that normal force coefficients increase linearly as tool wear increases, while increases in the frictional coefficient are approximately proportional to the square of the average flank wear.

Using similar approaches there has been further research into machine tool condition monitoring using force signals as the primary information medium [3.24-3.32]. Consequently, it is accepted as proven that cutting force signals measured using dynamometers can be used to monitor the health of the milling process. However there exist many issues which oppose their application for an industrial TCMS design. Most of the dynamometers are generally more suited to a laboratory environment rather than practical applications on production machines due to the limitation of workpiece size, mounting constraints, and their high sensitivity to overload [3.33]. Moreover the cost of a dynamometer is much higher than any other sensor normally used for such an application. In addition, cutting force sensors must have a bandwidth which can cover force frequency ranges of interest in common multi-tooth machining operations. All of these factors in combination provide support for adopting a research approach based upon using indirect force measurement. There now follows a review of some examples of this method and the benefits it can provide.

Albrecht et al [3.33] presented an indirect method of measuring cutting forces from the displacements of rotating spindle shafts. A capacitance displacement sensor was integrated into the spindle that measured static and dynamic variations of the gap between the sensor head and the rotating spindle shaft under any applied cutting load. The radial displacement of the rotating spindle shaft was used to measure the cutting forces indirectly via this setup. To calibrate the sensing system, the tool was loaded statically and its deflection measured with a capacitance probe. However, the measurement bandwidth was limited by the natural modes of the spindle structure. In order to increase the bandwidth of the indirect force sensor by compensating for the spindle dynamics, the design of a Kalman filter scheme based on the Frequency Response Function (FRF) of the displacement sensor system to the cutting force was used. The researchers have claimed to increase the frequency bandwidth of the sensor system significantly, from 350 to approximately 1000 Hz by employing the suggested sensing and signal processing method. The indirect force sensor system was tested experimentally by conducting cutting tests at up to 12,000 rpm with a five-fluted end mill. The measured cutting force signal may be used further for machine tool condition monitoring in any configuration as reported in earlier paragraphs.

Auchet et al [3.34] have reported an experimental approach to indirectly measure the cutting forces in a milling operation as a function of the measured command voltages of the milling spindle's magnetic bearings. A spindle is normally composed of two radial active magnetic bearings and one axial bearing. In this experimental approach, the spindle has been treated as a ''black box'', where the transfer functions linking the unknown cutting force with command voltages are established experimentally. The cutting forces have been analysed by the reaction of two radial electro-magnetic bearings due to movements of the rotor. The researchers applied FFT analysis to the acquired data to determine the frequency spectra of the signal. The researchers have shown the calculations for measuring the force value from either a single bearing command voltage signal or using the command voltages of both bearings and have concluded that adopting the later approach yields better results. It has been claimed that the cutting forces calculated from the command voltages of magnetic bearings are in good agreement with the ones measured with a Kistler four-component dynamometer.

Jeong and Cho [3.35] have reported the use of rotating and stationary feed motor currents as a measure of estimating cutting force rather than using a dynamometer. They established a relationship between the current of the stationary feed motor and the cutting force normal to machined surface with an error of less than 20%. The experimental variables used by the researchers were the tooth passing frequency and the depth of cut. They have shown a relationship between the cutting forces and feed motor current. The data sampling rate in their research has been fixed at 500 samples per second, which may be much lower than the actual encoder pulse rate for the motor control. This may result in missing the peaks in the actual signal and thus lead to the misinterpretation of results. This is a very important aspect in data analysis for this application and has been discussed in detail by the author in Chapter-6.

Kim and Kim [3.36] have developed an adaptive cutting force controller for a machining centre by using indirect cutting force measurement. The cutting forces of x, y and z axes have been indirectly measured by the information retrieved from the currents drawn by a.c. feed-drive servo motors. The researchers have developed a typical model for the feed-drive control system of a horizontal machining centre to analyze cutting force measurement from the drive motor. The pulsating milling forces are measured indirectly within the bandwidth of the current feedback control loop of the feed-drive system. The sampled data is fed to a signal processing card fitted in a PC which has the necessary signal processing algorithms. The PC provides necessary control signals to the CNC controller for the regulation of cutting force under various conditions. Despite of the fact that the designed system does not require a dynamometer, it still requires additional sensors and a PC for the processing of the data and issuing command signals back to the CNC controller.

Alauddin et al [3.37] have reported the development of a mathematical model for the average tangential cutting force in end milling. The predictive cutting force model was developed in terms of cutting speed and axial depth of cut using a response surface methodology. The researchers have claimed the validity of the predictive equation within the feed range of 0.06-0.088 mm/tooth and the axial depth of cut range 0.5-2.0 mm.

Spiewak [3.38] has also reported a similar methodology in which a milling cutter may be instrumented with a three-component accelerometer as an indirect sensor of dynamic cutting forces. The accelerometer measurements are transformed from the rotating coordinate system of the spindle to a stationary reference system of the machine tool. These transformed accelerations have been double-integrated to obtain the instantaneous error motion of the tool centre. It has been suggested that in static and quasi-static conditions the forces acting on the tool-spindle system can be obtained by multiplying the deflections of the spindle (relative to the housing) by suitable stiffness coefficients. It has been recommended that an impact of the inertial and dissipative forces, which are due to the spindle mass and viscous damping, should be taken into account if the measured forces vary rapidly.

This section of review does not contain all the research publications in this area to date but is deemed sufficient to give an idea of the popularity of force signal used as a medium of information retrieval in designing a reliable TCMS. Although force signal based methods have been successful in tooth breakage detection and tool health monitoring applications their usage has mainly been limited to laboratory based systems or for result verification purposes. This is mainly due to the fact that normally a dynamometer is used as a force sensing element and that has many issues involved with its industrial applications as described earlier e.g. limited workpiece size, cost and mounting constraints. The sensors used as replacement to the dynamometer have also faced some practical problems e.g. calibration, mounting and range of application. These facts have encouraged researchers to explore other avenues and an alternative approach to force signal for data retrieval including the use of Acoustic Emission (AE) signals is reviewed in the following paragraphs.

3.2.2 Acoustic Emission (AE) Signals

Acoustic emission (AE) can be defined as "the spontaneous release of elastic energy by any material when it undergoes deformation". It refers to sounds, in the form of acoustic and ultrasonic energy, emitted from either a process or material which can provide further information about that process or material [3.39]. AE signals are generally classified as either continuous-type AE signals or burst-type AE signals. Continuous-type AE signals are associated with plastic deformations in ductile materials, while burst-type signals are observed during crack growth in the materials. It is generally agreed that during metal cutting, plastic deformation (continuous-type AE signals) and fracture of the material (burst-type AE signals) are the major sources for AE waves. Additionally, chip impacts or chip tangling generates burst-type AE signals.

In the last decade a significant amount of research work has been carried out in using AE sensors to monitor the tool condition in milling, turning and drilling operations. The general trend in AE is to monitor the sensory signals at a high frequency range, to obtain the Root Mean Square (RMS) value and to classify this signal by using various methods. The data retrieval options from milling process based applications in relevant research publications are reviewed here.

Axinte et al [3.40] have reported an approach to use the triangulation technique applied to arrays of acoustic emission sensors for the location of uneven events occurring during machining. They have suggested that most of the sensory signals (e.g. force, acceleration, spindle power) do not have enough sensitivity to detect such tiny events. In some of these situations, the AE signal shows enough sensitivity to detect surface anomalies.

Pai et al [3.41] have presented a tool wear estimation method in face milling operations using the Resource Allocation Network (RAN) technique. AE signals, surface roughness parameters and cutting conditions (cutting speed, feed) have been used to formulate input patterns. The researchers have compared the outputs from Multi Layer Perceptron (MLP) to the results obtained from RAN. The MLP consisted of 12 input nodes with one hidden layer. It is suggested that RAN produces smaller approximation errors than MLP and has faster learning ability. The disadvantage of MLP has been reported as its much higher number of nodes.

Wilkinson et al [3.42] have presented an application of AE sensors in conjunction with an artificial neural network towards the classification of tool wear stages. The input features of the monitoring system were derived from the measurements of acoustic emission during machining and topography of the machined surfaces. Five input features were applied to a back-propagating neural network to predict a wear category which was then categorised as light, medium or heavy.

Govekar et al [3.43] have reported the use of multiple AE sensors and an analysis and selection strategy for the monitoring of machining processes. They have further categorised important parameters of the cutting process into a monitoring system's sub-parts namely; chip formation, tool wear and the onset of chatter vibration. The AE signals were detected by a piezoelectric AE sensor with frequency bandwidth of 900 kHz. In all 36 AE signals were measured and transformed into a power spectrum in the frequency band from 100 to 900 kHz for further analysis.

Inasaki [3.44] has reported the application of an AE sensor and its retrieved data for monitoring cutting processes with single-point and multi-point cutting tools as well as the grinding process. The sensor placement in multi-point cutting tools has been discussed by the researchers in greater detail. As one of the practical solutions to meet the requirement in terms of the signal transmission, it has been proposed to effectively utilize the cutting fluids as the medium for transmitting the AE signal. The AE sensor is attached to the cutting fluids' supply nozzle so that the AE signal generated at the cutting point can be transmitted through the fluids and consequently detected by the sensor. The sensed signal by the AE sensor is pre-amplified and then fed to an amplifier with a gain of 40dB. The amplified signal is passed through a 400 KHz high pass filter. The filter signal is rectified and converted to digital format by using an A/D converter card for onward transmission to a PC which carries out the further processing. The processing technique has been reviewed by the author in Section 3.3 of this chapter.

Tansel et al [3.45] have reported the use of an acoustic emission sensor for the design of a tool wear and breakage detection system for micro milling applications. It has been suggested that acoustic emission signals are a good alternative to force signals in micro machining applications. This is mainly due to the fact that dynamometer signals include high noise associated with inertial forces in machine oscillations (at high speeds). At the same time it is also suggested that users should take extra care with acoustic emission signals because they also include extensive noise created by any moving components. In this application a specially designed piezo-electric sensor was used to detect the excitations. The system used a narrow band pass filter at 40 KHz centre frequency to obtain the meaningful low frequency spectrum of the signal.

It has been a general approach across this category of research to pre-process the AE signal at the first stage using analogue hardware to get a low frequency spectrum, and then digitise the signal for transmission to the next medium (generally a PC) for further processing. The researchers have followed the same approach and have used a PC for further processing of the data to reach a conclusion.

In addition to the above, many other authors have contributed to this area. For example Ramalingam et al [3.46] have reported the use of acoustic emission signal for the detection of tool breakage. However they indicated practical limitations such as a milling cutter with several cutting edges can lead to different signal interactions. Entry and exit transients, due to sudden loading and unloading, also produce a large acoustic emission burst. Tlusty and Andrew [3.47] carried out a survey of the unmanned condition monitoring possibilities. They concluded that two of the approaches can be considered to be of worthy of further development. One approach is based upon the analysis of the acoustic emission signal coinciding with the tool breakage. The second approach is based upon the analysis of feature changes in the cutting force signal. However the major disadvantage of both these approaches is that they require additional sensors.

In a wider context, the AE technique has provided some successful applications in tool monitoring during turning operations. However, its applications in the milling processes have been less straightforward. The major problem in using AE signals for condition monitoring in milling operations is that pulse shock loading occurs during the entry and exit of each individual tooth. It is possible that the magnitude of these shock pulses may be equivalent to those generated during tooth fracture itself. Moreover during metal cutting operations, a substantial amount of AE is generated and it is hard to provide a separation between the AE generated by metal cutting and the AE generated by tool breakage itself. It is also argued that the generated AE in such operations is dependent more on the structure of the cutting material than on the cutting tool, with its signal reflecting the behaviour of the response from the machine tool setup rather than the cutting tool [3.48]. Finally, choosing a suitable area to place the AE sensors for better results is another major parameter in designing such TCMS. These factors have limited the practical application of this technique in this area.

3.2.3 Vibration Signals

The field of vibration signal analysis for machine tool condition monitoring has also been the basis of extensive research interest. In principle, the vibration of the machine tool or workpiece is observed and investigated as a means of assessing the health of a machine tool. Accelerometers are typically used as the vibration sensor. The following is a brief review of the research in this area.

Li and Tzeng [3.49] presented a study to establish a signal processing methodology that can infer the state of milling insert wear from translational vibration measured on the spindle housing of a milling machine. They used a vertical milling machine and a 5-insert face milling cutter for experimental data collection. A torsional accelerometer was fitted on top of the machine and a translational vibration sensor was fitted on the spindle housing. Data acquisition was performed with a 486-based computer and a Metrabyte DAS-20 multi-channel data acquisition board. Both the translational vibration signal and torsional vibration signal were digitised. At the first stage, a tool wear signature in the form of a translational vibration is accentuated by mapping the translational vibration into a torsional vibration using a previously identified non-linear relationship between the two. Secondly, a time-frequency distribution is calculated from the torsional vibration. The data were transferred to the PC after necessary pre-processing for further processing which will be discussed in Section 3.3.4.

Chen and Jen [3.50] used a dynamometer and an accelerometer as a vibration sensing system along with PC based data acquisition. The high sensitivity accelerometer was attached to the frame of the spindle shaft. The response of the detected signal was found to be affected by the position of attachment. It was reported that attaching the sensor close to the bearing increased the amplitude of the response signals. The extraction of the feature elements from the independent data sets using data fusion techniques was applied to extract useful tool wear information.

Vafaei et al [3.51] reported the vibration monitoring of high speed spindles using spectral analysis. The researchers monitored the vibration in spindle systems while running in the horizontal radial plane (i.e. X and the Y directions if Z is considered to be the spindle's vertical direction) and linked it to the tool's health using the Autoregressive Moving Average (ARMA) technique.

Jun and Sue [3.52] obtained a time-domain vibration signal from a sensor attached on the spindle bracket of a CNC milling machine. They elected to convert the sensor signal to an appropriate voltage level and to show the analogue signal on an oscilloscope. This approach is important since it supports local decision making i.e. at the machine itself. The acquired data file can be subsequently analysed using a PC to support further conclusions. It was suggested that this is a good approach in detecting catastrophic tool breakage but may not be very effective for tool wear monitoring. Moreover the average performance of the system has shown that a rate of 2% of false alarms may be generated and around 25% or more breakages may not be detected at all. It also highlighted that there is a trade off between both types of errors. If efforts are made to detect the missed breakages, the number of false alarms goes up and vice versa.

Insperger et al [3.53] have reported more analytical and experimental identification research for chatter frequencies in milling operations. They have suggested that the stability of the milling action can be linked to the resulting vibrations and analysis of the produced chatter signals. They reported the use of a single non-contact, eddy current displacement transducer. A commercial data acquisition hardware system was used to acquire the data which was then transferred to PC for further processing. They mathematically modelled the milling action and suggested that for healthy milling there are certain chatter frequencies which should not arise. The presence of these frequencies in the frequency spectra of a vibration signal should always be taken as an indication of possible problems concerning the machine tool's health.

Klamecki [3.54] has reported another very relevant and promising example of applying vibration signals as condition monitoring tools. It was suggested that output from a vibration sensor is normally swamped by noise in a machining environment and that this needs some powerful data filtering methods before it can be used for reliable decision making. Klamecki reported the use of stochastic resonance for enhancement of such a signal. The stochastic resonance normally refers to the increase in certain aspects of a non-linear system's output with the addition of noise to the system's input. It has been argued that it could prove to be a very useful technique in extracting useful information for industrial condition monitoring applications. The intent of the development is the prediction of the threshold crossing rate when noise is added to a signal. That is, the initial-signal-plus-noise augmented signal is characterised by its threshold crossing frequency. More specifically, the threshold crossing rate for different components of a multi-component signal is sought. The results from the experiments conducted for enhancing the low-level vibration signals for further processing and decision making were discussed.

Again, there have been many more research publications in this area but as is evident that a final practical solution has not yet been achieved. This approach bears some disadvantages which limit its applicability. These include a PC based system to start with, choice of an appropriate sensor, location of the sensor and need for excessive hardware for signal acquisition, amplification and filtering etc. These restrictions can be overcome and there have been some interesting solutions presented e.g. as Klamecki [3.54] reported using stochastic resonance to gain important information from a signal buried in the noise. Other alternative approaches which researchers have been exploring include the use of information from the machine itself. The next section presents a review of research following this route.

3.2.4 Spindle System Signals

There are various existing machine signals which can be used as the source of process information. Two of the most important sources of information from machine itself are in the Spindle System and Axis Drive System (Section 3.2.5). The analysis of these signals has a basic advantage of no extra need for additional sensors at the information retrieval stage. Different indirect methods which are normally used to evaluate tool wear and determine tool failure can be implemented by monitoring the spindle motor variables. These include spindle speed, spindle current and spindle power. Various researchers have used a single parameter, multiple parameters or a combination of these and added sensors in designing such systems. A brief review of data retrieval methods suggested in some of the research papers is presented below.

Cho et al [3.55] have reported a tool breakage detection system which utilizes multiple sensors to record cutting forces and power consumptions in a milling process for the detection of tool breakage. The researchers used Kistler and Artis sensing systems for the data acquisition of force and spindle power consumption measurements respectively. The cutting forces are measured by the dynamometer during machining. True power consumption (Ps) in the spindle drive motor is measured using two Hall Effect sensors, which are embedded in the machining centre. The signals obtained from the Hall sensors are amplified before further processing and analysis. It has been reported by the researchers that the cutting power is proportional to cutting force in general and power consumption data has been used to support the cutting forces for more precise failure detection using a Support Vector Machine (SVM) learning algorithm in this research. In the approach outlined the cases that are identified as 'failures' based on the force data are re-evaluated by the power data for more accurate detection. They argue in favour of using the force signal in addition to the spindle power signal (i.e. multiple signals) for reaching a reliable decision about the tool's health.

Shao et al [3.56] have reported a cutting power modelling strategy for online machine tool condition monitoring for variable cutting conditions. They have suggested that among all of the tool condition monitoring systems, the spindle motor power monitoring system is considered to be one of the most applicable systems for shop floor applications because it is relatively simple and its mounting hardly affects machining operations. The researchers have presented a constantly updating threshold comparison strategy, as compared to a single threshold value by taking into account the varying cutting conditions. The data acquisition system was composed of a motor power transducer, an A/D conversion card and a personal computer. The systems have been described as being capable enough to make an online identification of cutting conditions and calculating cutting power threshold values accordingly for decision making about the health of the tool.

Tseng and Chou [3.57] interfaced a PC based system to the machine tool. The software was divided into four parts; namely I/O data reading and calculating, rules and judgement, communication and finally the user interface. The spindle work load fluctuations have been used as an indicator for the determination of the machine tool's health. The detection system is based on the concept of extracting the workload of the spindle motor from the CNC controller, and then transmitting the data using the I/O card for further processing. Observation of the data indicated that when workload exceeded 8-15% above that of the normal processing operation the tool was close to breaking point. Depending upon the variations of the motor load signal, the researchers derived three rules to categorise the operation within normal, semi normal and abnormal states. However the designed system may encounter practical problems of generating false alarms because of the absence of any counter verification strategy before generating any alarm or process stoppage.

Cuppini et al [3.58] have selected the use of cutting power as a system variable to design a tool wear monitoring system. They have confirmed from experimental results that the cutting power increases in parallel to tool wear and shows repeated patterns. A power monitoring device was connected to the machine tool spindle motor. This device measures the current, voltage and power factor of the spindle motor and computes the power consumption at any instant. They further researched the computation of net cutting power and its relationship with tool wear. It was also observed that power consumption of the spindle in idle running is strongly affected by the operating temperature. Based upon these findings, they suggested a system which used a power monitoring device, a tachometer and a thermocouple as sensors to be used in the system for sensing power, spindle speed and system temperature respectively. Using the sensor signals and after making necessary calculations from the equations provided, it can be decided whether to carry on with the cutting or change the tool.

Rao and Hope [3.30] have suggested using fuzzy based reasoning for developing an on-line tool condition monitoring system. The work is based on using power and force sensors for data acquisition, an investigation into the appropriate features required to represent tool wear states and the use of a technique they called 'feature filtered fuzzy clustering' which was developed for the classification of tool wear states under various cutting conditions. The spindle power signal (using a power transducer) and the cutting force signal (using dynamometer) were acquired and processed for final decision making.

Liang et al [3.59] reported a method deploying a fuzzy controller system which monitored the spindle power in end milling applications. They suggested the simultaneous adjustment of both feed rate and spindle speed in case of any abnormality in the cutting process to avoid any potential machine overloads and tool failures. This control system has two inputs and two outputs. The inputs include: power error and power change. The two outputs are: adjusted feed rate and spindle speed.

The spindle power was measured and the processed output signals were filtered by a 4th order Butterworth low-pass filter to eliminate the signal noise. The filtered signals were then digitized and used as the inputs for a fuzzy logic controller. The control commands were sent to the Digital to Analogue Converter (DAC) section of the converter and then to the feed drive and spindle speed control box. The feed command, in a form of overriding percentage of the full scale feed rate and the speed command in actual rpm are converted to analogue voltage signals. The output signals from the controller to the feed and spindle speed drivers were obtained from relevant control boxes. They have suggested that the feed rate can be changed to a suitable percentage of the full scale feed rate at the System Operation Console (SOC) whereas the spindle speed limits were specified in the control program via a PC. They have shown the cutting test result using various metals and the effectiveness of the proposed system for applications of avoiding the tool breakage and spindle overloading.

Takata et al [3.60] used the fluctuations in the rotational spindle speed of a vertical milling machine in describing a method for the tooth breakage detection. The fundamental fluctuation frequency of spindle speed was determined by the number of revolutions of the spindle per second multiplied by the number of teeth in the cutter. The fluctuation signal of the spindle rotation is obtained through a pulse generator installed in the AC spindle motor. The pulse signal is converted to a voltage signal by a frequency to voltage converter and pre-processed by a bandpass filter to enhance the frequency component corresponding to the speed signal variations. The acquired data are transferred to a PC and processed for further decision making about the health of the tool. It was reported that although the use of spindle current signal is also very useful and cheap route to follow it is only reliable with the heavy breakages of the cutting tools. The researchers have suggested that an AE sensor technique is very sensitive for small sized tool health monitoring applications only.

Kaye et al [3.61] also reported the use of spindle speed variations for tool wear monitoring in metal cutting operations. The spindle speed changes were monitored by mounting an optical encoder at one end of the spindle shaft and checking the speed. The encoder's output has been interfaced to custom designed electronics to estimate the tool condition based on a suggested mathematical model.

As is evident from the brief review already presented above that there has been extensive research in the area of using information from the spindle system as a source for designing TCMS. It is noticeable that in most of the cases focus has been on observing the spindle power consumption variations and their verification using force sensors before reaching a reliable conclusion. Moreover, it is also evident that mostly power sensors have been used for measuring spindle power thus in reality not making it a sensor-less system. A very similar scenario can be observed with the system designed using spindle speed variations as the heart of the system. These systems can be made sensor-less at the data acquisition stage by exploring the machine electronics in detail and acquiring the signal from appropriate locations, but the most important issue which has not been paid enough attention in this area of research is the sampling rate of acquired data. The NC controller for a normal machine (e.g. Kondia B500) receives more than 1000 feedback pulses/revolution about the position and velocity of spindle itself. Exploring the fact further reveals that for a normal spindle speed of 500RPM, the controller sends over 8000 control pulses per second. In the research presented in this thesis it was observed that the sampling rate for any data acquisition from such sources if they are to be used for TCMS applications should normally match the controller's control pulse rate or the variations will normally be controlled by the controller before the data are acquired. This does not mean that all the variations will be missed at lower sampling rates, but actually means that the variations of point of interest may be missed out before taking decisions about a tool's health.

3.2.5 Axis Drive System Signals

As reviewed in Section 3.2.1 force measurements are commonly acquired by using a dynamometer mounted on a worktable or a tool holder of a machine tool. The physical characteristics of the dynamometer mounted on a worktable not only limit the size of the workpiece but its cost is also a major concern. This has encouraged researchers to explore the advantages of feed axis motor current-based TCMS. These methods either process the motor current signal directly or estimate cutting force by means of the motor current, and then the estimated cutting force is used to monitor the tool's health during end milling operations. There has been extensive research in this area and a brief overview of data retrieval options for such systems is presented in the following.

Xiaoli and Guan [3.62] reported an algorithm which consisted of wavelet-based de-noising, discrete-time-frequency analysis, FFT and second differencing of the feed motor current signal for the detection of cutting edge fracture during end milling. The three axes feed motor currents were acquired using Hall Effect current sensors and passed through low pass filters for noise removal. The analogue signal was converted to digital format at 1 KHz. They have reported wavelet based de-noising of the signal before applying the Discrete Time-Frequency analysis approach for feature extraction. The wavelet based de-noising has been reported as being very effective in removing the influence of non-linear friction and cogging force (cyclic physical resistance felt in some alternator designs from magnets passing the coils) to the motor current signals. These non-linearities are introduced by the feed screw and gear systems and must be removed before reaching a reliable decision about the health of the cutter. The tooth passing frequency was also taken into consideration for final decision making.

Romero-Troncoso et al [3.63] have reported the design of a Field Programmable Gate Array (FPGA) based stand alone tool breakage detection system. The technique uses the cutting forces on the feed axes to compute the discrete wavelet transform of the resultant force. The current signals of axis motor drives have been used to estimate the cutting force for a non-dynamometer based system. The researchers have used the control currents to the axis drive as indicator of the force and these signals are fed to the signal conditioner and filtering stage. This stage has been used not only to limit noise but also to eliminate the interfering signals by using an 8^{th} Order anti-aliasing Chebyshev filter. The data acquisition system was based on a 12-bit, 2-channel simultaneous sampling analogue to digital converter (ADC). The processing was done on a Hardware Signal Processing (HSP) system as part of a "System on Chip" (SoC) implementation for specific application designs. They have also reported another system [3.64] which takes into account the influence of the most important spurious signal components in order to determine the optimal parameters for signal conditioning. The most undesirable components within the spectrum of a current drive signal are generated by high frequency noise, current control commutation and ball screw effects. In order to extract the desired cutting force signal for further analysis, the dynamic ranges of the signal to specify the analogue filter parameters have been determined. Different formulae showing the calculations of the different frequencies being generated by responsible components are shown and the overall driver current spectra are shown with all the required as well as undesired frequencies.

The Intelligent Process Monitoring and Management (IPMM) centre at Cardiff University has published various papers on monitoring applications including machine tool condition monitoring. For example, Grosvenor et al [3.65] have reported the evolution of a hybrid approach to machine and process condition monitoring. The advantages and implications of this approach have been illustrated with practical examples in different areas including machine tool monitoring. It is emphasised that whichever route is being followed, the intelligent maintenance of data is very important. To this end, the authors propose different processing methods depending upon the application and requirement.

The same authors [3.66] reported a non-sensor based integrated approach to machine tool and cutting process condition monitoring. The approach suggested using the embedded sources of information from the machine e.g. encoders, switches, sensors and signals for the information retrieval for further analysis rather than employing additional sensors. The use of three existing machine tool signals to detect tool breakage was reported namely; velocity feedback signal, armature current and the velocity command signal generated by the controller. The variations in the tachometer velocity feedback signal are used to monitor the tool's health. The system uses additional Data Acquisition (DAQ) cards consisting of the filtering and ADC stages before the data are transferred to the PC for further processing and decision making.

Szecsi [3.67] has reported a cutting tool condition monitoring system based on the measurement of the main DC motor current. It consists of current and speed sensors, a cutting tool-part touch sensor, analogue memory, amplifier stage, filters and a PC. It was reported that there is an increase in cutting force with the progression of flank wear. To avoid the use of an expensive dynamometer for the force measurement, the design and development of the system based on DC motor armature current and its relationship to the cutting force has been suggested. The system is trained by a genetic algorithm based fuzzy rule set to support its application.

Stein and Wang [3.68] reported the possibility of using an AC induction motor drive system as torque sensors. The motor drive system has been modelled with a view to using it as a torque sensor to support the monitoring of tool wear or breakage detection as well as machine component failures. The CNC milling spindle drive system has been modelled to show that the rotor input power is linearly related to the static as well as dynamic cutting torques under normal process conditions. It has also been reported that the static sensitivity of the spindle system as a sensor increases and the bandwidth decreases as the spindle speed is increased. It is accepted by the researchers that though extensive research has been done in this area, there is not a generic solution to all possible scenarios for tooth breakage detection, nor is this system capable enough to deal with all possible scenarios. It is reported that the system is reliable enough to deal with spindle speeds up to 2000 RPM.

Lee et al [3.69] reported the use of induction motor current for the design of a tool breakage detection system. The research is based on the theory that square of the stator current of induction motor is approximately proportional to the motor torque. The occurrence of tool fracture will cause cutting force and torque variations and the stator current of the motor will change accordingly i.e. the changes in the current can be used in identification of the tool's health. They measured and analysed only one of the stator currents reasoning that each stator current has the same peak-to-peak amplitude, but is displaced in time by a phase angle of 120 degrees. In order to perform the sensitivity analysis for the square of the stator current signal, a dynamometer was also used.

Y. Altintas [3.70] has researched the usage of the feed drive current for the prediction of cutting forces and to determine tool breakage. The importance of periodicity of milling forces at tooth passing intervals has been highlighted. It is suggested that the bandwidth of the current loop is important, so the spindle drive motor current which has a low bandwidth is identified as being not very useful for such applications when compared to the feed drive motor current loop. He has modelled the velocity and position loops of the feed drive system of a particular vertical milling machine system. The friction in a steady state machining feed is considered and the current required to overcome this friction is calculated. The three feed axes of the machine used for this research had recirculating ball screw drives and directly driven by Pulse Width Modulated (PWM) permanent magnet DC motors. The average current was sampled by an analogue circuit with the data acquisition being determined by the tooth passing interval, as obtained by an encoder mounted on the spindle shaft using a PC. It was suggested that whenever a tooth breaks, it does not remove any metal and the current will drop, whereas the next tooth will be removing more metal as compared to a normal one and the current will increase. The current will be the same for the remaining two cutters. These variations in the current will clearly indicate the breakage of a tooth.

The proposed algorithm uses the current value of the feed drive current and compares it against the dynamically set threshold values to determine the state of the cutting tool. The sampling rate for the current signal has been set at the tooth passing frequency, which could normally be very low as compared to the CNC encoder providing the axis motor speed variations to the controller. This could result in the control of current to the motor by the controller before the system takes current samples i.e. the controller could act to reduce the effect of a broken tooth before the monitoring system is able to provide an accurate diagnosis. This is a potential drawback to the system potentially in high speed milling.

Despite the reviewed and other research in area of using axes current drives for the monitoring of machine tool's health there has not been a great success in designing a standalone monitoring system. One of the major reasons behind this is the existence of non-linearity of friction, cogging and temperature variations in the feed drive system which contains screw and gears. It makes it very hard to estimate an accurate cutting force from the motor current. Meanwhile, the dynamic characteristics of the current feedback control loop of the feed-drive system limit the bandwidth of the current sensing system, so the motor current cannot track the cutting force under high speed conditions.

3.2.6 Vision Sensors

Vision sensor based systems have been widely researched, but their industrial applications are still at an early stage because of their high complexity, costs and low reliability and flexibility. With respect to other methods, the main advantages of vision are: natural human like operation, ability to recognise different morphologies, high information content in images, high availability of image processing algorithms, independence from the cutting conditions and sufficient accuracy. Lanzetta [3.71] has reported the use of a vision system as part of such a monitoring system. An exhaustive classification of defects in cutting inserts and the design of an automated sensor to recognise the defects and to measure the tool wear for an automatic tool condition monitoring system has been researched. The classification of the tool morphologies has been based on standards available in technical and scientific literature. The quantitative parameters required to be used as threshold values for automatic recognition have also been selected from the established standards. The researchers have proposed a defect detection and wear measurement flowchart which deals with a variety of cutting conditions and scenarios. The author has used an auto-focus zoom lens to maintain uniformity when dealing with different tool sizes and varying distances.

Although the field looks exciting and promising there have not been any astonishing results in this particular area of research for the applications in machine tool condition monitoring applications. There are different reasons behind this and some of them are:-

- Sensitivity of such systems to normal industrial disturbances.
- The presence of chips, fluids and dirt in such an environment.
- Mechanical influences.
- A very high maintenance need in such systems which accounts for unnecessary down times.
- High investment costs.

3.2.7 Multi-Sensor Systems

In parallel to sensor-less or single sensor based TCMS there has been ongoing research into multi-sensor TCMS. The overall objective of this has been to design a TCMS to monitor the loss of functions of a machine tool and the reduction of machining accuracy and performances in order to detect an abnormal state as soon as possible. It must also indicate to the controller of the machine tool the conduct of proper corrective or safe action. Most common methods of tool breakage detection have focused on the development of signal processing techniques that can enhance the effect of tool breakage on the measurements, such as cutting force, acoustic emission and spindle motor current. The effect of tool breakage is usually revealed by an abrupt change in these processed measurements for example the exceeding of a threshold value. However, a tool breakage signal from a single measurement may make a misjudgement due to the complicated dynamic characteristic of the cutting process and the instability of the machine tool itself [3.72]. To prevent this from happening integrated approaches based on measurements from several sensors have been proposed by various researchers.

Al-Habaibeh and Gindy [3.2] have reported an Automated Sensory and Signal Selection System (ASPS) for milling tool condition monitoring. They have used many of the major methods of signal processing including wavelet analysis, average value, signal deviation and FFT. In addition, the system uses a number of sensors including an AE sensor, a Dynamometer, a piezoelectric sensor, thus adding to the overall cost of the system. They have identified the benefits of different sensors and have shown the related accuracy of the system versus its cost. The cheapest system costs around £3900 with an accuracy of around 70%, whereas a system with accuracy of around 91% costs around £19,000.

Fu et al [3.73] used power, force, AE and vibration sensors for the design of an intelligent condition monitoring system for on-line classification of machine tool wear. They favoured the multi sensor fusion technique to develop a more reliable TCMS. The signals from AE sensor, dynamometer, accelerometer and current sensor are pre-amplified and filtered for noise elimination. The filtered signals are acquired by a PC at different sampling rates which are corresponding to each signal's characteristics. The PC is used for further processing of the signals using fuzzy pattern recognition technique before final decision making.

Ertekin et al [3.74] discuss an identification approach towards the sensory features that can be used for the control and monitoring of milling operations under varying cutting conditions. They have reported cutting experiments and multi-sensor data acquisition, signal processing, data reduction, analysis and feature selection, and multiple regression analysis of multi-sensor data. The sensor data includes cutting force measurements, spindle quill vibration, and acoustic emission, each of which has been further divided into measurable components which were acquired simultaneously. Although the suggested system is said to be capable of detecting tool breakage effectively it does have a very high cost involved and the implementation issues do not really support its practicality in an industrial application.

Kang et al [3.75] have also reported a monitoring technique using a multi-sensor approach. The researchers have used the combination of a dynamometer, AE sensor, acceleration sensor and gap sensor to determine the tool condition. The signals were acquired from the sensors and frequency filtering was performed in accordance with the frequencies of the signals after necessary amplification. The signals were acquired by a PC and analysed using a specialist software package before making any further decisions.

Although the multi-sensor machine tool monitoring systems may be very effective in certain applications; the additional cost involved in the installation of these sensors adds to the overall cost of the system. As is clearly evident from the research reported by Al-Habaibeh and Gindy [3.2] that to get sufficiently reliable results, the cost factor may be as high as £19,000, which is almost half way to the price of a normal machine tool system used in Small to Medium Enterprises (SMEs). The need for more affordable systems has thus guided researchers towards sensor-less TCMS activity in the area, including the research outlined in this thesis.

3.3 Signal Processing & Feature Extraction

Signal processing and feature extraction is the second major consideration in designing any TCMS. The ability of any condition monitoring system depends upon two basic elements: first, the number, type and effectiveness of any sensor (if) used and second, the associated signal processing and simplification methods utilised to extract the necessary important information from acquired signals before decision making. Signal processing plays the key role in feature extraction from the acquired and filtered data before final decision making. Feature extraction can be described as being a process that deploys an algorithm that reconstructs features from data and/or other features of the source. The idea of using a mathematical model to describe the behaviour of a physical phenomenon is well established. In particular, it is sometimes possible to derive a model based on physical laws, which enables the calculations of some time dependent quantity nearly exactly at any instant of time. If exact calculations are possible, such a model is named as "deterministic". In actual circumstance this is not always possible. In such situations a model is derived to calculate the probability of a future value lying between two specific limits and is referred to as "stochastic model" [3.76].

In model based approaches observations are considered as a time ordered stochastic process. The techniques used in this area include parameter estimation, state estimation, use of observers and parity equations. It is true to say that the better the model used to represent the dynamic behaviour of the system the better will be the chance of detection of faults. However, modelling errors and disturbances in complex engineering systems are almost certain. One of the approaches emphasised to overcome such issues is to generate models in which residuals are insensitive to uncertainty and sensitive to system faults. This approach is termed as "active" and the examples are unknown input observers and robust parity equations. On the other hand there is another approach termed as "passive" which uses an adaptive threshold strategy at the decision making stage and propagates the effects of system uncertainties observed to the model for future actions. In the passive approach, the uncertain parameters of the model may be bounded in intervals which are generally named as interval models. These may be generally classified as linear interval observers [3.77] and non-linear interval observers [3.78]. Considerations needed in developing this approach include the accuracy requirement of the designed model which should be as high as possible. In addition measurements have to be made on a healthy system, and healthy response needs to be retained for reference. Different measurements and models are required for each machine and process to be monitored. Whilst automated testing can reduce the time (and cost) associated with this process the need for complete and accurate models of the process under all possible conditions remains an important consideration.

In contrast to the model based approaches, a feature based approach has no strict requirement regarding the full prior knowledge database about the faults in the application area of such system [3.79]. The feature extraction techniques in this area are based on extracting the information from real time signals coming directly from the machine or process. It is normally required in any feature extraction technique to retain the original variables but to process a smaller set to reduce the processing burden in order to get the maximum information from minimum processing power. It is also required to remove those input variables which do not contribute significantly to the actual monitoring system. All of this contributes significantly to the design of a much faster and efficient system at a lower cost. This has been the driving theme of the research activity being reported here. A review of research work carried out in the area of signal processing/feature extraction from different signals for assessing the machine tool's health is presented in the following sections. This builds upon the data acquisition and signal processing activities already reported.

3.3.1 Mathematical Modelling

The study of the interaction between cutting tool and work piece is as old as machining process itself but it gained a real momentum with the advancement in technology and in knowledge that has become available over the last few decades [3.5]. One of the most frequently used methods for machine tool condition monitoring is time domain mathematical modelling of the process. There are various time series modelling techniques used including Autoregressive (AR) modelling, Moving Average (MA) modelling, the mixture of both Autoregressive and Moving Average (ARMA) modelling and Autoregressive Integrated Moving Average (ARIMA) modelling. These methods form the basis of many approaches outlined in this section.

An example of a modelling based approach was reported by Tansel et al [3.10] who developed a Genetic Tool Monitor (GTM) for micro end milling operations. The milling operation is modelled by considering the trajectory of the tip of the cutting edges of the tool. The monitoring strategy is based on parameter estimation. Key parameters such as operating conditions and tool geometry are input into the model. Depending upon the operating conditions one or more of the parameters are estimated by the system and are used for the estimation and analysis of major affecting conditions. For example, the cutting force may be estimated by the analytical model. The accuracy of the estimated cutting force parameter is evaluated by comparing its value to one which is sampled by using a dynamometer. The validity of the model is thus confirmed and over time the need for the verification process is reduced.

Zhu et al [3.12] reported a model based monitoring and fault diagnosis methodology for machining processes. A dynamometer was used as a source of force signal inputs to the system. The process modelling was carried out using cutting conditions, cutting coefficients, tool path geometry and critical run out as inputs. They proposed a two step process; a fault detection step and a fault diagnosis step. In the fault detection step of the system, a monitoring index has been calculated as the deciding factor. The monitoring index is based on the spectrum analysis of the measured force signal. For the given tool path geometry and cutting conditions, the cutting engagement conditions are determined and used in the process model to obtain the threshold values along the tool path. The measured monitoring index is then compared against the threshold value for fault detection. After the fault has been detected (by the fault detection step) the fault diagnostic step is used to determine whether the fault is due to run out, chipping/breakage or both.

The estimated and measured force signals were analysed by using a wavelet transform to obtain a measured feature vector and an estimated feature vector. After obtaining the measured and estimated feature vectors, both of these were normalised and synchronised. These vectors were then used for a mathematical calculation to diagnose the fault. One problem with the designed system was that it requires a great detail of information before it can be employed. For example it has to be provided with the tool path geometry which may prevent the system from being applied in general purpose applications. Moreover the use of the dynamometer, a data acquisition card and a PC along with Lab View software adds to the overall cost of the system.

Lin and Yang [3.23] reported a force signal based model for wear monitoring in face milling operations. They have suggested a relationship between the flank wear and average cutting force coefficients using cutting parameters. The continuous variations arising in milling operations, in contrast to single point tool operations (e.g. turning) have been considered. The force equations have been modelled based on the effective lead angle and nominal axial rake angle. The cutting force equations have been used to estimate cutting force coefficients (normal force coefficient and friction force coefficient). The estimated cutting force coefficients are dependent upon the cutting parameters. These effects have also been analysed in detail in order to categorise the significance of each parameter in this context. They used least squares estimation to determine the model for cutting force coefficients as functions of the average chip thickness. It was shown that the normal force coefficient linearly increases as tool wear increases while the increase in the frictional coefficient was approximately proportional to the square of the average flank wear. It was also suggested that the cutting force coefficients are decreased as the depth of cut increases. Moreover the cutting force coefficients decrease as the feed rate per tooth increases and they slightly change with an increase in the cutting speed.

Choudhry and Rath [3.25] proposed a cutting force model for the estimation of cutting tool wear using relationship between flank wear and the average tangential cutting force coefficient. It has been approximated for the model building that the feed rate is much smaller than the cutter radius in order to assume the cutter path as a circle rather than a cycloid. The same concept was supported by the author and is explained in Chapter-6. They have claimed to experimentally establish the relationship between the tangential cutting force and the cutting parameters. A dynamometer was used to acquire force signals for experimentation and testing of the approach. It has been claimed that the cutting force coefficient is inversely proportional to the feed per tooth as well as depth of cut. In other words as either the depth of cut or feed per tooth or both increase, the flank wear increases.

Tansel and McLaughlin [3.19] reported the use of a time series based Tooth Period Modelling Technique (TPMT) for the detection of tool breakage. They have used the dynamometer to acquire the force signal. TPMT uses data which has been sampled in phase with the pulses of an encoder at predetermined rotational angles of the spindle. For each data point the estimation error is calculated by using an AR model of the signal at the end of the previous tooth period. The sum of the squares of the estimation error is calculated for each tooth period. Tool breakage can then be detected from the sum of squares pattern. The parameters of a 20^{th} to 24^{th} order AR model were used for this application. At the end of each tooth period, the parameters of the estimated model of the last data point are selected as a reference. If the cutting conditions change (i.e. by an increase in the depth of cut etc.) during any tooth period, the sum of squares of the estimation errors will increase. In the following tooth periods will keep changing until the transition period ends and the cutting process stabilises. For a broken tooth, the sum of squares of the estimation error will be high as long as the broken tooth stays in the workpiece. However, when the broken tooth leaves the workpiece, the perfect tooth starts cutting and the sum of squares of the estimation errors will be reduced. This makes it possible for the TMPT method to detect the difference in signals arising due to tool breakage from a new tool as well as from changes in the cutting parameters. They have also reported the use of a neural network approach for the tool breakage detection [3.20]. Here they have used the force signal and have applied both supervised and unsupervised learning methods for training the applied neural networks. They proposed simulation based training of the neural networks for real time applications, as it may not be possible to train them for all the possible practical situations. This is clearly indicative of one of the problems faced by neural networks for such applications. It was noted that, if the cutting conditions continuously change or heavy tool wear is allowed, the RCE may classify a large number of inputs as "unidentified". The system's success rate in best conditions was around 97.4% using the force signal. The use of force signal has been advocated because of its purity. This could be a possible limitation because of the cost involved and the restriction of the workpiece dimensions due to the dynamometer size.

Kaye et al [3.61] used spindle speed changes for tool condition monitoring. They derived a mathematical model of the cutting process. The model required initial flank wear information prior to the first point-to-point calculation. Since it is practically not possible to monitor initial cutting with every new tool to populate the monitoring application with this information before it can be used for its actual job; they used a response surface methodology to generate these values from the results of specific cutting tests. The initial value of the flank wear was obtained by using different ranges of the independent variables (cutting speed, feed rate, and depth of cut). However it should be noted that performing a complete statistical analysis is never a very simple process if it is necessary to obtain a complete picture by changing all the involved variables at all possible levels. They also used spindle speed as an input to the model and the tangential cutting force was taken as a predictor of the tool condition.

3.3.2 Real Time Series Signal Analysis

Another route to follow in order to extract useful information from acquired and filtered signals for further decision making is real time signal analysis using either statistical approaches or an algorithm. In such applications the signals from the sensors or machine sources are directly analysed after necessary filtering and signal conditioning without using any mathematical models of the system. The output of these analysers is normally based on a comparison between a healthy signal and the acquired signal. Reliability has been a major challenge in the design of such monitoring applications as the cutting process parameters are subject to change all of the time and the presence of transients in monitored signals can also be misleading.

The method for Tool Wear Estimation (TWEM) reported by Kuljanic and Sortino [3.9] used a dynamometer to measure force signals for real time statistical analysis. They developed feature parameters to represent the information contained in the cutting force signal. These parameters are numeric values which quantify one or more characteristics of the cutting force signal for a given set of data. For example the mean cutting force during a cut, i.e. between the entrance and the exit of the tooth, was chosen and adopted as a feature parameter. Similarly, the mean cutting perpendicular force, the mean axial cutting force and the mean torque during a cut were also adopted as feature parameters. It was established that all cutting forces were influenced by feed per tooth and depth of cut, while cutting speed had a significant effect only on mean axial cutting force. They have reported that all mean forces were influenced by tool wear, but their sensitivity was different. The mean cutting force was very sensitive to tool wear. In general, the cutting force and the power both increase when the tool wear increases. It was observed that there is a power increase of approximately 20–22%, when the face milling cutter is worn, in comparison to the power when the cutter is sharp. The Mean Axial Force is most sensitive to tool wear detection, however, the signal is noisy at lower degrees of tool wear.

Tansel et al [3.14] have reported two different encoding methods namely; Force Variation Based Encoding (FVBE) and Segmental Average Based Encoding (SABE) to estimate tool wear from the cutting force signal using a back-propagation type neural network. The FVBE method calculated the variation of the feed and thrust direction cutting forces. These two variations were used as inputs to the neural network for further wear classification. In the SABE method, the feed and thrust direction forces were sampled and normalised. The researchers acquired data for one complete revolution and divided it into ten segments of equal length. The segments were then averaged. In all 20 segments were presented to the neural network as the input for further decision making. They used a dynamometer to acquire cutting force signal.

Tansel et al [3.15] have also presented an approach for tool condition monitoring during the machining of a non-metal workpiece. It deals with situations when the cutting forces are so low that the signal to noise ratio is really not significant enough to be analysed as is the case when machining some non-metals. The system is referred a neural network based periodic tool inspector. As is evident from the name, the system evaluates the tool's efficiency using a test cut on a test material (normally a metal piece) periodically. The researchers have used a dynamometer to acquire the force signals. The test piece is attached to the dynamometer whereas the machine does the normal operation without cutting on the test piece for a predetermined period. The tool is periodically moved to the test piece for inspection and the acquired data are analysed. Whilst this approach removes the established restriction on workpiece size normally related to dynamometer based methods it does not then support continuous tool monitoring.

Wilcox et al [3.80] reported the use of cutting force and acoustic emission signals from a milling operation simultaneously in determining the tool wear. They have used a table mounted dynamometer, a charge amplifier, an acoustic emission sensor and low pass filters for data acquisition. The acquired data is transferred to a PC through an A/D card for further processing and decision making. The research focussed on drawing quantitative conclusions as to how local insert geometry at the cutting edge affects the cutting force and how this is represented in AE data. Acoustic emission and force measurements were made for a range of wear geometries and the effects of these geometries were estimated from basic mechanical principles. The component of cutting force perpendicular to the feed direction was averaged over the central part of each cut and the mean plus one standard deviation was used as a rough measure of the force pulsation peak height. A similar type of processing was applied to the root mean square (rms) value of the AE signal. The test results for the worn inserts were compared against the data obtained from new cutter experiments. The researchers suggest that flank wear can be expected to produce an increase in both cutting force and acoustic emission when it affects all inserts in a milling cutter approximately equally and edge damage such as notch wear or crumbling increases the overall cutting force.

Axinte et al [3.40] proposed an approach using an array of three acoustic emission (AE) sensors to locate uneven events (e.g. tool breakage) in the machining process. A triangulation technique was used for the sensor placement and by analysing the arrival times of the acoustic waves the exact location of the energy release can be calculated. They carried out extensive testing of the proposed system and have mentioned the possible practical applications of the system along with certain limitations. The major limitation of this approach in tool breakage detection is the inability of the system to reach a decisive conclusion about the tooth breakage since energy releases may not only arise due to tooth breakage but may occur normally in the machining process.

Wilkinson et al [3.42] reported a tool wear estimation strategy using acoustic emission sensing and presented a combination of time and frequency domain analysis of these signals to neural networks for final decision making. In their reported approach, during each pass of the milling cutter through the workpiece, acoustic emission was detected by a non-contacting fibre-optic probe and a conventional piezoceramic transducer. The variations of the mean frequency components of the AE signal along with the variations in the flank wear were obtained by performing an FFT analysis of the AE signal. They extracted five different features from the processed data before presenting it to the neural networks. The features used were: mean frequency, rms value, surface finish integrated spectral content in a low frequency spectral band (below the tooth passing frequency), surface finish integrated spectral content in a kinematic frequency spectral band (around the tooth passing frequency) and surface finish integrated spectral content in a high-frequency spectral band (above the tooth passing frequency). The training process presented the five features and associated targets, at random, to the neural network for a total of 96000 iterations. The system presented satisfactory results.

Tansel et al [3.45] applied real time signal analysis methodologies to acoustic emission sensor signals to detect tool wear and breakage. The proposed system is claimed to separate tool entry and exit conditions from those arising due to tool breakage in the acquired signal. The proposed monitoring system evaluates characteristics of the impact of each tooth with the workpiece. It has been reported that AE frequencies of excitations by such impacts are normally higher than 20 KHz. He selected 40 KHz for the application design. To detect a tool breakage from this signal, he used two different signal processing approaches. In the first one, the signal from the system was simply compared against a preset threshold value. In case of the signal crossing the threshold, the slope of the curve was calculated to reach a final decision about tool breakage. In the second approach, a low pass filter was used to filter the signal coming from the system. The use of this additional low pass filter along with linear interpolation on a set of obtained data made it possible to distinguish tool entry, exit, breakage, avoiding aliasing and eliminating sudden jumps and decays.

Jun and Suh [3.52] reported the use of vibration sensor time domain statistical signal processing methodologies for tool breakage detection. They have focused only on the steady state milling and have excluded the transient phases of tool entry and exit in the reported research. The Statistical Process Control (SPC) measures *X-bar* control schemes, Exponentially Weighted Moving Averages *(EWMA)* and Adaptive *(EWMA)* schemes have been applied to the vibration signal for decision making. It has been reported that these control schemes automatically determine their threshold values independent of cutting conditions under the proposed design. To undertake the minimum possible experiments encountering maximum possible cutting conditions, they have used the orthogonal array approach *(L27)* in determining cutting test parameters. The factors considered for the orthogonal array approach were the diameter of the cutting tool, number of flutes in the tool, spindle rpm, feed rate, axial depth of cut and workpiece material. The proposed system has a trade off between the detection of the faults and generation of false alarms.

As is evident from the brief review presented above, most of the signals in practice are time domain signals in their raw format. That is, whatever that signal is measuring, is a function of time. When we analyse the signals in the time domain itself we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for some signal processing related applications. In some of the cases most distinguished information is hidden in the frequency content of the signal. This fact has always been an encouraging factor for researchers to also investigate this area. The frequency domain analysis based systems for TCMS designs are reviewed in the following section.

3.3.3 Frequency Domain Analysis

As stated, in addition to real time signal analysis, frequency domain analysis has also been the basis of tool monitoring application designs. The FFT of any time domain signal shows its frequency amplitude representation. Although FFT is probably the most popular transform being used, it is not the only one. There are many other transformations that are often used by engineers and mathematicians e.g. Short-Time Fourier transform and Wigner distributions. Although the FFT gives a very clear spectrum of the signal being analyzed it does not indicate the exact time scale of the existence of those frequency components. This information is not required when the signal is stationary, but it is of vital importance in a non-stationary signal analysis application. This problem was overcome to some extent by the introduction of the Short Time Fourier Transform (STFT). The signal is divided into smaller segments for STFT analysis and these segments are considered as "stationary". For this purpose a window function is chosen and the width of the window must be the same as chosen segment of the signal where the stationary characteristic is applicable.

Sarhan et al [3.13] reported the relation between cutting force variation and tool wear in end milling. They examined and presented the effect of wear variation on the magnitude of the cutting force harmonics. They have used a model based simulation of the force signal of the machining process. In parallel a dynamometer was used to measure the actual force signal from the machine at different wear levels of the tool. Both of these signals have been analysed using FFT. It has been observed that the magnitude of certain harmonics in the force signals (both simulated and measured) increases significantly with flank wear whereas some of the harmonics are unaffected. For example in the case of a four-tooth cutter, the second and third harmonics are unaffected by flank wear. On the other hand; the first harmonic increased significantly with flank wear. At the same time, any changes in the cutting conditions or on the tool performance lead to changes in the amounts of flank wear, leading to changes in the cutting forces harmonics.

Elbestawi et al [3.31] reported the use of cutting force signatures in determining tool wear. They have analytically and experimentally shown that the magnitudes of the individual harmonics of the cutting force are affected differently by flank wear and claim that this phenomenon can be used as an indicator of the amount of flank wear. Mathematical simulations of the cutting process with respect to cutting force and frequency spectrum have been presented. They have shown that, since milling is a dynamic metal cutting process, any changes in the condition of the tool, such as that caused by an increased amount of flank wear, would also appear as changes in the signature profile of the cutting force spectrum. They show that the fundamental tooth passing frequency and its harmonics are related to flank wear. Thus the effects of flank wear on the cutting force will be manifested as an increase in the magnitude of the cutting force harmonics provided the cutting conditions remain unchanged. One possible limitation with the system could be the breakage of a tooth, which would change the tooth passing frequency and all its harmonic values to new ones. They have reported that the magnitude of certain harmonics increases significantly with flank wear whereas others remain unaffected. This is dependent upon the number of teeth in the cutter as well as the nature of the cutting process being undertaken which could be another practical limitation in implementing this system in a real time tool condition monitoring system.

Tarng [3.32] presented a mechanistic model for the prediction of the cutting force and its analytical analysis and verified the results through practical experimentation. This assumed that cutting force in the run out free cutter is periodic with tooth frequency. Therefore, the characteristics of the cutting force signal and its frequency components change with the event of a tooth breakage. A table type dynamometer was used to acquire the force signal which was processed in the frequency domain to examine the frequency spectrum. It was suggested by the frequency domain analysis that the tooth passing frequency and its harmonics are dominant for a new cutter. In the event of breakage however since one of the teeth is missing and the next one has to do extra cutting, a clear indication of the rise in the cutting force for that particular tooth was seen. This was responsible for the change in overall frequency spectra. This one rise per revolution introduces a frequency component of tool rotation and its harmonics. These frequency components get stronger and stronger with time and could be used to give clear indication of the breakage. However it was suggested that it is difficult to detect tool breakage using the instantaneous cutting force directly. This was mainly due to the reason that cut geometry; run-out, vibration, measurement errors and noise are all involved. To overcome these problems, Tarng has suggested using a data acquisition system and digital filtering techniques. The cost factors associated with using a PC based system in addition to using a dynamometer could limit the practicality of this approach for industrial applications.

Inasaki [3.44] reported the use of acoustic emission sensor and a spectral analysis technique for the monitoring of turning, milling and grinding operations. This work suggested that the ratio of two characteristic peaks in the power spectrum of the refined AE signal change due to tool chipping. The first peak in the frequency spectrum is associated with the tool rotation frequency. The second peak is related to the tooth rotation frequency. The tooth rotation frequency can be calculated by multiplying the tool rotation frequency by the number of teeth in the cutter. The amplitude ratio of these peaks was used by the researcher as an indicator of tooth breakage in the milling operation using a reasonable threshold value for making a decision about the tool breakage. The usage of a single threshold may prove to be a practical limitation of this system because of many dynamically varying parameters involved in the milling process.

3.3.4 Combined Time & Frequency Domain Approach

The previous sections have shown that time domain signal analysis and frequency domain signal analysis techniques have their own merits and limitations. This has encouraged researchers to use techniques which are based on a combination of both time and frequency domain (e.g. wavelet transform). Another approach is to use these methods together and to confirm and verify the results as part of a decision making procedure. Short Time Fourier Transform (STFT) is a well established technique for frequency analysis but suffers from a resolution problem.

The Wavelet Transform (WT) was developed as an alternative approach to the STFT to overcome the resolution problem. Wavelet analysis is done in a similar way to STFT analysis, in the sense that the signal is multiplied by a function, (similar to the window function in the STFT) and the transform is computed separately for different segments of the time-domain signal. There are two main differences between the STFT and the wavelet transform. Firstly Fourier transforms of the windowed signals are not taken and therefore single peaks are seen corresponding to a sinusoid, i.e. the negative frequencies are not computed. Secondly the width of the window is changed as the transform is computed for every single spectral component. This is probably the most significant characteristic of the wavelet transform.

Lee and Tarng [3.28] reported the use of the discrete wavelet transform for the analysis of the force signal in its application to the detection of tooth breakage in the cutting tool. The overall system was based on a dynamometer, charge amplifier, data acquisition board and a PC. The detection algorithm was based on the concept of tooth passing frequency and its strength under normal and broken cutter scenarios. It is reported that under normal conditions, the tooth passing frequency is dominant in the spectrum, whereas with a broken insert signal the tool rotation frequency becomes important. This frequency shift has been linked to the concept of broken tooth engaging in the cutter once every revolution. The shift in the frequency may alternatively be due to the engagement of the tooth following the broken one into the cutting as it is bearing more cutting load which increases the strength of this particular frequency component. These researchers used a discrete wavelet transform and produced a technique that gave satisfactory results following a process of signal decomposition and analysis.

Tansel et al [3.18] reported a tool failure detection system for end milling by using Wavelet Transformation and Neural Networks (WT-NN). They favoured the wavelet transformation method arguing that it required fewer calculations when compared to FFT in order to achieve the same results. Cutting force signals were used as the basis to apply the technique. The variations in the cutting force for a normal cutter and a cutter with a broken insert were analysed as the spindle turned through discrete rotation angles. This gave a clear indication, using a Daubechies type Wavelet transformation, of a marked difference between the cutting state with a new cutter and that with a broken one. An ART2-type neural network was also used in combination to the wavelet transformation to classify the tool conditions from the acquired data.

Govekar et al [3.43] reported a method which used both time and frequency domain analyses of dynamometer and AE sensor outputs for tool wear detection. To maintain high quality machining three important parameters; chip form, tool wear and chatter vibration were monitored. The characterisation of the measured sensor signals and corresponding phenomenon has been attempted by a set of time invariant characteristics. The measured AE signal, for example, was filtered using a moving average filtering approach to reduce the statistical fluctuations before further processing to characterise chip formation. To support tool wear estimation, the dynamometer signal was acquired in the time domain. The time series of feed force *(F_f)* and cutting force *(F_c)* components were sampled at 25 KHz and spectral analysis was carried out at different wear levels of the tool in order to correlate tool wear with the spectral components. They suggested that a high value of entropy rate is typical for a chatter free cutting environment. Therefore, a threshold value was established which was reported to be particularly appropriate to detect the onset of chatter.

Li and Tzeng [3.49] reported a signal processing methodology to infer the state of milling insert wear from translational vibration measured on the spindle housing of a milling machine. The acquired signal was filtered against the line frequency and segmented into pieces that begin at the moment of initial contact between an insert and the work-piece and end just before the next insert comes into contact with the work-piece. Variation in the rotational speed causes the segments to contain different numbers of samples. Linear interpolation has been used to make every segment have the same number of points. They applied a Fourier transform to each segment of data separately. The transforms were averaged and the result was converted back into the time domain. They employed a 500x75 Choi-Williams time-frequency Distribution (CWD) matrix that spans a time period between 0 and 20 ms (where initial contact between the insert and the work-piece occurs at 2 ms) and a frequency range from 0 to 9.375 kHz. To reduce the computational burden for the wear size estimator in the next stage of signal processing, the resolution was lowered to reduce the number of CWD elements to 50x5 matrix. Thereafter a neural network has been suggested to estimate the size of flank wear from the values of the 15 CWD elements.

Chen and Jen [3.50] advocate a data fusion strategy before presenting the data to a neural network for decision making regarding tool wear. A dynamometer for force sensing and an accelerometer for vibration sensing were used. The detected raw signals were pre-processed to identify the feature elements of each independent signal data set. Several data fusion methods were deployed to calculate the fusion indices from the obtained feature elements. The first of the fusion techniques used was to calculate the average of the magnitude of the detected signals. The sampling rate was kept variable as the total data points were linked to one sample at each degree of the tool rotation. The average was calculated for each data set where data set defines the data collected within the time period of one cutting cycle. A feature index was also defined based on the result of average of a single cutting cycle. A further average of the ten repeated feature indices was used to represent the real feature index of the data.

For a normal cutting process, these average values remain within a reasonable range. When the cutting tool is worn or damaged, these values vary significantly. The variations of operating parameters normally arising in real cutting processes will also affect the results. They have therefore suggested using operating parameters as one of the data input for training the neural networks before final decision making. The acquisition of data from multi-sensors was synchronised using a trigger sensor. They have also suggested data fusion methodologies for investigating variance of the amplitudes of the detected data as well as the frequency components in the same data.

Xiaoli and Guan [3.62] used wavelet-based de-noising, discrete-time-frequency analysis, FFT and second differencing as data processing techniques on the acquired feed motor current signal for the detection of cutting edge fracture during end milling. They suggested that the ideal feed motor current during end milling varies periodically with frequency, which is equal to the product of spindle rotational frequency per second and the number of flutes in the cutter. After necessary data filtering through a wavelet based filter, the signals were analysed by the discrete time-frequency approach. According to the calculated frequency of signals based on the given spindle speed and the number of cutter flutes, the primary frequency components were selected from the time-frequency plan and named as "feature signals". The maximum value of the FFT of the "feature signals" was taken as a feature point for detecting cutting edge fracture. Furthermore, they have suggested using a second differencing method to extract a marked feature to indicate the tool condition from the feature point and the previous two feature points during end milling. Finally, the marked feature value was compared against a threshold value. If the marked feature was found to be over the threshold value, the tool was considered as broken. They have suggested that the system is capable of clearly distinguishing between the entry/exit and tool breakage conditions and is much more reliable than other sensor-less systems.

Zanardelli et al [3.81] reported wavelet based methods for the fault prognosis in electrical motor failures. They investigated the detection of problems in electric motors and in associated systems. Machine tool operation and health is a good example in which such a system can be employed. The merits of wavelets based methods with classical frequency domain analysis techniques such as Fourier series for the analysis of non-stationary signals were compared to support decision making in an industrial environment. They presented two examples of the application of proposed system namely: wiper motor and fuel pump motor monitoring in automobile applications. The acquired data were analysed using three different wavelet based algorithms before decision making.

This part of the review has dealt with most if not all of the signal processing methodologies used in the design of TCMS. Each of these approaches has its own merits and demerits as discussed. These factors are responsible for making each approach a more or less researched area. For any TCMS, the signal processing can be named as the heart of the system and has to be as accurate as possible as the final decision is based on the information provided by this stage. The next section of the review explores different decision making techniques used in the final phase of TCMS design as reported by various researchers.

3.4 Decision Making

The final and most important stage in the design of any TCMS is decision making regarding the health of the tool based on the information obtained from processed signal. In any industrial environment the importance of this particular stage is further increased by the fact that any misjudgements due to the complicated dynamic characteristics of the cutting process may result in unnecessary down times. This tendency has thus far limited the implementation of many of the previously researched systems. There are various methodologies which have been used by various researchers at this stage of the TCMS. These include: fuzzy logic, neural network, control charts, threshold and pattern recognition. The research in the area of using a predefined threshold is moving forward and more attention is being paid to designing adaptive thresholds which vary with the changes in machining parameters thus avoiding the generation of false alarms.

There has been a recent increase in the use of artificial intelligence in the design of TCMS. The two main areas of artificial intelligence used in this context are fuzzy logic and neural networks.

3.4.1 Fuzzy Logic

As the name suggests Fuzzy logic is a system of logic dealing with the concept of partial truth with values ranging between completely true and completely false. There are several features of fuzzy logic which make it a suitable basis for TCMS applications. These include the point that it does not require precise and noise free inputs, it can be independent of the number of feedback inputs and it can deal with non-linear systems more easily than mathematical models are able to.

Rao and Hope [3.30] used a 'feature filtered fuzzy clustering' technique for the classification of tool wear states under various cutting conditions. A characteristic relationship was developed between mean spindle power and mean cutting force signals at the 'learn' stage. In the classification stage, they determined the cluster centres from the characteristic coefficients obtained in the learn stage. Furthermore they then determined a membership function based on the normalised distance between the measured features and the evaluated cluster centres under specific cutting conditions. The final classification result provides information regarding the milling cutter tool's health. It is the composite result of the membership functions of the two features namely; mean power consumption and mean cutting force.

Chen and Black [3.29] reported a "Fuzzy-Nets-In-Process" (FNIP) system for tool breakage monitoring in milling operations. The FNIP system consists of two components: a Fuzzy Search Classifier (FSC); and a Fuzzy Adaptive Controller (FAC). Tool breakage detection was approached using Fuzzy Associative Memory (FAM) rules that solve the non-linear behaviour problem of the milling action. The FSC has been used to perform a mapping operation of a state vector into a recommended action using fuzzy pattern recognition. The FAC maps a state vector and a failure signal into a scalar grade that indicates state integrity. The FAC was also used to produce the active value to upgrade FSC mapping according to the variation of the input state. They used the force signal derived from a dynamometer linked to a PC based Data Acquisition (DAQ) system. A five-step learning procedure was proposed for generating FAM rules which include dividing the input space into fuzzy regions, generating fuzzy rules from input-output data pairs, avoiding conflicting rules by using Top-down and Bottom-up methodologies, developing a combined fuzzy rules base and finally, determining a mapping based on the fuzzy rule base. After the thorough training of the FNIP system, the researchers carried out the experimental tests and reported a success rate of approximately 90%.

Fu et al [3.73] used fuzzy pattern recognition for the final classification of a tool's health. In order to classify the tool wear value, they selected several groups of inserts with typical wear values as models. These models were considered as fuzzy sets. By calculating the 'distance' between the tool being monitored and the wear value models it was possible to determine to which model the tool should be classified. The acquired signals from various sensors including spindle load, force, AE and vibration were processed and membership functions for every feature were determined. They reported that experimental results showed a highest closeness grade of 0.9086 which represents a level of performance similar to the system considered above [3.29].

Sokolowski [3.82] suggested that the design of a fuzzy logic system must be based on provided data, instead of using a human expert's knowledge, in order to increase its implementation accuracy. A fuzzy logic system consisting of five layers was used. The nodes at the first layer have been used as input nodes for the linguistic variables. The nodes at the second and fourth layer act as Gaussian input and output membership functions respectively. Each node in the third layer has been used as a rule node which represents one fuzzy rule. The links between second and third layer define the premises of fuzzy rules and links between third and fourth layer define the consequents of fuzzy rules. The nodes at the fifth layer are used for defuzzification. This research has shown experimental results which suggest that the results obtained using fuzzy logic in the monitoring of drilling applications were much superior to those obtained in cutting applications. It suggests that for cutting applications the feed forward back propagation neural networks provide much better results when compared to fuzzy logic.

3.4.2 Analytical Neural Networks

Neural networks are analytic techniques which are modelled on the processes of learning in cognitive systems and the neurological functions of the brain. Neural networks use a data 'training set' to build rules capable of making predictions or classifications on data sets. The idea is to have a human-like reasoning emerge on the macro-scale. Neural networks can carry out some form of pattern recognition and are able to analyse data to discover predominant features and patterns within it. After initial training, neural networks continue to learn from the experience of later data. The learning methods of neural networks fall into two major categories namely: supervised learning and unsupervised learning. The supervised learning methods include back-propagation and probabilistic methods whereas unsupervised methods include Kohonen's method and Adaptive Resonance Theory (ART) networks.

Researchers working on the design of TCMS and using neural networks for decision making make claims regarding their importance stating that "no diagnostic system can ever be complete without the aid of neural networks"[3.30]. A very brief review of some of the research in this area is presented below. This is not a comprehensive review of this particular field but an indication of the current application of this approach in this area.

Dimla and Lister [3.27] reported a neural network based modular tool condition monitoring system based upon the acquisition and analysis of cutting force and vibration data. Wear on the tool edges was measured, and the results, together with the processed data, were fed to a neural network which was thus trained to distinguish between tool states. Threshold values were used on the flank wear in deciding whether or not a tool was still sharp. The researchers used a Multi Layer Perceptron (MLP) topology and its configuration has been chosen through an investigation that involved training several networks containing a different number of nodes in a single hidden layer. The network with the least errors was selected with 12 inputs, one binary output and 20 hidden nodes in one hidden layer. They have reported the success rates of up to 90% but only for constant and known cutting conditions. They reported that changing the data presented to the system from one cutting condition to another does affect the accuracy of the system. It was also reported that the system was capable of fault detection for a chipping event, but was incapable of reasonable tool state classification for sharp and partly worn tool states. The improvement of the system to make it robust from changes occurring in the signal due to the changes in machining parameters has been recommended for further investigation.

Baek et al [3.83] reported the use of a Digital Signal Processor (DSP) chip for tool breakage detection. They suggested using several neural networks in a system working simultaneously to determine different conditions. This is because if a neural network is used to learn many states (e.g. chatter, breakage and wear) its accuracy becomes low. In view of this, the proposed system performs parallel processing with two neural networks to monitor tool breakage and tool chipping states respectively. They used signal processing techniques such as FFT, AR modelling and band energy using digital filters and compared their performance by applying them on the cutting force signal. The features extracted from these techniques were used as inputs to a pattern classifier with a back propagation learning algorithm for final decision making about the health of the tool. The health index feature extraction was based on the phenomenon that a broken tool will not engage in cutting and the next insert will be cutting double the amount of its normal cutting. Both the AR model of the filtered output of the cutting force and the band energy show that there is a change when a broken tool is cutting compared to the signals acquired under normal cutting conditions. Threshold values could be set to decide about health of the cutter using these methods.

Haber and Alique [3.84] presented an intelligent supervisory system supported by a model-based approach. They have used the system for predicting tool wear in machining processes. An artificial neural network based model was created which is used to predict the process output. They used residual errors as the basis for decision making about the health of the cutting tool. The difference between the actual cutting-force and the cutting force estimated from the neural network based model was used to generate the residuals. The deviation of the cutting force has therefore been used as the primary criterion for inferring tool condition. Residual evaluation and diagnosis decision making were performed using a Weighted Sum Squared Residuals (WSSR) method. To deal with the inherent uncertainty in the model, generated residuals are not expected to be zero in the fault free case. They have therefore suggested that a "nonzero" threshold must be applied to reject ''false'' residuals. An adaptive threshold strategy has been used to increase the robustness of the overall system.

In addition to the above mentioned research activities, Neural Network based decision making has been utilised in several of the research publications previously reviewed [3.4, 3.15, 3.18, 3.20, 3.42, 3.49, 3.50]. In each case the balance between the accuracy and the training of the system means that the continuously changing conditions met during normal milling procedure still present a major challenge.

3.4.3 Use of Threshold & Adaptive Threshold Strategies

The use of threshold values to support decision making about the health of the tool or process is a very commonly used strategy, particularly within the fuzzy logic and neural networks based approaches described above. In this strategy if the value of the observed parameter is below or above (as appropriate) a certain level, it is considered to be normal. If it crosses the limits, some remedial action may be taken. A fixed threshold scheme can be relatively easily implemented in practice due to its simplicity, but it requires presetting with possibly different threshold values [3.52]. It may be noted that setting threshold values is not a trivial problem since they may well vary according to cutting conditions, cutting tools and workpiece materials.

The adaptive threshold technique is a relatively new one and is receiving more attention and popularity in the field due to its flexibility and reliability. The most important factor in the design of any tool monitoring application is that the decision making stage is independent of the cutting conditions i.e. the threshold values for decision making must be irrelevant to the cutting parameters. This is only possible if an adaptive threshold strategy is implemented [3.73] for such applications designs.

Kim and Choi [3.72] reported a multi-sensor based tool breakage detection. They used the deviation of average cutting force, peak value of acceleration and relative displacement between the tool and the workpiece to determine the tool state. The detection of any observed values in excess of the threshold values represents tool breakage. In order to monitor on-line and to be capable of setting up the threshold adaptively irrespective of the cutting condition, an X-bar control chart scheme was used to yield upper and lower control limits. The current threshold values were updated using both the mean and deviation of the previous signal and these were used for final decision making.

Takata et al [3.60] used fluctuations in the spindle rotational speed of a vertical milling machine for tooth breakage detection. The spindle rotational speed and fundamental frequency of the fluctuations in the speed were chosen as the main focus of research. It is basically a time domain approach which compares the values in a reference vector (prepared and stored in the system earlier for each tool) to the values obtained in an observed vector using a tachometer or pulse generator (for spindle rotational speed) for every spindle revolution. The distance between the vectors is the key in identifying the state of the cutting tool. The most important aspect of the approach is setting the threshold values for the distance between the vectors to avoid generating false alarms. They have further suggested the use of a normalisation technique in order to make the reference as well as observed vectors as insensitive to the cutting conditions as possible to avoid false alarms.

Jun and Suh [3.52] applied a modified version of Statistical Process Control (SPC) measures including X-bar control schemes, Exponentially Weighted Moving Averages (EWMA) and adaptive EWMA schemes to vibration signals for decision making. These control schemes automatically determine their threshold values independent of cutting conditions. In the X-bar control scheme, subgroup averages are calculated over time and modified so that the Upper Control Limit (UCL) and the Lower Control Limit (LCL) for the subgroup are obtained. They also used an exponentially weighted moving average to produce a smoothing constant which was useful in detecting minor variations in the mean of a process. An adaptive EWMA scheme was also tested. After the practical implementation and testing of these schemes, the authors have reported that the X-bar scheme is outperformed by both the EWMA and adaptive EWMA schemes. The adaptive EWMA scheme was proposed as the most suitable for such application designs.

3.4.4 Cutting Process Control Strategies

Apart from detecting tool condition (i.e. breakage and wear) there are some other areas related to machine tool operation which have received considerable attention by the researchers in recent past. These include controlling the process variable (e.g. machine power, depth of cut or spindle speed etc.) in case there is any abnormality observed by the monitoring system. This technique not only prevents damage to involved components but also helps in maintaining high quality operations. A brief review of some of the related research is presented in this section of the review.

Charbonnaud et al [3.22] argued in favour of force control in the milling operation in order to increase a tool's operational life. They have suggested that, due to the variations in radial depth of cut and feed per tooth, chip thickness represents an important factor in the assessment of chip load on the cutting edge. The correct value of the feed per tooth not only increases the tool's performance but also gives increased efficiency to the machining process. The deteriorating quality of the cutting edge and tool wear induces the force variations. In the reported application, the start of the machining cycle undertaken is done by a predefined feed rate set point having an initial feed per tooth value. The force signal acquired using a dynamometer is observed and if the mean cutting force does not exceed a preset threshold value the workpiece will be machined. If the mean cutting force exceeds the preset threshold value, the force controller is called into action. During force control action the force regulation decreases the speed to the level that the problem may be overcome or can be reduced. During the end of the pass, the feed per tooth increases to maintain the cutting force at a reference level. If the critical value of the mean cutting force is achieved during milling, a machine stopping procedure is activated to avoid any catastrophic damage.

A similar approach reported by Tansel [3.17] et al monitors the cutting force in a milling operation and reduces the metal removal rate when it predicts tool breakage. The approach is based on calculating the average cutting force values and predicting their future values up to 0.3-0.5 seconds ahead in time using the least squares method. This is based upon findings which indicate that cutting force increases with tool wear. It is said to be 10-30% different at the same cutting conditions when two different cutting tools are used. In view of the above it was recommended that simply using the force variations to generate alarms about tool breakage may not be very reliable. This favours the argument of controlling the cutting parameters to avoid not only the false alarms but unnecessary down time. However, there may be a practical limitation in the implementation of such systems since although the number of false alarms may be reduced; the associated reduction in metal removal rates may affect the Overall Equipment Effectiveness (OEE).

Kim and Kim [3.36] have used the same approach of controlling the cutting force to avoid tool failures in practical cutting conditions. The difference between this approach and others reported is the usage of low cost sensors as compared to a dynamometer. They use the current signals of the feed drive motors in order to avoid the cost effect of dynamometer. A typical model for the feed-drive control system of a horizontal machining centre has been reported to analyse cutting force measurement from the drive motor. The pulsating milling forces have been measured indirectly within the bandwidth of the current feedback control loop of the feed-drive system. It is shown that indirectly measured cutting force signals can be used in the adaptive controller for cutting force regulation.

3.5 The Current Situation – A Summary

The evidence gained from previous and current research work strongly supports the fact that the design and development of a standalone TCMS is an important goal. There is unlikely to be a single globally accepted solution to the problem. Factors to be determined when devising a solution include: the overall cost of the system, size of the system, practical implementation issues, use or non-use of sensors and the response time. The solutions to these will combine to provide a system that meets the satisfaction level of industrial users. The research activity in this area should be interfaced with actions taken at the machine tool manufacture level in order to further enhance the diagnostics of machine tool problems. There are many instances in which diagnostic and monitoring actions may be implemented within the machine control system but currently these are not being produced.

All the technologies and techniques above have advantages and disadvantages. Mathematical modelling techniques are not absolute and measurements have to be made on a healthy system before defining acceptable models. The resulting healthy responses are stored for further comparisons for generating residuals. Every machine normally needs specific measurements to be taken, as the measurements taken from one machine can not simply be applied to another. This adds to the overall cost and the time for such system design and implementations.

The use of additional sensors adds to the overall cost of the system in addition to the logistical problems and inconvenience of placement of the sensor. There has been an extensive usage of Data Acquisition (DAQ) cards in addition to PCs for the signal acquisition, storage, data processing and decision making which again adds to the overall cost. The majority of the systems have been based on using PCs as their processing unit after acquiring the data from different additional sensors applied in the system. This route of TCMS is generally opposed by industrial managers as it not only affects their prioritised shop floor settings but also adds to the costs involved.

The recent developments in embedded technology have laid the foundation for a route which if followed can be more successful. There has been considerable research in this field [3.82, 3.85-87]. There are various factors which support this approach. Microcontrollers are being developed with an increased processing power, lower size, increased memory and moreover with a much higher reliability [3.87]. All these factors have encouraged their use in areas where computer based systems were the only choice in previous years. One of these areas is machine tool condition monitoring and the essence of this research is also based on these simple facts. The author has endeavoured to research tool condition monitoring techniques both in the time and frequency domain using microcontrollers, and counter verify the results before making a final decision about the health of the tool. This route has been adopted in order to satisfy the industrial management about their requirements from a 21st century's TCMS.

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CHAPTER 4

TECHNOLOGICAL FUNDAMENTALS & SYSTEM REQUIREMENTS

4.1 Introduction

Having conceived an idea for any system design, the next stage normally is to carry out a detailed survey of available supporting technology which can be used for the implementation of designed system. It includes a comparative analysis of these supporting hardware technologies in terms of cost, reliability, their functional capabilities and efficiency viewed in the overall context of the actual requirements of the system being designed. These design principles were adhered to in this research. The monitoring system's actual requirements in terms of data acquisition, data processing, further communication, Ethernet connectivity as well as GSM connectivity were assessed. These findings were used as the basis of a technological analysis of possible supporting hardware including PCs, Microcontrollers and Digital Signal Processors. The aim was to choose a cost effective design hardware which had sufficient capabilities to meet the system requirements.

The main aim of this research was to establish data processing techniques efficient enough to detect tool breakage and yet simple enough to be implemented and supported by cost effective hardware. The initial design of the system was based on a three tier architecture both for software and hardware implementation. The design is based on the concept of a distributed monitoring system thus adding extra processing power along with adequate simplicity to the overall architecture. A distributed system as defined by Tanenbaum is "A collection of independent computers (microcontrollers/microprocessors in the case of embedded systems) that appears to its users as a single coherent system" [4.1]. A distributed system design not only adds to the flexibility of the system but also improves its overall capability in terms of data processing [4.2]. The technology selection for such a design is an important aspect in terms of its capabilities and needs to be carefully analysed before making the final choice about system implementation.

4.2 General Requirements of a Monitoring System

A monitoring system is normally interfaced to a process and collects data in real time in addition to undertaking dynamic analysis and making decisions. As an embedded monitoring system's role is performed close to the process itself it should be reliable and robust enough to withstand an industrial environment. The block diagram of a generic monitoring system is shown in Figure-4.1. Any monitoring system needs the appropriate interfaces for digital and analogue signals. These interfaces need protection to limit any damage in the event of a fault in the process, controller, monitoring system or any other part of the system. It has also to be ensured that interfaces must not significantly load the signals, add any disturbances or change the operation of the process.

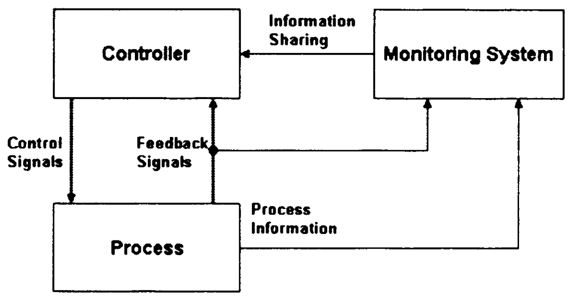

Figure-4.1, Generic Monitoring System

The installation of any designed monitoring system should normally be simple enough so that it does not interact with the operation of the process/machine itself. Moreover access to the machine should not be limited in case of any maintenance requirements. It should be able to provide interfaces for external inputs as required. For example; a machine tool condition monitoring system may need some of the operating parameters (e.g. depth of cut) and the designed system should provide necessary interface for the communication of such inputs. Furthermore, the monitoring system must be able to operate reliably in accordance with the industrial environment.

In terms of the software requirements of a monitoring system; it should be able to acquire data at the required acquisition rate, self calibrate and scale any signal or sensor values dynamically. These values should be temporarily stored until either being finally discarded if normal process/machine condition is observed or communicated to the next tier for analysis if required. This temporary storage and any other storage must be managed to prevent software failure in the case of the storage medium reaching its capacity.

The system should have the capability to take necessary precautions in order to prevent data loss in the event of communications failure. In large factories, normally more than one monitoring and/or analysis system are networked together. Therefore, precautions need to be taken to prevent conflicts between the systems and the transfer of the incorrect information.

The analysis capabilities of an effective and reliable monitoring system should normally be able to efficiently handle the acquired data. Generally, a data analysis stage has a number of elements e.g. the deviation detection element determines if the collected data relates to a normal process condition or not. The fault diagnosis element relates these deviations to the likely cause behind the actual process/machine failure.

4.3 General Architecture of the Researched System

A simple representation of the hardware architecture of the developed system is shown in Figure-4.2. The tiered architecture increased the system capabilities not only in terms of data processing but also for data and message communications using either Ethernet or GSM access. All of these functions were incorporated into the designed monitoring system to provide the true capabilities of a generalised e-Monitoring system.

The architectures used are described briefly to give an idea of technological requirements. Figure-4.2 shows the first tier of the system comprising of Front End Nodes (FENs). The signals from the system being monitored are interfaced to these FENs after necessary signal conditioning and anti-aliasing. The parameter monitoring and decision making node and FENs at tier one are connected by a Controller Area Network (CAN) for information sharing and for the transfer of data to the second tier for further analysis as and when required. CAN is one of the connectivity mediums used in industrial applications due to its reliability of operation. The second tier node uses a Tiny Internet Interface (TINI) board. This acts as an interface for the FENs and provides Ethernet connectivity and Global System for Mobile communications (GSM) connectivity. The second tier also acts as an additional source of data processing thus adding extra processing power to the system capabilities. In the initial design stage of the system it was expected that the third tier of the system will be used to perform up to 4% of the data analysis but in the actual testing of the system (Chapter-7) it was concluded that not many cases need to be referred to this stage. Therefore the third tier was not implemented in the final design stage of this research.

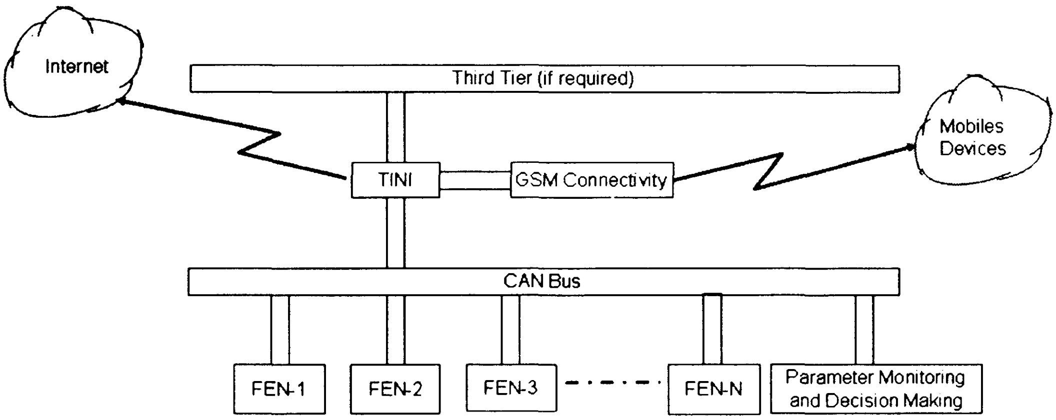

Figure-4.2, Generic Hardware Architecture of the System

The software architecture of the system presented in this research is shown in Figure-4.3. It was targeted that the supporting software for first tier nodes should be capable of dealing with around 80% of the situations in addition to performing continuous data acquisition. In actual system testing it was observed that it can deal with 85% of the cases (Chapter-7). The acquired data for normal situations are stored for a required length of time in a cycle before it is eventually discarded or passed on to avoid memory overloads. Software in the second tier node deals with around 16% of the situations out of the remaining 20% (in the actual testing it dealt with all of the referred cases therefore removing the need for implementing the third tier) which are referred by the FENs. The following sections explain the selection criteria and their implementation within the hardware used at tier one and two of the proposed TCMS.

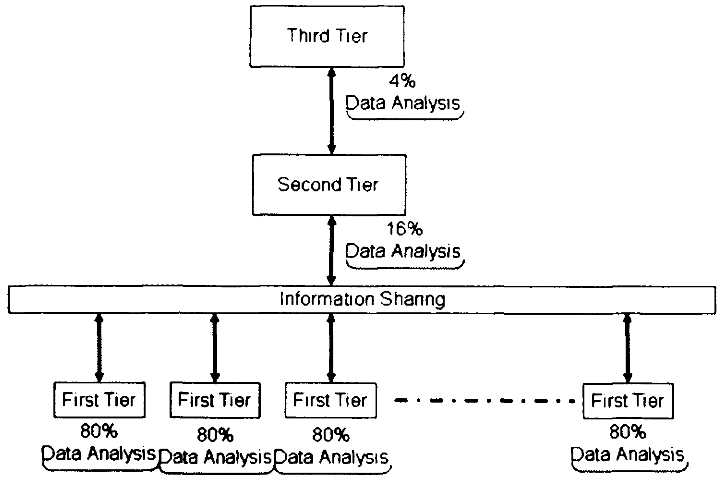

Figure-4.3, Generic Software Architecture of the System

4.4 Selection of Processing Hardware at First Tier

The core hardware is the most important part in the processing layer of a system. It is crucial because it plays an important role in determining the system's overall capabilities as well as limitations. In recent years, the alternatives available for use at the front end of monitoring systems have increased. This has been due to recent advancements in electronics and its use in designing embedded systems. The majority of embedded systems are designed to perform specific functions at a low cost. Such systems are based on the integration of software engineering, microcomputer hardware, digital and analogue electronics, electrical engineering, and data communications. The term "embedded" illustrates that they are generally an integral part of the system where they are being used. These may also be differentiated from general purpose computers in a way that these are special purpose devices and normally their capabilities are restricted to the application supporting environments.

The technological breakthroughs and introduction of microcontrollers has revolutionised this area. These are single chip devices not only capable of storing an actual programme but also of performing a number of tasks e.g. data acquisition, data processing, temporary and permanent storage. They can communicate with the outside world both in digital and analogue format. The following sections examine in detail the devices selected in this implementation.

4.4.1 Processing Hardware Selection

After finalising the idea of using microcontrollers the next phase was to make the selection. It was a complex situation and resolving it was challenging. There are different manufacturers providing microcontrollers in the market including Atmel, Dallas Semiconductors, Hitachi, IBM and Microchip. These are not the only manufactures but just a few examples. The microcontrollers are categorised as 8-bit, 16-bit and 32-bit according to their processing capabilities. Furthermore, different products from the same company are divided into different families in terms of their features for example availability of memory space, analogue and digital signal acquisition capabilities. Lastly, there are different microcontrollers in a particular family and a final choice has to be made based on design requirements.

A comparative analysis of different microcontroller manufacturers in terms of their products, features, cost and market standing was carried out to finally select a processing core for system design. This revealed that Microchip Technology Inc(R) was the leading 8-bit microcontroller supplier according to the 2002 microcontroller market share and unit shipments [4.3]. An important consideration was the established expertise and facilities in the IPMM Centre were almost exclusively based upon Microchip hardware. In addition the previous exposure of the author in the course of MSc project work within IPMM Cent was also to the Microchip hardware.

These considerations supported the choice of the PIC microcontroller as the heart of the TCMS design. The system's overall requirements in terms of data acquisition, data storage, processing and communication were investigated. It was concluded that the monitoring system needs both digital and analogue data acquisition capabilities, more than 1K Random Access Memory (RAM), a Controller Area Network (CAN) interface, a pulse width modulation module, a hardware multiplier for faster processing, hardware and software interrupts and timer modules. The features of different PIC microcontroller families were analysed and are tabulated in Table-4.1

After carefully analysing different features of PIC families presented in Table-4.1 and the research application's requirements the PIC18F458 microcontroller was selected for this application. The selected microcontroller meets the demand requirements of the research.

An important fact to be considered is that Table-4.1 presents a brief summary of Microchip's microcontrollers which were available at the start of this research in 2002. With technology advancements the demands from embedded design engineers grew in terms of product differentiation, lower cost, and low risk development. To meet these requirements Microchip has expanded its product portfolio to include new compatible families of 16-bit PIC24 microcontrollers and dsPIC® Digital Signal Controllers (DSC) offering a new level of performance and higher integration [4.4]. Recognising that this was bound to occur the system operation and supporting architecture was designed in such a way so as to allow its eventual uploading into new devices.

The main features of the selected PIC microcontroller and a brief summary of their usage for TCMS presented in this research are presented below:-

- 40MHz clock speed, which is an important requirement as designed system operates at a high Data Acquisition rate (normally more than 8000 samples per second for time domain analysis). It also supports real time processing for immediate decision making.
- 1536 Bytes of data memory and 32K Bytes of programme memory. The size of data memory is important to allow the system to store data temporarily before discarding it for normal situations.
- The availability of both serial and CAN interfaces. The serial interface was used in the design and testing phase. The system was interfaced to a PC for data analysis. In the next phase of research CAN was a necessity for interfacing different FENs and the TINI board.
- Analogue to Digital Converter (ADC) module. This module was an absolute necessity. The proposed TCMS used internally available analogue signals from the machine i.e. spindle speed and spindle load, and these were converted to digital format using ADC before actual processing.
- The timer was used for sampling rate calculations of the ADC. The timer runs in the background and can generate interrupts on completion of set values; this

allows the processor to analyse/communicate (if required) the previously acquired data before the next sample is acquired.

- The PWM module of the microcontroller was used to provide the clock to the filter IC.
- PIC18F458 has an 8x8 hardware multiplier. This multiplier was used for data processing in the developed Tooth Rotation Energy Estimation (TREE) technique (explained in Chapter-6). A simple illustration of increase in efficiency is that for an 8x8 unsigned multiplication; a microcontroller without such multiplier executes 69 instruction cycles whereas this controller performs the same operation in 1 instruction cycle at the same clock speed.
- Relatively small instruction set consisting of 75 instructions for a powerful microcontroller.
- PIC18F458 has three communication modules implemented onboard capable of providing powerful communication features including Controller Area Network (CAN) module used in this research.

The embedded peripherals and other main features like timers, ADCs, comparators, and I/O control add to the versatility of the selected microcontroller and provide design flexibility. The technical details of each element summarised here is considered in more detail in Appendix "A". This analysis supports the choice of the selected PIC18F458 as the FEN in the developed monitoring system.

Family	Pins	Frequency (Max)	Program Memory	Data Memory	I/O Pins	Analogue	Timers	Serial	CAN
PIC10Cxxx	6	8MHz	750 Bytes	24 Bytes	4	Yes	1	No	No
PIC12Cxxx	8	4-20MHz	750 Bytes-3.5 Kbytes	25 Bytes–128 Bytes	6	Yes	1-2	No	No
PIC14Cxxx	28	20MHz	7 Kbytes	192 Bytes	20	No	2	No	No
PIC16Cxxx	20-64	10-40MHz	750 Bytes-14.3 Kbytes	24 Bytes-368 Bytes	6-33	Yes	2-3	Yes	No
PIC18Cxxx	18-80	40MHz	4KBytes-128KBytes	128 Bytes-1536Bytes	16-70	Yes	2-5	Yes	Yes

Table-4.1 PIC Families of Microcontrollers and their Characteristics

4.5 Supporting Technology Selection for Second Tier

The second tier of the system deals with more challenging processing tasks as compared to FENs. It also acts as a bridge between the first tier and the Ethernet/GSM connectivity. It needs more processing and data storage capacity to facilitate decision making for complicated situations. After finalising the supporting hardware for the first tier of system architecture the next requirement was to analyse the architecture for the second tier according to the system requirements.

The design analysis for TCMS under research (shown in Figure-4.2 and Figure-4.3) revealed that in the following tier two features were very important:-

- Extra programme memory to store software capable of interacting with both tier one and Ethernet as well as the GSM connectivity module.
- Extra temporary storage space to store data communicated by parameter monitoring and decision making node for further analysis.
- The availability of a CAN controller to provide interfacing with FENs, preferably with at least eight different message centres. These message centres store data from different FENs separately before further analysis and decision making.
- Ethernet connectivity was required to add extra flexibility to the system making it capable of not only communicating globally but also able to present data/results wherever required.
- A higher system clock frequency to process data in the minimum possible time to communicate results and/or data to tier one and/or Ethernet about tool condition.
- The availability of hardware support for mathematical functions.
- Serial port support - an important requirement in the design and testing phase of the research.

4.5.1 Technology Survey and Selection

A survey of available market technology revealed different available options. Several network enabled controllers and their features are tabulated in Table-4.2. Analysis of these features and TCMS requirements helped in choosing Tiny Internet Interface (TINI) from Dallas Semiconductors for this research application.

4.5.2 Factors Supporting Selection

There are various factors supporting the selection of a TINI as the second tier hardware and these are summarised below [4.5]:-

- Availability of a CAN controller with 15 message centres. The CAN controller provided connectivity between first and second tier. The availability of extra message centres made it possible to store data temporarily before transferring it to RAM for analysis and decision making.
- The Ethernet support for connectivity between second tier and internet. The TINI has onboard 10/100 Ethernet MAC which provides it a unique MAC address.
- Onboard math accelerator and capability for accessing 1MB data memory supports the mathematical functions for complex data analysis.
- The capability of providing a maximum clock rate of 75MHz resulting in a minimum instruction cycle time of 54nSec. The higher speed enabled the controller to cope with the highly loaded network reliably to provide Ethernet access in addition to achieving minimum time processing capabilities.
- TINI supports Java as a higher level programming language. Java is a no cost solution available to the programmers.
- The last but most important factor is its actual price. It is the cheapest internet enabled microcontroller based module in the list tabulated in Table-4.2.

4.5.3 TINI Characteristics and Operational Requirements

The TINI CPU is Dallas Semiconductor DS80C400 TINI Single Inline Memory Module (SIMM) which requires the support of a socket board to enable its connectivity with external peripherals. The analysis of supporting socket boards in terms of associated costs, available tools and implementation support helped in choosing DSTINIs400 socket board. TINI provides an interface between tier one and tier two as well as Ethernet and processing capabilities needed at tier two (TINI acts as the basic hardware for tier two). The block diagram of generic system connectivity is shown in Figure-4.4. The CAN module of TINI is interfaced to the FENs at tier one. Since there are fifteen different message centres in TINI, the software is structured to handle the interfacing of fifteen different microcontrollers. This provided a "Plug and Play" capability to the system design. The software has the ability to detect the addition of any microcontroller on the CAN network by accepting its messages and sending back appropriate instructions. This adds to the overall flexibility of design hardware and software as the system can be used in different applications where different numbers of microcontrollers (as compared to this particular application) are used. The complete details of the TINI hardware are attached as Appendix "B" and may be referred to by the reader if further understanding of modules is required.

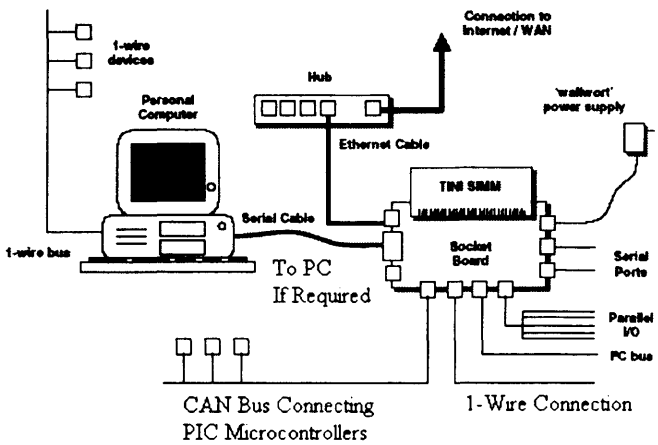

Figure-4.4, Block Diagram of TINI System Connectivity [Adapted from 4.6]

Family	Processor	Programme Memory	Data Memory	Network	Protocols	Serial Port	Preferred Language	Price
EtherNut	Atme Atmega 103	128K	32K	10base-T	TCP/IP HTTP	RS232	C	$125
Net186	AMD AM186-EX	512K	512K	10base-T	TCP/IP HTTP	2x RS232	C Assembly	$420
Orlin Technology	PIC16F877	128K	368 Bytes	2400 baud Modem	TCP/IP PPP UDP	RS232 RJ11	PIC Assembly	$299
Picoweb	Atmel AT90S8515	8K	512K	10base-T	TCP/IP HTTP	RS232	Assembly	$149
Rabbit TCP/IP	Rabbit Processor	512K	128K	10base-T	TCP/IP HTTP SMTP FTP	RS232 RS485	C	$199
Siteplayer	Philips 8051	48K	768 Bytes	10base-T	TCP/IP HTTP	-	Site Objects	$99
TINI	Dallas 80C400	1MB	1MB	10/100 base-T	TCP/IP FTP Telnet SMTP	RS232 CAN	Java	$85

Table-4.2 Comparison of different features offered in a range of TINI socket boards available, tabulated from [4.6]

To enable access to the network, a full application-accessible TCP IPv4/6 network stack and Operating System (OS) are provided in ROM. The network stack supports up to 32 simultaneous TCP connections and can transfer up to 5Mbps through the Ethernet MAC. Access to large program or data memory areas is possible with a 24-bit addressing scheme that supports up to 16MB of contiguous memory.

To accelerate data transfers between the microcontroller and memory, the DS80C400 provides four data pointers, each of which can be configured to automatically increment or decrement upon execution of certain data pointer-related instructions. With extensive networking and I/O capabilities, the DS80C400 can serve as a central controller in a multi-tiered network. The 10/100 Ethernet MAC enables the DS80C400 to access and communicate over the Internet. While maintaining a presence on the Internet, the microcontroller can actively control tier one FENs with dedicated on-chip hardware. The FENs were connected to the hardware using CAN bus and reliable results were obtained which are discussed in Chapter-5, 6 and 7.

Instant connectivity and networking support are provided through an embedded 64KB ROM. The ROM firmware realizes a full, application-accessible TCP/IP stack, supporting both IPv4 and IPv6, and implements UDP, TCP protocols. The DS80C400 incorporates five internal memory areas, four of which are RAM and one is ROM. These include: 256 Bytes of scratchpad RAM, 8KB of SRAM for Ethernet MAC transmit/receive buffer memory, 1KB of SRAM configurable as various combinations of data memory and stack memory, 256 Bytes of RAM reserved for CAN message centres and 64KB embedded ROM firmware. The DS80C400 has resources that far exceed those normally provided on a standard 8-bit microcontroller. Many functions, which might exist as peripheral circuits to a microcontroller, are integrated into the DS80C400 microcontroller. The DS80C400 also incorporates a 10/100Mbps Ethernet controller.

4.5.4 Controller Area Network (CAN) Module

DS80C400 has an on-chip CAN controller fully compliant with CAN 2.0B specification. CAN is used in a wide range of applications including automotive, medical, heating, ventilation, and industrial control. CAN architecture allows for the construction of sophisticated networks with a minimum of external hardware. The CAN controller supports the use of 11-bit standard or 29-bit extended acceptance identifiers for up to 15 messages, with the standard 8-Byte data field, in each message. Fourteen of the 15 message centres are programmable in either transmit or receive modes, with the 15th designated as a (First In First Out) FIFO-buffered, receive-only message centre to help prevent data overruns. Each message centre was programmed independently to test incoming data. Global controls and status registers in the CAN unit can be used to evaluate error messages, generate interrupts, locate and validate new data, establish the CAN bus timing, establish identification mask bits, and verify the source of individual messages. Since each message centre is individually equipped with the necessary status and control bits these were used to establish direction, identification mode (standard or extended), data field size, data status, remote frame request and acknowledgments and performing masked or non-masked identification-acceptance. Since CAN has been used as the main transmission medium between tier one and tier two its brief overview is presented in section 4.6.1 of this chapter.

4.6 Industrial Networks and Selection of CAN

In this research it was proposed to design and implement a practical, cost effective, distributed and reliable e-Monitoring system. The simultaneous achievement of all these functions in one single system was not easy. However; using embedded hardware capable of providing interconnectivity by using industrial networking standards in conjunction with internet protocols made it possible. Therefore a brief review of industrial networks and supporting internet protocols is presented along with the appropriate details of networks used and their implementation in this research. A detailed analysis was carried out to analyse the advantages of different fieldbus standards in order to finalise the selection of networking strategy at the lower level of the system (between tier one and tier two). The results showing the capabilities of different standards are presented in Table-4.3.

Standard	Encoding	Access Method	Media Type	Topology	Trasmn Speed	Max Length	Max Nodes
FIP	Manchester With Violation bits	Centralised Polling	Twisted Pair/ Fibre optics	Bus/Star	31.25Kbits	1500m	32/256
					1 Mbits	500m	
					2.5 Mbits	500m	
					5 Mbits	100m	
PROFIBUS	NRZ Asynchronous	Token Passing with Polling	Twisted Pair	Bus	9.6Kbits	1200m	32/127
					19.2Kbits	1200m	
					93.75Kbits	1200m	
					187.5Kbits	600m	
					500Kbits	200m	
SERCOS	NRZI with Bit stuffing	Slotted Ring	Fibre Optics	Ring	2Mbits	Longer due to FO	255/255
CAN	**NRZ**	**P2P**	**UTP**	**Bus**	**1Mbits**	**40m**	**Unlimited**
					250Kbits	**500m**	
					50Kbits	**1Km**	

Table-4.3, Industrial Communication Standards, Tabulated from [4.7, 4.8]

Criterion	FIP	CAN	PROFIBUS	SERCOS
Speed	Good	**Good**	Medium	Good
Cost	Medium	**Good**	Good	Medium
Availability	Medium	**Good**	Good	Medium
Reliability	Good	**Good**	Good	Good
P2P capability	Medium	**Good**	Medium	Medium
Memory Requirement	Poor	**Good**	Medium	High
Availability of tools	Medium	**Good**	Good	Medium

Table-4.4, Characteristics of Industrial Communication Standards, Tabulated from [4.9, 4.10, 4.11]

After considering different technological aspects of some of the fieldbuses; their important features were also analysed and are tabulated in Table-4.4. The different fieldbuses, their technical capabilities and related aspects were analysed with respect to selected hardware. The built-in CAN controllers in the PIC and TINI helped to conclude that CAN was the best choice for the research presented in this thesis. A brief overview of CAN is next presented illustrating different aspects of its use in this research and providing logical justification for its selection. A more detailed review is contained in Appendix “C”.

4.6.1 Controller Area Network

Controller Area Network (CAN) protocol is an ISO standard (ISO 11898) for serial data communication. CAN is used as an embedded network for machine control within industries like manufacturing, textile, injection moulding and packaging [4.2]. This protocol is based upon a broadcast mechanism where every node gets the message transmitted by a node. It defines Physical and Data Link layers of the network protocol as well as some message types, arbitration rules for bus access, and methods for fault detection and confinement. The CAN arbitration method ensures that each CAN node deals with the relevant messages only [4.12]. It operates on a 2-wire balanced wiring system using a twisted pair.

4.6.2 Supporting Facts for Selecting CAN

In addition to the fact that both PIC18F458 and TINI (using DS80C400) had built in CAN controllers; there were some very important supporting facts for selecting the CAN as a communication medium in this research. Some of these are:-

- The protocol was designed for noisy environments therefore in industries where various machines are used it provides reliable communication.
- The messages are small, at most eight data bytes and are protected by a checksum. Therefore communication between tier one and tier two is reliable.
- There is no explicit address in the messages; instead, each message carries a numeric value that controls its priority on the bus.
- There are effective means for isolating faults which was a primary requirement of an effective TCMS.

Microchip offers different microcontrollers both with CAN and stand-alone peripherals to meet the demand for CAN bus solutions. PIC microcontrollers can be interfaced to a CAN bus using the following two approaches depending upon the hardware features of the microcontroller:-

- Through a CAN Controller (e.g. MCP2510) and CAN Transceiver (e.g. PCA82C250).
- Using just a CAN Transceiver (e.g. PCA82C250) if the micro-controller offers a built-in CAN controller. Both these approaches are shown in Figure-4.5. In

this research a CAN transceiver was used for interfacing as the selected microcontroller has a built in CAN controller.

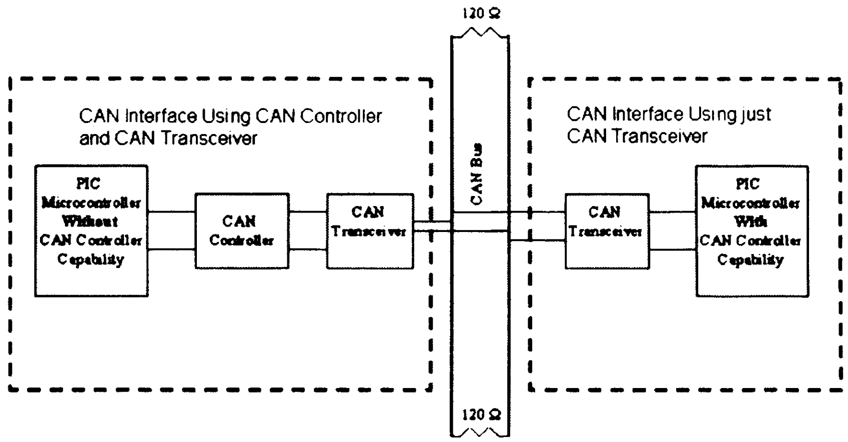

Figure-4.5, Block diagram to illustrate PIC Microcontroller Interface to CAN Bus. (With and without on-chip CAN controller capabilities.)

4.6.3 Implementation CAN Connectivity between Tier One and Tier Two

Figure-4.6 shows the Block diagram of a six node CAN network developed using PIC18F458 microcontrollers and a PCA82C250 as a CAN transceiver. This presents the actual networking implemented for communication between tier one and tier two in this research. A brief summary of implementation is presented in the succeeding paragraphs. The CAN bus has the capacity to add more nodes as and when required thus providing "Plug and Play" functionality to the architecture. As shown in the system architecture both time and frequency domain analyses of the signals were carried out. The results were integrated for verification and accuracy thus avoiding the generation of false alarms. The details of these operations are discussed in Chapters-5, 6 and 7.

All nodes on the network performed their assigned monitoring tasks and used CAN as the communication medium for information sharing. For example if a node in the time domain detected a problem it sent a signal to the parameter monitoring and decision making node using the CAN bus. The parameter monitoring and decision making node has complete information from other FENs using the CAN bus which it uses for decision making. Depending upon the complexity of the problem the decisions are made.

There are two types of decisions made at this level: whether the situation can be handled at tier one or if the situation is more complex and there is a need to involve the second tier in the data processing and decision making. The information sharing between tier one and tier two is again using CAN bus connectivity.

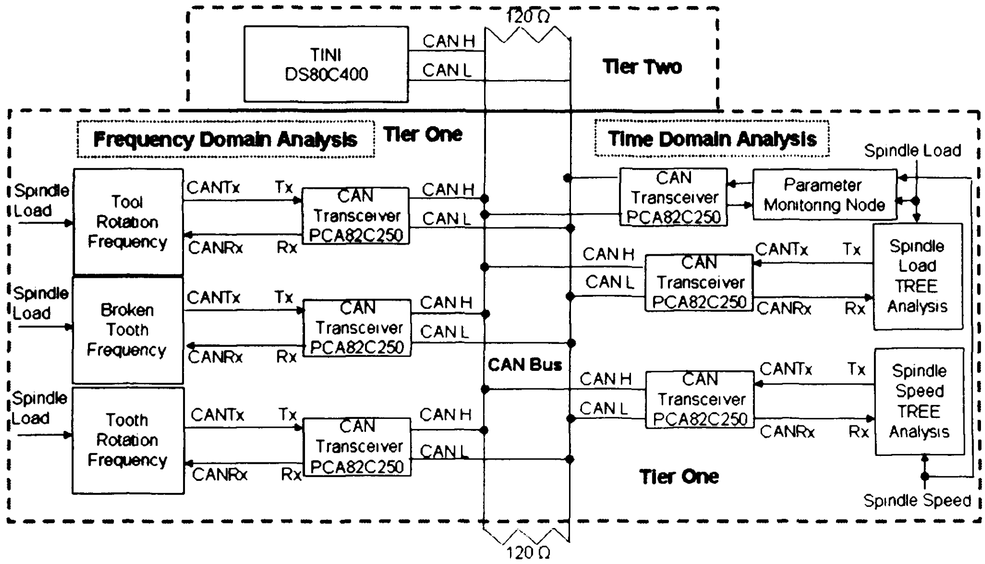

Figure-4.6, Block Diagram of CAN Connections for a 5 Node Network . (Note 120Ω Termination resistors at both ends of the CAN are very important for the functionality of the network.)

4.7 Audit of Machine Tool Kondia B500

The testing and implementation of researched techniques for TCMS and its final implementation were carried out on a CNC Machine Tool Kondia B500. Therefore before implementing the actual techniques developed an audit of the machine was carried out. The main objective of this audit was to explore the mechanical feature and corresponding electrical characteristics/signals in order to gain the required knowledge about machine functionality. These details were used later to test the developed techniques by simulating machine functions in MATLAB as well as on developed hardware. In the simulation phase, acquired data from the machine tool was used for the testing of the designed hardware architecture.

One of the major motivations for this research was to develop a sensorless low cost TCMS. The main signals which were finally used are spindle speed and spindle load. Both these signals were available from the machine controller without using any additional sensors. Before interfacing these signals to the actual system directly, these along with other signals such as X-axis current, Y-axis current, Z-axis current and power supply references were acquired using a DAQ card. The acquisition of these signals through the DAQ card was carried out in order to ensure the reliability and accuracy of developed techniques. In the final phase of TCMS design and implementation the signals were directly interfaced to the system through necessary anti-aliasing filtering circuitry thus eliminating the need of a DAQ card. In all, ten analogue inputs were used to acquire spindle speed, spindle load, current signals from three axes and power supply references. The current signals were also used in the simulation stage of this research for cross verification of the machine behaviour for different faulty conditions. These current signals were not used in the final implementation stage as spindle speed and spindle load signals provided the required information for decision making about health of the tool.

4.7.1 Machine Controller

The CNC controller of the Kondia machine tool has a power supply card, graphics card, axes control card, I/O card and memory card. These cards generate different signals in order to perform the required operations. For example the axes control card generates appropriate commands to control the feed rate after getting necessary position and velocity feedback from the pulse coder of the AC servo motor. The required signals from I/O and power supply card were acquired for this research.

The spindle unit of the machine tool consists of an AC spindle servo unit, AC spindle motor, encoder, cooling fan, thermal switch and drive belt. The encoder's main components are a pulley, shaft, toothed belt and ball bearings. The AC spindle servo motor is a three phase motor operating at 220-230 V using a 50Hz 3-phase supply. It has a transistor PWM inverter, regenerative braking and analogue outputs which correspond to running speed and load at different conditions.

The running speed of spindle is represented by a corresponding analogue DC signal named Speed of Machine (SM) which ranges from 0-10 Volts. The maximum speed for the spindle is 6000RPM and this corresponds to an output of a 10V analogue DC signal. The load consumption of the spindle motor at any instant is shown by the Load of Machine (LM) signal ranging from a 0V to 10V analogue DC signal. The important point to be noted is that a LM signal of 6.1V corresponds to 100% load consumption (i.e. 3.7kW) 8.3V to 136% (i.e. 5.5kW) and 10V corresponds to 164% load (i.e. 6.6kW).

4.7.2 Speed Control

There are certain digital outputs generated by the spindle unit. These are used by the controller to control the spindle speed dynamically. These signals are labelled as zero speed (SSTA) which is in logic "High" in cases where the spindle speed is less than 45 rpm, Speed arrival signal (SARA) which goes to logic "High" when spindle speed is within 15% of the demand speed and Speed detection signal (SDTA) which is the inverse of the speed arrival signal. The operation of spindle speed demand by the input parameters and corresponding response of these signals is shown in Figure-4.7.

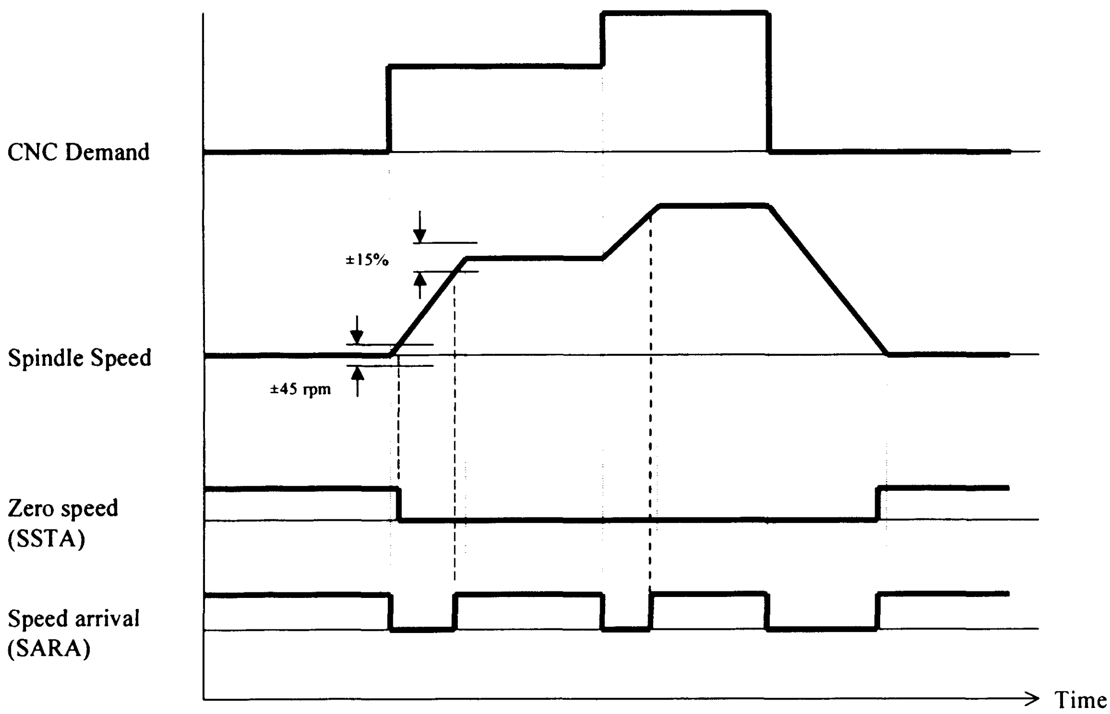

Figure-4.7, Relationship between CNC demand, spindle speed and digital signals

The speed of the AC spindle motor ranges from 100RPM to 6000RPM. The encoder generates 1024 pulses per revolution of the spindle to provide feedback to the controller about the actual speed of the spindle motor. It means that for a spindle speed of 500RPM, the encoder will generate 8530 pulses per second. This is a high pulse rate and correspondingly the variations caused by different problems including tooth breakage are very difficult to detect via monitoring systems using a low sampling rate. It is worth noting that the vast majority of the TCMS designed in the past use a sampling rate of around 500-1000 samples per second. This indicates that by the time a sample is acquired, the machine controller normally has controlled the variations in the speed and an accurate picture of the situation may not be drawn. This issue is discussed in detail in Chapter-6.

4.7.3 AC Servo Axes Controllers

The feed rate in all three axes (i.e. X, Y and Z) is controlled by individual digital AC axis servo controllers. A block diagram representing the configuration of a digital AC axis servo control unit is shown in Figure-4.8. These servo control systems have different operational parameters and characteristics. The main operational characteristics of X, Y and Z axes servo systems are tabulated in Table-4.5 for ease of reference.

Axes	Servo Type	Operation	AC Motor	Speed	Encoder Pulse Rate	Ball Screw
X-axis	AC	Left to Right	1 kW	2500 RPM	2500 Pulses/rev	Dia 32mm
						Pitch 10mm
						Travel 560mm
Y-axis	AC	Front to Back	1 kW	2500 RPM	2500 Pulses/rev	Dia 32mm
						Pitch 10mm
						Travel 380mm
Z-axis	AC	Vertical	1.2 kW	2000 RPM	2500 Pulses/rev	Dia 32mm
						Pitch 10mm
						Travel 380mm

Table-4.5, Operational Characteristics for X, Y, Z axes servo systems.

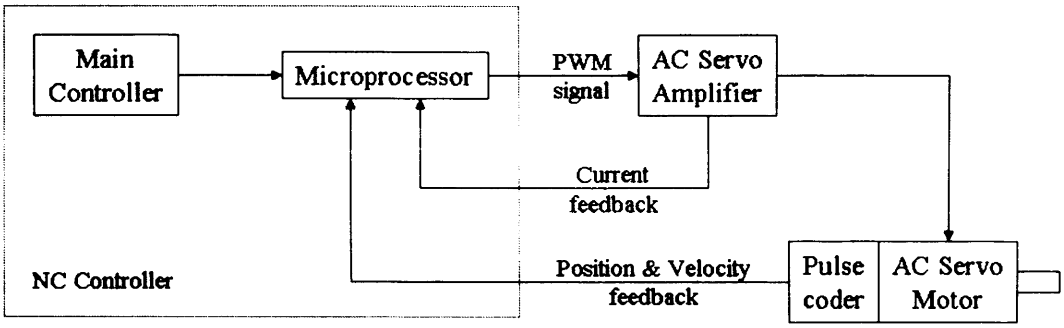

Figure-4.8, Configuration of digital AC axis servo

4.8 Conclusion

The manufacturing industry is implementing more and more automation aimed at reducing product costs, improving product quality, reducing lead times and providing a greater degree of operational management in order to remain competitive in the market. All these factors are being supported by developments emerging from the electronics industry providing solutions to these requirements.

In this chapter a detailed review has been presented about the importance of monitoring systems, their general architecture and the actual architecture of the monitoring system implemented in this research. In addition technological requirements of system implementation were analysed. The availability of supporting hardware in terms of system requirements was surveyed and discussed in terms of cost, supporting resources and technical details. Technological comparisons have been presented and discussed before choosing hardware for implementation at different levels of the system. The facts of fast moving technology change have been established.

In order to achieve practical functionality and general architecture discussed in this chapter, there was a requirement to actually investigate some practical and implement-able techniques using the resource limited 8-bit microcontrollers. These were investigated and are discussed in detail along with their actual implementation in Chapters-5, 6 and 7.

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CHAPTER 5

SWEEPING AND PARALLEL FILTERING TECHNIQUES FOR FREQUENCY ANALYSIS OF MACHINE SIGNALS

5.1 Introduction

This chapter describes a microcontroller based application design for frequency domain analysis of machine tool signals to provide the basis for tool breakage monitoring. In order to improve the overall reliability of the system diagnosis is integrated with time domain analysis. The technique used to do this and corresponding results for different machine signals will be discussed in Chapter-6. Frequency domain analysis reveals information about the overall signal content which is otherwise hidden in time domain analysis.

The objective of frequency analysis is to breakdown a complex signal into its various frequency components. Mathematicians and theoretical engineers generally tend to interpret "components" as being the result of a Fourier Transform whereas practical engineers often think in terms of measurements made with filters tuned to different frequencies [5.1]. Normally for frequency domain analysis a signal is sampled in the time domain and its frequency response is calculated using different mathematical techniques e.g. Fast Fourier Transform (FFT). Although the FFT is the most popular technique, it is not the only one. There are many other transforms used for the same purposes including Short Time Fourier Transform (STFT) and Wigner Transform.

Signals are normally classified as being one of the two basic types: stationary and non-stationary. A stationary signal is assumed to be in a particular state of statistical equilibrium. This means that the signal properties are unaffected by a change in the time domain. A stationary signal may be characterised by its mean and auto-covariance or its mean, variance and auto-correlation function being constant. If these conditions are not satisfied the signal is characterised as a non-stationary signal [5.2].

The FFT is widely used for frequency analysis. The FFT is normally only suitable for stationary signals and is not very effective for non-stationary signals; it cannot reveal complete information about a non-stationary signal [5.3]. This does not mean that the FFT cannot be used for machine tool monitoring. The FFT can also be used in cases where average energy at each frequency line is to be calculated. In machine tool monitoring application, some specific frequencies are monitored constantly and therefore the FFT can be reliably used.

However, there are some issues which need to be dealt with. The most important one is the resources available to perform such a mathematical operation. As was mentioned in Chapter-4 the microcontroller which has been used in this research (which was the latest microcontroller available at the start of the research) has constraints in its capacity to perform the FFT. In the context of this research these are discussed below.

Frequency resolution is one of the most important features to differentiate different frequency components in a signal. At low resolutions it is difficult to differentiate closely related frequencies. The frequency range and resolution on the x-axis of a spectrum plot depends on the sampling rate and number of data points acquired. The frequency components as a result of the FFT are half of the sampling rate. The first frequency is normally at zero and the last one can be calculated as shown in equation 5.1.

$$Lf = (Fs/2) - (Fs/N) \qquad \text{(eq.5.1)}$$

Where Lf is the last frequency in the range, Fs is the sampling rate and N is the number of acquired samples. The frequency resolution or frequency separation interval can be defined as:-

$$\Delta f = Fs/N \qquad \text{(eq.5.2)} \qquad \text{or}$$

$$\Delta f = 1/(N.\Delta t) \qquad \text{(eq.5.3)}$$

Where Δt is the sampling period.

These equations illustrate that sampling rate determines the frequency range and for a given sampling rate the number of data points acquired in the time domain determine the resolution. Therefore to increase the frequency resolution for a given signal at a constant sampling rate the number of data points used must increase. The execution time is another limiting factor in this scenario. The higher the number of data points used to increase the resolution, the longer it will take to acquire and process these. For example acquiring 500 samples at a sampling rate of 500 samples per second will yield a resolution of 1Hz but there will be a waiting time of 8.33 spindle revolutions (at 500RPM) before the processing starts.

Microchip Technology Inc[(R)] states that the PIC18F458 (chosen for this application) is capable of performing FFT operations. This has certain limitations with regard to machine tool signal analysis. One of these is the resolution required for differentiating different frequencies accurately and another is the data acquisition time needed to achieve the required resolution. As shown in equations 5.2&5.3, the separation between two frequency components is directly proportional to sampling rate (keeping the number of data points constant) and inversely proportional to the number of points used for the FFT analysis (keeping sampling rate constant).

For machine tool breakage detection systems it is a very important requirement to detect tool breakage as soon as it happens. In this research a target of two revolutions was accepted for a practical implementation. Considering the fact that PIC18F458 can perform a 256 point FFT operation in order to achieve a 1Hz resolution (at 500 RPM) the sampling rate should be 256 samples per second. At 500 RPM using such a low sampling rate data acquisition will take 8.33 machine tool revolutions. In addition, the processing (including windowing which is a requirement to avoid spectral leakage) and the result communication times will add to this. The processing time for 256 point FFT is around 150 mSec [5.4] meaning a delay of 1 tool revolution at spindle speed of 500 RPM and 6 revolutions at a spindle speed of 3000 RPM. This indicates that the available PIC may be capable of performing small number FFT operations but for higher speed machining operations where higher number FFT is required, it cannot do so. Some of these situations are tabulated in Table-5.1 to illustrate this.

The objective of this research as stated in Chapter-3 was to investigate a low cost distributed embedded solution for tool condition monitoring. Therefore low cost microcontrollers for Front End Nodes (FENs) were chosen which normally have limited resources to perform complex mathematical operations. To overcome these constraints, emphasis was given to developing techniques which can be implemented using this hardware.

Case Number	Spindle Speed	Sampling Rate	Data points FFT	Resolutions	Machine Tool Revolutions
1	500	256	256	**1Hz**	**8.33**+ PT+CT
2	500	512	256	**2Hz**	**4.16**+PT+CT
3	500	1024	256	**4Hz**	**2.08**+PT+CT
4	500	2048	256	**8Hz**	**1.08**+PT+CT
5	1000	256	256	**1Hz**	**16.66**+PT+CT
6	1000	512	256	**2Hz**	**8.33**+PT+CT
6	1000	1024	256	**4Hz**	**4.16**+PT+CT
8	1000	2048	256	**8Hz**	**2.08**+PT+CT
9	3000	256	256	**1Hz**	**50**+PT+CT
10	3000	512	256	**2Hz**	**25**+PT+CT
11	3000	1024	256	**4Hz**	**12.5**+PT+CT
12	3000	2048	256	**8Hz**	**6.25**+PT+CT

Table-5.1, PIC18F458 capabilities and constraints for FFT operation in terms of machine tool requirements (PT: Processing Time, CT: Communication Time.)

The FFT can be referred to as a set of parallel filters having a bandwidth of Δf centred at each frequency increment. As has already been discussed the PIC18F458 cannot normally handle the monitoring tasks using this technique at higher spindle speeds (normally more than 2000RPM). Therefore, the option of using some other time-frequency analysis technique was considered. STFT is one of these techniques but given its similarities to FFT its implementation was not a practical solution at the FENs. In addition, STFT has some inherent problems with regard to such applications. One of these is that it provides a constant resolution for all frequencies as it uses the same window for the entire signal. Therefore by using a wide window, good frequency resolution can be achieved for low frequency components but it will not yield the same results for high frequency components [5.5]. FFT is one of the most reliable techniques for frequency analysis. As such it was proposed to be used at the second tier of the system to handle complex situations referred up by the FENs. The details of this are discussed in the System Integration chapter (Chapter-7).

Having analysed most of the frequency transformation techniques with regard to resources available at the FENs, the application of using filters for frequency analysis was also considered and analysed. Filters are normally categorised as analogue or digital filters. Both types have different preferences with regard to application domains. For example, when using analogue filters, the emphasis is on the handling limitations of the electronics such as the accuracy and stability of resistors and capacitors. In digital filters this emphasis shifts to signal limitations and theoretical issues regarding processing requirements [5.5].

There has been consistent research in the past decade relating to multi-channel multi-rate filtering of digital signals in the field of digital signal processing. Although the roots of this research stem from switched capacitor filters (discussed in the next section) it is mostly based on using software based digital signal processing techniques. A common task in digital signal processing is to pass a signal through a filter in which the widths of the pass band and the transition band are a small fraction of the sampling frequency [5.6]. If a Finite Impulse Response (FIR) filter is used for this task, the order of the filter required to meet the specifications is usually very high, entailing a heavy computation burden. On the other hand, an Infinite Impulse Response (IIR) filter can perform these operations using a design of a much lower order. Microchip Technology Inc(R) has provided an application note for the implementation of this type of filter. This technique was not used in this application due to two reasons. Firstly; the PIC18F458 has three data pointers in all. These data pointers are used for data acquisition, data storage and communication purposes in the designed system whereas an IIR implementation technique requires all these data pointers for different calculations. Secondly it is a complex mathematical operation and it can only be effectively used for applications where a controller is not engaged in performing other real time tasks. Such a technique may not be suitable for an 8-bit controller which is involved in different tasks in real time.

In addition to the frequency estimation techniques discussed earlier there are other frequency estimation techniques such as Swept Spectrum Analysis. This approach is used for very high frequency estimation with correspondingly low resolution in conjunction with filter banks which are normally used in digital signal processing. A swept spectrum analyser is based on a different configuration to the FFT analyser. It uses a super-heterodyne configuration in which the attenuator and gain stages are used to adjust the signal to fit the input range of the analyser. A Voltage-Controlled Oscillator (VCO) sweeps through a range of frequencies that are mixed with the incoming signal. The signal from the input and the signal from the VCO are passed through a mixer, which is a nonlinear device that produces the sum and difference of the original signal and the signal from the VCO, as well as the original signals and their harmonics. An Intermediate Frequency (IF) filter extracts the desired sum or difference of the original signals. The detector produces a voltage level relative to the amount of power received from the incoming signal. This technique is normally used for the frequency analysis of high frequency signals where the use of the FFT is difficult due to the requirements of very high sampling rates. Since the swept spectrum analysers are normally used for higher frequency applications and require a VCO stage to sweep through a range of frequencies, these have not been researched for applications in machine tool monitoring.

After considering the limitations imposed by the FEN capabilities it was concluded that using analogue filters for this application was the only viable solution. However along with some advantages there are several limitations with analogue filters. There has been ongoing research to overcome these limitations. With the breakthroughs in digital technology and Integrated Circuit (IC) fabrications, there have been continuous efforts to implement analogue filters on ICs. There are still certain limitations in fabricating a number of RC filters on Metal Oxide Semiconductor (MOS) integrated circuits [5.7]. For example; in order to fabricate a low pass filter with a 100Hz cut off frequency and using a 100pF capacitor requires a resistor of 16MΩ. For implementing this resistor on an IC, a large space will be required thus drastically reducing the overall space available for further implementations. In addition to this, the tolerances of resistors are higher and filter accuracy cannot be guaranteed. Due to these issues research in this area has shifted to simulating resistors rather than using real resistors. The requirements for such an implementation are two switches and a capacitor and both are readily available in MOS form. Filters using the concept of simulated resistors are known as "Switched Capacitor Filters".

5.2 Switched Capacitor Filters

The concept of switched capacitor filters was researched and published by Ghaderi et al in 1982 [5.7]. This was not the first publication in this area but is intended to illustrate a simple representation of switched capacitor filters. Figure-5.1 shows a simple representation of three path bandpass filters using switched capacitors. The filters are interfaced in parallel and can have different centre frequencies depending upon the application requirements. The external switches are used to select a filter when required. The switched capacitor approach used to achieve this switching design for implementation on MOS ICs is shown in Figure-5.2.

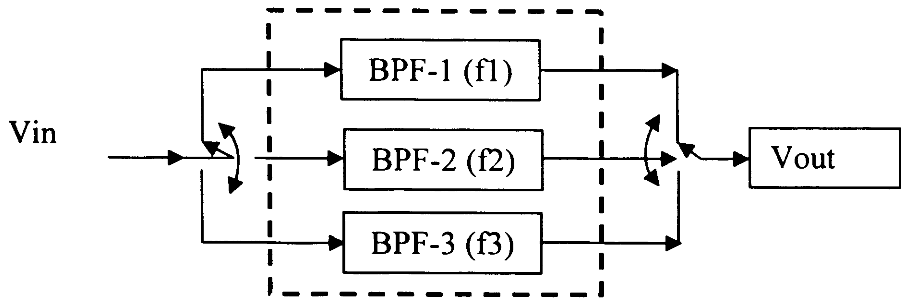

Figure-5.1, Three path Switched Capacitor Filter

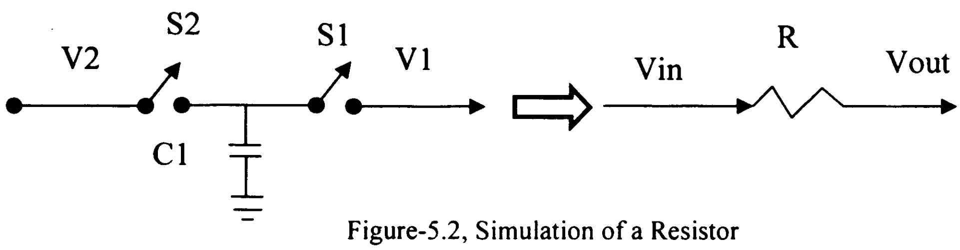

Figure-5.2, Simulation of a Resistor

In the switched capacitor circuit as shown in Figure-5.2, switch S1 and switch S2 open and close alternately. As a result a charge is transferred from V2 to V1. The charge transferred can be calculated as:-

$$\Delta q = C1(V2-V1) \qquad \text{(eq.5.4)}$$

If N is the number of capacitor switching and these are opened and closed at regular time intervals Δt, the amount of charge transferred per unit time is:-

$$(\Delta q/\Delta t) = C1(V2-V1)*(N/\Delta t) \qquad \text{(eq.5.5)}$$

The left hand side of eq.5.5 represents charge per unit time and that equals the current. The number of cycles per unit time is the switching frequency (f_{clk}). The current can be calculated as:

$$i = C1(V2-V1)*\ f_{clk} \qquad \text{(eq.5.6)}$$

The resistor value can be calculated as:-

$$(V2-V1)/i = 1/(C1*f_{clk}) = R \qquad \text{(eq.5.7)}$$

Eq.5.7 verifies that a switched capacitor is actually equivalent to a resistor. The value of this resistor is inversely proportional to the switching frequency as well as the capacitance. Based upon this idea the technique of switched capacitors for filter design was introduced a few decades ago and filters have been designed in band pass configuration for signal conditioning [5.7].

Switched capacitor filters have not been used for applications such as machine tool monitoring in the context of signal analysis where frequency analysis is generally a requirement. The major hindrance for such applications was the resolution of such bandpass filters. These limitations have been overcome in the recent past when due attention was given to this technique in the form of IC fabrications.

Since these filters have started to be fabricated on ICs, their availability in monolithic form has increased. This has resulted in their utilisation in various applications. In addition, the switched capacitor filter approach overcomes many inherent problems in standard active filters. The switched capacitor filters allow very sophisticated, accurate, and variable cutoff frequency analog circuits to be manufactured without using resistors. Switched capacitor filters do not need external precision capacitors or inductors like active filters and their cut off frequencies provide an accuracy of around 0.2% by using an external clock frequency [5.8]. This technique further improves the reliability, consistency and reduces temperature sensitivity as well as overall implementation costs.

5.3 Frequency Analysis of Machine Tool Signals

The frequency analysis of machine tool spindle axis signals reveal some very important features which are otherwise hidden and which cannot be detected in the time domain analysis. The frequency spectrum of machine tool signals has a link to cutting tool health. There are different frequency components in machine tool signals which reveal this information. In the discussion of the frequency analysis technique developed for tool condition monitoring three terms will be used. These are: tool rotation frequency, tooth rotation frequency and broken tooth frequency. Tool rotation frequency is the number of revolutions of the spindle per second. Tooth rotation frequency is the multiplication of tool rotation frequency with the number of teeth on the cutter. The broken tooth frequency is the multiplication of tool rotation frequency with the number of remaining teeth on the cutter after the breakage of one tooth. These will be referred to by the short names of *tool rotation frequency*, *tooth rotation frequency* and *broken tooth frequency* respectively in this thesis. The tool rotation frequency and the tooth rotation frequency and their harmonics are dominant for a new cutter. In the event of a tool breakage it is assumed that one of the teeth is now missing and the next tooth has to do extra cutting. Under these circumstances a clear indication of a rise in the cutting force corresponding to the action of the tooth undertaking extra cutting is seen. This is responsible for a change in the overall frequency spectra. In order to analyse the signal's frequency spectrum, switched capacitor filters were used to investigate techniques capable of revealing the required frequency components. This was undertaken with a view to the method being implemented on a resource limited 8-bit microcontroller.

There are many ICs available that use switched capacitors for implementing different types of analogue filters. This application uses a MAX264 filter IC. The PIC microcontroller was used to generate the necessary control signals for the filter IC in order to automatically configure it to handle varying parameters using the sweeping filter technique explained in the following section.

5.4 Sweeping Filter Frequency Analysis Technique

Given that the switched capacitor filter may be configured for different centre frequencies by changing its clock input the idea of a sweeping filter frequency analysis technique was investigated. Most signal acquisition and processing applications require a signal conditioning and filtering stage and these may be implemented with a programmable filter whose operating mode (i.e. low pass, band pass or high pass) and centre frequencies can be changed on-the-fly. In this case a programmable band-pass filter has been used and its band selection controlled by the input clock frequency of the filter IC. The programmable gain and control settings of the filter IC are then used to manipulate and optimise the frequency analysis for an anticipated range of frequencies of interest. These clock and control signals are generated by using the PIC microcontroller. The entire frequency range of interest is thus scanned to generate a total profile of the signal. The result is a simple, computationally efficient (requiring simple mathematical functions only) and easy to implement technique. After setting up for a specific application, the filter band frequency is selected and data acquired for a minimum of one complete cycle of the longest time period in the band. The number of samples per cycle is selected according to the tolerable error. Maximum and minimum values are determined and their difference is taken to determine the peak to peak amplitude. The peak-to-peak difference corresponds to the relative power of scanned frequency band. The process is then repeated for each incremental filter band frequency across a desired sweeping range and the frequency spectrum profile is accumulated.

The MAX264 filter was used to approximate the following second order filter function in this application:-

$$G(s) = H_{OBP} * \frac{\left(\frac{s}{Q*\omega_0}\right)}{\frac{s^2}{\omega_0^2} + \left(\frac{s}{Q*\omega_0}\right) + 1}$$

Where:- H_{OBP}=Gain at $\omega=\omega_0$ and $f_0 = \omega_0/2\pi$.

The centre frequency of the complex pole pair is f_0. It is measured as the peak frequency of the bandpass output. "Q" is defined as the quality factor/gain of the complex pole pair in the bandpass mode of the IC. It is ratio of the centre frequency (f_0) to the -3dB bandwidth of the 2nd order bandpass filter. "Q" is always measured at the bandpass filter's output. The notation "Q" is interchangeably used for the gain and quality factor for this IC when configured in the bandpass mode of operation.

The filter IC MAX264 has a programmable gain ranging from 1 to 64. It can be configured to 128 different values within this range depending upon the signals at the control pins, which are strapped to the microcontroller's digital output lines. A higher value of gain results in a relatively narrow bandwidth and increased resolution. However a higher gain selection also places a limit on the input voltage levels to avoid the saturation of the gain amplifier. For lower gain values and input clock/cut-off frequency ratios, the deviation from ideal response becomes more pronounced. This error is predictable and can be eliminated by using the values of error provided in the data sheet of MAXIM filter IC [5.9].

The block diagram of the sweeping filter signal analysis system is shown in Figure-5.3. It is a generalised illustration of the technique developed. The figure shows that the number of sweeping filters can be different for different applications depending upon the system/analysis requirements. This number can vary in accordance with the total input signals as well as scanning time limitations. For example for a faster response time, separate sweeps are recommended. This is due to the fact that although the PIC18F458 has eight different A/D converter channels it cannot scan more than one channel simultaneously. Therefore different microcontrollers and filter ICs can be used for scanning more than one input signal in a shorter time

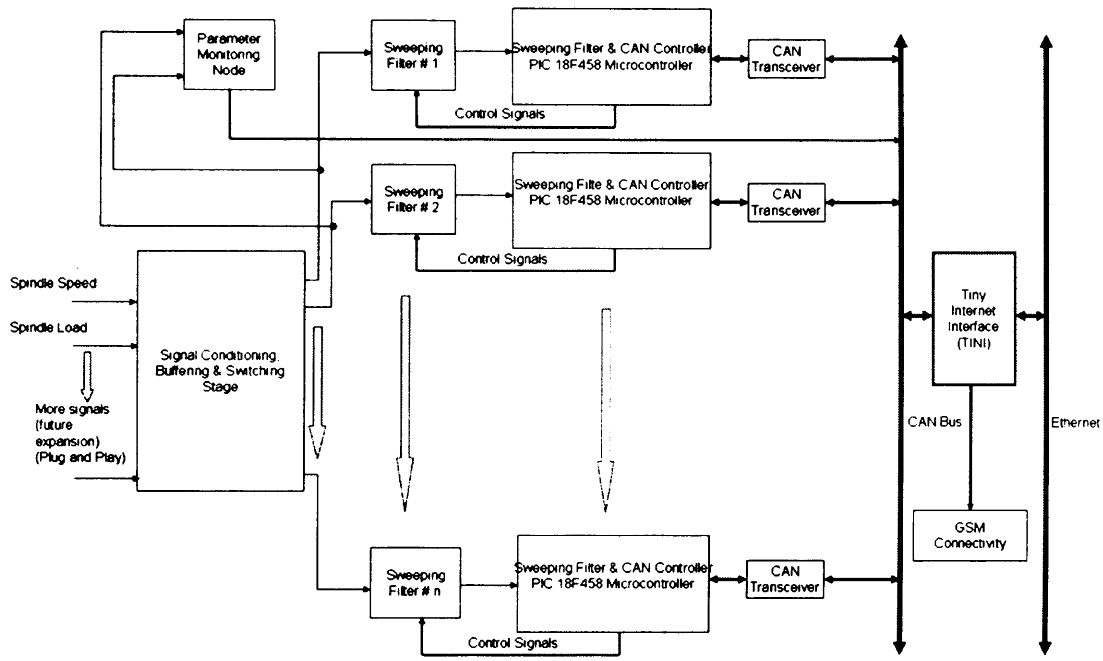

Figure-5.3, Block Diagram of Sweeping Filter Analysis System

Figure-5.3 shows more than one sweeping filter scanning different input signals to formulate their corresponding frequency response. For an application in which a faster response is not a crucial requirement, a single microcontroller can be used to control more than one filter IC. For such applications, after setting one filter IC for a bandpass configuration and acquiring the input signal, the control outputs of the microcontroller can be changed to the requirements of next filter IC and its output can be acquired. This operation can be repeated cyclically until the profile of the entire bandwidth of interest has been scanned and the frequency contents analysed.

5.4.1 Single Node Operation for Sweeping Filter Technique

The hardware and software block diagrams of a single node of sweeping filter functionality are shown in Figures-5.4(a) and 5.4(b) respectively. As shown in Figure-5.4(a), all of the control inputs of the filter (including Mode control, gain control and centre frequency) are connected to the MCU providing total control to the developer. This approach makes it possible to change different parameters of the filter by changing the controlling software whenever required rather than changing the overall hardware design each time. The signal conditioning system was primarily used to adjust the input level of the signal in accordance with the gain and mode of operation of the filter to avoid the saturation of the gain amplifier.

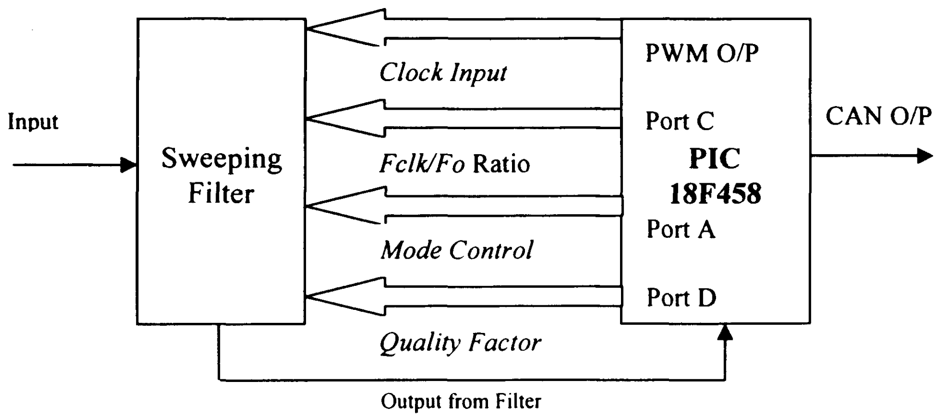

Figure-5.4(a), Block Diagram of Hardware of Sweeping Filter Node

In a bandpass configuration the gain of the filters can be selected by selecting the quality factor. In low pass configuration the gain of the filter varies between 0.5 and 2. In both configurations, the phase is shifted by 180 degrees which can be adjusted by using any suitable technique depending upon the application requirements.

The MAX264 has two internally implemented second order analogue switched capacitor filters which provide outputs of low pass, high pass or bandpass filters on different output pins simultaneously depending upon mode selection. For example in mode one configuration if a band pass filter is implemented for a centre frequency of f_o, the bandpass output centres at f_o, and the low pass output has a cut off frequency of f_o. This additional feature adds to overall design flexibility as for one configuration, two or more outputs can be acquired if required.

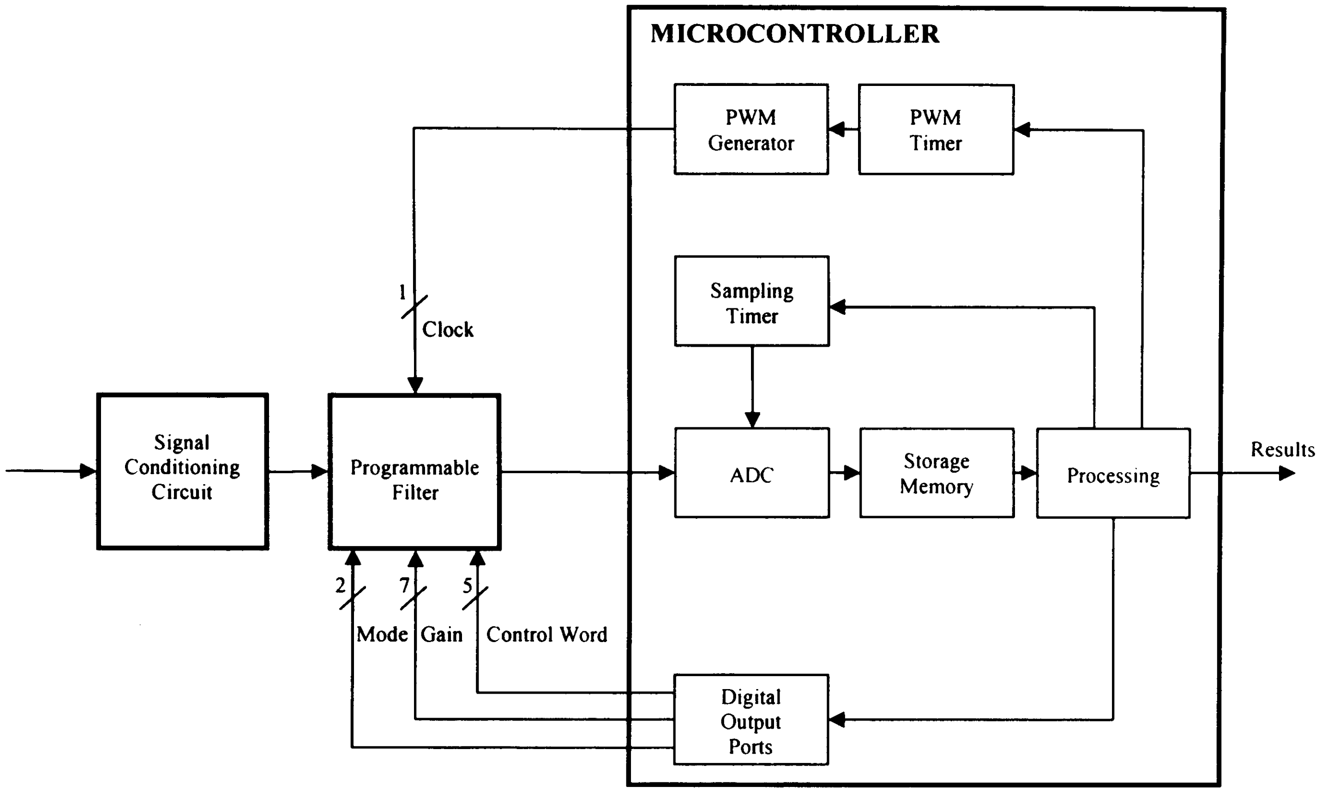

Figure-5.4(b), Block Diagram of Software of Sweeping Filter Node

The Centre frequency of the filter is adjusted by a clock input to the IC. This basically controls the switching frequency of the internal MOSFET configured as switches. A change in clock frequency changes the switching rate of the internal switches and the centre frequency shifts accordingly. In this application the Pulse Width Modulation (PWM) module (built-in to the PIC microcontroller) was used to generate the required clock signal for the filter, thus reducing software overheads.

As shown in Figures-5.4(a&b), the signal (spindle load for frequency analysis) is interfaced to the corresponding node after necessary signal conditioning. The parameter monitoring node as shown in Figure-5.3 constantly monitors the spindle speed signal and communicates the frequencies of interest to all other FENs on the network via the CAN bus which then adjust their sweeping band accordingly. The spindle speed signal is acquired in analogue voltage form and linked to the actual running speed of the spindle as discussed in Chapter-4. This node also monitors the spindle load signal in the initialisation stage to establish the starting of the cutting process. The sweeping band of this is dependent upon the running speed of the machine and the number of teeth on the cutter. The values for the starting clock frequency, required increments and the final clock frequency are calculated accordingly.

Each node acquires the signal and converts it to digital format using the ADC module of MCU. The signal acquisition rate (sampling rate) normally depends on the application requirements and is set in an initialisation phase of the software. In this technique the value of the sampling rate does not affect the overall performance of the system. This is due to the fact that in a comparative analysis technique the same filter settling time is used in each cycle. Therefore the frequency strength of a signal for a constant time band is compared each time which eliminates the chances of any comparison errors.

After the acquisition of a data sample the value is compared against the previously calculated maximum and minimum values. If the current value is lower than a previous minimum value it replaces it. A similar action is repeated against the previously acquired maximum value. The dynamic comparison of these data values makes it possible to store only the calculated peak-to-peak difference for each frequency band rather than storing the whole data and unnecessarily filling the memory.

Having completed the acquisition (of 32 samples in this application) for one frequency setting, the filter is re-configured to the next frequency range of interest and the next set of 32 samples are acquired and compared in a similar way. A timer interrupt has been used to generate accurate sampling times. There is ample time for the MCU programme to calculate the peak to peak amplitude of the previously acquired data during each interrupt phase. The microcontroller can be set up to trigger an alarm as soon as it senses some deviation from the expected profile for normal behaviour even when part way through an entire sweep. This approach is especially attractive in applications where the details of every frequency component are not required and only specific components indicate likely faulty conditions.

Four memory banks have been reserved for storing the peak-to-peak values of each frequency band. Therefore in one sweep, the relative peak-to-peak amplitude of 1024 different frequencies of interest can be calculated. In a machine tool operation the frequency spectra of spindle speed and spindle load signals of a healthy and broken tool are different. In this chapter the results of four toothed cutter rotating at a spindle speed of 500RPM and a feed rate of 100mm per minute are considered with a view to making comparisons of healthy and broken cutters under the same cutting conditions. This is a representative of a number of similar tests undertaken to develop the methodologies. A complete range of cutting tests and the results are discussed in Chapter-7 (System Integration chapter). The time required for scanning the profile of a signal depends upon various factors including:-

- Resolution requirements.
- Filter settling time.
- Frequency band of the signal to be scanned i.e. gap between first and last frequency of interest in a signal.
- Number of data points for each frequency band.
- Sampling rate.
- Application type e.g. single sweep or multi sweep operation.

The number of samples acquired for each frequency band analysis, sampling rate and filter settling time also have a combined effect on the system. For example; at a lower sampling rate and higher number of data samples taken the filter settles and the value of the peak-to-peak difference is higher; whereas for a higher sampling rate and same number of data samples, the peak-to-peak value of same signal is lower because the filter has not settled as yet. This indicates that for a single sweep operation these variation factors need to be normalised for each frequency bin (or band) to ensure the accurate frequency analysis of a signal. For multi sweep operations carrying out comparative signal analysis this factor does not have any effect on the overall system performance. For example if a comparison has to be made among the same frequencies in the same frequency band after making two consecutive frequency sweeps then the value of "*fo*" (any frequency in the sweep band) acquired in the first sweep can be compared with the value of "*fo*" (same frequency) acquired in the second sweep. This is due to the fact that the same parameters are being used each time and thus the acquired values are scaled by constant factors each time and the results only vary if there is a change in the frequency strength of the input signal.

For single sweep operations a higher sampling rate is not recommended for this technique. The logic behind this argument is that at higher sampling rates the filter does not have enough settling time and cannot reveal reliable information about the frequency contents in the signal. Therefore it is recommended that the sampling rate should be kept low to provide more settling time to the filter for each frequency acquisition.

5.4.2 Technique Verification by Simulation and Lab Testing

Extensive testing was carried out using Matlab simulation and lab testing to analyse a range of generated signals including sine, square and sawtooth. Moreover the actual machine signals were acquired and used as inputs to the designed system for verification of the functionality and reliability of this technique before any hardware implementation on the machine tool itself. These tests have produced excellent results to prove the functionality of technique. These are discussed in the succeeding paragraphs sequentially along with graphical representations.

Firstly the capability of the technique to pass a frequency of interest and suppress other frequencies when configured to specific frequency monitoring is shown in Figures-5.5(a&b). Figure-5.5(a) shows an 8Hz Sine wave input signal to a simple 8Hz bandpass filter designed using the MAX264 and PIC microcontroller hardware. Since the filter is configured to the 8Hz frequency pass-band the output of the system for this signal rises to the same value as input signal as shown in Figure-5.5(b).

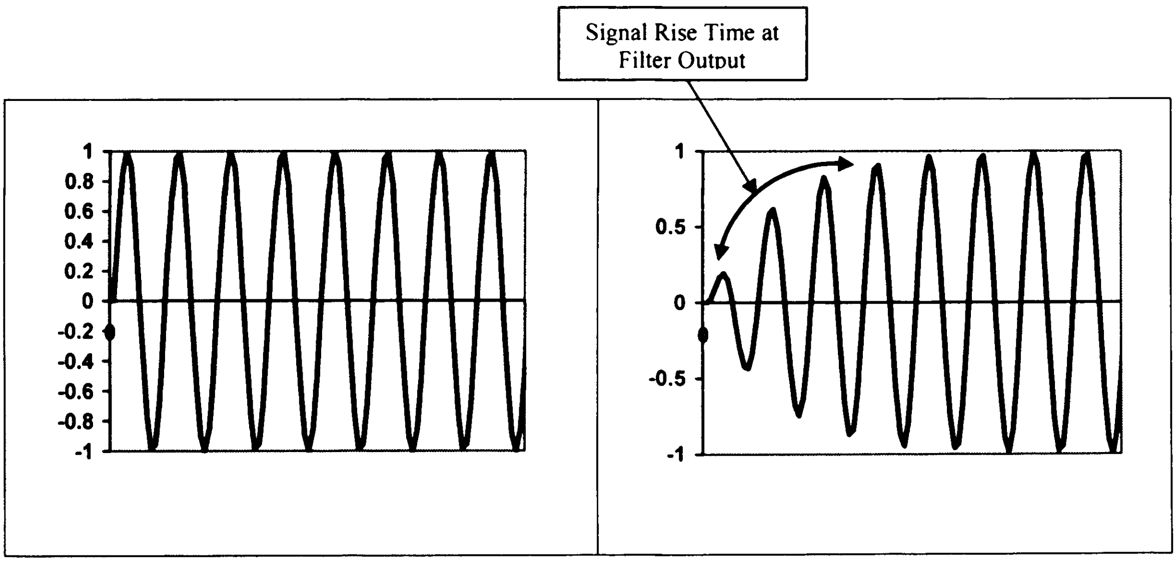

Figure-5.5(a) - 8Hz Sine Input for a filter configured at 8Hz. Figure-5.5(b) - Output from a filter configured at 8Hz.

(X-axis shows time and Y-axis shows relative strength, No sweep, Unity Gain).

The output signal indicates a delay before reaching its actual expected value. This delay is dependent upon the filter settling time and the frequency of the input signal. The signal rise time (or delay) may be important in some applications but in this application it can be ignored since this is a comparative value analysis technique that compares the strength of a particular frequency component against the same component (during the next sweep). Hence the signal rise time does not make any difference as long as it allows the output signal to gain a reasonable value.

Figures-5.6(a&b) prove the validity of approach taken to suppress unwanted frequency components in a signal. The filter's ability of suppressing the unwanted frequency components has been illustrated in these figures. Figure-5.6(a) shows a 16Hz sine wave input signal used for a filter configured at 8Hz pass-band using the designed system. The output shown in Figure-5.6(b) clearly shows the suppression of this unwanted frequency component. This validates the approach's capabilities to separate pass band frequencies from stop band.

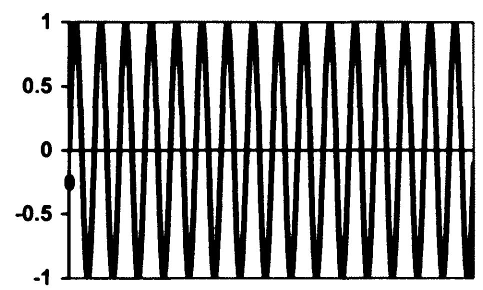

Figure-5.6 (a) - 16Hz Sine Input for a filter configured simply at 8Hz, No sweep, Unity Gain, X-axis shows time and Y-axis shows relative strength

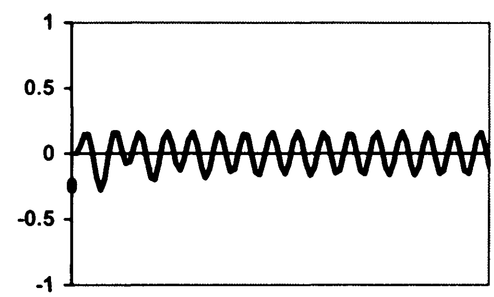

Figure-5.6 (b) - Output for 16 Hz sine from a 8Hz filter, No sweep, Unity Gain, X-axis shows time and Y-axis shows relative strength

Figure-5.6, Filter's capability to remove unwanted signal components.

Figures-5.7(a&b) show the results from the actual sweeping filter approach. The system is swept across a signal to determine its frequency components which range from 1Hz to 40Hz. Since the input signal is an 8Hz sinusoidal waveform, the results show the presence of this component only. As previously described in section 5.4, the analogue output signal from the filter for each pass band is acquired by the microcontroller and its peak-to-peak value represents the relative amplitude of that particular frequency. The main noticeable differences between these figures are: (a) relative amplitude value of frequency component detected and (b) the bandwidth. Both these factors are linked to the Quality Factor of the band pass filter.

For the MAX264 filter IC, the Quality Factor is equal to the filter Gain in the band pass configuration. Therefore for a higher Gain setting (Figure-5.7-b), the relative amplitude of the detected frequency component rises and the bandwidth of the filter decreases (as compared to Figure-5.7-a). These figures clearly indicate the benefits of using a Gain value of 16 for the final system design in order to achieve the required frequency resolution. Therefore this value has been used for the results discussed in this chapter.

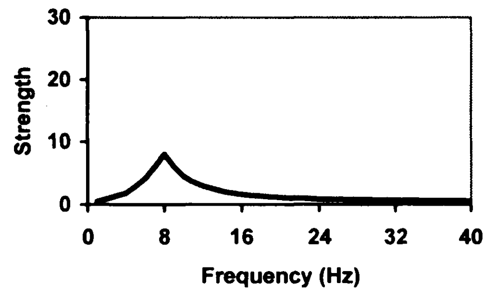

Figure-5.7(a) - Output for 8Hz Sine wave Sweeping filter; Gain= 4.

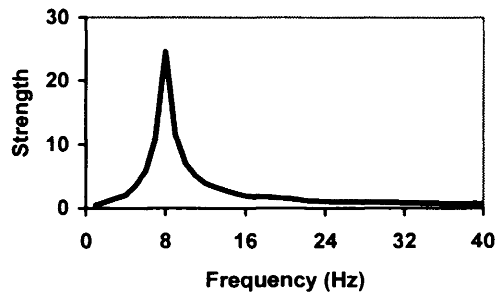

Figure-5.7(b) - Output for 8Hz Sine wave; Sweeping filter; Gain= 16.

Figure-5.7, Gain effect on the output of the filter.

The capabilities of the technique were similarly assessed for the multiple frequency component detection in a signal. Figure-5.8(a) shows the system's output for an input signal of 8 & 12Hz sinusoidal wave forms. Figure-5.8(b) shows the ability of the system to detect harmonics in addition to the original signal. The figure shows output of an 8Hz square wave input signal. Its base frequency and its third harmonic have been detected whilst there are no signs of the second harmonic which follows the square wave harmonic's theory. In addition to these tests various other laboratory tests were carried out to verify the functionality of the system and the results duly verified the technique and the system.

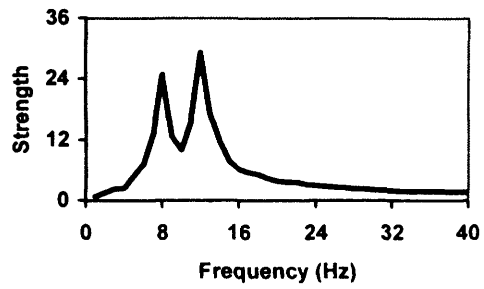

Figure-5.8, Output for 8+12 Hz Sine wave; Sweeping filter; Gain= 16.

Figure 5.8 (a), Detection of two frequencies

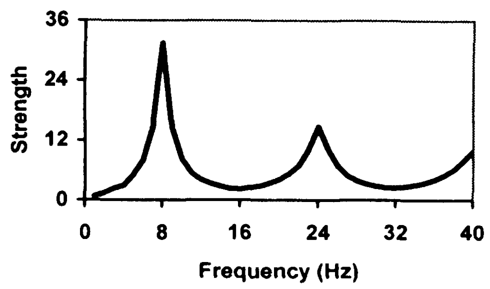

Figure-5.9, Output for 8Hz Square wave; Sweeping filter; Gain= 16.

Figure 5.8(b), Detection of a Square Wave

5.5 Machine tool Signal Analysis using Sweeping Filter Technique

After the functional verification and testing of the abilities of the proposed technique and supporting system in various circumstances, sample machine tool signals were interfaced to the system for its practical implementation. Both spindle load and speed signals were analysed and similar results were obtained. It is assumed that cutting starts with a healthy tool. The parameter monitoring and decision making node calculates the required process parameters and communicates these to all the FENs. The number of teeth in the cutter is calculated by generating a sweep at the start of cutting process. The base frequency information retrieved is used as a divisor to the highest frequency observed in the sweep and the result equates to number of teeth in the cutter. This information is communicated to other nodes in the monitoring network. Similarly the spindle speed is automatically determined by the system. After the start of the cutting process the system determines the start of actual metal cutting. The procedure is illustrated in Figure-5.9. The Spindle load signal is used to determine the start of the cutting process. The values of the spindle load signal prior to and during the cutting process are significantly different as is evident in Figure-5.10. This change allows the parameter monitoring node to determine the start of cutting and then to communicate this to all the other nodes via the CAN bus as a signal to start the monitoring process.

There is a time delay before the spindle load reaches the threshold which is also used as a tool entry period before the start of the monitoring process. Figure-5.10 shows the flow chart of the overall supporting software used for the system implementation. The parameter monitoring node determines the required range of frequencies to be swept depending upon the spindle running speed and the number of cutter teeth.

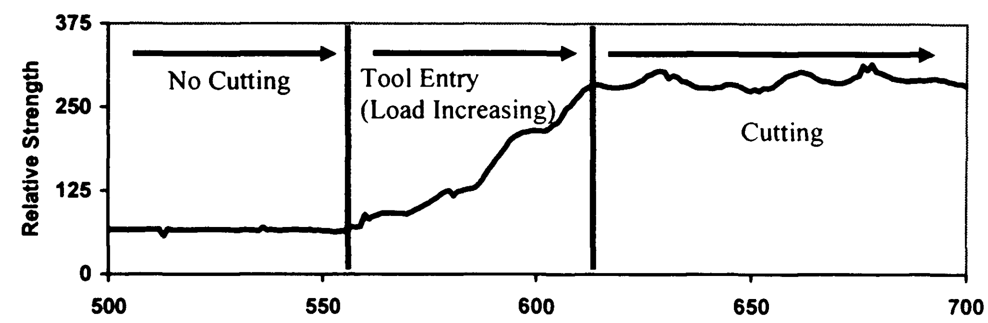

Figure-5.9, Start of the cutting process

For example for a four toothed cutter rotating at 500RPM, the frequencies of interest are 8.33, 25 and 33Hz. The parameter monitoring node communicates this information to other FENs again using the CAN bus connectivity. After finalising the sweep parameters, there is a further nominal delay to cater for the tool's full entry into the work piece. The delay is variable and is directly proportional to the tool diameter and inversely proportional to the feed rate. This completes the initialisation process as shown in Figure-5.10 and the system is ready to monitor tool's health.

A full range sweep is carried out to set the threshold values of the frequencies of interest. These threshold values are different to the threshold values used to determine the start of the cutting process and are used to generate a warning signal about the tool's health. Setting a reliable threshold value is very important for tool monitoring systems because it reduces the chances of false alarms and improves overall system reliability. A decrease in false alarms reduces unnecessary down time thus increasing the OEE of the system (explained in chapter-7) which is highly desirable.

Extensive testing was carried out to determine a full range of spindle load signal variations from a healthy cutter to a broken cutter. The cutting parameters of a four toothed cutter are tabulated in Table-5.2. It shows that cutting is smooth and evenly balanced for a healthy cutter whereas number of teeth engaged in cutting varies for the different angular windows for a broken cutter. These factors result in variations in the cutting process that are used to detect the breakage. With three teeth cutting after the breakage of one tooth (for a four teeth cutter) the variations in the angular displacement between consecutive teeth as well as the number of teeth engaged in cutting simultaneously (refer to Table-5.2) affect the strengths of the tool rotation frequency and its multiples such that they are different than the strengths of a healthy cutter. An increase of at least 400% (for Gain value of 4) and more than 1000% (for gain value of 16) in the strength of the frequency components of interest was observed in spindle load signal from a healthy cutter to broken one even for a nominal depth of cut (0.5mm). Therefore threshold values of up to 500% of the actual values were used in this design. Experiments also revealed that any increase in value is also dependent on the depth of cut to some extent i.e. at a higher depth of cut, the gap between the strength of the frequency components observed between a healthy and broken cutter increases. A brief comparison of the output signals observed for gain value of 16 is discussed later in this chapter. Considering various factors such as input signal amplitude, filter operation mode and its polarity of operation, a Gain value of 16 was selected. After analysing the different cutting situations in conjunction with the varying cutting parameters a threshold value of 5 times the initial value for a healthy cutter was set to avoid any false alarms.

In this application design tests were carried out using two different filter window lengths to assess the functional accuracy and efficiency of the system. These settings included acquiring 32 as well as 16 samples for each frequency window (one frequency of interest) at a sampling rate of 100 samples per second before moving the window settings forward. For a spindle rotational speed of 500RPM, the frequency range of interest is from 8Hz-33Hz meaning 25 different frequency windows.

After finalising the initial system setup it starts monitoring the tool health by using the cyclic sweep strategy. The cyclic sweeps entail carrying out a sweep from the first to the last frequency of interest and repeating the procedure cyclically. For one frequency window setting 32 samples are taken and the difference between the maximum and minimum values is calculated. This difference indicates the relative strength of that frequency. The sweep is completed in the same way and relative strengths of different frequencies are stored. The relative strength of frequencies of interest is compared against the thresholds set and decisions are made about tool health.

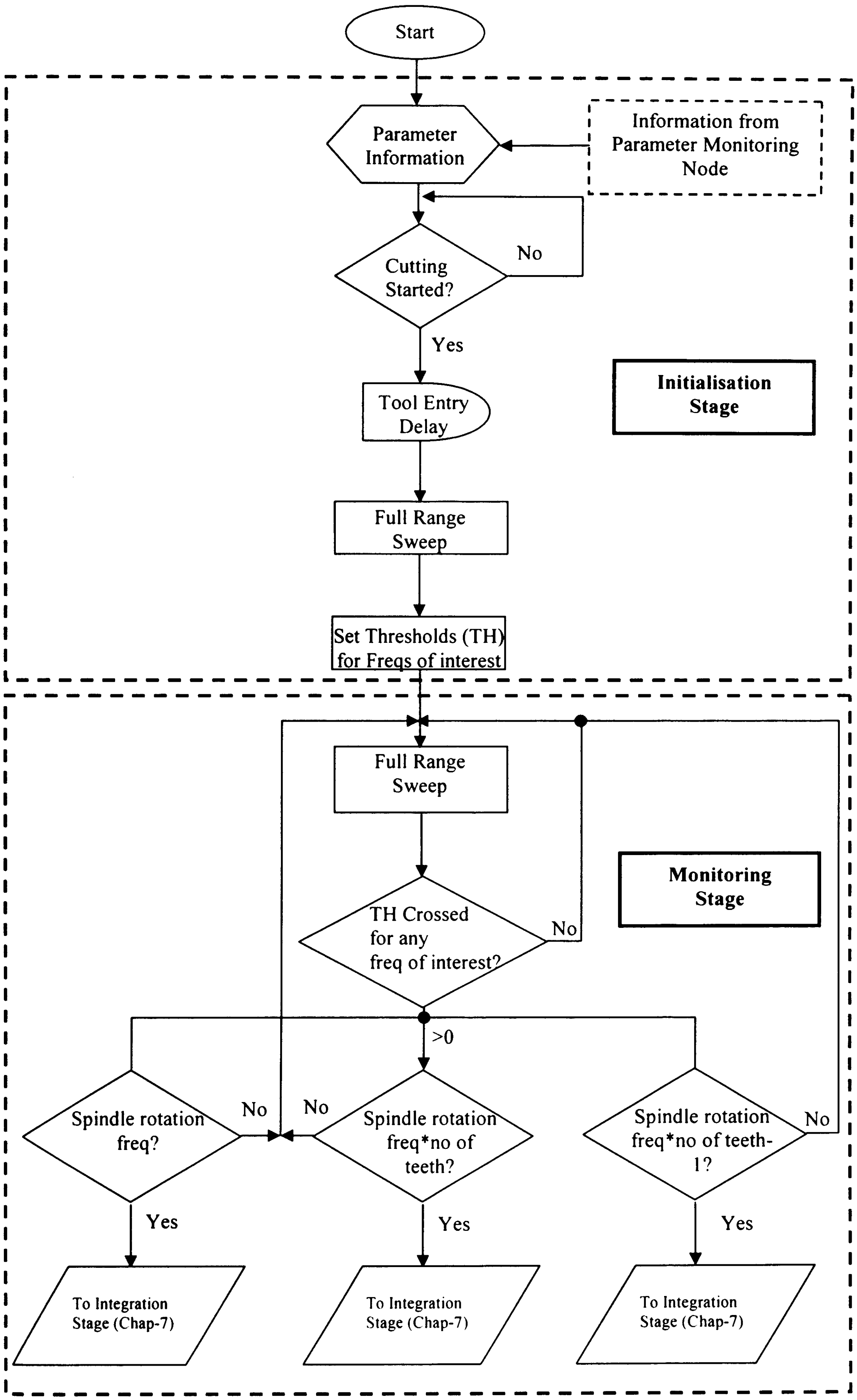

Figure-5.10, Sweeping Filter System Flow Chart

Parameter	Healthy Cutter	Broken Cutter
Number of teeth cutting (t)	4	3
Number of teeth cutting at one time (W)	2 for 360 degrees	2 for 180 degrees 1 for rest of the cycle.
Angular displacement between two adjacent healthy teeth *(degrees)*	90 degrees	90 degrees between two pairs 180 degrees between one pair.

Table-5.2, Cutting parameters for four-toothed cutter.

(Note: The detail of the cutting process and the effects upon it that a broken tool produces are outlined in Section 6.2.1 of this thesis).

The sweep results for a spindle speed of 500RPM, feed rate of 100 mm per minute and filter gain value of 16 are discussed in this chapter. These results for different values of depth of cut ranging from 0.5mm to 2.0mm are discussed to prove the reliability of the technique. The results for new, blunt and broken cutters are presented to show the difference of behaviour. The number of samples taken for each frequency window setting affects the overall system efficiency due to filter settling time. For example the relative frequency strength for higher number of samples is higher than lower number of samples for the same cutting parameters. This factor is discussed in detail later in this chapter. The results for a 32 samples per frequency window and 16 samples per frequency window are discussed for a comparative analysis.

Figure-5.11(a) shows the relative strength of different frequencies for a sweep ranging from 0Hz to 40Hz for new, blunt and broken cutters for a 2mm depth of cut. For these tests 32 samples per frequency windows were acquired to calculate the relative strength of each frequency. Similarly Figure-5.11(b) shows the results for the same parameters using 16 samples per frequency window to calculate the relative strength of each frequency. After a tooth breaks the variations in the spindle load signal are high therefore the sweeping filtering technique was implemented on the spindle load signal.

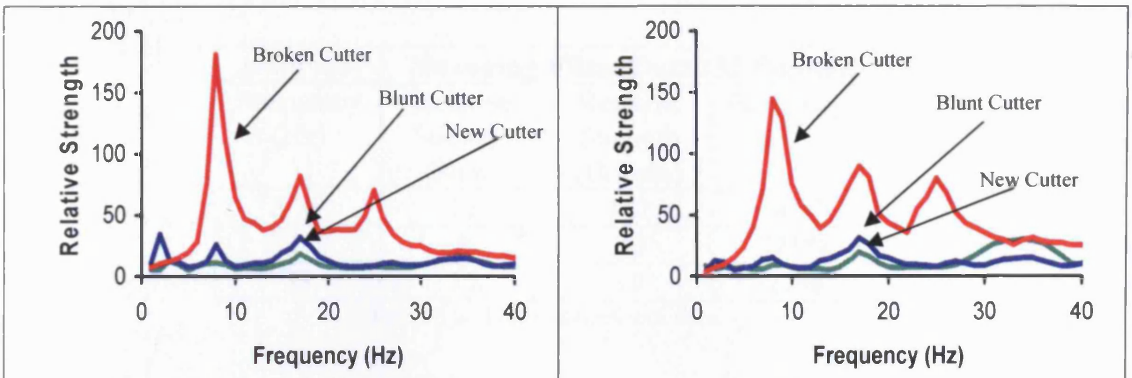

Figure- 5.11 (a) - DOC=2.0mm, Gain=16
32 samples per frequency window

Figure- 5.11 (b) - DOC=2.0mm, Gain=16
16 samples per frequency window

Figure-5.11, Sweeping Filter results for new, blunt and broken cutters.

New Cutter, Blunt Cutter, Broken Cutter

In these Figures (5.11-a&b) green lines indicate the relative strength of frequencies for a new cutter whereas blue and red colours correspond to the behaviours of blunt and broken cutters respectively. Both figures indicate that the technique has the capabilities to detect the tool breakage in either situation. A thorough analysis of the results presented in Figures-5.11(a&b) reveals that peaks of relative strength of frequencies detected are much sharper when 32 samples per frequency window are acquired as compared to 16 samples per frequency window. This means that higher number of samples result in a better resolution thus ensuring a more reliable decision. Higher resolution is required particularly for low spindle speeds when frequencies of interest are much closer as compared to high spindle speed where frequencies are far apart and can be easily detected. For example, for a four toothed cutter rotating at 500RPM, the frequencies of interests are 8.33, 25 and 33Hz. These frequencies are tool rotation frequency (8.33Hz), tooth rotation frequency (33Hz) and broken tooth frequency (25Hz). For the same cutter rotating at 1000RPM, the frequencies of interest are 16.66, 50 and 66Hz which are further apart as compared to the 500RPM speed. Therefore lower values of resolution can be used to detect tool breakage at high speed spindle rotations.

Typically observed relative strength values for different frequencies of interest for a cutting operation using four toothed cutter at a 500RPM spindle speed and 2mm depth of cut are tabulated in Table-5.3.

Gain=16	Sweeping Filter Data (32 Points)		
Frequency (Hz)	Relative Strength (New)	Relative Strength (Broken)	Percentage Increase
8.33	12	181	1408%
25	8	70	775%
33	15	19	27%

Table-5.3, Four-toothed tool data.

For a new cutter, the strength of the frequency components is very weak but noticeable on a smaller graphical scale. The presence of an 8Hz (tool rotation frequency) and a relatively higher strength 33Hz (tooth rotation frequency) as compared to 25Hz (broken tooth frequency) indicate that the tool is healthy. As the tool goes blunt the strength of these frequency components increases proportionally but retains the same trend as can be noticed in Figures-5.11(a&b). As soon as a tooth breaks there is a significant increase in the strength of the tool rotation frequency. This increase is basically an additive sum of the tool rotation frequency and the frequency of the tooth which is now required to undertake the cutting of the extra metal. Since both frequencies are the same the increase is much more significant (Table-5.3 – an increase of 1462% for 8.33Hz).

The frequency component corresponding to the broken tooth frequency (25Hz in this case) also increases. This increase is mainly due to two reasons: firstly, one of the teeth has broken and actual number of teeth actively engaged in cutting is one less than the total number of teeth which generate this frequency component. Secondly, the harmonic of tool rotation frequency is strong enough to show an additive effect. The increase can be noted in Table-5.3 (725% for 25Hz).

In accordance with the theory of number of teeth engaged in cutting; the tooth rotation frequency component (33Hz in this case) should disappear as there are only three teeth cutting but in practical situations this is not observed. This frequency component remains close to the previous value due to the harmonic effect of a very strong tool rotation frequency component (Table-5.3 – 33Hz). Although the reduction in this frequency component is desirable it is not mandatory because a significant difference in the strength of two other frequency components is sufficient to raise concerns about the health of the tool.

The reliability of the approach has been illustrated for a 2mm depth of cut. The relative strength of frequency components of interest gets even more prominent and easy to detect for higher depth of cuts. The technique is also efficient enough to detect tool breakage for lower values of depth of e.g. even at a nominal value of 0.5mm as shown in Figures-5.12(a-f). In Figures-5.12(a-f) green lines show the relative frequency strength in the spindle load signal acquired using a new cutter whereas blue and red colours correspond to blunt and broken tools respectively. Figures-5.12(a) shows results for 1.5 mm depth of cut. In these tests 32 data samples were acquired to calculate the relative strength of each frequency component ranging from 0 to 40Hz. Figure-5.12(b) shows the test results using the same parameters but using 16 data samples per frequency window. It can be noted that the peaks of the detected frequency components are much sharper and the resolution is better when using the higher number of data samples. This is because of the fact that the filter gets a higher settling time and the difference between the maximum and minimum detected values increases. The same trend can be noted in Figures-5.12(c-f). It is worth noting that even for a nominal value of 0.5 mm depth of cut the breakage can be detected (Figures-5.12- e,f).

The reliability of the developed technique required the consideration of another crucial factor; the response lead time. This can be defined as the time taken by a system to acquire, analyse and make a decision about a tool's health. A longer lead time in decision making results in a higher number of tool rotations and hence in the amount of cutting undertaken before stopping the machine if a tooth is broken. To ensure high quality machining a lower value of decision lead time is desirable. Lead time in the sweeping filter technique is directly proportional to number of cutter teeth and spindle rotational speed, since a reasonable time at each bandpass window is required to acquire the relative strength of different frequency components before decision making.

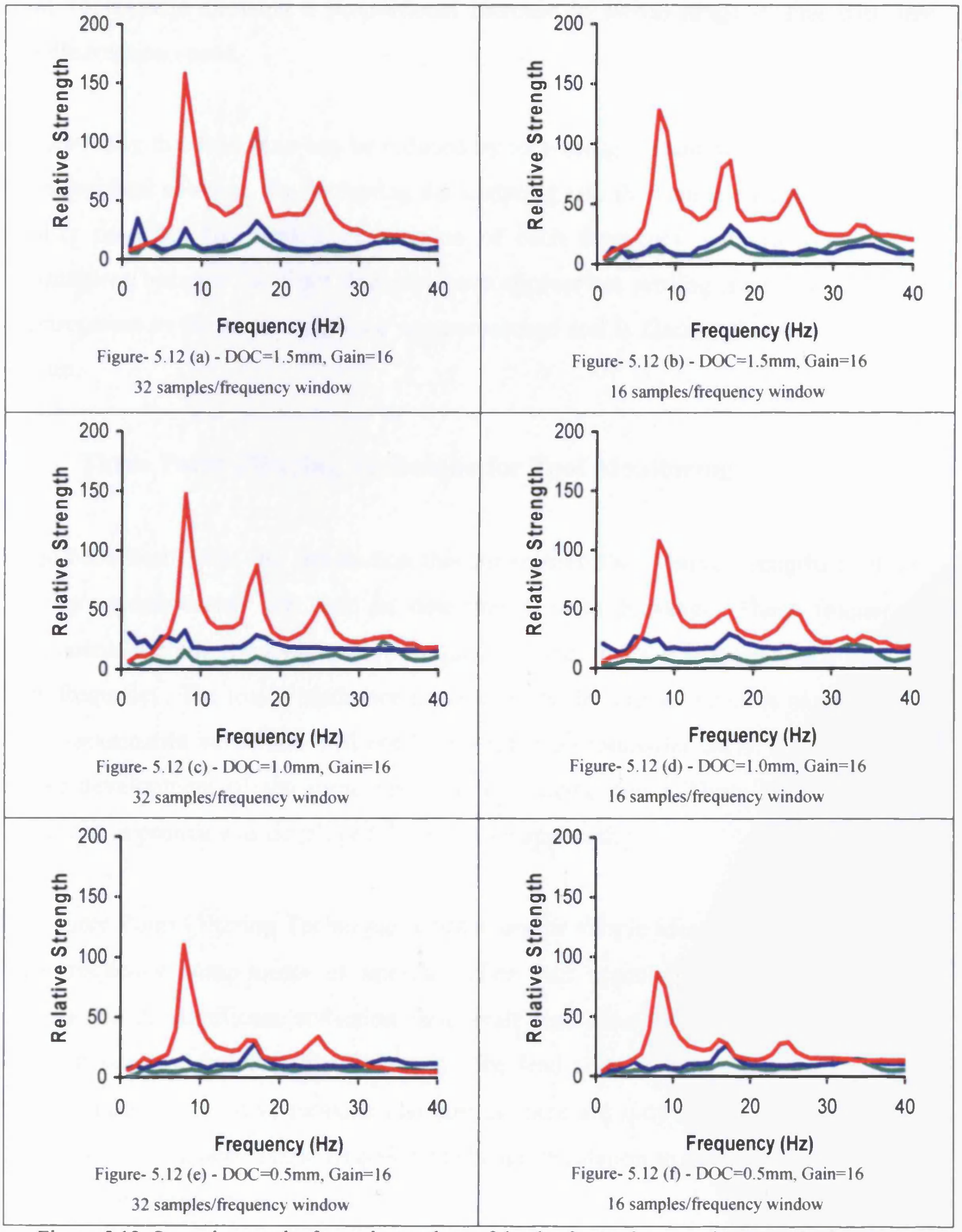

Figure- 5.12 (a) - DOC=1.5mm, Gain=16
32 samples/frequency window

Figure- 5.12 (b) - DOC=1.5mm, Gain=16
16 samples/frequency window

Figure- 5.12 (c) - DOC=1.0mm, Gain=16
32 samples/frequency window

Figure- 5.12 (d) - DOC=1.0mm, Gain=16
16 samples/frequency window

Figure- 5.12 (e) - DOC=0.5mm, Gain=16
32 samples/frequency window

Figure- 5.12 (f) - DOC=0.5mm, Gain=16
16 samples/frequency window

Figure-5.12, Sweeping results for various values of depth of cut using new, blunt and broken tools.

New Cutter, Blunt Cutter, Broken Cutter

A sweep operation acquiring 32 samples per window at the specified sampling rate takes 8 seconds to complete. For a spindle speed of 500RPM this setup will detect the breakage after 66 tool revolutions. Similarly, at 16 samples per window breakage can still be detected but there is a lead time of 33 tool revolutions. The lead time increases further for higher spindle rotation speeds as the frequency range of interest increases. For example; the frequency range of interest for spindle speed of 1000RPM ranges from 16Hz-66Hz showing a proportional increase in sweep range in line with the spindle rotation speed.

Theoretically this lead time can be reduced by increasing the sampling rate but this is not a practical solution. By increasing the sampling rate the data can be acquired in a smaller time but the peak-to-peak value of each frequency window is virtually meaningless because the filter does not have appropriate settling time. Therefore an improvement in the same technique was researched and is discussed in the following section.

5.6 Three Point Filtering Technique for Tool Monitoring

It has been verified in the last section that monitoring the relative strengths of three frequency components can help in detecting a tooth breakage. These frequency components include the tool rotation frequency, tooth rotation frequency and broken tooth frequency. The major hindrance however is the lead time, which is much higher than a reasonable value and will not be accepted by industrial users. Therefore the further development of the same idea was considered and a Three Point Filtering Technique approach was developed for the same application.

This Three Point Filtering Technique is based on the simple idea of investigating the three frequency components of interest rather than scanning the whole range of frequencies. A significant reduction in overall lead time towards tooth breakage detection is possible using this approach. The lead time is independent of spindle rotation speed and always remains constant as there are only three frequencies that need to be investigated. These frequencies change in relation to the spindle speed and the number of cutter teeth.

For a four toothed cutter and spindle rotation speed of 500RPM, the three frequencies of interest are 8.33Hz, 25Hz and 33Hz as discussed in Section 5.5. Using this technique, the filter is tuned to the first frequency and data is acquired and analysed before filter shifts to the second frequency of interest. In this approach these three frequencies are analysed cyclically and comparative analysis made using their relative strengths. Tests were carried out for different filter settling time settings and it was observed that 16 samples per frequency window at a sampling rate of 100 samples per second can reliably determine a tooth breakage by analysing either spindle load or spindle speed signals. A constant time of 0.48 second is required to determine a tooth breakage using this technique independent of the spindle rotation frequency.

Figures-5.13(a) shows the time spent on scanning the frequency components that are not actually required for monitoring the health of the machine tool. To save this time and improve the lead time for tooth breakage detection Figure-5.13(b) shows Three Point Filtering technique which monitors the frequencies of interest only. The green lines/dots represent the cutting test result of a healthy cutter whereas blue and red colours correspond to the blunt and broken cutters respectively.

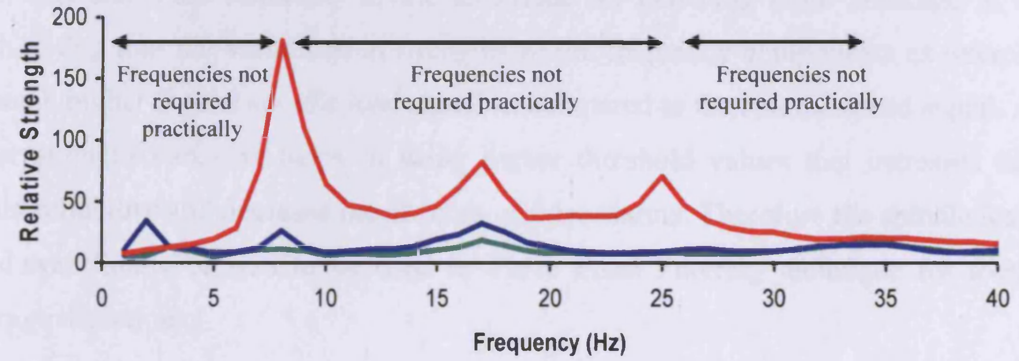

Figure-5.13(a) – Sweeping Filter Technique: Full frequency range scanned

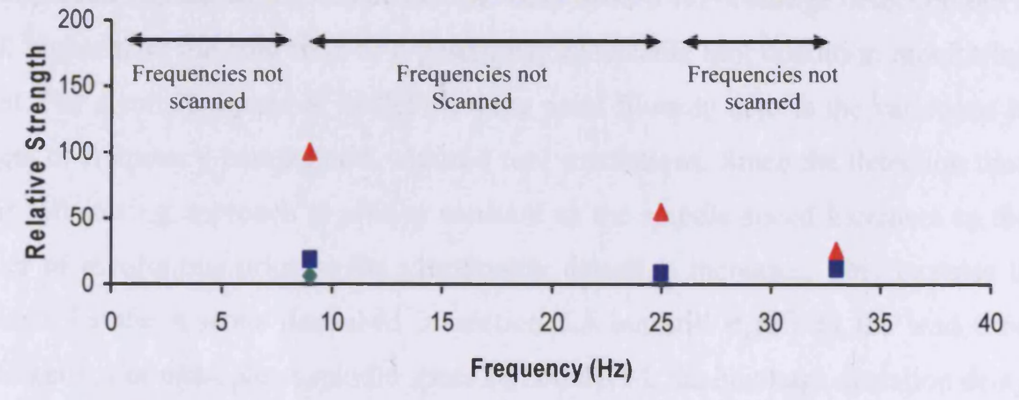

Figure-5.13(b) – Three Point Filtering Technique: Frequencies of interest scanned only

It can be noted that relative strength of detected frequency components in the Sweeping Filter technique is higher than the Three Point Filtering technique. This is due to the fact that in the Sweeping Filter technique the frequencies before and after the frequency of interest are also scanned which increases the overall settling time of the filter and difference between maximum and minimum values acquired is higher.

In the Three Point Filtering technique the filter is tuned to a specific frequency only before moving to the next frequency of interest. These are far apart. Therefore the overall settling time remains exactly the same as programmed which keeps the output signal relatively lower than full sweep technique. This factor does not affect the overall approach as it is based on the concept of comparative analysis. In comparative analysis if a fixed settling time is used for each frequency component monitoring, the results are not affected as one set of values is compared against another set where both have been acquired using the same settling time.

Figures-5.14(a) and 5.14(b) show the test results using the Three Point Filtering technique for analysing spindle load and spindle speed signals respectively. Both these tests show the reliability of the technique for detecting tooth breakage. It is worth noting that the variations in strengths of the frequency components of interest are much higher for the spindle load signal as compared to the spindle speed signal. A higher strength variation helps in using higher threshold values that increases the system reliability and decrease the chances of false alarms. Therefore the spindle load signal was finally chosen to be used in Three Point Filtering technique for tooth breakage detection.

This approach significantly reduces the lead time needed for breakage detection but it is still higher than the lead time of a practically acceptable tool condition monitoring system. For a spindle speed of 500RPM, three point filtering detects the variations in strength of frequency components within 4 tool revolutions. Since the detection time of this monitoring approach is always constant as the spindle speed increases so the number of revolutions prior to the abnormality detection increases. This increase is nonlinear for the reasons described in section 5.5 but still it affects the lead time significantly. For example at spindle speed of 2000RPM, the breakage detection delay is between 12-15 tool revolutions. Therefore the concept was further refined to reduce the lead time and enable it to provide a practical implementation as discussed in the next section.

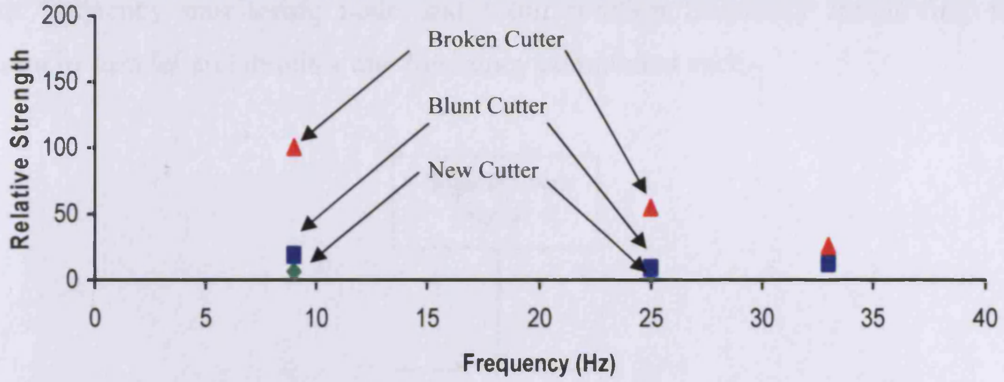

Figure-5.14(a) – Three Point Filtering Technique: Spindle Load Signal

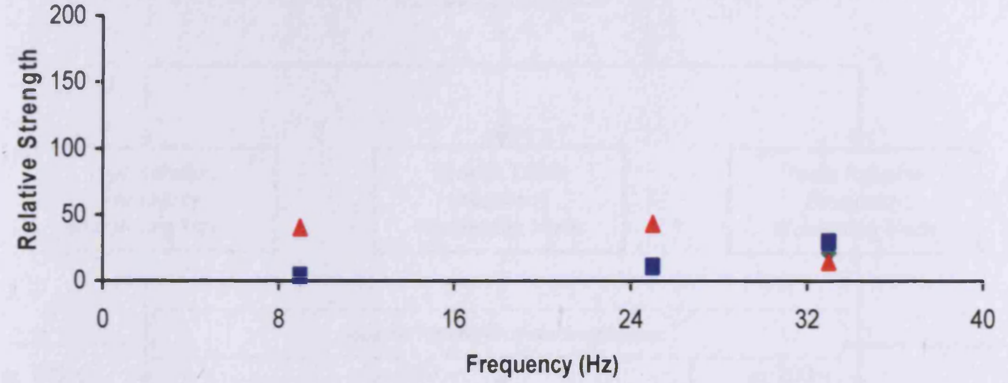

Figure-5.14(b) – Three Point Filtering Technique: Spindle Speed Signal

5.7 Parallel Filtering Technique (PFT)

It is proposed that a practical tool condition monitoring system should be able to detect signal abnormalities within 2 revolutions of the tool independent of its operational speed. Cost effectiveness is also an important requirement for such systems. The PIC microcontrollers are very cost effective embedded solutions.

Given the development, and limitation, of previously outlined solutions the use of more than one microcontroller in parallel was considered to reduce overall lead time of the system for breakage detection. This approach is simply based on the idea of using one frequency analysis subsystem for each of the three frequency components of interest. Three subsystems will then be used in parallel; each responsible for monitoring its frequency of interest and communicating results to parameter monitoring and decision making node for final decision making. The block diagram of the proposed system is shown in Figure-5.15 with corresponding results. As shown in the figure three nodes namely the tool rotation frequency monitoring node, broken tooth frequency monitoring node and tooth rotation frequency monitoring node operate in parallel and monitor one frequency component each.

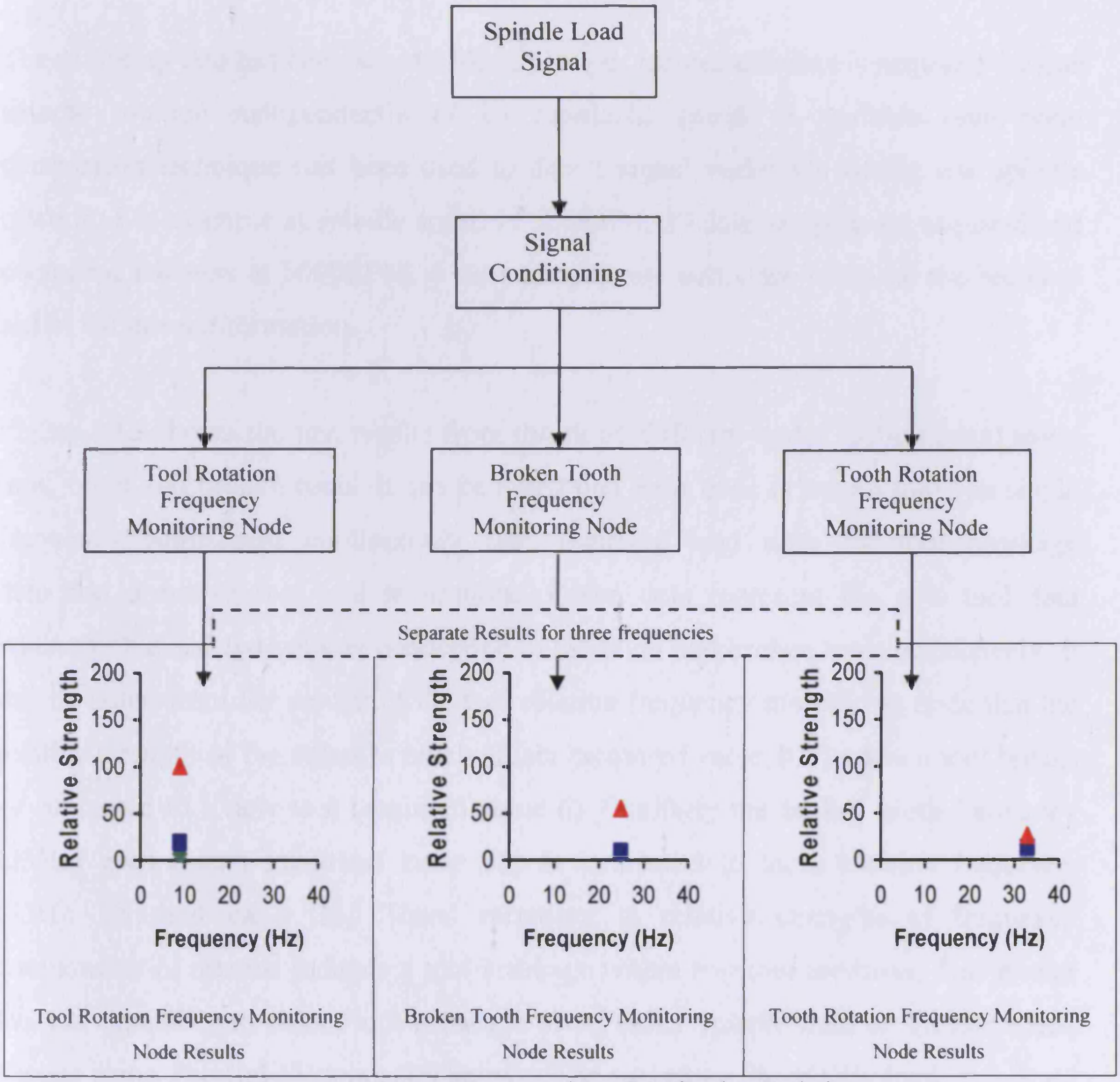

Figure-5.15, Block Diagram of Parallel Filtering Technique

5.7.1 System Efficiency

The start of the monitoring operation in this approach is similar to the Sweeping Filter approach. After the start of a cutting process each monitoring node sets its threshold value in relation to the initially acquired values for a healthy tool. The threshold value of broken tooth frequency monitoring node depends upon the observed value of tooth rotation frequency strength for a healthy cutter. This is due to the fact that it compares its strength against the tooth rotation frequency strength. Each monitoring node starts the monitoring process based on a comparative analysis of freshly acquired data with previously acquired values on the fly. There is no requirement for a filter settling time while using this approach as the filter output window is tuned permanently to one frequency of interest unless the spindle rotation speed is changed. This approach therefore is much faster when compared to both those discussed earlier.

The sampling rate has been set at 256samples per second and data is acquired for one spindle rotation independently of its rotational speed. A variable data point comparison technique has been used to detect signal variations within one spindle rotation. For example at spindle speed of 500RPM, 30 data samples are acquired and compared whereas at 3000RPM, 6 data samples are sufficient to reveal the required signal variation information.

Figure-5.15 shows the test results from the three different nodes (subsystems) using new, blunt and broken tools. It can be noted that each node is monitoring one single frequency component continuously thus reducing lead time for tool breakage detection down to two tool revolutions. Green dots represent the new tool data whereas blue and red colours correspond to the blunt and broken tools respectively. It can be noted from the results of the tool rotation frequency monitoring node that the relative strength of the signal is much higher (acquired value 100) when a tool breaks as compared to a new tool (acquired value 6). Similarly the broken tooth frequency (25Hz) goes higher (acquired value 55) as compared to tooth rotation frequency (33Hz, acquired value 25). These variations in relative strengths of frequency components of interest indicate a tool breakage within two tool rotations. The system has the capability to detect tool breakage using either spindle load or spindle speed signals using Parallel Filtering Technique. The variations in spindle load signal are more prominent and therefore it was chosen as the input to the system. The proposed technique also has the capability to detect tooth breakage for a minimal depth of cut ranging from 0.5 mm onwards.

5.8 Conclusion

The application of sweeping filters in general and the development of the parallel filtering approach in particular have been discussed in detail. The Frequency analysis nodes are part of a complete TCMS which includes the time domain analysis of the acquired signal as well. The time domain analysis technique developed is explained in next the chapter (Chapter-6). An alarm is not generated unless there is an indication of abnormality from both the time and the frequency domain monitoring nodes.

The technique is fairly simple to implement using cost effective microcontrollers. It has the potential to detect tooth breakage during a machining operation in almost real time. This approach is implemented at the Front End Nodes (FENs). More complex situations are referred to the second tier of the hardware design which is explained in the system integration chapter (Chapter-7).

The PIC Microcontroller implemented as the heart of the first tier monitoring node in the overall system design along with its communication features on the CAN bus have been proven successful for this application. The use of distributed embedded systems for machine tool condition monitoring applications has been verified as being reliable. The application of sweeping filter and parallel filtering techniques for a real life machine tool condition monitoring has been proven to be successful. It has thus been identified that a distributed machine tool monitoring application using these techniques can be implemented using PIC microcontroller.

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CHAPTER 6

TOOTH/TOOL ROTATION ENERGY ESTIMATION TECHNIQUE (TREE) FOR MACHINE TOOL SIGNAL ANALYSIS

6.1 Introduction

Much of statistical methodology is concerned with models in which the observations are assumed to vary independently. A great amount of data in engineering applications occur in the form of time series where observations are dependent and the nature of this dependence is used for the development of an analysis technique. The body of techniques available for the analysis of such a series of dependent observations is called time series analysis [6.1]. Time series is generally defined as an ordered sequence of values of a variable at equally spaced time intervals.

Time series data often arise when monitoring industrial processes or tracking corporate business metrics. Therefore the use of time series analysis is twofold: firstly to obtain an understanding of the underlying structure that produced the observed data and secondly to fit a model and proceed to forecasting, monitoring or even feedback and feed forward control. Since this thesis focuses on an industrial monitoring application design time series analysis has been investigated only in this perspective. Time series analysis accounts for the fact that data points taken over time may have an internal structure such as autocorrelation, trend or seasonal variation that may lead to information retrieval through different techniques for analysis and decision making.

Sweeping filter or parallel filtering as described in Chapter-5 are types of such data analysis techniques. There are many others available for frequency domain analysis. These have been used to analyse spindle speed and spindle load signals for machine tool condition monitoring as discussed earlier. In addition to frequency domain analysis, the time domain analysis of the same signals was researched for integration of results to increase the overall reliability of the system. This approach of synergistic decision making considerably reduces the percentage of false alarms and increases the reliability of the monitoring system.

As in most other analyses, it is assumed in time series analysis that data consists of a systematic pattern (usually a set of identifiable components) and random noise error which usually makes the pattern difficult to identify. Most time series analysis techniques involve some form of filtering out of the noise in order to make the pattern more salient. The majority of time series patterns can be described in terms of two basic classes of components: trend and seasonality. Trend represents a general systematic linear or (most often) nonlinear component that changes over time and does not repeat or at least does not repeat within the time range captured by the data e.g. exponential growth. Seasonality normally has a formally similar nature and repeats itself in systematic intervals over time.

For reliable time series data analysis it is very important to consider that any technique used should be sufficiently flexible to handle practical situations. In particular time series analysis often deals with non-stationary systems. For these situations trends and other characteristics change with time and therefore need to be treated as statistical (stochastic) phenomenon rather than deterministic [6.1]. There are various time series data analysis and modelling techniques starting from control charts and moving on to sophisticated techniques like Box and Jenkins Auto-regressive Integrated Moving Average (ARIMA) and Multivariate models. The selection and application of these techniques for a particular application depends upon the system requirements e.g. its complexity, needs and the resources available. Therefore it is very important to analyse the complexity of a process in terms of its application requirements and the available resources before finalising the choice of technique to be implemented.

Machine tool condition monitoring is an industrial application where time series data analysis can be correlated to a tool's health by using various analysis techniques. The field of time series data analysis and its correlation to a machine tool's health is not new and there has been extensive research in this area over the past few decades as mentioned in the literature survey chapter (Chapter-3). The aim of the research being described in this thesis was to detect a tool breakage in the milling process using existing machine tool signals and a minimum of hardware, thus avoiding the additional cost of sensors. In this research, time series data analysis was investigated with a view to develop a simple approach that can be implemented on a resource limited 8-bit PIC microcontroller and yet be capable of analysing data in real time for decision making. This chapter discusses in detail the concept of such a technique which observes variations in the spindle load and speed signals over time and correlates them to a tool's health with integration of the parallel filtering results.

6.2 Machine Tool Monitoring

A Tool Condition Monitoring System (TCMS) is essentially an information flow and processing system in which the information source selection and acquisition (sensors and data collection), information processing and refinement (signal processing and feature extraction), and decision-making based on the refined information (condition identification) are integrated [6.2]. An effective and time efficient on-line identification of machine tool failure plays a key role in enhanced productivity, better quality and lower costs particularly for unmanned, automated manufacturing systems. The most important success factor for a robust and reliable TCMS is to develop appropriate signal processing techniques to maximize the information utilization of the input signals. A major hindrance towards the design of these systems is the reliability of any decision made from the information retrieved from a source which may not be directly related to the decision making area [6.3]. Therefore in a non-sensor design a combinational approach is normally much more reliable in decision making.

6.2.1 Metal Removal with Regard to Tool Rotation

In normal milling operations the uncut chip area of the removed material at each tooth and the effective cutting force (which is proportional to spindle load) vary according to the rotation angle of a tool. Depending upon the number of teeth on a tool, the total cutting force on the tool shows some small variations and spectral analysis of the spindle signals show the existence of many frequency components. The spectral estimation and its variations for various tool health conditions have already been discussed in Chapter-5. In the past, data acquisition in monitoring systems has been carried out by using two approaches. In the first approach data are sampled at fixed intervals of time, independent of the spindle rotational angle, whereas in the second approach data are sampled with the pulses of an encoder at predetermined rotation angles of the spindle [6.4]. Both approaches have been used in various research applications for different reasons. Since this research is based upon the comparative analysis of spindle load variations within each tooth/tool rotation, acquiring data samples at predetermined spindle rotation angles is not a primary requirement. The supporting facts for this argument are described below.

Figure-6.1 shows the rotational area of each tooth in a cutting process for one spindle rotation using a four toothed healthy cutter. It can be noted that overall cutting contribution by different teeth in terms of rotational area is equal to eight segments of 90 degrees in each tool rotation that adds to 720 degrees of cutting. This is due to the fact that for a four teeth cutter; two teeth are always engaged in metal cutting process. The figure shows two different cases of tool rotation angles. In the first case (top left Figure-6.1) it can be seen that at the start of the data acquisition process, tooth-2 is at the entry stage and tooth-3 has completed half of its cutting cycle. Therefore tooth-2 and tooth-3 are engaged in the cutting process for the next segment of 90 degrees. If cutting contribution by one tooth for 90 degrees is represented by N then the total cutting contribution by both teeth is 2N. After this segment of cutting, tooth-3 leaves the workpiece and tooth-1 enters. These two teeth (tooth-2 and tooth-1) cut for the next cutting segment of 90 degrees. The total cutting contributions is again 2N.

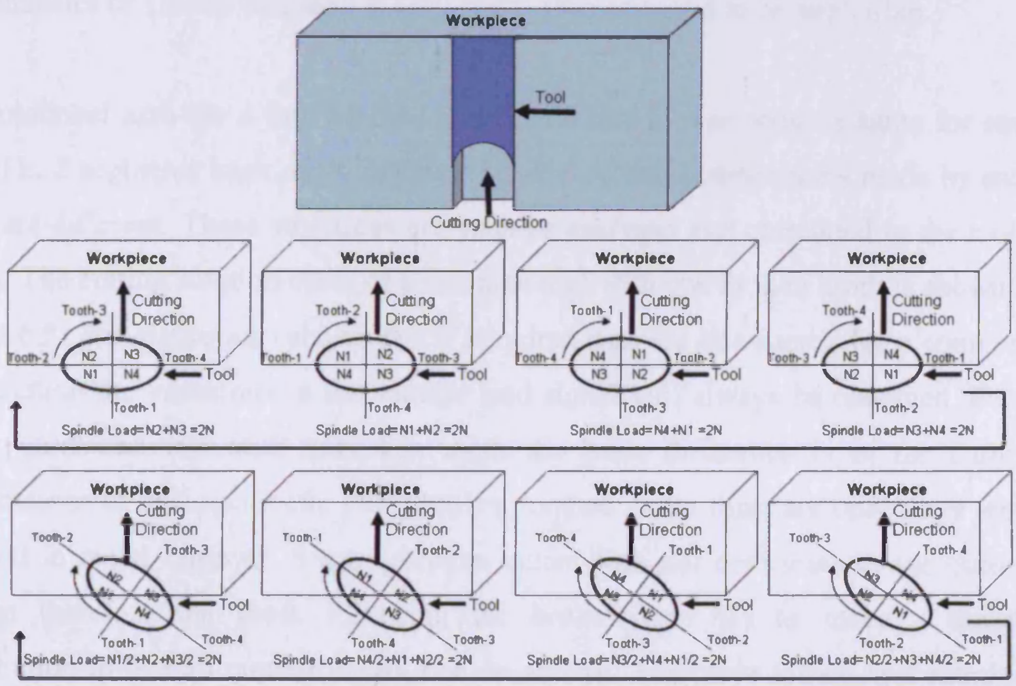

Figure-6.1, Rotational Area of each tooth in one tool rotation: 4 teeth new cutter

The cycle continues and each tooth cuts two segments of 90 degrees in one tool rotation (for a healthy cutter). Therefore ideally the variations in spindle load signal over one tool rotation should be zero or almost negligible (in actual cutting environments small but negligible variations are observed).

In the second case (lower row of Figure-6.1), tooth-2 is 45 degrees into the work piece from where a 90 degree segment has been measured. For the next cutting segment of 90 degrees, tooth-2 cuts for 90 degrees whereas tooth-1 and tooth-3 contribute for 45 degrees each. The total cutting contribution remains 2N (tooth-2 contributes N and tooth-1 and tooth-2 contribute 0.5N each). In both cases, the overall contribution for one complete tool rotation remains constant and the difference between the maximum and minimum spindle load for one tool rotation is negligible. It can also be noted that each tooth cuts for two segments of 90 degrees each i.e. 180 degrees in one tool rotation. Since this is an illustration of a healthy cutter no major variations can be seen and the sum of the normal cutting contributions made by the four teeth adds to 8 segments of 90 degrees each in one tool rotation.

It must be noted that feed rate also affects the overall metal removal contribution made by each tooth but in practical scenarios this can assumed to be negligible. For example at a feed rate of 100 mm per minute and spindle rotation speed of 500 RPM the machine tool only moves 0.2 mm into a workpiece for each tool rotation. For a tool diameter of 10 mm this ratio is 1:50 and is thus assumed to be negligible.

The rotational area for a four toothed cutter with one broken tooth is same for each tooth i.e. 2 segments each of 90 degrees, but the cutting contributions made by each tooth are different. These variations can thus be analysed and correlated to the tool's health. The cutting rotation cycle of a machine tool with one broken tooth is shown in Figure-6.2. The figure also shows that if acquired data are considered for a complete tool rotation the variations in the spindle load signal will always be observed. For a healthy tool and one with a broken tooth the basic difference is in the cutting contributions of different teeth. For a broken toothed cutter there are only three teeth engaged in metal removal. Since a broken cutter does not contribute to the cutting process therefore the tooth following the broken one has to make a double contribution in overall cutting within one revolution. Therefore in one tool rotation, two of the 90 degree tooth rotation segments are not contributing to the cutting process whereas two are contributing double what would be expected from a normal healthy tooth.

Figure-6.2 shows the same cases as discussed in Figure-6.1 with the difference that Figure-6.1 represented the load variations for a healthy cutter and Figure-6.2 represents these variations for a broken cutter. In the first case the data acquisition starts from the tool entry point and continues for one tool rotation. The figure shows that the healthy tooth following a broken tooth always cuts double the amount it is expected to cut in normal cutting conditions. Therefore the variations in the spindle load signal are much higher for a broken cutter as compared to a healthy cutter.

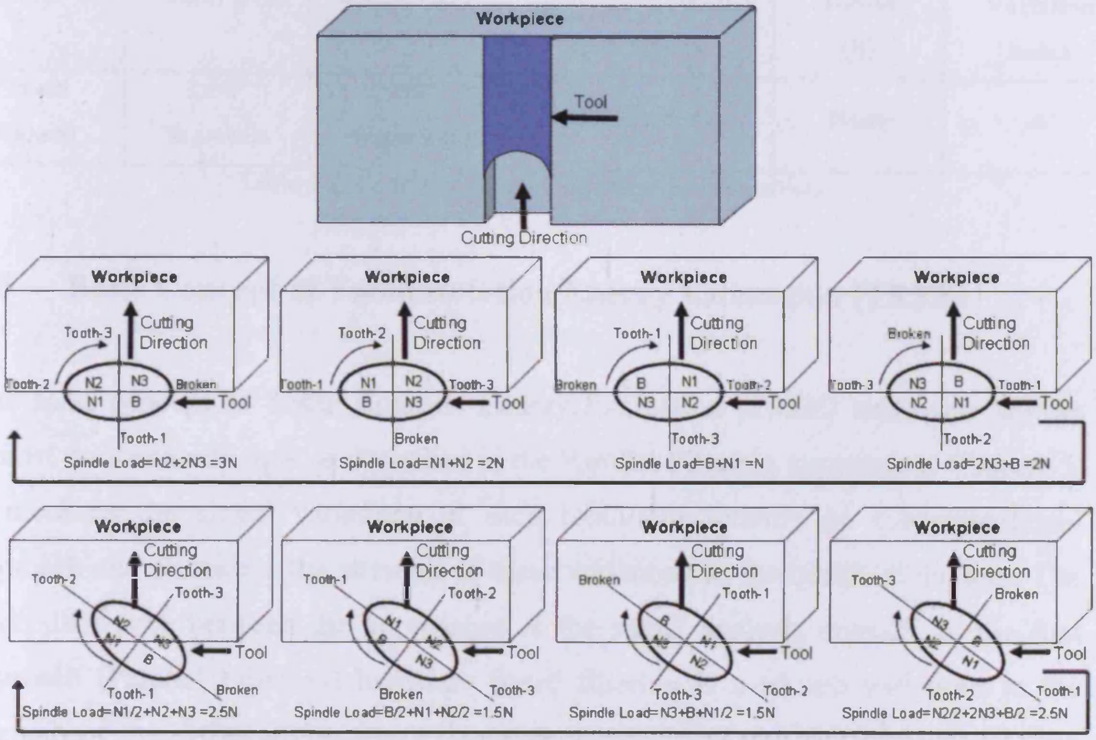

Figure-6.2, Rotational Area of each tooth in one tool rotation: 4 teeth broken cutter

It is evident that variations in cutting force or spindle load significantly increase for a tool with one broken tooth and therefore can be expected to affect respective monitored signals. The spindle load increases and spindle speed decreases when a healthy tooth following a broken one enters the workpiece as it has to do extra cutting. In order to compensate the speed drop, the machine controller increases the speed accordingly but as soon as a combination of healthy cutters is engaged in cutting, the speed increases and has to be controlled by the controller. Therefore variations in spindle speed and spindle load are much more significant when a tool with one broken tooth is engaged in cutting. These variations in acquired time series data reveal very useful information about health of a cutting tool. The spindle load variation indices for both healthy cutter and with one broken tooth are tabulated in Table-6.1 & 6.2 respectively.

Cutter	Cutting load for different teeth in one tool rotation (healthy tool)				
	Tooth1 (N1)	Tooth2 (N2)	Tooth3 (N3)	Tooth4 (N4)	**Variation Index**
4 Teeth (Healthy)	2x90° Segments	2x90° Segments	2x90° Segments	2x90° Segments	**Ideally None**

Table-6.1, Cutting load variation index, healthy cutter

Cutter	Cutting load for different teeth in one tool rotation (broken tool)				
	Tooth1 (N1)	Tooth2 (N2)	Tooth3 (N3), (B for 3 teeth cutter)	Tooth4 (B)	**Variation Index**
4 Teeth (Broken)	2x90° Segments	2x90° Segments	**4x90° Segments**	**None**	**4**

Table-6.2, Cutting load variation index, broken cutters

6.3 Basic Concept of Tooth Rotation Energy Estimation (TREE)

The basic concept of Tooth Rotation Energy Estimation (TREE) technique follows almost the same principle as described in the Parallel Filtering approach in Chapter-5. It monitors the signal variations in each tooth/tool rotation in a combinational approach and correlates the strength of these variations to the health of the tool. The main difference between the approaches is the signal analysis domain. In the first approach (Parallel Filtering) hardware based filtering is used and variations in the strength of the different frequency components are calculated and correlated to the tool's health in the software. In the second approach (TREE) there is no additional hardware involved and data is analysed in the time domain after direct acquisition from the machine through an anti-aliasing filtering stage only.

The spindle speed of machine tool Kondia B-500 ranges from 100RPM to 6000RPM. The feedback of spindle running speed is provided to the machine controller by using an encoder at a pulse rate of 1024 pulses per revolution. At such a high feedback rate the machine controller controls the speed variations almost instantaneously. Therefore to observe any changes in spindle speed it is important to keep the data sampling rate as near to the control rate as possible. Moreover the feedback rate is variable and depends upon the spindle speed. Therefore as speed increases, the feedback rate increases and vice versa. In order to meet varying feedback and control conditions a variable data sampling rate approach was used in this research.

Various laboratory simulation tests were carried out to find an appropriate data sampling rate that can be supported by the PIC18F458 and still reveals enough information about signal variations for tool breakage detection. It was concluded that there is a requirement to sample the spindle signals at a minimum rate of half the encoder pulse rate. Therefore for a spindle speed of 600RPM, a data sample rate of 5.12K samples per second or above is required. The PIC18F458 supports a maximum sampling rate up to 30K samples per second. In addition it also needs signal processing time. Therefore a maximum data acquisition rate of 25.6K samples per second was used in this application design. This means that the TREE technique, when implemented on a PIC18F458, can support tool monitoring of up to 3000 RPM spindle speed.

There are more modern versions of PIC Microcontrollers available now that support a much higher data sampling rate e.g. dsPIC30F6014 supports a data sampling rate of up to 1M samples per second. Using this new microcontroller and the same technique described in this chapter much higher spindle speeds can be monitored and is discussed in Chapter-9 (System Analysis, Discussion and Future Work).

6.4 Hardware Architecture

The proposed TREE technique architecture is based on the two tier system as shown in Figure-6.3 (it can be extended to three tiers depending upon the system requirements). In this technique there are two front end nodes that monitor variations in spindle speed and spindle load signals. Both front end nodes are based on PIC18F458 microcontrollers. The input signal is passed through an anti-aliasing filtering stage before interfacing it to the microcontroller. A parameter monitoring node is used centrally that monitors spindle speed and load signals and communicates necessary information about these variables to the FENs using CAN bus connectivity.

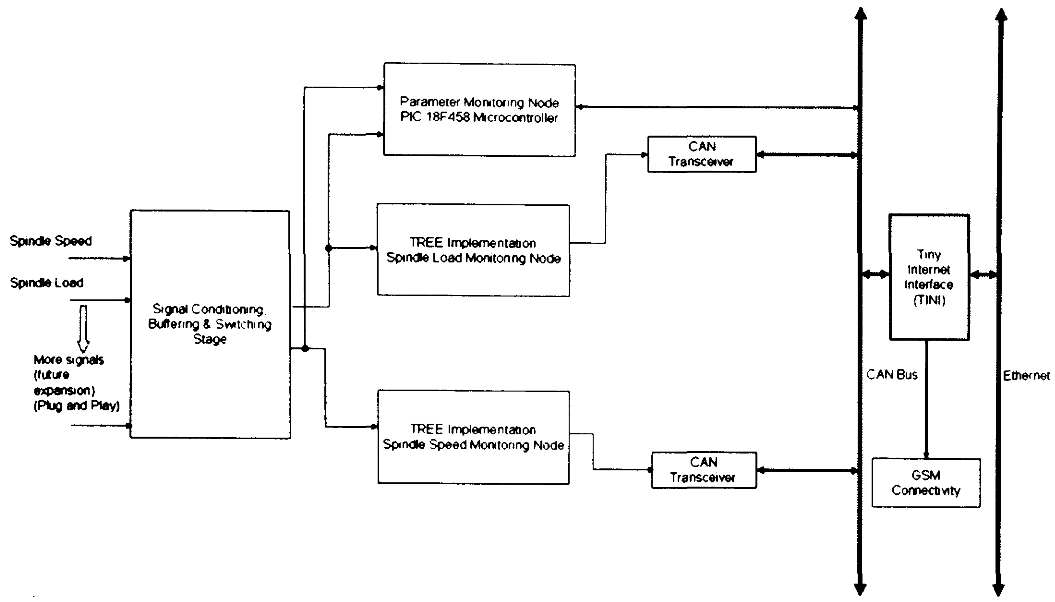

Figure-6.3, System Hardware Architecture.

The spindle speed and spindle load signals are tapped from the machine controller and interfaced to an isolation card. This card provides high voltage protection between the machine tool signals and analogue inputs to the system. The isolation card is housed in a signal conditioning card rack fitted into the machine tool for research applications and signal distribution. The hardware architectural design and details of these boards have already been reported by Jennings et al [6.5].

The outputs from the isolation card are interfaced to the first tier monitoring nodes. The first tier microcontrollers use 40MHz crystal oscillators. The microcontrollers are linked together using the CAN bus and PCA82C50 CAN transceiver. The system has been designed based upon extended data frame CAN protocol usage. The same communication medium is used to link the entire first layer of the system to second tier, which is based on a Tiny Internet Interface (TINI) system. Each front end node is responsible for monitoring the health of at least one machine signal. In the event of any abnormal situation developing the parameter monitoring and decision making node analyses the situation and a decision is made either at tier one or decision verification requested from tier two if higher computational power is required.

6.5 Software Considerations

The instruction set of a PIC18F458 Microcontroller is based upon 16 bit wide instructions (with the exception of three instructions). The machine signals are interfaced to the Analogue to Digital Converter (ADC) conversion module of microcontroller. The ADC module allows conversion of an analogue input signal to a corresponding digital number. A number of instructions are available for data manipulation in this device, which is ideal for such applications.

The initialisation block of the software in the first tier nodes sets up the micro-controllers' operating mode, selects and configures the digital and analogue I/O pins. It initialises the CAN activity and does essential handshaking to verify health of the system at initialisation as well as at regular operating intervals.

6.5.1 Software Architecture

The software of each monitoring node for time series analysis of acquired data has been organised to support the monitoring of one individual machine signal independent of the signal's origin i.e. each node can monitor spindle speed or spindle load signals or vice versa. Since it has to deal with a high speed data acquisition rate and real time processing to detect signal variations as well as needing instruction execution time, the implemented time windows have been carefully compared against available time windows to avoid any overlapping situations. These considerations are necessary to avoid false results as unexpected interrupts can change register values thus changing the whole architecture of the signal processing.

It is assumed that at the start of the cutting process a healthy cutter is used. At the start of the monitoring process, the system waits for the actual cutting process to start. The start of the cutting process is determined by a significant increase in the spindle load by the parameter monitoring node as explained in Chapter-5. After the start of the cutting process the parameter monitoring node calculates the necessary parameter information e.g. the spindle speed and frequencies of interest etc. and communicates to the other nodes on the monitoring network. This information is communicated to other nodes in the monitoring network.

The parameter monitoring node conveys the required data acquisition rate to the spindle load and speed monitoring nodes. The system waits for the tool's entry into the workpiece before making any decision. This delay time is used to discard higher tooth energy variations while a tool is entering a workpiece. This delay is important to set the accurate threshold levels at the start of the cutting process. The delay time is normally dependent upon feed rate and tool diameter. A delay time of three seconds was used in this application. This amount of delay ensures that a cutter of 5mm radius, cutting at 100 mm per minute feed rate enters the work piece in 3 seconds. The same delay time is sufficient for higher feed rates as entry time reduces for higher feed rates. The flow chart of this software architecture is shown in Figure-6.4.

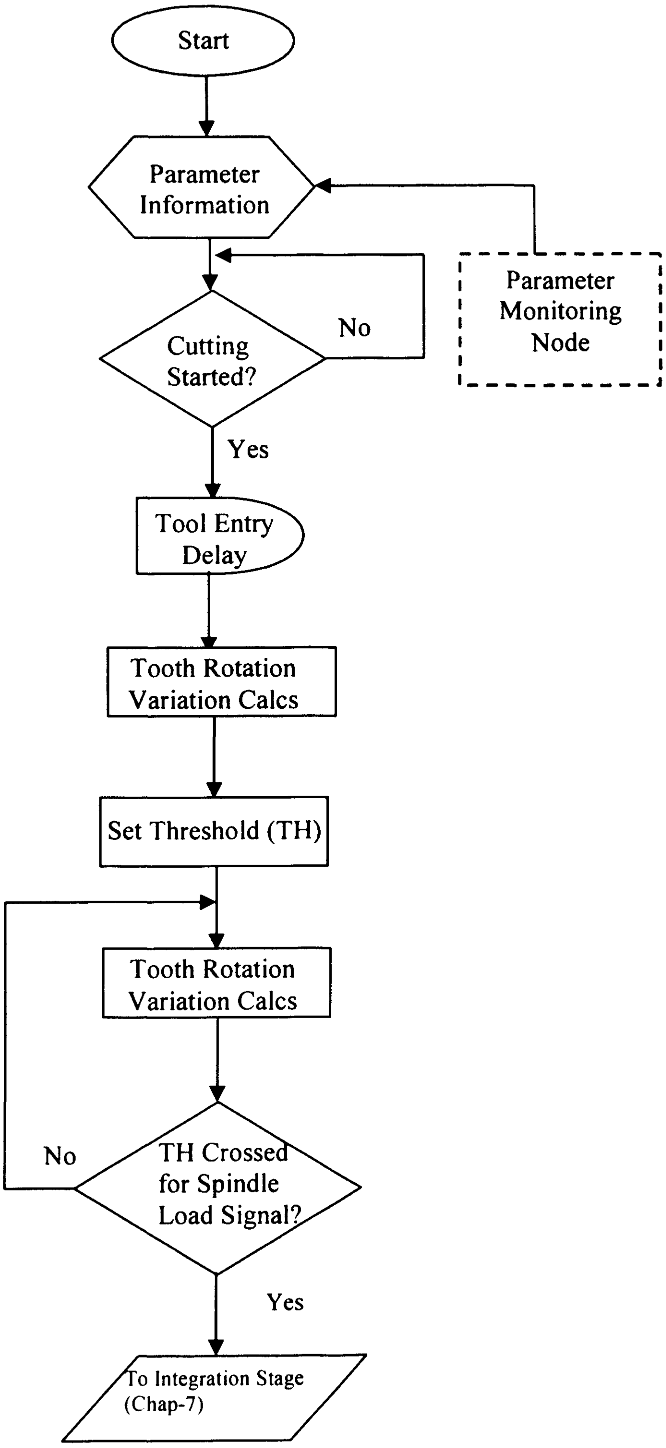

Figure-6.4, Software Flow Chart- Spindle Load monitoring node.

It shows the software flow for the spindle load monitoring node. The same approach is implemented in the spindle speed monitoring node as well. After the initialisation of the system a cyclic monitoring process starts. At the start of monitoring process, variations are observed in the signals that are used to set monitoring thresholds. In the monitoring process, each node observes variations in tooth and tool rotation periods and compares these to set thresholds. After detecting any threshold crossings, the information is sent to the integration stage which decides about the tool's actual health. This information is used for alarm generation in conjunction with the data from other FENs.

6.5.2 Technique Implementation

This technique uses a variable data acquisition rate which has been explained in the previous section. The data is acquired and analysed in segments of one tooth rotation each. During the data acquisition stage, tooth rotation energy variations are calculated in both spindle load and spindle speed signals. These variations are calculated in almost real time.

Even after passing the signal through an anti-aliasing filtering stage, it still contains considerable noise which needs to be removed before obtaining reliable results. Therefore at start of data monitoring, it is filtered by applying a moving average filtering technique. This technique has been used due to the fact that well modelled discrete-time systems can take a given input and process it to generate a desired set of output sequences. An effective implementation for this purpose is the moving average system, also known as an FIR averaging filter. The aim of a moving average system is to smooth irregularities and random variations in a data set or signal. A moving average filter is mathematically modelled as shown in equation 6.1. In this equation the upper limit "M" can be any number. The value of M also determines the order of the filter.

$$y(n) = \frac{1}{M}\sum_{k=0}^{M-1} x[n+k] \qquad \text{eq. 6.1.} \qquad [6.6]$$

A moving average filter is a convolution using a simple filter kernel. It can be referred to as convolution of the input signal with a rectangular pulse having an area of one.

The order of the implemented moving average filter in this application was variable. It is dependent upon the number of data samples acquired per tooth rotation. In simulations and during laboratory testing it was observed that an order proportional to the tooth rotation data samples was best suited. For example, at a data sample rate of 240 samples per tooth rotation, a moving average filter of the order of 240 was used. Although the order seems too high its assembly language based software was relatively simple and implementable for real time results. Moreover it was observed that it provides much better signal smoothing than lower order results.

The dividing factor M in equation 6.1 is a scalar value and it does not affect the final results if they are to be used for comparative analysis. It only scales down the final value if used for division. In this application, the dividing factor was implemented independent of the actual order of the filter because of its scalar property. This approach was adopted due to two factors. Firstly it is a comparative analysis technique and therefore a scalar division of two values by an appropriate constant does not affect the comparative results. Secondly, the implementation of higher order division in PIC18F458, although possible, takes unnecessary extra time especially in a case where there is no special advantage of using it. Therefore a simple technique of 8-bit division was implemented by discarding the lower 8-bits out of a cumulative 16 or 24 bits of data sum to divide it by 256. This approach provided a scalar downshift of the final value in moving average filtering stage. In this chapter the results specific to fixed cutting parameters are described to avoid unnecessary details. A complete range of tests and results are discussed in detail in Chapter-7. Theses parameters include a spindle speed of 500RPM and a feed rate of 100 mm per minute using a four toothed cutter. The results obtained by using different depth of cut values are shown to prove the functionality of technique for various situations.

The moving average filtering stage was implemented in the form of a circular buffer in the RAM of PIC18F458. By using this approach RAM locations equal to the order of implemented filter are required only, thus avoiding unnecessary overloading of the available memory. Moreover this implementation strategy provided a constant efficiency in terms of calculation time regardless of the filter order. The implemented equation is shown in equation 6.2 and Figure-6.5

$Sum_i = (Sum_{i-1} - Val_{i\text{-}order} + Val_i)/256$ Eq. 6.2.

Where Sum_i = Current Sum, Sum_{i-1} = Previous Sum, $Val_{i\text{-}order}$ = Starting data value of the filter order, Val_i = Current data value.

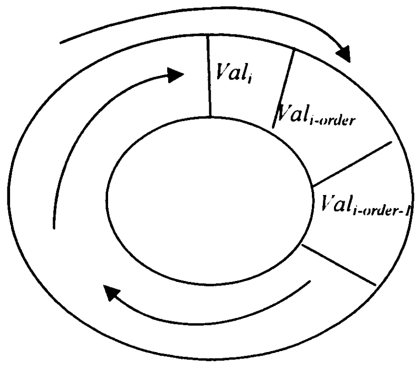

Figure-6.5, Circular buffer implementations for moving average filter in PIC18F458.

At the start of the process, data samples equal to order of the implemented filter are acquired and filtering is carried out in parallel. The calculations are carried out using a single equation based on three variables only. Therefore calculation time is not affected by the change in order of the filter and always remains constant. A moving average filter decreases the amount of random noise in a signal but at the same time it reduces the sharpness of the edges in an input signal. The amount of noise removal is equal to the square root of the order of a filter used. For example a moving average filter of the order of 100 removes the noise by a factor of 10 [6.6]. Therefore in this application design the order of designed filter was kept variable and in proportion to the data samples in a tooth rotation. The reason behind this strategy was that as the spindle speed increases, encoder pulses for its feedback also increase and a higher sampling rate is required to capture signal variations before they are controlled. Moreover a higher sampling rate increases the amount of acquired noise. Therefore a higher order filter more effectively reduces the signal noise. The moving average filter's effect on edge sharpness removal does not affect this application as variations in the spindle load signal for a broken cutter are not instantaneous and are more or less similar to a sinusoidal shape as can be observed in Figure-6.6(b).

The ability of this technique to remove noise in spindle load signal is shown in Figure-6.6. Figure-6.6(a) shows original spindle load signal whereas 6.6(b) shows filtered signal. The noise removal is an important requirement to observe signal variations while using the segmental averaging and comparison technique developed for this research application. The effectiveness of the developed technique is evident as the original spindle load signal acquired by the PIC microcontroller and its filtered output shown in the figures clearly indicate the difference.

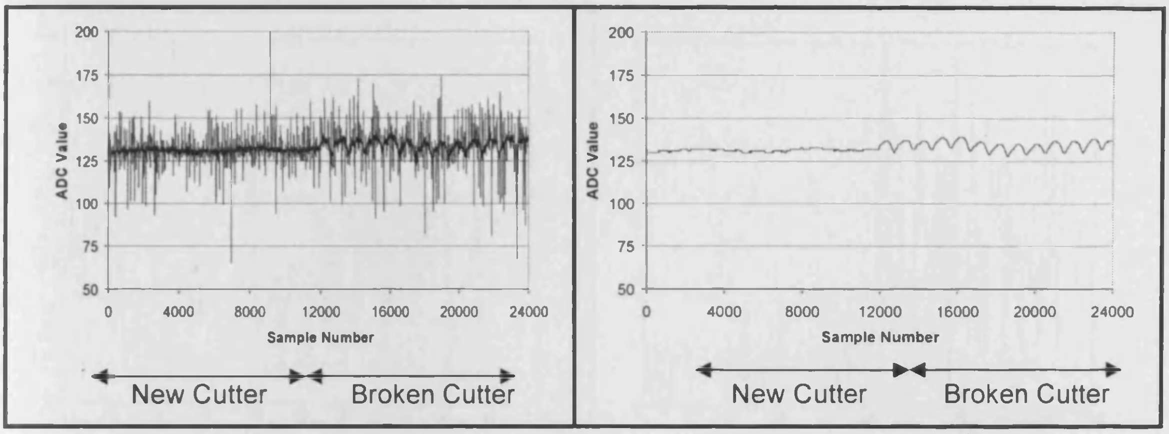

Figure-6.6 (a&b), Noise removal in spindle load signal using moving average filtering.

At the start of monitoring programme, two variables: "minimum value" and "maximum value" are defined. These are assigned hypothetical values. The minimum value variable is assigned the highest possible value that can be acquired and maximum value variable is assigned a lowest value i.e. zero. After acquisition of each filtered data sample, it is compared against the existing values of both variables. If the acquired data value is higher than the current maximum variable values, it replaces the current maximum variable. Similarly if the acquired data value is lower than current minimum variable value, it replaces it. The process runs until the data is acquired for one tooth rotation. The loop counter values for the required data samples in each tooth rotation are calculated and communicated by parameter monitoring node. At the end of one tooth rotation, the difference between the minimum and maximum values acquired gives the signal variation in that particular tooth rotation. In this way the signal variations for all four tooth revolutions are calculated for a four teeth cutter. The variations in the data acquired directly and the filtered data are significantly different and are shown in Figure-6.7 (a&b) respectively. Figure6.7(a) shows pure signal variations and 6.7(b) shows filtered signal variations. The results are based on integer calculations used in PIC microcontroller.

The observed variations in both figures clearly indicate the importance of moving average filtering before analysing the data for energy variations within each tooth/tool rotation. By using a moving average filter, the noise level in a signal is scaled down. It can also be observed that in Figure-6.7(a) signal variations range from 10-90 whereas in filtered data these variations range between 0-6. The signal processing includes software filtering, finding the peak to peak difference in the acquired samples, segmental average and variance (if required). A very simple flow diagram of the implemented software is shown in Figure-6.8.

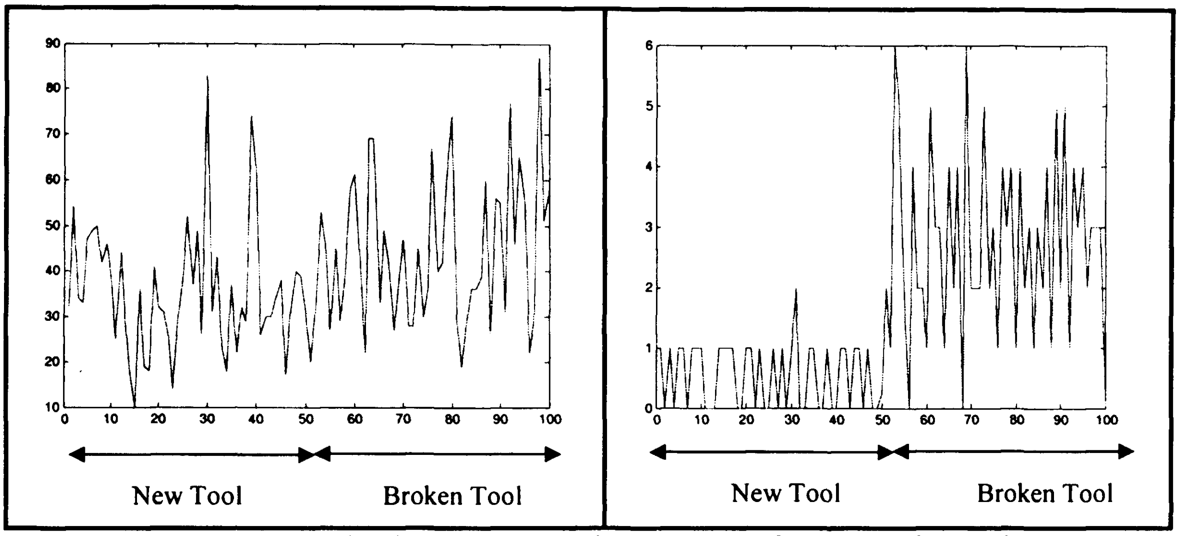

Figure-6.7 (a&b), Signal Variations in each tooth rotation for pure and filtered data.

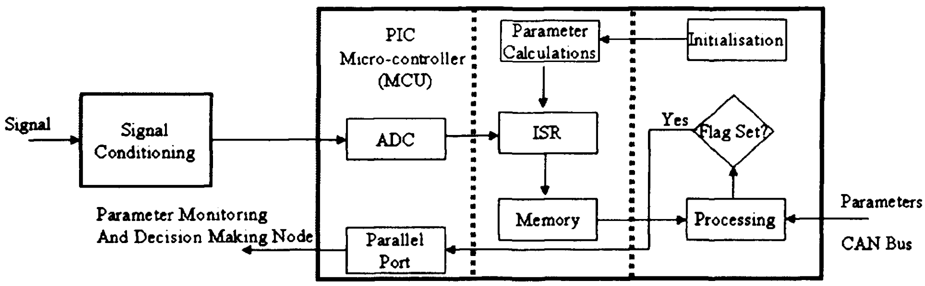

Figure-6.8, Block Diagram of Software Implementation

After the initialisation process the programme calculates the threshold values as shown in Figure-6.8. Data are acquired by the ADC after receiving a tool entry signal from the parameter monitoring node. An Interrupt Service Routine (ISR) is used to carry out these calculations independently and store them in the memory.

In the event of abnormal indications, the observant node communicates to parameter monitoring and decision making node for verification and depending upon results from other nodes it can generate a warning and or alarm or can send data to the TINI board for further analysis or advice. The CAN module of each node is configured to operate and support extended data frames. The CAN bus in this application is operating at a data rate of 125Kbits per second. This data rate was selected to keep a balance between the noisy industrial environment and timing requirements to enable the system to achieve its aim of calculating results within two tool revolutions.

6.6 Monitoring Results

The TREE technique compared both average tooth and average tool rotation energy estimation strategies and their variations to determine the tool condition. Tests were carried out using a range of machining parameters. The results discussed here are based on a spindle speed of 500 RPM, feed rate of 100 mm per minute and two different depths of cut 1mm and 2mm using a four teeth cutter. Under the described spindle speed and data sampling rate, 240 data samples per tooth rotation and 960 data samples per tool rotation were analysed.

Figure-6.9 (a) shows the acquired spindle speed signal for both healthy and broken cutters. In all 24000 data points are shown consisting of 12000 data points for healthy and broken cutter each. It is not possible to prearrange a tool breakage therefore the data files of two tests (one each for healthy and broken cutter) are interfaced midway to show the variations for both conditions and to simulate a tooth breakage.

The machining environment noise clearly dominates the signals although the signals have been acquired after a first stage of anti-aliasing filtering and signal conditioning. Therefore extracting some useful information in the time domain needs further filtration of acquired data. The moving average filtering technique was used to further filter the data. The order of moving average filter is variable for this application design, which depends on spindle speed. The order of the filter used for these tests was 240 (corresponding to one tooth rotation data samples). Figure-6.9(b) shows the results calculated using Matlab software. The noise has been filtered out very effectively.

Figure-6.9(c) shows the results of moving average filtering using the actual PIC microcontroller based designed system. Matlab uses floating point calculations of a much higher order as compared to the PIC microcontroller. Therefore the results are smooth in Matlab based graphs. Tests also revealed that integer calculations (PIC based) are efficient enough to detect signal variations although results are not as smooth as Matlab. Therefore to reduce the calculation load further, integer calculations were used in PIC microcontroller and still very reliable results were obtained as shown in Figure-6.9(c).

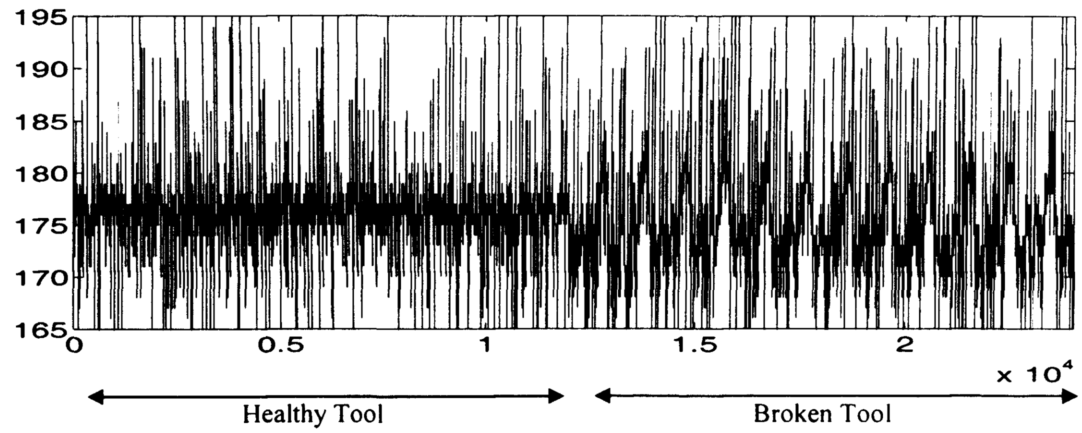

Figure-6.9 (a), Acquired Spindle Speed (ASS) Data (1mm Depth of Cut), X-axis shows sample number and Y-axis shows ADC value (relative strength)

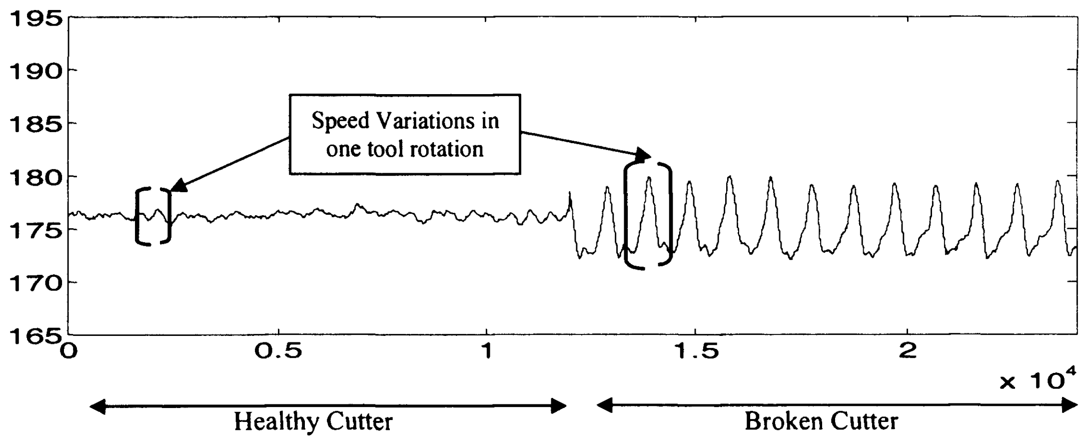

Figure-6.9 (b), Moving Average Filtering (MAF) of ASS Data, using Matlab (Floating point calculations), X-axis shows sample number and Y-axis shows ADC value (relative strength)

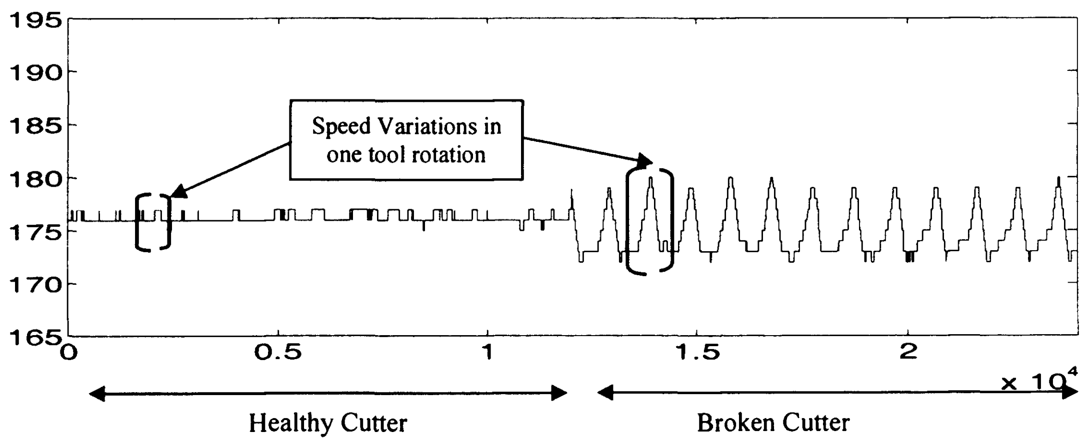

Figure-6.9 (c), Moving Average Filtering (MAF) of ASS Data, using PIC (Integer calculations), X-axis shows sample number and Y-axis shows ADC value (relative strength)

Figure-6.9, Moving average filtering results for spindle speed signal.

Figures-6.10 (a) – 6.10(c) show the corresponding results from the spindle load signal. It can be clearly seen that the variations in the spindle load signal are much higher as compared to the spindle speed signal after the simulated breakage of a tooth. The main reason behind these higher variations in the spindle load signal is that machine controller controls spindle speed dynamically whereas it cannot control the varying spindle load.

These results show overall variations in the signal for both healthy and broken cutters. Although these results graphically show enough information to detect a tool breakage a more intelligent and self detecting technique needs to be implemented for actual breakage detection. The estimation of tooth/tool rotation energy variations serves this purpose.

In the TREE technique these variations for both tooth rotation period and tool rotation period (tool rotation period corresponds to one tool rotation) were analysed and higher variations were observed for complete tool rotation period as compared to tooth rotation period. This is due to the fact that for a tooth that cuts extra metal or for a tooth that does not cut the overall load increases or decreases but the actual variations within that tooth rotation period are not significant. Whereas for a tool rotation period, load increases when a tooth cuts extra metal and it decreases when a tooth does not cut thus increasing overall variations in one complete rotation.

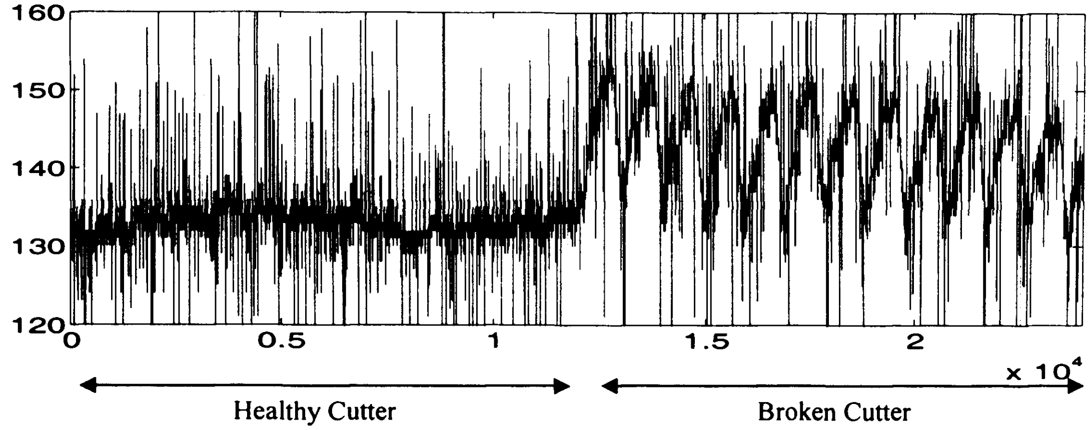

Figure-6.10(a), Acquired Spindle Load (ASL) Data (1mm Depth of Cut), X-axis shows sample number and Y-axis shows ADC value (relative strength)

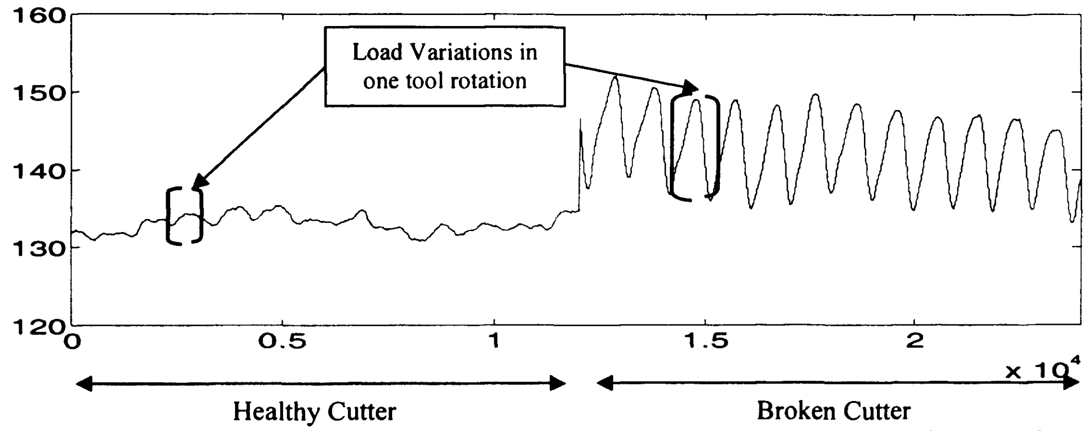

Figure-6.10(b), Moving Average Filtering (MAF) of ASL Data, using Matlab (Floating point calculations), X-axis shows sample number and Y-axis shows ADC value (relative strength)

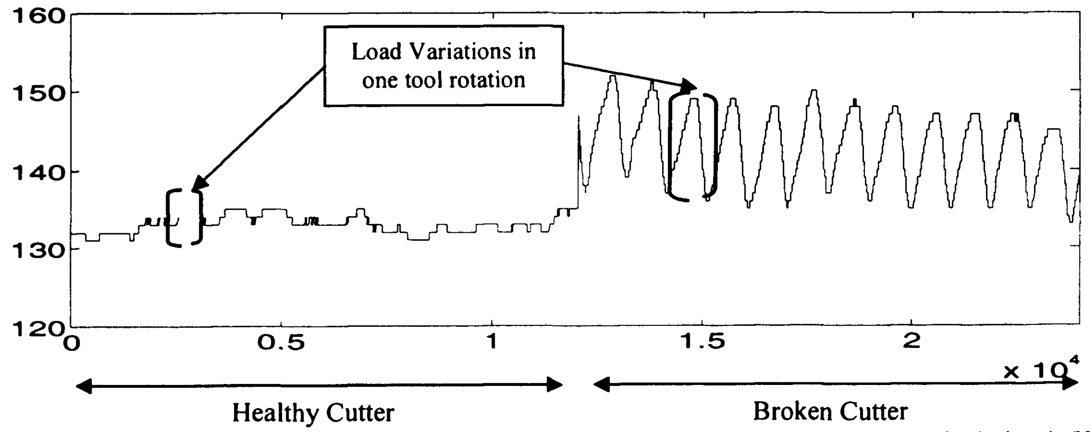

Figure-6.10(c), Moving Average Filtering (MAF) of ASL Data, using PIC (Integer calculations), X-axis shows sample number and Y-axis shows ADC value (relative strength)

Figure-6.10, Moving average filtering results for spindle load signal.

The variations observed for 20 tooth rotations and corresponding 5 tool rotations (as a four toothed tool was used) are shown in Figure-6.11 (a & b) for spindle speed signal and Figure- 6.12 (a & b) for spindle load signal.

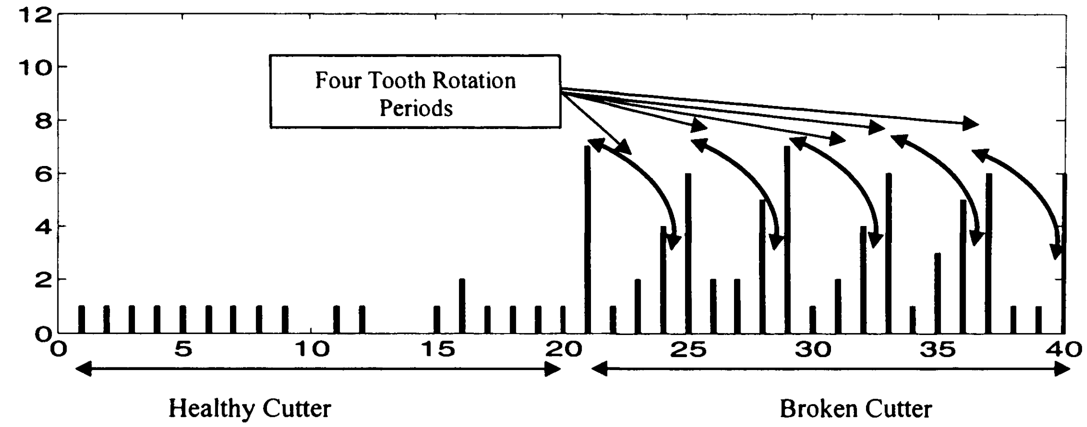

Figure-6.11(a) Signal variations observed in 20 tooth rotations each for new and broken cutters respectively in Spindle Speed Signal. (X-axis - tooth rotation number and Y-axis - variations)

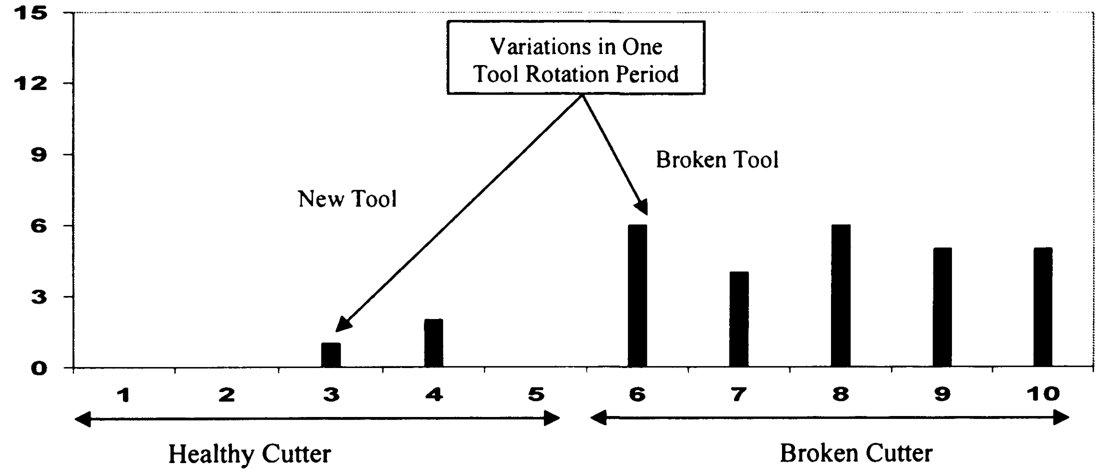

Figure-6.11(b) Signal variations observed in 5 tool rotations each for new and broken cutters respectively in Spindle Speed Signal. (X-axis - tool rotation number and Y-axis - variations)

Figure-6.11, Signal variations in Tooth and Tool rotation periods – Spindle Speed Signal

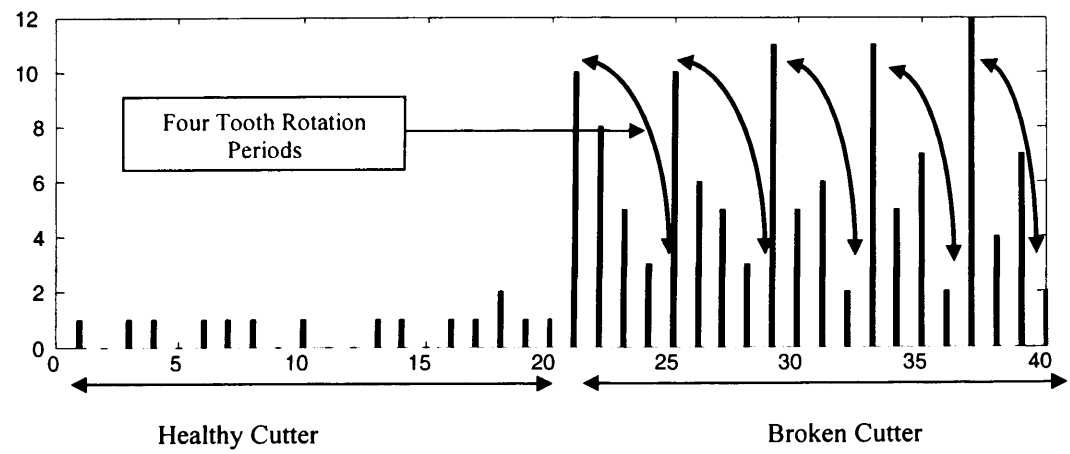

Figure-6.12(a) Signal variations observed in 20 tooth rotations each for new and broken cutters respectively in Spindle Load Signal. (X-axis - tooth rotation number and Y-axis - variations)

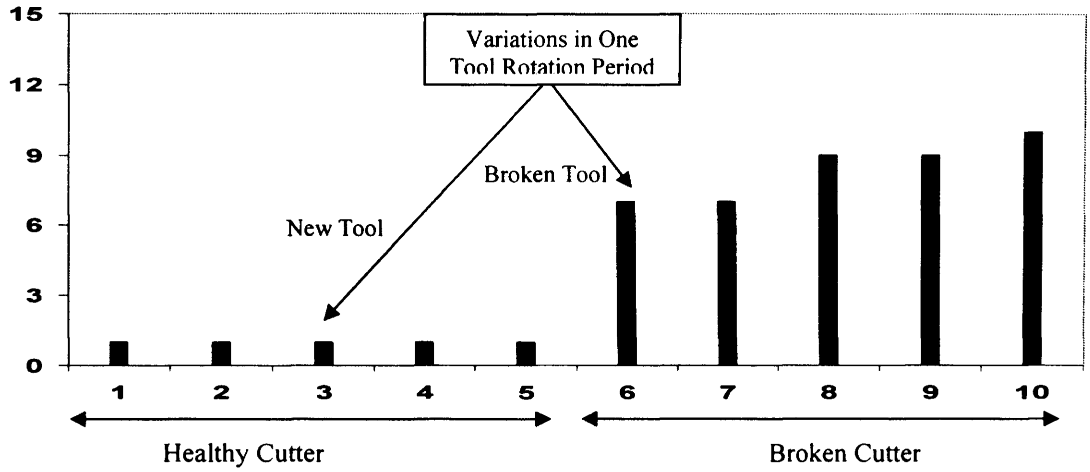

Figure-6.12(b) Signal variations observed in 5 tool rotations each for new and broken cutters respectively in Spindle Load Signal. (X-axis - tool rotation number and Y-axis – variations)

Figure-6.12, Signal Variations for tooth and tool rotation periods in the spindle load signal.

These signals show data for 20 tooth rotations each for new and broken cutters that are interfaced midway in each figure. It can be noted that spindle speed variations for a healthy cutter are almost constant but increase in a broken cutter signal. These variations increase almost linearly for four teeth and follow the same pattern. The variations in tooth cutting period can be linked to the signal variations with respect to cutting area of each tooth as shown in Tables-6.1&6.2.

Cutting load decreases at entry point of a broken tooth increasing the spindle speed. This increase is controlled by the machine controller. The healthy tooth following the broken one has to do extra cutting therefore spindle speed decreases and spindle load increases. This cycle of cutting continues and variations in each tool rotation follow the same pattern.

It can also be noted that for a healthy cutter, variations are almost constant and much smaller but are much higher for a broken cutter. These variations follow an almost linearly decreasing pattern in spindle load signal. This can again be linked to cutting cycle of a broken cutter as shown in Figure-6.2. The highest load variation or energy variation is observed at broken tooth entry point and it linearly decreases as the cutting cycle goes to normal as shown in Figure-6.2.

Although the variations shown in Figures-6.11(a) and 6.12(a) for healthy and broken cutters are significant they cannot be reliably used for tool breakage detection purpose as they follow an inconsistent pattern. This inconsistent pattern is due to the energy variations arising when cutting different amounts of metal during various cutting segments. Therefore complete tool rotation variations were analysed to find a consistent variation pattern. Figures-6.11(b) and 6.12(b) show these variations in spindle speed and load signals respectively for one complete tool rotation. Both figures show that signal variations for a healthy cutter are much smaller as compared to a broken cutter. The strength of these variations in the spindle load signal is higher as compared to spindle speed signal. This is due to the fact that speed is controlled immediately after any variation detection by the machine controller whereas load varies with respect to metal removal amount in each cutting segment of 90° for a four teeth cutter in all cutting cycles. Figures-6.13 and 6.14 show the variations in spindle speed and spindle load respectively for a different depth of i.e. 2mm. It can again be noted that signal variations for spindle speed and energy variations for spindle load signals are significantly different for healthy and broken cutters.

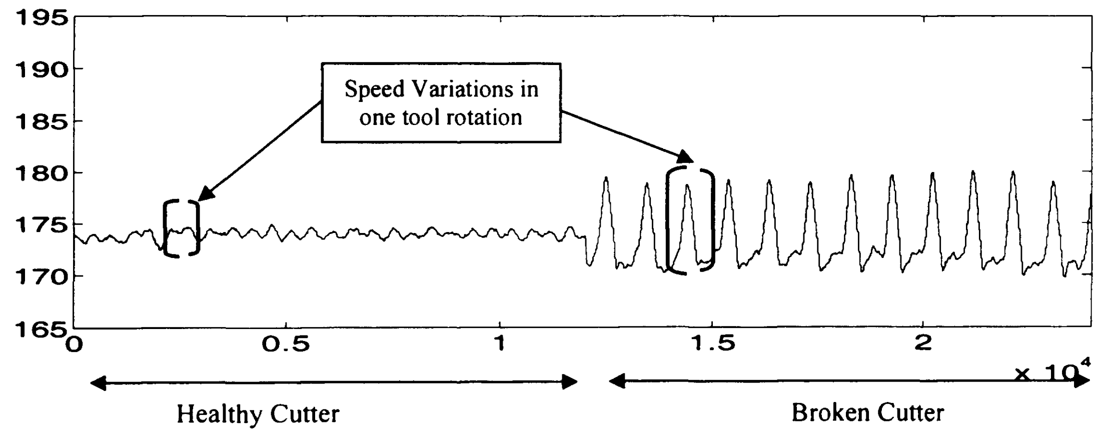

Figure-6.13, Moving Average Filtering (MAF) of ASS Data (2mm DOC). X-axis shows sample number and Y-axis shows ADC value (relative strength)

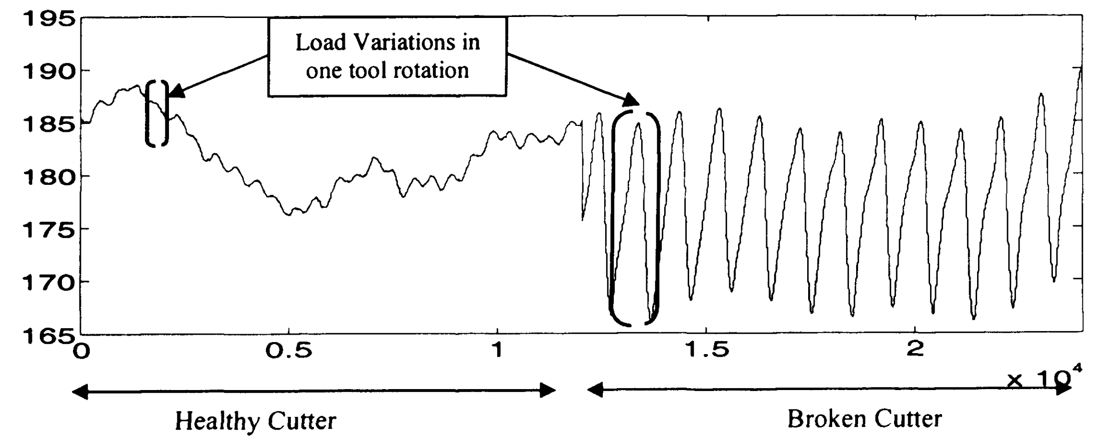

Figure-6.14, Moving Average Filtering (MAF) of ASL Data (2mm DOC). X-axis shows sample number and Y-axis shows ADC value (relative strength)

A comparison of Figure-6.15 (a) (for 1mm depth of cut) and 6.15(b) (for 2mm depth of cut) reveals that spindle speed variations are almost independent of the depth of cut because their strengths are similar. This is due to the fact that speed changes are immediately controlled by machine controller on detection and these are the maximum variations that can be detected. Furthermore it indicates the reliability of the system as variations for a healthy cutter are always significantly lower as compared to a broken cutter.

Most reliable results were obtained by calculating the variance of both spindle speed and load signals after applying the moving average filtering for a period of one tool rotation. Figures-6.16(a)&(b) show these results for spindle speed and load signals respectively. These figures show a highly reliable method of tooth breakage detection using the same acquired data. The variance in both signals for a healthy cutter is almost zero and it rises significantly while cutting with a broken tooth cutter.

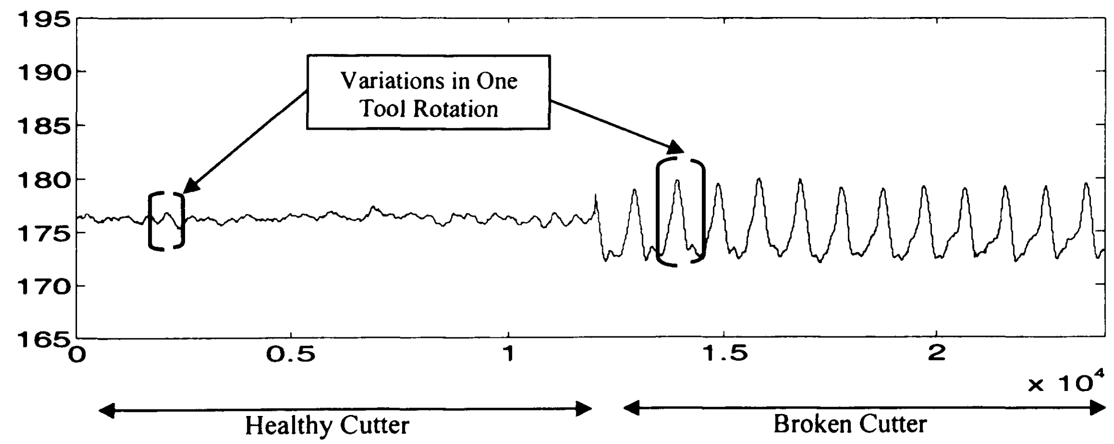

Figure-6.15(a), Moving Average Filtering (MAF) of ASS Data (1 mm DOC), X-axis shows sample number and Y-axis shows ADC value (relative strength)

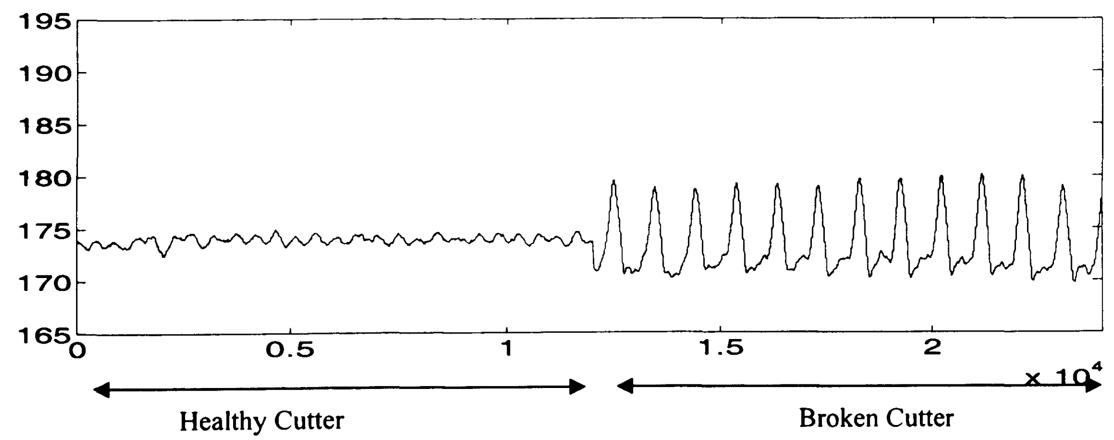

Figure-6.15 (b), Moving Average Filtering (MAF) of ASS Data (2mm DOC). X-axis shows sample number and Y-axis shows ADC value (relative strength)

Figure-6.15, Moving average filtering of ASS data at two levels of DOC

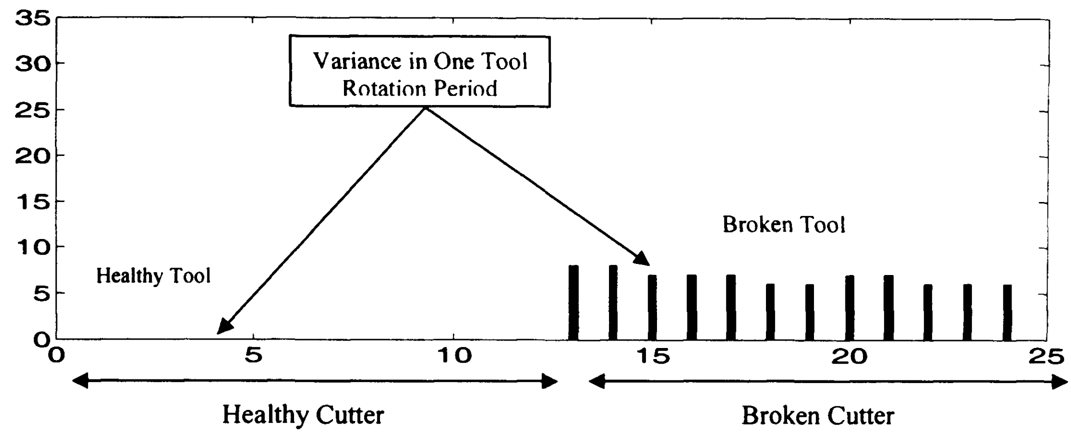

Figure-6.16(a) Variance in Spindle Speed Signal., X-axis shows rotation number & Y-axis variance.

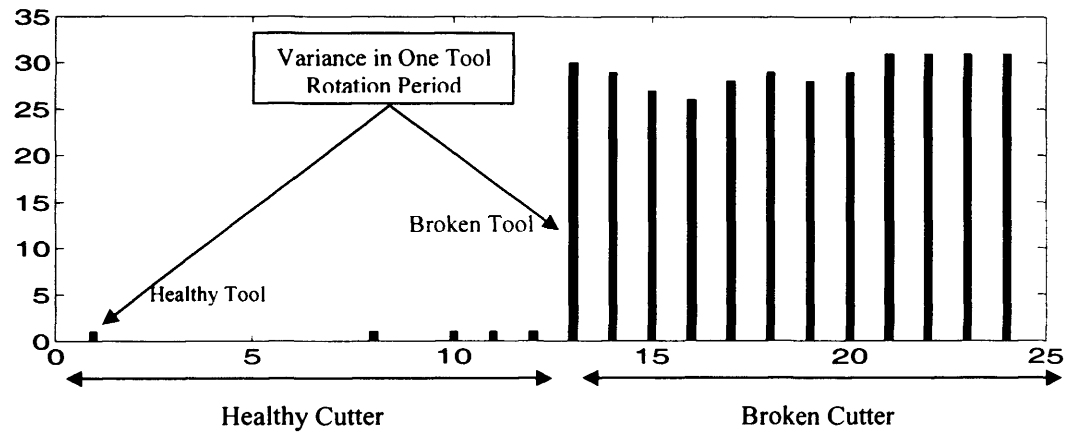

Figure-6.16(b) Variance in Spindle Load Signal., X-axis shows rotation number & Y-axis variance.

Figure-6.16, Variance in spindle speed and spindle load signals

Both the time and frequency domain signal analysis techniques have been discussed in detail with their implementation and processing requirements. The techniques are integrated and a reliable monitoring system is proposed in the next chapter. The integration increases the system reliability. For example if the time domain signal analysis technique is used independently it can generate false alarms at tool entry situations (explained in Chapter-7). These false alarms are avoided by using the integrated system (explained in Chapter-7).

6.7 Conclusion

A time domain data analysis technique along with its implementation on an 8-bit microcontroller based system and its results for a real world application have been reported. The capabilities of PIC Micro-controller implemented as a heart of the first tier monitoring node in the overall system design along with its communication features on the CAN bus have been fully explored. The use of distributed embedded systems for machine tool condition monitoring applications has been verified for its reliable applicability.

Use of the existing machine tool signals have proven very useful for its future applications. The monitoring system designed for any industrial applications needs to be extra robust and reliable to cater for noisy environments. The milling operation in particular needs extra care as is evident from the acquired signals shown in Figures-6.9(a) and 6.10(a). To increase the reliability of the designed systems further it is integrated with frequency domain analysis technique discussed in Chapter-5. The integration of both techniques for an overall application is discussed in detail in Chapter-7.

6.8 References

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CHAPTER 7

SYSTEM INTEGRATION AND DECISION MAKING

7.1 Introduction

The two signal analysis and feature extraction techniques developed in this research have been discussed individually in the last two chapters. This chapter describes the integration of these techniques, the supporting software/hardware and final decision making.

System integration has traditionally been referred to as combining two or more sub-systems and/or software packages which allow these systems to produce final results. The integrated system should be capable of analysing the overall system capabilities, its characteristics and reliability. The integrated system for this research has the capabilities of monitoring the system performance and identifying any problems arising in the system itself.

Decision making is the most important stage in any designed system. The reliability, effectiveness and success rate of any system is judged by the percentage of accurate decisions made by the system from the retrieved information. As the individual reliability of both techniques has been proved in the previous two chapters this chapter discusses in detail the decision making of the integrated system for a range of cutting tests carried out and the results obtained. There has been extensive research in the past in the area of machine tool monitoring but there have not been many practical success stories. There are various reasons behind this, with the most important one being the percentage of accurate decisions made by such systems. The Overall Equipment Effectiveness (OEE) of any system depends upon its availability rate, performance and quality rate. If a monitoring system generates false alarms by making inaccurate decisions then the overall availability rate decreases thus bringing down the OEE of the system. No manufacturing industry and in particular SMEs can afford such waste. Since this research work was aimed at providing a monitoring solution suitable for SME applications special attention was given to a reliable final stage of integration and decision making.

The communication of process related information and the decisions made from this information to concerned machines and individuals in a suitable format is another important requirement from such systems. The content requirements for various individuals in a setup may be different. Therefore various communication methodologies were investigated and implemented at this system integration stage of this research. CAN bus connectivity was used for information transfer between subsystems. Ethernet connectivity was implemented for process related data transfer over the Internet. GSM connectivity has been added to transfer messages such as tool breakage reports or OEE to concerned individuals. Using the latest technology mobile phones webpage access is also possible and it provides access to process information from anywhere. The details of these implementations are discussed in Chapter-8. The frequency and time domain signal analysis techniques investigated for this application design have been discussed in Chapter-5 and Chapter-6 respectively. The integration of these techniques in terms of initial information communication and final decision making is discussed in the next section.

7.2 System Integration at Tier One

There are five FENs in the first tier to monitor spindle signals in both the time and frequency domains. In addition there is a parameter monitoring and decision making node (adding the total FENs to six) which monitors the signals and calculates the system parameters at the initialisation stage and communicates this information to all FENs for setting their threshold values before starting the actual monitoring process. It also sends information about the start of the process to different FENs in the monitoring system. The parameter monitoring node also monitors these signals continuously in real time to detect any changes. If any changes are detected by this node, it communicates these to concerned FENs for dynamic adjustment of their parameters. The FENs process corresponding information using the Parallel Filtering and Tooth/Tool Rotation Energy Estimation Techniques which have been explained in Chapter-5 and Chapter-6 respectively.

The current status of the machine tool's health is dynamically communicated to the decision making node by all the FENs. These signals are communicated to the decision making node which analyses them by using two different approaches. Firstly an OR logic (Software based using CAN connectivity) is used for all five FEN messages to the PIC18F458 microcontroller. This technique ensures that as soon as any one of the five FENs reports an abnormality, the decision making node gets a message. Since all FENs have the CAN connectivity with the parameter monitoring and decision making node it checks the status of all signals on getting a message from one of them. This information is integrated to aid decision making about the tool's health. The actual process of decision making at tier one is discussed in the next section.

The software architecture of system integration at tier one is shown in Figure-7.1. There is a major change in spindle load signal which arises as the tool enters the workpiece which is used to indicate the start of the cutting operation. A threshold level on the spindle load signal is set at the start of a monitoring process and its crossing depicts the start of the cutting process. After the start of the cutting process the node responsible for parameter monitoring and decision making calculates all required system parameters e.g. spindle speed and number of teeth and communicates them to concerned FENs.

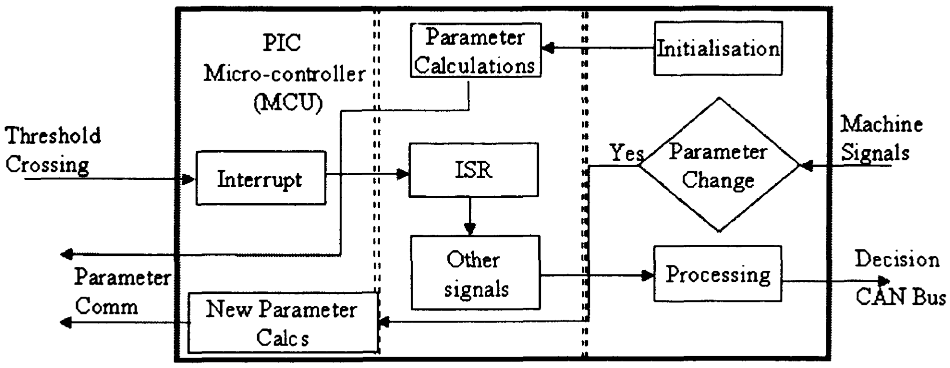


Figure-7.1, Software Architecture of Decision making.

After communicating initialisation parameters to all FENs, the parameter monitoring and decision making node performs two tasks in parallel: firstly to constantly monitor the changes in the process and corresponding parameters by observing spindle speed and load signals and secondly to make decisions in the case of any abnormalities detected by any FEN. The parameter monitoring continues and if any changes are observed, these are communicated to relevant nodes if required. For example if the spindle speed changes the parameter monitoring node sends the information to all FENs to adjust their monitoring frequencies/sampling rate. This technique of "real time" parameter monitoring and adjustment increases the reliability, flexibility and versatility of the implemented system.

7.3 Decision Making at Tier One and Two

The parameter monitoring and decision making node is not only responsible for decision making at tier one but is also responsible for data transmission to tier two if further analysis is required. All five monitored signals (three main frequency signals and two from time domain analysis) provide information to the parameter monitoring and decision making node. If there is any threshold crossing detected by any monitoring node the information is relayed to the parameter monitoring and decision making node. As soon as this information is received by the parameter monitoring node it checks the status of other FENs. The flow diagram of sequence of the events in the process is shown in Figure-7.2. The PIC microcontroller is interfaced to all monitoring nodes for real time data acquisition and decision making. It acquires signal status from all monitoring nodes and decides about the health of a tool. The presence of one time based together with one frequency based indication of tool breakage is sufficient to generate an alarm.

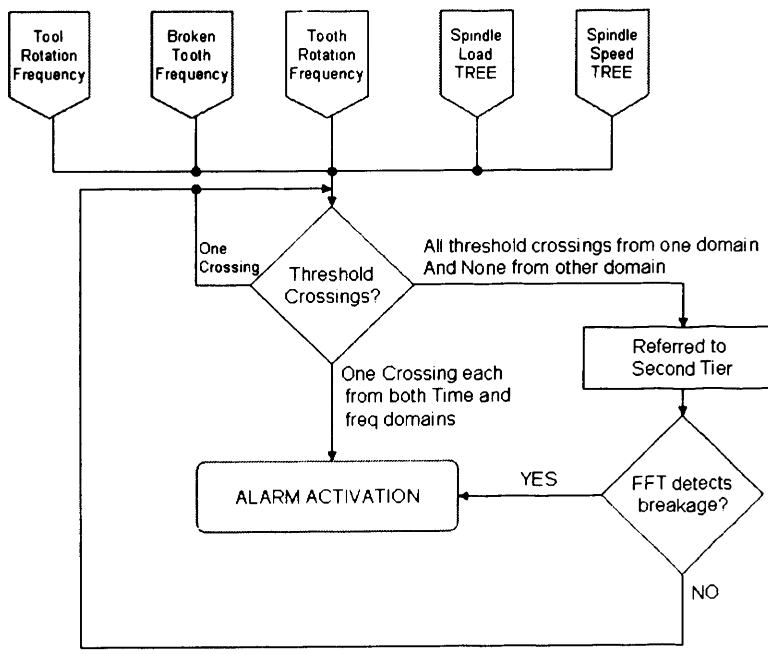


Figure-7.2, Decision making at tier one.

If there is only one threshold crossing (in total) detected in either the time or frequency domain, it is discarded and the monitoring cycle continues as normal. If a tooth breakage is detected by all the FENs in one analysis domain (whether it is in the time or frequency domain) and there is no detection by the other domain, the situation is referred to the second tier for further analysis and decision making.

Signal analysis is carried out at the second tier using FFT and an alarm is generated if this output verifies a broken tooth. If there is no detection of a breakage, then a message is sent to the decision making node at tier one to continue monitoring as normal. The 256 point FFT routine which has been implemented at second tier provides a 1Hz frequency resolution (as the data acquisition rate is also set at 256 (samples/second). Since FFT is a highly reliable signal analysis technique no further counter verification has been implemented. If a situation has been referred to the second tier whether by the time or frequency domain analysis nodes, the results of the FFT are considered final.

The parameter monitoring and decision making node transmits a data packet of 256 samples to the TINI board at the start of the monitoring process. The TINI carries out the FFT of the data and sets the threshold level for tool breakage detection in the initialisation stage. The dynamic phase of process monitoring starts after the initialisation of the monitoring system. As soon as an abnormality is detected the parameter monitoring and decision making node acquires 256 data samples and transmits it to the TINI. In the case of a broken tooth situation being detected at tier two, the TINI sends a message to the parameter monitoring and decision making node to take appropriate action i.e. to initiate an alarm generation (implemented in this research) or stopping the process (not implemented in this application).

7.3.1 Decision Verification using Laboratory Simulations

The decision making capabilities of the integrated system were tested using laboratory simulations before final implementation on the hardware. A machine tool emulator was designed using Lab Windows software. The designed emulator was used to simulate the generation of real time signals from data acquired from previous cutting tests. The designed emulator has the capability to generate any signal from a complete range of available signals taken from the machine tool. These signals include spindle load, spindle speed and three axis motor currents. In this research application only the spindle speed and spindle load signals were used to design the final monitoring system. A National Instruments PCI-6035E analogue output interface card was used to convert the stored data into the corresponding analogue signals. The system was programmed to use the same sampling rate for signal generation that was used at the signal acquisition stage. This is a primary requirement for such designs to avoid any information loss which may lead to false results. The generated signals were interfaced to the designed system for further analysis and decision making.

Figure-7.3 shows the Graphic User Interface (GUI) designed machine emulator that was used during the system testing phase. The generated signals were interfaced to the actual hardware of the system. The generated data was acquired from the machine running at 500RPM using a four teeth cutter (for various feed rates and values of depth of cut). Figures-7.4 and 7.5 show the results of the monitoring system from the generated signals using healthy and broken cutters respectively. These Figures show the information retrieved from all FENs.

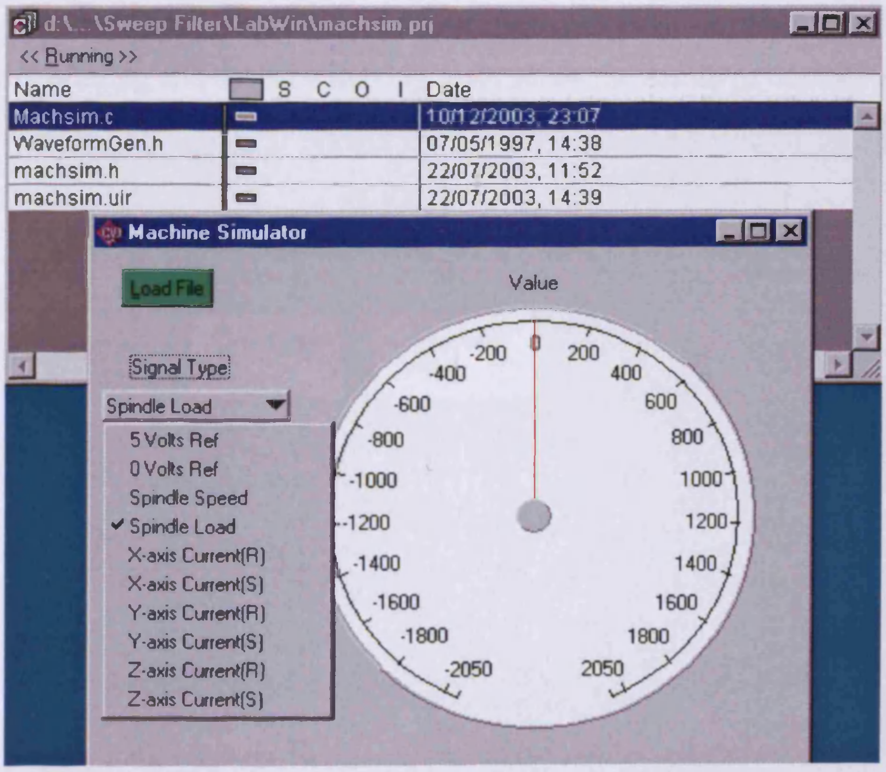


Figure-7.3, Machine tool Emulator.

These results represent the laboratory testing of the integrated system to prove its reliability. An in depth analysis of a complete range of practical tests carried out for normal milling, shoulder milling and tool entry situations are presented and discussed in Section-7.4 of this Chapter. It can be noted from both the figures that the strength of tool rotation frequency increases for a broken cutter. Moreover the strength of broken tool frequency also increases for a broken cutter thus indicating a tool breakage. In the time domain analysis the signal variations for both spindle load and speed signals also increase for a broken cutter.

The blue lines in Figure-7.4 represent the observed values of monitored process parameters for a cutting test using a new tool. The red dots indicate the threshold levels set for each parameter. It is worth noting that the values of thresholds are different for each parameter. This is due to the fact that frequency strength of various components is affected by a different percentage when a tool breaks. Similarly, the variations in spindle speed and load signals are also different.

As the speed signal variations are constantly controlled by the feedback controller the variations in speed signal are lower as compared to the variations observed in the spindle load signal. Figure-7.4 shows that none of the parameters being monitored has crossed the set threshold and therefore the final decision taken by the parameter monitoring and decision making node about the health of the tool is "OK".

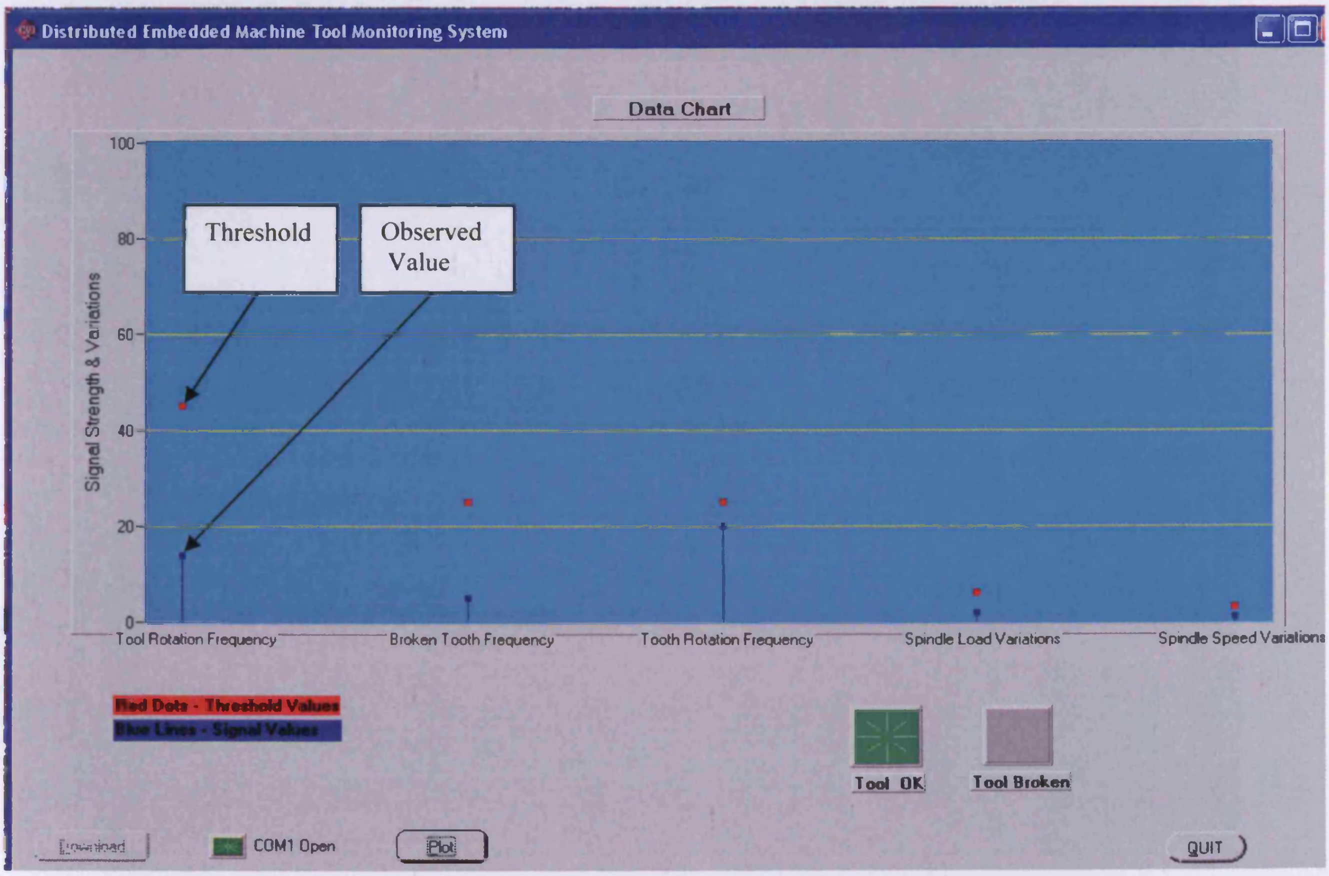


Figure-7.4, Data analysis results for a Healthy cutter (1mm depth of cut, 500RPM,100mm per minute feed rate).

Figure-7.5 shows the result of the system for a cutting test using a broken tool. It can be noted that tool rotation and broken tooth frequencies cross the threshold levels by a high percentage. In comparison the tooth rotation frequency crosses the threshold value by a very low percentage. In true argument its value should decrease as the cutting teeth are reduced as compared to a healthy cutter. But its value still increases due the harmonic effect of the tool rotation frequency. Therefore its implementation versus the advantages achieved have been analysed in the future work chapter (Chapter-9). In the monitoring result shown in Figure-7.5 all FENs have observed the crossing of threshold values and the tool breakage has been detected. After verification of the integrated system by using various laboratory simulations it was interfaced to the actual machining environment in the two tier architecture and very reliable results were obtained. These results and the decision methodologies used are discussed in the next section.

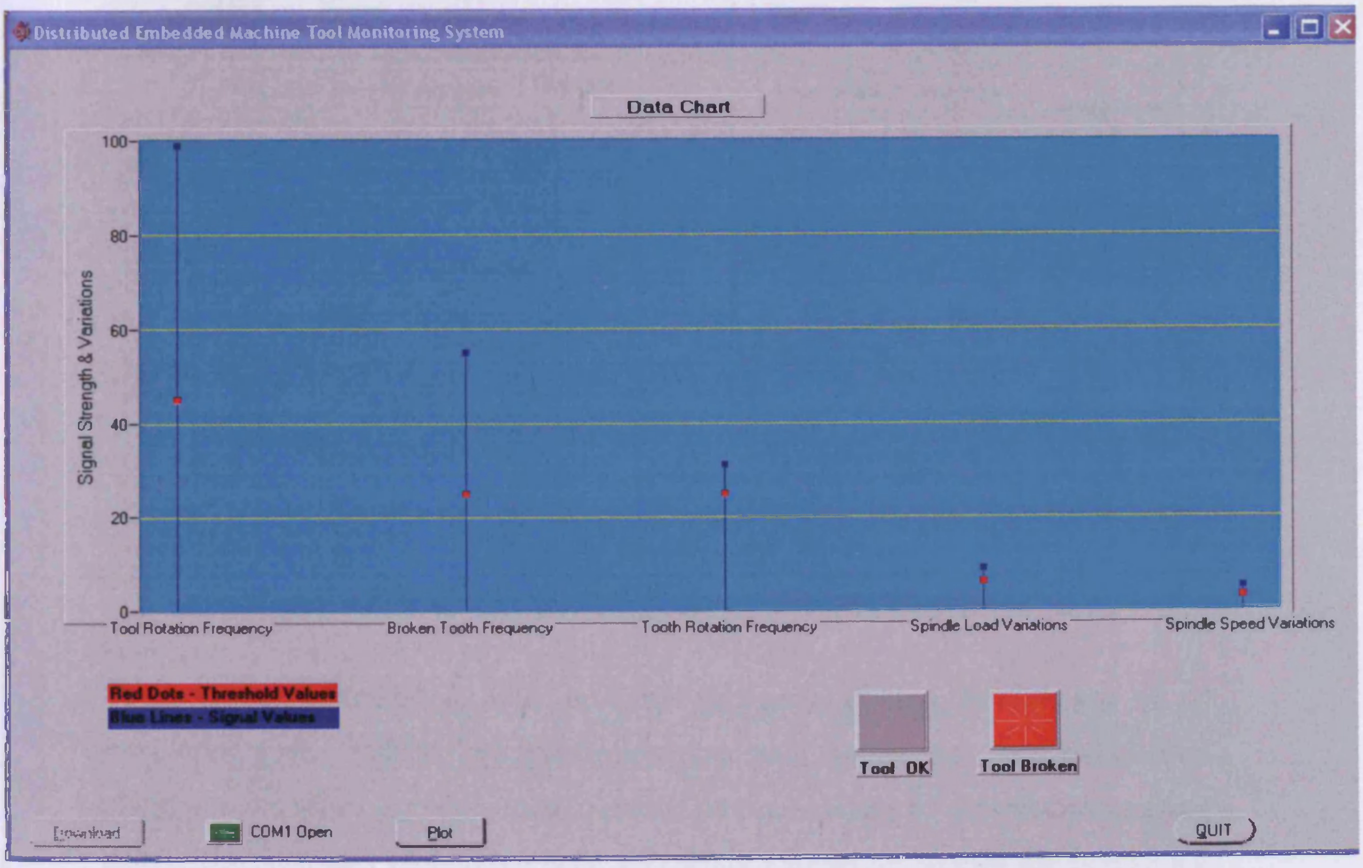


Figure-7.5, Data analysis results for a Broken cutter (1mm depth of cut, 500RPM,100mm per minute feed rate).

7.4 Integrated System Implementation and Decision Making

The final system was integrated and tested for its functional accuracy and reliability by interfacing it to the machine tool. The block diagram of the integrated system is shown in Figure-7.6. The first two tiers of the system have been implemented in this research application. CAN bus has been used as a communication medium between all monitoring nodes. It is simply a two wire system that connects all the nodes and is very reliable communication medium. The PIC 18F458 has a built in CAN controller but it needs a CAN transceiver to communicate the information over the CAN bus. PCA82C250 CAN transceiver was used in this application design. A small summary of system operation is described in the succeeding paragraphs.

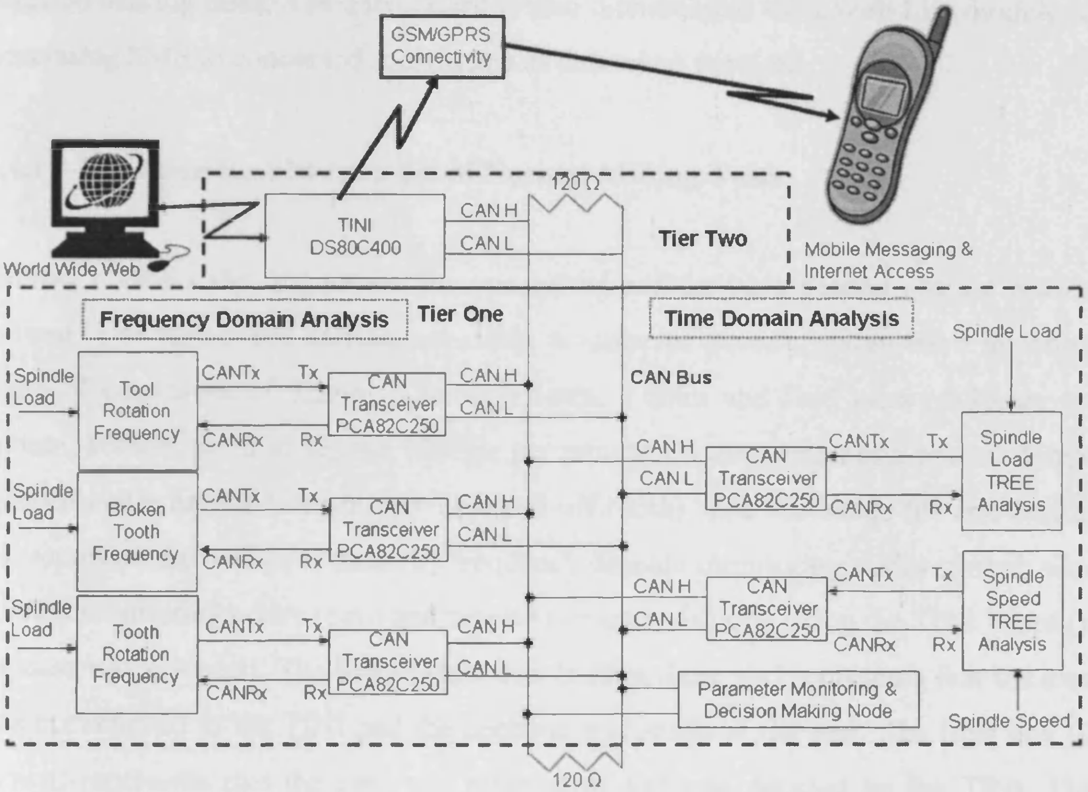


Figure-7.6, Block diagram of the Final system implementation.

The parameter monitoring node provides necessary process information to all monitoring nodes (both in time and frequency domain monitoring). This information along with the actual signals is used to set the threshold levels by different monitoring nodes. The parameter monitoring node also sends a signal to indicate the start of the process to all FENs. After receiving this signal the FENs start the monitoring process.

Any numbers of fault indications are reported to and monitored by the parameter monitoring nodes before making a decision. The parameter monitoring node also decides about using a localised decision making strategy or referring the situation to the second tier. The decision is referred to the second tier in cases where breakage is detected by all the monitoring nodes in one domain (time or frequency) and none in the other domain.

The parameter monitoring and decision making node also shares information about the tool's health with the TINI board using the CAN bus connectivity. The TINI board relays this information to the internet at pre-programmed intervals. In addition TINI board performs FFT operations on the data transferred from tier one for further analysis and communicates the final decision to the parameter monitoring and decision making node. The TINI board is also interfaced to the uWeb Lite module for generating SMS to concerned individuals as and when required.

7.4.1 Detection Results for a Set of Normal Milling Tests

Table-7.1 shows the test results for one set of cutting tests carried out for normal milling. The tests were carried out using a range of process parameters including depth of cut values of 0.5mm, 1.0mm, 1.5mm, 2.0mm and feed rates of 80mm per minute, 100mm per minute, and 120mm per minute for new, blunt and broken cutters (broken cutter had one completely chopped off tooth). The six boxes for one cutting test represent the decisions made by frequency domain monitoring nodes (three), time domain monitoring nodes (two) and second tier analysis node using the TINI board (if the case was referred). The blank white box (within these six) represents that the case was not referred to the TINI and the decision was made at tier one. The blue box (if shown) represents that the case was referred to and was decided by the TINI. The letter "OK" represents a healthy tool whereas "B" is used to indicate the breakage detected by the individual monitoring nodes. The results (OK or B) shown in Yellow indicate a false decision made by a particular monitoring node. If a letter "OK" is shown in yellow colour it represents that actually the tool was broken but the node detected it as healthy. The same rule applies for "B" shown in yellow. The overall green colour for five monitoring nodes shows a decision of "healthy" tool by the integrated system whereas red colour shows a "breakage". Table-7.1 shows that some of the "Individual Monitoring Nodes" missed the breakage detection at lower values of depth of cut e.g. 0.5mm. It happens due to the fact that the generated frequency components are not strong enough to cross the threshold levels.

Feed Rate	Tool Condition	Depth of Cut											
		0.5 mm			1.0 mm			1.5 mm			2.0 mm		
80 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Broken	OK	OK	OK	B	B	OK	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	
100 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Broken	B	B	OK	B	B	B	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	
120 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Broken	B	OK	OK	B	B	B	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	

Tool Rotation Frequency Node	Broken Tooth Frequency Node	Tooth Rotation Frequency Node
Spindle Load Variation Node	Spindle Speed Variation Node	Case referred to & decided by TINI- decision in blue, Blank white box indicates NO referral.

Breakage Detection missed by the Integrated System

Table-7.1, Monitoring Results for a Set of Normal Milling tests, The Six Boxes for each test represent different monitoring nodes (five FENs and one for TINI) - Yellow decisions are "False Decisions by individual nodes". The yellow dashed lines box represents a "Wrong Decision by Integrated System" i.e. it missed a Broken case (it is not a false alarm). [The Same rule applies for all the tables shown in this chapter].

It can be noted in Table-7.1 that the "Integrated System" has only missed the tool breakage detection for process parameters of 0.5mm depth of cut and a feed rate of 80 mm per minute. The major reason behind this is the same (i.e. the frequency strength of monitored frequencies do not cross the threshold levels for such a low depth of cut). Similarly the spindle speed variations were very low (for the same test) and did not cross the threshold level either. It can also be noted that the tooth rotation frequency for some of the cutting tests at 0.5 mm depth of cut does not cross the threshold value. This is due to the fact that harmonics of the tool rotation frequency are not strong enough to affect the tooth rotation frequency component. It is evident that the overall reliability rate of the integrated system increases (97.2%) as compared to the decisions made by the individual monitoring nodes (94.4%). This is due to the fact that the results are integrated before making the final decisions.

It is also worth noting that there has been no false alarm generated by the integrated system. The breakage has been missed in one case for the lowest depth of cut. The detailed analysis in terms of its implications reveals that missing the detection of tool breakage at low depth of cut though important does not affect the overall system drastically. This is due to the fact that the tooth following the broken one can easily manage the metal cutting thus avoiding major deterioration in the workpiece quality. Table-7.2 shows the overall reliability rate of the proposed system for a set of normal milling tests presented in Table-7.1.

Strategy	Total Cases	Tier One			Tier Two				
		Detected	Missed	Reliability Rate	Total Referred	Detected	Missed	Reliability Rate	Overall Reliability Rate
Single Node	180	170	10	94.4%	Not Applicable as system is based on single node only so cannot refer the cases.				-
Integrated System	36	35	1	97.2%	-	-	-	-	97.2%

Table-7.2, System Reliability Rate for a set of Normal Milling tests.

The reliability rate of single node monitoring system is 94.4% because 170 decisions out of 180 were correct. The reliability rate for the integrated system is 97.2% as 35 decisions out of the 36 in this set of tests are correct. It is also worth noting that no false alarms were generated. Therefore the idea of improved reliability using integrated approach is verified. It is not possible to prearrange a tool breakage for these tests. Therefore in the actual implementation, the threshold levels were set using a healthy cutter. After monitoring its performance a broken cutter was then used to verify that a reliable detection of its action would occur.

7.4.2 Detection Results for a Set of Shoulder Milling Tests

Table-7.3 shows the results for a set of shoulder milling tests. These results are very similar to the normal milling with the only difference that in certain cases the strength of the frequency components and signal variations for a broken cutter are lower than expected. This is due to the fact that if the milling area is less than the diameter of the tool, the metal removed in one tool rotation is less than normal milling. This reduces the strength of the frequency components as well as signal variations in some cases and certain cases of broken tooth go undetected.

Feed Rate	Tool Condition	Depth of Cut											
		0.5 mm			1.0 mm			1.5 mm			2.0 mm		
80 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Broken	OK	OK	OK	B	B	OK	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	
100 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Broken	OK	OK	OK	B	B	OK	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	
120 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Broken	B	OK	OK	B	B	B	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	

Table-7.3, Monitoring Results for a Set of Shoulder Milling tests.

Table-7.4 shows the reliability rate of the individual and integrated monitoring approaches for the set of tests presented in Table-7.3. The reliability rate of single node monitoring for shoulder milling is 92.8% and it increases to 94.5% when the integrated system is used. None of the cases has been referred to second tier during these tests and all decisions were been made at the first tier. It can be noted that no false alarm was generated.

Strategy	Total Cases	Tier One			Tier Two				Overall Reliability Rate
		Detected	Missed	Reliability Rate	Total Referred	Detected	Missed	Reliability Rate	
Single Node	180	167	13	92.8%	Not Applicable as system is based on single node only so cannot refer the cases.				-
Integrated System	36	34	2	94.5%	-	-	-	-	94.5%

Table-7.4, System Reliability Rate for a Set of Shoulder Milling tests.

7.4.3 Detection Results for a Set of Tests for Milling into a Shoulder

Table-7.5 shows the results for a set of tests carried out for milling into a shoulder. Three levels of shoulder depth (0.5 mm, 1.0 mm and 1.5 mm) were used for these tests as shown in Figure-7.7. A constant value of 0.5 mm for depth of cut was used before the tool entered into the shoulder.

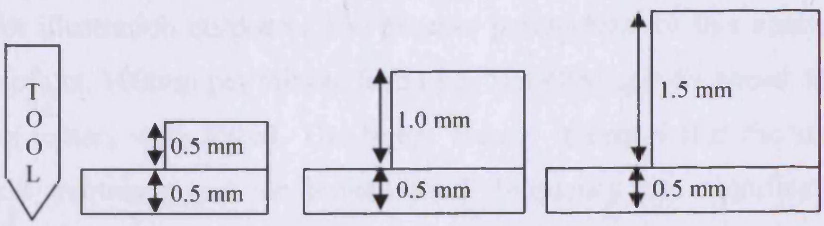


Figure-7.7, Different levels of Shoulder Depth.

Depth of Cut	Tool Condition	Depth of Shoulder								
		0.5 mm			1.0 mm			1.5 mm		
0.5 mm	New	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	B	OK	B	B	OK
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	B	OK	B	B	OK	B	B	OK
	Broken	B	B	B	B	B	B	B	B	B
		B	B		B	B		B	B	

Table-7.5, Monitoring Results for a Set of tests for Milling into a Shoulder.

As soon as the tool enters a shoulder the spindle load and speed variations increase. This increase causes the threshold crossing of spindle load and speed monitoring nodes. This results in a false decision by time domain monitoring nodes for a healthy cutter as shown in Table-7.5. The frequency monitoring nodes are not affected by these changes as the frequencies are not highly affected by the increase of depth of cut. Therefore a situation arises where the case is referred to the second tier by the parameter monitoring and decision making node. The second tier uses FFT to analyse the referred data. The "blue" boxes shown in Table-7.5 show the cases referred to and decision made by the TINI board at the second tier. It can be noted that five of the nine cases were referred to the second tier and a reliability rate of 100% was achieved. The reliability of the second tier has been very high due to the effectiveness of the FFT calculations.

Figure-7.8 shows the FFT results of an example data analysis that was referred to tier two for illustration purposes. The process parameters for this analysis were: 1.5 mm depth of cut, 100mm per minute feed rate, 500RPM spindle speed. Both a healthy and broken cutters were tested. The figure clearly indicates that the strength of the tool rotation frequency and the broken tooth frequency rise significantly for a broken cutter and the decision is reliable.

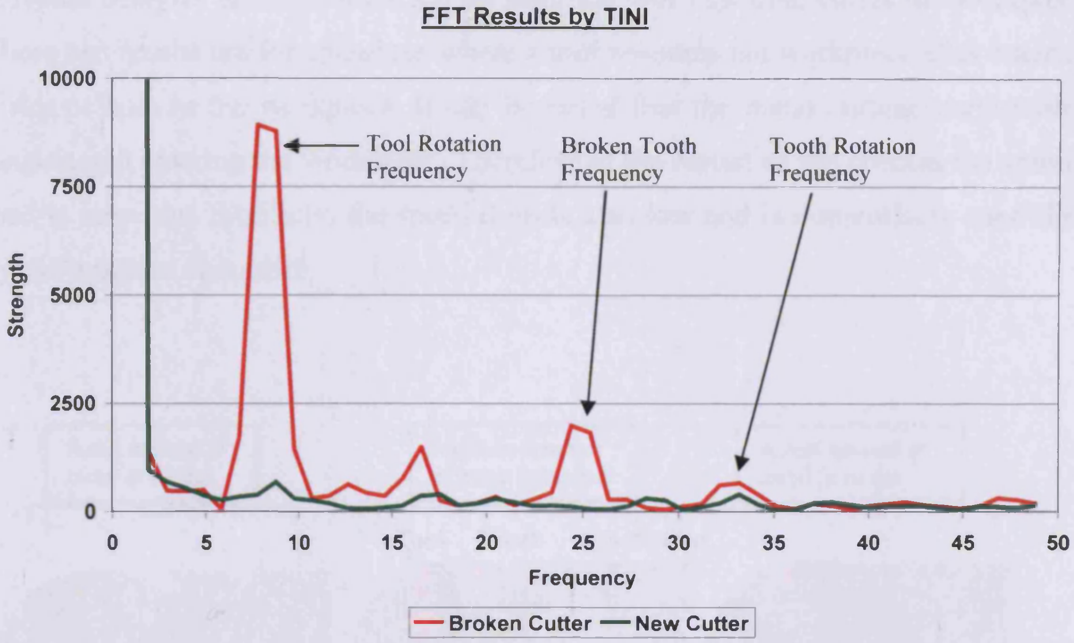


Figure-7.8, Second Tier data analysis using FFT.

Table-7.6 shows the reliability rates for single node monitoring as well as integrated monitoring approaches for the set of cutting tests carried out for milling into a shoulder. The reliability of single node monitoring approach is lower because of signal variations at the tool entry into the shoulder. The reliability of the integrated system is much higher and for the set of tests carried out in this research it remained 100%.

Strategy	Total Cases	Tier One			Tier Two				Overall Reliability Rate
		Accurate	False	Reliability Rate	Total Referred	Accurate	False	Reliability Rate	
Single Node	45	34	11	75.5%	Not Applicable as system is based on single node only so cannot refer the cases.				-
Integrated System	9	4	0 (5 Referred)	-	5	5	0	100%	100%

Table-7.6, System Reliability Rate for Set of Tests for Milling into a Shoulder.

7.4.4 Detection Results for a Set of Tests for Tool Entry into the Workpiece

Figure-7.9 represents the cutter-workpiece relationship as the tool enters into the workpiece. The first tool entry at the initialisation of the process is ignored by using a software delay as the thresholds are set after the tool first time enters the workpiece. These test results are for situations where a tool re-enters the workpiece after entering a slot or hole in the workpiece. It can be noted that the metal cutting starts with a single tooth entering the workpiece. Therefore at the restart of the process the spindle load is very low. Similarly, the speed drop is also low and is immediately controlled by the machine controller.

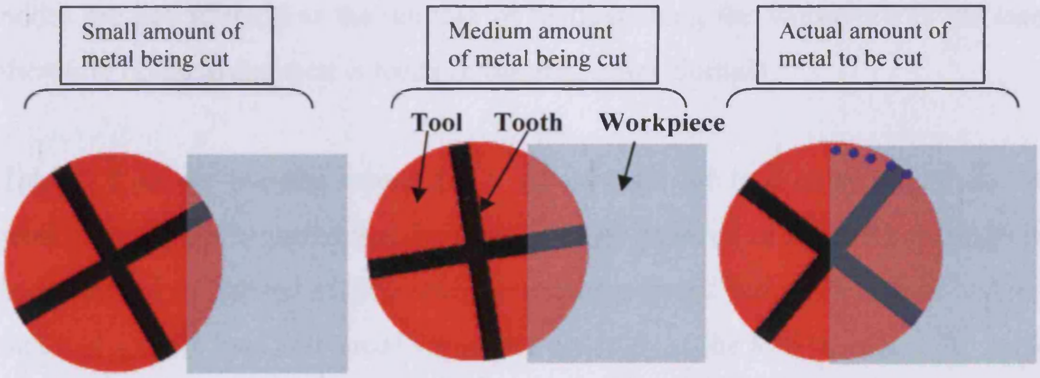


Figure-7.9, Cutting variations at tool entrance which result in the signal variations.

The process continues and two teeth start cutting spindle load increases. It continues until the tool enters the workpiece (the figure shows the tool entry at an exaggerated feed rate for illustration purpose). After the tool entry a normal cycle starts and the signal variations are almost the same until an abnormality is detected. Figure-7.10 shows the actual spindle load signal at the start of a cutting process. The initial rise of the spindle load proves this concept.

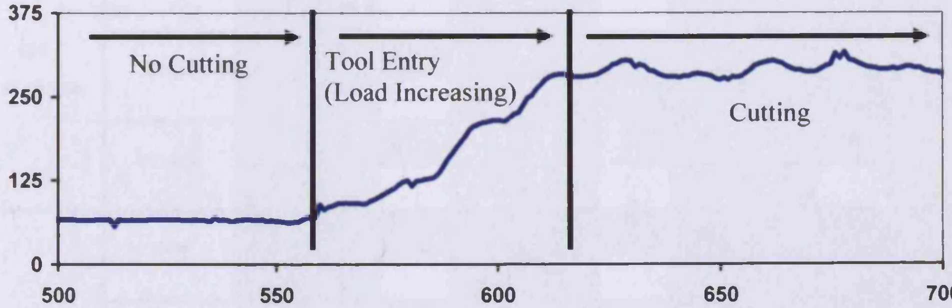


Figure-7.10, Actual spindle load signal at tool entry into the workpiece. X-axis - sample number and Y-axis - spindle load

At the start of the cutting process a delay is used and the threshold values are set after this period. But if the tool re-enters the workpiece after a hole in workpiece the described effects are observed. It can be noted that if a tool breaks in the initialisation delay period (i.e. before the threshold values are set) it cannot be detected. As soon as the tool re-enters the workpiece high signal variations are observed in the spindle signals. This is due to the fact that the amount of metal cutting in each tool rotation is different and the variations are high until the tool has re-entered. This causes a threshold crossing of time domain signals in most cases. The frequency monitoring nodes are not affected as the number of teeth striking the workpiece is the same and therefore no false decision is made in the frequency domain.

Table-7.7 shows the test results for a set of tests for tool entry situations into the workpiece. It can be noted that the ratio of cases referred to second tier has been high as compared to normal milling tests (14 cases referred out of 36). This is due to the fact that spindle load and speed variations are high as the tool re-enters the workpiece as explained in Section-7.4.3.

Feed Rate	Tool Condition	Depth of Cut											
		0.5 mm			1.0 mm			1.5 mm			2.0 mm		
80 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	OK		B	B	OK	B	B	OK
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	OK		B	B	OK	B	B	OK
	Broken	B	B	OK	B	B	OK	B	B	B	B	B	B
		B	B		B	B		B	B		B	B	
100 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	OK		B	B	OK	B	B	OK
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	B	OK	B	B	OK	B	B	OK
	Broken	B	B	OK	B	B	B	B	B	B	B	B	B
		B	B		B	B		B	B		B	B	
120 mm/minute	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	OK		B	B	OK	B	B	OK
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	B	OK	B	B	OK	B	B	OK
	Broken	B	B	OK	B	B	B	B	B	B	B	B	B
		B	B		B	B		B	B		B	B	

Table-7.7, Monitoring Results for a Set of Tests for Tool Entry Situations.

Table-7.8 shows the reliability rates for single node monitoring as well as integrated monitoring approaches. The reliability of single node monitoring approach is lower because of signal variations at the tool entry as explained earlier. The reliability of the integrated system is much higher and for the tests carried out in this research it remained 100%. It is due to the fact that the reliability of the second tier has been very high due to the FFT calculations at tier two.

Strategy	Total Cases	Tier One			Tier Two				
		Detected	Missed	Reliability Rate	Total Referred	Detected	Missed	Reliability Rate	Overall Reliability Rate
Single Node	180	139	41	77.2%	Not Applicable as system is based on single node only so cannot refer the cases.				-
Integrated System	36	22	0 (14 Referred)	61.1%	14	14	0	100%	100%

Table-7.8, System Reliability Rate for Tool Entry Situations.

7.4.5 System Results for a Set of Tests for Different Levels of Tooth Breakage

To assess the system reliability to detect different levels of tooth breakage a set of cutting tests was carried out. It included four different levels of tooth breakage (0.5 mm, 1.0 mm, 1.5 mm and 2.0 mm). The tests were carried out for four different levels of depth of cut (0.5 mm, 1.0 mm, 1.5 mm and 2.0 mm). The spindle speed was 500 RPM and a feed rate of 100 mm per minute was used.

Table-7.1 shows that some of the "Individual Monitoring Nodes" missed the breakage detection for lower value of tooth breakage. This is due to the fact that the tooth following the broken one has to remove a small amount of metal and can easily manage the situation. This results in situations where generated frequency components as well as spindle load and speed variations are not strong enough to cross the threshold levels.

Level of Breakage	Tool Condition	Depth of Cut											
		0.5 mm			1.0 mm			1.5 mm			2.0 mm		
	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
0.5 mm	Broken	B	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		B	OK		B	OK		B	OK		B	OK	
	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
1.0 mm	Broken	B	OK	OK	B	OK	OK	B	B	OK	B	B	OK
		OK	OK		B	OK		B	OK		B	OK	
	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
1.5 mm	Broken	B	OK	OK	B	B	B	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	
	New	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
	Blunt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
		OK	OK		OK	OK		OK	OK		OK	OK	
2.0 mm	Broken	B	OK	OK	B	B	B	B	B	B	B	B	B
		B	OK		B	B		B	B		B	B	

Table-7.9, Monitoring Results for a Set of Tests with Different Levels of Tooth Breakage.

It can also be noted that the tooth rotation frequency for most of the cutting tests at 0.5 mm depth of cut does not cross the threshold value. This is due to the fact that harmonics of the tool rotation frequency are not strong enough to affect the tooth rotation frequency component as explained in Section-7.4.1. It is also worth noting that there has been no false alarm generated by the integrated system. The breakage has been missed for low levels of tooth breakage. Table-7.10 shows the overall reliability rate of the proposed system for the set of tests presented in Table-7.9. The reliability rate of single node monitoring system is 86.7%. The reliability rate for the integrated system increases to 91.2% as 44 decisions out of the 48 in this set of tests are correct. Therefore the idea of improved reliability using integrated approach is verified.

Strategy	Total Cases	Tier One			Tier Two				Overall Reliability Rate
		Detected	Missed	Reliability Rate	Total Referred	Detected	Missed	Reliability Rate	
Single Node	240	208	32	86.7%	Not Applicable as system is based on single node only so cannot refer the cases.				-
Integrated System	48	44	4	91.7	-	-	-	-	91.7%

Table-7.10, System Reliability Rate for a set of tests for Different Levels of Tooth Breakage.

7.4.6 Overall System Reliability

In addition to the set of tests presented in Sections-7.4.1 – 7.4.5 a large number of tests were carried out in the course of this research to tests the reliability of the system. These included a number of sets of tests carried out for different cutting conditions including normal milling, shoulder milling, milling into a shoulder and tool entry situations. Since it is not possible to present all the tests in the thesis therefore a summary of the overall reliability rate of the data analysis and decision making capabilities of the system is presented in Table-7.11. It can be noted that the overall reliability rate of individual monitoring node approach is 87.7% and for the integrated approach it rises to 96.2%. It can be noted that breakage detection at low values of depth of cut particularly at 0.5 mm and low level of tooth breakage (0.5 mm) has been missed in a number of cases which brings the reliability rate down. At the same time it is also a fact that no false alarms have been generated which is a major achievement of using the integrated approach. These results verify that the approach of integrated monitoring increases the overall system reliability and eliminates the false alarms.

Strategy	Total Cases	Tier One			Tier Two				Overall Reliability Rate
		Detected	Missed	Reliability Rate	Total Referred	Detected	Missed	Reliability Rate	
Single Node	1850	1622	228	87.7%	Not Applicable as system is based on single node only so cannot refer the cases.				-
Integrated System	370	321	14 (35 Referred)	-	35	35	0	100%	96.2%

Table-7.11, Overall System Reliability Rate.

7.4.7 Overall System Analysis

The proposed system was originally designed in a three tier hierarchy. The overall data processing distribution for the system software at three tiers is shown in Figure-7.11. Tier one was designed to handle more than 80% of the monitoring cases. Tier one included both time and frequency domain analysis nodes in addition to the parameter monitoring and decision making node. Table-7.12 shows that in the tests discussed earlier around 85% of the decisions were made at tier one and remaining at tier two. In actual situations the tier one handles a much higher percentage of the cases. This is due to the fact that a number of tests discussed in this chapter represent the tool entry as well as milling into a shoulder situations and a majority of these needs to be referred to tier two. Tier two handled all of the cases reported by tier one. Therefore tier three has not been implemented in this research.

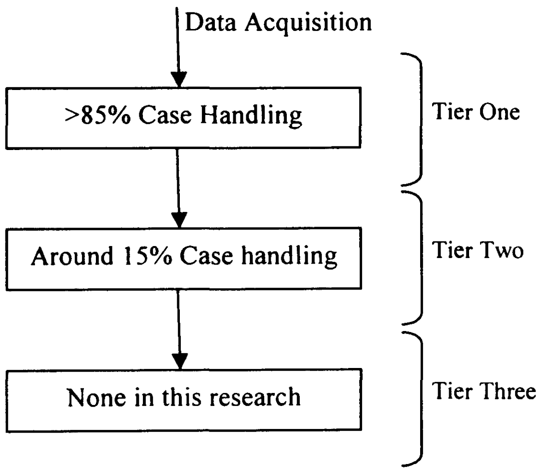


Figure-7.11, Analysis Hierarchy

7.5 Conclusion

Reliability is the most important requirement from any machine tool condition monitoring system. The practical implementation and its long term practical use depends upon its reliability. This is due to the fact that false alarms cause unnecessary delays in the manufacturing process. False alarms result in reduced equipment availability rate which is responsible for lowering the OEE of the machines and overall manufacturing plant.

The integrated system has been implemented and tested for its reliability. The overall reliability of the system has been very high (96.2% in this research, with no false alarms) while monitoring the milling cutting process. The system was used to monitor normal milling and shoulder milling operations and it has the capability to detect tool entry situations. Both time and frequency domain monitoring techniques proved very reliable for different cutting conditions. The energy variations for a tool rotation in the shoulder milling operation are lower but still can be detected for decision making. The system proves reliable for such operations due to cross checking of results in both domains (time and frequency) before making final decisions.

The cost effectiveness of such monitoring systems is another important requirement. SMEs can not afford high cost monitoring systems which use additional sensors. In addition these systems normally need an additional PC for interfacing and analysing the acquired data before final decision making. These factors not only add to the overall costs but also reduce the available space at the shop floor level. The cost of developing each FEN was around £10 for this system.

The designed system does not require any additional sensors as it uses the existing machine tool signals (spindle speed and spindle load) for analysis and decision making. Moreover it has been designed using very low cost 8-bit microcontrollers which fit on to one Printed Circuit Board (PCB) that can be fitted into a rack inside the machine tool. The TINI board is also based on an 8-bit microcontroller with some additional features like extended memory and extra CAN message centres etc.

CHAPTER 8

COMMUNICATION ARCHITECTURE

8.1 Introduction

The frequency and time domain signal analysis techniques and their integration into a reliable sensor-less tool condition monitoring system have been discussed. This chapter discusses the communication architecture of the system designed to relay data and results between tier one and two as well as tier two and internet/mobiles. Real time information transfer to concerned users results in timely actions. This approach reduces the equipment downtime and increases OEE of the systems. Therefore research was carried out to transfer data and results between two tiers of the system and the users in real time.

The overall communication architecture used CAN bus connectivity between tier one and two and internet and GSM connectivity between tier two and the remote users. The TINI board was used to relay information over the internet as well as for mobile messaging and mobile internet access. These techniques proved successful in transfer of relevant information to the users for immediate appropriate actions. Figure-8.1 shows a block diagram of communication architecture of the system.

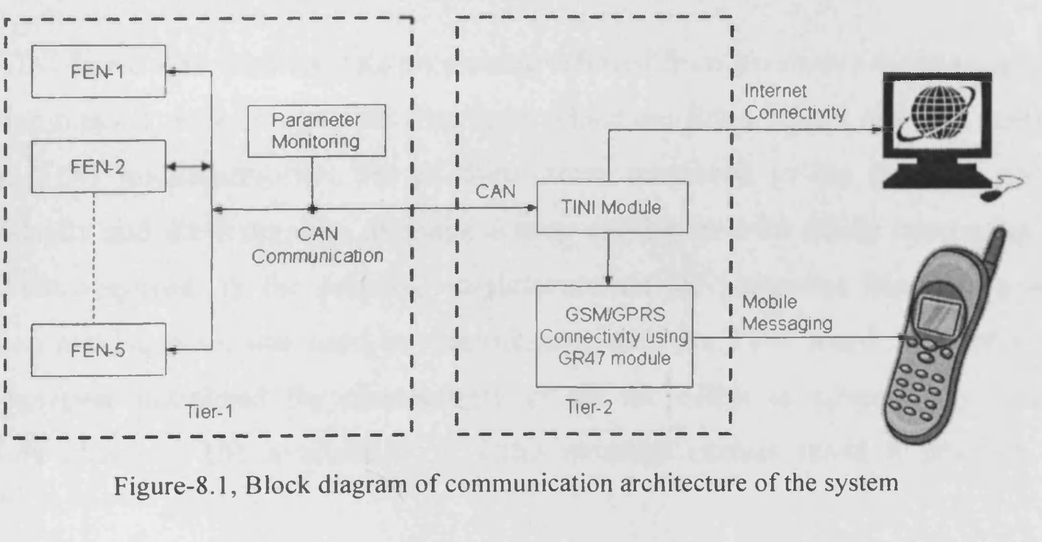


Figure-8.1, Block diagram of communication architecture of the system

In addition to transmission accuracy CAN provided additional benefits like reduction in wiring costs (a single pair of wires provides complete communication among all connected devices). This supported the building of intelligent data communication for the application. If one network node is defective in the entire hardware architecture the network is still able to operate. This characteristic of the network was used in the proposed system. The parameter monitoring and decision making node was used to send test messages at fixed intervals to all FENs in order to check their status. No checks have been implemented to detect the failure of the parameter monitoring node itself however its implementation requirements are considered as a future work in Chapter-9. The CAN bus communication was based on the broadcast concept where data transmitted by any FEN was received by all other nodes in the network. However data filters by each node were used to differentiate between messages that needed to be accepted or rejected. This characteristic of communication added to the overall reliability as all nodes share the same information.

8.2 Bridge and Communication Node

Tier two of the system not only processes the referred data but also acts as a communication bridge between tier one and the Internet/GSM. The TINI board which is based on DS40C400 network enabled microcontroller has been used as the heart of the second tier. The TINI board uses a Single Inline Memory Module (SIMM) that requires the support of a socket board to enable its connectivity with external peripherals.

The TINI board was used for data processing referred from parameter monitoring and decision making node in complex situations. There are fifteen CAN message centres in the TINI microcontroller. Six of these were interfaced to the tier one nodes individually and the remaining message centres can be used for future interfacing as and when required. In the practical implementation the parameter monitoring and decision making node was used to communicate with the TINI board. The software was however initialised for connectivity of all the FENs to support any future software changes. The availability of extra message centres made it possible to dynamically store data before its analysis and decision making and transmitting it further using the Ethernet.

The TINI microcontroller is capable of providing a maximum clock rate of 75MHz. This results in a minimum instruction cycle time of 54nSec. This capability was used to accelerate the data processing speed. In addition the higher speed enabled the controller to cope with the highly loaded university network (on which the system was tested) in providing reliable Ethernet access. Moreover it ensured that the data processing was carried in a minimum time for real time decision making.

8.2.1 Internet Connectivity

For two computers or embedded systems to communicate, they must speak the same language. A communication language framework is referred as a "protocol". Protocols do not just enable communication but also restrict them. So a protocol in addition to defining communication also provides a framework for information exchange [8.1]. However, in all networks, the purpose of each layer in a protocol is to provide certain specific services to the higher layers, shielding those layers from the details of how these services are actually implemented [8.2].

The TINI board has a unique Media Access Control (MAC) address as should any Ethernet device. It was given an IP address from Cardiff School of Engineering computer section. It was also allocated a network name to enable easy access by just typing http://u094.engi.cf.ac.uk rather than remembering its actual IP address. For such applications the DNS server finds the actual IP address of the device to ensure that the data packets are received by the actual device as discussed earlier.

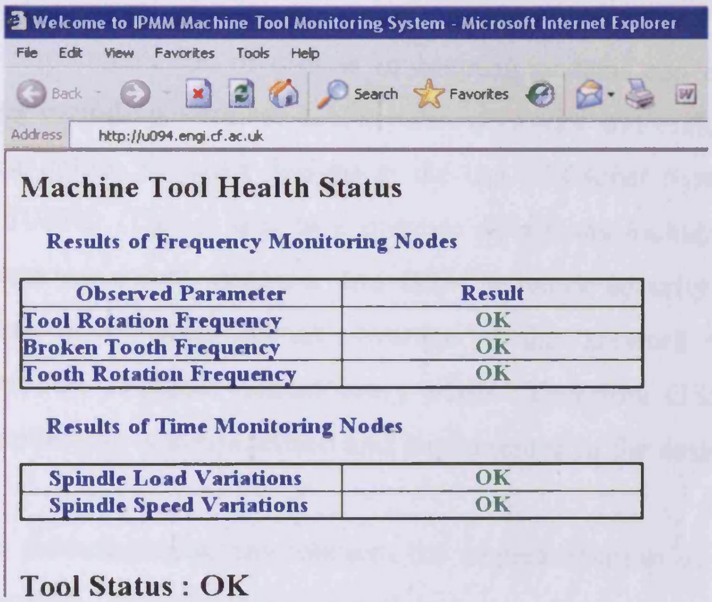
TINI supports three servers namely File Transfer Protocol (FTP), Telnet and Serial Port servers. One or more of these servers may be run at the same time. In this application FTP and Telnet servers were programmed to run simultaneously for data communication. Both of the FTP and Telnet serves were programmed to listen to the connection requests on different ports. Each connection started a new session to handle a particular request.

Telnet was used as an application layer protocol on top of TCP/IP stack. It provided an interface between a user (at application layer) and the transport layer. The Telnet server is designed as a password protected server in this application. Any access request by a remote user is verified through this password protected system and accordingly the request can be accepted or denied. The logged in users can be listed by using available commands on a command prompt. The "Slush" commands were used by the logged in user for starting or stopping an application. A list of useful Slush commands in attached as Appendix-D. Depending upon the application requirements it is possible to provide access for a normal user through Telnet. It can also be programmed to only listen to requests from certain users who are considered to be more relevant for a particular application. In this application Telnet was programmed to provide access to only a limited number of users.

The operations of uploading and downloading files to and from the TINI were performed using an FTP server. This server acts more efficiently as it is designed for these applications. Any computer running Internet Explorer software can perform the file downloading operation in a more user friendly way. An important limitation of Internet Explorer (IE) is its inability to upload files. In this application's implementation stage, the FTP server operation was only available to a limited number of registered users.

An HTTP server was programmed and implemented in addition to three servers described above. This server was used to present information to ordinary users. It was used to host a dedicated webpage. This webpage provides current process information to all users who need to access it. This webpage can be accessed using internet explorer. The webpage address for this application is http://u094.engi.cf.ac.uk . Any interested user can access this webpage and see the process information (only when the TINI board is powered on). Since an automated upload is not possible using IE it has been programmed to refresh its contents after a pre-programmed interval. This interval can be programmed depending upon the application requirement. In this application it has been programmed as 120 Seconds. The time interval for updating web information is not critical because the system has the GSM connectivity and an SMS is sent to the concerned individuals immediately after detecting a problem.

Figure-8.2 and 8.3 show the WebPages that display the tool status relayed to the internet by the TINI board. These show information when cutting using both healthy and broken cutters. The decisions made by each FEN about the tool health are shown on the internet. The webpage displays information from both frequency and time monitoring FENs. Figure-8.2 shows that none of the FENs has detected any breakage and the tool status is shown as "OK". Similarly a detected breakage relayed over the internet is shown in Figure-8.3.



Machine Tool Health Status

Results of Frequency Monitoring Nodes

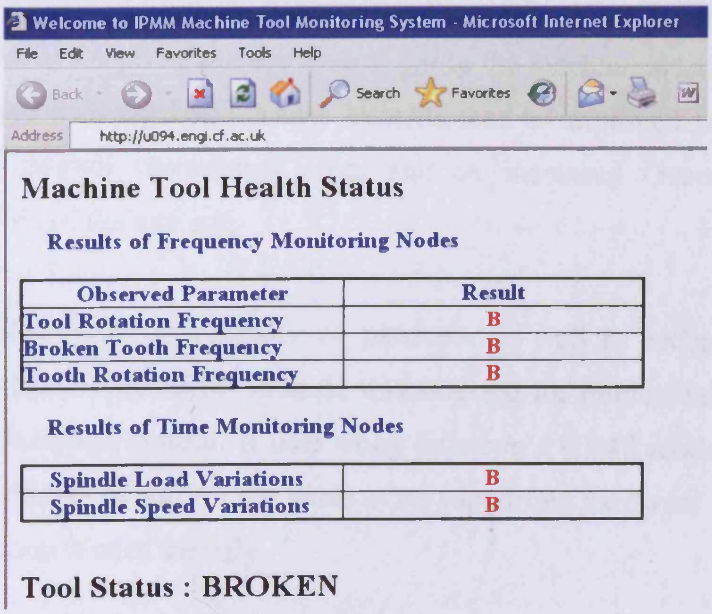
Observed Parameter	Result
Tool Rotation Frequency	OK
Broken Tooth Frequency	OK
Tooth Rotation Frequency	OK

Results of Time Monitoring Nodes

Spindle Load Variations	OK
Spindle Speed Variations	OK

Tool Status : OK

Figure-8. 2, Webpage information for a "Healthy" tool



Machine Tool Health Status

Results of Frequency Monitoring Nodes

Observed Parameter	Result
Tool Rotation Frequency	B
Broken Tooth Frequency	B
Tooth Rotation Frequency	B

Results of Time Monitoring Nodes

Spindle Load Variations	B
Spindle Speed Variations	B

Tool Status : BROKEN

Figure-8.3, Webpage information for a "Broken" tool

8.2.2 Machine-to-Machine/Man-to-Machine (M2M) Connectivity

M2M (Machine to Machine or Man to Machine or Machine to Man or Mobile to Machine or Machine to Mobile) is a concept of communication between a device that contains some data and a device which requires that data. The latest advancements in technology, more capabilities and coverage of wireless devices (e.g. cell phones) and reductions in the costs of using satellite data services is making this technology more effective and popular.

The design and implementation of remote monitoring systems can be done using a variety of options including wireless LAN, radio networks and dialup modems etc. However the best option for such designs is the use of Global System for Mobile Communication (GSM). This is due to a number of reasons including low cost as compared to preparing a new network and GSM network security. But the most important of these is the wide spread coverage of this network that makes the monitored information available almost every where. Therefore GSM connectivity system for this application was researched and implemented in the design stage.

Focussing on the manufacturing environment the implementation of such a system provides many benefits. These benefits are both in terms of reducing operational costs (e.g. the cost of labour that controls or monitors the machines) as well as saving time (e.g. when machine is far away and the time to get to the machine is long as compared to sending a simple text message). These benefits lead to improved product quality, the reduction of overall operational costs and an increased Overall Equipment Effectiveness (OEE) of the system.

Based on cost effects, the availability of products as well as technical literature Comtech's uWeb Lite GSM/GPRS module was selected for implementing the M2M capability in the designed system. It uses Sony Ericsson's GR47 module to provide communication facilities in addition to some extra supporting hardware for enhancing its feature and making it user friendly.

TINI was used as an external device as Data Terminal Equipment (DTE). It communicates with the module over its serial interface. It controls the module via a supported set of extended AT commands. The AT commands are used for establishing and controlling connections as well as sending/receiving SMS and data packets. Subscriber Identity Module (SIM) card was inserted in the GR47 module and used to communicate with the GSM engine. The communication was carried out on a system connector fabricated within the GR47 module. The messages/data were transmitted through the GSM/GPRS mediums through an external antenna. GSM connectivity was implemented at tier two of the system.

GR47 module was interfaced to uWeb Lite module for full functionality of the system. The TINI board has two built in serial communication ports and one of these was used to communicate with uWeb Lite. The messages can be sent using either text or Packet Data Unit (PDU). In this application the PDU transmission was used for communication between TINI and the uWeb Lite module.

Before sending any message TINI sends a "CMGS" AT command to the uWeb Lite and it gets attended for receiving further data. By using appropriate AT commands; the TINI board transfers required information to uWebLite for further transmission in the form of an SMS to the registered mobile numbers of different users depending upon the message contents. For example; any message about a fault needing immediate attention can be programmed to be sent to a concerned engineer/technician and the overall equipment productivity can be communicated to concerned managers. This was implemented at the final stage of the research and one mobile number was registered for sending the messages about process information. Figure-8.4 shows the message sent by the system about a broken tool on a mobile phone.

At the end of each message transmission the uWeb Lite sends the message communication information (message status report) back to the TINI board. The message sent from uWeb Lite contains information about the success or failure of the transmitted message. The system can also be programmed to receive message from these users to change/update future operations/requirements but this has not been implemented in this research.

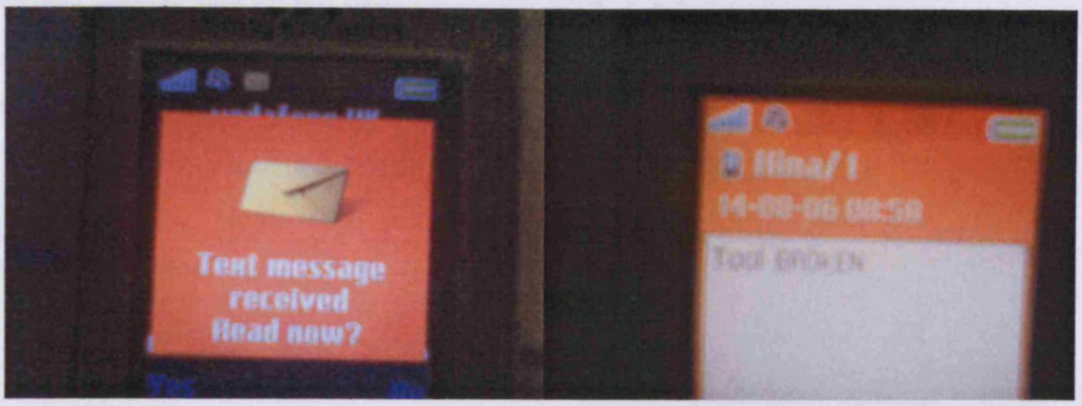


Figure-8.4, Real time mobile messaging using the designed system

8.2.3 Mobile Internet Access

With the latest advancements in mobile technology it is possible to access the Internet using mobile phones. The researched system has Internet connectivity as discussed in Section-8.2.1. The TINI board has its own unique web address http://u094.engi.cf.ac.uk and can be accessed using a mobile phone from any where in the world (provided mobile phone and the network being used have the capabilities and the TINI board is powered on). The system was programmed and tested for simultaneous access using PC based internet and mobile internet connections and it provided the information accurately. Figure-8.5 shows the monitoring web page hosted by the designed system that is accessed using a mobile phone.

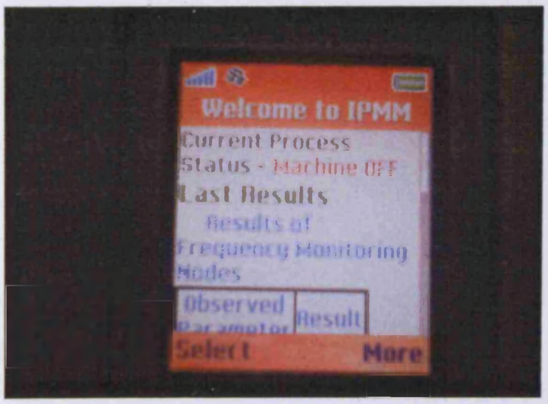


Figure-8.5, Monitoring system web page access using mobile phone.

The system updates its contents automatically after the pre-programmed interval as discussed earlier. Therefore the data download speed affects the mobile internet access to the information. This is due to the fact that mobile phones have smaller display screens and by the time screen is scrolled down and information read properly the TINI may upload the latest information. After the uploading of information the mobile screen goes back to the start and it has to be scrolled down again. This limitation was overcome by increasing the automatic upload interval.

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8.2 R.G. Lane, S. Daniels, X. Yuan, "An empirical study of reliable multicast protocols over Ethernet-Connected networks", Published in International Conference for Parallel Processing 2001, 3-7 September, 553-560.

CHAPTER 9

SYSTEM ANALYSIS, DISCUSSION AND FUTURE WORK

9.1 Introduction

There has been extensive research in the field of condition monitoring systems in general and machine tool monitoring systems in particular. The importance of machine tool condition monitoring to the manufacturing industry can not be over emphasized. It has been verified in the Chapter-5, 6 and 7 that a reliable and cost effective machine tool monitoring system increases the OEE of a manufacturing plant. Researchers have developed a number of techniques for data analysis and their linkage to the machine tool's health. It has also been reviewed (Chapter-3) that a vast majority of these techniques have been implemented using computer based technologies.

It has been verified in Chapter-4 that high speed computer systems with ever increasing resources and multi purpose data acquisition systems are readily available. The technological analysis presented in Chapter-4 shows that a range of sensor systems using latest detection hardware, analysis and communication facilities can be used in designing such systems. These subsystems when integrated together increase the reliability but at an increased cost. The concept of increasing reliability which is directly proportional to the cost is not acceptable in today's competitive manufacturing industry. Industrial users prefer a cost effective and reliable monitoring system. The cost effectiveness of any system depends on both fixed and variable costs. Theses are analysed in Section-9.5.

The reduction in the cost of such systems has become possible due to recent technological breakthroughs. The use of embedded systems in general and microcontrollers in particular for designing such systems reduces the overall cost. The use of existing machine tool signals for designing machine tool monitoring systems further reduces the overall cost of the system. Moreover the latest versions of microcontrollers have the capabilities to connect to the internet and send SMS to mobile phones. All these qualities when integrated together in the final design add to the overall significance of such monitoring system.

This chapter discusses the integral subsystems and important characteristics of the proposed monitoring system in comparison to the traditional approaches used in this area. The advantages of proposed methodologies/techniques and their implementation aspects are discussed and recommendations are made for future work in the area of machine tool condition monitoring.

9.2 Data Sources and Acquisition

Data acquisition is the basic foundation of any machine tool condition monitoring system. The data acquisition system needs to collect data from appropriate sources at the correct time and under correct conditions. The reliability, cost and flexibility of the monitoring system stem from this basic information. The reliability of the decisions made by any monitoring system directly depends upon the accuracy of the data used for processing purposes.

In this research the existing machine tool signals were selected as the primary source of information. These include spindle speed and spindle load as discussed in detail in Chapter-5 & 6. The advantages of using existing machine tool signals are twofold: firstly it reduces the overall cost of the system and secondly it provides reliable information as it originates directly from the source.

In this research the front end monitoring nodes were used for data acquisition in addition to data processing. These nodes were designed using the PIC18F458 microcontrollers. The output of the anti-aliasing filtering stage was directly interfaced to the ADC of the PIC microcontroller. The results of various tests showed that the lower 8-bits of the 10-bit ADC can be used due to limited memory resources of the microcontroller and an acceptable level of accuracy can be achieved. This resolution proved reliable enough for accurate data analysis which led to reliable decision making in the final design stage.

The data acquisition system used in this research is simple enough to be implemented on an 8-bit microcontroller but is reliable enough to provide accurate results. It is more cost effective than using data acquisition cards. A National Instrument 6035E data acquisition card costs around £500 whereas a PIC microcontroller costs less than £5.

9.3 Data Processing and Feature Extraction Techniques

The data processing and feature extraction is an important stage of machine tool condition monitoring systems. The effectiveness of monitoring systems depends on the associated data simplification and signal processing techniques used. In both model based and feature based approaches it is important that observed changes should be insensitive to uncertainty and sensitive to faults. These important aspects have been emphasized by the researchers in the past and have been used as primary requirements in this application design.

In comparison to the data analysis techniques and application specific algorithms used in the past, this research uses two signal analysis techniques; one each for time and frequency domain analysis of the acquired data. The results of both techniques are integrated before making any final decisions. To make best possible use of the system hardware these techniques were formulated to function within the resource limitations applying when using these microcontrollers.

The sweeping filter and parallel filter frequency analysis techniques provide the information required to assess the health of the machine tool. There are only three frequencies of interest for the machine tool condition monitoring system developed in this research. The idea of analysing only these frequencies in real time was implemented. The parallel filtering technique contributes to meeting these requirements.

The proposed time domain signal analysis technique uses the acquired data for real time variation detection. This technique is also implemented on an 8-bit microcontroller and has the ability to detect signal variations in each tooth/tool rotation period and link the observed variations to the tool's health. This technique does not use any complex mathematical modelling and therefore can be implemented on a PIC microcontroller. The tooth/tool rotation energy estimation technique does not require any external hardware apart from the microcontroller on which it is implemented. This quality of the developed technique makes it unique. It uses a low pass filter (moving average) to remove unwanted noise components from the acquired data. The filtered data is analysed to detect the signal variations within one tooth/tool revolution. The values of these variations are significantly different for healthy and broken cutters. These variations were used as the basis to make decisions about tool's health.

9.4 Hardware Design Analysis

The overall hardware architecture of any machine tool condition monitoring system plays an important part in its performance. The hardware components of different systems include sensors, data acquisition cards and PCs. Recent research applications have also used embedded systems and application specific ICs for designing such systems.

The designed system was implemented in a two tier hierarchy. The hardware for both tiers was based on 8-bit microcontrollers. Three FENs were used for frequency domain signal analysis and two for time domain analysis. These FENs were based on PIC18F458 microcontrollers. The system used existing machine signals thus avoiding the need for any additional sensors. The second tier of the system used a TINI board as its hardware base. The overall hardware architecture of the system was compact and can be fabricated on a single PCB to be fitted inside the machine being monitored.

9.5 Cost Effectiveness

The focus of this research was to provide a reliable and effective machine tool condition monitoring system. The cost analysis is based on using both variable and fixed costs of a designed system. The fixed costs include sensors and software packages, PCs and data acquisition cards etc. The variable costs are the costs of running the system e.g. manpower, computing resources for data management and running repairs. By way of an example Al-Habaibeh and Gindy carried out a detailed comparative analysis of different data analysis techniques and widely used sensors for tool condition monitoring systems [9.1]. They concluded that the lowest fixed cost for a monitoring system (using sensors) was around £3900 and the system had a reliability rate of 79.63%. They also proposed a high accuracy system (with a reliability rate of 91.11%) which costs around £19900 (fixed cost only).

The variable costs of any monitoring system increase if real time data analysis and decision making is not used. For example in the Tooth/Tool Rotation Energy Estimation technique a sampling rate of 8K samples per second was used. The implemented technique analyses the data in real time and discards the data if no further action is required unless programmed to store it. If real time data analysis is not implemented 29MB data will be stored per hour. The analysis of this data will incur added costs in terms of time and money. Therefore the implemented system is highly cost effective both in terms of fixed and variable costs.

The cost effectiveness of any monitoring system reduces if completely new hardware architecture has to be designed for any changes in the overall system requirements. Therefore to meet these requirements any monitoring system should be flexible to handle such changes. In this research application the required degree of flexibility was achieved by designing a system which is independent of the changes in the system being monitored. For example in frequency analysis approach the number of frequencies to be monitored is always three. The values of these depend on the number of teeth in the cutter and the spindle rotation speed. Similarly in the time domain analysis approach used in this system both spindle load and spindle speed signals are analysed for signal variations in tooth/tool rotation intervals using the software and the results are compared. Since the final implementation of the technique used one complete tool rotation period to determine the signal variations therefore the number of teeth in a cutter does not affect the results.

The overall cost of the system was relatively low as compared to normally available machine tool monitoring systems due to different factors. These included using existing machine signals (no additional sensors), the use of 8-bit microcontroller at both tiers of the designed hardware, using CAN as a communication medium for local communication, providing internet access by using most widely used internet explorer (rather than designing an application specific interface) and using a simple hardware kit for generating SMS (uWeb Lite was used in this application). In addition the TINI board supports Java as a higher level programming language. Java is a "no cost" solution available to the programmers anywhere. It can be downloaded from different internet sites and in particular from Sun (who originally launched the software).

9.6 System Reliability

The reliability of any machine tool condition monitoring system is the most important requirement. It has been a major challenge in the research area of machine tool monitoring. The major reason behind non-acceptance of many monitoring systems by industrial users has been their reliability. Any monitoring system that generates a higher number of false alarms is finally discarded in the actual industrial environment as it reduces the equipment availability rate thus reducing the OEE of the equipment.

There are two different types of false decisions made by the monitoring systems. The first type is in which a monitoring system fails to detect a broken tooth and the second is when a monitoring system generates an alarm for a healthy tool. Both types have different implications on the overall system performance. When a monitoring system misses the breakage detection the workpiece quality may deteriorate if there is a complete breakage. This could cause extensive damage to the expensive workpiece and should be avoided when possible. Perhaps thresholds could be varied for particular circumstances (i.e. finish cuts and for expensive workpieces). The implications of false alarms are higher. This is due to the fact the process has to be unnecessarily stopped which reduces the equipment availability.

Intensive practical testing was carried out of the proposed techniques for data analysis in this research and a very high reliability rate was observed. The technique of system integration was used and a reliability rate of 96.2% was observed. Moreover the designed system did not generate any false alarms. The system though missed breakage detection for some tests but these were for low depth of cut (normally 0.5 mm) and low breakage levels (0.5 mm). Both these situations normally do not affect the system performance drastically as the tooth following the broken one can easily manage the metal removal thus avoiding any deterioration in the quality. The cases of missing breakage detection can be overcome if the depth of cut can be estimated. This is explained and recommended in Section-9.7 of this chapter.

This high reliability rate from a cost effective system based on 8-bit microcontrollers added to the overall significance of the design. The definition of system's maximum reliability can be linked to the resources available in the FENs. It has already been discussed in Chapter-5 that frequency monitoring nodes based on PIC18F458 microcontroller can monitor a maximum spindle speed of 6000RPM. It has also been explained in Chapter-6 that FENs using PIC18F458 microcontrollers can monitor a maximum spindle speed of 2500RPM for tool rotation energy estimation purposes. This is due to a very high feedback rate in the machine controller and a limited data acquisition rate of the ADC in comparison. These constraints of the hardware have been highlighted and have not been ignored to keep the system's reliability rate as high as possible.

9.7 Recommendations for Future Work

The application areas of embedded systems have been growing almost exponentially in the recent past. It has led to the development of advanced embedded controllers with increased capabilities and resources. For example at the start of this research the PIC18F458 was the latest release by Microchip Technology Inc$^{(R)}$ with all available resources required for this application design. Whereas by the end of 2005, Microchip has marketed various advanced DSP controllers named as dsPIC family of microcontrollers.

The dsPIC are 16-bit microcontrollers (as compared to the PIC18F458 which is an 8-bit microcontroller). They have additional resources like extended memory, high speed clocks and better data analysis capabilities. These improved features and resources clearly indicate that these controllers can be used to improve the functionally of the techniques discussed in Chapters-5&6 and overcome the limitations described in the Section-9.6 of this chapter.

There is never a final design in any engineering application and the same applies to this research. There is always room for improvement with the advent of latest technology. The processing speed in the proposed sweeping filtering technique can be increased by implementing digital Infinite Impulse Response (IIR) filters. A dynamic digital filtering concept was tested at the very last stage of this research to monitor the same frequencies of interest and highly reliable results were obtained. The dsPIC30F6014 was used for dynamic bandpass filtering and signal analysis.

In the testing phase of proposed technique two different Infinite Impulse Response (IIR) bandpass filters were implemented in the controller simultaneously whose pass bands were dynamically determined and the filter coefficients adjusted by the controller depending upon the machine parameters "on the fly". The tool rotation frequency and the broken tooth frequency were used as the centre frequencies of the pass bands of these filters. The monitoring of tooth rotation frequency was discarded as these two parameters provided sufficient information for detecting a tooth breakage.

The linear relation of spindle speed signal with the actual spindle speed of machine was used by the controller in determining the working coefficients for the bandpass filters. The dsPIC microcontroller was operated using 7.3728MHz crystal oscillator. The clock speed although seem relatively low but the inbuilt clock multiplier was used to achieve the optimum rate of 30 Million Instruction per Second (MIPS). The Dynamic Coefficient Selection technique was used which utilised existing spindle speed and spindle load signals of the machine.

The sampling rate of spindle load signal was kept directly proportional to the spindle speed. For example; for a spindle speed of 500RPM a sampling rate of 500 samples per second was selected and for a speed of 1200RPM the sampling rate was 1200 samples per second. This linear relationship ensured that at any spindle rotation speed, there are 60 samples for each tool rotation available for analysis and decision making after the filtering stage.

The relative strength of frequency components of interest was used to monitor the tool's health dynamically as discussed in Chapter-5. This technique observed two frequencies (tool rotation frequency and broken tooth frequency) in parallel using one microcontroller. The monitoring technique used two different variables to achieve the dynamic monitoring characteristics. Firstly a fixed set of coefficients was used for a predefined frequency range and the sampling rate acted as a variable. For example for a range of spindle speeds from 250-750RPM, the filter coefficients for both the IIR bandpass filters were the same whereas the sampling rate varied with the spindle speed thus changing the centre frequency of the pass band to the frequency of interest. This technique was used for one range of spindle speed. Whenever the spindle speed shifted from that particular range to any other, the filter coefficients changed to that particular band's coefficients dynamically.

Figure-9.1 shows the filter's output for a new and broken cutter at 1mm depth of cut. It is obvious from the results that as soon as the cutter breaks, the frequency strength of frequency components of interest increases many fold. This increase was used as a signal for alarm generation about the tool breakage. To further support the same concept, Figure-9.2 presents a much clearer picture.

The normal value of Relative Energy Index (REI) for a broken cutter is significantly higher (around 9-10 times) than the normal value of REI for a new cutter. Although it may be noted that due to the impulse response of the filter there is a settling time before reliable results may be obtained. This settling time is one time affair and in this particular design it is around 500msec.

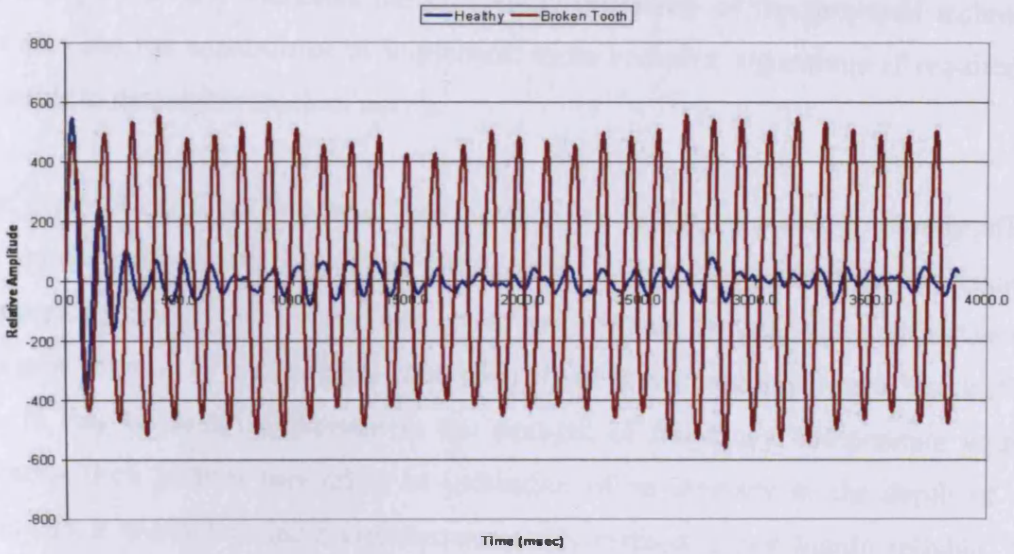


Figure-9.1, Filter's output for Spindle Load signal for healthy and broken cutters 1mm DOC.

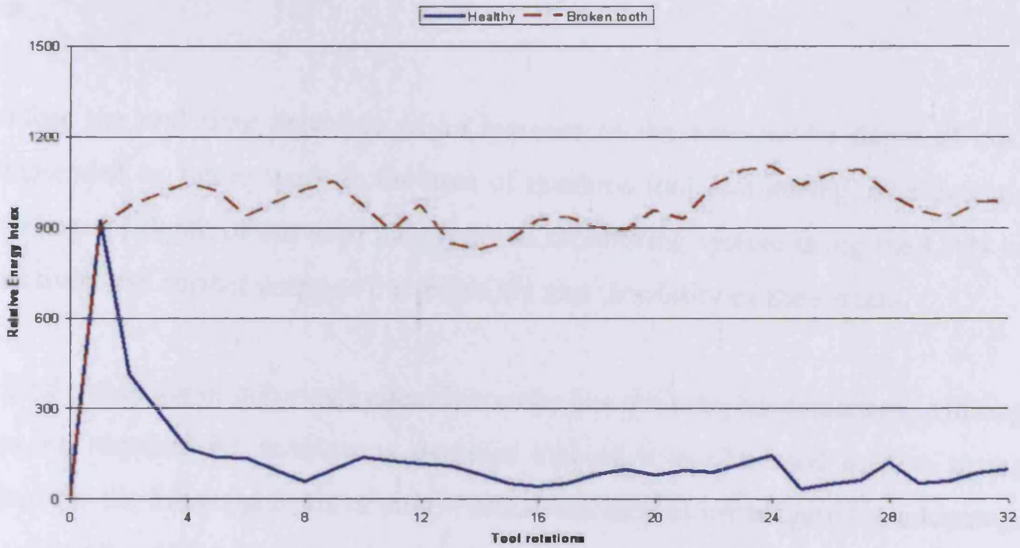


Figure-9.2, REI for a healthy and broken cutters at 1mm DOC

It is not a completely different research path to the one described in Chapter-5. The idea of digital IIR filters is simply a different approach to implement the parallel filtering technique. The parallel filtering technique as described in Chapter-5 is based on analogue filters whereas the one described here is based on digital filtering. It further proves that the idea of parallel filtering is a reliable approach for cutting tool breakage detection no matter which implementation methodology is selected. It was the basic testing of a proposed idea and therefore has not been implemented as an integral part of this research. It shows the possible avenues available for further research in this area by using the latest technology. The use of the available technology not only increases the processing efficiency of the proposed techniques but also has the capabilities to implement more complex algorithms if required for example to determine depth of cut etc.

The depth of cut is an important parameter in the cutting process. It directly affects the spindle load and the life of the cutting tool. The strength of monitored frequency components depends on the depth of cut to some extent. Despite of the importance of this area not a lot of research has been carried out in the past to estimate the depth of cut. In this research an increase in the strength of frequency components without affecting their pattern was taken as indication of an increase in the depth of cut. Although it worked in most circumstances this method is not highly reliable. The major reason supporting the argument is that any change in the hardness of the metal (particularly increased hardness) will have the same affect as an increase in the depth of cut.

Therefore the real time detection of an increase or decrease in the depth of cut is recommended as future work in the area of machine tool monitoring. The detection and linkage of depth of cut with the proposed monitoring system using the CAN bus connectivity can further enhance the reliability and flexibility of the system.

The third tier in the monitoring system hierarchy has not been implemented. Although it was not required for monitoring decision making it can be used as data storage medium for the future analysis of data. Further research to investigate the advantages versus overall cost for implementing this tier is also recommended.

The failure detection of any FEN has been implemented in this research. The parameter monitoring and decision making node sends messages to all FENs to detect their operational status. The status monitoring of the parameter monitoring node itself has not been implemented in this research because it was considered as the monitoring of the monitoring system. Using this approach will always increase the hierarchical tiers and increase overall cost and complicate the hardware unnecessarily. An analysis of the requirement to monitor the status of the parameter monitoring node is recommended.

It was observed during the testing of the system that FENs monitoring tooth rotation frequency, broken tooth frequency and spindle load variations provided highly reliable results. Although in the course of this research analysis of all possible signals/options was carried out but for system optimisation it is recommended that a monitoring system using only these three FENs be researched. If it proves successful the need for high sampling rate at time domain signal analysis nodes will be eliminated. This is due to the fact that there will be no need to cope with the high feedback rate of the speed signal as it will no more be monitored.

Application Specific Integrated Circuit (ASIC) design is a newly emerging and application intensive field. ASICs are the chips that have been built to act as a particular application. ASICs can consolidate the work of many chips into a single, smaller, faster package, reducing manufacturing and support costs while boosting the speed of the device built with them. ASIC design for such e-Monitoring applications is recommended to be investigated and its possibilities explored. Machine tool monitoring systems require a data acquisition system, a processor core, memory core, DSP core and communication protocol implementation. These requirements are general enough for investigating the potential applications of ASICs. Therefore it is recommended that:-

- A feasibility study of System On Chip (SoC) implementation of the machine tool condition monitoring be undertaken including, data acquisition core, processor core, DSP core and communication protocols.
- Research in the area of co-designing software and hardware functionalities in SoC design is also recommended.

REFERENCES

9.1 A. Habaibeh, N. Gindy "A new approach for systematic design of condition monitoring systems for milling processes" Journal of Materials Processing Technology 107 (2000) 243-251.

CHAPTER 10

CONCLUSION

10.1 Main Contributions of the Research

This research was aimed at developing intelligent and reliable signal analysis techniques for implementation on resource limited 8-bit microcontrollers for a machine tool condition monitoring system. The research has produced the following important contributions:-

- The application of two low complexity signal analysis techniques, one each for frequency and time domain analysis of the acquired signals that are capable of feature extraction to detect a tool breakage.
- Tooth breakage detection within two tool rotation by using the developed techniques.
- Achieving reliable results by using existing machine tool signals thus eliminating the requirements of additional sensors for tool breakage detection.
- A monitoring approach which keeps the hardware infrastructure independent from any major changes in the future. This is possible due to monitoring only frequencies of interest and signal variations for a complete tool rotation.
- The use of 8-bit microcontroller to implement these techniques in addition to providing the internet and GSM connectivity to the proposed system.
- The use of low cost communication mediums for both local and remote data/information transfer.
- The use of integrated system strategy for decision making which enhances the system reliability.
- The CAN bus connectivity to provide two wire communication to the entire hardware architecture.

Both signal analysis techniques have been intensively tested and the achieved results have been demonstrated for a range of different process parameters. The integration of both subsystems and the addition of some important features like internet and GSM connectivity have been reliably tested, verified and demonstrated. The overall cost effect index of the proposed system in comparison to the achieved results was found highly satisfactory.

10.2 Conclusions

The most important conclusion drawn from the research can be summarised as:-

- The main frequencies of interest in a machine tool condition monitoring system are tool rotation frequency, broken tooth frequency and tooth rotation frequency. The number of these frequencies is fixed (i.e. always three) and the values depend on the number of teeth in the cutter and the spindle rotation speed.
- The strength of these frequencies for healthy and broken cutters is significantly different and these variations can reliably be used to detect a tooth breakage.
- The energy variations in a tool rotation period are significantly different for a healthy and broken cutter. These variations can be reliably used to detect a tooth breakage.
- The system integration increases the overall reliability of a monitoring system.
- The proposed data analysis techniques can be implemented on resource limited 8-bit PIC18F458 microcontrollers.
- The PIC18F458 microcontrollers are reliable and flexible embedded devices for the implementation of reliable and cost effective machine tool condition monitoring system.
- Low cost embedded hardware is available and can be used to provide internet connectivity to such motoring systems.
- GSM connectivity can be provided using low cost hardware that provides multiple advantages to the monitoring system including an increase in overall flexibility.
- The depth of cut is an important process parameter in machining process and its automated detection is recommended.

- The PIC18F458 microcontroller is a highly multiplexed controller i.e. most of its port pins can be used for different applications depending upon the configuration of the pins. Such multiplexing features make the PIC microcontrollers adaptable to industrial monitoring application

Considering these points in more detail it is evident that the process information can be extracted from machine tool signals by analysing them in the time or frequency domain. Both domains clearly show the signal variations that can be used to detect a tooth breakage. Designing a monitoring system which uses information of process variation from both domains and cross verifies the results has a higher reliability. This monitoring strategy reduces the false alarms and increases the OEE.

The PIC18F458 microcontroller fulfils the requirements for the implementation of low-cost machine tool monitoring system. The PIC18F458 microcontroller uses multiplexed input and output functions and is capable of implementing the proposed monitoring techniques.

The designed monitoring system is a low cost solution as the count of external components in the final design is very low. Moreover the FENs are designed for multitasking i.e. data acquisition, processing and result/data communication. Although frequency domain signal analysis approach requires external analogue filter ICs (their cost is also very low) the time domain analysis technique is purely software based and does not require any external components. It was concluded that the best use of the microcontroller is based on using its embedded resources as used in this design (using single chip for multiple functions).

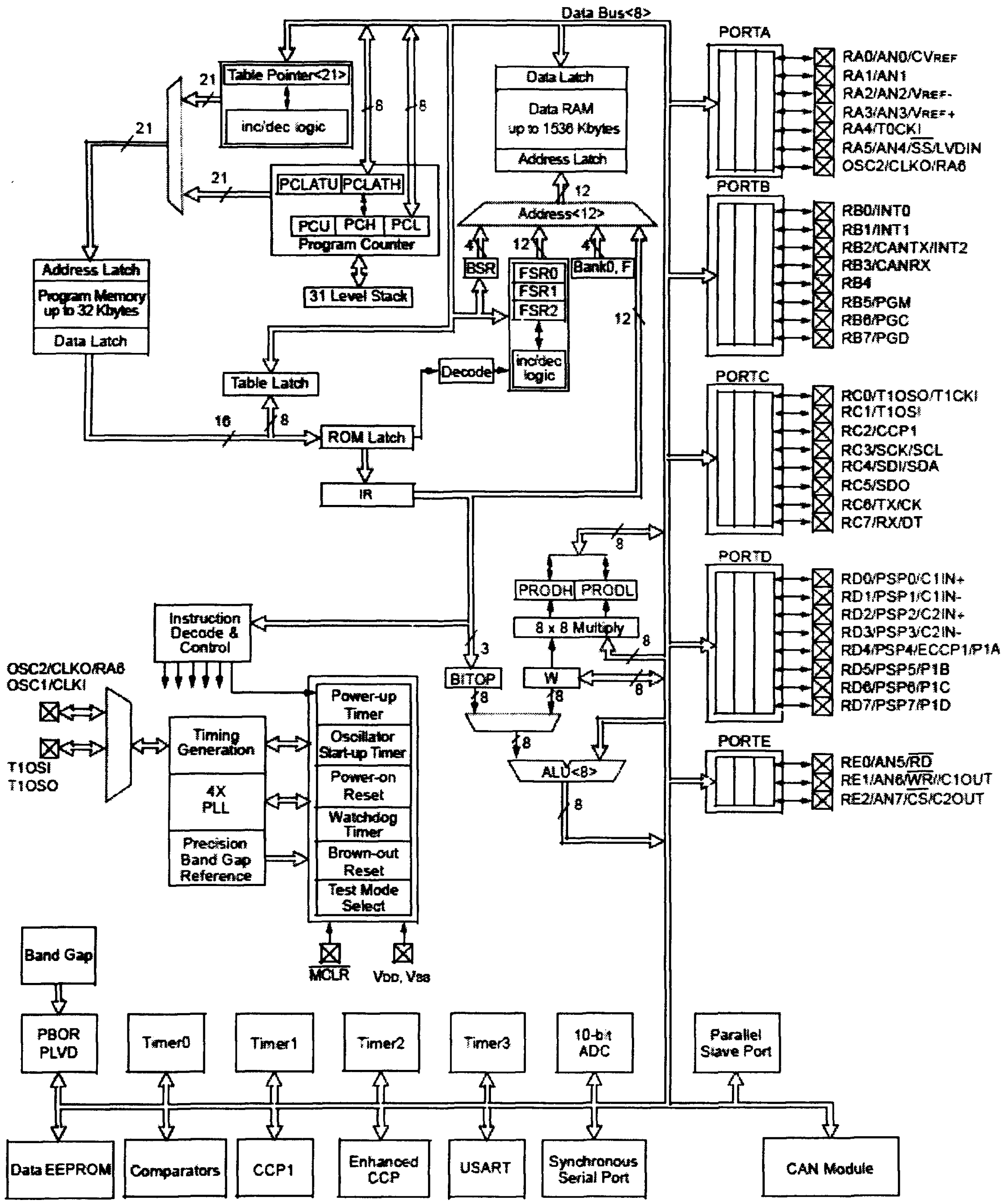
It is also concluded the CAN bus is a reliable and efficient communication medium and can be effectively used for communication among all monitoring nodes. The distributed approach used in this architecture represents an appropriate choice to achieve reliable results.

Based on the testing and verification of the proposed data analysis techniques, their implementation and the results obtained it is possible to conclude that the proposed monitoring system is capable of providing a low cost machine tool condition monitoring. It fulfils the main requirements by providing information for monitoring and maintenance activities. This information can be made available on the Internet or can be sent to mobile phones in the form of SMS. In comparison to the complexity of some tool monitoring systems, the proposed architecture provides a reliable yet easily implementable solution.

APPENDIX "A"

PIC 18F458 Microcontroller

Schematic Block Diagram



PIC18F458 Features

High-Performance RISC CPU:

- Linear program memory addressing up to 2 Mbytes
- Linear data memory addressing to 4 Kbytes
- Up to 10 MIPS operation
- DC – 40 MHz clock input
- 4 MHz-10 MHz oscillator/clock input with PLL active
- 16-bit wide instructions, 8-bit wide data path
- Priority levels for interrupts
- 8 x 8 Single-Cycle Hardware Multiplier

Peripheral Features:

- High current sink/source 25 mA/25 mA
- Three external interrupt pins
- Timer0 module: 8-bit/16-bit timer/counter with 8-bit programmable prescaler
- Timer1 module: 16-bit timer/counter
- Timer2 module: 8-bit timer/counter with 8-bit period register (time base for PWM)
- Timer3 module: 16-bit timer/counter
- Secondary oscillator clock option – Timer1/Timer3
- Capture/Compare/PWM (CCP) modules; CCP pins can be configured as:
  - Capture input: 16-bit, max resolution 6.25 ns
  - Compare: 16-bit, max resolution 100 ns (TCY)
  - PWM output: PWM resolution is 1 to 10-bit
Max. PWM freq. @:8-bit resolution = 156 kHz
10-bit resolution = 39 kHz
- Enhanced CCP module which has all the features of the standard CCP module, but also has the following features for advanced motor control:
  - 1, 2 or 4 PWM outputs
  - Selectable PWM polarity
  - Programmable PWM dead time
- Master Synchronous Serial Port (MSSP) with two modes of operation:
  - 3-wire SPI™ (Supports all 4 SPI modes)
  - I^2C™ Master and Slave mode
- Addressable USART module:
  - Supports interrupt-on-address bit

Advanced Analog Features:

- 10-bit, up to 8-channel Analog-to-Digital Converter module (A/D) with:
  - Conversion available during Sleep
  - Up to 8 channels available
- Analog Comparator module:
  - Programmable input and output multiplexing
- Comparator Voltage Reference module
- Programmable Low-Voltage Detection (LVD) module:
  - Supports interrupt-on-Low-Voltage Detection
- Programmable Brown-out Reset (BOR)

CAN bus Module Features:

- Complies with ISO CAN Conformance Test
- Message bit rates up to 1 Mbps
- Conforms to CAN 2.0B Active Spec with:
  - 29-bit Identifier Fields
  - 8-byte message length
  - 3 Transmit Message Buffers with prioritization
  - 2 Receive Message Buffers
  - 6 full, 29-bit Acceptance Filters
  - Prioritization of Acceptance Filters
  - Multiple Receive Buffers for High Priority Messages to prevent loss due to overflow
  - Advanced Error Management Features

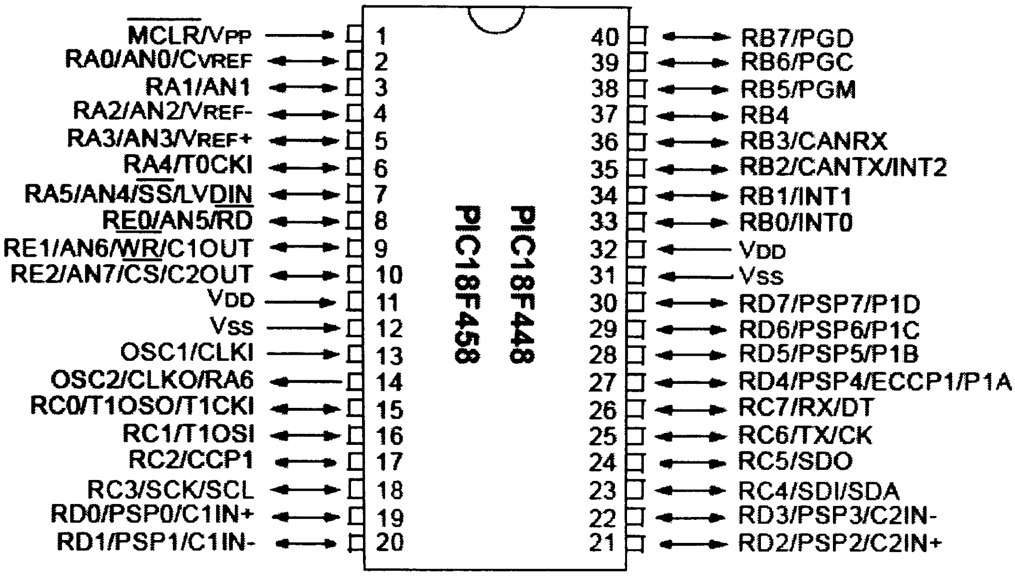
Special Microcontroller Features:

- Power-on Reset (POR), Power-up Timer (PWRT) and Oscillator Start-up Timer (OST)
- Watchdog Timer (WDT) with its own on-chip RC oscillator
- Programmable code protection
- Power-saving Sleep mode
- Selectable oscillator options, including:
  - 4x Phase Lock Loop (PLL) of primary oscillator
  - Secondary Oscillator (32 kHz) clock input
- In-Circuit Serial Programming™ (ICSP™) via two pins

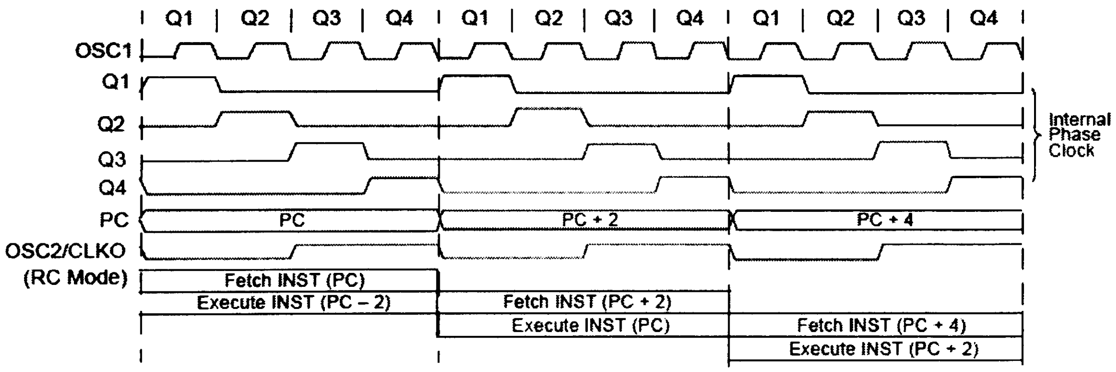
Flash Technology:

- Low-power, high-speed Enhanced Flash technology
- Fully static design
- Wide operating voltage range (2.0V to 5.5V)
- Industrial and Extended temperature ranges

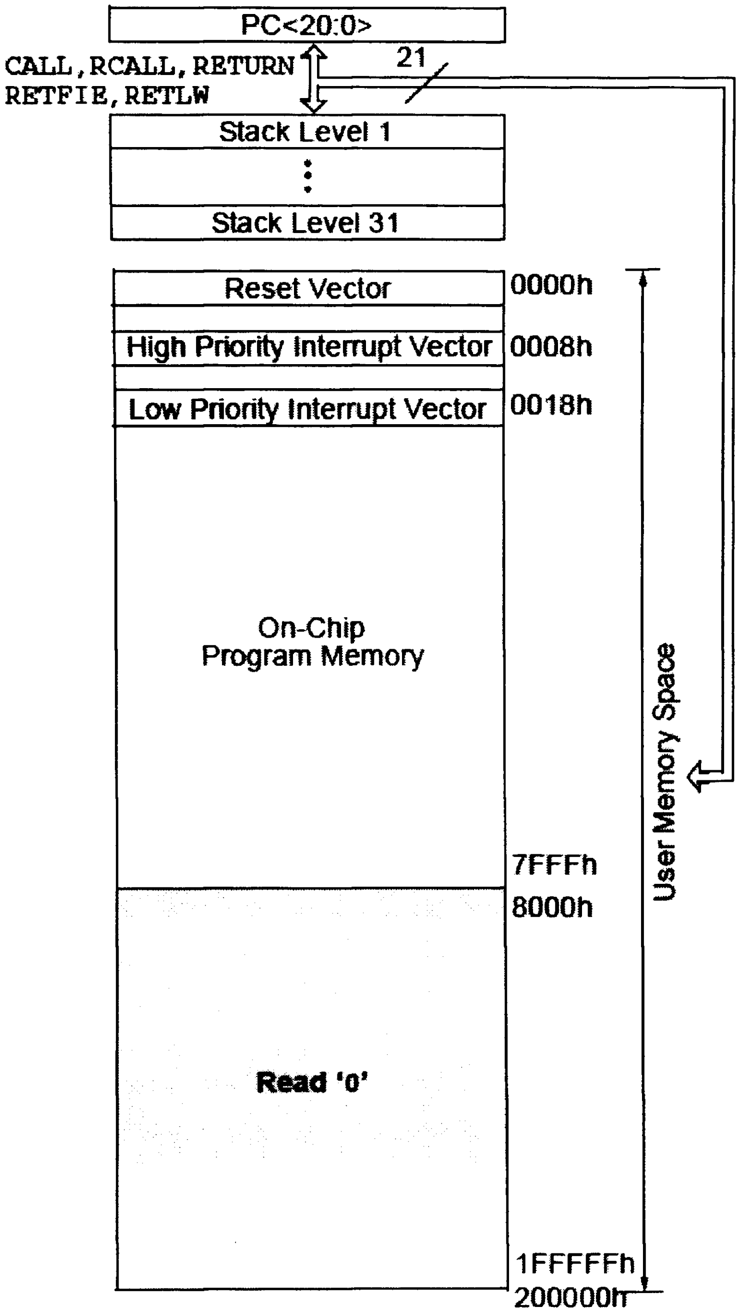
Pin Diagram



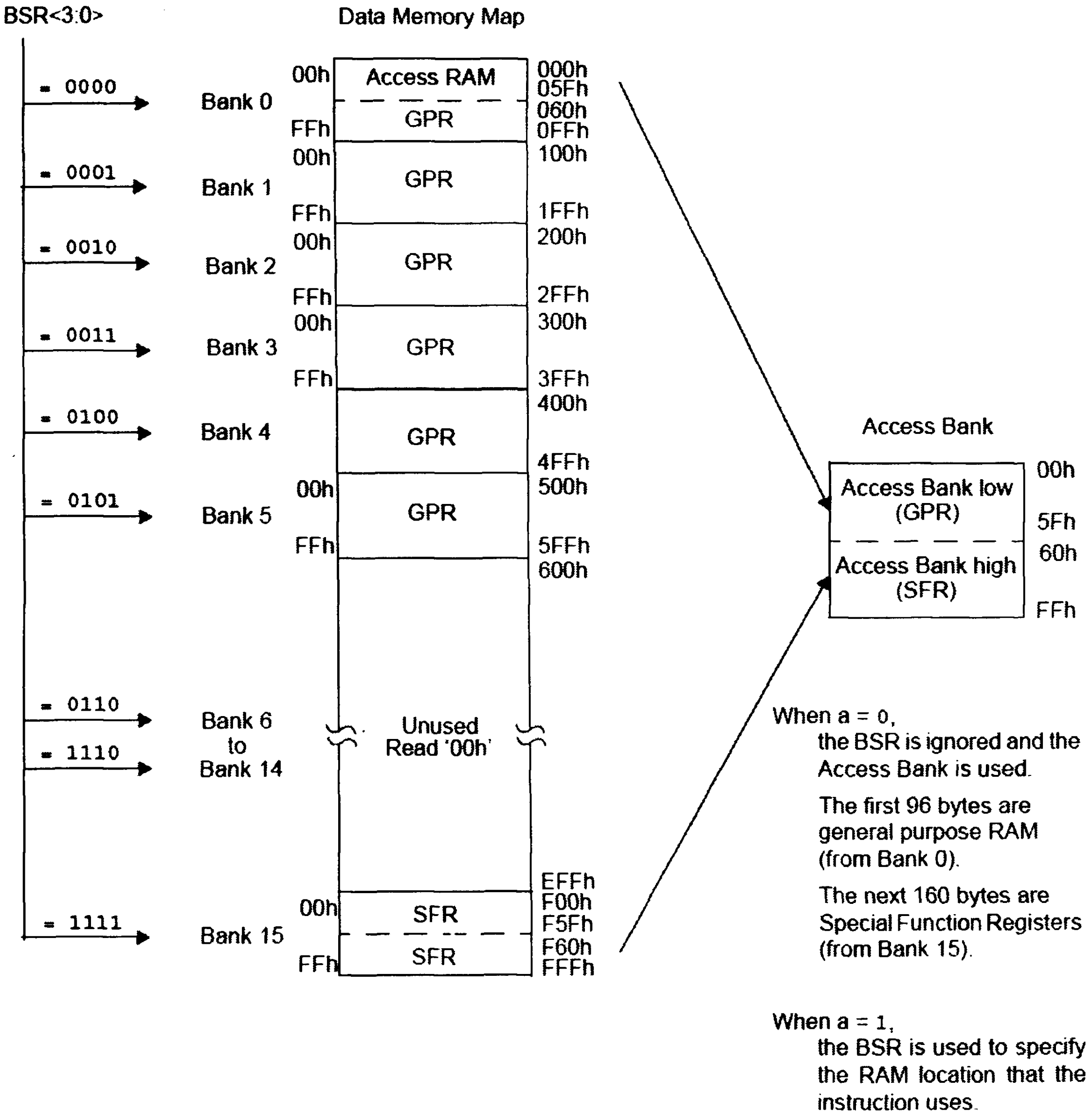
Pipelined Execution of Code



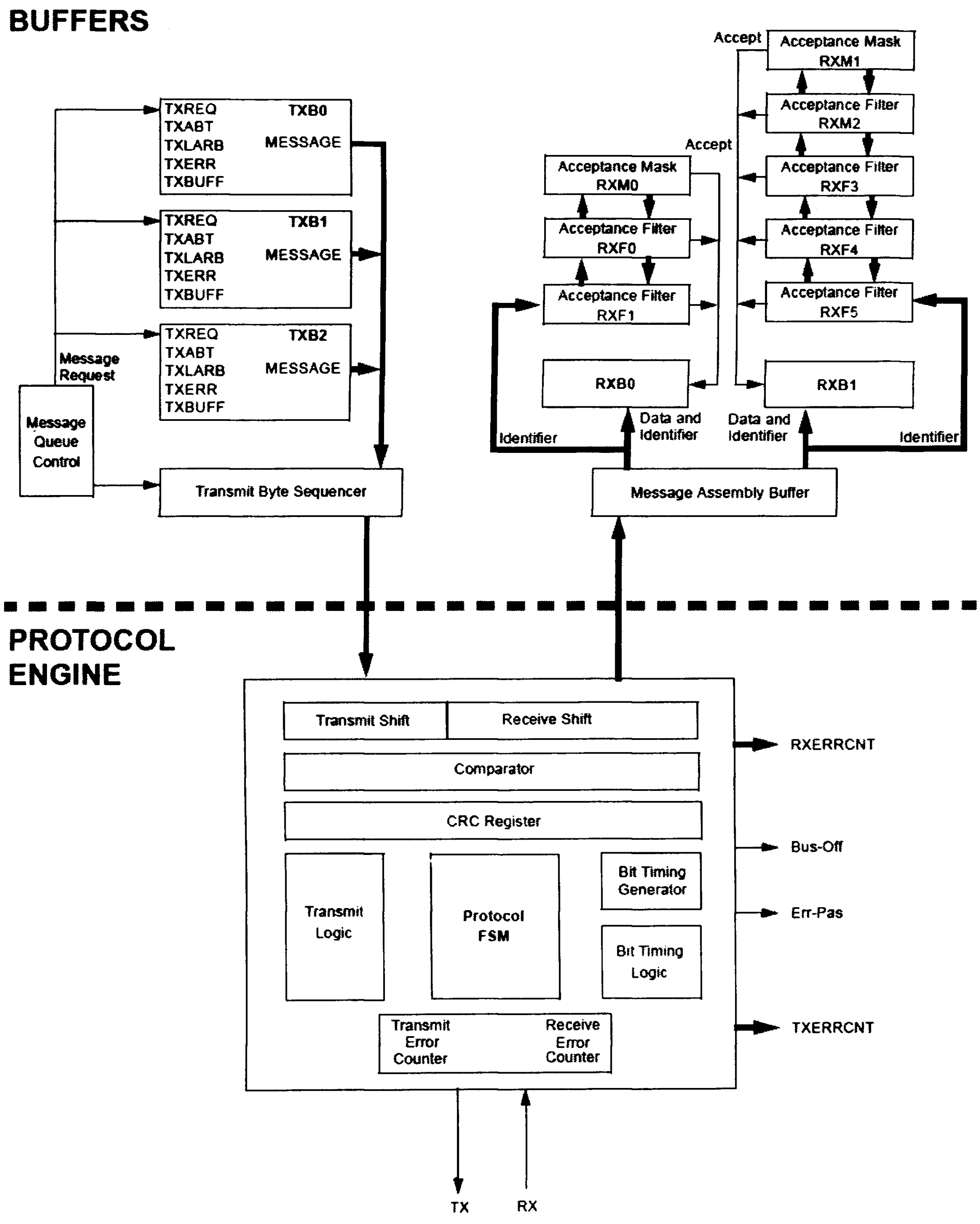
Program Memory Map



Data Memory Map



CAN Buffers and Potocol Engine

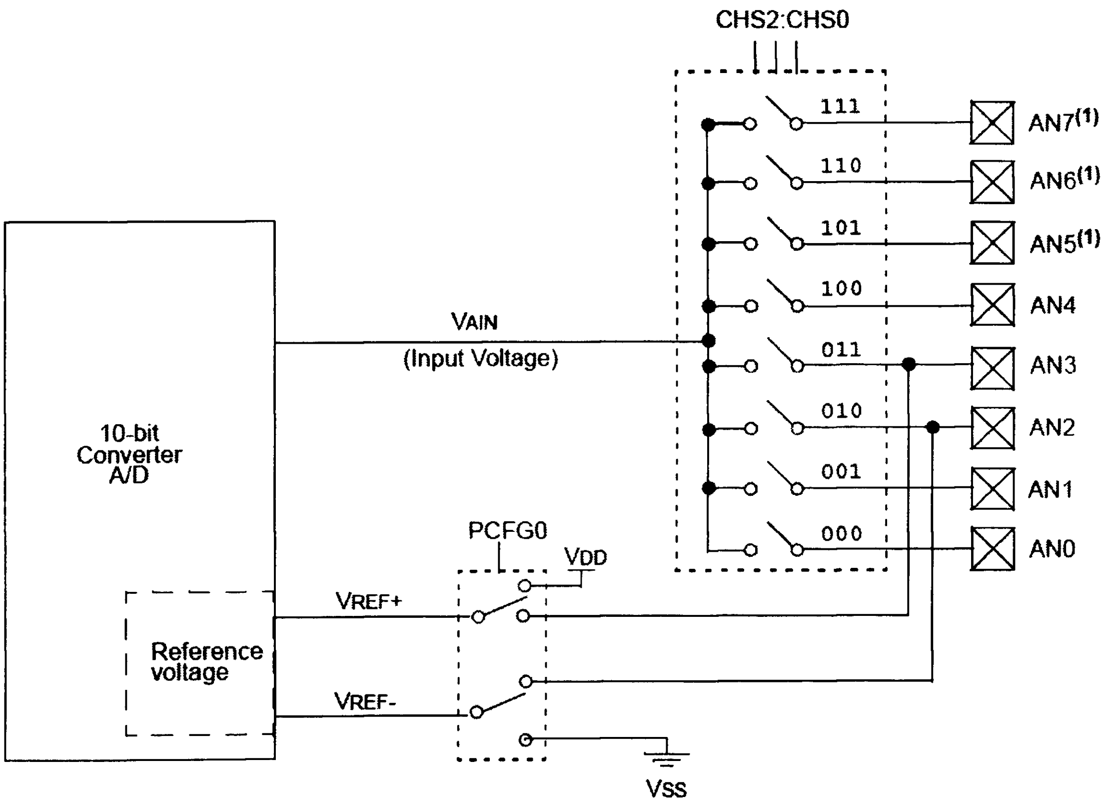


CAN Filter/Mask Truth Table

Mask bit n	Filter bit n	Message Identifier bit n001	Accept or Reject bit n
0	x	x	Accept
1	0	0	Accept
1	0	1	Reject
1	1	0	Reject
1	1	1	Accept

Legend: x = don't care

A/D Block Diagram



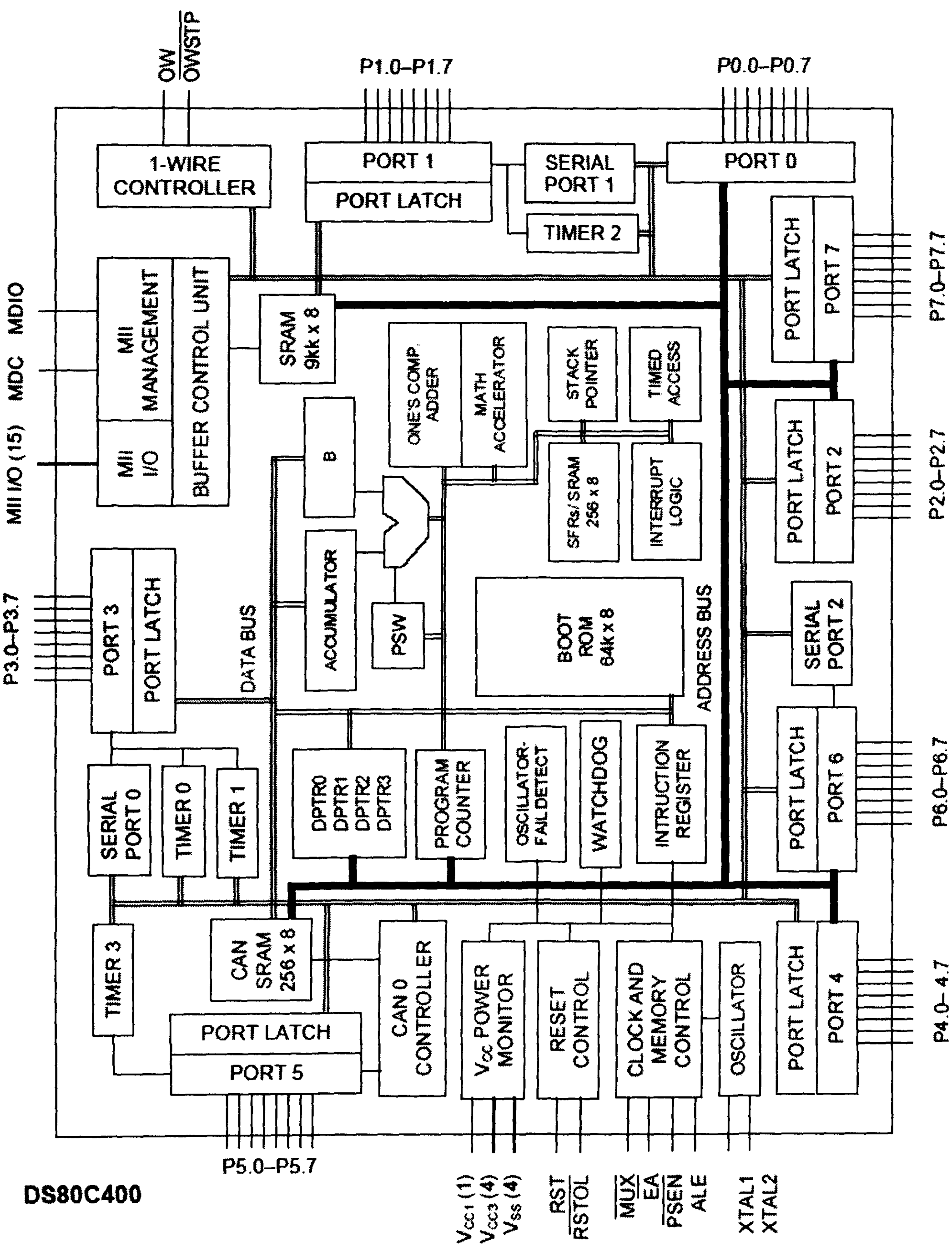
Note 1: Channels AN5 through AN7 are not available on PIC18F2X8 devices.

2: All I/O pins have diode protection to VDD and VSS.

APPENDIX "B"

DS80C400 Microcontroller

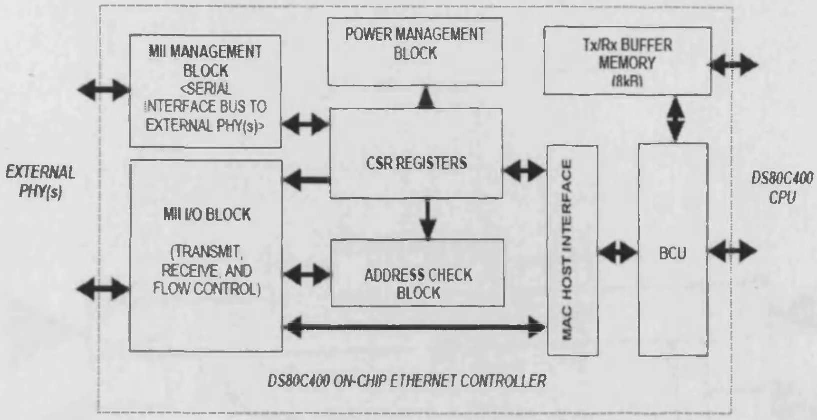
Schematic block diagram



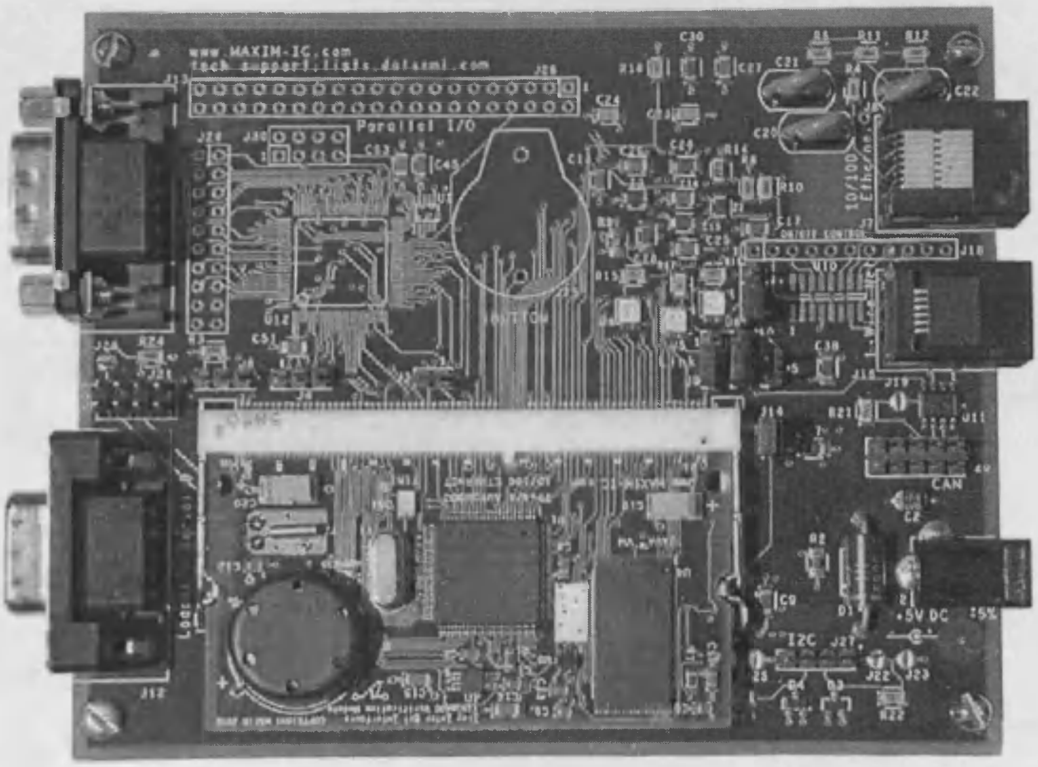
Microcontroller Features

- **High-Performance Architecture**
  - Single 8051 Instruction Cycle in 54ns
  - DC to 75MHz Clock Rate
  - Flat 16MB Address Space
  - Four Data Pointers with Auto-Increment/Decrement and Select-Accelerate Data Movement, 16/32-Bit Math Accelerator
- **Multi-tiered Networking and I/O**
  - 10/100 Ethernet Media Access Controller (MAC)
  - CAN 2.0B Controller
  - 1-Wire Net Controller
  - Three Full-Duplex Hardware Serial Ports
  - Up to eight Bidirectional 8-Bit Ports (64 Digital I/O Pins)
- **Robust ROM Firmware**
  - Supports Network Boot Over Ethernet Using DHCP and TFTP
  - Full, Application-Accessible TCP/IP Network Stack
  - Supports IPv4 and IPv6
  - Implements UDP, TCP, DHCP, ICMP, and IGMP
  - Pre-emptive, Priority-Based Task Scheduler
- **10/100 Ethernet MAC**
  - Low-Power Operation
  - 8kB On-Chip Tx/Rx Packet Data Memory with Buffer Control Unit reduces load on CPU
  - Half- or Full-Duplex operation with flow control
  - Multicast/Broadcast Address Filtering with VLAN Support
- **Full-Function CAN 2.0B Controller**
  - 15 Message Centres
  - Supports Standard (11-Bit) and Extended (29-Bit) identifiers and global masks
  - Media Byte Filtering to Support DeviceNet™, SDS, and Higher Layer CAN Protocols
  - Auto-Baud Mode and SIESTA Low-Power Mode

- **Integrated Primary System Logic**
  - o 16 Total Interrupt Sources with Six External
  - o Four 16-Bit Timer/Counters
  - o 2x/4x Clock Multiplier Reduces Electromagnetic Interference (EMI)
  - o Programmable Watchdog Timer
  - o Oscillator-Fail Detection
- **Advanced Power Management**
  - o Energy Saving 1.8V Core
  - o 3.3V I/O Operation, 5V Tolerant
  - o Power-Management, Idle, and Stop Mode Operations with Switchback Feature
  - o Ethernet and CAN Shutdown Control for Power Conservation
- **Enhanced Memory Architecture**
  - o Selectable 8/10-Bit Stack Pointer for High-Level Language Support
  - o 1kB Additional On-Chip SRAM Usable as Stack/Data Memory
  - o Merged Program/Data Memory Space Allows In-System Programming
  - o Defaults to True 8051-Memory Compatibility

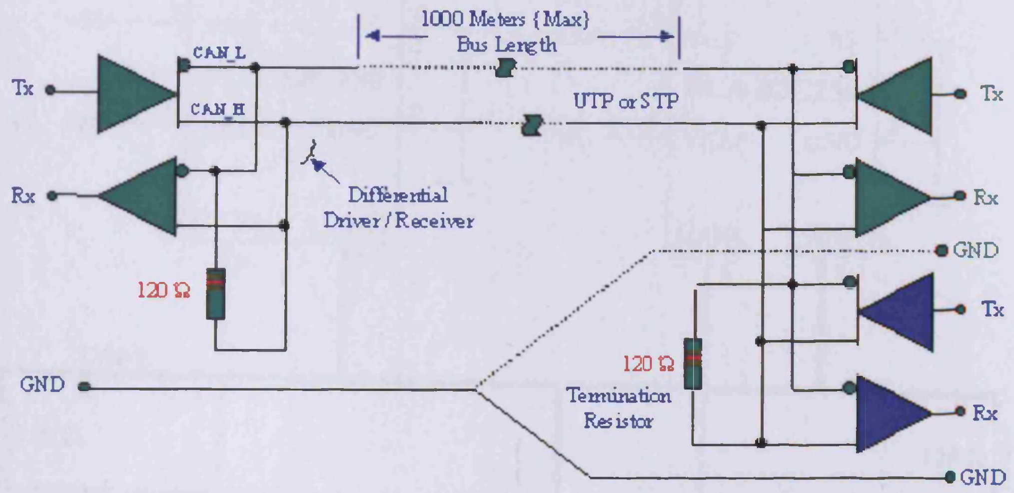


Block Diagram of Ethernet Controller

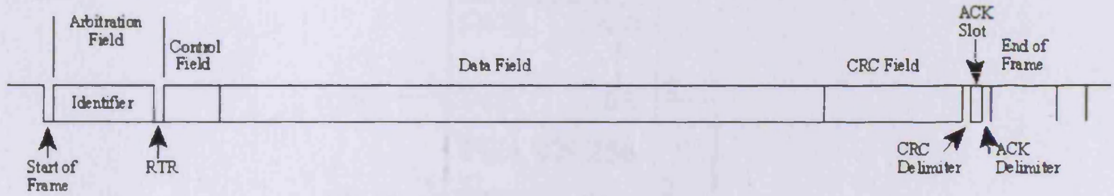


TINI Stick Mounted on Socket

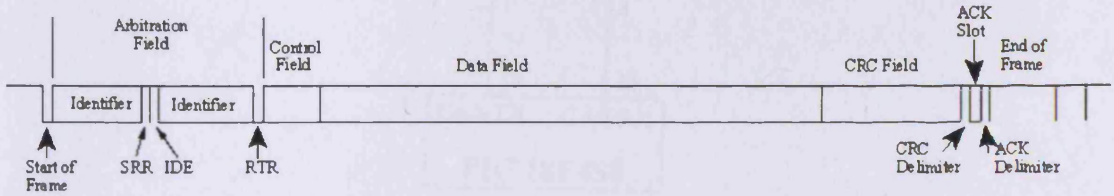
APPENDIX "C"



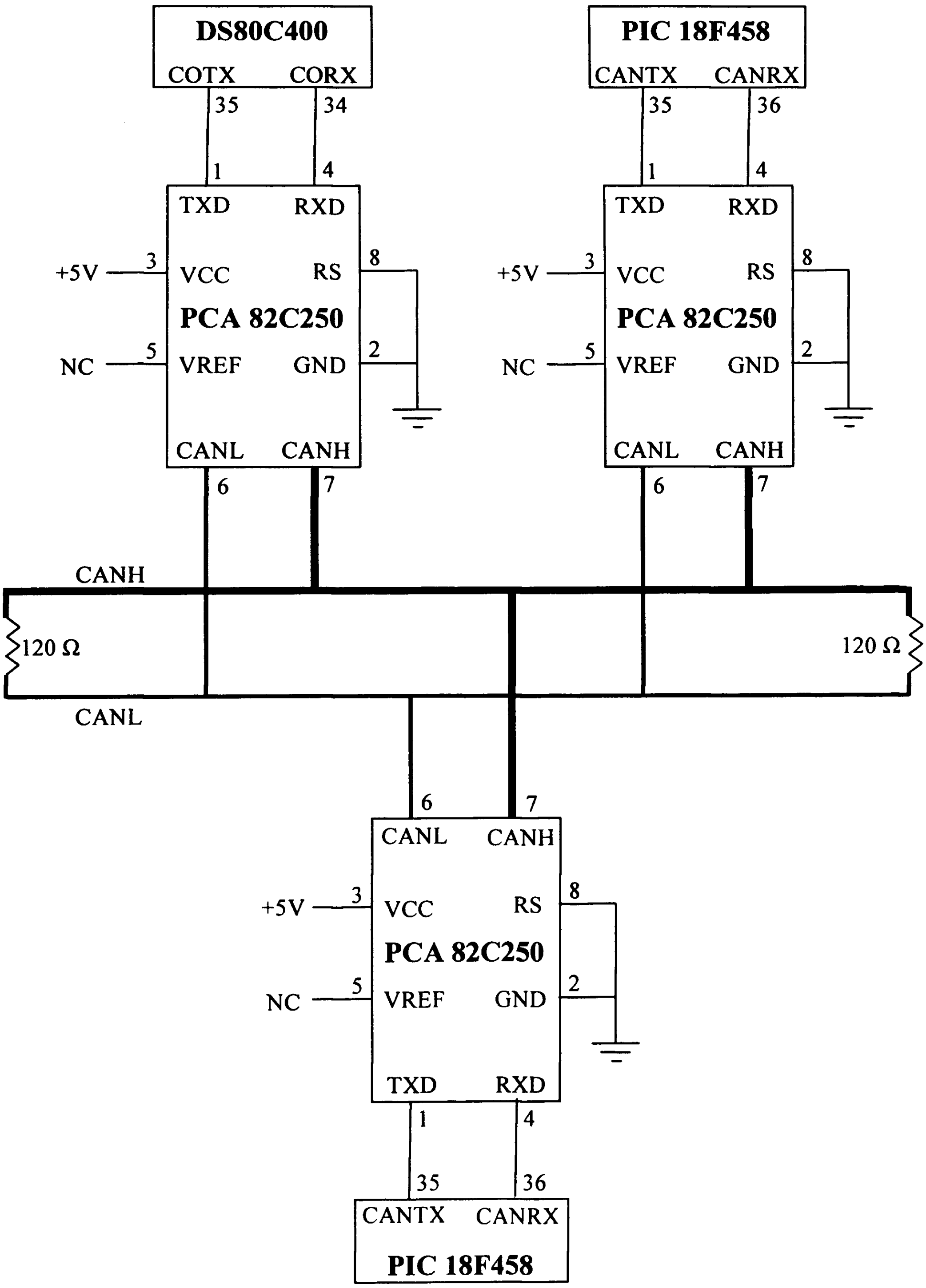
CAN Bus



CAN 2.0A - Standard CAN Data Frame

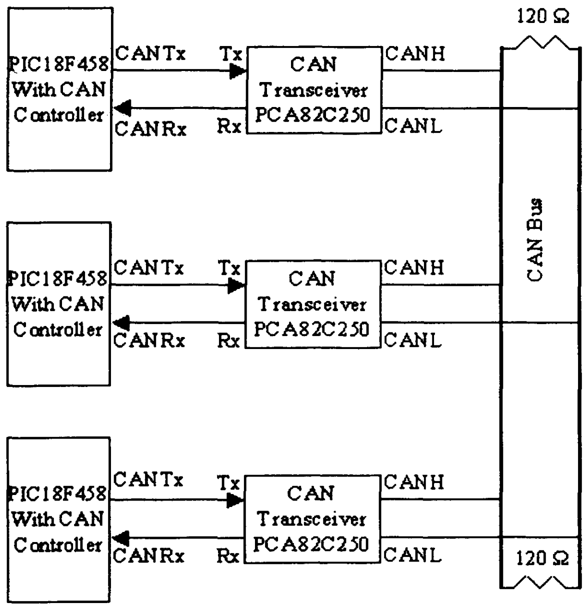


CAN 2.0B - Extended CAN Data Frame



CAN Bus Connections

Initialisation and Messaging in a Three Nodes CAN Network



Block Diagram of a 3 Node Network.

Initialisation Routine

An example setting is shown in the following code.

```
BCF       TRISB,2;CANTX
BSF       TRISB,3;CANRX
MOVLW     H'80'
MOVWF     CANCON      ;Configuration mode
CLRF      CANSTAT
CLRF      COMSTAT
MOVLW     H'20'       ;Disable CAN capture (Don't use RC2 pin)
MOVWF     CIOCON      ;Tx pin High when inactive
```

Setting for CAN baud rate Registers for 125000 bps, At 40MHz Oscillator Frequency.

```
MOVLW     H'49'       ;Tq = (2*10)/Fosc
MOVWF     BRGCON1     ;Sync jump width time = 2*Tq
MOVLW     H'AB'       ;Propagation time = 4*Tq, Sample once
MOVWF     BRGCON2     ;Phase seg1 time = 6*Tq, Max of IPT & PHEG1
MOVLW     H'03'       ;Phase seg2 time = 4*Tq
MOVWF     BRGCON3     ;CAN not used for wake-up
```

Transmit buffers, receive buffers, filters and masks are then initialised as required. After completing the initialisation, CAN may be set to operate in normal mode by clearing the CANCON register. If a message is now received on CAN bus, RXBnIF bit will be set in PIR3 register. An interrupt will also be generated, if enabled.

Let us suppose that Node 1 wants to transmit a message using transmit buffer 0. It will execute the following example code.

```
BTFSC  TXB0CON,TXREQ,BANKED    ;Any pending transmission?
BRA    $-2                     ;Wait for completion
BSF    TXB0CON,TXREQ,BANKED
BTFSS  PIR3,TXB0IF             ;Wait until transmission completed
BRA    $-2
```

The transmitted message will be received by the other two nodes. The identifier bits reaching the second stage will be matched with corresponding bits of receive filters. Suppose it does not match with any of the filters in Node 2. The node 2 will discard the message as it is not interested in this type of messages. Suppose the identifier bits match with a receive filter for receive buffer 0 in Node 3. This means that Node 3 is interested in receiving this message. Bit RXB0IF will be set in register PIR3 to indicate reception of the message. I Filter hit bits in RXBnCON register will show which filter has accepted the message. Node 3 will be executing the following example code.

```
Loop
        BTFSC  PIR3,RXB0IF        ;Any message received?
        GOTO   Recv               ;YES, go to receive message
        BRA    Loop               ;No, check again
Recv
        ;Do whatever is required with the received message here
        BCF    PIR3,RXB0IF        ;Clear in software
        BCF    RXB0CON,RXFUL      ;Clear in software
```

RXB0IF and RXFUL bits are to be cleared in software to enable next reception in this receive buffer. This gives a protection from a new message accidentally overwriting the old one.

APPENDIX "D"

System Related Details

FEN Main Loop

```
Main
        ;Check if a new CAN message is available
        MOVF            CAN_RCount,W
        CPFSEQ          CAN_WCount
        CALL            CAN_PROC

        ;Check if a new sample is available
        ;FSR0 and FSR1 (writer and reader)
        MOVF            FSR0H,W
        CPFSEQ          FSR1H
        GOTO            New_Sample
        MOVF            FSR0L,W
        CPFSEQ          FSR1L
        GOTO            New_Sample
        GOTO            No_Sample       ;No new sample available for processing

New_Sample
        ;Process the new sample
        CALL    Process_Sample

No_Sample
        GOTO    Main
```

FEN CAN Initialisations

```
        BCF             TRISB,2         ;CANTX
        BSF             TRISB,3         ;CANRX

        ;Setting for CAN control registers
        MOVLW           H'80'
        MOVWF           CANCON          ;Configuration mode
        CLRF            CANSTAT
        CLRF            COMSTAT

        ;Setting for CAN I/O control register
        MOVLW           H'20'           ;Disable CAN capture (Don't use RC2 pin)
        MOVWF           CIOCON          ;Tx pin High when inactive

        ;Setting for CAN baud rate Registers for 125000 bps for 40 MHz oscillator
        MOVLW           H'49'           ;Tq = (2*1)/Fosc, Prescaler is 10 for 40 MHz crystal
        MOVWF           BRGCON1         ;Sync jump width time = 2*Tq
```

```
        MOVLW      H'AB'            ;Propagation time = 4*Tq, Sample once
        MOVWF      BRGCON2          ;Phase seg1 time = 6*Tq
        MOVLW      H'04'            ;Phase seg2 time = 5*Tq
        MOVWF      BRGCON3          ;CAN not used for wake-up

;Setting for CAN transmit registers
;Transmit Buffer 0
        MOVLW      H'03'
        MOVWF      TXB0CON,BANKED       ;Priority level 3 (highest priority)
        MOVLW      H'06'                ;EID28-EID21
        MOVWF      TXB0SIDH,BANKED
        MOVLW      H'08'
        MOVWF      TXB0SIDL,BANKED      ;Extended identifier and EID20-EID16
        MOVLW      NodeNum              ;NodeNum defined for each node
        MULLW      D'16'                ;Multiply node number with 16
                                    ;(lower nibble --> higher nibble in PRODL register)
        MOVF       PRODL,W              ;Move result in W
        ADDLW      D'01'                ;Make SUIN the destination
        MOVWF      TXB0EIDH,BANKED      ;EID15-EID8
        MOVLW      H'00'
        MOVWF      TXB0EIDL,BANKED      ;EID7-EID0
        MOVLW      H'00'
        MOVWF      TXB0DLC,BANKED       ;TXRTR bit clear, 0 data bytes

;Setting for CAN receive registers
;Receive Buffer 0
        MOVLW      H'40'
        MOVWF      RXB0CON              ;Receive valid messages with extended identifier

;Set Receive Mask 0 to check only the destination node number (same for all FENs)
        MOVLW      H'00'
        MOVWF      RXM0SIDH,BANKED      ;EID28-EID21
        MOVLW      H'00'
        MOVWF      RXM0SIDL,BANKED      ;EID20-EID16
        MOVLW      H'0F'
        MOVWF      RXM0EIDH,BANKED      ;EID15-EID8
        MOVLW      H'00'
        MOVWF      RXM0EIDL,BANKED      ;EID7-EID0

;Set Receive Filter 0 to accept messages for current node only
        MOVLW      H'00'
        MOVWF      RXF0SIDH,BANKED      ;EID28-EID21
        MOVLW      H'08'
        MOVWF      RXF0SIDL,BANKED      ;Extended identifier, EID20-EID16
        MOVLW      NodeNum              ;Current node
        MOVWF      RXF0EIDH,BANKED      ;EID15-EID8
        MOVLW      H'00'
        MOVWF      RXF0EIDL,BANKED      ;EID7-EID0

;Set Receive Filter 1 to accept broadcast messages (same for all FENs)
        MOVLW      H'00'
        MOVWF      RXF1SIDH,BANKED      ;EID28-EID21
        MOVLW      H'08'
        MOVWF      RXF1SIDL,BANKED      ;Extended identifier, EID20-EID16
        MOVLW      H'00'                ;For broadcast message
        MOVWF      RXF1EIDH,BANKED      ;EID15-EID8
        MOVLW      H'00'
        MOVWF      RXF1EIDL,BANKED      ;EID7-EID0
;--------------------------------------------------------
```

```
        CLRF        CAN_RCount
        CLRF        CAN_WCount
        LFSR        FSR2,400H       ;Start address of CAN buffer for , 12 bit operation

        ;CAN interrupt configuration
        BCF         PIR3,RXB0IF     ;Clear to initialize
        MOVLW       01H             ;Set high priority for RXB0 interrupt
        MOVWF       IPR3
        MOVLW       01H             ;Enable RXB0 interrupt
        MOVWF       PIE3

;--------------------------------------------------------
        BSF         RCON,IPEN       ;Enable interrupt priorities
        MOVLW       0C0H            ;Enable all high & low priority interrupts globally
        MOVWF       INTCON

        MOVLW       H'00'
        MOVWF       CANCON          ;Normal mode for CAN
```

Some Useful Slush Commands

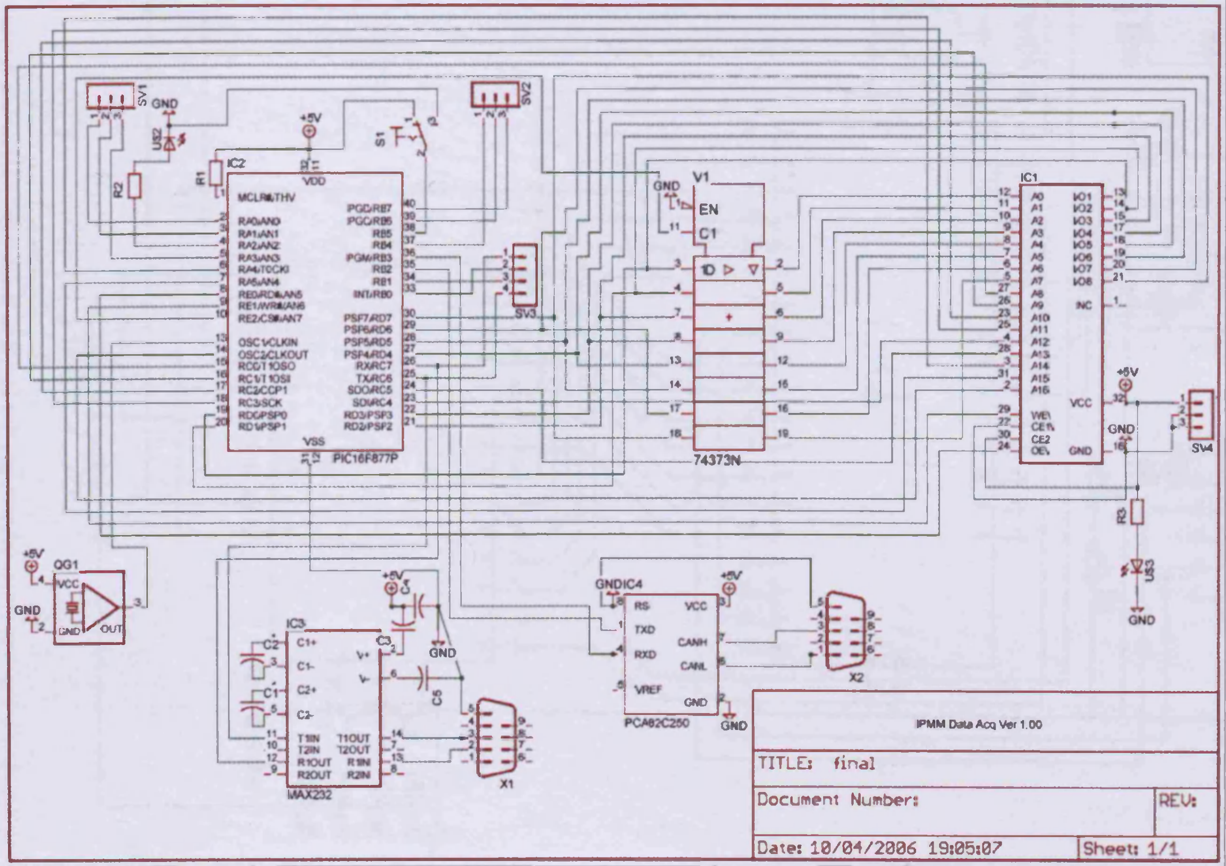
Command	Description
date	Set the system date and time
del	Remove the named file
ftp	Connect to a remote FTP server
help	Display usage information for Slush commands
ipconfig	Configures and displays the network settings
java	Executes a Java program
kill	Kill the identified process
ls	List the contents of the current directory
md	Make the named directory
netstat	Displays all TCP connections
passwd	Set the password for the specified user
pwd	Present working directory
rd	Remove the named directory
sendmail	Send email to designated recipients
startserver	Start up the specified server
stopserver	Shut down the specified server
useradd	Add a new user account
userdel	Delete the specified user account
who	List all currently logged in users

Some Useful AT Commands

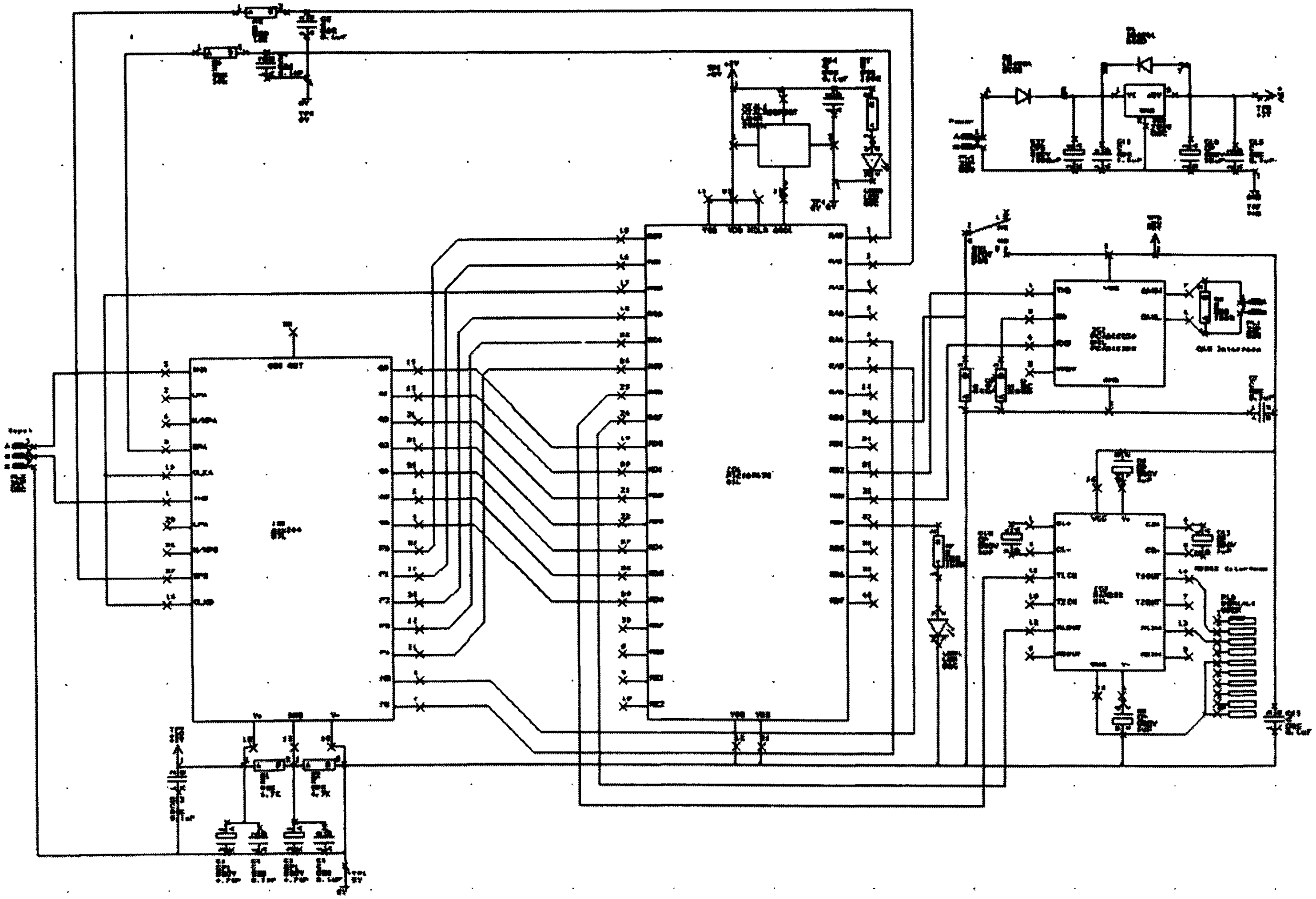
Command	Description
AT	Attention command
AT&F	Set to factory default
AT+CHUP	Hang up call
AT+CLCK	Lock facility (including all incoming barring services 'AC')
AT+CLIP	Enable/disable calling line identification (CLI)
AT+CMAR	Master reset
AT+CMGF	Select message format
AT+CMGS	Send message
AT+CMSS	Send message from storage
AT+CSCS	Select character set
AT+CSIL	Silent mode
AT+CSQ	Signal strength

APPENDIX "E"

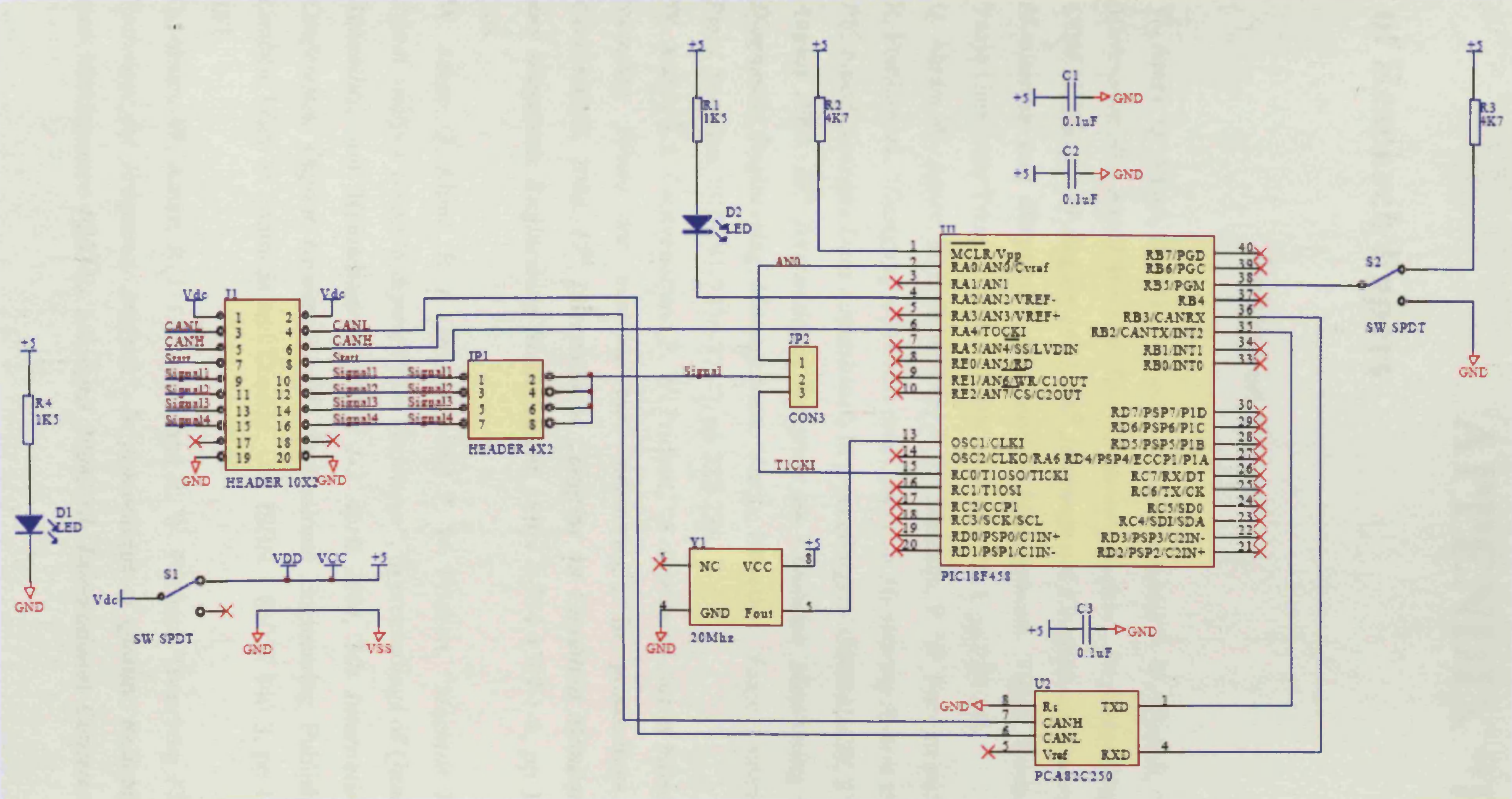
TREE Data Analysis FEN (with external memory)



Sweeping Filter FEN Circuit Diagram



TREE FEN (without external memory)



APPENDIX "F"

List of Research Papers

Published Papers

1. **W. Amer**, Q. Ahsan, R. I. Grosvenor, A. D. Jennings and P. W. Prickett, "*PIC Micro-controller based Machine Tool Monitoring System*", ***In proceedings of COMADEM, 27-29 August 2003, 16th International Congress on Condition Monitoring and Diagnostic Engineering Management***. Vaxjo, Sweeden. Vaxjo University Press, Sweeden. ISBN 91-7636-376-7, pp 219-225.
2. Q. Ahsan, **W. Amer**, R. I. Grosvenor, A. D. Jennings, P. W. Prickett and M. R. Frankowiak, "*Design of a Process and Condition Monitoring System using PIC based Analogue Data Acquisition*", In proceedings of ***COMADEM, 27-29 August 2003, 16th International Congress on Condition Monitoring and Diagnostic Engineering Management***. Vaxjo, Sweeden. Vaxjo University Press, Sweeden. ISBN 91-7636-376-7, pp 227-235.
3. **W. Amer**, R. I. Grosvenor and P. W. Prickett, "*A distributed system based on Sweeping Filters for machine tool monitoring*", In proceedings of ***COMADEM, 2004, 17th International Congress on Condition Monitoring and Diagnostic Engineering Management***. ISBN 0-954 1307-1-5, pp 195-203.
4. **W. Amer**, Q. Ahsan, R. I. Grosvenor and P. W. Prickett, "*Machine Tool Signal Analysis Using Sweeping Filter Technique*", In proceedings of ***Quality, Reliability, and Maintenance (QRM), 1-2 April 2004, 5th International Conference. Oxford University, UK***. Professional Engineering Publishing Limited, Bury St Edmunds and London, UK. ISBN 1 86058 440 3, pp 189-192.
5. Q. Ahsan, **W. Amer**, R. I. Grosvenor and P. W. Prickett, "*Sweeping Filter Technique for Frequency Analysis*", ***In proceedings of Quality, Reliability, and Maintenance (QRM), 1-2 April 2004, 5th International Conference.***

Oxford University, UK. Professional Engineering Publishing Limited, Bury St Edmunds and London, UK. ISBN 1 86058 440 3, pp 185-188.

6. **W. Amer**, Q. Ahsan, R. I. Grosvenor and P. W. Prickett, "*Machine Tool Condition Monitoring System using Tooth Rotation Energy Estimation (TREE) Technique*". In proceedings of ***10th IEEE International Conference on Emerging Technologies and Factory Automation, 19-22 September 2005. Catania, Italy***. ISBN 0-7803-9402-X, pp 529-536.
7. Q. Ahsan, **W. Amer**, R. I. Grosvenor and P. W. Prickett, "*A Compact Monitoring System for Process Valves*". In proceedings of ***10th IEEE International Conference on Emerging Technologies and Factory Automation, 19-22 September 2005. Catania, Italy***. ISBN 0-7803-9402-X, pp 1043-1046.
8. **W. Amer**, R. I. Grosvenor and P. W. Prickett, "Sweeping *filters and Tooth Rotation Energy Estimation (TREE) techniques for machine tool condition monitoring*", ***International Journal of Machine Tools & Manufacture 46 (2006) 1045–1052.***
9. Q. Ahsan, **W. Amer**, R. A. Siddiqui, M. Al-Yami, R. I. Grosvenor and P. W. Prickett, "*Distributed Process Monitoring and Management*", In proceedings of ***IEEE International Conference on Engineering and Intelligent Systems, 22-23 April 2006. Islamabad, Pakistan.***

Accepted for Publication

1. **W. Amer**, R.I. Grosvenor, P.W. Prickett, "*Machine Tool Condition Monitoring using Sweeping Filter Techniques*", Submitted for Publication in the ***Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering.***

Submitted for Publication

1. R. A. Siddiqui, **W. Amer**, Q. Ahsan, R. I. Grosvenor and P. W. Prickett. Multi-band Infinite Impulse Response Filtering using Microcontrollers for e-

Monitoring Applications. Submitted for Publication in the ***Journal of Microprocessors and Microsystems***.