THE DESIGN OF AN EFFECTIVE SENSOR FUSION MODEL FOR CONDITION MONITORING SYSTEMS OF TURNING PROCESSES

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Abstract

High energy price and the increasing requirements of quality and low cost of products have created an urgent need to implement new technologies in current automated manufacturing environments. Condition monitoring systems of manufacturing processes have been recognised in recent years as one of the essential technologies that provide the competitive advantage in many manufacturing environments.

This research aims to develop an effective sensor fusion model for turning processes for the detection of tool wear. Multi–sensors combined with a novelty detection algorithm and Learning Vector Quantisation (LVQ) neural networks are used in this research to detect tool wear and provide diagnostic and prognostic information.

A novel approach, termed ASPST, (Automated Sensor and Signal Processing Selection System for Turning) is used to select the most appropriate sensors and signal processing methods. The aim is to reduce the number of sensors needed in the overall system and reduce the cost. The ASPST approach is based on simplifying complex sensory signals into a group of Sensory Characteristic Features (SCFs) and evaluating the sensitivity of these SCFs in detecting tool wear. A wide range of sensory signals (cutting forces, strain, acceleration, acoustic emission and sound) and signal processing methods are also implemented to verify the capability of the approach. A cost reduction method is also implemented based on eliminating the least utilised sensor in an attempt to reduce the overall cost of the system without sacrificing the capability of the condition monitoring system. The experimental results prove that the suggested approach provides a responsive and effective solution in monitoring tool wear in turning with reduced time and cost.

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My highest appreciation goes to my wife for her unconditional support and love that continuously fed my strength and desire to succeed. She was beside me regardless of good and bad times making my life happy and complete and my sons Homood, Mohammad, Ahmad and lovely daughters Tahreer, Shaima, Amnah and Fatmah who filled my life with joy.

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Nomenclature

Sensory Signals and Sensors

Fx = Cutting force in the x direction measured by a dynamometer (N).

Fy = Cutting force in the y direction measured by a dynamometer (N).

Fz = Cutting force in the z direction measured by a dynamometer (N).

AE = Acoustic Emission Signal/Sensor (V).

AE_RMS = Root Mean Square of the AE signal (V).

Sd = Sound Signal (dB).

Vb = Vibration Signal (m/s^2).

DOC = Depth of Cut (mm).

Signal Processing Methods

std = standard deviations.

FFT (*f1*,*f2*) = Average value of the FFT between frequencies *f1*and *f2*.

FFT1= *FFT* (20 Hz, 200 Hz)

FFT2= *FFT* (200 Hz, 400 Hz)

FFT3= *FFT* (400 Hz, 600 Hz)

FFT4= *FFT* (600 Hz, 800 KHz)

FFT5= *FFT* (800 KHz, 1 KHz)

FFT6= *FFT* (1 KHz, 1.2 KHz)

FFT7= FFT (1.2 KHz, 1.4 KHz)

FFT8= FFT (1.4 KHz, 1.6 KHz)

FFT9= FFT (1.6 KHz, 1.8 KHz)

FFT10= FFT (1.8 KHz, 2 KHz)

FFT11= FFT (2 KHz, 2.2 KHz)

FFT12= FFT (2.2 KHz, 2.5 KHz)

Wav_i = Standard deviations of the ith level of the wavelet analysis.

S = Sensor.

SP = Signal Processing Method.

ASPST Terminology

ASPST = Automated Sensory and Signal Processing Selection System for Turning.

SCF = Sensory Characteristic Feature.

SFM = Sensory Feature Matrix

ASM = Association Matrix

RV= Range Value Detection Method.

SCIV = Sudden Change In Value Detection Method

SU = Sensor Utilisation coefficient (%).

SUA = Overall average utilisation of a monitoring system (%).

S= Number of SCFs used from the sensor.

T= Total number of features in the system.

P= Number of signals produced by the sensor.

A_{SPK} = Average sensitivity of the *kth* signal processing method.

A_{SP} = Average sensitivity of all signal processing methods implemented in a system.

A_{SK} = Average sensitivity of the *kth* sensor (or sensory signals).

A_S = Average sensitivity of all sensors (or sensory signals) implemented in a system.

A_c = Average of the summation of sensitivity coefficients of the ASM matrix.

d_{ij} = Sensitivity coefficient of a SCF obtained using the machining signal of the *i*th sensor and the *j*th signal processing method.

f_{ij} = The SCF obtained using the machining signal of the *i*th sensor and the *j*th signal processing method.

Classification Systems

ND = Novelty Detection Algorithm.

LVQ = Learning Vector Quantisation Neural Networks.

Chapter 1

Introduction

1.1 General Introduction

Global competition and increased requirements for high quality, low cost and increased volatility in the surroundings create an urgent need for implementing new technologies and using existing commercial technologies for industrial survival. In modern competitive manufacturing industry, machining processes are expected to have high accuracy, improved reliability and excellent quality with reduced costs. From the technical side, new demands are being placed on monitoring systems in the manufacturing environment because of recent developments and trends in machining technologies such as high speed machining, hard cutting and dry cutting. Condition monitoring systems of manufacturing processes have been recognised in recent years as one of the essential technologies that provide the competitive advantage in many manufacturing environments. Such a system is capable of providing an essential means to reduce cost, increase productivity, improve quality and prevent damage to the machine or work-piece. Machining such as milling, turning, grinding and drilling are material removal processes which have been widely used since the industrial revolution.

In the 20th century there has been a major advancement in machining processes technology, from a single machine tool to computerised machining processes, leading to fully automated and independent manufacturing operations. In order to fully recognise the potential of these systems it is essential to monitor and control the performance of the machine intelligently [1]. Among the parameters to be monitored, is tool wear which is clearly one of the most significant faults.

Conventional condition monitoring procedures can be utilised using as off-line method that is by determining the amount of tool wear when the tool is at rest or at station. Once the determined tool wear gets to a predefined level, the worn tool is replaced by a fresh tool. This direct method is costly and time consuming due to equipment cost and the time necessary for careful measurement. Therefore, an on-line method would be extremely useful in terms of cost, quality and performance effectiveness. It is thus necessary to develop an on-line monitoring system which can recognise different levels of tool wear monitoring [2].

1.2 Research Background

Machining processes have played an important role in recent manufacturing history. In addition, to being a primary manufacturing process, the machining process is also a finishing operation implemented to achieve very high dimensional precision and close to a preferred surface finish**.** The most general machining processes are drilling, turning, milling and grinding. These machining processes relied on highly skilled human operators until the last 60 years when automated machining began to replace human operators with more efficient and less costly automated machining processes. Moreover, automated machining, soon, captured a great deal of consideration from the main manufacturers, who were looking for product with reduced costs and improved quality. Manufacturers recognised that automated machining processes could replace the human operator to increase productivity, minimise costs and improve the quality of the product [3-5]. Thus, automated machining processes soon replaced highly skilled operators in many conventional industrial environments.

For the time being, the industry also demanded an additional task of manufacturers. Product demands became more varied and the complexity of manufacturing processes increased. Manufacturers needed new technologies and methods that would allow small production to gain the economic advantages of mass production [6, 7]. The expansion of automated manufacturing systems seemed to be the perfect solution for many of these problems. Although, the automated technologies showed great promise as a cost-effective solution to meet new demands, automated manufacturing systems could not be implemented until certain requirements were met. One major requirement is continuous machining. Manufacturing processes must be non-stop to achieve maximum efficiency [8]. On the other hand, faulty process conditions frequently force manufacturers to stop machining processes to react to faulty production conditions such as tool wear. Therefore, developing an effective method of monitoring tool conditions has become one of the most important issues in the automation of the machining process [9].

1.3 Problem Definition

Among the many possible tool conditions that can be monitored, tool wear is the most significant for ensuring continuous machining. Any effective monitoring system must sense tool conditions, allow for effective tool change strategies when tools fail, and keep proper cutting conditions throughout the process [10]. If the monitoring function cannot maintain proper cutting conditions, the cutting process can result in poor surface quality, dimensional workpiece damages, and even machine damage [9].

Manufacturers have required methods to monitor tool wear. These methods are an area of active research because tool condition strongly influences the surface finish and dimensional reliability of the workpiece. In addition, a consistent tool wear monitoring system can decrease machine downtime caused by changing the tool, hence leading to fewer process disturbances and higher efficiency. The information obtained from the tool wear sensors can be used for several reasons, including the tool change policy, online process actions to compensate for tool wear and the avoidance of catastrophic tool failure.

On-line tool wear monitoring is one of the main problems in automating turning processes. Several attempts have been made previously to develop on-line tool wear monitoring methods in the machining process domain.

Condition monitoring system methods can be classified into direct and indirect methods, depending on the source of signals collected by sensors. Direct methods sense tool conditions by direct measurement of the tool. Direct methods include optical, radioactive and electrical resistance. On the other hand, indirect methods sense the tool condition by measuring secondary effects of the cutting process, such as cutting force, acoustic emission (AE), motor current, sound and vibrations. Direct methods are advantageous because they take close readings directly from the tool itself. However, direct methods are limiting because the machining process must be stopped to make the direct measurements [11]. As a result, machine downtime increases and the costs of the tool condition monitoring. Researchers then have desired indirect methods to study on-line tool condition monitoring systems.

Recent research findings show that no single process variable (such as force, temperature, acoustic emission, or vibration) by itself is sufficient to monitor tool wear states under all conditions [12].

A limited number of sensors have been adopted in most studies involving indirect sensing systems. The most widely used indirect sensor is the dynamometer, which has been used to measure the forces during the cutting processes [10, 13-15]. However, applying the dynamometer is not practical because of its high cost and lack of overload protection [16]. On the other hand, temperature is good for tool wear monitoring under certain conditions but not for tool wear detection. The acoustic emission (AE) sensor is another sensing technology that has been used in a number of studies [17, 18], but it is limited in its application by its noise integrity [19]. Machining processes are one of the most complex manufacturing processes. The variability in the process parameters, material types, machine types, fault variation and machined features makes it one of the most difficult processes to be monitored. Using one sensor might be insufficient to detect the required fault for a specific process or all the required faults. Single sensory systems have often proven to be ineffective due to the relatively large number of parameters and the complexity of manufacturing processes reliability, etc [20].

There has been a significant number of researches in on-line condition monitoring systems of machining operations, and specifically on turning operations using several sensor fusion models [12]. Many types of sensor fusion models have been already suggested in research, see for example [12, 21-26]. However, the success in the industrial application of such systems has been limited. So far, little success has been reported on the implementation of condition monitoring systems for turning operations in industry. This is mainly caused by the absence of sensor-fusion models that provide effective information about the process in a hostile machining environment [12, 23] and the effective flexible pattern recognition and classification system. More research is needed in this area to construct an effective approach towards the development of indirect online monitoring for turning processes using an efficient sensor fusion model and effective pattern recognition system. This is becoming important due to the fact that many new sensor technologies are available for researchers to use in developing new sensor fusion systems [27].

The sensor fusion approach described in reference [28] uses a combination of several sensors (e.g. acoustic emission, vibration, power, infrared, temperature, and force) to improve the reliability of the diagnostic and prognostic capabilities in milling operations. Because of its importance, the proposed research will focus on the turning process and its associated family of processes that could be performed on a lathe machine. There are many types of faults associated with turning processes including high surface roughness, catastrophic cutter breakage, gradual tool wear and collision.

This requires the development of techniques for using multiple sensors and classification methods. Therefore, in the present research a method based on sensor data fusion and artificial intelligent classification systems (Novelty Detection, Neural Networks) for fault detection is developed. The present method is based on the understanding that a machining process produces dynamic signals which contain information about the changing process conditions such as high surface roughness, catastrophic cutter breakage, gradual tool wear and collision, and that this information can be extracted and related to the type of failure. The proposed method relies on the possibility that these dynamic signals from the machining process can be measured and processed in real-time to obtain on-line tool wear monitoring.

The main issue addressed in this research is development of an efficient sensor fusion model for a condition monitoring system for the turning process, minimising cost, decreasing down time and increasing product quality. This includes the selection of multi-sensors signals and signal processing methods which give the minimum error for the decision-making system. This research work is building on the available information in condition monitoring systems to advance the state of the art and present a more comprehensive, simple and efficient sensor fusion model for condition monitoring of manufacturing operations.

1.4 Research Aims and Objectives

The aim of this research is to develop an effective condition monitoring system for turning processes with reduced time and improved performance.

The nature of the problem suggests that to develop a method for practical and accurate tool wear monitoring, the following four criteria should be considered:

1. The capability to develop a self-learning approach.
2. The approach could be used for different machining parameters and different faults (i.e. fault and parameters independent).
3. No understanding necessary regarding the process/fault mechanism.
4. Learning could be developed from experience.

The aim of the research is supported by the following objectives:

1. To perform a literature review of machine and process condition monitoring systems and their applications.
2. To determine the process variables in turning processes that contain useful information related to tool wear.
3. To determine the appropriate sensors that can be used for monitoring the process variables that are related to tool wear.
4. To design a data acquisition system for machine and process condition monitoring including a data acquisition card and computer selection, data acquisition software, sensors installation and an overall system calibration.
5. To design and implement an effective sensor fusion model for turning processes for the detection of the most common industrial faults (e.g. gradual wear).
6. To design the experimental investigation needed to obtain the necessary machining data.
7. To integrate a wide range of sensory systems and their signal processing methods into a novel and effective sensor fusion model. The sensors to be used are: force, acoustic emission, strain, vibration, and sound.
8. To investigate an efficient pattern recognition and classification system.
9. To test and evaluate the novel sensor fusion model.

1.5 Thesis Structure

The structure of the thesis is designed to cover the background of the subject, the suggested methodology and results of the experimental work as follows:

Chapter 1: Introduces the competitive global market and the need for condition monitoring systems. This chapter states the current problems in process condition monitoring and the aims and objectives of this reported research.

Chapter 2: Describes the fundamental information of metal removal processes with special emphasis on turning operations and turning characteristics and terminology.

Chapter 3: Outlines tool wear and chip formation in metal cutting with emphasis on turning processes.

Chapter 4: Describes the basic concepts of machine and process condition monitoring. It presents an overall survey of the condition monitoring technologies that have been implemented in research and industry in recent years.

Chapter 5: Presents a review of condition monitoring methods that have been developed or implemented in industry. It displays the problems in current monitoring methods to obtain an understanding of the current research on condition monitoring systems in turning processes. In addition, this chapter briefly reviews the potential sensors available for monitoring turning processes.

Chapter 6: Presents the methodology and the requirements of the research. It provides a description of how the project aims and objectives are developed and how the condition monitoring methodology is conceived. The chapter also explains the main steps of the suggested methodology and the assumptions which require testing as a part of the study. The chapter also provides a detailed description of how the subsequent chapters are organised to prove the proposed methodology.

Chapter 7: Describes the components and stages of condition monitoring system implemented in this research. The chapter briefly explains the sensors and signal processing methods used in this research to produce the required sensory characteristic features. In addition, it explains the implemented neural networks and novelty detection systems.

Chapter 8: Includes a detailed description of the main experimental set-up of the research. It includes a description of the machine tools and the condition monitoring system including sensors and related hardware, the data acquisition system, and sensors placement.

Chapter 9: Presents a practical description of the implemented ASPST (Automated Sensor and Signal Processing Selection System for Turning) approach and the way it can be used to systematically develop a condition monitoring system for multi-sensors. The ASPST approach is explained through a gradual wear of a turning cutting tool.

Chapter 10: Shows the implementation of different applications of the ASPST approach to detect tool wear with different multi-sensory signals groups and different classification systems.

Chapter 11: This chapter presents the full capabilities and testing of the implemented ASPST approach. The application of the ASPST approach to detect tool wear for several sensors and two classification systems is described. It includes a description of how the ASPST approach can be used to detect wear in cutting tools. Twenty similar sets of experiments are used to evaluate the system and to optimise cost and performance. Neural networks and novelty detection are also used to evaluate the design process. The ASPST approach is also expanded in this chapter to show how to use the ASM matrix as an evaluation of signal processing methods which can be used as independent features for condition monitoring design.

Chapter 12: Present a summary of the thesis and a discussion of the results obtained. It explains how new knowledge has been generated and tested. It includes the contribution to knowledge and outstanding problems and constraints on methods, testing and findings. It also contains general conclusions and further work in the filed of condition monitoring systems.

Chapter 2

Metal Removal and Machining Processes

2.1 Introduction

The final shape of most mechanical parts is obtained by a machining operation. Metal removal operations in their various forms contribute to over 70% of manufacturing processes practised in industry. Machining is the process of removing unwanted material from a workpiece in the form of chips. The process is called metal removal or metal cutting if the workpiece is metal. Industries spend significant money to perform metal removal operations because the huge majority of manufactured products require machining at some stage in the production to high precision. This chapter describes the fundamental information of a metal removal process with special emphasis on turning operations and turning characteristics and terminology. In addition, it outlines the wear and chip formation in turning.

2.2 Fundamentals of Metal Removal

Metal removal forms include turning, boring, forming, facing, drilling, shaping and milling. Generally, cutting tools can be grouped into two groups: single point tools such as turning, planning, and shaping which have one and only one cutting part and a shank, while multiple tool points have more than one cutting part such as milling, drilling and broaching. This research will focus on turning processes, where turning is defined as a machining process of producing external surfaces by engagement of a cutting tool on a turning workpiece, regularly done on a lathe machine [29, 30].

The final shape of most mechanical parts is obtained by a machining operation. Metal removal operations in their various forms contribute to over 70% of manufacturing processes practised in industry [30, 31]. The machining operations can be classified under two major categories: cutting and grinding processes. In cutting operations the material is removed by shear action. The most common cutting operations are turning and milling. All metal cutting operations can be linked to the process shown in Figure 2.1, where the tool has a straight cutting edge and is constrained to move relative to the workpiece in such a way that a layer of metal is removed in the form of a chip. Figure 2.1 (a) shows the case known as orthogonal cutting where the cutting tool approaches the workpiece at right angles to the direction of cutting, with the cutting edge parallel to the uncut surface. Figure 2.1 (b) shows the general case of cutting known as oblique cutting, where the chip flows over the rake face and have an angle more than zero with the normal to the cutting edge. Since orthogonal cutting represents a two-dimensional rather than three-dimensional problem, it lends itself to research investigations where it is desirable to eliminate as many of the independent variables as possible. The relatively simple arrangement of orthogonal cutting is therefore widely used in theoretical and experimental work. It could be argued that orthogonal cutting is the most common form of cutting and represents a reasonable approximation of cutting on the major cutting edge [30].

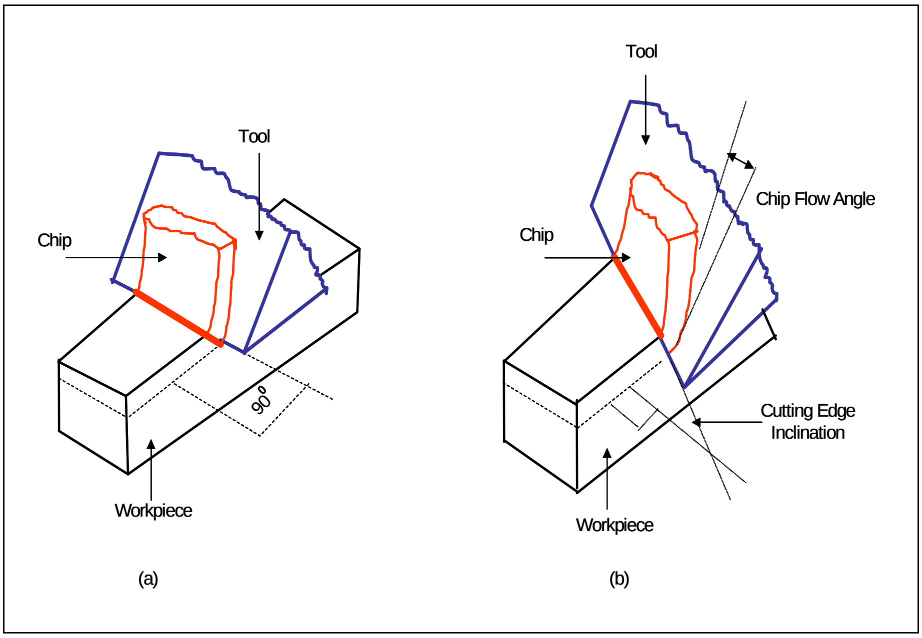

Figure 2.1: (a) Orthogonal cutting; (b) Oblique cutting.

2.3 Procedure of Orthogonal Cutting

Orthogonal cutting is a two-dimensional cutting process. In orthogonal cutting, as shown in Figure 2.2, the material is removed by a cutting edge that is perpendicular to the direction of relative tool/workpiece motion. Orthogonal cutting resembles a shaping process with a straight tool whose cutting edge is perpendicular to the cutting velocity (V). A chip with a width of cut (w) and depth of cut (d) is sheared away from the workpiece.

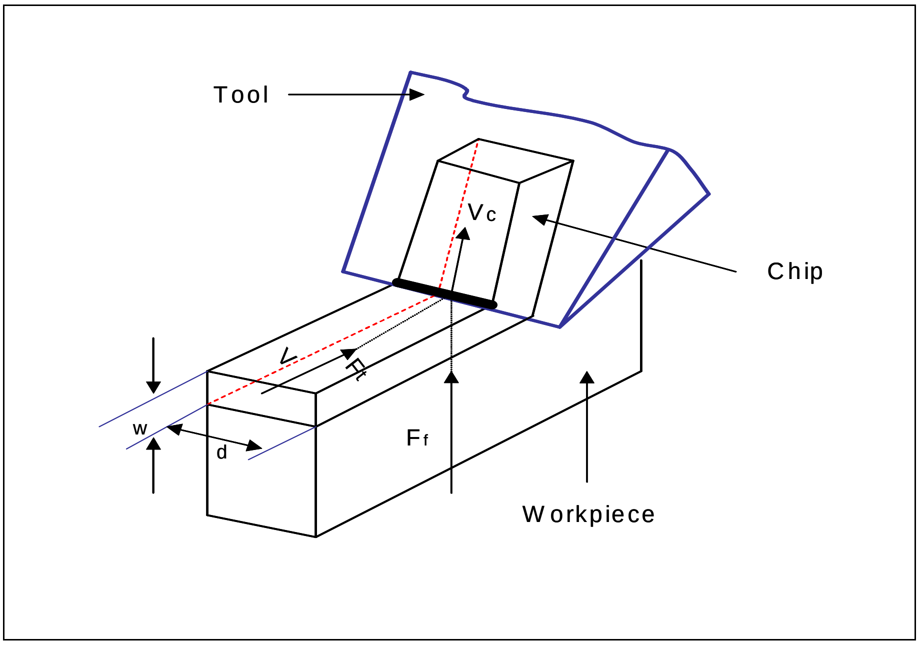

Figure 2.2: Orthogonal cutting.

In orthogonal cutting, the cutting is assumed to be uniform along the cutting edge. Therefore, it is a two-dimensional plane strain deformation process without side spreading of the material. Hence, the cutting forces are applied only in the directions of velocity and uncut chip thickness, which are called tangential (Ft) and feed forces (Ff). There are three deformation zones in the cutting process as shown in the cross-sectional view of the orthogonal cutting in Figure 2.3. As the edge of the tool goes through into the workpiece, the material ahead of the tool is sheared over the primary shear zone to form a chip. The contact area between the chip and the rake face of the tool is called the secondary deformation zone. The friction area, where the flank of the tool rubs the newly machined surface, is called the third zone (Tertiary zone) [32].

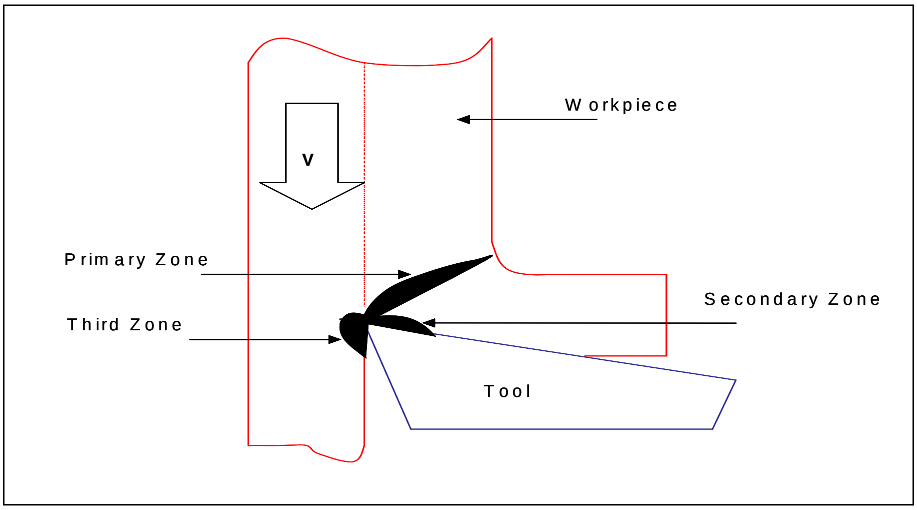

Figure 2.3: Deformation zones in metal cutting.

2.4 Procedure of Oblique Cutting

Oblique cutting is a three-dimensional cutting operation that is widely used in industry. In oblique cutting, the cutting edge is oriented with an inclination angle and there is an additional third force acts in the radial direction *(F_r)* as shown in Figure 2.4.

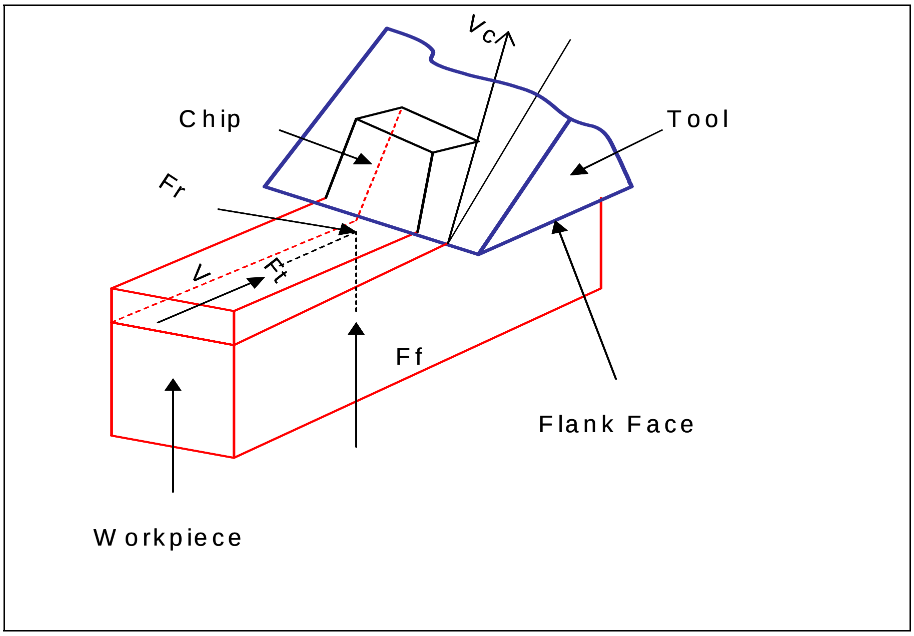

Figure 2.4: Oblique cutting geometry.

2.5 General Terms and Definitions

The wedge-shaped cutting tool basically consists of two surfaces intersecting to form the cutting edge as shown in Figure 2.5. The surface along which the chip flows is known as the rake face, and the surface that is ground back to clear the new or the machined workpiece surface is known as the flank. The unreformed chip thickness is the depth of the layer of the material removed by the action of the tool as illustrated in Figure 2.5. The slope of the tool face is considered as one of the most important variables and is specified in orthogonal cutting by the angle between the tool face and a line perpendicular to the new work surface as shown in Figure 2.5. This angle is known as the rake angle.

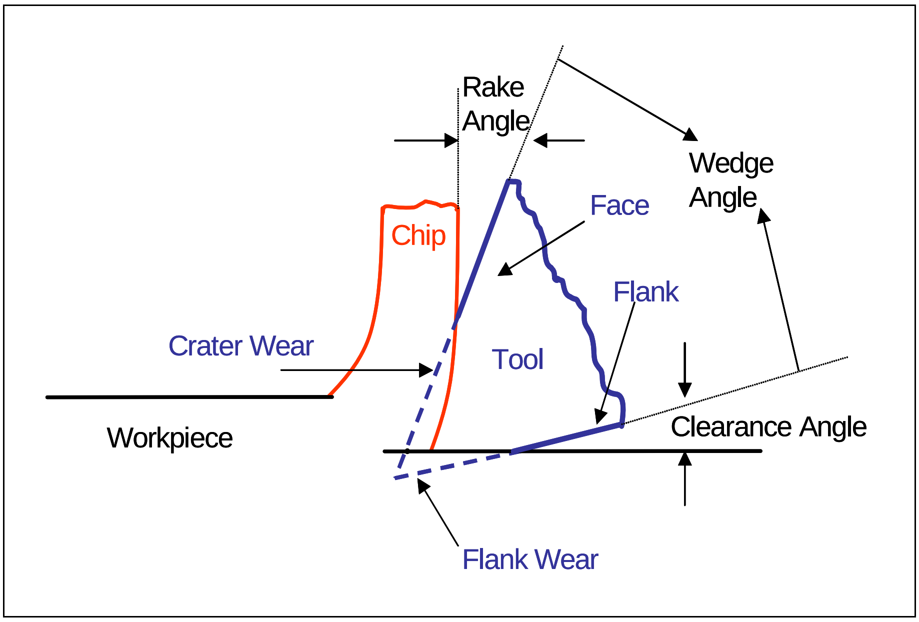

Figure 2.5: Terms used in metal cutting.

The tool flank has no serious influence on the process of chip removal. However, the angle between the flank and the new workpiece surface can significantly affect the rate at which the cutting tool wears and is defined as the "clearance angle". As shown in Figure 2.5 the sum of the rake, clearance, and wedge angles is equal to 90° degrees where the wedge angle is the angle included between the face and the flank [33].

2.6 Tool Geometry

The geometrical aspects, terms and definitions relating to single-point cutting tools are illustrated in Figure 2.6.

2.6.1 Clearance Angle

It is the angle between the flank face and the newly generated surface.

2.6.2 Nose Radius

The nose radius strengthens the finishing point of the tool and improves the surface finish on the workpiece. The nose radius of most cutting tools should be more or less double the amount of feed per revolution. An over-sized nose radius may cause chatter and under-sized radius weakens the tool tip [34].

2.6.3 Side Rake Angle

In order to allow the chips to run away from the workpiece readily, without weakening the cutting edge, the side rake angle should be as large as possible as shown in Figure 2.6. The type and grade of the cutting tool, the type of material being cut, and the feed per revolution will determine the amount of side rake. The included angle formed by the side rake and side clearance is called the angle of keenness. This angle will vary depending on the material being cut. For difficult to machine metals, it may be advisable to use a small side rake angle or at times even a negative side rake [34].

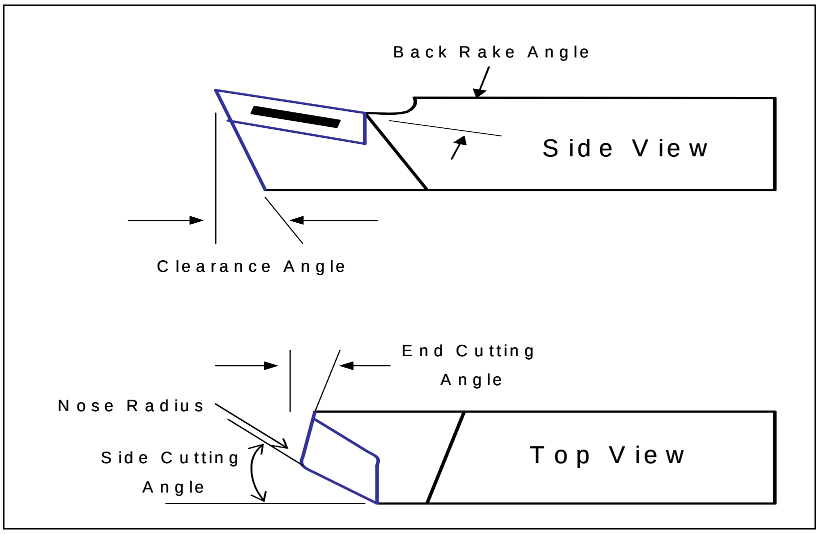

Figure 2.6: Single-point tool classifications.

2.6.4 Back Rake Angle

The angle formed between the top face of the tool and the top of the tool shank, is known as the back rake angle. It may be positive, negative, or neutral. When a tool has negative back rake angle, the top face of the tool slopes upward away from the point. Negative back rake angle protects the tool point from the cutting pressure. When a tool has positive back rake angle, the top face of the tool slopes downward away from the cutting point. This allows chips to flow away freely from the cutting edge. For tools with inserts, the cutting inserts are usually flat, because the manufacturer builds the required side and back rake angles into the tool holder. The type of rake angle used depends on the machining operation performed and the characteristic of the work material, as each type of rake angle serves a specific purpose. Rake angles can be ground on cutting tools or, in the case of cutting tool inserts, they can be held in suitable holders, which provide the rake angle preferred [34].

2.6.5 Positive Rake Angle

A positive rake angle is considered to be the best for an efficient removal of the metal. It creates a large shear angle at the shear zone, reduces friction and heat, and allows the chip to flow freely along the chip-tool interface. Positive-rake angle cutting tools are not too hard or abrasive, thus they are used for continuous cuts on ductile materials. Even though positive rake angle tools remove metal efficiently, they are not recommended for all work materials or cutting applications [34].

The following factors must be considered when the type and the amount of rake angle of a cutting tool are being determined:

- The type of the cutting operation (continuous or interrupted).
- The strength of the cutting edge.
- The shape and material of the cutting tool.
- The hardness of the workpiece material.

2.6.6 Negative Rake Angle

A negative rake angle is used for interrupted cuts and whenever the metal is hard (brittle) or abrasive. It creates a small shear angle and a long shear zone on the tool; hence more friction and heat are created. Although the increase in heat may seem to be a disadvantage, it is desirable when tough metals are machined with carbide cutting tools. Cutters with carbide tool inserts are a good example of the use of negative rake for interrupted and high-speed cutting [34].

The advantages of negative rake on cutting tools are:

- Surfaces with interrupted cuts can be readily machined.
- Higher cutting speeds can be used.
- The outer hard scale on the metal does not come into contact with the cutting edge.
- The shock from the workpiece meeting with the cutting tool is on the tool's face, not on its point or edge, which extend the life of the tool.

2.7 Essential Features of Metal Cutting

While metals and alloys are too hard, therefore, tool materials must be strong enough to withstand the stresses, which are imposed on a very fine part of the cutting edges. The cutting layer must be thin enough to allow the tool and the work to withstand the forced stress and a clearance angle must be formed on the tool to ensure that the clearance face does not make contact with the newly-formed work surface.

In practical machining, the angle included between the tool edges varies from 55° to 90°, so that the chip which is the removed layer is diverted through an angle of at least 60° as it moves away from the workpiece, across the rake face of the tool. In this process, the whole volume of the metal removed is "plastically deformed"; therefore a large amount of energy is required to form the chip and to move it across the tool face. In this process, two new surfaces are formed, the new surface of the workpiece and the lower surface of the chip. The formation of new surfaces requires energy. In metal cutting, the theoretical minimum energy required to form the new surfaces is insignificant when compared to that required to plastically deform the metal removed [35].

2.7.1 Chip Formation

Similar to other machining processes the chip is formed in turning by a localised shear process that takes place over a very narrow region. The process is characterised by large strain with high strain rates such that the stress state evolves from elastic compression to plastic compression and finally to shear when the work hardening reaches a saturated condition. The shear takes place along a shear zone, which is usually referred to as the shear plane [36, 37].

Generally, in turning, the chip is formed by the main cutting edge, the nose and a small part of the secondary cutting edge of the tool. The shape and type of chips that are produced control significantly the surface finish, the tool life, vibration and chatter. The chip is extremely variable in shape and size. Forming a chip involves a shearing of the work material in the region of a plane extending from the tool edge to the position where the upper surface of the chip leaves the work surface. Most strain takes place in this region in a very short interval of time, but not all metals can withstand this strain. For example, grey cast iron chips are always fragmented and the chip of more brittle materials may be produced as segments, particularly at very low cutting speeds. This "discontinuous chip" is one of the principal classes of chip form that is easily cleared from the cutting area and has a practical advantage; under a majority of cutting conditions, the ductile metals and alloys do not fracture on the shear plane and a "continuous chip" is produced.

2.7.2 Types of Chips

Three basic types of chip are produced by the machining operations performed on lathe machines as follows [35]:

- Discontinuous.
- Continuous.
- Continuous Chip with Built-Up Edge.

2.7.3 Discontinuous Chip

When brittle metals such as cast iron and hard bronze are cut, and even when some ductile metals are under poor cutting conditions, a discontinuous or segmented chip is produced. As the point of the cutting tool contacts the metal some compression occurs, and the chip begins flowing along the chip-tool interface. The stress applied to brittle metal by the cutting action increases until it reaches a point where it breaks, and the chip separates from the un-machined portion. When this cycle is repeated the break (split) of each segment occurs on the shear plane. As a result of these succeeding breaks, a poor surface is produced on the workpiece. Machine tool chatter or vibration sometimes causes a discontinuous chip, which is produced when ductile metal is cut [34]. The following conditions help the production of discontinuous chips:

- Low cutting speed.
- Large chip thickness.
- Excessive machining chatter.
- Brittle work material.
- Small tool rake angle.

2.7.4 Continuous Chip

The second type of chip is a continuous chip produced when the flow of metal next to the tool face is not highly retarded by friction at the chip-tool interface. This chip is considered ideal for efficient cutting action because it results in better surface finishes. The crystal structure of the ductile metal is extended when it is compressed by the action of the cutting tool and as the chip separates from the metal. The process of chip formation occurs in a single plane extending from the cutting tool to the un-machined work surface; and the area where plastic deformation of the crystal structure and shear occurs is called the "shear zone". The angle on which the chip separates from the metal is called the "shear plane or shear angle".

As the cutting action progresses, the metal instantly ahead of the cutting tool is compressed, with a resultant deformation of the crystal structure. This deformation takes place in the direction of shear. As this process of compression and deformation continues, the material above the cutting edge is forced along the chip-tool interface and away from the work [34]. Machining steel generally forms a continuous chip (unbroken) with little or no built-up edge when machined with a cemented-carbide cutting tool or a high-speed steel tool bit. To reduce the amount of resistance occurring as the compressed chip slides along the chip-tool interface, a suitable rake angle created on the tool and cutting fluid is used during the cutting operation. These features allow the compressed chip to flow relatively freely along the chip-tool interface. A shiny layer on the back of a continuous chip type shows ideal cutting conditions with little resistance to chip flow.

The conditions that produce a continuous chip are:

1. Sharp cutting-tool edge.
2. High cutting speeds.
3. Cutting tool and workpiece are kept cool by using cutting fluids.
4. Small chip thickness.
5. Ductile work material.
6. A large rake angle on the cutting tool.
7. A minimum resistance to chip flow by: -
    - Use of cutting fluids to prevent the formation of a built-up edge.
    - Free-machining materials (those alloyed with elements such as lead, phosphor and sulphur).
    - A high polish on the cutting-tool face.
    - Use of cutting-tool materials, such as cemented carbides, which have a low coefficient of friction.

2.7.5 Continuous Chip with Built-Up Edge

When cutting low-carbon steel material at a low cutting speed with a high speed steel cutting tool and without the use of cutting fluids, a continuous-type chip with a built-up edge is generally produced. The metal ahead of the cutting tool begins to flow along the chip-tool interface, which is compressed and forms a chip. As a result of the high temperature, high pressure and high frictional resistance against the flow of the chip along the chip-tool interface, small particles of metal begin adhering to the edge of the cutting tool while the chip shears away. As the cutting process continues, more particles adhere to the cutting tool; a larger buildup results, which affects the cutting action. The built-up edge increases in size and becomes unstable; to a point where fragments are torn off. Portions of the fragments that break off stick to both the chip and the newly generated surface. The buildup and breakdown of the built-up edge occur rapidly during cutting action and cover the machined surface with a multitude of built-up fragments usually identified by a rough and grainy surface. These fragments adhere to and score the machined surface, resulting in a poor surface finish [34]. The main cause of the poor surface roughness is the continuous chip with the built-up edge. It also shortens the cutting-tool life. When a cutting tool starts dulling, it creates a rubbing action on the workpiece and a work-hardened surface is produced [38]. This type of chip affects cutting-tool life in two ways:

- A cratering effect is caused a short distance back from the cutting edge where the chip contacts the tool face. As this cratering continues, it eventually extends closer to the cutting edge until fracture or breakdown occurs
- The fragments of the built-up edge scrape the tool flank as they escape with the workpiece and chip [36, 37].

2.8 Turning Characteristics and Terminology

The basic operation of turning is the most commonly employed metal removal process. In turning, the workpiece is clamped in a lathe using a chuck or other workholding device and subjected to a rotary motion around the spindle axis. The tool is fed into the workpiece at a certain rate to generate an external or internal surface concentric with the axis of rotation. Figure 2.7 presents the schematics of a simple turning operation with the representation of the main forces acting on the cutting tool.

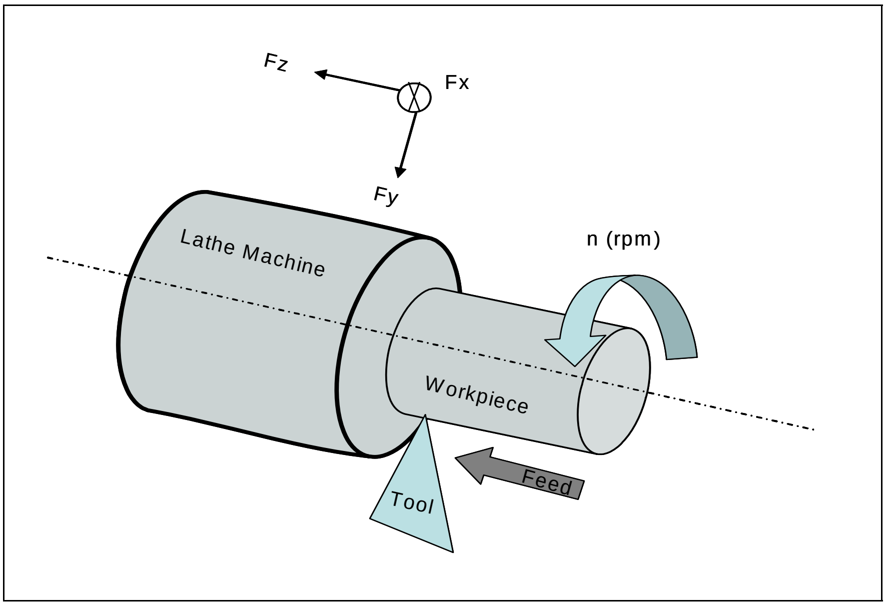

Figure 2.7: Turning schematics.

In addition, Figure 2.8 presents the nomenclature of a basic cutting tool used in turning. The cutting speed is the rate at which the uncut surface of the workpiece passes the cutting edge of the tool. The distance moved by the tool in axial direction at each revolution of work is the feed rate, in turning machine. The thickness of metal removed from the bar is the depth of cut and measured in the radial direction. Mainly, these three parameters determine how quickly or slowly the metals are removed, and their product, the metal removal rate measured as a volumetric quantity, could be considered an efficiency indicator of the cutting operation [33]. A large quantity of energy is needed to shape the chip creating two new surfaces by shearing, during the orthogonal cutting, the new surface of the workpiece and the underside of the chip. Most of the energy in metal removal is used to plastically deform and remove the chip. Therefore, considerable research investigation is needed to understand the phenomenon [33]. It is not intended here to discuss the full understanding of the mechanics of the orthogonal cutting process, as it is out of the focus of the research. However, it is reasonable to assume that high strain and stress rates developed as the cutting tool works through the workpiece give rise to high temperatures, complicated forces and dynamic behaviour across a broad spectrum of frequencies. Orthogonal cutting causes considerable amounts of heat and energy at a rate proportional to both the cutting speed and the consequential tool force. The elastically deforming materials cause a small quantity of energy which is accumulated in the material strain energy. The plastically deforming materials generate large amounts of heat as the workpiece material is subjected to high strain levels that is changed to heat energy at the sections of primary and secondary deformation [33]. Due to friction between the tool and the new workpiece surface some heat also arises. Static and dynamic forces make up the cutting forces in any metal cutting processes; the dynamic force represents the degree of fluctuation in the cutting force, where the static force gives an indication of force magnitude levels.

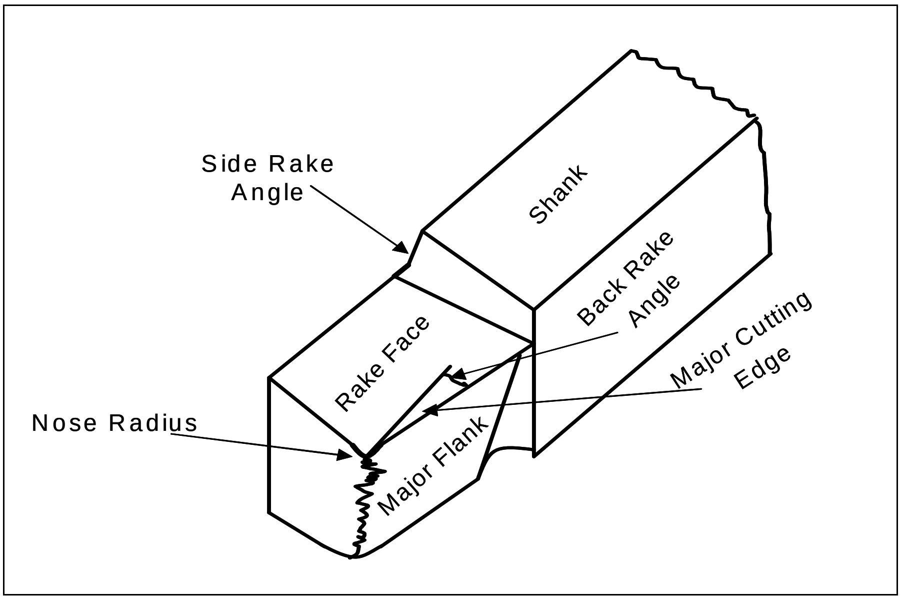

Figure 2.8: Nomenclature for right hand-cutting tool.

The cutting force become larger as the depth of cut increases and should be therefore limited to the available power of the machine. Feed rate depends on the rigidity, strength of the machine and the finish desired. Roughing cuts are often large with the cutting speed dependent totally on workpiece hardness whereas finish cuts require a light feed rate. Many other machining processes can be carried out in combination with turning like reaming, facing, boring. In turning the only limit may be the accessibility of equipment size to grasp and swivel the workpiece with difficulties in holding and handling as size and weight rises [29].

2.9 Conclusion

As most manufacturing systems are increasingly converting into fully automated environments (such as computer integrated manufacturing (CIM), flexible manufacturing systems (FMS) and computerised numerical control (CNC) machines), condition monitoring without doubt will become an automated aspect of such a manufacturing environment. A protective detection to recognise a worn tool and have it replaced as soon as possible becomes necessary to implement a condition monitoring system. Failure might lead to damage to the machine and the workpiece. In view of the damage that tool could cause to machine and workpiece material, there has been a need to develop and implement systems aimed at providing early warnings of imminent tool failure such as condition monitoring systems.

In this chapter, the fundamental of metal removal and machining processes are described. This chapter summaries the fundamental information of a metal removal process with special emphasis on turning operations. The chapter has also described the turning characteristics and terminology. In addition, it has outlined the wear and chip formation in turning. From condition monitoring point of view, there are many parameters and cutting conditions that could influence the signal of the process for the design of a condition monitoring system.

Chapter 3

Tool Wear and Tool Life

3.1 Introduction

Tool wear is a result of physical and chemical interactions between the cutting tool and workpiece as a consequence of the removal of small parts of the cutting material from the edge of the tool. To determine the real cause of tool wear is very difficult because the wear mechanisms in cutting tools are highly non-linear and complicated processes associated with many variables such as contact stress, nature and composition of the workpiece and cutting tool, temperature on the cutting edge, cutting speed, feed and cutting fluid, etc. Basically a cutting tool wears because of higher loads on the wear surface than normal loads and because of rapid movement of cutting chips and workpiece over the wear surface.

If tool wear reaches a certain limit, then it may cause catastrophic failure of the tool and can result in high forces. This is a highly undesirable situation in machining since severe damage may occur to the workpiece material or the machine. To solve this problem and to determine the time when a cutting tool should be changed, condition monitoring systems are needed to monitor the machining processes [34].

Tool life is an important cost factor in manufacturing operations. It is one of the most important economic considerations in metal cutting. In roughing operations the various tool angles, cutting speeds, and feed rates are usually chosen to give an economical tool life. Conditions giving a very short tool life are uneconomical because tool replacement and tool grinding costs are high. In addition, the use of very low speeds and feeds to give long tool life is uneconomical because of the low production rate. Clearly, any tool or work material improvements that increase tool life will be useful. This chapter discusses wear in metal cutting, forms of tool wear and modes of tool wear such as flank, crater and nose wear. In addition, it describes the factors affecting tool life.

3.2 Wear in Metal Cutting

Cutting tool failures can be classified into two main groups according to the processes by which failure occurs [35]:-

1. Gradual tool wear that progressively develops on the tool flank face (flank wear) or on the tool rake face (crater wear).
2. Failure mechanisms that bring the life of the cutting tool to a sudden, early end.

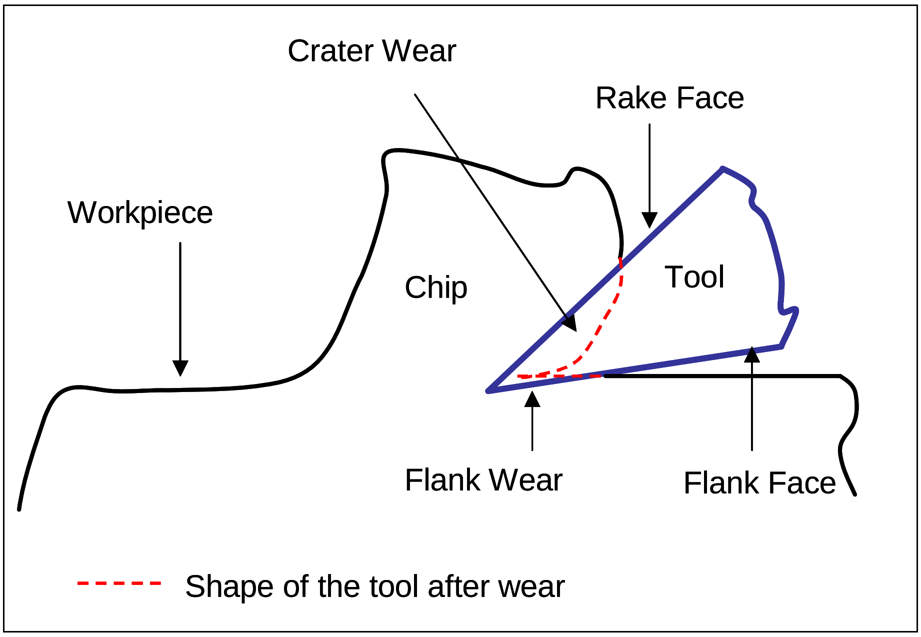

Figure 3.1: Schematic of the effect wear on the tool geometry.

The gradual wear of a cutting tool occurs mainly in the two areas as shown in Figure 3.1. The second group can be subdivided into failure modes based on either excessive temperatures or excessive stresses.

3.2.1 Progress of Tool Wear

Wear in a cutting tool is a regular incident, which cannot be avoided and is a function of time. In metal cutting, three main forms of wear are likely to occur: adhesion, abrasion, and diffusion [35].

Adhesion wear is caused by the fracture of welded roughness junctions between the two metals. In metal cutting, junctions between the chip and tool materials are formed as part of the friction mechanism. When these junctions are fractured, small fragments of tool material can be torn out and carried away on the underside of the chip or new workpiece surface. The conditions that exist in metal cutting are suited to adhesive wear as new material surfaces uncontaminated with oxide films are continually produced, and this facilitates the formation of welded roughness junctions [34]. This mechanism contributes to flank wear as well as to the formation of the crater wear.

Another form of wear which is known as ***"abrasion wear"*** occurs when hard particles underside of the chip pass over the tool face and remove tool material by mechanical action. These hard particles may be high strain hardened fragments of an unstable built-up edge, fragments of the hard tool material removed by adhesion wear, or hard constituents in the work material. This mechanism is significant for tool wear only in those instances where the workpiece material is very hard or contains hard particles. The machined surface is cooler than the tool flank and it may happen that the tool material is softened more than some of the constituents of the workpiece materials, and this creates the conditions for abrasion.

The third form of wear which is known as ***"diffusion wear"*** occurs when atoms in a metallic crystal lattice move from a region of high atomic concentration to one of low concentration. This process is dependent on the existing temperature and the rate of diffusion increases exponentially with increases in temperature. In metal where close contact between the work and tool materials occurs and high temperatures exist, diffusion can occur where atoms move from the tool material to the work material. This process takes place within a very narrow reaction zone at the interface between the two materials and causes a weakening of the surface structure of the tool [34]. Diffusion plays a significant role at higher cutting speeds in some workpiece/tool material combinations. The diffusion rate depends on the affinity of the materials in contact, very strongly on temperature, and on the gradient of concentration of the penetrating atoms in the solvent material. Diffusion plays an important role in the development of crater wear.

3.2.2 Tool Failure Due to Excessive Temperature

The high temperatures that take place in the primary and secondary deformation zones could cause an initially sharp cutting tool to lose some of its strength and flow plastically under the pressures developed by the cutting force. The flow of the tool material along the flank surfaces causes the cutting tool to assume a configuration resembling that shown in Figure 3.2.

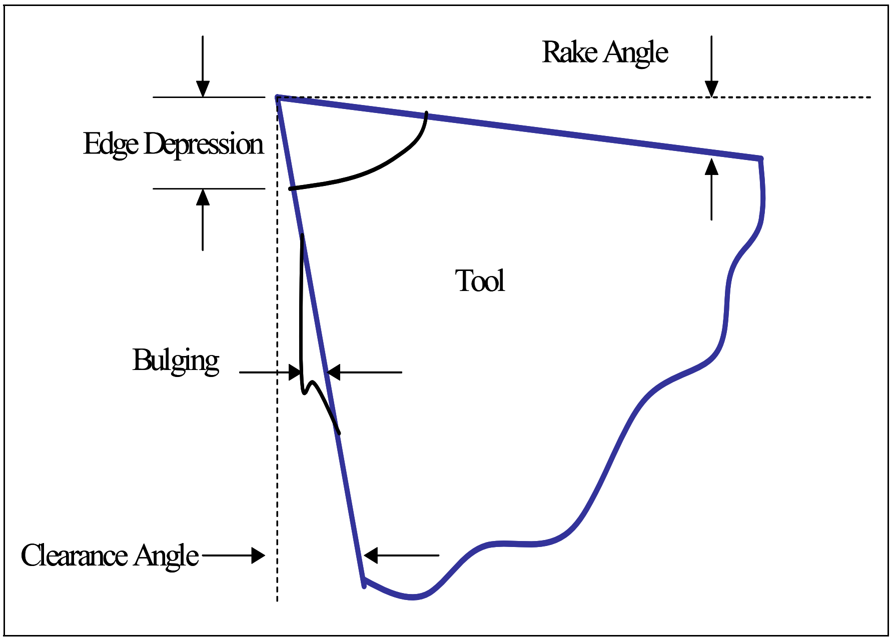

Figure 3.2: Schematic of edge depression due to plastic deformation.

As shown in Figure 3.2, the clearance angle of the cutting tool is reduced to zero for a portion along the flank and for some period of time, the contact area between the tool and workpiece increases. Throughout this period, layers of the tool material in contact with the workpiece gradually separate. For a short period of time, the tool may carry on cutting with this form, for stability. The large area of close contact results in greater friction between the cutting tool and workpiece, causing the temperature to increase rapidly. The cutting tool after that loses its form stability and fails quickly because of additional softening of the tool material in the cutting area due to the increased temperature level. This kind of tool failure is not limited to high-speed steel cutting tools; even though cemented carbide cutting tools are relatively brittle, they have a certain amount of ductility under the high compressive loads and high temperatures which happen during cutting [34].

3.3 Forms of Tool Wear

Cutting tools are subjected to an extremely severe rubbing process. They are in metal to metal contact with the chip and workpiece under conditions of very high stress and high temperature. The situation is further forced by the existence of great stress and temperature gradients near the surface of the tool. Cracks on both the flank and the rake face are usually due to irregular cutting. Three types of wear are generally associated with cutting tools: flank wear, crater wear and nose wear [30, 34, 35]:

3.3.1 Flank Wear

Wear on the flank of a cutting tool occurs on the side of the cutting edge as a result of friction between the newly machined workpiece surface and the contact area on the tool flank. The damaged area, referred to as the flank wear land, is parallel to the resultant cutting direction [34]. Too much flank wear increases friction energy along the tool workpiece interface and deteriorates the machined surface.

3.3.2 Crater Wear

The crater formed on the tool face conforms to the shape of the chip underside and is restricted to the chip-tool contact area. In addition, the region near the cutting edge where sticking friction or a built-up edge occurs is subjected to relatively slight wear. Crater wear starts at a certain distance from the tool point and grows deeper. It should be noticed that once the crater is established, its depth grows more rapidly than its top width. The edge of the crater approaches the cutting edge, both by crater wear and by flank wear. This weakens the tool close to the cutting edge and a major failure may occur by fracture from the crater through to the clearance face. This scenario is more likely to occur under discontinuous cutting conditions. In metal cutting, the highest temperatures along the chip tool interface is located at some distance along the tool face; at high cutting speeds these temperatures can easily reach the order of 1000^{o} c. Under these high-temperature conditions high-speed steel tools wear very rapidly because of thermal softening of the tool material. In experimental work, the maximum depth of the crater is usually a measure of the amount of crater wear and can be determined by a surface-measuring instrument. The rate of wear is high at the tool nose, generally under very-high-speed cutting conditions; crater wear is often the factor that determines the life of the cutting tool [30, 34].

3.3.3 Nose Wear

This kind of wear occurs on the nose or point of the cutting tool as a result of friction between the nose and the metal being machined. Wear on the nose of the cutting tool affects the quality of the surface finish on the workpiece. A small reduction in speed may eliminate excessive nose wear and could give a large increase in the tool's life [34].

3.4 Factors Affecting Tool Life

The following factors affect the life of a cutting tool [34]:

- Tool geometry.
- Work material.
- Cutting fluid.
- Tool material.
- Cutting conditions (i.e., speed, feed, and depth of cut).
- Built-up edge.

3.4.1 Effect of Tool Geometry

Tool geometry will influence tool life. Increasing the normal rake angle reduces the cutting forces and the heat generated during cutting. This would suggest that the cutting temperatures are lowered so that tool life is increased. Generally an increase in rake angle usually leads to an improvement in cutting conditions; a longer tool life would be expected. On the other hand, large rake angles will also reduce the mechanical strength of the cutting tool. So, that, although the forces are lowered, tool failure by chipping of the cutting edge or fracture can occur. However, when the tool rake is large, the cutting edge is mechanically weak, resulting in higher wear rates and shorter tool life. Build-up-edge formation, which may develop at low speeds, can be more detrimental to the mechanically weaker large rake angle tools [34, 39].

It is common practice to:

- Increases in side cutting edge angle, results in some improvements in tool life (load per unit length of edge is better).
- For the same wear land, larger clearance angles require greater tool wear by volume so that longer tool life values are obtained. Using large clearance angles, on the other hand, may reduce the tool mechanical strength.
- Use small or negative rake angles for the harder and relatively more brittle cutting tools such as carbides and ceramics.

3.4.2 Effect of Workpiece Material

The common variables considered are workpiece material composition and microstructure (heat treatment), its hardness and work-hardening properties. The workpiece material hardness is the easiest variable to measure and relate to tool life. As might be expected the harder the work material, the shorter the tool life [34]. It should also be noted that the hardness of the work material constituents and their proportions would influence the average hardness and the tool life.

3.4.3 Effect of Tool Material

The requirements of cutting tools are high hardness and toughness, good wear resistance, mechanical and thermal shock resistance, and the ability to maintain these properties at the temperatures occurring during cutting [34]. High hardness usually gives the tool good wear resistance, but may be associated with low toughness and poor mechanical shock resistance. The lack of chemical similarity between the tool and work material will also improve wear resistance. Thermal shock resistance is obtained when the tool material has high thermal conductivity and specific heat, a low coefficient of thermal expansion and high tensile strength.

3.4.4 Effect of Cutting Conditions

The variables, feed, speed, and depth of cut are of significant importance since they control the metal removal rate (MRR) and the production rate. If we begin with Taylor's equation [39]:

$$VT^n = C \quad \text{OR} \quad T = \frac{C^{1/n}}{V^{1/n}} \qquad 3.3$$

Alike trends happen for the feed and depth of cut. So, the tool life may be expressed as:

$$T = \frac{K}{V^{1/n} f^{1/n1} a^{1/n2}} \qquad 3.4$$

Where T= Tool Life min V = Cutting speed ft/min

f = Feed inch/rev a= Depth of cut inch

n= Constant C= Cutting speed for T = 1 min

K = Constant for a given tool-work combination and tool geometry

(1/n, 1/n1, 1/n2) are exponents.

3.4.5 The Effect of Built-up Edge on Tool Life

The presence of a built-up edge on the tool face during cutting can affect the tool-wear rate in different ways [34, 40]:

- In the presence of a stable built-up edge, it would protect the tool surface from wear and perform the cutting action itself, which would be beneficial and increase the tool's life especially when very hard materials are being cut.
- Due to an unstable built-up edge the highly strain-hardened fragments, which adhere to the chip undersurface and the new workpiece surface, can increase the tool-wear rate by abrading the tool faces [34, 38, 40].

3.5 Additional Comments on Tool Wear

Crater wear, flank wear and chipping of the cutting edge affect the performance of the cutting tool in various ways:

- The cutting forces normally increase due to tool wear. Crater wear may, however, under certain circumstances, reduce forces by effectively increasing the rake angle of the tool. Flank wear and chipping increase the cutting forces as a result of more rubbing forces.
- The surface finish produced in a machining operation usually deteriorates as the tool wears.
- Flank wear influences the geometry of the tool, which may affect the dimensions of the components produced.

The final result of tool wear is the complete removal of the cutting point. This may come about by temperature rise, which causes the tool tip to soften until it flows plastically at very low shear stress. An alternative mechanism by which failure may take place is that of mechanical fracture of a relatively large portion of the cutting tip. This often results from a weakening of the tool by crater formation[34, 39].

3.6 Tool Wear Monitoring

Although in many machining processes the cutting tool is the least expensive component of the cutting system, compared to the machine and workpiece, most of the monitoring effort is concentrated on ensuring that the tool is in good working condition. This is because damage to the cutting tool results in unproductive time which is costly. Therefore, an essential part of an untended machining system is the ability to change cutting tools before they are worn or broken. The cutting tools need to be changed before catastrophic failure damages the workpiece and the machine. For this reason a conventional approach is mostly used at present which estimates expected tool life based upon past wear data such as Taylor's equations. Tools are then replaced when this tool life is reached, regardless of the actual tool condition. This, however, means that in many cases tools are underutilised and down time has been unnecessarily increased.

Tool wear is an important factor in assuring the quality of the machined product. In particular, finish turning requires close attention to the cutting tools condition. A worn tool produces a poor surface finish. If deterioration of the tool is not monitored continually, the workpiece surface finish may be insignificantly degraded, with the consequent loss of the workpiece and associated machining time. Tool wear, if undetected, can also result in catastrophic failure and damage to the machine and workpiece resulting in significant down times and loss in productivity. This again requires a tool condition monitoring system. Frequently, subjective wear levels are set which translate on the workpiece as the maximum or minimum permitted tolerance. If this value of wear is replaced, a costly result could occur in the rejection of the workpiece during quality control assessment and probably an increase in scrapped material levels. Tool wear examinations focus on common tool wear forms such as flank, crater and nose wear. Different mechanisms could be responsible for these failures, such as diffusion wear, plastic deformation and built-up edge. These mechanisms depend partly on a combination of the type of the required shape, cutting condition, workpiece material and the nature of the cutting tool.

As most manufacturing systems are increasingly adapting and changing into fully automated environments, tool wear monitoring certainly would become an automated aspect of such a manufacturing environment. Defensive measures are needed to recognise a worn cutting tool and have it replaced as soon as possible. Failures might lead to a catastrophic tool breakage causing excessive power overloads and damage to the machine tool and the workpiece. In cases of high replacement costs, prevention or limitation of such a failure becomes paramount. In view of the damage that tool failure can cause to a machine tool and its marginal components, there has been a big drive to develop a system aimed at providing advanced warnings of coming up tool failure. These devices have taken the form of tool wear detection and identification mechanisms, referred as Condition Monitoring Systems (CMS).

3.7 Conclusion

Tool wear and tool life in metal cutting are described in this chapter. The chapter covers the main forms of tool wear that occur in machining processes. The chapter summarises the modes of tool wear and the factors affecting tool life. It could be concluded that the complexity of the cutting process necessitates the utilisation of a condition monitoring system. In addition, tool failure and wear in turning could be complex phenomena for condition monitoring systems. Therefore, a system that would ease the variety of underlying effects occurring during such a machining process is required for flexible monitor because different types of wear could have different effects on the cutting signals. Therefore, the use of a condition monitoring system is needed in machining processes and has to be explored.

Chapter 4

Condition Monitoring Systems

4.1 Introduction

In competitive manufacturing, condition monitoring provides a powerful means in the manufacturing operation to improve productivity and reduce cost. Condition monitoring technologies can be used in order to determine the machining process condition, and potentially predict failure. It gives a fast and accurate picture of what is happening in the machining processes. In addition, it can help to reduce machine downtime, maximise equipment performance, increase reliability, save operating cost and prevent catastrophic failure of machinery. In this chapter, a review of the condition monitoring concept, basic stages and elements is presented. The review seeks to show machine and process condition monitoring and monitoring methods. In addition, it shows the condition monitoring system structures.

4.2 Monitoring Systems

The global manufacturing competition in recent years has attracted the manufacturer's attention to the application of condition monitoring systems as a method of enhancing manufacturing productivity, eliminating inspection, and improving quality of products. An effective condition monitoring system depends mainly on the ability of the system to identify any faults and react, in real time, with a suitable action.

Manufacturing systems have become automated and more complex but generally become more reliable because of the new and improved design and the implementation of improved condition monitoring and maintenance strategies [31, 41]. Condition monitoring involves the process, the machine characteristic and the health of the machine. In terms of machine health, this could be divided into [42]:

- **General maintenance**: Technical and any associated actions intended to keep the machine perform its required function.
- **Unplanned maintenance**: Maintenance carried out to no programmed plan or when a fault occurs.
- **Preventive maintenance**: Maintenance carried out at programmed intervals or corresponding to predescribed criteria and intended to reduce the probability of failure.
- **Condition based maintenance (CBM)**: Preventative maintenance based on the condition of the machine using condition monitoring techniques. Under this approach, maintenance is only conducted as and when it is needed.
- **Condition monitoring**: Continuous or periodic measurements and interpretation of data captured using a condition monitoring system to indicate the condition of an item to determine the requirements for maintenance. Condition monitoring includes the monitoring of machine tools and machining processes to ensure the quality of the products and the health of the machine during production. This is different from maintenance since that objective is to define the state of the product based on the health/characteristic of the machine tool and the process. It also can be used for condition monitoring and diagnostic systems in machining processes to detect machine and process failure. Machine and process condition monitoring and diagnostic can be defined as "*providing a manufacturing system with the reasoning capability and knowledge to adaptively control its actions and thereby optimise its operations in response to given criteria, environmental and system stimuli*" [43].

4.3 Machine and Process Monitoring

Machine tools are extremely complex systems which include electronics, electrical, hydraulic and pneumatic drive systems, mechanical systems, control systems, measurement systems, gears, bearings, ball screws, lubrication systems and coolant systems. Therefore, there is a great complication in dealing with the large number of parameters that determine the process characteristics without the use of a condition monitoring system [44]. To fully understand and attempt to control the behaviour of a machine tool and the machining process, effective condition monitoring systems should be developed which guarantee the reliability of the system operations and quality of products. These signals can provide useful inputs to a machine and process condition monitoring and diagnostic system. The evaluation process of the signals may be used to determine the health of the machining process and the machine tool in addition to the kind of feed-back that can be used for on-line control.

In order to extract useful information from machine condition monitoring data, several stages are normally needed. The original machining signals, such as force, vibration, AE, temperature, sound, etc., contain noise and extra unusable information for monitoring purposes. It is extremely difficult technically and mathematically to derive any information from such signals. A pattern recognition strategy, which includes signal processing and data analysis, is therefore needed to simplify and analyse machining data for pattern recognition and classification of the signals. The ultimate goal of data analysis is to search for the needed structure in the data for patterns that can relate to a physical event [45]. Generally, data analysis can be considered as a task in which starting from some given data set, information about a specific unit can be extracted [46]. In machining, signals are described by some sensory characteristic features or attributes. Such features are essential to classifying or recognising the physical phenomena. This leads to complexity simplification in the considered application which permits enhanced decisions based on the extracted information.

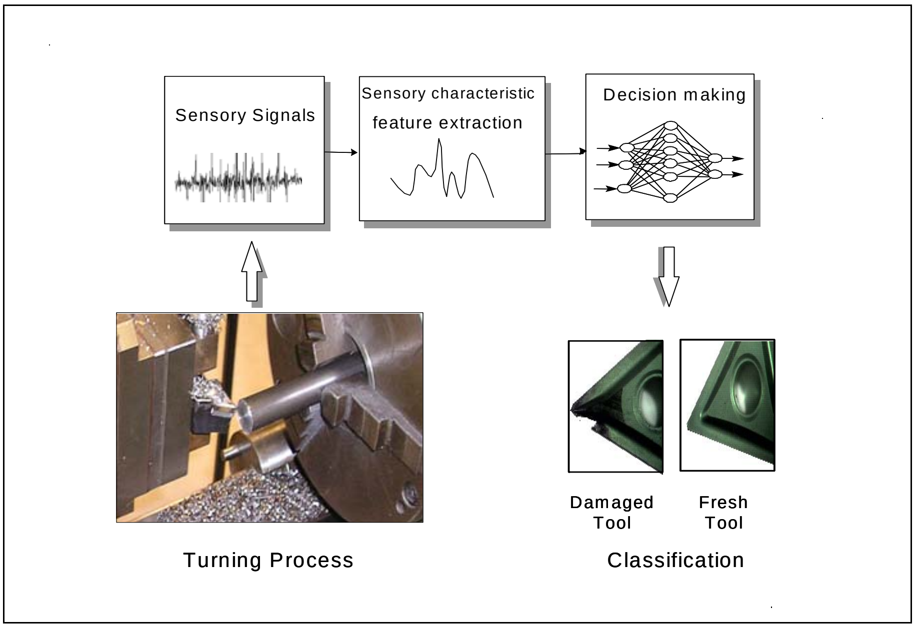

Figure 4.1: Stages of a condition monitoring system for turning.

A condition monitoring system consists of sensors, signal processing stages, and decision-making systems to interpret the sensory information and to decide on the essential corrective action as shown in Figure 4.1. The capability of a condition monitoring system relies on two basic elements: firstly, the number and type of sensors used and secondly, the associated signal processing and simplification methods utilised to extract the important information from signals. The first element involves expensive hardware which influences the cost of the system. The second element affects the efficiency and the speed of the system. The main issue addressed in condition monitoring is the efficient design of a condition monitoring system, minimising cost, development time and the number of sensors used [47]. This includes the selection of sensors and associated signal processing methods which provide the minimum error for the pattern recognition system.

4.4 Monitoring Methods

On-line and off-line are two methods that can be implemented for the condition monitoring of the machine tools and machining processes.

4.4.1 Direct Method

Off-line monitoring is performed when the machine is not running or machining. It could also be performed by measuring the work-piece dimensions. [28]. Off-line monitoring also includes calibration routines that can be done on the machine tool [28]. The main use of off-line monitoring is not for condition monitoring of the machine, but to correct the error in dimension by adjustment on the machine. It also could be used to condition monitoring the process. It is the normal quality monitoring method used in all processes at some stage. The advantages of the off-line monitoring methods which include simplicity of use, direct measurement in most cases and measurement principles, are well recognised. However, there is one major disadvantage: the process is considered unproductive and could waste considerable time and resources. In addition, errors are recognised long after the product has been completed. The direct method is also unable to determine the cause of some specific failures. Direct methods measure the real values of certain characteristic such as wear parameters (the size of wear area) [12]. The measurement technology of direct methods is expensive and these methods are liable to faults due to environmental conditions in a machine tool (chips, coolant, etc.) [12]. The direct technique can be implemented using procedures such as optical sensors, touch trigger probes and proximity sensors to measure the cutting edge [48].

4.4.2 Indirect Method

The on-line method monitors the parameters while the machine is in actual production. On-line simply means that the monitoring process does not occur at a particular time and there is no need to stop the production to perform on-line monitoring. The monitoring process in this case occurs independently from the production schedule. The advantage of this is saving time and improves productivity. Moreover, on-line monitoring has the benefit of more real-time diagnosis of machine faults and provides competitive advantage for automation [49]. Indirect methods measure some process parameters which are associated with process faults. For example, for tool wear some signals (such as cutting forces, AE, vibration, etc.) can be used for monitoring [12, 48]. Indirect methods utilise parameters which are easier to measure, but the computer computational efforts could be extremely demanding

[12, 48, 50]. The indirect techniques are based on the acquisition of signal features from which process/machine condition can be determined when compared to healthy known signal features.

4.5 Structure of Condition Monitoring Systems

As described in Figure 4.1, condition monitoring systems includes three main components: sensors, signal processing methods, and pattern recognition and identification systems. This section will discuss in some detail modern development and difficulties associated with each component.

4.5.1 Signals and Sensors

When a machine tool is operating, several types of signals are produced from the machine tool and the machining process. Figure 4.2 shows some of the signals produced during machining process. These signals can provide significant inputs to the condition monitoring system. The evaluation process of the signal could be used to establish the condition of the machining process.

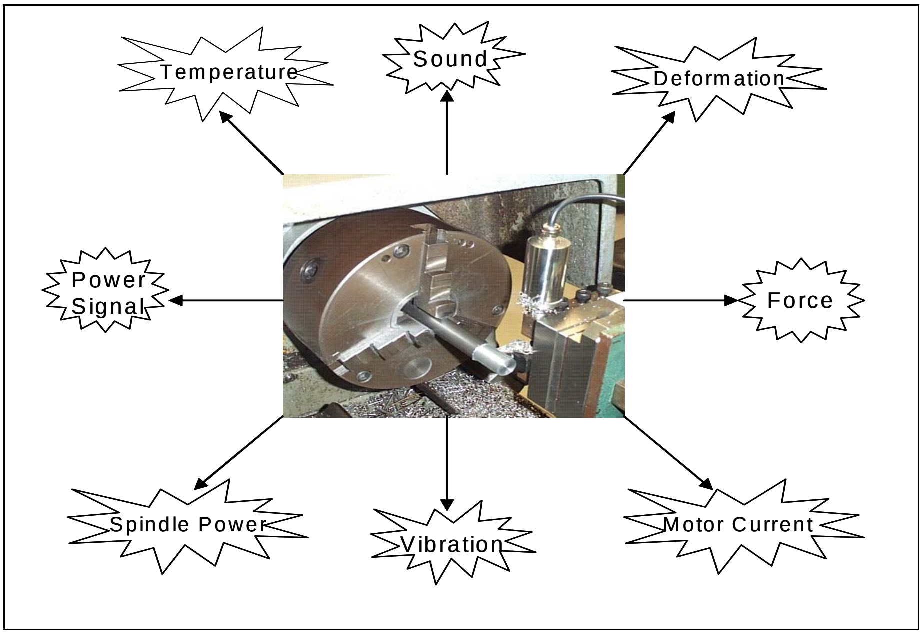

Figure 4.2: Signals emitted from the machining process.

To carry out a condition monitoring system effectively and rapidly, the machine must be fixed with sensors that convert the status of the manufacturing process into measurements. The success of a condition monitoring system depends on the type, suitability and reliability of information captures by the sensors [51]. According to the "Sensor Markets 2008" report, the sensor market, under very conservative assumptions, is expected to reach $50–51 billion by 2008. Figure 4.3 shows an overview of the sensor market development for the major application sector.

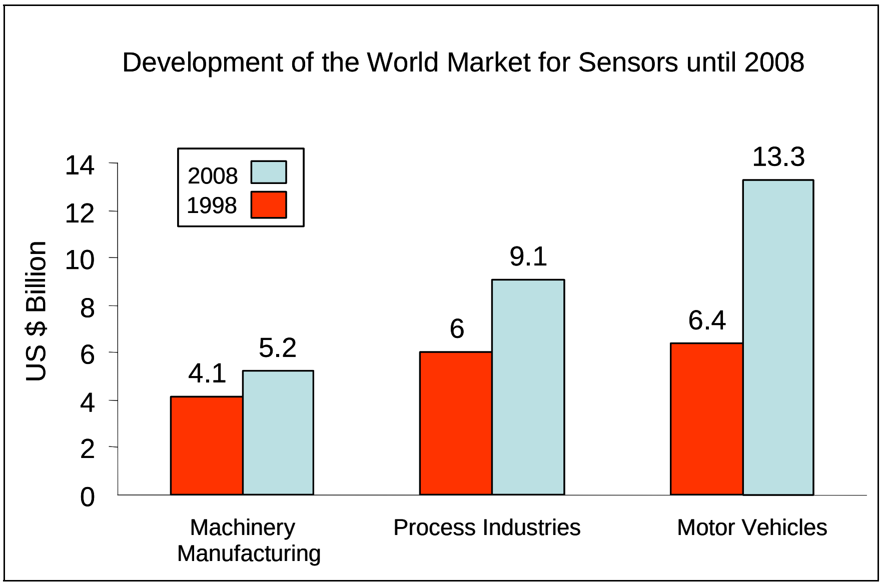

Figure 4.3 Sensor market developments for the major application sector.

In the sensors manufacturing sector the leading sectors are motor vehicles with around 20% of the global demand for sensors in 1998. A 30% price reduction for sensors in the motor vehicle industry is expected over the next 10 years. The sensors market for the manufacturing industries is about 18.5 % of the total market. For example, the process industries market is expected to grow from US $ 6 billion in 1998 to US $ 9.1 billion in 2008. Different types of sensors have been commercially available, see for example [51, 52]. The sensors should be sufficiently durable to survive the hostile environment and they should be simple to operate and robust and comply with the expected requirements in manufacturing operations. They should also be close to the machining point, supporting the static and dynamic solidity on the machine tool, maintain the working space and cutting parameters, wear and maintenance free, be easily replaceable and cost-effective, resistant to dirt, chips and mechanical, electromagnetic and thermal influences, functionally independent of tool and work-piece and reliable in signal transmission [23, 51]. New and diverse technologies have been reached over the last two decades in the area of sensor technology [42]. Reliable sensors are required to identify the behaviours of the machine tool and the process. Various sensors have been developed and implemented for the monitoring of tool failure, part dimensions, surface roughness, surface burn, chatter, etc. The selected sensor depends on the particular fault to be monitored as well as on the type of machine. Therefore, a large variety of sensors and signals have been investigated in literature [53]. The type and the nature of the signal being monitored will determine the most appropriate sensor to capture that particular signal.

The selection of sensor and signal processing in the field of condition monitoring systems is essential for setting up a reliable system [54]. This is due to the fact that manufacturing processes are difficult to model mathematically and sensors are used to provide the data that are needed to describe the process. It is possible by using this data to describe the process through different approaches where these include empirical modelling expert systems, neural networks and fuzzy logic [23]. Many types of sensors have been implemented in condition monitoring research. The types of sensory signals such as force, temperature, vibration, sound, acoustic emission, motor current, coolant pump pressure, motor voltage and speed, have been verified to be effective for condition monitoring applications [55]. Also other off-line monitoring techniques using tool probing have been found useful [2, 56]. Many sensors have been developed to meet their demand. For a given process and fault, a minimum number of sensors that are most sensitive to the measured parameters need to be selected. However, the problem of selecting suitable sensors for a specific process remains under investigation or untested in some areas. Solving this problem requires a thorough understanding of the monitoring process, types of failure and the sensory system [47]. The ASPS method [57-63] has been modified and implemented in this thesis to ease the turning processes by providing an automated method for selecting the most appropriate sensor and signal processing method for monitoring tool wear. The ASPS approach helps to design a condition monitoring system for a machining process using an automated simple procedure to detect the sensory characteristic features which are most sensitive to process faults but less sensitive to other machining variables and parameters. The sensory characteristic features provide essential information for the detection or classification of machining faults. The ASPS approach uses the "black box" concept where the monitoring system is designed based on the inputs and outputs of the process rather than its mechanics and the faults mechanism. More details will be mentioned in Chapter 6 section 6.4.

4.5.2 Signal Processing

The sensory data acquired usually includes high level of noise and some random characteristic. Therefore, signal analysis is required to simplify and abstract the meaningful characteristics for the decision-making process. Pre-processing methods such as filtering and amplifying are sometimes used to reduce noise and improve signal-to-noise ratios. Once complete, the next step is to gain an understanding of what type of data is being measured. Monitoring systems rely on data analysis. Industrial problems of machine condition monitoring demand sufficient interpretation of data which occurs in particular applications such as: process monitoring and diagnostics; quality control; and tool condition prediction. An effective tool wear monitoring system, for example, should have a good signal processing algorithm able to identify the signals of tool wear from those due to changes in cutting conditions, such as a change in depth of cut. Filtering signals is important to be performed, when needed, to solve the noisy input problems and aliasing. Generally, signal processing methods include frequency domain, time domain and the other statistical methods. Frequency domain analysis produces frequency spectrum analysis such as FFT which has been a commonly applied signal processing technique in engineering applications [64]. Discrete wavelet transformation (DWT) is a signal processing technique in the time–frequency domain which gives signal decomposition with reasonable resolutions in both the time and the frequency domains and a better reconstruction of the original signal in terms of the decomposition results [57]. Time domain methods include RMS, peak level value [57], kurtosis analysis [57], crest factor analysis [60, 61], moving average techniques [64], time domain average (TDA) [62, 63] and shock pulse counting [65]. Singular spectrum analysis (SSA) is a new non-parametric technique of time series analysis based on principles of multivariate statistics [47]. The role of signal processing could be described as a tool which tries to pick up the meaningful knowledge out of the mass of information [57, 59]. Investigations have shown the signals of particular conditions normally have particular spectral distributions [61]. A relatively modern approach to conventional signal processing techniques is the application of wavelet transformation. [66]. Statistical methods are also used to discover relations within a data set describing a special kind of application. In this area, correlation analysis and regression analysis could be applied [67].

The type of the signal processing technique is important for a successful condition monitoring system. Some researchers believe that if the calculated signal includes the needed information about the process, then it could be possible with an intelligent diagnostic tool to produce successful prognostic and diagnostic results. Processing of the signal data from the sensors is very significant for precise estimation of the condition of the cutting tool. Several algorithms are applied for condition monitoring systems. Lately, more than one algorithm has been used for improving the efficiency of the system [68]. New signal processing methods appear frequently in literature that could also be used to improve the signal processing methods.

4.5.3 Artificial Intelligence and Pattern Recognition

The majority of manufacturing processes are basically noisy and non-deterministic [69, 70]. Because of this complex nature, it is difficult to build a perfect mathematical model from captured and processed signals. With the increases in computer technology, the last decade has monitored the development of several artificial intelligence methods to the area of condition monitoring systems [71]. Artificial Intelligence (AI) is a broad term used to explain computerised approaches that use knowledge, reasoning, self learning and decision-making to make machines operate or 'think' as human beings. Generally, artificial intelligence may be separated into two groups: symbolic intelligence contain expert systems, knowledge based systems, case-based reasoning, etc; and the second is computational intelligence which contains artificial neural networks (ANN) [72, 73]. The problem of the machine can be identifying from the signals gained from the sensors by the pattern recognition to identify the condition of the manufacturing process. Many artificial intelligence techniques which have been developed for manufacturing systems have been found reasonably successful [74]. In addition, all pattern recognition techniques described in the literature have disadvantages, not all are absolute. Measurements have to be made on the healthy system to store the healthy response [66] and in most cases the information contained in the data is not utilised adequately or the data base is uncertain [75]. In the pattern recognition technique the response of some parameters is recorded and it is repeated over time as the failure generates and the record will be changed over that time. If the parameter which has been chosen is good then the record will change in a different shape if a different fault is generated, though, the response demonstrates different patterns depending on the fault. If the pattern is recognised then the fault can be diagnosed [75-77]. In this work, two unsupervised approaches have been selected. The approaches are Novelty Detection (ND) and Learning Vector Quantisation (LVQ).

Novelty detection [77] requires no comparison between healthy and unhealthy signals. Only normal conditions are needed to characterise the normal process. Any deviation from normal conditions will be identified as novel. Novelty detection [77] is a classification technique that recognises a presented data as novel (i.e. new) or non-novel (i.e. normal). The training data for the novelty detection algorithm consists of only the normal class which is often much easier to obtain than data for multiple classes. Since a degree of overlap is normally expected between different classes, classification problems have a probabilistic nature [78]. Novelty detection involves estimating the probability-density–function (PDF) of a normal class from the training data and then estimating the probability that a new set of data belongs to the same class. The accuracy of novelty detection classification is dependent on the accuracy of the modelled density functions [79]. Three main methods are normally used to model the PDF: parametric methods [80], non-parametric methods [77] and semi-parametric methods [81]. The parametric methods assume sufficient statistical information about the training data set which is not normally available. In non-parametric methods no assumptions are made regarding the underlying density functions and they depend on the training data to find the probability-density-function for a new input. Reference [82] classifies such methods as being Kernel based techniques and K-Nearest Neighbour techniques. The K-Nearest Neighbour method depends on the probability that K number of data points of a vector fall within a specific volume. The Kernel-based technique calculates the volume by defining width parameters for a number of known probability distribution functions (Kernels) to provide a general model for the training set. However, non-parametric methods require long computations for every input vector. Semi-Parametric density estimation is used in this research for novelty detection because it combines the advantage of both parametric and non-parametric techniques and does not require extensive computational effort. Semi parametric methods use fewer numbers of Kernels. A Gaussian Mixture Model (GMM) is used in this research to estimate the PDF. Unlike non-parametric methods the training data are used only during the process of construction of the density model and are not needed for calculation of the PDF for new vectors. Different novelty detection algorithms and applications have been reported. Reference [83] generalised radial basis function neural networks. These are used to form a Bayesian classifier that is capable of detecting novel data. The advantage of novelty detection comes from the ability to distinguish between training data and new data that have not been seen before. Reference [84] uses the novelty detection approach to diagnose failure in structure. In reference [85], novelty detection is used for the detection of special causes in multivariate statistical process control.

Learning Vector Quantisation neural network (LVQ), which implements competitive neural network, is an unsupervised neural network which uses Associative Learning Rules which allow the network to learn the association between the inputs and the outputs in reply to the data presented to them. A competitive neural network belongs to Self-Organising neural networks where such networks can learn to detect regularities and correlation in their inputs and adapt their future responses according to that input. A competitive neural network basically learns to recognise similar input vectors and to classify them together in one group. The basic structure of this network is that the input vector to the competitive layer is obtained by calculating the negative distance between an input vector p and the weight vector w and adding the bias b. For any layer, the neurons are in competition, all the output of the neuron will be zero, except the winner neuron, which its output will be one. When the weight w of a neuron is the closest to the input vector p, it will have least negative input, and then it will win the competition and its output will equal to 1. The user has to select the length of the input vector and the number of layers and then the network will group the inputs according to the needed groups. The advantage of using LVQ is that it learns to classify input vectors into target classes chosen by the user. Though, the learning rules are done according to the competitive layers depending on the distance between the input vectors and the weight and not according to the error between the output and the target unlike to back propagation neural networks [86]. Therefore, there is no mechanism in the network to dictate whether or not any two input vectors belong to the same category. LVQ has an input layer, a competitive layer, and a linear output layer. The competitive layer learns to classify the input vectors to subclasses while the output linear layer transforms the competitive subclasses into the desired target classes. The results of a literature review shows that novelty detection and LVQ have the potential to be applied successfully in many applications. More details about novelty detection and LVQ will be described in Chapter 7 section 7.4.

4.6 Sensor Fusion

Monitoring methods based on a single sensor may not be accurate for the identification of the nature and the location of tool wear because tool wear is a very complex process and dependent on diverse machining factors such as cutting velocity and feed rate which affect the reliability of detecting tool wear and failure. For example, cutting forces are a function of cutting velocities and in the case of significant change of the cutting velocity, thrust and torque signals change remarkably. This may not result in meaningful information on the tool condition monitoring [87]. Hence, there must be another type of sensor, e.g. vibration or acoustic emission (AE) sensors, which can complete the force sensors. Besides, some sensors are sensitive to particular types of fault. Thus, the information from a single sensor may simply not be good enough to make a reliable decision on tool condition monitoring.

In order to increase the predication reliability sensor fusion is used. Multiple sensors are combined to measure the same phenomena. This is called sensor fusion. The integration of various sensors and therefore the analysis of rich data from several different sources may improve the success of the condition monitoring system. Other typical applications of sensor fusion are robotic systems, automatic target recognition, autonomous vehicle navigation, etc.

Because of the rising complexity of recent machines and the increasing demand for reliability, availability, cost effective and safety, condition monitoring has become an ordinary strategy in industry. Successful condition monitoring is becoming extremely dependent on the ability to interpret multi-sensor data based on advanced signal processing methods [88]. Sensor fusion has already been widely used in various applications in which multiple sources of information are presented. It is well known from recent research that employing multiple sensors using sensor fusion methods provides improved and robust estimates.

If the quantitative relationships between simple sensor measurements and physical or chemical characteristics of a sample are known, or can be empirically calibrated, these relationships can be used to determine the characteristics of a new sample from sensor measurements on that sample. Simple sensors are easily calibrated using standards, and occasionally, calibrations made by the sensor manufacturer can be used. When two or more sensors are used jointly, the calibration is called multivariate calibration. Two or more characteristics can be determined at the same time if at least the same number of sensors is used. However, there are advantages in using more sensors than the minimum number. Not only will the precision in the determination of a characteristic be increased, but also error control is possible, for example, to detect a malfunctioning sensor or a process failure [89].

Sensor fusion is capable of producing an improved model for system estimation by using a set of independent data sources [90]. It manages to make full use of information and can effectively increase the fault signal to noise ratio, and improve the information quality and strength and thus help improve diagnosis accuracy [91].

4.7 Conclusion

Condition monitoring systems are widely used in research and industry for condition-based maintenance activities as well as process and machine monitoring for fault diagnostic and to maintain an acceptable product's quality. Condition monitoring systems include three main stages: sensors, signal processing methods, and decision-making. The success of the condition monitoring system depends on the integrated results produced by the complete system. This chapter has presented an overall concept of the condition monitoring technologies that have been implemented in research and industry in recent years.

Chapter 5

Review of Implemented Condition Monitoring Systems in Turning Processes

5.1 Introduction

A broad range of monitoring methods have been proposed and developed in the last decades. Only a limited number of methods, however, have been implemented in a real industrial environment. This chapter presents a review of condition monitoring methods that have been developed or implemented in industry and research. The review seeks to display the problems in current monitoring methods and to obtain an idea about the current research in condition monitoring systems in turning processes. A wide variety of direct and indirect methods of condition monitoring systems are described. Some successful and descriptive references found in the field of condition monitoring systems have been analysed and introduced. In addition, this chapter briefly reviews the potential sensors for monitoring process output variables useful for tool wear monitoring in turning processes and discusses the criteria for sensor selection based on their applicability, robustness, and reliability in a real industrial environment. This chapter concludes with a summary of the current problems in condition monitoring systems.

5.2 Monitoring Methods

As mentioned earlier, tool condition monitoring methods can be classified into direct and indirect methods, depending on the source of signals collected by sensors. Direct methods sense tool conditions by direct measurement of the tool. Direct methods include contact switched, optical, radioactive and electrical resistance. Alternatively, indirect methods sense the tool condition by measuring the secondary effects of the cutting process, such as vibration, sound, acoustic emission (AE), cutting force, spindle and feed motor current. Direct methods are beneficial because they take close reading directly from the tool itself. By contrast, indirect methods must rely on conditions other than the tool itself to judge tool condition. However, direct methods are limited because the machining process must be interrupted to make the direct measurement[92]. As a result, machine down time increases, as does cost for tool condition monitoring. Researchers therefore have preferred indirect methods to examine on-line tool condition monitoring systems. Since indirect methods do not require access to the tool itself to measure tool condition, signals that indicate tool condition can be gathered in real time, while the machine is running [11]. In the following sections some of the more successful direct and indirect methods of tool wear monitoring will be introduced and their merits and shortcomings will be discussed. Because of the large amount of literature in this area, the following section aims to provide the reader with a general outline of the state-of-the-art.

5.3 Direct Methods

5.3.1 Optical measurement

Since the tool wear land has a higher reflectivity than its surface, optical and electro-optical methods can be used to measure tool wear directly by using contrast. Using the increased computing power and reliability of electronic devices, optical systems have been designed to analyse the image of the illuminated wear zone. A system which employs CCD cameras coupled to an expert system has been proposed for tool life management in flexible manufacturing cells [93, 94]. This method has the advantage of being persistent and interference with machining hardware is kept to a minimum. One problem with this approach is that optical sensing can only be used between cutting cycles when the tool is removed from the workpiece (i.e. off line process). In addition, distinguishing the worn area is made difficult when a built-up edge or metal deposit is present. This kind of method is inflexible and cannot be applied to on-line monitoring.

5.3.2 Workpiece Dimensions

As the cutting tool wears, particularly on the edge in contact with final machined surface, the workpiece size changes. For example, the depth of cut will be decreased with tool nose and flank wear in turning. Therefore, by measuring the workpiece size, tool wear can be estimated directly. Reference [94] planned a method for tool wear monitoring based on measurement of workpiece difference. Two electromagnetic probes are employed on opposite sides of the workpiece so that the electromagnetic waves flow from the probe to the metal thus allowing precise measurements of the workpiece diameter. The sensor outputs a voltage directly related to the gap between the sensor and the workpiece. Since the machine has to be stopped in order to measure the workpiece size, systems of this type cannot be implemented on line. These systems are not able to diagnose different tool failure modes. For example, it is not possible to distinguish between flank or nose wear. Moreover, errors can be introduced by thermal expansion or lead screw inaccuracies.

5.3.3 Electrical Resistance Measurement

It has been observed that the electrical resistance of the tool/workpiece interface decreases with progression of wear due to increases in the contact area. Measurement of this change in electrical resistance has, therefore, been used as a tool wear monitoring method. Simply measuring the electrical resistance has proved ineffective because of the resistance change due to the variations in temperature and cutting forces during the machining process. A more accurate method has been found to be one in which a thin film conductor is bonded to the tool flank. As the tool flank wear progresses, part of the conductor is also worn, increasing the resistance. This increase is then correlated to flank wear. The problems with this method include the need for special tooling, the high level of noise due to high temperatures and plastic deformation and the possible separation of the conductor from the flank surface due to high pressure and temperature. In addition, this method cannot be used to measure other modes of wear [96].

5.3.4 Tool-workpiece Distance Measurement

As the turning tool wears, the distance between the tool holder and the workpiece decreases as the tool wears. To use this observation for tool wear monitoring, the distance between tool holder and workpiece can be measured by a variety of sensors such as electronic micrometers, reflected ultrasonic waves and pneumatic gauges. The distance can be measured by proximity sensors such as feeler micrometers and touch trigger probes and sensed by using an electronic micrometer fixed on the tool post or a stylus attached to the tool post [97]. However, these methods are not suitable for use in condition monitoring systems because the measurement of this distance is influenced by the thermal expansion of the tool, surface quality, vibration of the workpiece, cutting fluid and the deflection of the tool due to the cutting force, etc.

5.3.5 Radioactivity

It is well known that, in turning processes, most of the wear particles of cutting tools are carried away adhering to the surface of the chip. Therefore, a practical way for measuring wear could be to track these lost particles. Radioactive sensors have been used to measure the volumetric overall loss of the tool material. In most cases, the tools are made radioactive by irradiation in atomic reactors [98]. Tool wear is then monitored by measuring the radioactivity transferred to the chip. Since the total amount of wear at the normal wear rate is very small, the chips have to be collected and their radioactivity measured. This means that radioactive methods cannot be used as an on-line wear monitoring system. Environmental and health considerations also limit use of radioactive material on the shop floor.

5.4 Indirect Methods

5.4.1 Force Sensor

One of the more common indirect tool wear monitoring methods is the use of cutting force measurements. Typical cutting force components are shown in Figure 5.1. It has been reported that cutting force signals are more sensitive to tool wear than vibration or power measurement [99]. The reliability of force measurements is another factor for their popularity in tool wear monitoring applications. The relationship between cutting force components and tool wear has been investigated by many researchers. Reference [100] found that the tangential force decreased as the insert broke while the feed force might decreases or increases depending on the cutting edge. Reference [101] recognised the relationship between the wear and the tangential force. The amplitude of the dynamic force increased with tool wear and decreased before tool failure.

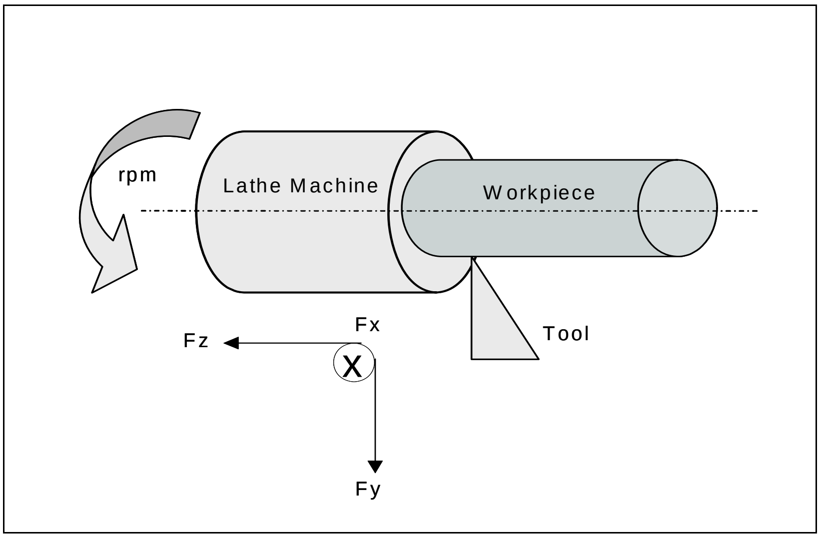

Figure 5.1: Cutting forces in turning operations.

Reference [102] proposed and implemented a model for tool wear prediction using cutting force signals. Turning tests are performed on a lathe and the required data collected and resulting wear measured. A number of tests are initially performed under a variety of cutting conditions. From these tests, the force components least sensitive to process parameter change but most sensitive to tool wear are identified. The results showed close correlation between actual data and estimated values. With varying cutting speed and depth of cut, an error estimate of 6-9.5% is reported for constant feed-rate, chip breaker and workpiece data. Therefore, this error is high for tool wear prediction.

Reference [103-105] proposed a combined method of cutting tool flank and crater wear estimation. In the implementation stage of their method, data from experiments performed on a vertical lathe were used. The experiments involved recording the pre-processed (low pass filtering) components of the cutting forces from two sets of tests conducted. For the first set, used coated carbide inserts and carried out the tests at low cutting speeds. The second set of tests used ceramic inserts and was carried out at higher speeds. The same workpiece material, feed-rate and depth of cut were utilised in both test sets. Force-wear relationships partly based on the same principle as reported in [3, 103] were employed to select the input coefficients for training the network. Results showed relatively good flank wear estimation but poor crater wear estimation. Overall, the proposed method demonstrated an ability to estimate tool wear closely, over a wide range of cutting conditions but lacked vital accuracy. The inaccuracies could be attributed to poor input coefficient estimation; researchers related the cutting forces to tool wear with linear equations. It is therefore misleading to contemplate combining the two data types and expect unanimity.

References [3, 101, 102, 106] performed cutting tests from which researchers recorded the dynamic cutting force signature. A dimensional space features selection process and three different implementations were carried out. In [102] researchers used a wavelet technique to extract such features from the convoluted force signal. Results obtained showed inaccuracies due to changed chip shape as a result of tool state change. The main reason for this, the researcher claimed, is the fact that in any cutting process more than two classes of cutting states actually exist, and a network with just one output can only recognise two of them. Thus, the final classification results would not be entirely correct.

References [107] also used the cutting forces signal. The net output gave an indication of the product surface finish established earlier as representative of the tool state. Effectively, reference [107, 108] used this experiment to relate tool wear, surface finish and cutting forces, and reported a high but un-quantified achievement rate. Reference [3] approach and methodology was similar to that of [109], but differed in terms of sensor signal inputs, data processing. Reference [3] argued that there is no need to use dimensionally selected features. Instead, the amplified components of the cutting force signal are used as samples, together with the three cutting parameters [110].

Reference [111] utilised the cutting forces as sensor signal inputs with an additional component, depiction of the occurrence of tool breakage to monitor the cutting process. The reference incorporated the cutting condition parameters (cutting speed, radial and axial depth of cut) with the chosen sensor signals and workpiece material. Reference [112] utilised the integration of cutting forces and AE signals in their studies of the influence of flank wear on the individual signals. Machining test cuts were performed from which the cutting forces and the AE signals were recorded.

Researchers concluded that by combining different source signals for tool wear and classifying their success rate significantly improved the performance of the system.

Reference [112] carried out single-point cutting test experiments and measured and recorded the tool tip temperature, the true root mean squared value (RMS) of the AE signal, and the three components of the cutting forces. The reference reportedly achieved very precise wear evaluation but no quantification of the results was provided.

Reference [107, 108, 112] used the vibration and cutting forces from both turning and milling tests to perform tool state classification, continuous estimation of tool wear and the inverse modelling of the cutting process. Reference [113] experiments involved carrying out milling and turning test cuts utilising both fresh and worn inserts, recording the cutting forces, and vibration components from each cut. Using the measured signals, statistical and spectral features were computed, followed by performance of a sequential forward search or feature selection process using the same selection criteria as [114] used the force data to perform classification tests.

5.4.2 Sound Sensor

The concept of sensing tool wear from the sound signal during a cutting process goes back more than thirty years. Sound from a machining operation contains a variety of information on cutting. There have been several studies using sound signals in this situation [6], and their results confirm the correlation between tool wear and the sound emitted during the turning process.

It has been reported that tool wear is correlated with an increase in the amplitude of the high frequency bands of the sound signal [115]. In this research work, a sound signal was used to extract valuable information correlated with tool wear.

The main problem of using this signal in the development of a tool condition monitoring system is the ambient noise, as has been identified and studied in several research studies [116]. These studies concluded that in the region between 0 and 2 kHz the influence of the surroundings and of the noise from adjacent machines, motors, conveyors, etc. or processes may contaminate the signals. However, they concluded that this effect can be moderated by using noise cancellation methods in the signal processing algorithm. In this way, several researchers focused their studies on certain frequency bands in the region 2–20 KHz. Tool failure can be detected also by using the noise spectra resulting from the rubbing action of the tool and the workpiece. Reference [117] discovered that noise in the 2.75 – 3.5 kHz frequency range is significantly increased from 9 to 24 dB as the sharp tool becomes worn. Reference [118] developed a pattern recognition analysis of sound radiation as basis for tool condition monitoring. They recorded the sound pressure signals radiation using a sharp tool, a worn tool and a broken tool. They used the spectral component in the 0 – 10 kHz range as a feature with the fresh and worn tool resulting in a 100% classification with just two features and an average of (0-5 kHz) and a high of (5-15 kHz) range. Reference [115] used a microphone sensor to detect the nearest approaching point of the workpiece. The investigations showed that ultrasonic and AE sensors are good enough for detecting the nearest approaching point. Reference [91] presented research work based on texture analysis of machined surfaces and signal processing of sound generated by the machining process. They investigated the correlation between tool wear and the quantity of the machined surfaces and sound patterns. The results indicate that tool condition monitoring in this investigation between sharp, semi-worn and worn tool can be successfully accomplished by combining sensory data from a camera and microphone.

5.4.3 Power/Motor Current Sensor

Reference [119] studied the relationship between the power or the current of the main drive motor of the spindle and tool breakage and tool wear. He found that the motor current dropped and then improved to a level before the drop as the tool broke. At the steady spindle speed of the cutting state, the percentage increase of the motor current from the start to the end of the tool life was almost constant when similar material was machined. The spindle motor power from a vertical milling machine is measured by [24] as well as the power spectral density. It was proven that the variation of the spectral energy of the motor power was linearly linked to the tool wear rate and that these were affected by the tool geometry and the cutting conditions.

Reference [24] carried out cutting tests in order to examine tool breakage detection and compared success rates achieved by these methods on a lathe machine. The sensor signal inputs used included the fusion of vibration ultrasonic energy, and current inputs to the carriage drive motors. Additional to these signals, the feed-rate and the spindle speed were used as further inputs. Data having the breakage signatures were recorded as cutting progressed until a breakage happened. The recorded signals were then analysed by application of selective time windowing and block averaging, to reduce the data size. Using four methods of measurements from each test the relative success of each method was evaluated. Reference [24] used AE and motor power sensors to detect the tool breakage in the turning machine. To process different AE signals emitted from cutting process, reference [65] used time–frequency analysis and observed four types of power signal variation in the experiments when tool breakage occurred. Reference [120-122] suggested that the change of power signals in the time domain is stochastic and proposed a delayed variance to extract features from the power signals.

5.4.4 Acoustic Emission Sensor

Acoustic emission (AE) can be defined as the transient elastic energy released in materials undergoing deformation, fracture or both. In metal cutting processes, AE is attributed to many sources, such as elastic and plastic deformations of both the workpiece and the cutting tool, friction, fracture of the workpiece, wear and failure of the tool. AE provides a means of sensing tool wear or tool fracture, since it is generated from the process that causes tool failure. The emission signal is usually detected by transducers, then amplified and transmitted to a processing device. Spectral analysis has been found to be the most informative analysis tool for monitoring tool failure in turning. In [123] burst type AE and continuous AE waves are the two kinds of acoustic emission waves that can in general be met during the machining processes. The burst type of AE is a sign of discrete actions with its main source being tool and chip breakage. The other is the continuous kind which results from the shear of the workpiece, the contact between the workpiece and the cutting tool, and tool and chips are the main area of focus of the continuous AE type. During the machining process considerably AE is thought to be produced compared to the larger amount accompanying tool fracture and breakage [124].

Consequently, AE has been found to for more dependent on the workpiece structure than on the cutting tool. The signals of AE reflect more the behaviour response from the machine tool set up than the cutting tool [93] since AE may be available on the whole machining area. The disadvantage of the application of AE as an indicator of tool failure is that the signals are more sensitive to variation in the cutting conditions and the noise more than the tool itself. Therefore, the use of the AE sensor by itself to monitor the condition of the tool is difficult [125]. AE is suitable to be used as an additional sensing technique to increased reliability.

Reference [126] utilised acoustic analysis to predict tool wear in the turning process. The parameters chosen were recorded at the same time and the resultant tool wear length measured. Analysis showed that the AE signals can determine clearly the cutting condition of a sharp, worn or damaged tool. Reference [127, 128] reviewed AE sensing methods in machining processes. Among other methods mentioned, it reported that tool wear detection in machining process could be done by applying AE. Reference [129] used AE and force signals combined with a pattern recognition analysis system to carry out progressive tool breakage detection and tool wear monitoring. References [108] applied the combination of AE and force sensors to gradient adaptive lattice analysis and pattern recognition. Reference [130], inspired by previous successful works by [131] and others, proposed and investigated an in-process method of tool condition monitoring. The method principally involved monitoring the progressive increase of tool wear during a turning operation. Cuttings tests were conducted using a lathe machine from which 300 samples of raw AE_RMS, signals were recorded at three seconds intervals. From the recorded AE_RMS, four dimensional features were extracted: integral (energy), skew, kurtosis distribution and the auto-regressive coefficients. Reference [132, 133] extended [134] work by conducting turning experiments from which the cutting forces and AE signals were recorded under different cutting conditions. They continued to extract 100 features from all the measured force and AE signals and these were used as inputs. References [89] proposed four methods for integrating several sensor signals from a machining process. Test cuts were performed from which the cutting forces, temperature, and acoustic emission were recorded for known tool conditions. Reference [132, 133] proposed an approach based on sensing the AE signals from carbide inserts to develop a new method for the automatic detection of cutting tool wear and life in turning operations, making use of its characteristic features for worn and sharp states. The results confirmed that tool wear and life were correctly identified. However, no clear justifications of the findings were provided. Reference

[135] proposed, examined, and compared the performance of two approaches of multi-sensor information from a machining process. These approaches concerned the fusion of multiple sensor signals through ANN and compared the results with those gained from methods based on statistical analysis. This is an addition of the work reported in [136]. Test cuts were performed using a CNC lathe, and the cutting forces, tool-workpiece interface temperature, and AE signals were recorded for identified values of tool wear. The recorded signals were processed through a combination of techniques. Initially, four sets of tests were performed at a constant feed rate, depth of cut and cutting speed. Each set consisted of machining experiments with each experiment in turn consisting of a particular machining time period.

Reference [137] investigated data from spindle power and acoustic emission sensors. Face milling and drilling processes were combined to successfully identify a state of tool wear, workpiece hardness, and a stock size dimensional variation. The results showed that the system is capable to correctly identify the correct state.

5.4.5 Vibration Sensor

Vibration is a method that has been widely used in tool failure detection. The vibration sensor can be installed easily on the tool holder. The vibration signals vary with tool failure in some ranges of frequency. Vibrations are created due to the rotation difference in the dynamic components of the cutting forces. Regularly vibration action starts as small chatter, practical for the roughness on the finished surface and chip thickness irregularity and development to what has come to be normally called vibration. Because of the periodic wave motion, it generally produces mechanical vibration. The vibration produced in the machining processes is a mix of different types such as forced, free, random and periodic [138]. Because of the dependent frequency of the vibration, it is difficult to achieve a direct measurement of the vibration because of its determining characteristic features. Therefore, a parameter like the acceleration is measured and obtained the vibration from the pattern. Reference [138] studied and discussed the detection and estimation of groove wear at the minor cutting edge of the total monitor vibration. An accelerometer attached to a lathe machine was used to perform the cutting test. Measurement of the wear was taken after each cut when it was interrupted. The analysis showed the cutting and thrust vibration components. Reference [139] performed turning tests using a CNC lathe machine and measured the vibration signals on the tool holder. An extensive feature selection process utilising the sequential forward selection algorithm with respect to clustering properties was performed. It concluded that the main disadvantage in the investigation was the large amount of data and required extensive time for analysis. Reference [140] mostly concentrated on the problems related with varying the cutting conditions for tool condition recognition using vibration and force features fuse all the way through a neural network. The concern was in classifying whether or not the tool condition had been damaged or not. The main disadvantage in this study is its limited validity over a broader range of machining parameters.

Reference [141] argued that tool wear levels alone were responsible for the level of chattering on a machine tool. To examine this, a test was carried out on a conventional lathe machine using carbide inserts, and existing records of the vibration and AE signals. Time displays of the recorded signals clearly showed the coupling between chatter and tool wear with the surface outline becoming rougher as the AE and acceleration signals increased.

5.4.6 Temperature Sensor

As a cutting tool wears, the temperature developed at the tool edge increases due to increased forces, contact area and friction. In most cases the final breakdown of the tool is due to this increased temperature. Therefore, the cutting temperature can be used to indicate the condition of the tool wear, and the rapid increase in temperature near the end of tool life could be used to predict the final breakdown.

During the machining processes, heat is generated within the primary and secondary shear zones due to plastic deformation of the material. Along the tool chip interface, heat is generated. If the cutting edge is not perfectly sharp, an additional frictional heat is generated due to ploughing. Thermocouple is an application to monitor temperature at the tool chip interface that may be practical for an on-line monitoring system [142].

In the tool-workpiece thermocouple technique both the tool and workpiece are electrically isolated from the machine tool structure. This technique is used for tool failure detection, controlling the machining process, and tool wear monitoring. It has been found that the reliability of the tool-workpiece thermocouple method is affected by the material properties at a junction and by the noisy thermocouple voltage signal which is sensitive to cutting conditions. On the other hand, in embedded or remote thermocouple technique, one or more thermocouples are located on the cutting tool remote from the cutting edge. Usually thermocouples are located at the seat of the tool inserts. This approach can be used for predicting tool wear from temperature measurements. Using this approach, it is difficult to measure temperature at the cutting edge because the thermocouples are embedded within the cutting tool a distance away from the cutting edge. Temperature measurement in this method tends to have errors primarily because the temperature gradients near the edge are steep, and the heat conduction characteristics in the cutting tool are alerted by presence of holes in which the thermocouples are embedded [143]. Moreover, there are two more drawbacks associated with the application of this type of sensor. First, the relationship between cutting temperature and wear must be known in advance with great reliability and under various cutting conditions. Secondly, due to the time lag during heat transfer, the response time is very poor. In summary, the reliability of the temperature signal is affected by material properties and noisy thermal voltage signals. The on-line application of temperature sensors is generally difficult due to the inaccessibility of the cutting zone.

5.4.7 Infrared Sensor

There has been significant progress into the development of infrared technologies for the measurement of temperature. An infrared sensor is a non-contact technology of measuring the temperature of an object based on its emitted infrared energy. The radiation emitted by the tool/work-piece includes the infrared radiation which can be detected by an infrared sensor. The amount of infrared emitted by the tool is partly a function of the temperature of the tool. The infrared energy emitted increases as temperature increases. Infrared radiation is electromagnetic waves of a length between 0.7μm and 1000μm. However, the available infrared cameras in the market normally work between 0.7μm and 20μm. [144]. The temperature information of the tool or work-piece is extracted by an infrared sensor and analysed using a variety of signal processing methods to extract the necessary information to identify the tool condition. The extracted information is the key information to recognise faults and classify signals. Reference [145] used an infrared sensor to measure the shear plane temperature in a metal chip and the clearance face temperature of the cutting tool.

Reference [146] used an infrared sensor to measure the temperature distribution in the tool during cutting. An improved design of this detection equipments and calibration was introduced by [147] which decreased the amount of setup time and improved the reliability of the method.

Reference [148] used an infrared camera to relate wear of a cutting tool, to the cutting temperature. This was done by measuring the chip back temperatures as well as the tool chip interface temperature using cutting tools with different wear values. Reference [149] used the infrared camera successfully to study the temperature effects in chip formation. Reference [150] also used an infrared camera to determine the temperature distribution during turning process.

Reference [21] described several cases studies which showed that the new low-cost technology could provide an inexpensive and autonomous methodology for monitoring machining processes. A novelty detection technique was used to compare normal and faulty conditions to provide an automated system for fault detection. Reference [151] devised a direct method of tool wear monitoring based on infrared images of the cutting tool utilising a sensor system for optical tool wear monitoring comprising a camera and infra-red flashlight. The set-up was such that an external trigger system synchronous with tool wear was selected.

Clearly none of these measurements can be applicable in industrial condition monitoring of tool wear/faults. The suggested off-line methods are time consuming, inflexible, highly inaccurate and cannot be applied on-line.

5.5 Single Sensor

The use of a single sensor signal in the development of a tool condition monitoring system fails to recognise the complex and diverse nature of the cutting process [108]. Such models are often less robust, unreliable and generally not capable of total tool condition monitoring (ability to recognise incipient, partial, complete or catastrophic tool failure). The adoption of feature space dimensioning as a means of increasing input dimension whereby various wear sensitive features are identified and extracted from a single signal, is debatable. This is because multi-feature extraction from a single signal does not constitute multi-sensing. Feature space dimensioning involves the representation of statistically independent probability distribution in just a single signal with minimal common information acquired compared to features extracted from more than one different source signal [27, 28, 126]. As a result, it is better to employ more than one singular sensor as they will hold more information, particularly when they are used as an input to decision-making.

If the noise level in a sensor signal totally contains its tool wear sensitivity feature without the attendance of other sensor signals, its tool wear sensitivity is lost. If several sensors are positioned the loss of sensitivity information from one sensor could be off-set and substituted if dependable information can be obtained from the other sensors i.e. improved and enhanced performance of such a system could be expected. Monitoring methods based on a single sensor may not be accurate for the identification of the nature and the location of tool failure because tool failure is a very complex process and dependent upon diverse machining factors such as cutting speed, feed rate and depth of cut which affects the reliability of detecting tool failure. For example, cutting forces are a function of cutting velocities and in the case of significant change of the cutting velocity, thrust and torque signals change extremely. This may not result in meaningful information on the tool condition monitoring. Hence, there must be another type of sensor, for example, an acoustic emission sensor, which can complement the force [16]. Thus, the information from a single sensor may simply not be good enough to make a reliable decision on tool condition monitoring [152, 153].

5.6 Sensor Fusion

Tool condition monitoring methods are categorised into direct and indirect methods, based on the type of sensor technology used. Direct methods collect information from the tool itself. A number of studies using optical sensors (e.g., CCD camera, optical fiber, laser, etc.) showed the accuracy of the information directly related with the amount of tool wear. However, these studies were limited because they could not be used on-line and were affected greatly by the presence of other materials, such as coolant and debris. Therefore, direct methods have no benefit for use in this proposed tool condition monitoring system in a non-laboratory environment. In contrast, indirect methods sense secondary details of the machining process such as vibration, sound, cutting forces, acoustic emission, temperature, etc, to determine tool condition. Indirect methods are optimal for integration into on-line tool condition monitoring systems. However, indirect methods require additional processes to determine the relationship between the signal and the amount of tool wear. Indirect methods rely on sensors, for example, among which the dynamometer sensor has achieved the greatest correlation with tool condition. However, the dynamometer is limited because it may affect the tool capability when it is installed on the machine. In addition, it is limited because of its high cost and lack of overlap protection [13, 18, 154-157].

Acoustic emissions (AE) also have been used in tool condition monitoring researches. However, AE is limited as a sensing technology because noise contamination interferes with accurate data collection [158]. To overcome the limitations of sensor methods, many investigations have proposed the use of multi-sensors to create a stronger correlation between indirect signals and actual tool condition [157, 159]. These investigations demonstrate that multi-sensor systems could give additional signals for better prediction results. However, the distribution of different weights to each signal brings more complexity to the tool condition monitoring system. Tables 5.1-5.5 summarise some of the sensor methods employed by other researches.

Table 5.1: Optical Sensor.

Author(s)	**Sensor**	**Year**	**Ref.**
Cao et al.	Optical Sensor	2006	[158]
Bouzakis, et al.	SEM	2001	[159]
Lanzetta	CCD	2001	[160]
Zawada et al.	CCD	2001	[161]
Kassim et al.	CCD	2000	[163]

Table 5.2: Force Sensor.

Author(s)	Sensor	Year	Ref.
Bhattacharyya, et al.	Dynamometer	2007	[64]
Huang et al.	Dynamometer	2007	[162]
Martinho et al.	Dynamometer	2007	[164]
Shi et al.	Dynamometer	2007	[165]
Ghosh	Dynamometer	2007	[166]
Devillez et al.	Dynamometer	2007	[167]
Cakir et al.	Dynamometer	2005	[22]
Topal et al.	Dynamometer	2005	[168]
Choudhury et al.	Dynamometer	2004	[169]
Oraby et al.	Dynamometer	2004	[170]
Devillez et al.	Dynamometer	2004	[171]
özel et al.	Dynamometer	2002	[172]
Choudhury et al.	Dynamometer	2000	[173]
Liu et al.	Dynamometer	1999	[174]
Grabec et al.	Dynamometer	1998	[175]
Purushothaman et al.	Dynamometer	1998	[3]
Szecsi	Dynamometer	1998	[176]
Lee et al.	Dynamometer	1998	[10]
Venkatesh et al.	Dynamometer	1997	[8]
Zhou et al.	Dynamometer	1997	[103]
Obikawa et al.	Dynamometer	1996	[177]

Table 5.3: Vibration Sensor.

Author(s)	Sensor	Year	Ref.
Alonso et al.	Accelerometer	2008	[136]
Devillez et al.	Accelerometer	2007	[178]
Orhan et al.	Accelerometer	2007	[179]
Salgado et al.	Accelerometer	2006	[65]
O’Donnell et al.	Accelerometer	2001	[5]
Li et al.	Accelerometer	2000	[9]
Jun et al.	Accelerometer	1999	[180]

Table 5.4: Acoustic Emission Sensor.

Author(s)	Sensor	Year	Ref.
Marinescu et al.	AE	2008	[181]
Lee et al.	AE	2005	[182]
Guo et al.	AE	2005	[183]
Nakao et al.	AE	2003	[184]
Li et al.	AE	2002	[18]
Al-habaibeh et al.	AE	2001	[185]
Chiou et al.	AE	2000	[186]
Govekar et al.	AE	2000	[187]
Liang et al.	AE	1989	[17]

Table 5.5: Sensor-Fusion.

Author(s)	Sensor	Year	Ref.
Lin et al.	Force, Temp.	2008	[188]
Aliustaoglu et al.	AE &Acc.	2008	[189]
Ghosh, et al.	AE & Dynamo	2007	[166]
Salgado et al.	Sound, Current	2007	[6]
Chung et al.	Force, AE	2003	[21]
Chungchoo et al.	Force, AE	2002	[190]
Mannan et al.	Sound, Temp.	2002	[91]
Scheffer et al.	Acc & Strain	2001	[154]
Chen et al.	Dynamo & Acc.	2000	[157]
Dimla et al.	Dynamo & Acc.	2000	[152]
Dimla et al.	Dynamo & Acc.	1999	[191]

As discussed previously, each method has its advantages and disadvantages. The optical measurement methods disadvantage is the off-line method because measurement can be taken only when the machine is not running or when the tool is not cutting. However, the method looks to be accurate and reliable. The disadvantage of the other method, the radioactive method, is that safety and good protection are needed to eliminate or minimise the effects of radiation on the operator and the shop floor. The disadvantage of the changing size method is the movement of the machine tools and the heat of the workpiece expansion. The disadvantage of the use of cutting forces is the dependence on the properties of the workpiece and the cutting tool materials and changes in the cutting conditions. The sound method has limitation because the noise on the shop floor is higher than that of the tool. The on-line direct methods are mainly unachievable in a continuous moving system [108, 109, 194]. Indirect methods have been tried and used by many researchers in order to improve reliability and sensitivity. Multi-sensor data fusion is used where the loss of sensitivity in one sensor can be made up for by another sensor. Reference [130, 138] concluded that where several tool failure monitoring methods had been developed in laboratories few of these methods were being used effectively in industry. In order to increase the prediction reliability, multiple sensors are combined to measure the same phenomena. The integration of various sensors, and therefore the analysis of rich data from several different sources, may improve the success of tool failure monitoring systems. Other typical applications of sensor fusion are robotic systems, autonomous vehicle navigation, automatic target recognition, etc. Multiple sensors can be advantageously used in a complex system, such as tool condition monitoring for manufacturing operations, to get opposite information about the process. This helps to improve the assurance factor of the resulting diagnosis. The use of multiple sensors, though, requires integration and fusion of the sensory information to draw the necessary features from the data by removing the redundancy present in the data [107, 108, 195].

Sensor fusion serves the following purposes:

- Enhances the richness of the underlying information contained in each signal.
- Increases the reliability of the monitoring process as loss of sensitivity in one signal could be offset by that from other.
- Sensitivity of failure potentially increases number of times for number of sensors fused [153].
- Confirms that previous effort to find a unique signal for all tool condition monitoring applications have failed [9].

On the other hand, focusing on non-linear principles and foundations of metal cutting would be useless, as the tool condition monitoring system could become fully sophisticated. Therefore, as substitute for the use of a single sensor, the integration of a number of sensors has been investigated. This has led to what is now normally termed a multiple sensor tool condition monitoring system [196]. There are still some problems with tool monitoring systems and the issues which need serious consideration are the sensitivity and reliability. This will involve research into multi-sensor data fusion and multi-sensor planning and multi-sensors system structural design.

5.7 Conclusion

The chapter has outlined the current knowledge in condition monitoring of turning processes. Several sensors have been suggested in literature including forces, vibration, acoustic emission, temperature and sound. Each suggested technique seems to have its own drawbacks and practical problem. The literature survey carried out seems to suggest that most of the surviving tool condition monitoring systems have not been successfully implemented in industry because adequate sensor information and machining models have been utilised, even though they do not satisfactory reflect the process complexity. There is still a need to design and evaluate more comprehensive approaches to condition monitoring. The outlined study involves the utilisation of not one sensor but several. While it is difficult to emulate the human operator who is subjective and inaccurate in order to develop a tool condition monitoring system, multi-sensors are evaluated for monitoring faults in the turning process combined with artificial neural networks and novelty detection algorithms to detect the difference between a normal and novel condition for automating the machining process. This literature review has demonstrated a need for a new tool condition monitoring system that can provide accurate information using modem sensing and signal processing technologies

Chapter 6

Methodology

6.1 Introduction

This chapter presents current problems found in the area of the development of condition monitoring systems and compares them with current best practice in the field. It provides an explanation of the research aim, objectives and the condition monitoring methodology used. It also seeks to explain in detail important assumptions behind these aims and objectives which are described both definitively and in experimental terms. The chapter describes the general stages of the approach. In addition, it explains how the following chapters are structured to assess the planned methodology.

6.2 Problem Definition

Among the many possible tool conditions that could be monitored, tool wear is the most significant for ensuring continuous machining. Any effective monitoring system must sense tool conditions, allow for effective tool change strategies when tools fails, and keep proper cutting conditions throughout the process [10]. If the monitoring function cannot maintain proper cutting conditions, the cutting process could result in poor surface quality, dimensional workpiece accuracy, and even machine damage [196].

Researchers have attempted to develop reliable methods to monitor tool wear. These methods are an area of active research because tool condition strongly influences the surface finish and dimensional reliability of the workpiece. In addition, a consistent tool wear monitoring system can decrease machine downtime caused by changing the tool, hence leading to fewer process disturbances and higher efficiency. The information obtained from the tool wear sensors can be used for several reasons, including tool change policy, online process action to compensate for tool wear and the avoidance of catastrophic tool failure. In order to identify the problems in condition monitoring development and the draw-backs of current practice, it is important to describe the basic structure of a monitoring system.

In order to monitor an on-line machining process the system must provide for [185]:

1. The selection of suitable sensory signals.
2. The selection of suitable signal processing methods.
3. The extraction of valuable information from the suitable sensitive sensors and the suitable signal processing methods.
4. The improvement of a classification system strategy.

Machining processes can produce different types of information. Consequently, it has to be possible to select one or a set of sensors to recover information about the process which recognises the condition of the machining process. The selection of a suitable sensor is a difficult task. When the process to be monitored on-line is complex, such as tool wear, it is difficult to instantly recommend a suitable sensor for on-line monitoring the condition of the machining process. Hence, the selection of appropriate sensors is most important. The selection of an appropriate signal processing technique is necessary as well. The information extracted by a sensor could be set for use directly or it might include noise or other unnecessary information. Therefore, certain signal processing techniques are required to extract the essential information. The classification system is an extremely important stage in categorising the extracted information by the sensors and taking the decision regarding the condition of the machining process. The decision-making approach changes according to the application of a simple threshold value to more complex strategies. Machining processes have dissimilar levels of complication. Therefore, direct measurements which are found useful in some simple processes might not be successful, or even applicable, for more complex machining processes.

6.2.1 Problems in Condition Monitoring

Based on the previous argument and the review of literature, the following common problems and needs are:

1. How to choose a suitable sensor or group of sensors.
2. How to choose efficient signal processing techniques.
3. How to choose an efficient and cost effective sensor fusion model.

These problems are general problems in the development of condition monitoring systems. Some problems have been solved in some areas of condition monitoring while others remain unsolved due to differentiation and complications of the monitored machining processes. Complications in the second group, due to indirect measurement, make it more difficult to solve the technical problems. In addition, the decision-making stage is normally dependent on the process to be monitored and the form of reaction required.

The existing practices in condition monitoring design cover all aspects of the monitoring design but with different levels of success in different areas. The decision-making stage has been well investigated in the monitoring area using different approaches such as statistical methods, artificial neural networks, etc. But it has been found that the decision making stage is not considered as the main difficulty in condition monitoring design for the following reasons [185, 196, 197]:

1. The achievement of any decision-making method is governed by the quality of the information. When the data extracted from the process and fed to the decision-making stage is useful and contains the required information about the process and its conditions, the decision-making stage is normally expected to produce acceptable results. However, whatever decision-making method is used, it is expected to produce misleading results when the data used does not include helpful information about the process and its conditions.
2. The methods used can be assessed by general means. In spite of the source of data used in the decision stage and what it presents, the decision-making technique can still be used to evaluate the processed data and make a decision on the essential prediction or classification and any further decision-making.
3. The response required from this stage is application dependent. For the same processes and faults, different techniques can be used based on the requirements or the outputs of every technique. Therefore, it has been found from the literature that the success of a condition monitoring system relies on two significant aspects [27]:
    - The selection of appropriate sensors.
    - The selection of appropriate signal processing techniques.

Research in condition monitoring systems has examined and assessed most of the major types of sensors existing in today's commercial market. Some common methodologies have been found practical in selecting the sensors used in a condition monitoring system. The techniques described provide broad guidance on which sensors can be used, and how to maximise the failure coverage and minimise the number of sensors used. However, these techniques do not provide practical information or a structured methodology on how to select sensors which can provide high quality information about the process with minimal costs. When investigating sensor selection in machining processes in particular, this point becomes more significant. The selection of sensors based on previous research can provide a primary point to start from. However, it might not be good engineering practice in this field to assume that the same types of sensor can provide the same results. This is because machining processes show high complexities and differences which make dependency on previous research in selecting suitable sensors a starting point in the design process rather than a perfect solution [47].

The next problem to be solved in the design of condition monitoring systems is the selection of appropriate signal processing techniques. The selection of these techniques is reliant on the type of sensor used. If the selected sensors are not useful, then the applied signal processing techniques are not expected to give satisfactory information. Different signal processing techniques have been suggested and implemented in condition monitoring systems including statistical methods, time domain and frequency domain methods. The current practice in selecting the signal processing techniques is normally done in a manual procedure of visual inspection to search for the information within the signals. This approach, although it is successful, can be considered costly and time consuming. Another current practice is to build a complete monitoring system in order to test the applicability of the sensors and the associated signal processing techniques. Therefore, if the system performance is acceptable, then the sensors and the signal processing techniques are assumed appropriate and satisfactory. When the system does not work as effectively as expected, then another search for other sensors or signal processing techniques is restarted. This technique of constructing a complete system could also include a detailed examination of fault processes to view the signals and search for the sensory features which allow the pattern recognition system to provide better results. In addition, when automated pattern recognition methods are used, such as neural networks, the training and testing procedures recur and require lengthy periods of time and computational effort. If the sensors or signal processing methods are not appropriate, the recurring training methods could take longer to reach different results.

From the above discussion and the literature review in Chapter 5, it can be concluded that the research which examines the design problem of condition monitoring is limited. Even if a wide range of monitoring methods has been examined, not many have been implemented in complex industrial environments. All the methods reviewed so far look to have variable capabilities. A method found to be successful in one situation may not give an adequate outcome in another. The methods found in the literature cannot provide an automated design methodology of monitoring systems even when providing sufficient results. There is a need to use methods in order to reduce the experimental work in turning processes. Moreover, cost of the implemented systems is rarely considered in current practice during the design process. Hence, current practice in condition monitoring design, particularly in machining, does not provide structured and automated design methodology which can provide practical selection criteria of sensors and signal processing methods with reduced experimental work, time and cost.

A novel method, called ASPS (Automated Sensor and Signal Processing selection) has been presented in [196]. This methodology, which will be described in section 6.4, depends on a self-learning multi-sensor approach. The method has been tested for milling. This thesis modifies and develops the approach for turning and defines a new automated sensor and signal processing selection for a turning (ASPST) approach which deals with turning processes.

6.3 Problem Domain and Objectives

The aim of the investigation is the development of condition monitoring systems for machining operations with specific emphasis on turning processes. The domain of this research is in implementing the ASPS approach in selecting the sensors and signal processing techniques essential for monitoring turning processes and conditions. This new modified methodology is called ASPST (Automated Sensor and Signal Processing selection for Turning). The use of the decision-making stage is to confirm and assess this methodology for selecting sensors and signal processing methods.

6.3.1 Aim and Objectives

The aim of this research is to develop an effective sensor-fusion model for turning processes using a cost-effective methodology with reduces experimental work. This research is supported by the following objectives:

1. To perform a literature review of machine and process condition monitoring systems and their applications.
2. To determine the process variables in turning processes that contain useful information related to tool wear.
3. To determine the appropriate sensors that can be used for monitoring the process variables related to tool wear.
4. To determine the appropriate signal processing methods.
5. To design a data acquisition system for machine and process condition monitoring including data acquisition card and computer selection, data acquisition software implementation, sensor installation and overall system calibration.
6. To design and implement an effective sensor-fusion model for turning processes to detect the most common industrial faults (e.g. gradual wear).
7. To design an investigatory model to obtain the necessary machining data.
8. To integrate a wide range of sensory systems and their signal processing methods into a novel and effective sensor fusion-model. The sensors to be used are: force, acoustic emission, strain, vibration, and sound.
9. To implement the ASPST (Automated Sensor and Signal Processing Selection for Turning) approach and investigate an efficient pattern recognition and classification system.
10. To test and evaluate the novel sensor fusion-model.

In order to achieve these objectives within the problem domain, the methodology is implemented in turning processes. The turning process is selected to implement and evaluate the ASPS approach [47] as this approach has been implemented and evaluated in an end-milling process in previous research. In addition, the turning process is selected for the following reasons:

1. The turning process is an important process in manufacturing environment as one of the main metal removal processes.
2. It is a complex process where signals show high variations and complexity and information cannot be extracted directly from the sensors.
3. ASPST is used to develop an effective sensor-fusion model for turning processes based on ASPS approach.

6.3.2 How the ASPST Approach is Conceived

This research builds on the recent knowledge in industrial environment and current practice in condition monitoring for advanced performance. In addition, it does not recommend new sensors or signal processing methods. Nor does it suggest new classification methods. The tools used in this methodology have already been examined and investigated in different fields' of condition monitoring [196]. The suggested approach (ASPST) utilised sensors, signal processing methods and classification methods to develop an automated methodology of condition monitoring for turning processes.

The methodology of the ASPST approach meant is to be generic for turning with reduced time and cost. In addition, it provides quality of information regarding the turning process and its conditions.

The ASPST approach is utilised to discover the best combination of sensitive sensors and signal processing methods to design a monitoring system with reduced cost and experimental work. The objective is to extract sensory characteristic features (SCFs) obtained from the sensory signals using different signal processing methods and to find out the sensitivity of such features on the machine which has gone faulty. If a specific feature from a specific sensor shows high sensitivity to the fault this simply means this SCF is useful in detecting or evaluating the fault. This research extends the methodology into monitoring gradual tool wear in turning. In this section a description of how the suggested condition monitoring design methodology is conceived is based on previous evaluation and implementation of this approach in end milling process [185]. In addition, it is based on enhancing the design tools and methods of previous research described in the literature.

The author's main contribution is to implement the ASPST approach and to combine previous points with the idea of developing a generic structured sensor-fusion model using the following three techniques:

1. Evaluating the new ASPST approach (Automated Sensor and Signal Processing Selection for Turning).
2. The automated simplification of complex signals into simple sensory characteristic features (SCFs).
3. Automated detection techniques of sensitive SCFs and hence the associated sensors and signal processing methods.
4. Testing novelty detection and neural networks for turning processes.
5. The technique of cost-reduction based on removing the unused sensors when possible.

The details of the main techniques developed will be described in the following sections with more technical description and examples in the subsequent chapters.

6.4 The General Concept of the ASPST Approach

The main idea of the implemented approach is described in general terms in this section. The detailed procedure for using the implemented approach for turning operations will be described in section 6.5 of this chapter and with more detail and experimental examples in the subsequent chapters of this thesis. The implemented approach aims to design a condition monitoring system for turning processes using an automated simple procedure to detect the sensory characteristic features which are most sensitive to the process states or faults and show less sensitivity to other process operating variables and parameters. The ASPST approach is based on the ASPS approach and on conducting studies to prove that there is a dependency between a measured sensory value (SCF) and the monitored state or physical phenomenon [196]. The cost of the system should also be considered; if a low-cost sensor can be used to do the same task instead of an expensive sensor, then the expensive sensor should be eliminated from the system.

6.4.1 The ASPST Approach

The implemented approach is named ASPST, Automated Sensor and Signal Processing Selection System for Turning. Figure 6.1 shows the basic principle of an ASPST approach. It systematically relates the sensory signal and the signal processing methods used to the state or the physical phenomenon which needs to be detected or evaluated.

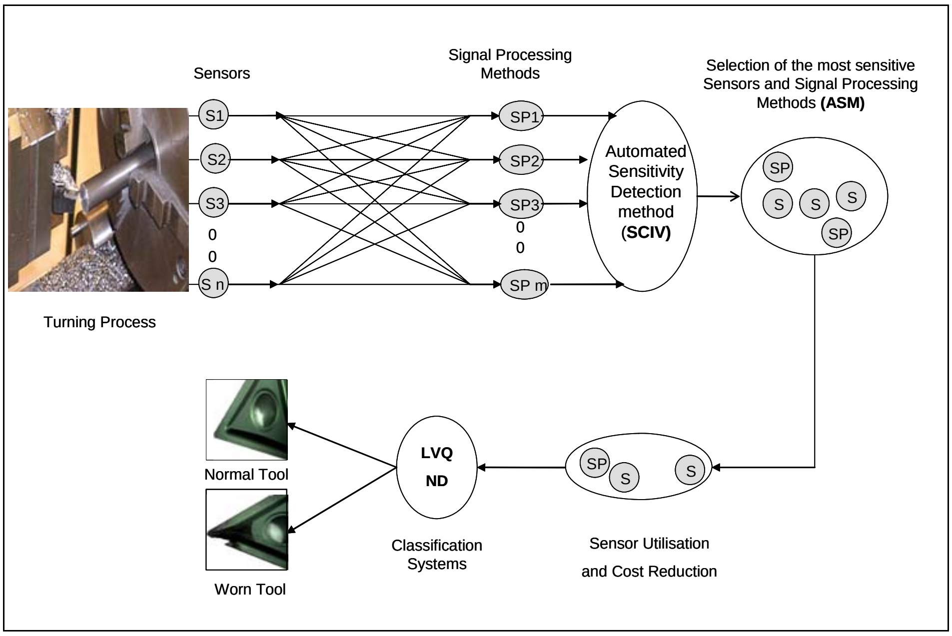

Figure 6.1: The Basic Structure of the ASPST approach.

The ASPST approach starts by defining the process to be monitored and its states (e.g. healthy or faulty condition). Then, a wide range of sensors is installed for process monitoring in order to produce sensory signals that contain information about the process. The following stage of the proposed approach is for extracting sensory characteristic features (SCFs) obtained from the sensory signals using a wide range of signal processing methods and then discovering the sensitivity of such features on the investigated process state. If a specific feature from a specific sensor shows high sensitivity to the fault, this means this sensory characteristic feature is useful in detecting or evaluating that fault. A particular number of sensitive sensors and signal processing methods are then selected as an initial monitoring system. Cost reduction can then be performed based on the number of SCFs extracted from the selected sensors. If insignificant numbers of SCFs are extracted from a sensor, then that sensor might be eliminated from the monitoring system to reduce its cost. More details about the main concept of the ASPST approach are followed in the next sections of this Chapter.

6.5 Techniques Developed within the ASPST Approach

6.5.1 Simplification of Complex Signals

For a complex process such as the turning process with different signals to be processed to extract the required information, the first stage is to remove signals from a complex shape into a group of simplified sensory signals called Sensory Characteristic Features (SCFs). SCFs can be obtained from any signal processing technique or combination of signal processing techniques as long as the output is, or can be presented as, a real number. The complex sensory signals and the machining process are presented as a function of time. Consider the machining process begins gradually or in an unexpected way with a fresh cutting tool and moves to worn condition. It is difficult to consider the condition of the process from the generated complex signal and a simplification method is needed to take out the sensory characteristics features (SCF). Several numbers of SCFs can be calculated when taking samples of the complex signals at constant intervals and processes these signals using a broad variety of signal processing methods. These sensory signals, during the processing time, can be simplified into a number of SCFs. The SCFs could be a perfect tool to investigate the essential information regarding the presented process conditions. SCFs can be attained from any or a number of processing methods since the output is a real number or entered as a real number.

6.5.2 Automated Sensitivity Detection

A sensitive sensory characteristic feature (SCF) is a SCF which includes an important amount of information about the state of the process which should lead to superior recognition. It is expected to react to the change in a process condition by an important change in its values. The sensitivity of a SCF can be evaluated by several methods such as:

1. The use of manual observation and visual inspection of the signals.
2. The use of a classification system as they are automated processes with complete independence such as novelty detection, neural networks, etc
3. The use of statistical techniques to detect the change in the SCFs levels.

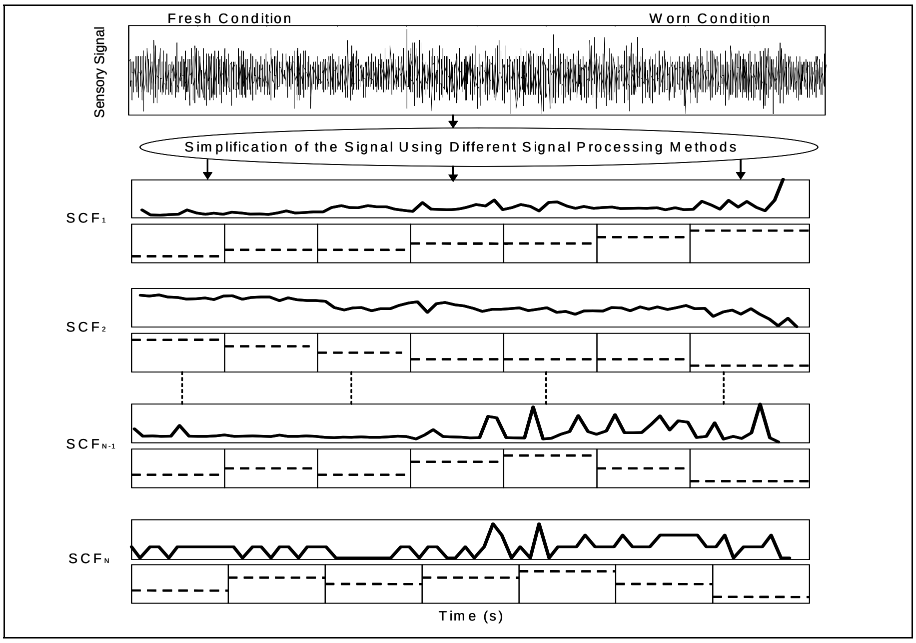

Figure 6.2: Simplification of complex sensory signal into simple SCFs.

The sensory signals information, simplified signals, can be detected visually. Figure 6.2 shows a simplification of a complex sensory signal into simple sensory characteristic features (SCFs), SCF_1 is increasing gradually between the two conditions of the process. In addition, SCF_2 is decreasing gradually between the conditions of the process when the process changes from one condition to the other. SCF_{N-1} and SCF_N are changing randomly between the process conditions with time. These sensory characteristics features (SCF_{N-1} and SCF_N) are identified as insensitive SCFs while both SCF_1 and SCF_2 are identified as sensitive SCFs. The detection of the sensitivity of the SCFs has to be automated in order to develop a rapid and structured methodology of selecting sensors and signal processing methods. Several methods can be utilised for sensitivity measurements. For example, Figure 6.3 shows an example of two methods which can be used for sensitivity detection measurement.

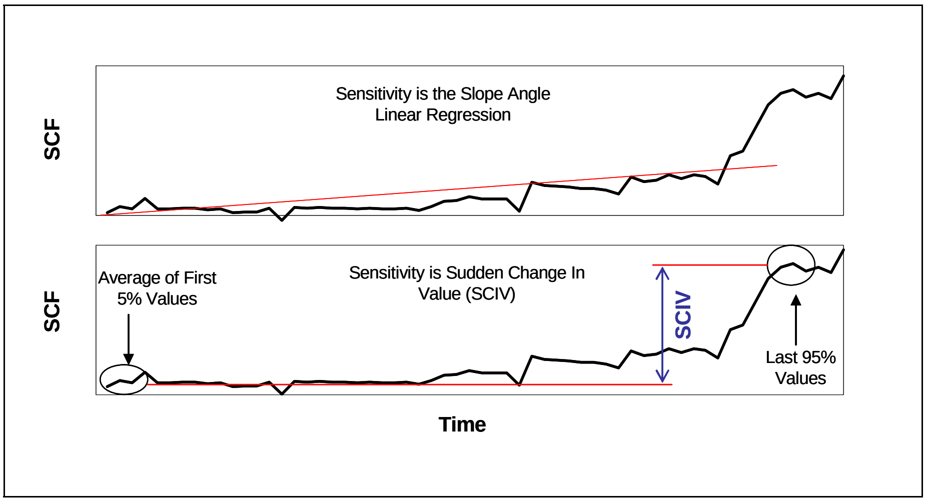

Figure 6.3: Example of two measuring sensitivity methods of the SCFs.

It is essentially a detection of a change in the SCF level forming a precise pattern or trend as a function of time. In order to keep the automated sensitivity measurement simple, the Sudden Change In Value (SCIV), the difference between the initial minimum and the final maximum values, is developed in this work as a sensitivity detection method, a sensitivity indicator. For a turning process with several sets of machining parameters, detecting the change of the level of the SCFs with time should be sufficient to detect their sensitivities. More details about the equations to calculate the average difference are described in Chapter 7.

6.5.3 Sudden Change in Value Method (SCIV)

There is an essential assumption to be made that the change in the SCF value is due to the change in the process condition. For example, if the cutting force is increasing gradually during a machining process, this could be due to a specific reason such as gradual tool wear. The possibility that a SCF demonstrates a specific and clear trend and change in values as a random behaviour is rather low and it is ignored in this study mainly when using several SCFs. As shown in Figure 6.4 when utilising a linear regression method to detect the sensitivity and to monitor SCFs with time, the values of an SCF can behave randomly producing high and low values of the SCF as a function of time. When a SCF changes randomly then it is described as being a Low-Sensitivity SCF, which means that it includes no information about the process, and expected to have relatively low-Sensitivity which does not change in a specific pattern. The ASPS approach [47] used linear regression method which is not an accurate and sensitive measure for turning processes in this work while SCIV is more sensitive and accurate measure.

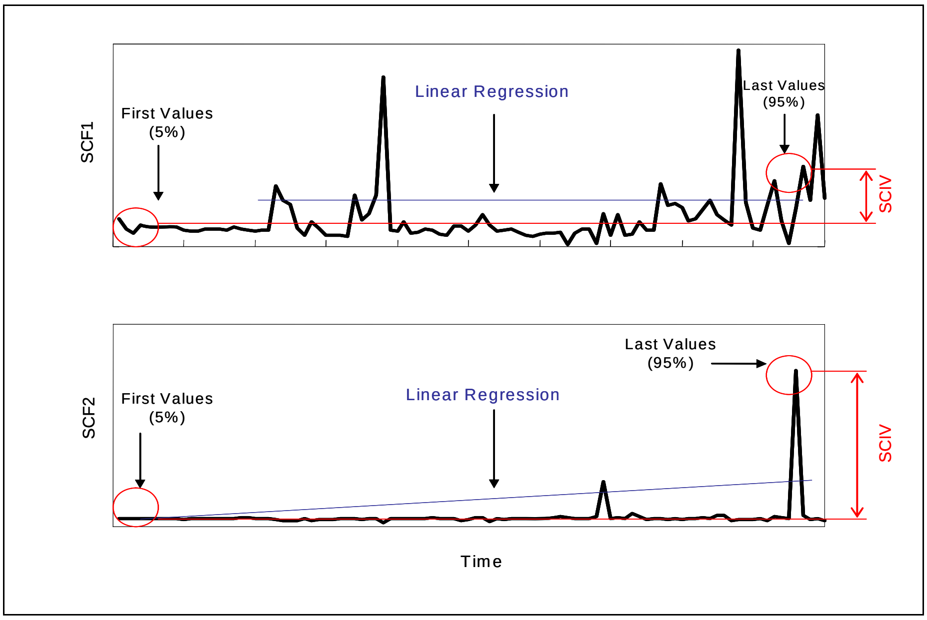

Figure 6.4: Examples of SCFs using linear regression and SCIV method.

As shown in Figure 6.4 both signals (SCF1 and SCF2) have high sensitivity when utilising the SCIV method. The SCIV method calculates the difference between an average of 5% of the first sample and 5% of the last sample maximum value. On the other hand, utilising a linear regression method shows high sensitivity of one of the signals while the other shows low sensitivity. However, the problem with the utilisation of a linear regression method is its sensitivity to the number of data points used to calculate the linear regression and the position of the data to the condition to be monitored.

The SCIV is a relative measure and it depends on the process information. The advantage of using SCIV can be summarised as follows:

1. Relatively accurate, simple to calculate and automated.

2. Easy to compare the results of several SCFs obtained from different sensors and signal processing methods by normalising the SCF values during the same period of time.
3. SCIV can present a good indication of the sensitivity of the SCFs by indicating the average change in the SCF values (i.e. the higher the difference in values the higher the sensitivity of the SCFs).

6.5.4 Association Matrix (ASM)

After calculating the sensitivity of each sensory characteristic feature on the machining conditions, another matrix is constructed called the Association Matrix (ASM). The Association Matrix (ASM) is a matrix which associates the obtained sensitivity values for the corresponding sensory features. It gives a simple presentation of the sensitivity values associated with each feature. The ASM for a fault Y is defined as follows:

$$ASMY = \begin{pmatrix} d_{11} & d_{12} & d_{13} & d_{14} & \dots d_{1m} \\ d_{21} & d_{22} & d_{23} & d_{24} & \dots d_{2m} \\ d_{31} & d_{32} & d_{33} & d_{34} & \dots d_{3m} \\ \dots & \dots & \dots & \dots & \dots \\ d_{n1} & d_{n2} & d_{n3} & d_{n4} & \dots d_{nm} \end{pmatrix} = dij$$

Where $1 \leq i \leq n$ and $1 \leq j \leq m$

The element *dij* is called the sensitivity coefficient of the machining feature obtained using the machining signal of the *i*th sensor and the *j*th signal processing method. The ASM gives the essential evaluation for the most appropriate sensor and signal processing method to be used since each column is associated with one signal processing method while each row is associated with one sensor. Basically, the sensory characteristic features with relatively high sensitivity coefficient are the most sensitive to the cutting conditions and they are the most appropriate features to be used. Therefore, the related sensory signals and signal processing methods are the most appropriate ones to be used.

6.5.5 Sensor Fusion and Cost Reduction

In order to design a monitoring system with high sensitivity and constancy, a group of high-sensitivity SCFs should be used in combination. When all SCFs extracted from the sensors are ranked according to their sensitivity values, the highest sensitive number of SCFs can be used together to form the initial monitoring system. The cost of the system can be easily calculated according to the number and type of sensors used. The value of the highest sensitive number of SCFs can be selected based on the cost of the system, the required quality of interpretation, the speed of signal processing and the implemented decision making method. The value chosen in this research is 10 based on a previous implementation of the ASPS approach for end-milling processes and on using a decision-making method in the end-milling process [198]. The last value is also found satisfactory in providing sufficient monitoring capability with reasonable signal processing speed.

Consider Figure 6.5 where *n* sensors are processed by *m* signal processing methods to produce $(n \times m)$ sensory characteristic features. These features need to be calculated during the process in order to identify the sensitivity of the SCFs to the process states. The SCFs are arranged in order of sensitivity and the most sensitive number of SCFs are selected to create the initial condition monitoring system, the cost of the system can be calculated based on the sensors of the selected SCFs.

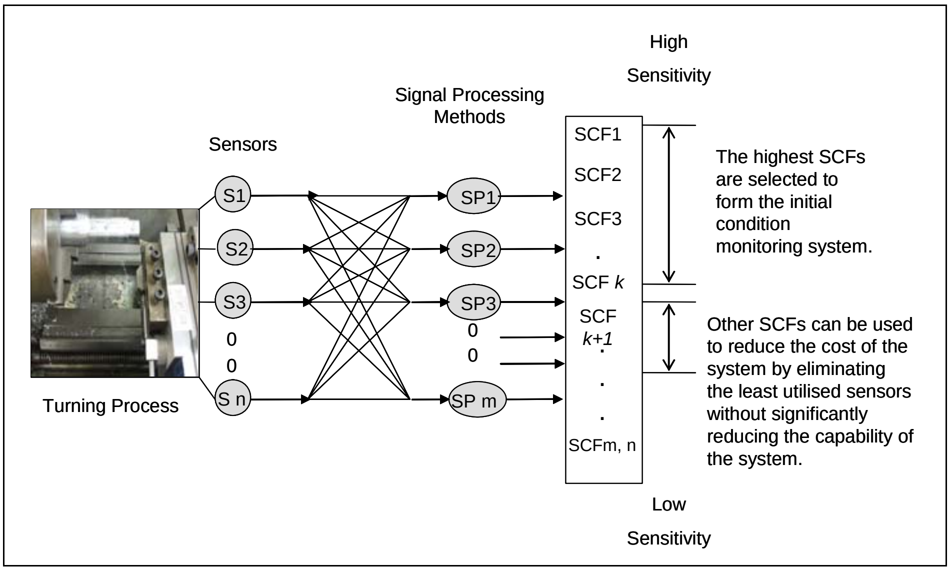

Figure 6.5: Structure of sensors, signal processing methods and SCFs.

A cost reduction stage can also be implemented in order to minimise the cost of the system. This might or might not decrease the monitoring capability of the system. The cost reduction of the system is performed by eliminating sensors which do not significantly contribute to the selected number of SCFs by removing their SCFs from the system and replacing them from SCFs which come next on the rank, see Figure 6.5, from sensors already in the system without having to significantly reduce the overall sensitivity of the system (i.e. the new SCFs should still have relatively high sensitivity). The contribution of a sensor in a system is defined as the utilisation of a sensor. It is defined as the number of SCFs used in a system from that sensor relative to the total number of SCFs used in the overall system. The utilisation is also defined in this research to be dependent on the number of signals produced from a sensor. More details are described in the following chapters. Assume, for the process shown in Figure 6.5, that the first sensitive number SCFs are found from sensors (S_1, S_3, S_5, S_i, S_{n-1}, S_n). Therefore, the cost of the hardware will be the cost of the sensors in addition to their signal conditioning devices. Assume CS_j is the cost of the jth sensor and its signal conditioning devices and all the associated hardware.

Therefore, the cost of the system will equal to:

$$\text{Cost} = CS_1 + CS_3 + CS_5 + CS_i + CS_{n-1} + CS_n$$

Assume that the sensor S_{n-1} contributes in only h SCFs where h is much less than the contribution of the other sensors. Then that SCF from the S_{n-1} can be removed from the system and exchanged by another h SCF from the other sensors (S_1, S_3, S_5, S_i, S_n) as long as these new SCFs have relatively high sensitivity on the rank. Now, the cost of the new system will be:

$$\text{Cost} = CS_1 + CS_3 + CS_5 + CS_i + CS_n$$

Where the new system is reduced by CS_{n-1}

The number of SCFs in the system is still not changed, even though, the number of sensors is reduced and therefore the cost of the system is also reduced. This removal process can be very efficient as long as:

- The new SCFs have high sensitivity so that the overall system performance does not deteriorate.
- The removed sensor is relatively expensive.

The previous discussion will be explained in much more detail in the subsequent chapters.

6.5.6 The Sensitivity of a Group of SCFs

Since the ASPST approach is based on using different types of sensitive SCFs together in order to form the required monitoring system, an assumption should be made regarding the sensitivity of a group of SCFs with relation to the sensitivity of an individual SCF in the system. A group of sensitive SCFs should form a monitoring system with minimum sensitivity equal to the sensitivity of the most sensitive SCF within that group, which means that the system should have more or equal sensitivity to the maximum sensitivity of the most sensitive SCF. The sensitivity values are calculated in this research work using the sudden change in value (SCIV) method. The overall sensitivity of a monitoring system is the average sensitivity of the SCFs in the system. The explanation of the assumption is based on the definition of the sensitivity of SCFs, where sensitive SCFs include more information than low sensitivity features. If the information is totally independent, then the overall system sensitivity will increase as a reason of more information included in the system. When high sensitive SCFs include the same information, then the overall system will have the sensitivity of the most sensitive one only. This fact will be proven practically in the next chapters. For low sensitivity SCFs, the monitoring system of low sensitivity SCFs could still have high sensitivity in some cases when a group of SCFs develop unexpectedly a unique combination of patterns when fused together.

6.6 Criteria for Sensor Selection

The methodology in this thesis considers multiple sensors for tool wear monitoring because more reliable and consistent tool wear monitoring is possible through sensor fusion. Sensor fusion refers to the combination of information from multiple sensors into a single result. The potential advantages of integrating information from multiple sensors are as follows [89]:

1. The quality of decisions will be better if the information comes from multiple sensors rather than from a single sensor because using information from multiple sensors means using more information at the same time. Using information from several sensors is similar to taking several samples from a random population. This clearly narrows the mean confidence interval and reduces uncertainty in a decision.
2. The decisions based on multiple sensors will be more fault-tolerant because even if some of the sensors fail, the other sensors will compensate for the lack of information from the defective sensors.
3. The reliability of information from different sensors might change relative to another depending on the process input parameters. If this change can be correlated, a sensor integration scheme can be designed to selectively weight the appropriate sensors at different conditions to make the decision more reliable for a wide range of cutting conditions.

Most of the techniques for tool wear monitoring described in the literature use one or more combination of cutting force, temperature, vibration, and acoustic emission sensors. To a lesser degree, other process variables such as power/motor current, sound, and workpiece surface roughness have also been used for the same purpose. All these possible sensors for the present application are evaluated using the following criteria [199]:

- The process variable being monitored by a sensor should have a good correlation with tool wear.
- A sensor should be able to give consistent and reliable measurements of the process variable being measured.
- A sensor should be able to provide a signal of high signal to noise ratio. Even if the signal carries noise, it should be possible to filter out the noise from the signal.
- A sensor should have a short response delay. This is necessary to implement on-line tool wear monitoring.

- It should be possible to physically locate a sensor on the tooling set up without obstructing the machining operation. The sensor should be robust enough to resist the impact of chips and temperature fluctuations.
- A sensor should have a long life and be cost efficient.

6.7 The Application of the ASPST Approach for Turning

The ASPST approach has been implemented in this thesis over the following three stages:

1. Initial implementation of the ASPST approach.

This part can be considered as a self-learning methodology for the classification of the system normal and faulty states and the selection of the most appropriate sensors and signal processing methods for detecting machining faults in turning. The ASPST approach is performed by installing multi-sensors (force and strain) on the machine tool. The experimental evaluation will be described in Chapter 9.

2. Initial implementation of the ASPST approach using pattern recognition systems.

The ASPST approach for turning operations, similar to the previous section, is performed by installing another group of multi-sensory signals on the machine tool. The ASPST approach is performed by installing acoustic emission, accelerometer and sound sensors using Learning vector quantisation (LVQ) neural networks in the first investigation and acoustic emission, accelerometer and strain sensors using novelty detection algorithm in the second investigation. The experimental evaluation will be described in Chapter 10.

3. ASPST approach using multi-sensor fusion model and pattern recognition systems.

In this part the ASPST approach is performed by installing a group of sensors (force, acoustic emission, strain, accelerometer and sound) on the machine tool. The experimental evaluation will be described in Chapter 11.

6.8 Structure of Subsequent Chapters

The subsequent chapters of this thesis are organised to investigate the applicability of the ASPST approach for designing condition monitoring systems for turning processes and to explain, in detail, the main steps for the approach. The subsequent chapters are outlined in order to provide a logical basis for testing the assumptions and describing the findings. Figure 6.6 shows a simplified flow diagram of the basic structure of the subsequent chapters.

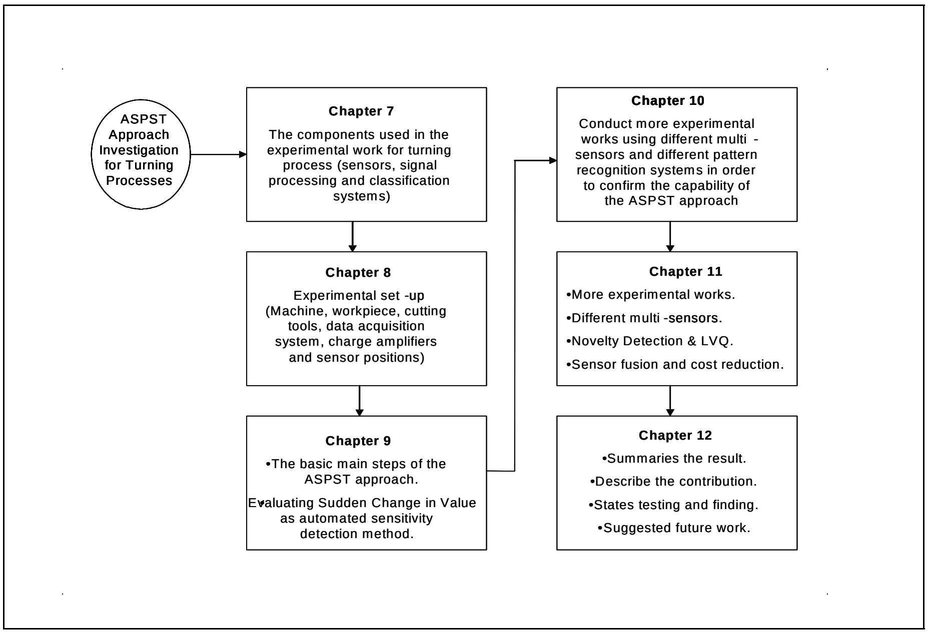

Figure 6.6: Diagram of the basic structure of the subsequent chapters.

Chapter 7 describes the components of the implemented monitoring system. It presents the tools used in designing the monitoring system including:

- Sensors.
- Signal processing and simplification methods.
- Classification techniques including neural networks and novelty detection.

The chapter outlines the tools which have been used to prove the applicability of the methodology for turning processes.

Chapter 8 describes the general experimental set-up which has been performed to prove the capability of the ASPST approach for turning processes. It describes the machine tools used, the faults investigated and the data acquisition software.

Chapter 9 explains how the ASPST approach can be used to design a monitoring system for a turning process with four sensory signals (force and strain). The main aim of the chapter is to describe the details of the ASPST approach in a practical way aided by real experimental tests. The chapter presents a monitoring design for monitoring gradual tool wear in turning processes. The chapter introduces the following points:

1. The common problem of selecting the most appropriate sensors and signal processing method for designing a condition monitoring system in turning.
2. The basic main steps of the ASPST approach for two sensory signals. It describes how the SCFs are created and how they can be arranged in order to calculate their sensitivity for gradual tool wear detection.
3. The capability of sudden change in value (SCIV) analysis to detect the sensitivity of SCFs. The response of the SCFs is visually investigated and compared to the sudden change in value (SCIV) analysis.
4. The method of choosing the most sensitive SCFs to form the required condition monitoring system.

Chapter 10 presents further applications of the suggested ASPST approach described in Chapter 9. The chapter presents more experimental work to prove the capability of the ASPST approach in designing a condition monitoring system by selecting the most sensitive sensors and signal processing methods with reduced cost and less experimental work. The aim of this chapter is to confirm the theory and the technique established in Chapter 9 using pattern recognition systems.

Chapter 11 presents the full capability of the ASPST approach and confirms the results obtained in Chapter 9 and 10. It builds on the results found using two types of pattern recognition systems (LVQ and Novelty Detection). The chapter addresses the following key issues:

1. A group of SCFs with high average sensitivity produce a high sensitivity system compared with a group of SCFs with low average sensitivity.
2. The reduced cost of the system based on sensor utilisation and overall SCF sensitivity. Novelty detection and neural networks (LVQ) are used to prove the results.

Chapter 12 summarises the use of the design methodology. It also investigates whether the results in previous chapters indicate that ASPST is a re-usable structured methodology for selecting sensors and signal processing methods with reduced cost and experimental work in the turning process. It explains how new knowledge has been generated and tested, and what remains to be tested. It also describes the contribution of the author, quotes outstanding problems and identifies constraints on the methods. Tests and finding are clearly stated and future work is suggested to assist subsequent researchers.

6.9 Conclusion

This chapter has summarised the methodology used and the investigations of this research work. The aim is to develop a systematic structured methodology for the design and implementation of the ASPST approach of condition monitoring systems for machining operations with experimental conformation for turning processes. The problems of condition monitoring design have been described and compared with the current practice in the field. Not only the way the ASPST approach is conceived has been described but also techniques modified as a result of previous research and more recent development. The chapter has explained the general steps of the ASPST approach and described its applicability for turning processes with multi-sensor fusion. The chapter has also described how the subsequent chapters are organised to prove the proposed methodology.

Chapter 7

Elements of the Implemented Condition Monitoring Systems

7.1 Introduction

This chapter covers the elements and stages of the machine condition monitoring system implemented in this research. It includes a brief description of sensors, signal processing methods and pattern recognition systems utilised for developing the proposed model. Force dynamometers, accelerometers, sound, strain and acoustic emission sensors are used for monitoring the machining processes. Signals are processed in the time and frequency domains using different types of signal processing methods to extract the sensory characteristic features. Statistical methods are used to calculate the sensitivity of the sensory characteristic features of the monitored physical phenomena. The last part of this chapter addresses all pattern recognition techniques used in developing the model including neural networks and the novelty detection classification method. More details regarding the experimental set-up, sensor positioning, and the complete data acquisition system can be found in Chapter 8.

7.2 The Implemented Sensors

The sensors used in this research are force dynamometer, strain sensor, accelerometer sensor, acoustic emission sensor and microphone for measuring sound.

7.2.1 Force dynamometers

Force dynamometers have been used widely in research for the following reasons [200]:

- Less dependent on the structure of the machine tool.
- Cutting forces can be easily simulated.

In addition, there are investigations on implementing force dynamometers in real industrial environments [200], though, since the ASPST approach is an experimental model which does not use simulation, the earlier mentioned advantages are not the only reason for using an expensive sensor such as force dynamometer sensor. The main reason is to compare how useful an expensive sensor could be compared with much cheaper ones (e.g. strain, sound) in developing an effective condition monitoring system.

Figure 7.1: Photo of the Kistler Dynamometer (9257) [200].

Figure 7.1 shows a photo of the Kistler Dynamometer (9257) used in this research which is attached to the tool holder. The force dynamometer is simply a piezoelectric transducer for measuring forces in three directions perpendicular to each other. The charge produced from the piezoelectric transducer is proportional to the force applied on the device. Hence, the charge can be measured as an output voltage following an amplification stage by a charge amplifier. The tool is mounted on the dynamometer to allow direct measurement of the turning forces to which it is subjected.

7.2.2 Accelerometer

The significant relationship between tool conditions and vibrations during machining is well recognised, and the comparably low noise implication of the vibration sensors is discussed in other tool condition monitoring investigations. Accelerometers are used to measure acceleration and vibration. Among the several vibration detection techniques, piezoelectric accelerometers are often adopted for tool wear investigations for measuring vibrations. These instruments rely on the piezoelectric effect of quartz or ceramic crystals to generate an electronic output related to acceleration. The piezoelectric effect produces an opposed accumulation of charged particles on the crystal. This charge is proportional to the applied force or stress. The main advantage of using vibration based monitoring systems for monitoring machine tools and industrial machinery is that they are simple, accurate and inexpensive. Moreover, they are easy to use and no modification to the machine or the work-piece fixture is normally required. However, vibration methods do have drawbacks such as dependency of the vibration signals on work-piece materials, cutting conditions, and machine structure.

The accelerometer mounting position in turning operations has been proposed in a number of studies. In this study, the sensor is mounted on the top of the shank, determined to be an efficient position to detect the vibration from the cutting tool. After the mounting position is decided, a thread hole is cut in the shank, and a thread pin is installed to connect the sensor and the shank. Vibration has been found useful in machine tools as well as continuous process industries [39]. Figure 7.2 shows a photo of the Kistler accelerometer (8704B) used in this research.

Figure 7.2: Photo of the Kistler accelerometer [200].

7.2.3 Acoustic Emission

Acoustic emission (AE) refers to the generation of transient elastic waves during the rapid release of energy from localised sources within a material. The source of these emissions in metals is closely associated with the dislocation movement accompanying plastic deformation and the start and extension of cracks in a structure under stress. Other sources of acoustic emission include: melting, phase transformation, thermal stresses, cool down cracking, and stress build up. Reference [200] classified the source of acoustic emission during metal cutting process into the following categories:

- Plastic deformation of a workpiece.
- Plastic deformation of the chip.
- Frictional contacts of workpiece and tool having flank wear and crater wear.
- Collisions between chip and tool.
- Chip breakage.
- Tool fracture.

In recent years, AE instruments have been adopted for use in structure integrity valuation, non-destructive testing, and quality testing for advanced material industries. AE is also proposed as a possible signal source to detect the tool condition in a number of studies. AE can be defined as: low amplitude, high frequency elastic stress wave generation due to a rapid release of strain energy within a solid material associated with the plastic deformation, fracture and phase transformation of the material. Frequency analysis of measured AE levels during machining shows that vibrations of the tool and work-piece due to shear, friction, and impact forces are the main sources of this AE radiation. An AE sensor is attached to the tool holder to monitor AE signals transmitted during machining. The proposed sensor provides an improved installation method since it does not require close setup to workpiece. As a result, it can avoid frictional damage caused by chips formed during the cutting process. Recently, acoustic emission (AE)-based monitoring systems are finding increased applications in condition monitoring. Acoustic emission and audible sound waves produced during cutting have been found useful in several researches for the identification of process condition. Figure 7.3 shows a photo of the Kistler AE sensor (8152B) used in this research.

Figure 7.3: Photo of the Kistler AE sensor (8152B) [200].

7.2.4 Strain

The strain sensor is suitable for measuring dynamic and quasistatic forces on fixed or moving machine parts. The sensor measures the force-proportional strain at machine or structural surfaces (indirect force measurement). The high sensitivity and acceleration-compensated design of the sensor allows process monitoring on fast-running process machinery (e.g. presses, automatic assembly machines). The strain of the basic material acts via the two contact surfaces on the sensor as a change in distance. The sensor enclosure serves as an elastic transmission element and converts the change in distance into a force. The particular advantages compared with the familiar wire strain gauge technology rest in the high sensitivity, large overload resistance and practically unlimited life even under fluctuating loads. The measuring signal can be further processed as a relative value [201]. Figure 7.4 shows a photo of the Kistler strain sensor (9232A) used in this research.

Figure 7.4: Kistler strain sensor (9232A) [200].

7.2.5 Sound

The concept of sensing tool wear from the sound signal during a cutting process goes back more than thirty years [202, 203]. There have been several studies using sound signals in this context, and their results confirm the correlation between tool wear and the sound emitted during the turning process [202, 204, 205].

It has been reported that tool wear is correlated with an increase in the amplitude of the high frequency bands of the sound signal [196]. In this thesis, a sound signal is used to extract valuable information correlated with tool wear. The main problem of using this signal in the development of a tool condition monitoring system is the ambient noise, as has been identified and studied in several research papers [196]. These papers conclude that in the region between 0 and 2 kHz the influence of the surroundings and of the noise from adjacent machines, motors, conveyors, etc. or processes may contaminate the signals. However, they conclude that this effect can be moderated by using noise cancellation methods in the signal processing algorithm. Figure 7.5 shows a photo of the microphone used in this research

Figure 7.5: Sound sensor (microphone).

7.3 Signal Processing

To utilise the information (or signal) obtained from the sensor mounted on a machine tool (e.g., turning machine in this research), a signal processing technique is required.

The signal processing methods applied in this work are chosen carefully from the most commonly used methods. The ASPST approach utilise similar methods used in the ASPS. However, it is not limited to those methods only and is general enough to allow other methods to be used. The signal processing methods used in this research are: average value, standard deviations (std), maximum, minimum, range, power, kurtosis value, skew value, wavelet analysis and Fourier Transformation (FT). In the case of wavelet analysis, the standard deviation of the sub-signals, as will be described later, are used as system sensory characteristic features. More details are described below.

7.3.1 Time Domain Methods

Standard Deviations (std)

The standard deviation (std) which is normally represented by the Greek symbol σ, where σ measures the variation of the data from the average. It is defined as:

$$\sigma = \sqrt{\left(\frac{\sum_{k=1}^{N}(x_k - \mu)^2}{N-1}\right)} \qquad 7.1$$

Power (P)

Power is a measure of the amplitude of a signal. The power value is proportional to the square of the amplitude of the signal values. The power value can be defined as follows [128]:

$$\text{Power} = \frac{\sum_{k=1}^{N} x_k^2}{N} \qquad 7.2$$

Average (μ)

The average value of a signal is the mean of the values of the vector. It is one of the simplest signal processing methods. Mathematically, the average value of a signal can be defined for a vector of length (*N)* as follows:

$$\mu = \frac{\sum_{k=1}^{N} x_k}{N} \tag{7.3}$$

Where $\sum_{k=1}^{N} x_k = \quad x_1 + x_2 + x_3 + x_4 + \ldots.., x_N$

Where x is the sensory signal

Skew Value

The skew of a signal measures the symmetry of the distribution about its mean level. The skew value can be defined for an assumed β distribution as [52]:

$$\text{Skew} = \frac{2(s-r)}{r+s+2}\sqrt{\left(\frac{r+s+1}{rs}\right)} \tag{7.4}$$

Where:

$$r = \frac{\mu}{\sigma^2}(\mu - \mu^2 - \sigma^2)$$

$$s = \frac{1-\mu}{\sigma^2}(\mu - \mu^2 - \sigma^2)$$

Kurtosis Value

Kurtosis values are useful in identifying transients and spontaneous events within signals. The kurtosis value of a time series is defined as the fourth central moment of Gaussian distribution. The Kurtosis value simply measures the sharpness of the peaks in the signals [64] and can be calculated as follows [52]:

$$\text{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \mu)^4}{\sigma^4} \tag{7.5}$$

7.3.2 Frequency Domain Analysis Methods

Fourier Transformation

It is essential to break down the signal into its frequency spectrum in order to confirm the presence of certain frequencies. Because of this the frequency content of a signal is not regularly clear from the time domain. The discrete Fourier transformation (DFT) algorithm is used to exchange a digital signal from time domain into a signal in the frequency domain. The discrete Fourier transformation is a very computationally intensive algorithm which contains a huge number of mathematical operations, though when the length of the signal is a power of two, then Fast Fourier Transformation (FFT) can be used which reduces the computation necessary to make the transformation from time domain to frequency domain [83, 206].

$$X[k] = \sum_{n=0}^{N-1} x[n] \ W_N^{nk} \qquad 7.6$$

for $k = 0,1,2,........, N-1$

where:

$$W_N = e^{-j2\pi/N}$$

Wavelet Analysis

Fourier transformation has an important disadvantage. The transformation process from the time domain to frequency domain removes the time information. Consequently, when looking at a frequency spectrum, it is not possible to know when an exact event has happened. Wavelet analysis provides an alternative technique of breaking a signal down into sub-signals or levels with different frequencies which carry the time information. In wavelet analysis, the length of the signal, i.e. number of values contained in the signal, determines how many wavelet levels there will be in the decomposition. In general, for a signal of length N, where N = 2^n there are n+1 wavelet levels. The shape of the wavelet levels depends on the mother wavelet signal which is used to build these levels. Wavelet analysis involves breaking the signal into sub-signals, each of which is generated from a combination of shifted and scaled wavelet signals. For every level the number of wavelet signals used to construct the signals equals 2^n where n is the level number. The standard deviation (std) of the wavelet levels is used as sensory characteristic features for the condition monitoring system. The standard deviation of each level reflects the actual contribution of that level in building the original signal [77].

7.3.3 Statistical Methods

Linear Regression

Linear regression is used to find the linear equation which best represents the linear relationship between two variables. The first variable is the independent variable which could be the degree of cutter wear, etc. The second variable is the dependent variable and this variable is a sensory characteristic feature which changes according to the change in the independent variable. The line is obtained by using the least squares straight line fitting. The least squares line is defined as:

$y^1 = b_a + b_1 x_1$

Where

$$b_1 = \frac{N\sum_{i=1}^{N} x_i y_i - \left(\sum_{i=1}^{N} X_i\right)\left(\sum_{i=1}^{N} Y_i\right)}{N\sum_{i=1}^{n} y_{i1}^2 - \left(\sum_{i=1}^{N} X_i\right)} \qquad 7.7$$

$$b_0 = \bar{y} - b_1 \bar{x} \qquad 7.8$$

Equation 7.8 represents the slope of the least squares straight line. The absolute value of b_1 is to find out the most sensitive sensory feature to the independent variables (e.g. degree of cutter wear) of machining parameters.

Range Value (RV)

The Range Value (RV) statistical method is used in this research to find the difference between the highest value and the lowest value. RV is defined as:

RV= Highest Value – Lowest Value.

Sudden Change in Value (SCIV)

The Sudden Change In Value (SCIV) statistical method is used in this research to find the average difference between the firs points and the last points. The first variable is the minimum average value of the first values (5%). While the second variable is the maximum value of the last values (95%). The sudden value is the difference between the last value and the first values. SCIV is defined as:

Last values = maximum of (Last point - (0.05* Last point)).

First values = mean of the (0.05* Last point).

SCIV = Last values – First values.

This method has been found the best statistical method to use in this research for turning. The theory behind using this method is described in Chapter 6, section 6.5.3. More details regarding the application of this method and the reason for using it are shown in Chapter 9.

7.4 Data Analysis and Pattern Recognition

A machine condition monitoring problem will be finally transformed into a pattern recognition problem to identify, from the sensory signals, the machine or process conditions. Two types of pattern recognition systems are used to demonstrate the application of the ASPST approach. The application of two systems is used to compare their result in order to evaluate the ASPST approach independently from specific pattern recognition. Novelty detection and Learning vector quantisation neural networks (LVQ) are implemented in order to compare their result directly. These methods are implemented to compare the result of each one. More details about these methods are briefly described. The ASPST approach is not limited to these methods but can be implemented with other methods such as the Back Propagation Neural Network (PB) and the Radial Basis Neural Network (RB), etc.

7.4.1 Novelty Detection

Novelty detection is used in this research as a self-learning approach to characterise the “fresh” or normal state of the cutter. Novelty detection [83] is a classification technique that recognises a presented data as novel (i.e. new) or non-novel (i.e. normal). The training data for the novelty detection algorithm consists of only the normal class which is often much easier to obtain. Since a degree of overlap is normally expected between different classes, classification problems have a probabilistic nature [78]. Novelty detection involves estimating the probability-density–function (*PDF*) of a normal class from the training data and then estimating the probability that a new set of data belongs to the same class. The classification decision in novelty detection is based on Bayes' theorem as shown in equation 7.9.

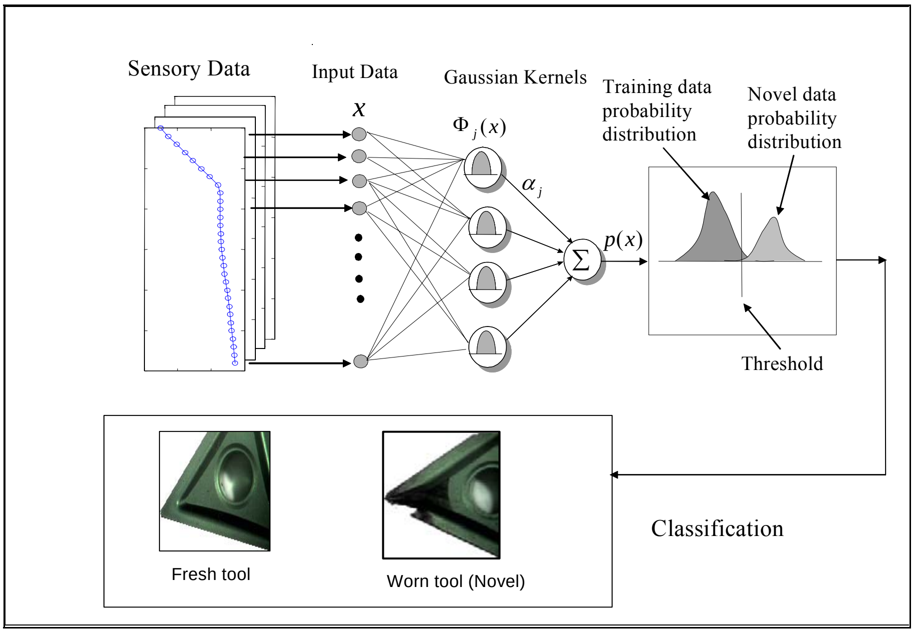

Figure 7.6: The application of novelty detection.

$$P(C_i \mid x) = \frac{p(x \mid C_i).P(C_i)}{p(x)} \qquad 7.9$$

Where

$P(C_i \mid x)$: *The Posterior Probability*, the probability that a given vector, x, belongs to class C_i.

$P(C_i)$: *The Prior Probability*, the probability that a future input, x belongs to a class, C_i, based on the ratio of training examples that belong to the same class.

$p(x \mid C_i)$: *The Class-Conditional Probability Density*, the probability of obtaining an input vector from a given class based on estimating the PDF of a class.

$p(x)$: *Unconditional Probability Density*, probability density of x regardless of which class it belongs to.

The Unconditional Probability Density should also satisfy the following equation:

$$p(x) = \sum_{i=1}^{k} p(x \mid C_i).P(C_i) \qquad 7.10$$

Where

$0 \le P(C_i) \le 1$ and

$$\sum_{i=1}^{k} P(C_i) = 1$$

The accuracy of novelty detection classification is dependent on the accuracy of the modelled density functions [79]. Three main methods are normally used to model the PDF: parametric methods [80], non-parametric methods [77] and semi-parametric methods [77]. The parametric methods assume sufficient statistical information about the training data set which is not normally available. In non-parametric methods no assumptions are made regarding the underlying density functions and they depend on the training data to find the probability density function for a new input. Reference [83] classified such methods as being Kernel based techniques and K-nearest neighbour technique. The K-nearest neighbour method depends on the probability that K number of data points of a vector fall within a specific volume. The Kernel-based technique calculates the volume by defining width parameters for a number of known probability distribution functions (Kernels) to provide a general model for the training set. However, non-parametric methods require long computations for every input vector. Semi-parametric density estimation is used in this research for novelty detection because it combines the advantage of both parametric and non-parametric techniques and does not require extensive computational effort. Semi-parametric methods use fewer numbers of Kernels. A Gaussian Mixture Model (GMM) is used in this work to estimate the PDF. Unlike non-parametric methods the training data are used only during the process of construction of the density model and are not needed for calculation of the PDF for new vectors.

The probability density estimation of GMM is obtained by Bayes' theorem, similar to equation (7.10), as follows [207] :

$$p(x) = \sum_{j=1}^{M} p(x \mid j).p(j) \qquad 7.11$$

Where

$0 \leq p(j) \leq 1$

M is the number of components in the mixture model

$p(j)$ is the Prior probability of selecting the jth kernel function

$p(x \mid j)$ is the conditional density of x on the jth kernel.

For a Gaussian Mixture Model, the following equation is derived:

$$p(x) = \sum_{j=1}^{M} \phi_j(x).\alpha_j \qquad 7.12$$

Where

ϕ_j is the response of the jth Gaussian component

α_j is the mixing coefficient (priors) of ϕ_j

When the probability distribution function is calculated, a threshold value can be used to define the boundaries between a novel vector and a normal data set [77, 207]. Figure 7.6 explains the methodology through which the novelty detection is used in this work to detect faulty conditions. Novelty detection software NETLAB [208] is incorporated with Matlab programs as a decision-making algorithm for the diagnostic and prognostic of tool wear. More details regarding the novelty detection can be found in [84].

7.4.2 Learning Vector Quantisation Neural Networks (LVQ)

Neural networks, or artificial neural networks to be more specific, represent an emerging technology rooted in many disciplines. They are endowed with some unique attributes: universal approximation (input–output mapping), the ability to learn from and adapt to their environment, and the ability to invoke weak assumptions about the underlying physical phenomena responsible for the generation of the input data. The operation of a neural network can be divided into two steps. The first step is called the learning phase, whilst the second step is called the retrieving phase. During the learning phase, the learning rule can be also divided into supervised learning and unsupervised learning. The supervised learning rule includes the error correction rule and delta algorithm, and the unsupervised learning rule includes the competitive learning rule. The back propagation algorithm is one of the supervised learning rules. The other algorithm used in this research is LVQ, which is one of the competitive learning rules.

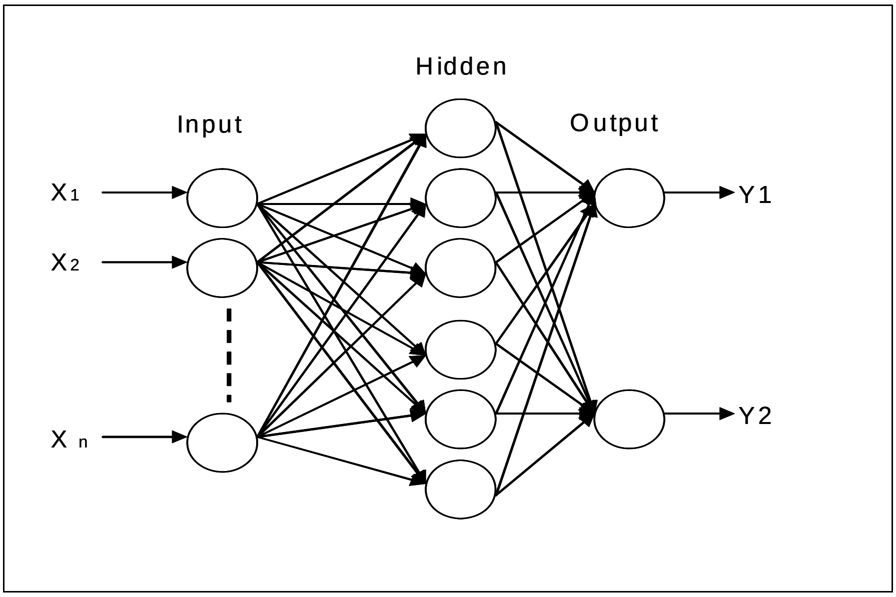

Figure 7.7: Artificial neural networks.

An artificial neural network (ANN), is a mathematical model or computional model based on biological neural networks. It consists of an interconnected group of artificial neurons and process information using a connectionist approach of compution. In most cases the ANN is an adaptive system that changes its structure based on external or intenal information that flows through the network during the learning phase. Neural networks are an expanding field of interest in the area of condition monitoring. In machine condition monitoring, there is a complication in dealing with the large number of signals and data that determine the condition of the cutter, process, and the machine itself. In theory, neural networks are able to learn complex relationships between inputs and outputs without a preceding knowledge of the system or any of its mathematical models. Neural networks can be a very effective signal analyser for pattern recognition systems in condition monitoring. They can be implemented to optimise the control system used. Neural networks in this research are used for pattern recognition and data fusion. However, neural networks have been mentioned in literature to be used in other applications such as: function approximation and complex regression, data reduction, process control and unfamiliarity detection. The main advantage of using neural networks is the full automation of the learning and classification processes. Therefore, neural networks can be implemented in fully automated condition monitoring systems to recognise and classify patterns without human involvement. The basic issues in the application of neural networks are the selection of the neural architecture type and choice of the most appropriate sensory features to be introduced to the neural networks. Selecting the best architecture with the most appropriate input information is a key factor in establishing a successful application [209]. Many different neural network structures have been developed to achieve different learning and processing speed capabilities. Neural networks are classified as supervised and unsupervised according to their learning characteristics. The decision is greatly dependent on the data obtainable for training the networks. If there is a target class or output for each pattern, then a supervised neural network can be used. However, when the input data do not have target output specified previously, then "unsupervised" neural networks have to be implemented. Unsupervised neural networks, such as LVQ use a special algorithm to group similar patterns in the input data space into similar output classes.

The functional behaviour of the whole system is determined mainly by the pattern of connectivity of the nodes. As a system, they are capable of performing some high level functions such as adaptation, generalisation and target learning. These capabilities are particularly attractive for tool wear monitoring applications. The one developed and applied in this work, is the Learning Vector Quantisation (LVQ) [210] which implements a competitive neural network. LVQ constitutes a particularly intuitive and simple though powerful classification scheme which is very appealing for the following reasons:

1. The method is easy to implement.
2. The complexity of the resulting classifier can be controlled by the user.
3. The classifier can naturally deal with multi-class problems.

For these reasons, LVQ has been used in a variety of academic and commercial applications such as image analysis, telecommunication, robotics, etc. A competitive neural network is an unsupervised neural network which uses Associative Learning Rules which allow the network to learn the association between the inputs and the outputs in reply to the data presented to them. A competitive neural network basically learns to recognise similar input vectors and to classify them together in one group. The basic structure of this network is that the input vector to the competitive layer is obtained by calculating the negative distance between an input vector ***p*** and the weight vector ***w*** and adding the bias ***b***. For any layer, the neurons are in competition. All the output of the neurons will be zero, except the winner neuron, whose output will be one. When the weight ***w*** of a neuron is the closest to the input vector ***p***, it will have least negative input, and then it will win the competition and its output will equal **1**. The user has to select the length of the input vector and the number of groups and then the network will group the inputs according to the needed groups. LVQ has an input layer, a competitive layer and a linear output layer. The competitive layer learns to classify the input vectors to subclasses while the output linear layer transforms the competitive subclasses into the desired target classes. The advantage of using LVQ is that it learns to classify input vectors into target classes chosen by the user. Nevertheless, the learning rules are done according to the competitive layers depending on the distance between the input vectors and the weight and not according to the error between the output and the target unlike back propagation neural networks. Therefore, there is no mechanism in the network to dictate whether or not any two input vectors belong to the same category. LVQ is a very useful network in the application of classification because its output is logically '0' and '1'.Figure 7.8 shows the LVQ network architecture. LVQ neural networks can be seen in reference [84].

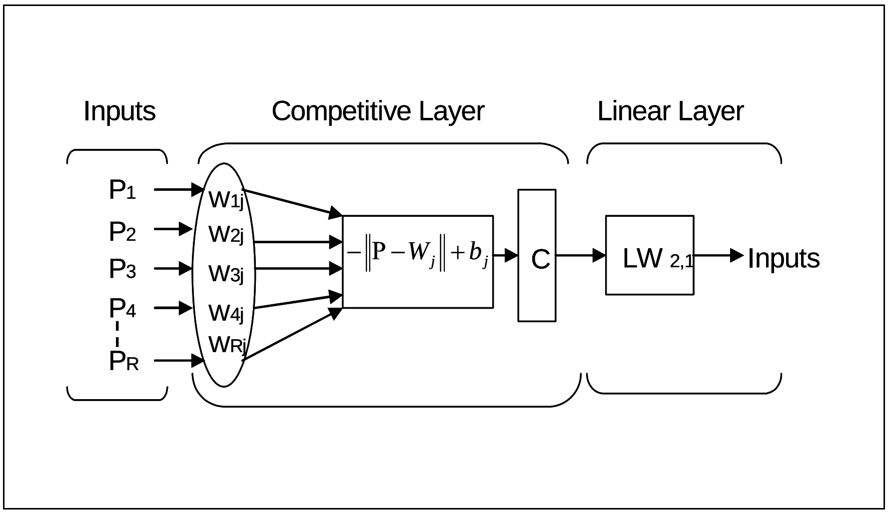

Figure 7.8: LVQ network architecture.

7.5 Conclusion

This chapter covers the components and stages used to implement the experimental condition monitoring systems, including: sensors, signal processing methods and artificial intelligence recognition systems. Different types of signals, including force, AE, sound, strain and vibration, are used to obtain the process information. Time and frequency domain signal processing methods are used to extract sensory features for the design process of the monitoring system. The most appropriate sensory features are chosen by the ASPS approach to be introduced to the pattern recognition system to identify process faults. Two types of pattern recognition system learning vector quantisation neural networks and novelty detection are used in this research to classify process states independently.

Chapter 8

Experimental Set-up

8.1 Introduction

In order to develop a condition monitoring system, it is necessary to undertake cutting tests from which the chosen process parameters can be measured and their trend used in accessing their true indication of on-line monitoring. This chapter describes the main experimental set-up for this research work. It covers a description of the machine tools and the condition monitoring system set-up including the placement of sensors, the data acquisition system and programmed software.

8.2 Machine Tools and Process

The type of machining process used in this research is a turning process on a lathe machine as it is the most common and flexible machining process. Like any other machining process, the ultimate economic performance of a lathe depends on the cutting tool that actually takes the chip off the workpiece. The experimental work is done on a Colchester Student (1800) Lathe machine shown in Figure 8.1.

Figure 8.1: Colchester Student (1800) Lathe Machine.

8.3 Workpiece and Tool Insert

The experimental work is designed to present and simulate a real industrial environment. The work mainly involved turning processes of stainless steel material for the gradual tool wear test. The tool inserts used, Sandvik Coromant P25 (SCMT 120408 UM), is cemented carbide coated via chemical vapour deposition and consisting of grades of “throw-away” indexable inserts with integral chip-breaker geometry, held in place by a negative rake tool holder. P25 had a thick layer on top of titanium carbon nitride (TiCN) giving it a high wear resistance and good edge security. This combination gives P25 excellent wear resistant properties. No cutting fluid is used. The workpiece material used is stainless steel which is relatively hard in order to accelerate tool-wear at the expense of a shorter tool life. In addition, stainless steel is used in this research as it is a very common material used in domestic applications, application in automotive market and other industrial applications. The stainless steel work piece had a diameter of 30 mm.

The type of machining process carried out is semi-orthogonal turning on a lathe as it is the most regular and adaptable form of machining process. Similar to any other machining process equipment, the ultimate economic performance of a lathe depends on the cutting tool that actually takes the chips off the workpiece. Productivity and economy have made indexable inserts the primary tooling method for lathes. With due thought to the power limitations of the machine and the tool/workpiece combination, the tool manufacturers particularly recommend cuts be carried within the following ranges (minimum–maximum) for each cutting parameter to incorporate various tool wear modes[185].

The selection of these parameters for any particular turning operation requires a complex variety of considerations involving the interaction of the workpiece, machine tool and tooling material as a system [196]. Using the tool insert manufacturer's guidelines, a cutting range is selected based on the insert type and the resulting cutting parameters are chosen accordingly. This involves reading the maximum and minimum values of the feed-rate and depth of cut values of ISO charts that corresponded to the chosen tool inserts. For the tool selected, the recommended values are as follows: feed-rates, 0.1–0.5 mm/rev while DOC varied from 0.5 to 3 mm. Cutting speed is selected based on the toughness of the workpiece to be machined. The recommended cutting conditions for the workpiece-tooling geometry configuration are as follows: feed-rate of 0.5 mm/rev; DOC of 2 mm, and cutting speed of 500 m/min. A decision is made to conduct the wear tests at a fixed cutting condition to achieve significant wear within a short time.

8.4 Sensors

The chosen process parameters monitored are the cutting forces (three axes), strain, vibration, acoustic emission (RMS and AE signal), and sound. Figure 8.2 shows a schematic diagram of the complete monitoring system.

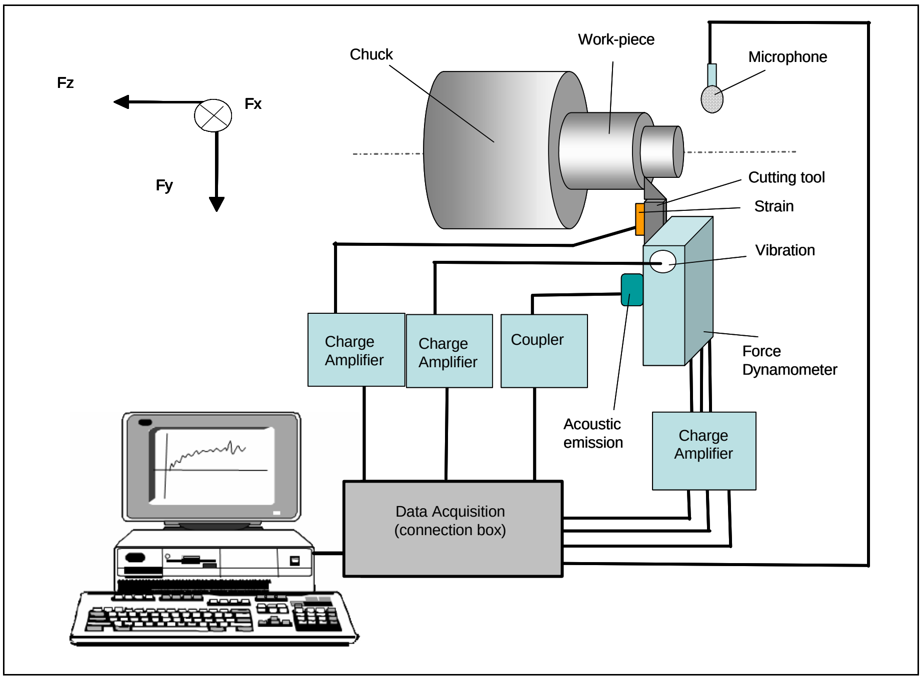

Figure 8.2: Schematic diagram of the complete monitoring system.

The force signals are monitored using 3-component Dynamometer (Kistler 9257A) and the cutting tool is fixed on the dynamometer bolted rigidly on the tool turret so that the turret speed and the feed components of the cutting forces can be measured. The vibration signals are monitored using an accelerometer (Kistler 8704B) which is mounted close to the tool holder in order to measure the radial acceleration due to the workpiece-cutting tool system vibration. Both the force dynamometer and the vibration accelerometer are connected to a 4-channel charge amplifier (Kistler

5070A). The acoustic emission signals are monitored using an AE-Piezotron Sensor (Kistler 8152B) which is mounted close to the tool holder and is connected to AE-Piezotron Coupler (Kistler 5125B) which gives the AE signals and the RMS of the AE signals. The dynamic and quasistatic force signals are monitored using a strain sensor (Kistler 9232A) which is mounted at the side of the tool and it is connected to a charge amplifier (Kistler 5855A). The sound signals are monitored using a Back Electret Condenser Microphone (Yago EM-400) which is mounted in a post on the tool turret and is connected directly to the DAQ card. The signals are monitored using data acquisition card NI PCI-6071E from National Instruments using special data acquisition software written using the National Instrument CVI programming package and a computer. Matlab software is used for the complete analysis of this research. Figure 8.3 shows a photo of the sensors installed on the machine.

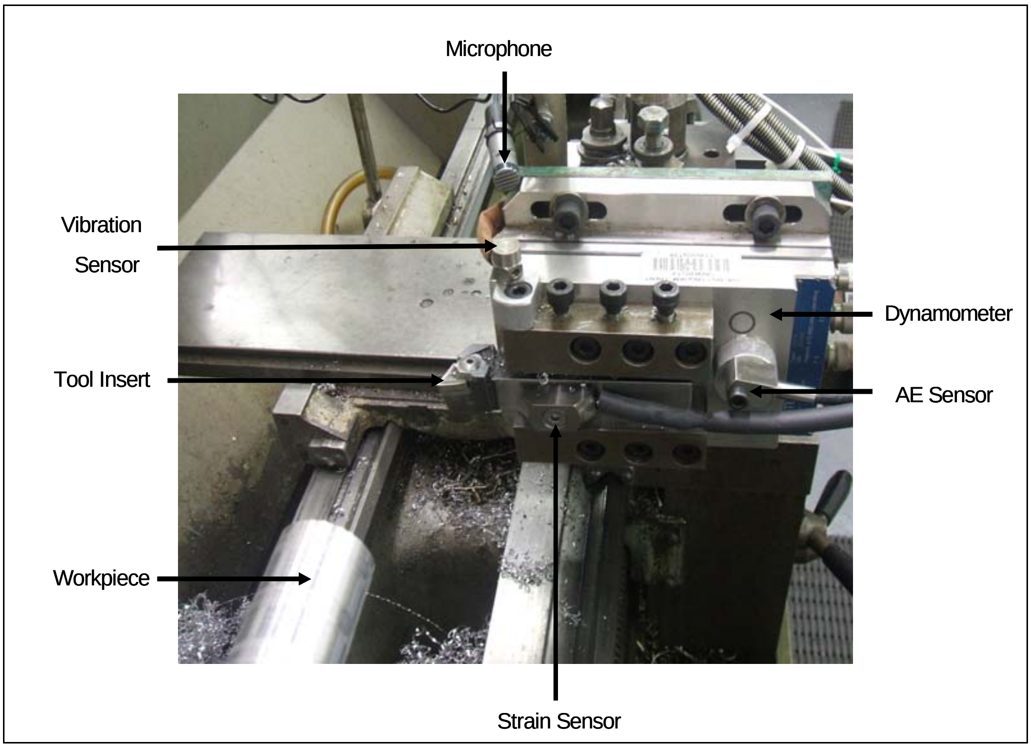

Figure 8.3: The sensors installed on the lathe machine.

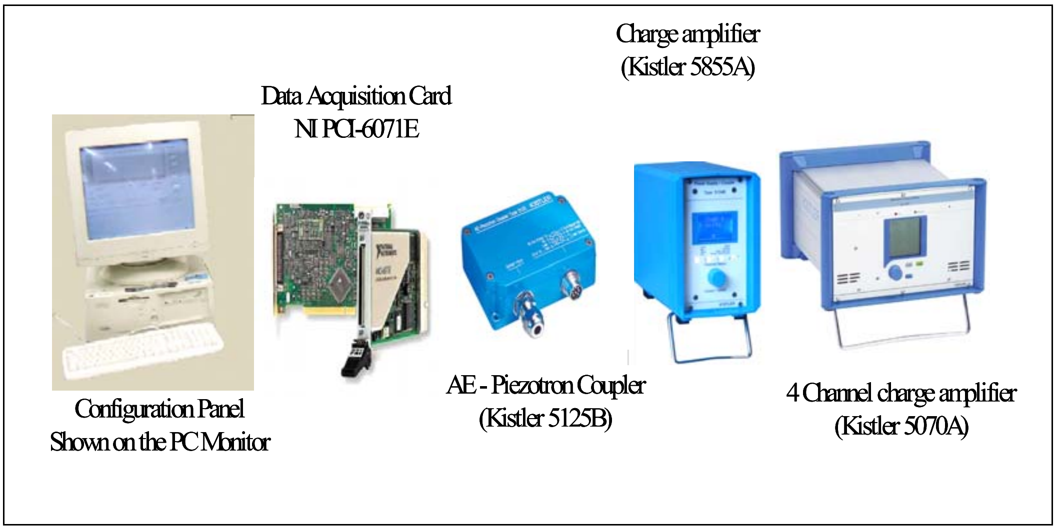

Figure 8.4: Shows the equipment used in the monitoring system.

8.5 Data Acquisition Card

The data acquisition card used is the NI PCI-6071E from National Instruments, a multifunction analogue, digital, and timing I/O boards for PC AT. The card has 12-bits ADCs with 64 analogue input single ended or 32 differentials with a guaranteed sampling rate up to 500k sample. The analogue input used was configured as differential inputs because of the low voltage levels involved, the noisy environment, and long wires used in connecting the signals to the data acquisition card. The analogue channel is used to acquire the machining data using a sampling rate of 15000 or 16000 samples per channel. The card is used in a bipolar mode of +10V or -10V with a board gain of 0.5. Hence, for 12-bit data samples the resolution is up to 9.76 mV.

8.6 Data Acquisition Software

The data acquisition card is programmed using LabWindows/CVI from National Instruments, a developed software package for data acquisition and monitoring. The data acquisition software is flexible multipurpose data acquisition software using the LabWindows/CVI package from National Instruments. The software also has simple GUI panels which give the user a friendly and fast interaction. The software loads the acquired data to the computer memory first, draws it on the screen and then gives the user the option to save the data. Consequently, it gives the user more flexibility for data analysis, but at the same time, it limits the maximum number of samples which can be acquired. The Configuration Panel is used to choose the channels to monitor their colour, save the configuration to a file and load any configuration file to the program. Figure 8.5 shows the Configuration Panel.

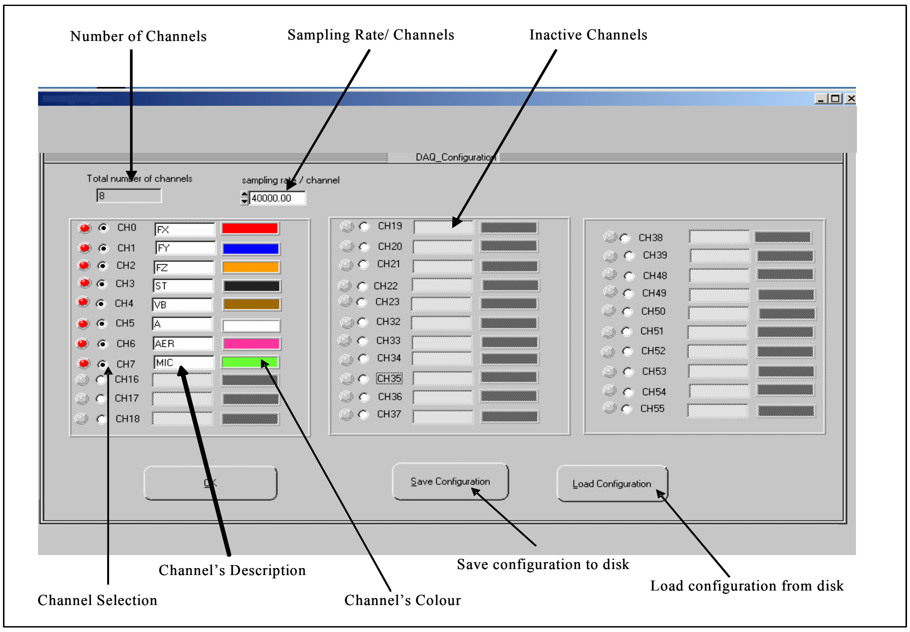

Figure 8.5: The configuration panel used for channel selection.

The configuration file contains the sampling rate, number of channels, their colour, and description. The configuration panel allows the user to enable or disable any channel monitored, either on line or off line, just by clicking the toggle button. The LED indicator next to the channel will indicate if the channel is active or not. The user can add the description of each channel and the required colour. All these configurations can be either saved to a configuration file or loaded from a configuration file. The software also utilises an option to start the acquisition process after the value of one of the operating channels exceeds a specific threshold value with an option to delay the acquisition until the cutting process reaches a steady state. An example of a data file format is shown in Figure 8.6. Each data file includes the original configuration information contained in the configuration panel. The data file also includes any description the user would like to add such as the date of the test, and the time.

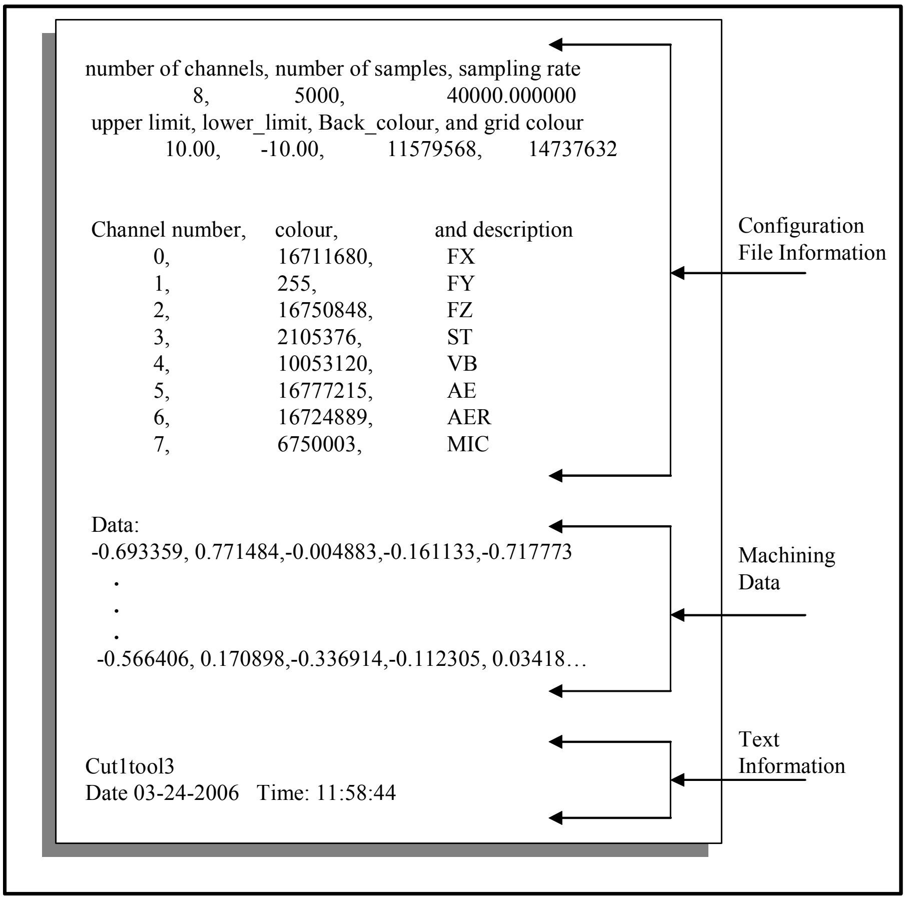

Figure 8.6: An example of a saved data file.

8.7 Conclusion

This chapter outlined the general experimental set-up of this research work. The descriptions dwelled on the lathe machine tool. Similarly, it also describes the sensor types and their position focusing on cutting tools, workpiece materials, software and the data acquisition system.

Chapter 9

ASPST Initial Evaluation

9.1 Introduction

This chapter explains the initial evaluation and implementation of the Automated Sensor and Signal Processing Selection for Turning (ASPST). The chapter shows how the ASPST approach can be utilised to develop a sensor fusion model of a condition monitoring system to detect tool wear in turning processes in an efficient way. The chapter introduces the details of the ASPST approach using a gradual tool wear fault with multi-sensor signals during a turning process. This chapter uses force and strain sensors to examine the suitability of the ASPST condition monitoring. It covers the main stages of the ASPST approach, the Association Matrix (ASM) of the wear test, the sensitivity detection, the selection of the most sensitive SCFs for a condition monitoring system and the cost of the implemented monitoring system. More experimental work for the evaluation of the ASPST approach for other sensors will be described in the following chapters. The implementation of the ASPST approach will answer the following questions:

1. What is the difference between the two groups of signals for monitoring turning processes?
2. Which is the most sensitive signal to tool wear for turning processes?
3. Is one machining signal sufficient to monitor tool wear or is more than one sensor needed?
4. If a signal is chosen for the condition monitoring system, how can it be fed to the pattern recognition system?
5. How can we choose between those sensors so that we can design an efficient monitoring system?

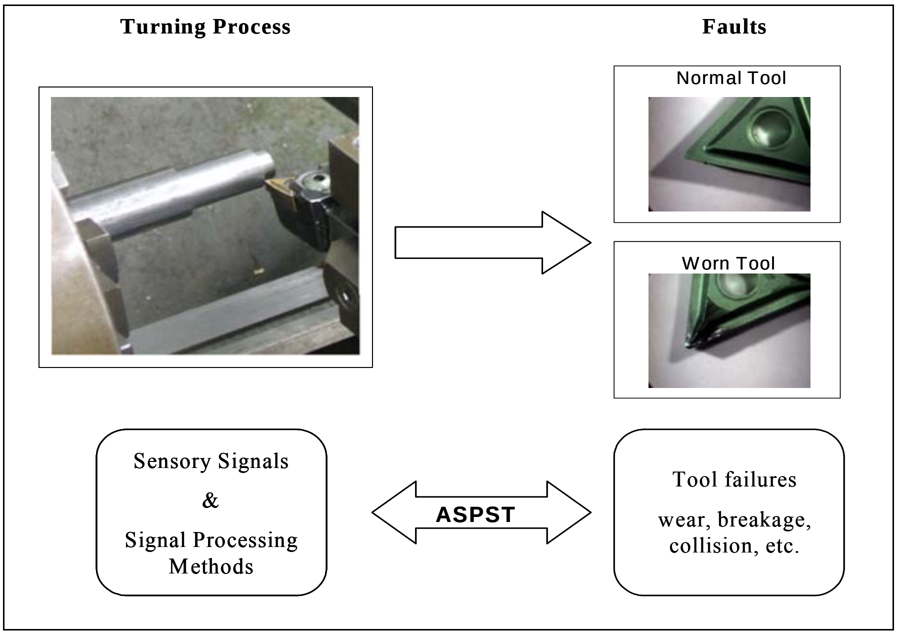

Figure 9.1: The basic principles of the ASPST approach.

Figure 9.1 shows the basic principles of the ASPST approach. It is designed to systematically relate the sensory signal and the signal processing methods utilised to the fault which is to be detected.

9.2 Experimental Work

The experimental work in this chapter is conducted to examine the behaviour of the signals for fresh and worn tools and to find the most sensitive sensory characteristic features to tool wear. The experimental work is performed on a turning process using a stainless steel workpiece. It is a relatively hard material in order to accelerate tool-wear at the expense of a shorter tool life. In addition, stainless steel used in this research as it is a very common material used in domestic applications, application in automotive market and other industrial applications. The stainless steel work piece has a diameter of 30 mm; and a total machining distance of 1500 mm is machined during the full tests to transfer the tool from fresh to completely worn. The machined distance are divided into 6 machining samples with lengths of 250 mm each (i.e. 6 machining samples are obtained during the test for analysis). In total, 6 independent experiments are conducted on the turning of stainless steel bars with a fresh tool used for each experiment, all with the same basic configuration. The tool insert used, Sandvik Coromant P25 (SCMT 120408 UM), is cemented carbide coated via chemical vapour deposition and consisting of grades of indexable inserts with integral chip-breaker geometry, held in place by a negative rake tool holder. Care is taken to ensure that all experimental conditions remained the same. The machining parameters are selected to resemble industrial practice. The experimental cutting conditions are chosen to cover the manufacturer's recommended interval for inserts type. Figure 9.2 shows a schematic diagram of the implemented monitoring system for this chapter. For more details see Chapter 8, section 8.3.

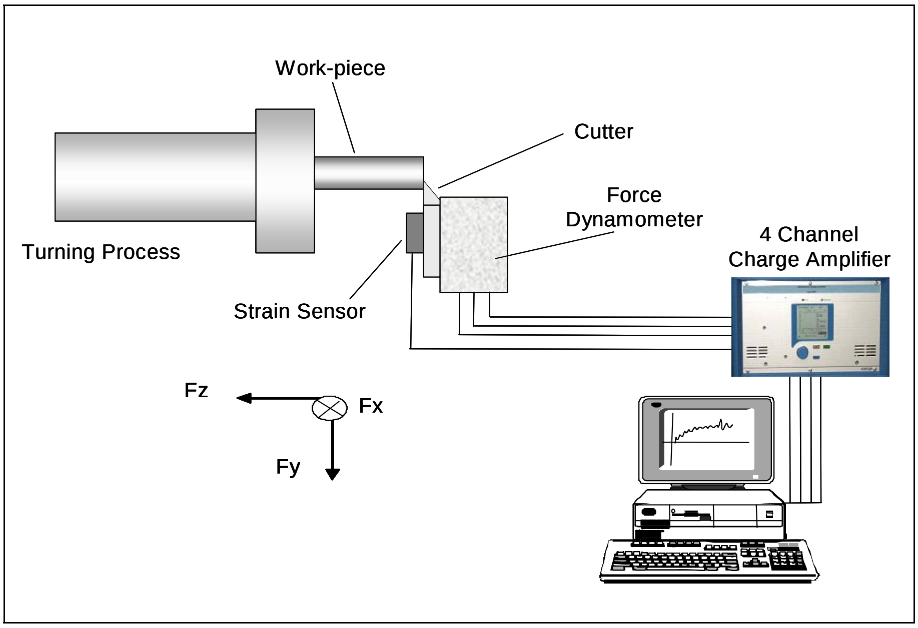

Figure 9.2: Schematic diagram of the monitoring system.

The chosen process parameters monitored are the cutting forces (three axes) and strain. The force signals are monitored using 3-component Dynamometer (Kistler 9257A) and the cutting tool is fixed on the dynamometer bolted rigidly on the tool turret so that the turret speed and the feed components of the cutting forces could be measured. The dynamic and quasistatic force signals are monitored using strain sensor (Kistler 9232A) which is mounted at the side of the tool. Both the force dynamometer and the strain sensor are connected to a 4-channel charge amplifier (Kistler 5070A). The level of tool wear is visually monitored in this experimental work and the experimental work shows that wear increases with machining time.

9.3 Signal Simplifications

For a complex machining process such as turning, the first step is to transfer signals from its complex form into a group of simplified sensory signals denoted Sensory Characteristic Features (SCFs). For example, if a turning process sensory signal can be transformed into a group of SCFs with relatively simple nature with less variation, then it is expected to be much easier to retrieve the necessary information which presents the state of the process based on the change in the level of the extracted SCFs. As explained in Chapter 6, a sensitive SCF is a SCF which includes a significant amount of information regarding the state of the process. This should lead to better recognition. The sensitivity of the SCFs for this experimental work in this chapter is evaluated by the following methods:

1. Visual inspection of the signals.
2. Using Sudden Change In Value (SCIV) method.

9.3.1 Visual Inspection Method

In this section the simplified sensory information are detected visually. Figure 9.3 and 9.4 shows examples of the machining signals for the fresh and worn tool respectively.

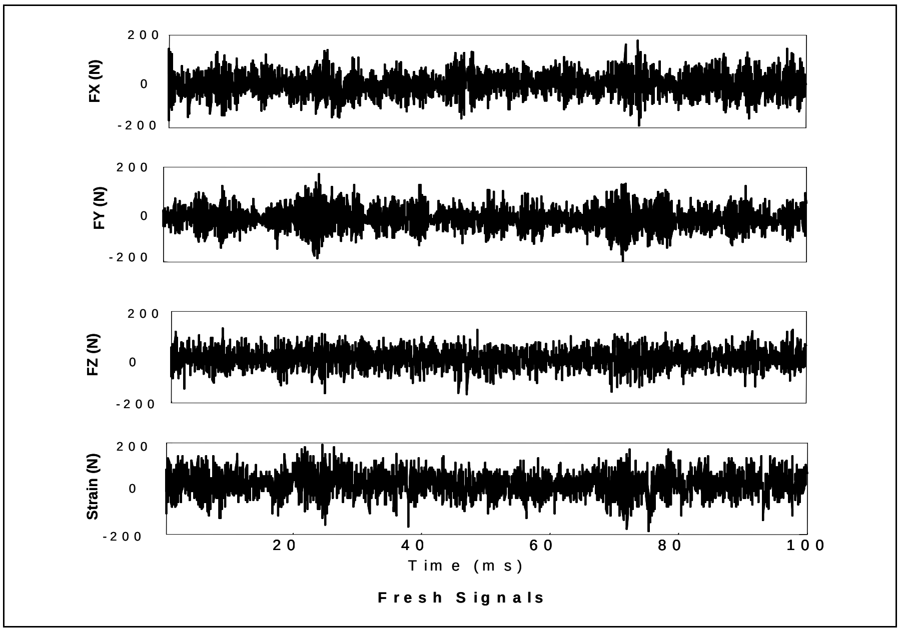

Figure 9.3: The machining signals for fresh tool.

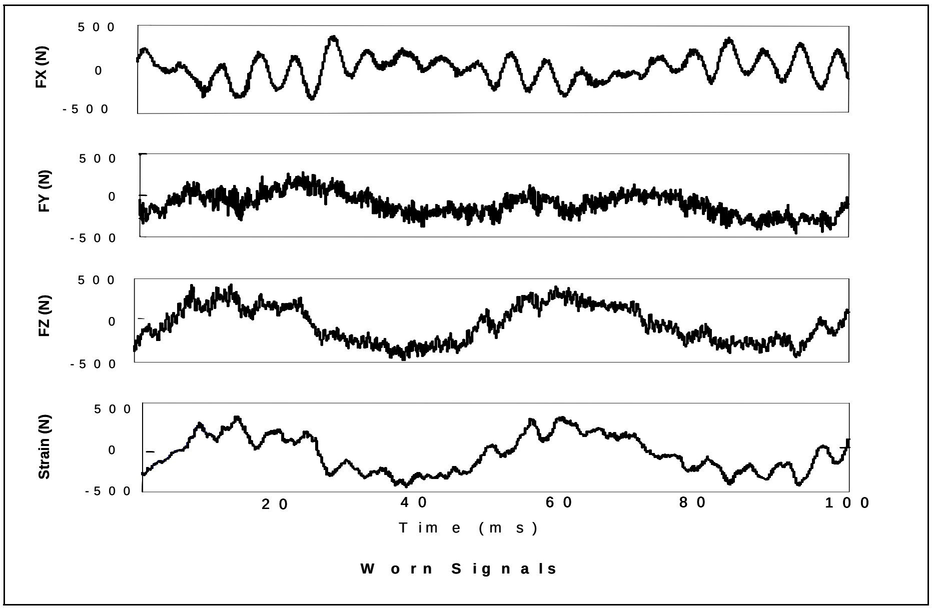

Figure 9.4: The machining signals for worn tool.

It can be observed from Figures 9.3 and 9.4 that the vibration level of some signals has decreased for the worn tool, as in the cutting forces signals. In addition, the level of some sensory signals has changed such as the strain signal. Because turning has complex machining signals, it has been found difficult to predict the most sensitive signals to tool wear directly from the raw data.

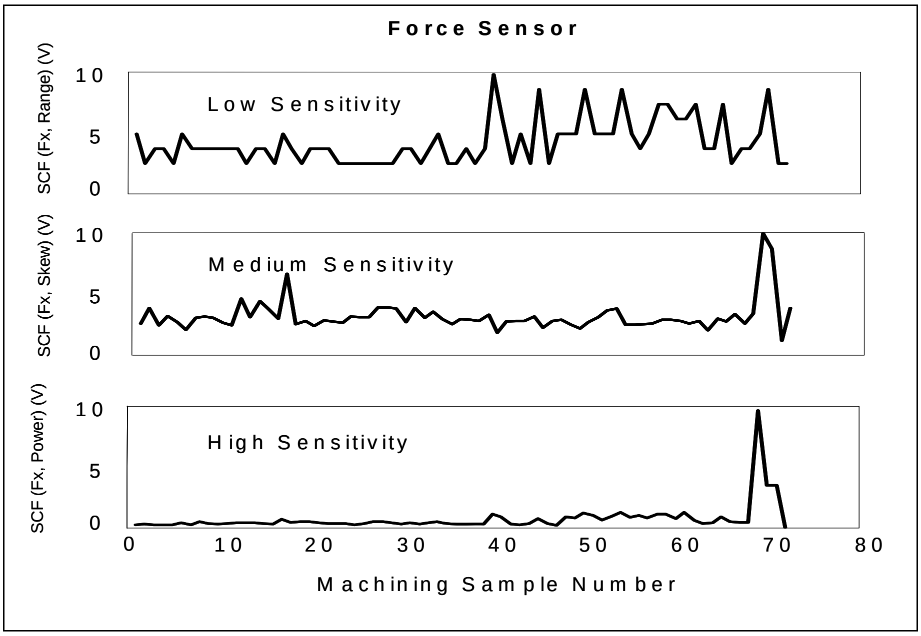

Figure 9.5: Example of the SCFs of the signals.

Figure 9.5 presents an example of the general visual observation of the sensory signal which includes the sensitivity of SCFs of the force sensor. Looking at Figure 9.5, it is apparent that the force signal (Fx) has three different sensitivity levels, low, medium and high, with different signal processing methods. It shows low sensitivity with the std, medium sensitivity with the skew and high sensitivity with the power. It can be observed that among the signals, some signal processing methods are more sensitive with the sensory signal than others. Therefore, it can be concluded that manual investigation could help in finding the sensitivity of the sensory signal. Table 9.1 shows general visual observation of the Association Matrix (ASM) which includes the sensitivity of all SCFs implemented in this monitoring system. Figure 9.6 presents an image of the SCFs of the signals.

Table 9.1: Example of ASM for Tool 1.

Sensory Signal	**Signal Processing Methods**							
	Std	Avg.	Max	Min	Range	Kurtosis	Skew	Power
Fx	L	H	L	H	M	L	M	H
Fy	M	H	H	H	L	L	L	H
Fz	M	M	H	H	H	L	L	H
Strain	L	H	H	H	H	M	H	H

(H: High sensitivity, M: Medium sensitivity, L: Low sensitivity).

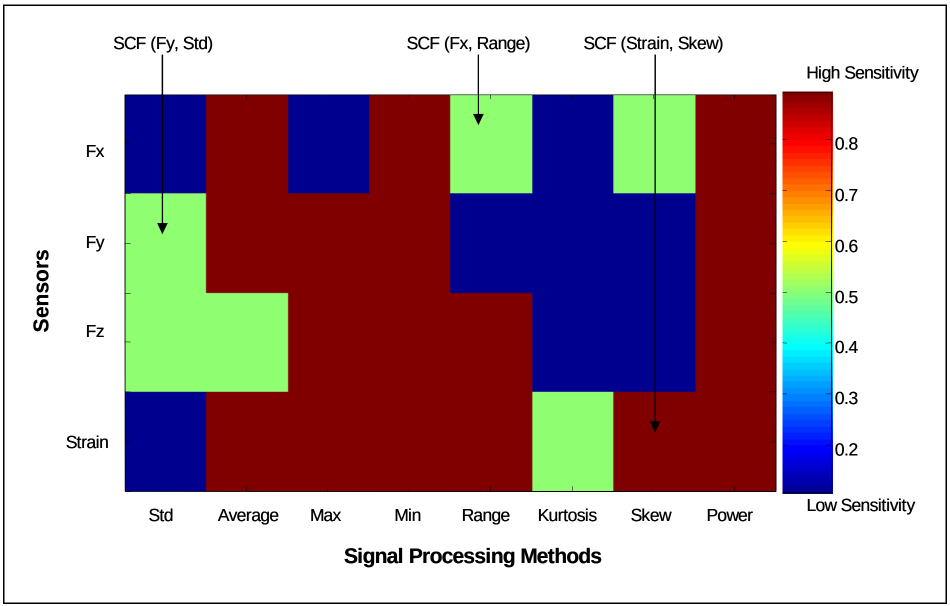

Figure 9.6: Example of the SCFs images of the signals.

Table 9.1 shows general visual observation of the Association Matrix (ASM) which includes the sensitivity of all SCFs implemented in this monitoring system. In addition, Figure 9.6 presents an image of the SCFs of the signals. For example, the strain sensor shows high sensitivity with the skew signal processing method, while the force sensor (Fy and Fz) shows low sensitivity with the same signal processing method. Although such general visual observations as shown above might helps to find some sensory features which are sensitive to the tool wear. But it still does not provide a systematic method to study the system and there could be more sensitive sensory characteristic features which are obtained from less expensive sensors than the force dynamometer, for example strain sensor in this experimental work. From the above discussions it may be concluded that manual investigation of the monitored signals is time consuming and should be automated in order to develop a faster and more structured methodology for selecting sensors and signal processing methods. In this research, the Sudden Change In Value (SCIV) automated sensitivity method is utilised to automate the system.

9.3.2 Sudden Change In Value (SCIV) Method

The discussion in the previous section suggests that manual investigation of the monitored signals could be time-consuming and the system should be automated. Therefore, in this section the practical steps of the ASPST approach for the same four (Fx, Fy, Fz, strain) sensory signals are described. The theoretical ideas of the ASPST approach are presented in Chapter 6. In general, assuming that the monitoring system has *n* number of sensory signals which can be processed by *m* number of signal processing methods to produce a sensory characteristic features (SCFs). For example, a sensory characteristic feature extracted from the skew value of the Fy sensory signal can be presented as SCF (*Fy, skew*). The sensory feature matrix (SMF) can be calculated for every set of signals, or machining samples, during the machining process. For any sensory characteristic feature, it is possible to study its behaviour in relation to tool wear. There are different mathematical ways to study the effect of a machining fault as an independent variable on a sensory characteristic feature as a dependent variable.

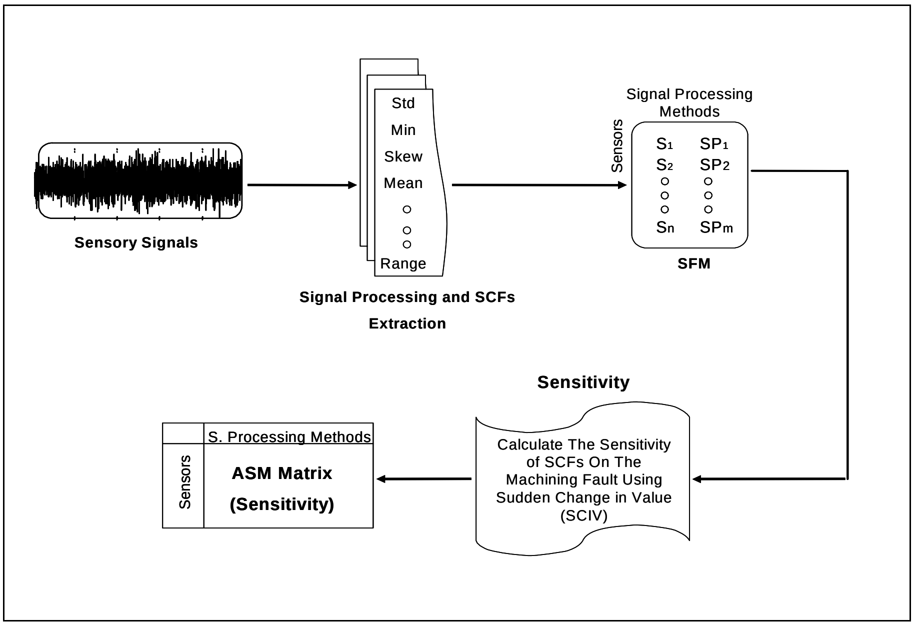

Figure 9.7: The practical steps of the ASPST approach.

Figure 9.7 shows a schematic diagram of the practical steps of the ASPST approach. The sensory signals are simplified and processed to give specific sensory characteristic features arranged in the SFM which can be used to calculate the sensitivity of every feature on tool conditions. The sensitivity coefficients are then arranged in the ASM matrix for further analysis. After calculating the sensitivity of each sensory characteristic feature on the machining conditions, tool wear level in this case, another matrix is constructed. This is Association Matrix (ASM). It is a matrix which associates the obtained sensitivity values for the corresponding sensory features. It gives a simple presentation of the sensitivity values associated with each feature. The sensitivity coefficient of the machining feature is obtained using the machining signal of the sensor and the signal processing method. The ASM gives the key evaluation for the most appropriate sensor and signal processing method to be used since each column is associated with a signal processing method while each row is associated with a sensor. Therefore, the sensory characteristic features with relatively high sensitivity coefficient are the most sensitive to the cutting conditions and they are the most appropriate features to be used. Therefore, the related sensory signals and signal processing methods are the most appropriate ones to use.

For the described cutting tool wear test, 8 signal processing methods are used to process 4 sensory signals. The signal processing methods are standard deviations (*std*), the average (μ), maximum (max), minimum (min), the range, kurtosis value (*K*), skew value and power. For more details regarding the signal processing methods see Chapter 7. The sensory signals monitored during this test are the cutting forces in three directions and the strain sensor. Therefore, the ASM for this system has a dimension of (4 × 8) which makes a total of with 32 sensory characteristic features for the selection process. The sensors and signal processing methods used here are just an example and the ASPST approach is not limited to the used sensory characteristic features. More signal processing methods and sensory signals will be used to develop condition monitoring systems in the following chapters.

The statistical method used in this research is the Sudden Change In Value (SCIV) instead of the line regression methods used in ASPS for end-milling [47] process as this has some drawbacks when applied to turning processes. The linear regression method is not sensitive to turning processes and the SCIV method found to be appropriate. The application of the sudden change in value method will be described in this section.

From the previous discussion, there is a need to find a method to calculate the sensitivity of every feature to the wear of the cutting tool. Since the importance of a feature is in its relative value compared to others, a normalising process is performed using equation 9.1 below so that any sensory characteristic feature will have a value between 0.1 and 0.9 making it possible to compare all calculated sensory features relative to each other [196]. There is no specific reason for using this type of normalising and any other normalising values could be used. The only reason is that such values are expected to have better effect on the classification systems [196]. Also, in order to be able to compare the sensitivity of SCFs of this test with the sensitivity of SCFs in similar tests, all features are normalised using the same equation [211].

$$x = 0.1 + \frac{0.8}{\max - \min}(x_i - \min) \qquad 9.1$$

Where:

max: is the maximum value of a sensory characteristic feature.

min: is the minimum value of a sensory characteristic feature .

The sensitivity coefficient for this type of test is the Sudden Change In Value (SCIV) (i.e. absolute value) using the difference between the maximum and the minimum of the data (see Chapter 7, section 7.3.3). Hence, features which have high relative value are sensitive to tool wear. The SCFs are visually tested for their sensitivities to gradual tool wear. Figure 9.8 shows an example of two sensory characteristics features with high sensitivity to tool wear.

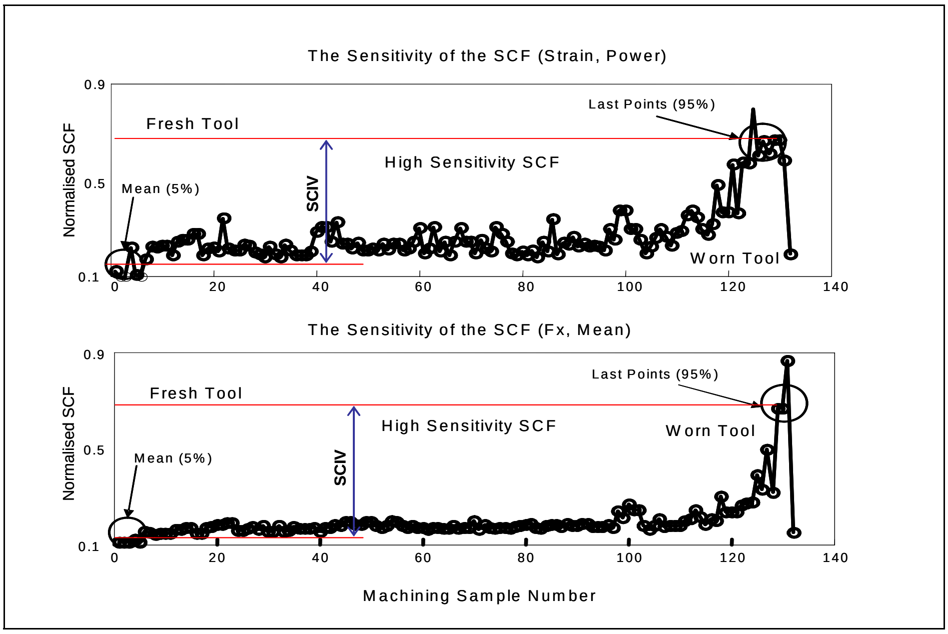

Figure 9.8: Example of high sensitivity features.

Figure 9.9 shows two features with low sensitivity to the tool wear. As can be observed from the figures, the absolute value of the difference of the maximum and minimum presents a good indication of how sensitive a sensory feature is to tool wear.

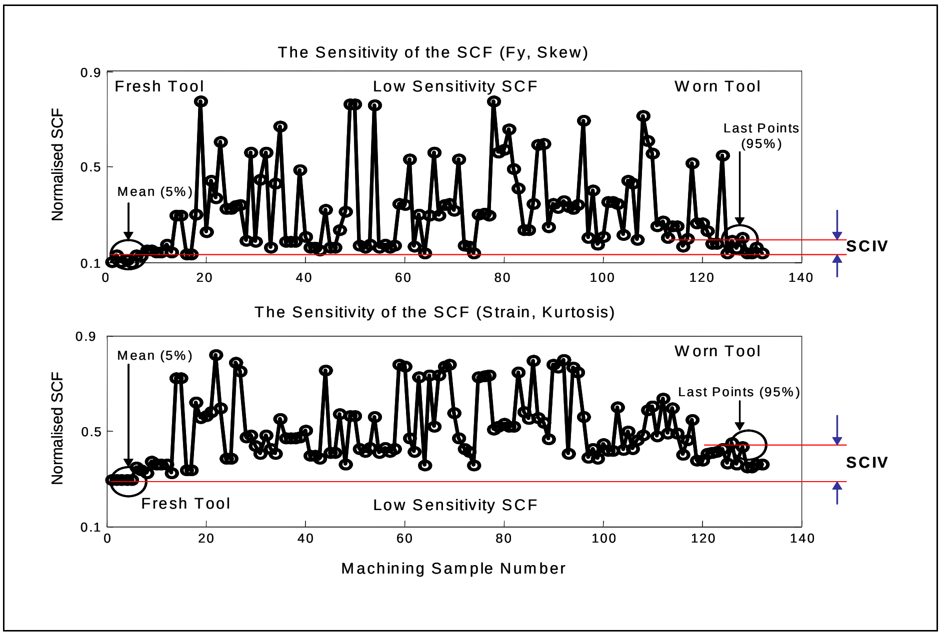

Figure 9.9: Example of low sensitivity features.

Table 9.2 shows the ASM matrix for this particular tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised features.

Table 9.2: ASM matrix for tool wear test.

	Std	Avg.	Max	Min	Range	Kurtosis	Skew	Power
Fx	0.1348	0.7826	0.0875	0.7519	0.1915	0.0485	0.6602	0.7879
Fy	0.402	0.7797	0.7806	0.7363	0.1588	0.0634	0.1698	0.7788
Fz	0.3001	0.3666	0.5953	0.6916	0.5645	0.01	0.008	0.7867
Strain	0.0144	0.7832	0.765	0.7786	0.7055	0.334	0.7254	0.7756

Figure 9.10 shows images of the ASM matrix for the tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised features. The numbers with small value in Table 9.2 are shown in navy in the images in Figure 9.10. This mean low sensitivity, numbers with medium values are shown in blue which means medium sensitivity, and numbers with high values are shown in red which means high sensitivity.

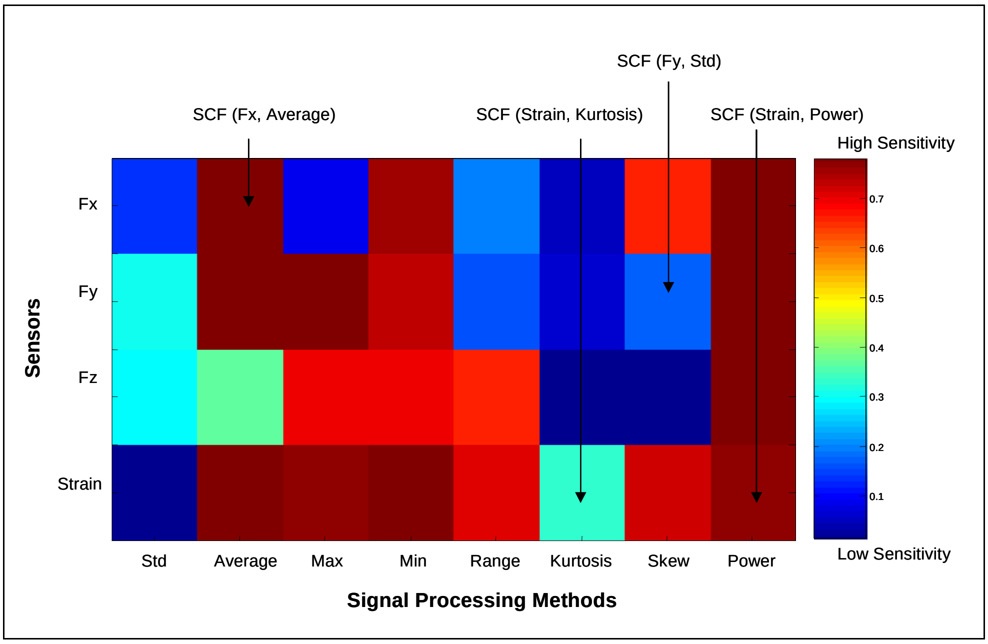

Figure 9.10: Example of the SCFs images of the signals using SCIV.

As can be observed from Table 9.2 and Figure 9.10 using the SCIV and Table 9.1 and Figure 9.6 using manual investigations, there is significant similarity between the two methods. This proves that using an automated sensitivity detection method such as Sudden Change In Value (SCIV) to calculate the ASM matrix could minimise time and effort. For example, if we take the SCF of the strain and power signal processing method and investigate it manually it shows that it has high sensitivity (H) as in Table 9.1 and Figure 9.6. On the other hand, when applying the automated method, SCIV ASM matrix, it shows that SCF for Strain and power signal processing method is 0.7756; this means high relative sensitivity as in Table 9.2 and red in Figure 9.10 which means high sensitivity also. It can be concluded from this discussion that using the automated method, Sudden Change In Value (SCIV) analysis method, and utilising the Association Matrix (ASM) to find out the most sensitive features to detect tool wear in turning processes, is useful and less time-consuming when compared to manual investigation.

9.4 Selection of Sensory Characteristics Features (SCFs)

To enable the classification system to be fast and to give good classification, it has been decided based on previous applications of the ASPS approach (end milling process) [211] to base the implementation and the design of the ASPST condition monitoring system of this test on a set of 10 SCFs. The sensory characteristic features are grouped into 3 systems, with 10 features in each. A Matlab computer program is used to arrange the ASM features according to the absolute Sudden Change In Value (SCIV) and arrange every 10 as a separate system. The three systems have the average sensitivity as shown in Figure 9.11. It can be observed that the first system has the most sensitivity features for tool wear detection compared to the other systems.

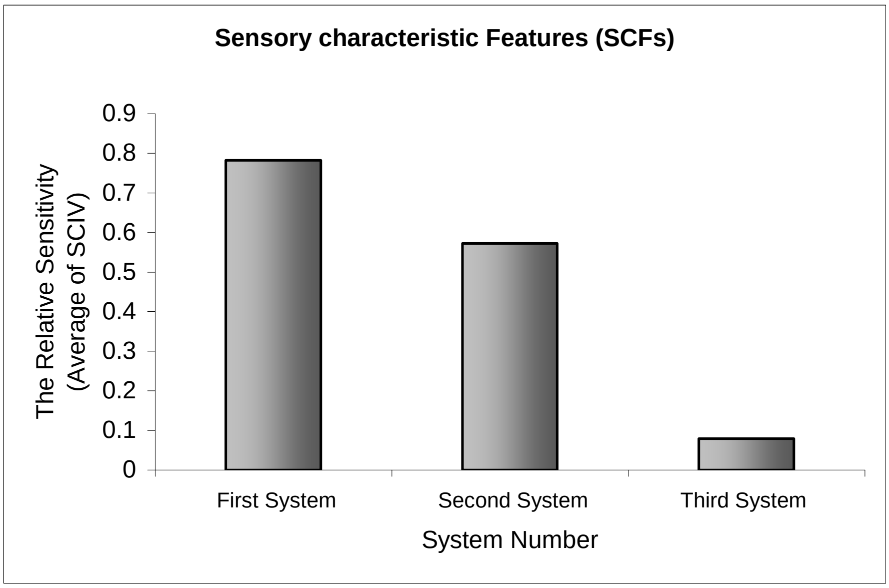

Figure 9.11: Comparison between the systems sensitivity.

The first system which includes the most sensitive 10 features is shown in Table 9.3. In addition, Table 9.4 shows the next 10 features and Table 9.5 shows the least sensitive 10 feature to tool wear.

The first system is found to have relative sensitivity (SCIV average of 0.782) which is much more than the average sensitivity of the second. In addition, the third system is found to have the lowest sensitivity for the detection of the tool wear.

Table 9.3: First system with the SCFs sensitivity (SCIV).

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
Fx	Power	0.7879
Fz	Power	0.7867
St	Maximum	0.7865
St	Average	0.7832
Fx	Average	0.7826
Fy	Maximum	0.7806
Fy	Average	0.7797
Fy	Power	0.7788
St	Minimum	0.7786
St	Power	0.7756
Average		**0.7820**

Table 9.4: Second system with the SCFs sensitivity (SCIV).

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
Fx	minimum	0.7519
Fy	minimum	0.7363
St	Skewness	0.7254
St	Range	0.7055
Fz	minimum	0.69165
Fx	Skewness	0.66025
Fz	maximum	0.5953
Fz	Range	0.5645
Fy	Std	0.4021
Fz	average	0.3666
Average		**0.6199**

Table 9.5: Third system with the SCFs sensitivity (SCIV).

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
St	kurtosis	0.3342
Fz	Std	0.3001
Fx	Range	0.1915
Fy	Skewness	0.1698
Fy	Range	0.1588
Fx	Std	0.1348
Fx	maximum	0.0875
Fy	Kurtosis	0.0634
Fx	Kurtosis	0.0485
St	Std	0.0144
Average		**0.1503**

As can be observed from the above tables, the first system has the highest sensitivity, for example, the force (Fx) and power have the highest sensitivity (0.7879). The second system has a medium to high level of sensitivity and third system has the lowest sensitivity. For example, strain sensor and standard deviation have the lowest SCFs (0.0144) in the third system. Looking at the above tables, it can be seen that the first 16 SCFs are almost the same but then the sensitivity of the other SCFs drops considerably. Therefore, the ASM matrix is found very useful in predicting the sensitivity of the SCFs. The sensitivity of the SCFs is proven to be measurable.

The details of the first few SCFs structure can be used to optimise system cost without significantly affecting system performance. It is important to notice that the statement of high sensitivity means high information is based on the visual inspection of each feature and the way it behaves during the fault's development. Therefore, a statement is made that the average sensitivity of a system is a reflection of the expected behaviour of the system. The proof of this statement will be described in the next chapters using neural networks and novelty detection classification systems.

9.5 System Cost and Utilisation

It is necessary in real industrial applications to control the cost of a condition monitoring system. In an industrial environment, the main target is not only to develop and implement a successful condition monitoring system, but to minimise cost. The ASPST approach can be used to minimise the cost of a condition monitoring system without significantly affecting its performance. The cost of the monitoring system can be easily calculated according to the number and type of sensors used. It is important to reduce the cost of the system by eliminating sensors which do not significantly contribute to the selected SCFs. This is achieved by removing their SCFs from the system and replacing them by SCFs which come next on the rank from sensors already in the system. This cost reduction is possible without having to significantly reduce the overall sensitivity of the system (i.e. the new SCFs should still have relatively high sensitivity). The contribution of a sensor in a system is defined as the sensor utilisation (U). The U for a sensor is defined as shown in equation 9.2:

$$U = \frac{S}{T \times P} \times 100 \qquad 9.2$$

S: number of SCFs used from the sensor.

T: total number of features in the system (10 in this case)

P: number of signals produced by the sensor (e.g. 3 for the 3-components force dynamometer, 1 for the strain, 1 for Vibration).

The UA, the overall sensor utilisation average factor for a system, is defined as the average value of the sensor utilisation (U) of all the sensors used in the system. When removing the least used sensors in the system, it has been found that the sensor utilisation (U) factor is useful in minimising the cost of the system. The changeable supposed cost of each system is calculated and compared to optimise the performance of the system related to its cost. The cost reduction process is discussed in Chapter 6, section 6.5.5. It explains and evaluates the cost reduction process with the aid of the tool wear experimental work. Figure 9.12 shows the sensor set-up for the experimental work in this chapter. In this work, cost means the supposed variable cost of the monitoring system since the objective is to compare systems.

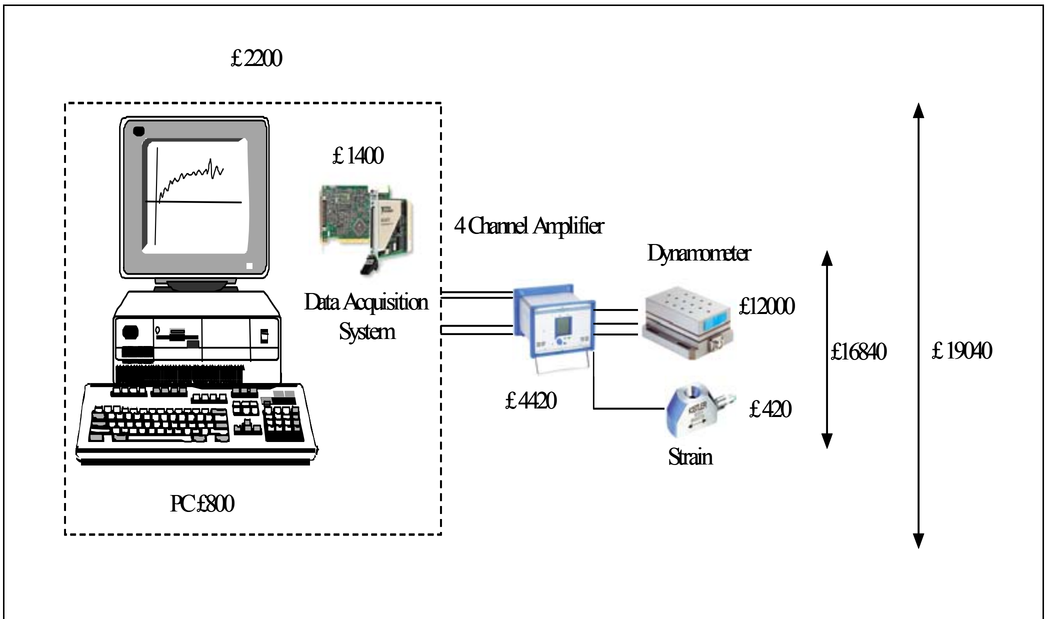

Figure 9.12: The sensors set-up used to calculate the cost of the system.

9.5.1 System Optimisation

From Tables 9.3 and 9.4, it can be observed that there is no significant difference in the average sensitivity for both systems. The cost of both systems is the same (£19,040). But it is still can be optimised by increasing the system utilisation. By replacing the sensory characteristic features of the strain sensor from the first system with the forces sensory signals from the second system to reduce the cost and still have the sensitivity level.

Table 9.6: Sensors utilisation.

Sensors	**U** **1st System**	**U** **2nd System**	**Optimised System**
Dynamometer	20%	23.3%	33.3%
Strain	40%	30%	------
UA Utilisation Average	30%	26.65%	33.3%
System Cost	£19,040	£19,040	£18,620
Average Sensitivity	**0.7820**	**0.6199**	**0.7537**

As shown in Table 9.6, the overall average utilisation has increased in the first system from 30% up to 33.3% and from 26.65% up to 33.3% in the second system and the cost is reduced by 3% from £19040 to £18620. In addition, the average sensitivity of the system did not significantly change as can be seen in Table 9.7. In fact the average sensitivity has increased to 0.7537 compared with the second system.

Table 9.7: The optimised system (1st and 2nd system).

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
Fx	Power	0.7879
Fz	Power	0.7867
Fx	Average	0.7826
Fy	Maximum	0.7806
Fy	Average	0.7797
Fy	Power	0.7788
Fx	minimum	0.7519
Fy	minimum	0.7363
Fz	minimum	0.69165
Fx	Skewness	0.66025
Average		**0.7537**

From the previous discussion, it has been found that the force sensor is the most appropriate sensor to monitor tool wear based on the ASPST approach. The above results prove that the ASPST approach can be used to reduce the cost and the number of sensors while keeping high sensitivity.

9.5.2 System Evaluation

The ASM matrix could be utilised to evaluate the effectiveness of a sensor or signal processing method based on the sensitivity of every sensor and signal processing method to the fault which is embedded in the ASM matrix.

The average sensitivity of all the sensory characteristic features, for a Signal Processing method *SPk*, obtained using all the sensory signals (A_{SP}) can be used as an indication of how relatively the signal processing method is valuable. The average value of the *k*th column of the ASM matrix for a signal processing *SPk* is the average sensitivity of the *k*th signal processing method and can be defined as [211]:

$$A_{SpK} = \frac{\sum_{i=1}^{n} d_{ik}}{n} \qquad 9.3$$

where n is the number of rows in the ASM.

In addition, the average sensitivity of the *k*th signal (As) can represent the general sensitivity of a signal to the failure and can be defined as:

$$A_{SK} = \frac{\sum_{i=1}^{m} d_{jk}}{m} \qquad 9.4$$

where m is the number or columns in the ASM.

For the ASM matrix, the average of the summation of sensitivity coefficients (A_C) can provide an evaluation of the condition monitoring system sensitivity in the detection of the failure under investigation. And can be defined as:

$$A_C = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij}}{n \times m} \qquad 9.5$$

The A_s values for the sensory signals used in the system are shown in Figure 9.13 and the A_{sp} values for the signal processing methods used in the system are shown in Figure 9.14. As can be noticed from the figures, the results reflect what is found in the optimum system where the strain sensor is the most sensitive sensor to tool wear.

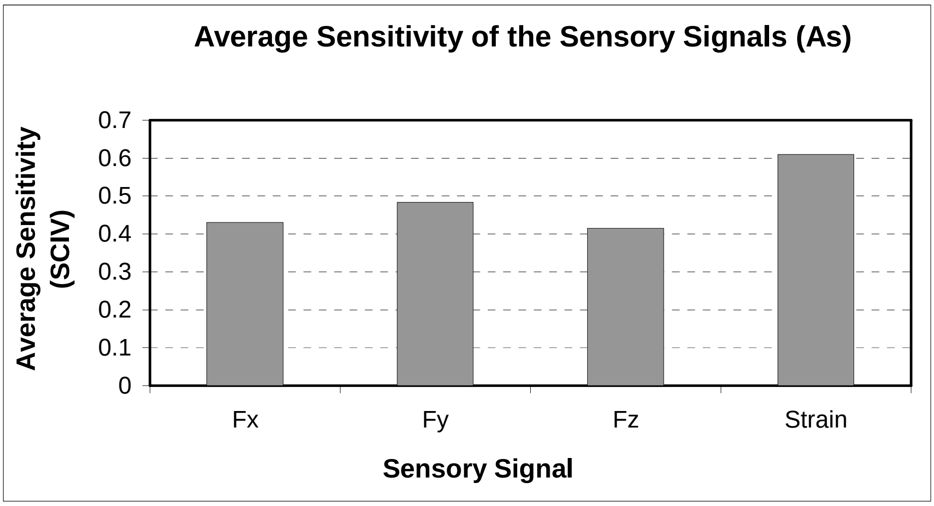

Figure 9.13: A_s values for the sensory signals.

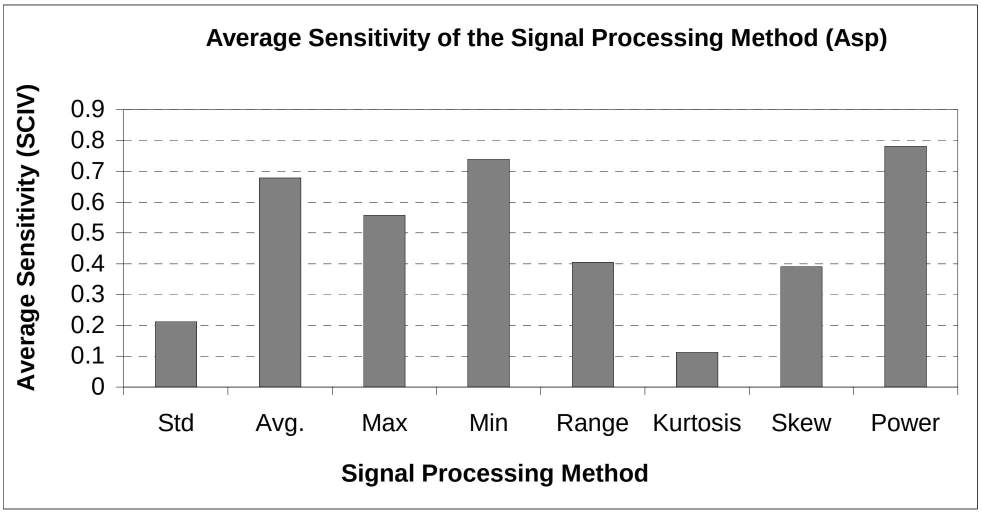

Figure 9.14: A_{sp} values for the signal processing methods.

The Ac factor of this system is found to be (0.48). However, to find the effectiveness of the selection of the utilised sensors and signal processing methods, the evaluated values can be compared with other systems. The high A_c value mean high sensitivity level, meaning high information and low Ac, means low sensitivity value and less information. But a low Ac could include features with high sensitivity.

9.6 Conclusion

In this chapter, the practical details of the ASPST approach are introduced. The ASPST approach for four sensory signals is explained using an experimental machining test to monitor a gradual tool wear in turning process. The implemented ASPST approach utilises a matrix, named the Association Matrix (ASM), to compare the sensitivity of the features to the fault under investigation and also to evaluate the overall monitoring system using the average sensitivity of sensors and signal processing methods. The sudden change in value (SCIV) analysis is used to find out the most sensitive features to detect tool wear. The SCFs are visually examined and examples of high-sensitivity and low sensitivity SCFs are presented. Sensory utilisation is implemented within the ASPST approach to reduce the cost of the system without affecting the sensitivity of the system. The ASPST approach is found useful in selecting the most sensitive sensors and signal processing methods to design a condition monitoring system for turning process.

Chapter 10

The Applications of ASPST Approach Using Pattern Recognition Systems

10.1 Introduction

In this chapter, different applications for the implementation of the ASPST approach for different groups of multi-sensor fusion models are presented. The chapter provides more experimental work to prove the capability of the implemented ASPST approach in developing and designing a sensor fusion model of a condition monitoring system for turning process by selecting the most sensitive sensors and signal processing methods using pattern recognition systems. It presents the same implemented methodology and steps discussed in the previous chapter for the following investigations:

- **LVQ Investigation**: The chosen process parameters monitored are acoustic emission (AE), accelerometer and sound sensors using Learning Vector Quantisation (LVQ) neural networks.
- **ND Investigation:** The chosen process parameters monitored are strain, acoustic emission and accelerometer sensors using a Novelty Detection Algorithm (ND).

Both investigations present the same methodology and experimental work to detect tool wear and provide diagnostic and prognostic information. This chapter seeks to confirm the methodology and the technique implemented in Chapter 9 for the turning process with different multi-sensors using different pattern recognition systems. The main assumption to be tested is that sudden change in value (SCIV) method is capable of detecting the sensitivity of the SCFs.

10.2 General Experimental Set-Up

The experimental work for both investigations in this chapter is performed on the lathe machine tool for machining stainless steel. Gradual tool wear is examined as the fault to be monitored. The stainless steel work piece used in this experiment has a diameter of 30 mm and a total machining distance of 1750 mm is machined during the full tests to transfer the tool from fresh to completely worn. The machined distance is divided into 7 machining samples with lengths of 250 mm each (i.e. 7 machining samples are obtained during the test for analysis for each investigation). In total, 7 independent experiments are conducted in the machining of stainless steel workpieces for each investigation. Every test starts with a fresh tool and finishes with a completely worn tool. The tool inserts used are Sandvik Coromant P25 (SCMT 120408 UM). The machining parameters are selected to resemble industrial practice. The experimental cutting conditions are chosen to cover the manufacturer's recommended interval for insert type. For more details see Chapter 8, section 8.3.

10.3 LVQ Investigation

The chosen process parameters monitored in the first investigation are vibration, sound and acoustic emission (AE and AE-RMS signal). The vibration signals are monitored using an accelerometer (Kistler 8704B) which is mounted close to the tool holder in order to measure the radial acceleration due to the workpiece-cutting tool vibration and it is connected to a charge amplifier (Kistler 5855A). The acoustic emission signals are monitored using an AE-Piezotron sensor (Kistler 8152B) which is mounted close to the tool holder and it is connected to an AE-Piezotron coupler (Kistler 5125B) which gives the AE signals and the Root-Mean-Square (RMS) of the AE signals. The sound signals are monitored using a Back Electret Condenser Microphone (Yago EM-400) which is mounted in a post on the tool turret and it is connected directly to the DAQ card. The level of tool wear is visually monitored in this experimental work and shows that wear increases with machining time. Figure 10.1 shows a schematic diagram of the implemented monitoring system for the first (LVQ) investigation.

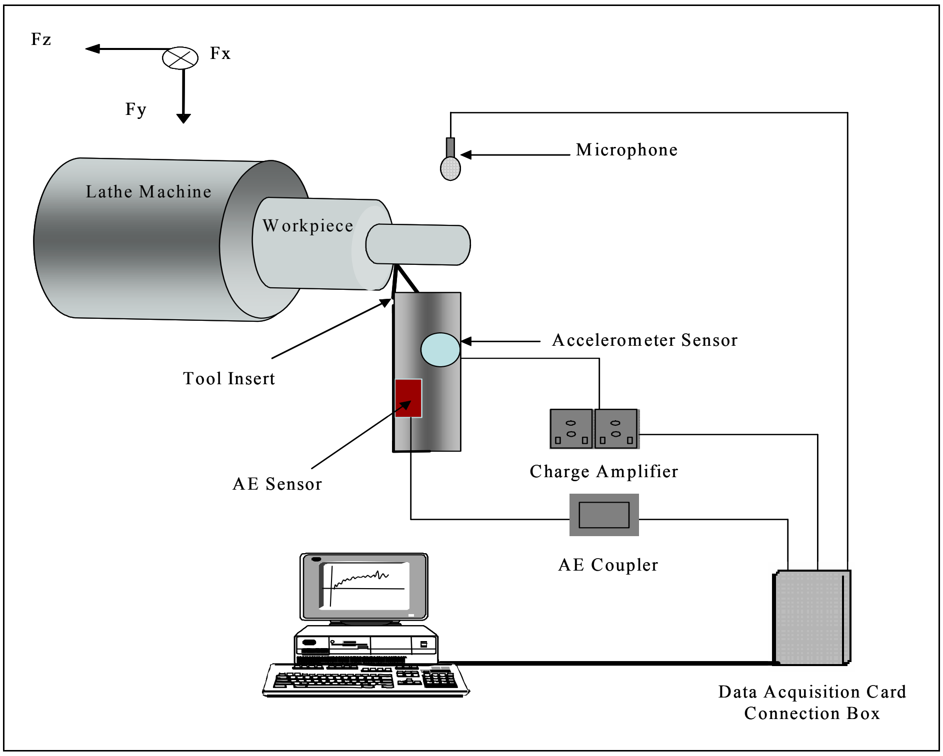

Figure 10.1: A schematic diagram of the monitoring system.

10.3.1 Signals Simplifications

10.3.1.1 Visual Inspection Method

Examples of the machining signals for the fresh and worn tool for a turning process are shown in Figure 10.2 and 10.3 respectively. It can be noticed that the vibration level has decreased for the worn tool. In addition, the level of the other signals has changed. The acoustic emission signals have less variation. However, the sound signal has included more audible vibration noise. The microphone signal level is relatively low, and the variation could have been related to external noise. In addition, the level of some sensory signals has changed such as the AE (RMS) signal. Because turning has complex machining signals, it has been found difficult to predict the most sensitive signals to tool wear directly from the raw data. Therefore, the ASPST approach should be able to detect if the variation is random or consistent due to tool wear. Although such general observations can help to find some sensory features which are sensitive to tool wear, signal processing and analysis is needed to extract the important information from the signals (i.e. Sensory Characteristic Features (SCFs)).

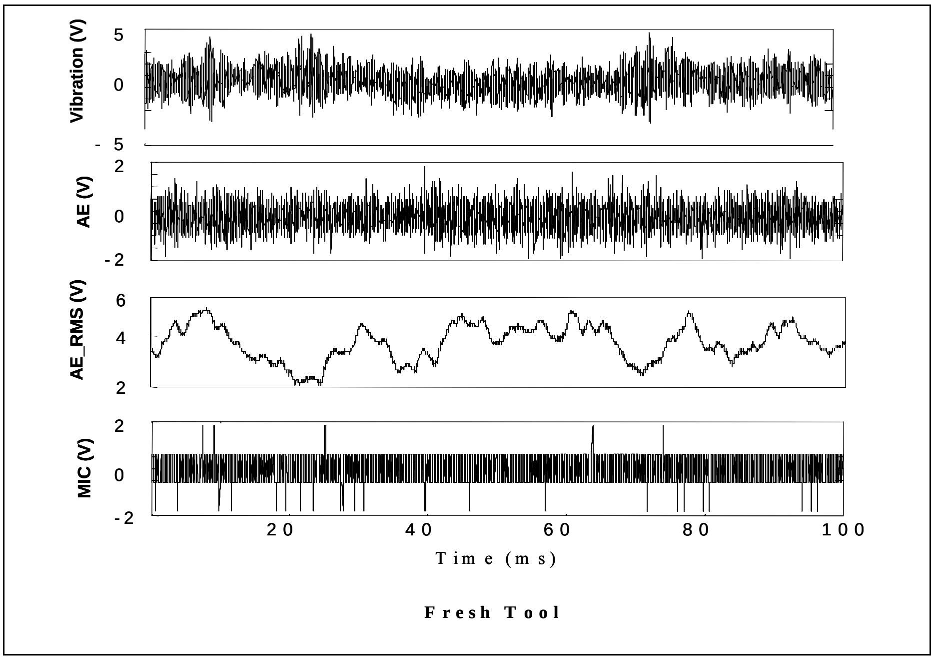

Figure 10.2: Signals from a fresh tool.

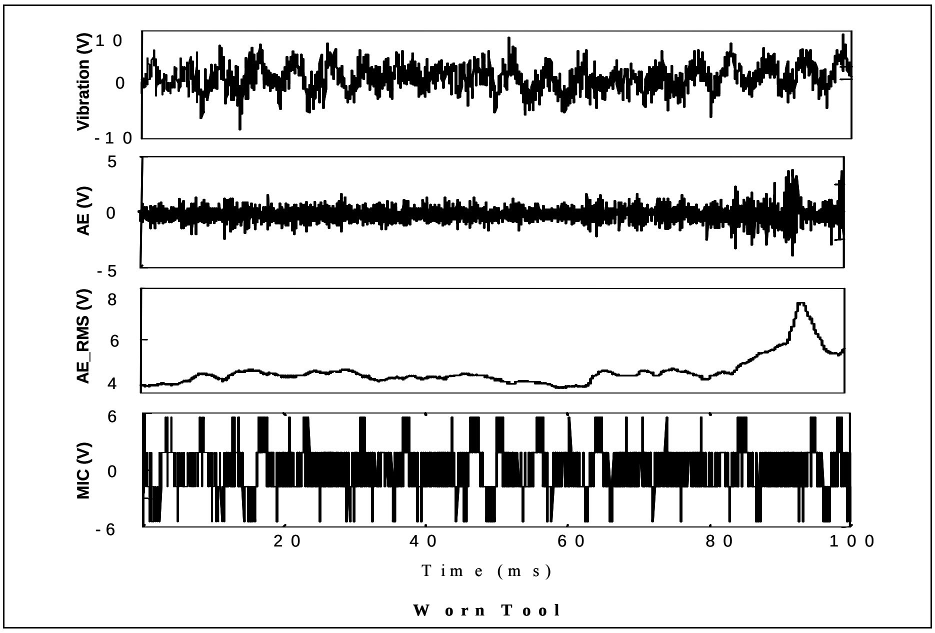

Figure 10.3: Signals for the worn tool.

Table 10.1 shows general visual observation of the Association Matrix (ASM) which includes the sensitivity of all SCFs implemented in this monitoring system. Figure 10.4 presents an image of the SCFs of the signals.

Table 10.1: Example of ASM for Tool 1.

Sensory Signal	**Signal Processing Methods**							
	Std	Avg.	Max	Min	Range	Kurtosis	Skew	Power
Vibration	L	H	H	M	L	H	L	H
AE	L	H	H	H	L	L	L	H
AE_RMS	L	H	H	H	L	M	L	H
Sound	H	H	H	M	H	H	M	H

(H: High sensitivity, M: Medium sensitivity, L: Low sensitivity).

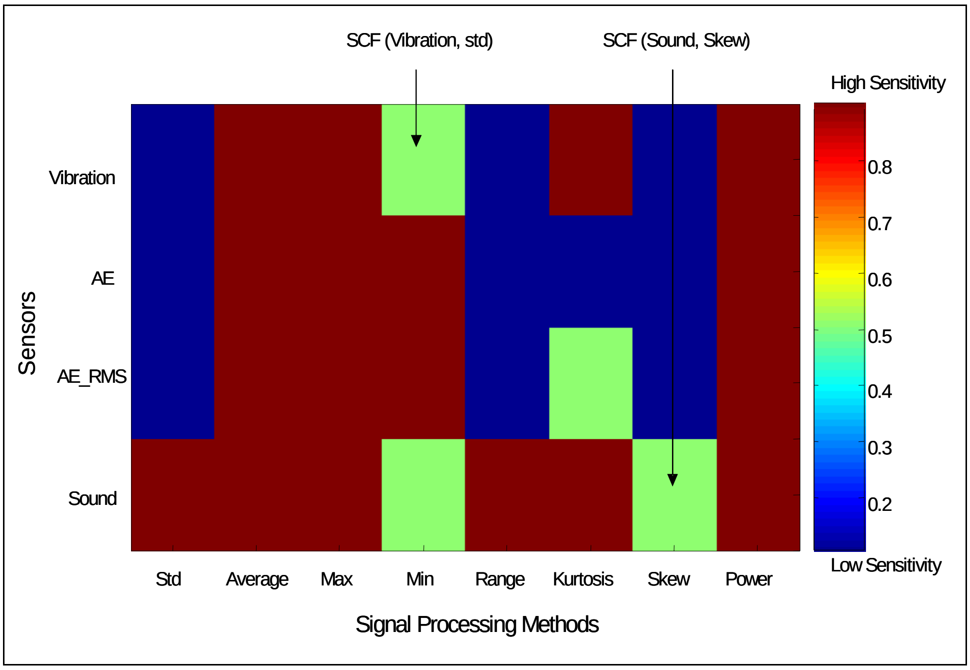

Figure 10.4 Example of the SCFs images of the signals.

Table 10.1 shows a general visual observation of the Association Matrix (ASM) which includes the sensitivity of all SCFs implemented in this monitoring system. In addition, Figure 10.4 presents an image of the SCFs shown in Table 10.1. For example, sound sensor shows high sensitivity with all signal processing methods except the minimum and Skewness signal processing methods show medium sensitivity, while the vibration sensor shows medium sensitivity levels with minimum signal processing methods even though such general visual observations as shown above could help to find some sensory features which are sensitive to the tool wear. But it still does not provide a systematic method to study the system and there could be more sensitive sensory characteristic features to be obtained from less expensive sensors than the acoustic emission sensor such as sound sensor in this experimental investigation. It can be observed that among the signals, some signal processing methods are more sensitive with the sensory signal than others. Therefore, it can be concluded that manual investigation could help in finding the sensitivity of the sensory signal. In this research, the implementation of the ASPST for tool wear detection in the turning process will be tested to automate the system.

10.3.1.2 Sudden Change In Value (SCIV) Method

The raw signals are processed using several time-domain signal processing methods to extract 8 SCFs form every sensory signal. The 8 signal processing methods are used to process the 4 sensory signals establishing an ASsociation Matrix ASM of (4 × 8) which allows the investigation of 32 sensory characteristic features (SCFs) for the design of the monitoring system. The ASM matrix for this test has 4 sensory signal and 8 signal processing methods. The 32 sensory characteristic features of the ASM matrix for this work are calculated for the 7 tools and then the Sudden Change In Value (SCIV) method is calculated from the normalised features. The SCFs are arranged according to their sensitivity to tool wear based on the SCIV method. The SCFs are visually inspected and it has been observed that the features which show a high value of the (SCIV) have better sensitivity for the wear of the cutting tool. Figure 10.5 shows an example of two sensory characteristic features with high sensitivity and Figure 10.6 shows an example of two features with low sensitivity to wear.

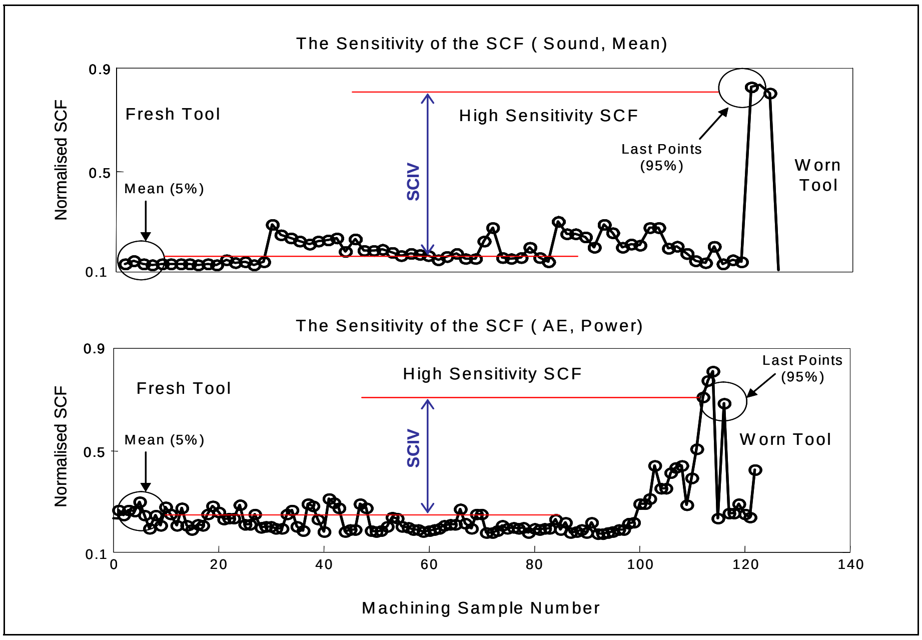

Figure 10.5: Example of high sensitivity SCF.

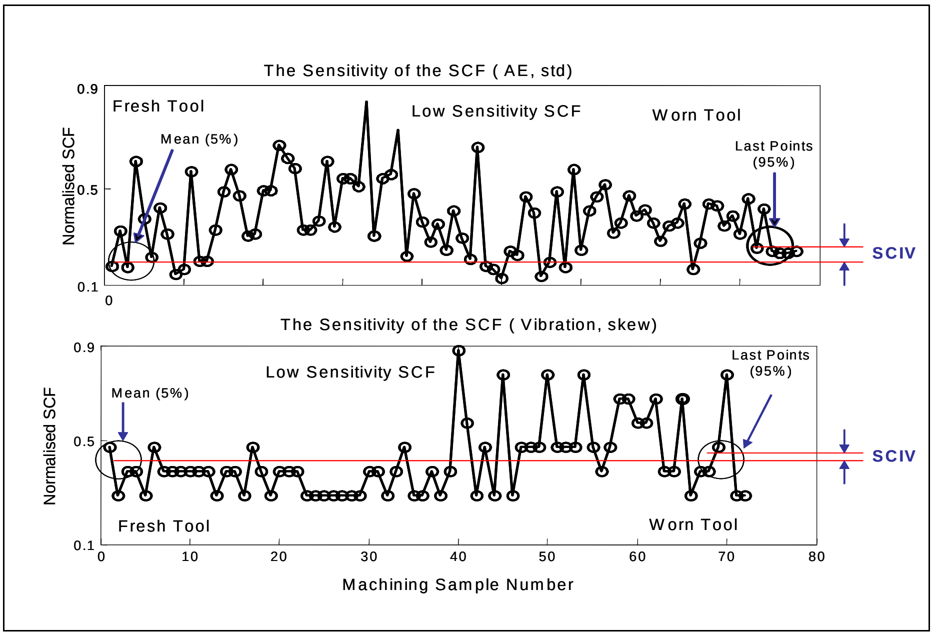

Figure 10.6: Example of low sensitivity SCF.

As it can be observed from the above figures, the absolute value of the Sudden Change In Value (SCIV) method presents a good indication of how sensitive a sensory feature is to tool wear.

Table 10.2 shows the ASM matrix for this particular tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised features.

Table 10.2: ASM matrix for tool wear test.

	Std	Avg.	Max	Min	Range	Kurtosis	Skew	Power
Vibration	0.0893	0.6812	0.6222	0.5771	0.2301	0.65245	0.01697	0.6815
AE	0.1463	0.6816	0.6752	0.6356	0.1376	0.01409	0.0078	0.6818
AE_RMS	0.0762	0.6590	0.6481	0.6624	0.0996	0.09265	0.0007	0.6807
Sound	0.6803	0.6743	0.6814	0.6221	0.6807	0.6457	0.5989	0.6817

Figure 10.7 presents images of the ASM matrix for the tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised features. The numbers with small values in Table 10.2 which appear in navy in the images figure mean low sensitivity; numbers with medium values which appear in green mean medium sensitivity; and numbers with big values which appear in red in the images mean high sensitivity.

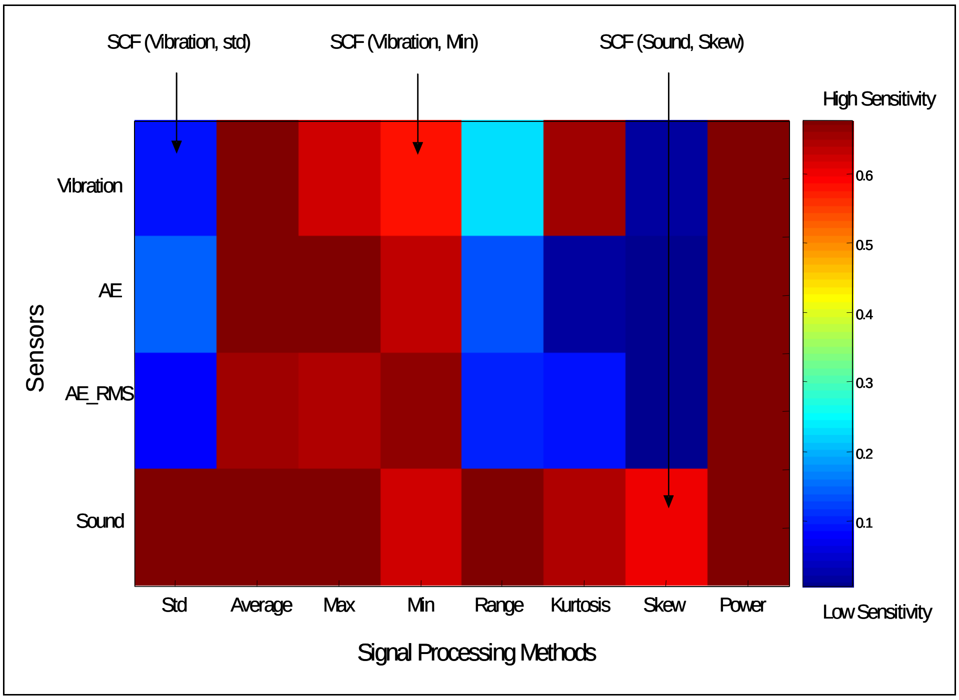

Figure 10.7: Example of the SCFs images of the signals using SCIV.

As can be observed from Figure 10.4, using manual investigation, and Figure 10.7, using the SCIV, there is a similarity between the two methods. This proves that using an automated sensitivity detection method such as Sudden Change In Value (SCIV), ASM matrix, could minimise time and effort. For example, if we take the SCF of the sound and average signal processing method and investigate it manually, it shows that it has high sensitivity (H) as in Table 10.1 and Figure 10.4. On the other hand, when applying the automated method, SCIV, it shows that the SCF for the sound and average signal processing method is 0.674; this means high value as in Table 10.2 and red as in Figure 10.6 which means high sensitivity also. In addition, using the SCIV method shows more accuracy than visual investigation. For example, when investigating the SCF of sound and skew visually it shows medium sensitivity and appears as light green colour in Table 10.1, but when utilising the SCIV method it shows light red. When comparing these two colours it can be observed that their values are between 0.4 and 0.5 which is not too far from the value shown in Table 10.2. It can be concludes from the discussion that using the automated method, Sudden Change In Value (SCIV) analysis and utilising the Association Matrix (ASM), to find out the most sensitive features to detect tool wear in turning processes, is found useful and time-consuming compared to manual investigation.

As in the previous chapter, it is decided to base the implementation and the design of the ASPST condition monitoring system on a set of 10 SCFs. The sensory characteristic features are grouped into 3 systems, 10 features each. A computer program is used to arrange the ASM features according to the absolute Sudden Change In Value (SCIV) and arrange every 10 as a separate system. The three systems have the average sensitivity as shown in Figure 10.8. It can be observed from that the first system has the most sensitivity features for tool wear detection compared to the other systems.

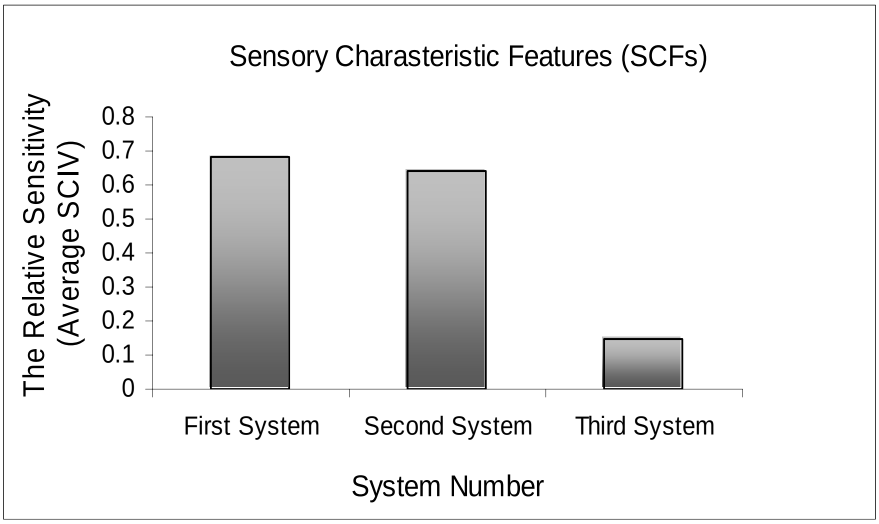

Figure 10.8: Comparison between the systems sensitivity.

The first system which includes the most sensitive 10 features is shown in Table 10.3. In addition, Table 10.4 shows the next 10 features and Table 10.5 shows the least sensitive 10 features to tool wear. The first system is found to have relative sensitivity (SCIV average of 0.6806) which is much more than the average sensitivity of the second. In addition, third system is found to have the lowest sensitivity for the detection of the tool wear.

Table 10.3: First system with the SCFs sensitivity (SCIV).

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
AE	Power	0.6818
Sound	Power	0.6817
AE	Average	0.6816
Vibration	Power	0.6815
Sound	Maximum	0.6814
Vibration	Average	0.6812
AE_RMS	Power	0.6807
Sound	Range	0.6806
Sound	Std	0.6803
AE	Maximum	0.6752
Average		**0.6806**

Table 10.4: Second system with the SCFs sensitivity (SCIV).

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
Sound	Average	0.6743
AE_RMS	Minimum	0.6624
AE_RMS	Average	0.6590
Vibration	Kurtosis	0.6523
AE_RMS	Maximum	0.6481
Sound	Kurtosis	0.6457
AE	Minimum	0.6356
Vibration	Maximum	0.6222
Sound	Minimum	0.6221
Sound	Skewness	0.5989
Average		**0.6421**

Table 10.5: Third system with the SCFs sensitivity (SCIV).

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
Vibration	Minimum	0.5771
Vibration	Range	0.2301
AE	Std	0.1463
AE	Range	0.1376
AE_RMS	Range	0.09965
AE_RMS	Kurtosis	0.09265
Vibration	Std	0.08933
AE_RMS	Std	0.07624
Vibration	Skewness	0.01697
AE	Kurtosis	0.01409
Average		**0.1480**

As can be observed from the above tables, the first system has the highest sensitivity; for example, the AE signal and power has the highest sensitivity. In addition, the first and second systems have no significant difference between them in the average which means that it is excellent when optimising the system with low cost sensors and high sensitivity. On the other hand, the third system has the lowest sensitivity. For example, the AE signal and Kurtosis signal processing method are the lowest SCFs in the system. Looking at the above tables and figures, it can be observed that the first 21 SCFs have similar sensitivity. Then the sensitivity of the other SCFs drops to the lowest value. Therefore, the ASM matrix is found very useful in predicting the sensitivity of the SCFs. The previous discussion proved that high sensitivity of the SCFs means high information and low sensitivity means low information.

The details of the first few SCFs structure can be used to optimise the system cost without affecting the system performance significantly. It is important to notice that the statement of high sensitivity means high information is based on the visual inspection of each feature and the way it behaves during the fault's development. Therefore, a statement is made that the average sensitivity of a system is a reflection of its expected behaviour. The proof of this statement will be described in the next sections using Learning Victor Quantisation (LVQ) neural networks.

10.3.2 System Cost and Utilisation

The same method used in Chapter 9 to calculate the cost of the system is used here again. Figure 10.9 shows the sensor set-up for the experimental work in this section.

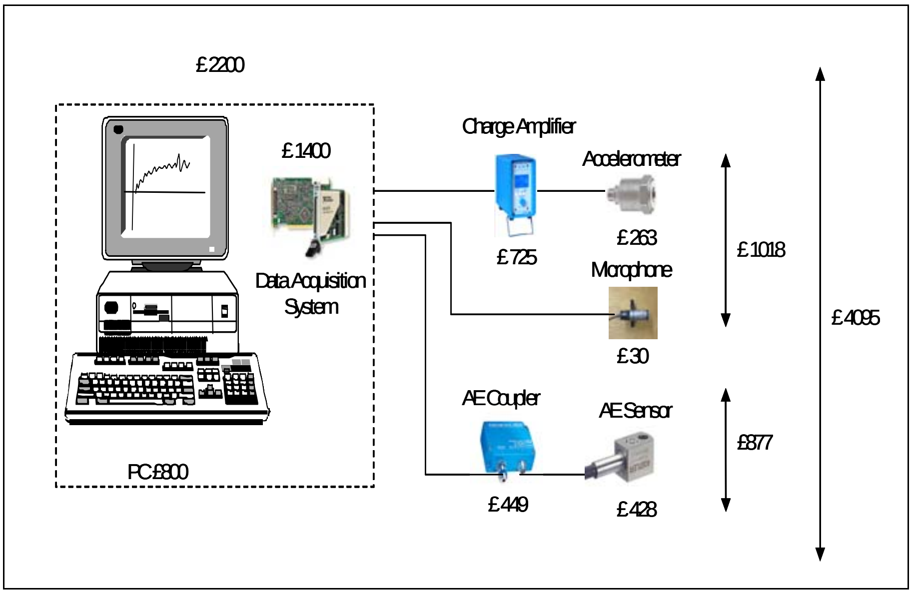

Figure 10.9: The sensor set-up used to calculate the cost of the system.

10.3.2.1 System Optimisation

The same method used before to optimise the system is used here again. From Table 10.3 and Table 10.4, it can be seen that there is no significant difference in the average sensitivity for both systems. The cost of both systems is the same. But it can still be optimised by increasing system utilisation. By replacing the sensory characteristic features of the vibration sensor from the first system with the sound and acoustic emission sensors from the second system to reduce the cost and have no affects on the sensitivity level.

Table 10.6: Sensors Optimisation.

Sensors	**U 1st System**	**U 2nd System**	**Optimised System**
Vibration	20%	20%	--------
AE	40%	40%	50%
Sound	40%	40%	50%
UA Utilisation Average	**33.33%**	**33.33%**	**50%**
System Cost	**£4095**	**£4095**	**£3107**
Average Sensitivity	**0.6806**	**0.6421**	**0.6780**

As shown in Table10.6, the overall average utilisation has increased from 33.33% up to 50% in the first and the second systems and the cost is reduced by 25% from £4095 to £3107. On the other hand, the average sensitivity of the systems did not significantly change; the average sensitivity has increased in the second system from 0.6421 to 0.6780.

Table 10.7: The optimised system (from systems 1 and 2).

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
AE	Power	0.6818
Sound	Power	0.6817
AE	Average	0.6816
Sound	Maximum	0.6814
AE_RMS	Power	0.6807
Sound	Range	0.6806
Sound	Std	0.6803
AE	Maximum	0.6752
Sound	Average	0.6743
AE_RMS	Minimum	0.6624
Average		**0.6780**

From the previous discussion, it has been found that the sound and acoustic emission sensors are appropriate sensors to monitor tool wear in turning processes based on the ASPST approach. The above results prove that the ASPST approach can be used to minimise system cost and to reduce the number of sensors while keeping sensitivity high.

10.3.2.2 System Evaluation

The same method used previously to evaluate the system is used here again.

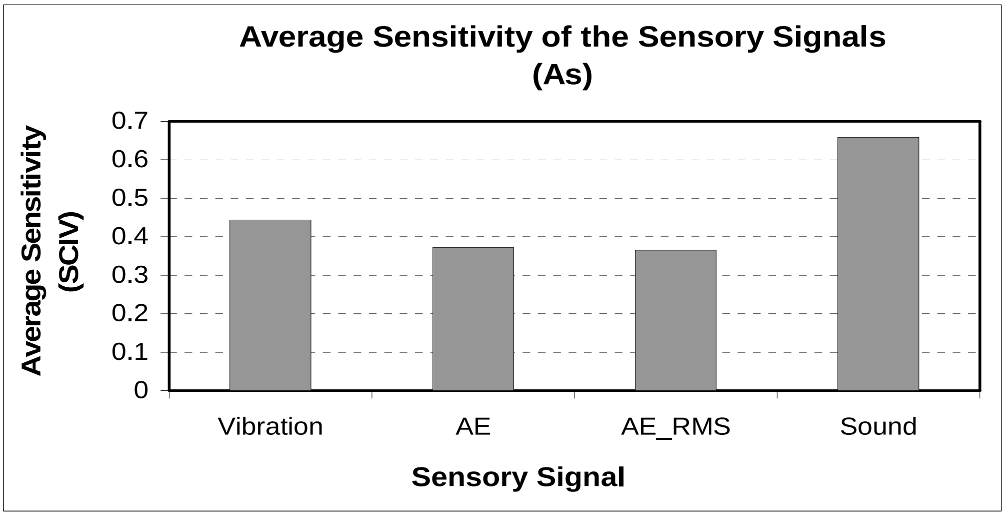

Figure 10.10: A_s values for the sensory signals.

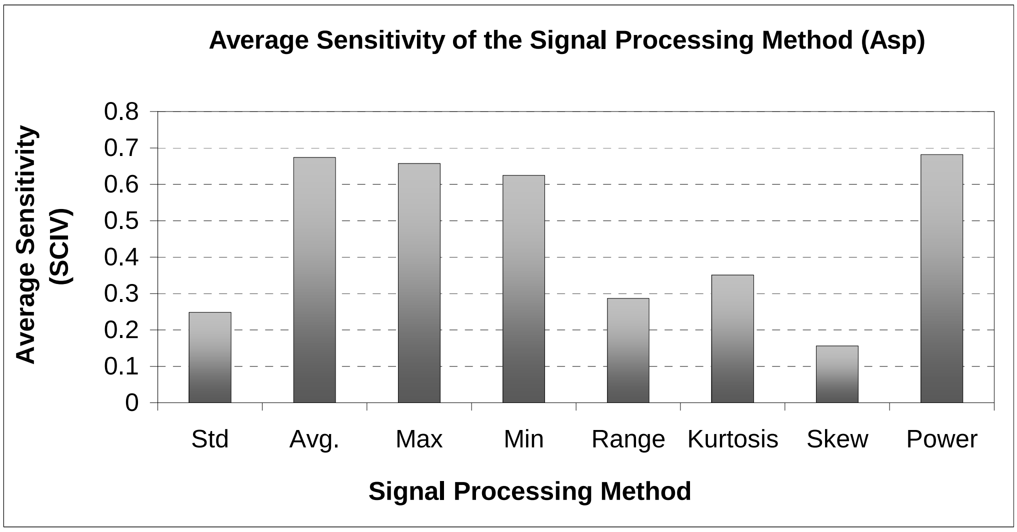

Figure 10.11: A_{sp} values for the signal processing methods.

The Ac factor of this system is found to be (0.46). However, to find the effectiveness of the selection of the utilised sensors and signal processing methods, the values obtained can be compared with other systems. A high A_c value means a high sensitivity level meaning high information, and low Ac means low sensitivity value and less information. But a low Ac value could include features with high sensitivity.

10.3.3 Performance of LVQ Neural Networks

The sensitivity of a sensory characteristics feature to detect tool wear in the turning process is visual and using automated method (SCIV) tested for several sensors and signal processing methods. It is noticed that sensitive characteristics features will indicate the fault with a significant change in their values. In order for the ASPST approach to be a useful methodology, the sensory characteristics features which are assumed to have a higher sensitivity on the tool wear should result in better identification when it is tested by a pattern recognition system. For this purpose a Learning Vector Quantisation (LVQ) neural network is used to test the complete monitoring system. The details of the LVQ neural network are briefly explained in Chapter 7 section 7.4.2. The SCFs from the first tool are used to train the LVQ neural networks. Then SCFs from all tools are fed to the neural networks for testing. Figures 10.12 present the result of using the LVQ for detecting tool wear in turning process. It can be seen that the arrows show the maximum number of cuts for each tool (i.e. tool-life) until complete wear or failure. The number 0 means that the tool is in normal condition where 1 means that the tool is in worn condition.

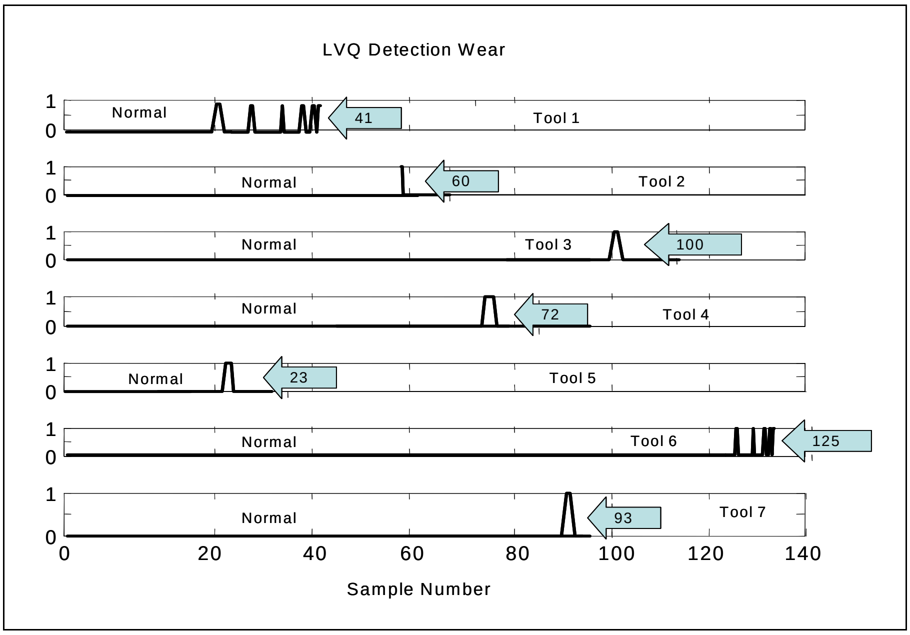

Figure 10.12: The result of the LVQ neural network to detect tool wear.

For example, for tool 1 the LVQ neural networks has identified that cut/sample 25 is the start of tool failure. However, the actual tool failure happened at 38 cuts/samples. The ASPST approach has been found successful in detecting tool wear in the turning process. However, looking at Figure 10.13, there has been early warning regarding the end of the tool life. When examining the signals, it has been found that there is less stability on the nature of the signal for tool 1. This explains the early warning. In some cases, unexpected wear or tool breakage does occur. However, the subsequent machining cuts could re-sharpen the tool and extend its life for a specific period before total failure.

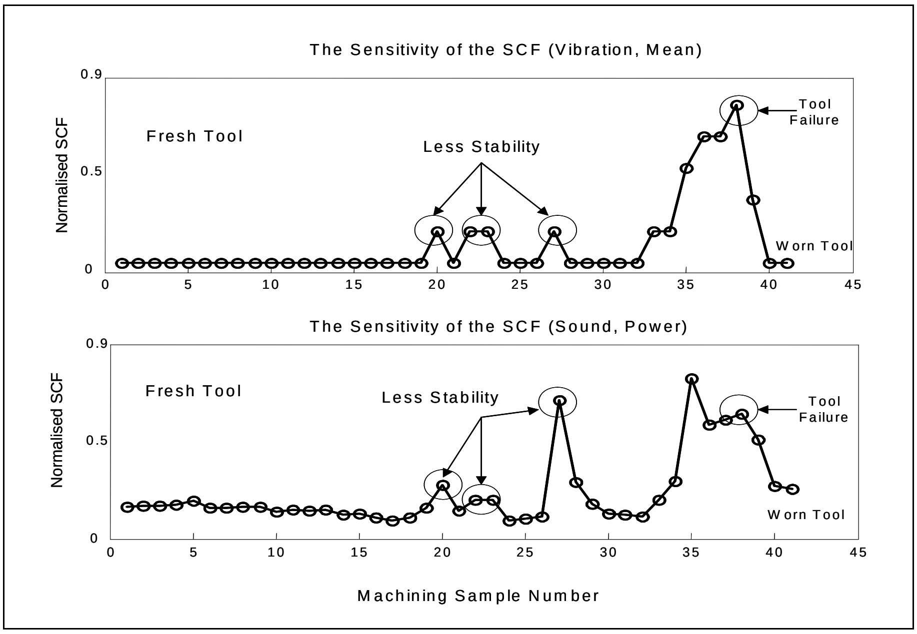

Figure 10.13: Sensory Characteristic Features of tool 1.

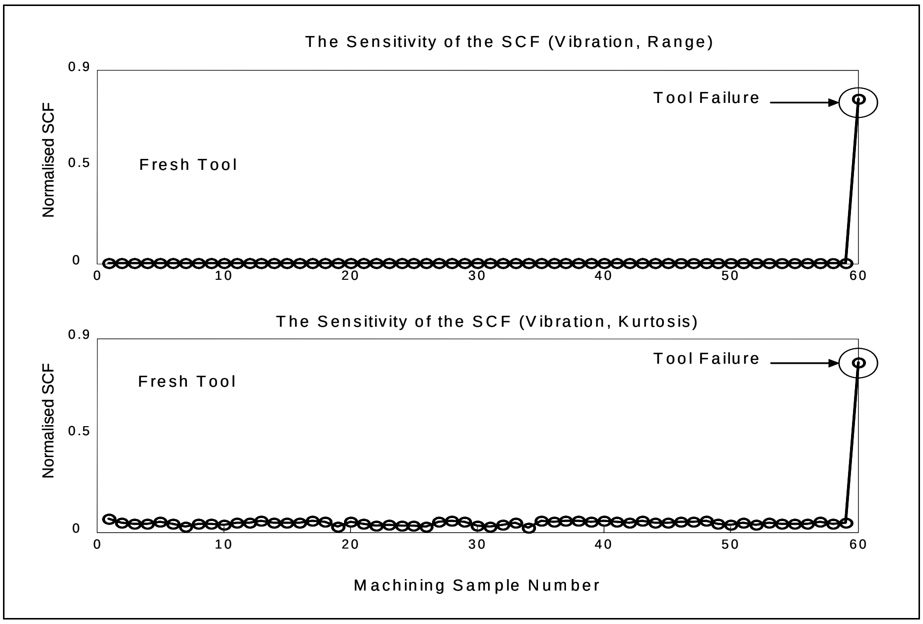

Figure 10.14: Sensory Characteristic Features of tool 2.

For tool 2 as shown in Figure 10.14, the maximum number of cut is 60, and failure is identified at sample 59. The number of cuts/samples needed to produce a worn tool is significantly different for each tool. This proves that using statistical methods is not a suitable option. Also the system has been found successful in detecting tool wear before the end-of-life of the tool. Because this approach uses the 'black-box' concept (i.e. looking at the process signals and outputs without studying the intermediate tool conditions), it is difficult to confirm the conditions of the tool at every stage of the process.

10.4 Novelty Detection Investigation

This part of this chapter presents the second investigation of the experimental work using Novelty Detection. The same experimental set-up is conducted. The sensors used to monitor the process in this investigation are vibration, acoustic emission (AE and AE-RMS signal) and strain. The vibration signals are monitored using an accelerometer (Kistler 8704B) which is mounted close to the tool holder in order to measure vibration. The acoustic emission signals are monitored using AE-Piezotron Sensor (Kistler 8152B) which is connected to AE-Piezotron Coupler (Kistler 5125B) which gives the AE signals and the AE-RMS of the AE signals. The dynamic and quasistatic force signals are monitored using strain sensor (Kistler 9232A) which is mounted at the side of the tool. Both the vibration accelerometer and strain sensor are connected to a charge amplifier (Kistler 5070A). Figure 10.15 shows a photo of the sensors installed on the machine.

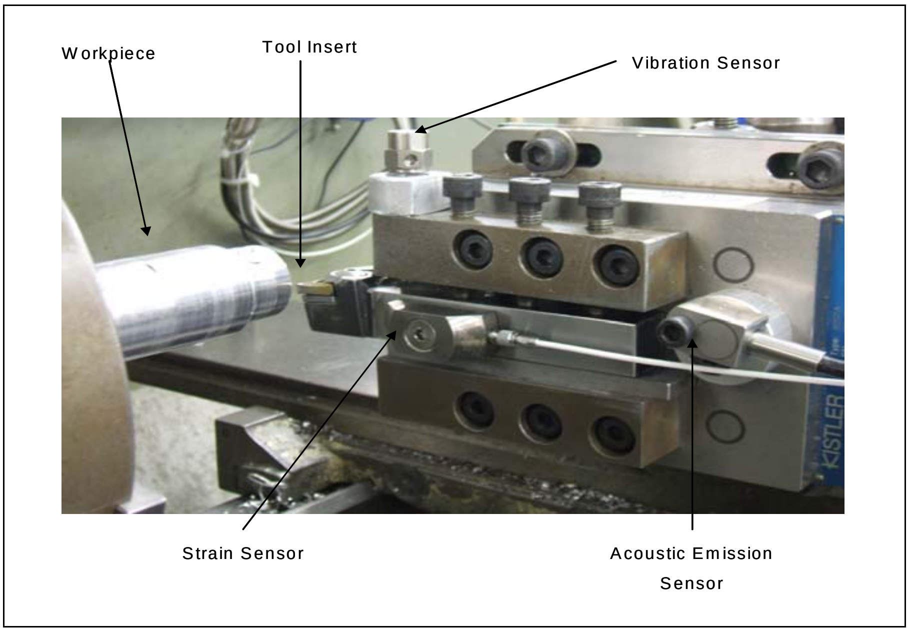

Figure 10.15: Photo of the sensors installed on the machine.

10.4.1 Signals Simplifications

10.4.1.1 Visual Inspection Method

The level of tool wear is visually monitored in this experimental work and it shows that wear increases with machining time. Examples of the machining signals of a fresh and worn tool of turning process are shown in Figure 10.16 and Figure 10.17 respectively.

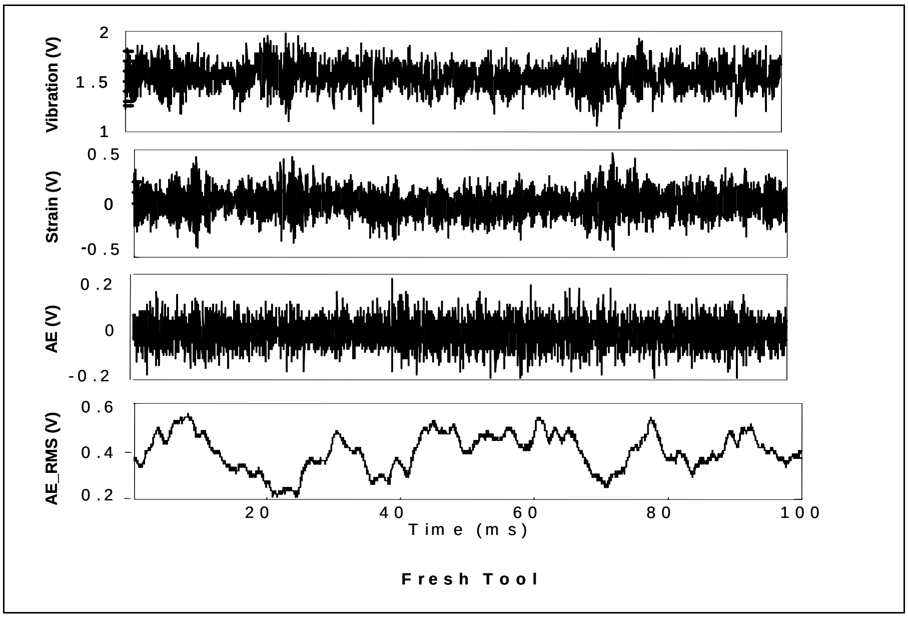

Figure 10.16: Signals from a fresh tool.

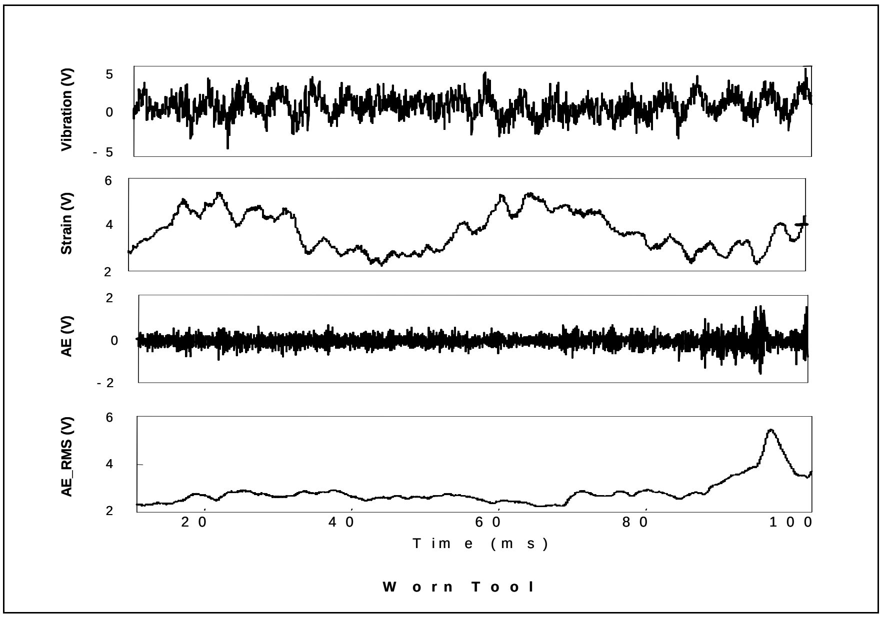

Figure 10.17: Signals from a worn tool.

It can be observed from Figure 10.16 and Figure 10.17 that the signals have more variation when a worn tool compared with a fresh tool. This could be related to a worn edge of the tool. Because turning has complex machining signals, it has been found difficult to predict the most sensitive signals to tool wear directly from the raw data. Therefore, the ASPST approach should be able to detect if the variation is random or consistent due to tool wear. As has been discussed previously, although such general observations can help to find some sensory features which are sensitive to tool wear, signal processing and analysis are needed to extract the important information from the signals (i.e. Sensory Characteristic Features (SCFs)). Table 10.8 shows general visual observation of the Association Matrix (ASM) which includes the sensitivity of all SCFs implemented in this monitoring system. In addition, Figure 10.18 presents an image of the SCFs shown in Table 10.8.

Table 10.8: Example of ASM for Tool 1.

	Std	**Avg.**	**Max**	**Min**	**Range**	**Kurtosis**	**Skew**	**Power**
Strain	L	H	H	H	M	M	L	H
Vibration	M	H	H	H	M	M	L	H
AE	M	H	H	H	M	L	L	H
AE_RMS	L	H	H	H	L	M	L	H

(H: High sensitivity, M: Medium sensitivity, L: Low sensitivity).

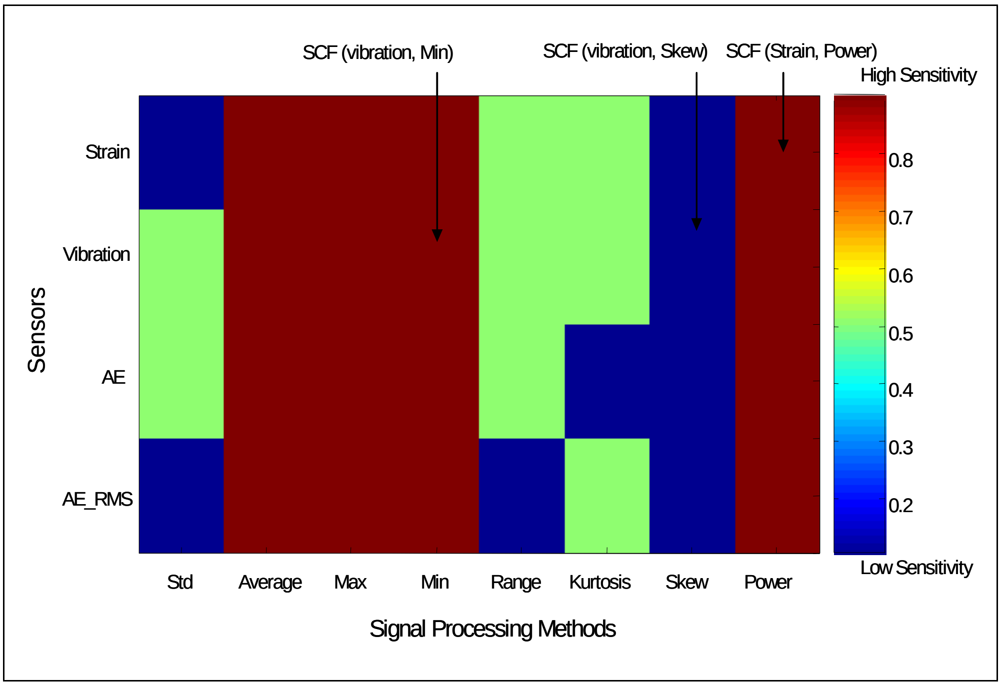

Figure 10.18: Example of the SCFs images of the signals.

As can be observed from Table 10.8 and Figure 10.18, all the sensory signals have a high sensitivity level with power, average, minimum and maximum signal processing methods. Even though such general visual observations as shown above could help to find some sensory features which are sensitive to the tool wear, but it still does not provide a systematic method to study the system and there could be more sensitive sensory characteristic features which are obtained from less expensive sensors than the acoustic emission sensor, such as the strain sensor in this experimental investigation. It can be observed that among the signals, some signal processing methods are more sensitive with the sensory signal than others. Therefore, it can be concluded that manual investigation could help in finding the sensitivity of the sensory signal.

10.4.1.2 Sudden Change In Value (SCIV) Method

In order to extract the sensory characteristic features (SCFs), the test from the first tool is used to investigate the process characteristic and to select the sensitive Sensory Characteristic Features (SCFs) using the ASPST approach. The raw signals are processed using several time domain signal processing methods to extract 8 SCFs form every sensory signal. The 8 signal processing methods are used to process the 4 sensory signals establishing an ASsociation Matrix ASM of (4×8) which allows the investigation of 32 sensory characteristic features (SCFs) for the design of the monitoring system. The ASM matrix for this test has 4 sensory signal and 8 signal processing methods. The 32 sensory characteristic features of the ASM matrix for this work are calculated for the 7 tools and then the Sudden Change In Value (SCIV) is calculated from the normalised features. The SCFs are arranged according to their sensitivity to tool wear based on Sudden Change In Value (SCIV) method. The SCFs are visually inspected and it has been observed that the features which show a high value with the SCIV method have better sensitivity for the wear of the cutting tool. Therefore, the ASPST approach is used to find out the most appropriate sensors and signal processing methods for the detection of tool wear in turning using other sensor and novelty detection. Figure 10.19 shows an example of two sensory characteristic features with high sensitivity and Figure 10.20 shows an example of two features with low sensitivity to the wear.

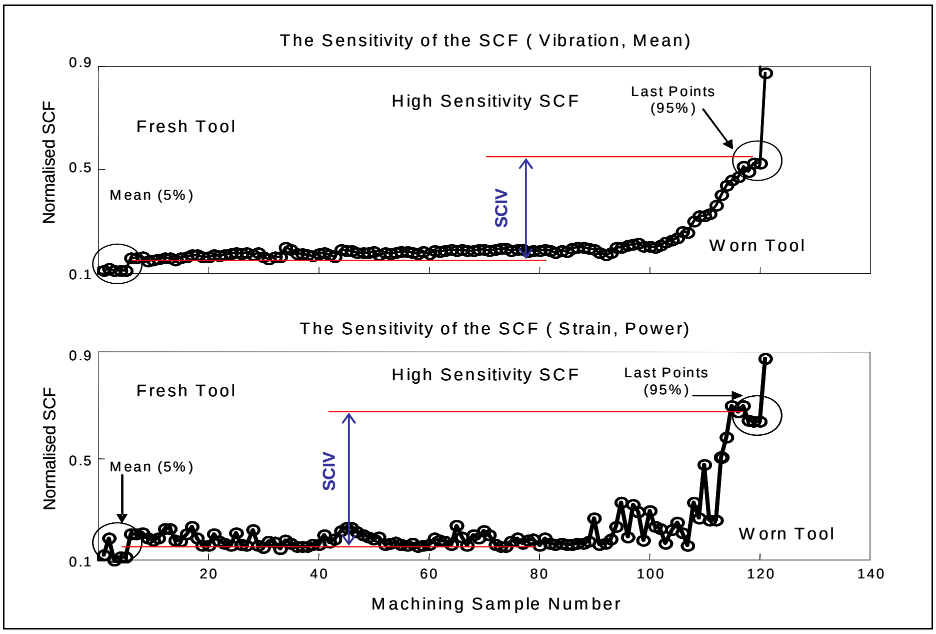

Figure 10.19: Example of two sensory features with high sensitivity.

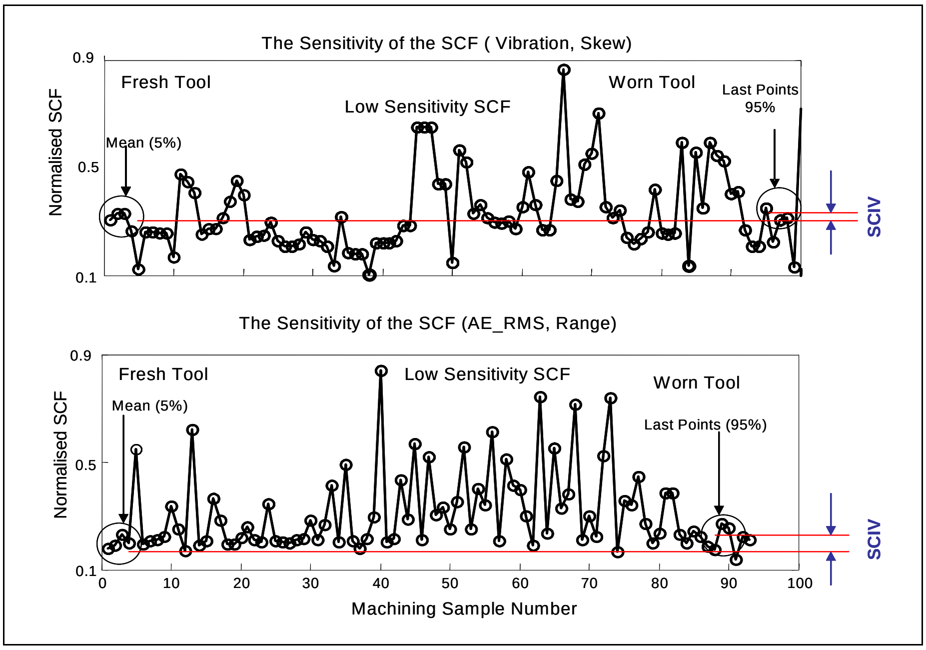

Figure 10.20: Example of two sensory features with low sensitivity.

As can be seen in Figure 10.19 and 10.20, the absolute value of the difference of the maximum and minimum presents a good indication of how sensitive a sensory feature is to tool wear.

Table 10.9 shows part of the ASM matrix for this particular tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised features.

Table 10.9: ASM matrix for tool wear test.

	Std	Avg.	Max	Min	Range	Kurtosis	Skew	Power
Strain	0.107	0.676	0.676	0.67	0.132	0.216	0.061	0.781
Vibration	0.148	0.602	0.553	0.505	0.187	0.171	0.018	0.601
AE	0.186	0.603	0.590	0.565	0.177	0.036	0.038	0.603
AE_RMS	0.105	0.573	0.558	0.580	0.128	0.126	0.028	0.599

Figure 10.21 shows part of the ASM matrix for tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised features. The numbers with small values in Table 10.9 which appear in navy in the images figure means low sensitivity; numbers with medium values appear in green or yellow means medium sensitivity; and numbers with high values which appear in red in the images means high sensitivity.

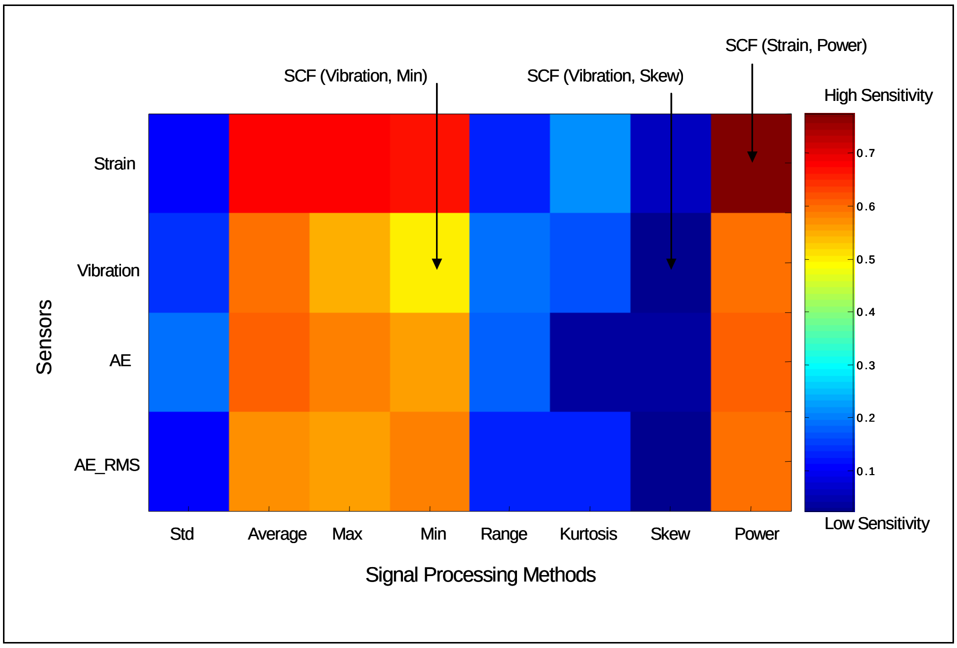

Figure 10.21: Example of the SCFs images of the signals using SCIV.

As can be noticed from Table 10.9 and Figure 10.21 utilising the SCIV method, and Table 10.8 and Figure 10.17 using the visual method, there is similarity between the two methods. This proves that using an automated sensitivity detection method such as Sudden Change In Value (SCIV) method could minimise time and effort. For example, if we take the SCF of the strain and power signal processing method and investigate it manually, it shows that it has high sensitivity (H) as in Table 10.8 and

Figure 10.18. On the other hand, when applying the automated method, SCIV method, it shows that SCF for strain and power signal processing method is 0.781. This means high value in Table 10.9 and the red in Figure 10.21 mean high sensitivity also. In addition, using the SCIV method shows more accuracy than visual investigation. For example, investigation of the SCFs of vibration sensor and minimum signal processing method visually shows high sensitivity and the colour red in Table 10.8, but when utilising the SCIV method yellow is shown. When comparing these two colours it can be seen that their values are between 0.5 and 0.6 which is not too far from the value shown in Table 10.9. It can be concludes from the discussion that using the automated method, Sudden Change In Value (SCIV) analysis and utilising the Association Matrix (ASM), to discover the most sensitive features to detect tool wear in turning processes is found useful and time consuming comparing to manual investigation. To enable the classification system to be fast and to give a good classification, it is decided, as in the previous sections/chapter, to base the implementation and the design of the ASPST condition monitoring system of this test on a set of 10 SCFs. The sensory characteristic features are grouped into 3 systems, 10 features each. A computer program is used to arrange the ASM features according to the absolute Sudden Change In Value (SCIV) and arrange every 10 as a separate system. It can be seen from Figure 10.22 that the first system has the most sensitivity features for tool wear detection in turning process compared to other systems.

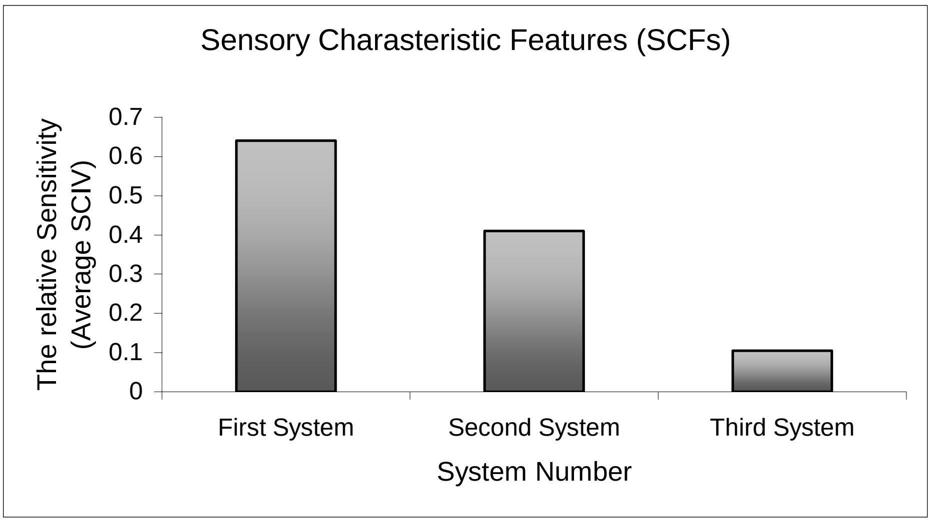

Figure 10.22: Comparison between systems' sensitivity.

Looking at Table 10.10, it can be observed that the first system includes the most sensitive 10 features. In addition, Table 10.11 shows the next 10 features and Table 10.12 shows the least sensitive 10 feature to tool wear. The first system is found to have relative sensitivity (SCIV average of 0.6402) which is much more than the average sensitivity of the second. In addition, third system is found to have the lowest sensitivity for the detection of tool wear.

Table 10.10: First system with the SCFs sensitivity.

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
Strain	Power	0.7806
Strain	Maximum	0.6760
Strain	Average	0.6758
Strain	Minimum	0.6705
AE	Power	0.6029
AE	Average	0.6029
Vibration	Average	0.6022
Vibration	Power	0.6006
AE_RMS	Power	0.5999
AE	Maximum	0.5905
Average		**0.6402**

Table 10.11: Second system with the SCFs sensitivity.

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
AE_RMS	Minimum	0.5800
AE_RMS	Average	0.5732
AE	Minimum	0.5654
AE_RMS	Maximum	0.5585
Vibration	Maximum	0.5532
Vibration	Minimum	0.5051
Strain	Kurtosis	0.2165
Vibration	Range	0.1868
AE	Std	0.1865
AE	Range	0.1761
Average		**0.4101**

Table 10.12: Third system with the SCFs sensitivity.

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
Vibration	Kurtosis	0.17138
Vibration	Std	0.14767
Strain	Range	0.13184
AE_RMS	Range	0.12763
AE_RMS	Kurtosis	0.12602
Strain	Std	0.10679
AE_RMS	Std	0.10508
Strain	Skewness	0.06018
AE	Skewness	0.03744
AE	Kurtosis	0.03636
Average		**0.1050**

As can be seen from the above tables, the first system shows the highest sensitivity level of the SCFs. On the other hand, the third system shows the lowest sensitivity level of the SCFs. Therefore, the ASM matrix is found very useful in predicting the sensitivity levels of the SCFs. The sensitivity of the SCFs has proved that a high sensitivity level of the SCFs means high information and a low sensitivity level means low information. In addition, the details of the first few SCFs structure can be used to optimise system cost without affecting system performance significantly. However, it is important to notice that the statement of a high sensitivity level means high information is based on the visual inspection of each feature and the way it behaves during the fault's development. Therefore, a statement is made that the average sensitivity level of a system is a reflection of the expected behaviour of the system. The proof of this statement will be described in the next sections using Novelty Detection.

10.4.2 System Cost and Utilisation

The same method used in section 10.3.2 to calculate the cost of the system is used here again. Figure 10.23 shows the sensors set-up for the experimental work in this section.

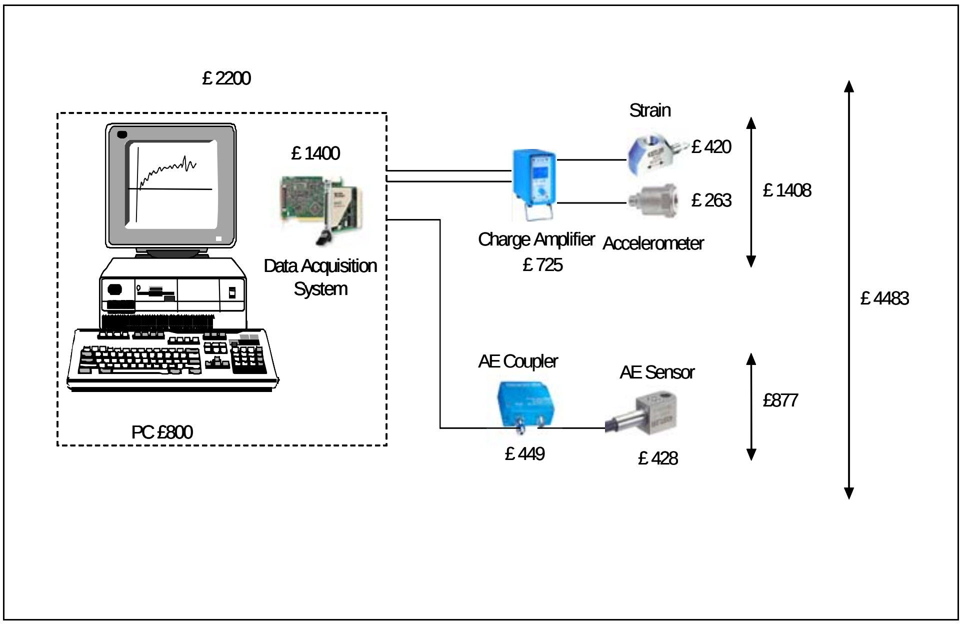

Figure 10.23: The sensors set-up used to calculate the cost of the system.

10.4.2.1 System Optimisation

The same method used previously to optimise the system is used here again. It can be noticed from Table 10.10 and Table 10.11 that the sensors are utilised in both system and cost could be minimised by optimising the systems to increase the system utilisation. To optimise the system by replacing the SCFs of the AE sensor from first system with SCFs of vibration and strain sensors from second system to minimise cost with affecting the sensitivity.

Table 10.13: Sensors utilisation.

Sensors	**U 1st System**	**U 2nd System**	**Optimised System**
Strain	40%	10%	50%
Vibration	20%	30%	50%
AE	40%	60%	---------
UA Utilisation Average	**33.33%**	**33.33%**	**50%**
System Cost	**£4485**	**£4485**	**£3606**
Average Sensitivity	**0.6402**	**0.4101**	**0.5467**

As shown in Table10.13, the overall average utilisation has increased from 33.33% up to 50% in the first and the second systems and the cost of the system is reduced by 20% from £4485 to £3606. On the other hand, the average sensitivity of the systems showed no significant change.

Table 10.14: The optimised system (from systems 1 and 2).

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
Strain	Power	0.7806
Strain	Maximum	0.6760
Strain	Average	0.6758
Strain	Minimum	0.6705
Vibration	Average	0.6022
Vibration	Power	0.6006
Vibration	Maximum	0.5532
Vibration	Minimum	0.5051
Strain	Kurtosis	0.2165
Vibration	Range	0.1868
Average		**0.5467**

From the above results and discussion, it has been concluded that the strain and vibration sensors are appropriate sensors to monitor tool wear in turning processes based on the ASPST approach. The above results prove that the ASPST approach can be used to minimise system cost and to reduce the number of sensors while maintaining high sensitivity.

10.4.2.2 System Evaluation

The same method used previously to evaluate the system is used here again. To evaluate the effectiveness of the condition monitoring system elements (sensors and signal processing methods) the ASM matrix can be used based on the sensitivity of every sensor and signal processing method to the faults which are included in the ASM matrix.

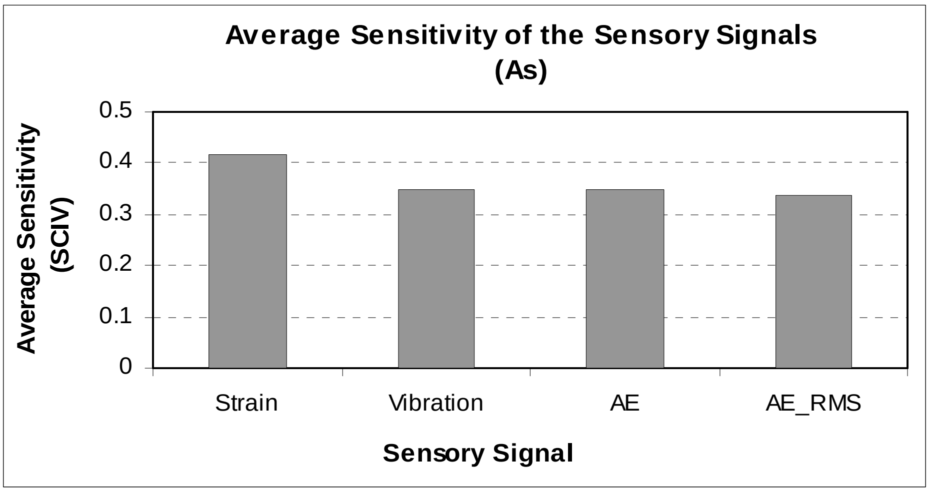

Figure 10.24: A_s values for the sensory signals.

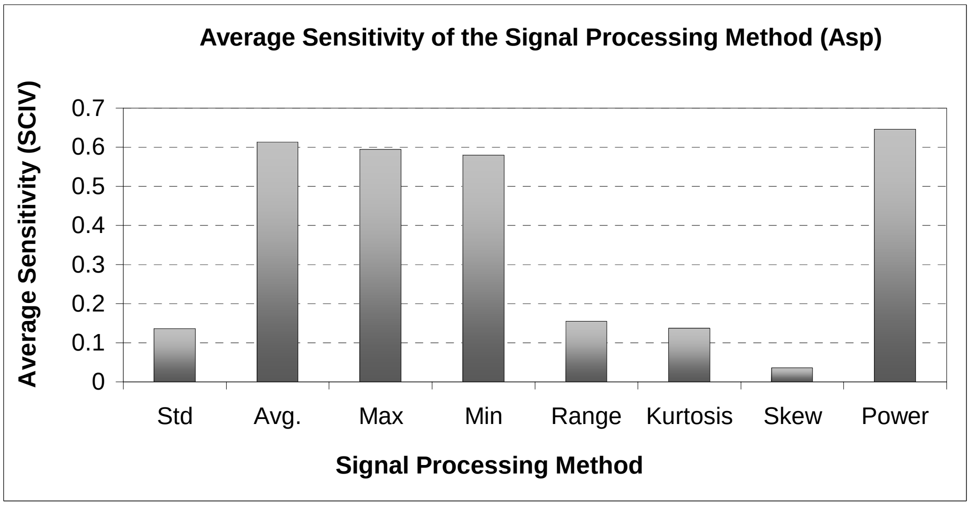

Figure 10.25: A_{sp} values for the signal processing methods.

The Ac factor of this system is found to be (0.36). However, to find out the effectiveness of the selection of the utilised sensors and signal processing methods, the values obtained can be compared with those of other systems. Therefore, the high A_c values mean high sensitivity, high information; and low Ac means low sensitivity value and less information. But low Ac values could include features with high sensitivity. From results of the first and second investigation and from the previous discussions, it can be concluded that the ASM matrix can be helpful to evaluate the significance of a sensor or a signal processing method to a monitoring system. In addition, it can be employed to evaluate and compare the sensitivity of the monitoring system with other similar monitoring systems.

10.4.3 Performance of Novelty Detection Algorithm

In order for the ASPST approach to be a useful methodology, the sensory characteristics features which are assumed to have a higher sensitivity on the tool wear should result in better identification when they are tested by a pattern recognition system. For this purpose Novelty Detection is used to test the complete monitoring system. The details of the Novelty Detection algorithm are briefly explained in Chapter 7 section 7.4.1.

The SCFs of all the 7 tools are then fed into a novelty detection algorithm to investigate the capability of the ASPST approach and the complete monitoring system. NETLAB software is used for the implementation of the novelty detection. The response of the Gaussian kernels ϕ_j is defined by a covariance matrix (a spherical matrix in this case) and a centre (i.e. the centroid of the input clusters). A single variance parameter for each Gaussian component is calculated using 6 centres in the mixture which has been found to be a suitable structure that gives a relatively quick learning process and consistent results.

Following the training of the novelty detection on normal samples from the first test, the complete captured of normal and faulty features are tested. Figure 10.26 presents the results of using the novelty detection for testing the sensory characteristic features. One of the problems of the novelty detection algorithm is the need to establish a suitable threshold value; sometimes, because of the variation in the machining process parameters, it is difficult to establish this threshold. As shown in Figure 10.26 it is difficult to create a threshold value. A single threshold value could either give false detection or fail to detect tool wear before complete wear.

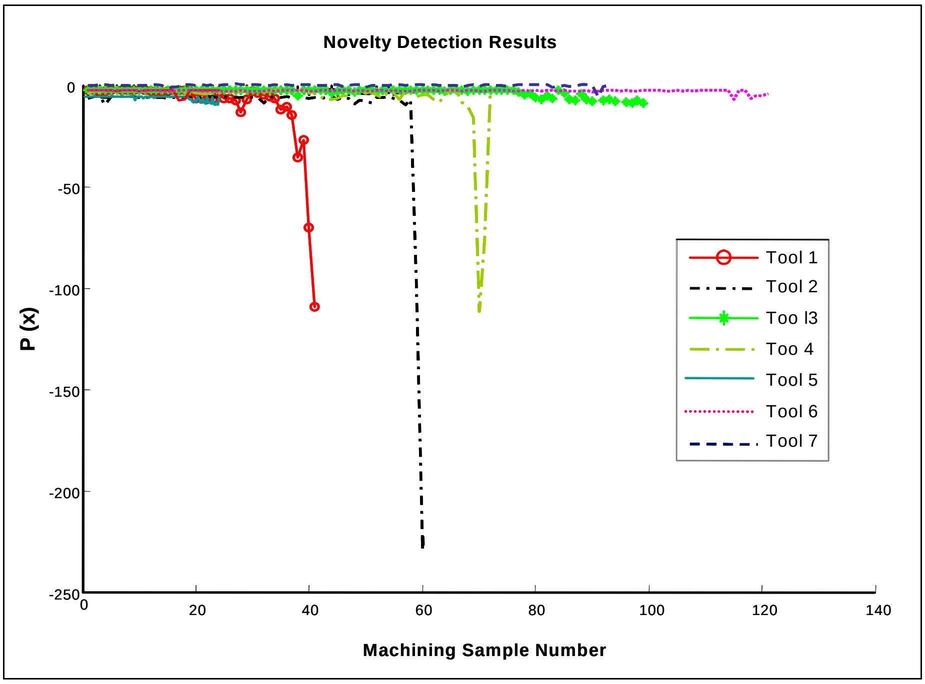

Figure 10.26: Results of the novelty detection of all tools.

In order to solve the threshold problem, this work suggests a novel approach by utilising the moving average ($\bar{X}_t$), and the standard deviation of the novelty detection output to create a dynamic threshold value.

The moving average ($\bar{X}_t$), is defined mathematically as:

$$\bar{X}_t = \frac{1}{n}\sum_{i=0}^{n-1}(x_t - i) \qquad 10.1$$

where x_t, is the average of the novelty detection output; and n is the number of samples. Hence, the dynamic threshold value could be defined as:

Dynamic threshold value= $\bar{X}_t - m\sigma$ 10.2

where,

σ is the standard deviation number of samples (4 to 6); and *m* is a constant.

The standard deviation, σ, is calculated for the first initial samples (e.g. 4 to 6 samples) when the tool is still fresh and there is no wear in the first cuts. The constant, *m,* depends on the process and it has a typical value of 2-20 depending on the material, and the process (i.e. case dependent). The success of the novelty detection algorithms and the moving average dynamic threshold equation is found to be 100%. Moreover, the dynamic threshold value could be selected for each individual tool wear prediction to be efficient before the actual tool wear occurs. Figures 10.27 – 10.30 shows the dynamic threshold for the tools. The threshold show that the points above the threshold indicate that the tool is normal (fresh tool) and the points falling under the dynamic threshold indicates that tool is novel (worn tool).

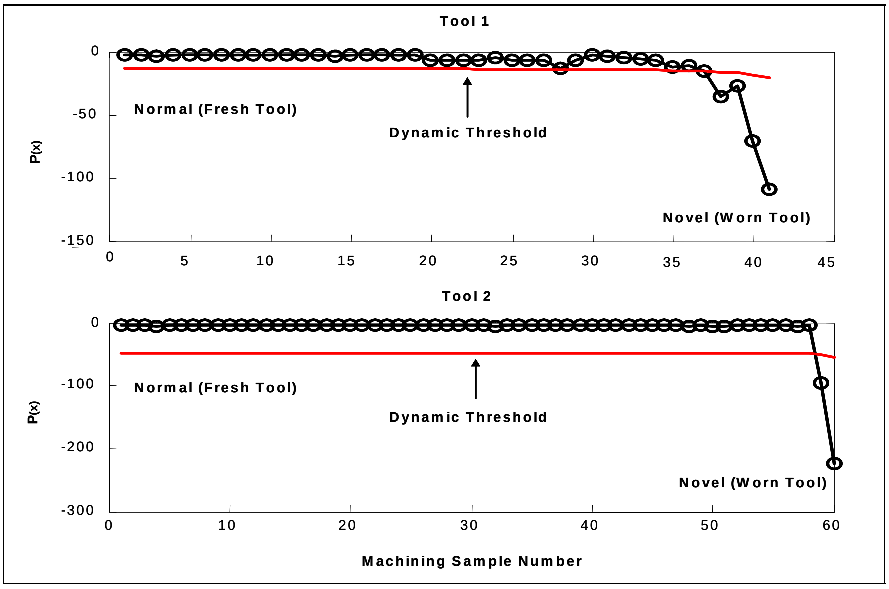

Figure 10.27: The dynamic threshold for tools 1 and 2.

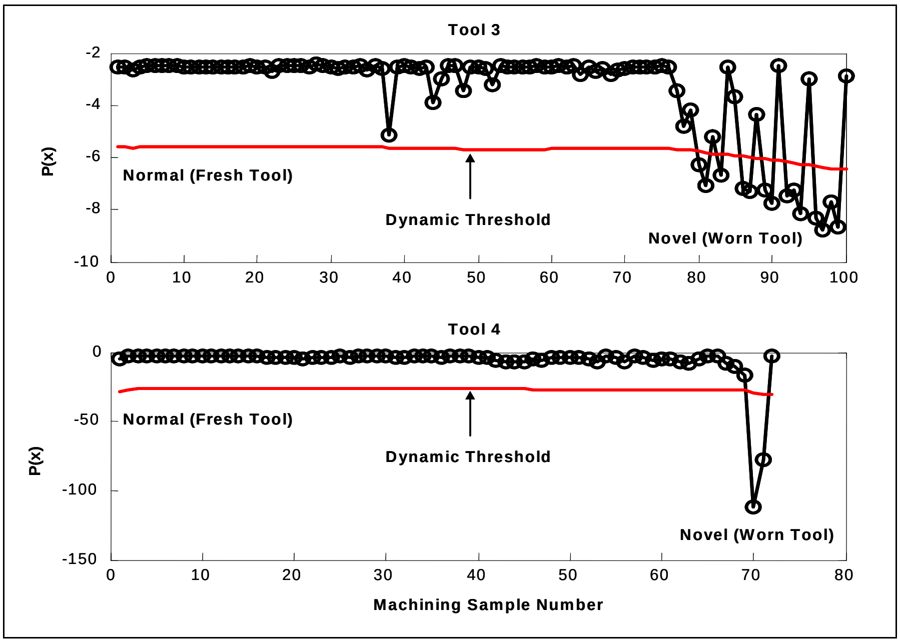

Figure 10.28: The dynamic threshold for tools 3 and 4.

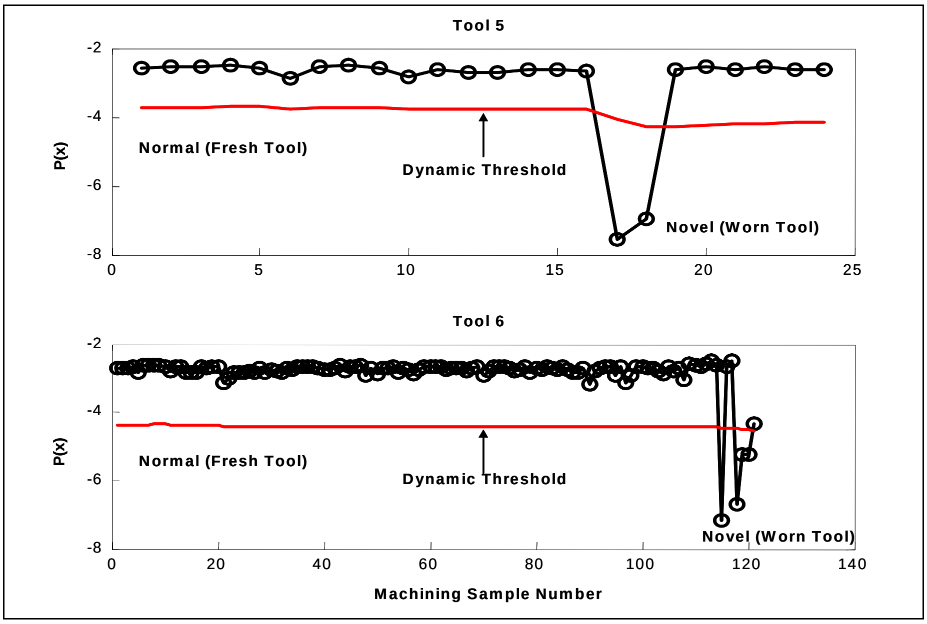

Figure 10.29: The dynamic threshold for tools 5 and 6.

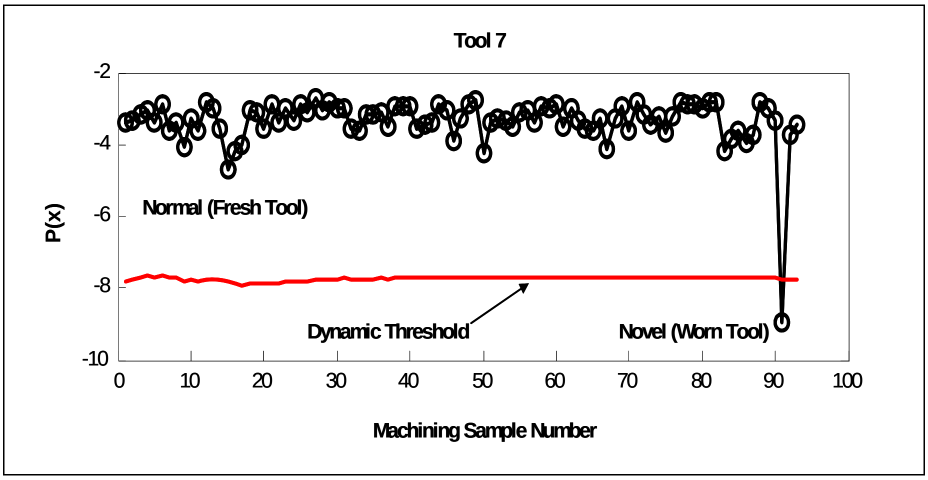

Figure 10.30: The dynamic threshold for tools 7.

From Figures 10.27 -10.30, it can be noticed that the life of each tool is different in each case. This proves that it is difficult to use statistical methods to predict tool failure time and an ASPST approach implementing for condition monitoring is the most suitable technique to predict when a tool will fail.

10.5 CONCLUSION

In this chapter, the ASPST approach for multi-sensors combined with artificial neural networks (LVQ) in the first experimental test, and novelty detection in the second experimental test, is explained using two experimental machining tests to monitor gradual tool wear in the turning process. The ASPST approach utilises the Association Matrix (ASM) to compare the sensitivity of the feature to the fault under investigation. In addition, it evaluates the overall monitoring system using the average sensitivity of sensors and signal processing methods. The Sudden Change In Values (SCIV) analysis is used to find the most sensitive features to detect tool wear in turning processes. The SCFs are visually examined and examples of low sensitivity and high sensitivity SCFs are presented. Sensory utilisation is implemented within the ASPST approach to minimise the cost of the system without affecting the system sensitivity. The ASPST approach has been found useful in selecting the most sensitive sensors and signal processing methods to design a condition monitoring system with low experimental work and minimised cost.

Chapter 11

The Application of ASPST Approach Using Multi- Sensor Fusion

11.1 Introduction

This chapter examines the full capabilities of the ASPST approach using a wide range of sensors. The approach is utilised in this chapter to design a condition monitoring system which can detect gradual tool wear in turning processes. The design process for monitoring tool wear in turning processes is presented. Turning cutter tool is used to investigate gradual tool wear using the ASPST approach. The chapter shows how the ASPST approach can be utilised in turning processes in an efficient way taking into consideration the cost of the implemented monitoring system. The chapter builds on the results found in Chapters 9 and 10 to prove the following key issues:

1. The sudden change in value (SCIV) method can be used as a measurement of sensitivity for group of SCFs.
2. A group of SCFs with high average sensitivity produce a high sensitivity system compared with a group of SCFs with low average sensitivity.
3. A partial number of tests are adequate to design a condition monitoring system for the gradual tool wear tests in turning processes.
4. The cost of the system can be reduced based on sensor utilisation and overall SCF sensitivity.
5. Novelty detection and learning vector quantisation neural networks (LVQ) are used to confirm the results.

11.2 Experimental Work

The experimental work in this chapter is conducted to examine the behaviour of 8 sensory signals and 33 signal processing methods for fresh and worn tools and to find out the most sensitive sensory characteristic features to tool wear in turning processes. The experimental work is conducted on a turning process using stainless steel workpiece. This is a relatively hard material which can accelerate tool-wear at the expense of a shorter tool life. In addition, stainless steel used in this research as it is very common material in domestic, automotive market, and other industrial applications. The stainless steel work piece which has a diameter of 30 mm and a total machining distance of 5000 mm is machined during the full tests to transfer the tool from fresh to completely worn. The machined distances are divided into 20 machining samples each with a length of 250 mm (i.e. 20 machining samples are obtained during the test for analysis). In total, 20 independent experiments are conducted in the turning of stainless steel bars using a fresh tool in each experiment, each with the same basic configuration. The tool inserts used, Sandvik Coromant P25 (SCMT 120408 UM), are cemented carbide coated via chemical vapour deposition and consist of grades of indexable inserts with integral chip-breaker geometry, held in place by a negative rake tool holder. The chosen process parameters monitored are the cutting forces (three axes), strain, vibration, acoustic emission (RMS and AE signal) and sound. Care is taken to ensure that all experimental conditions remain the same. The machining parameters are selected to resemble industrial practice. The experimental cutting conditions are chosen to cover the manufacturer's recommended interval for insert type. Figure 11.1 shows a schematic diagram of the implemented monitoring system for this chapter. For more details see Chapter 8, section 8.3.

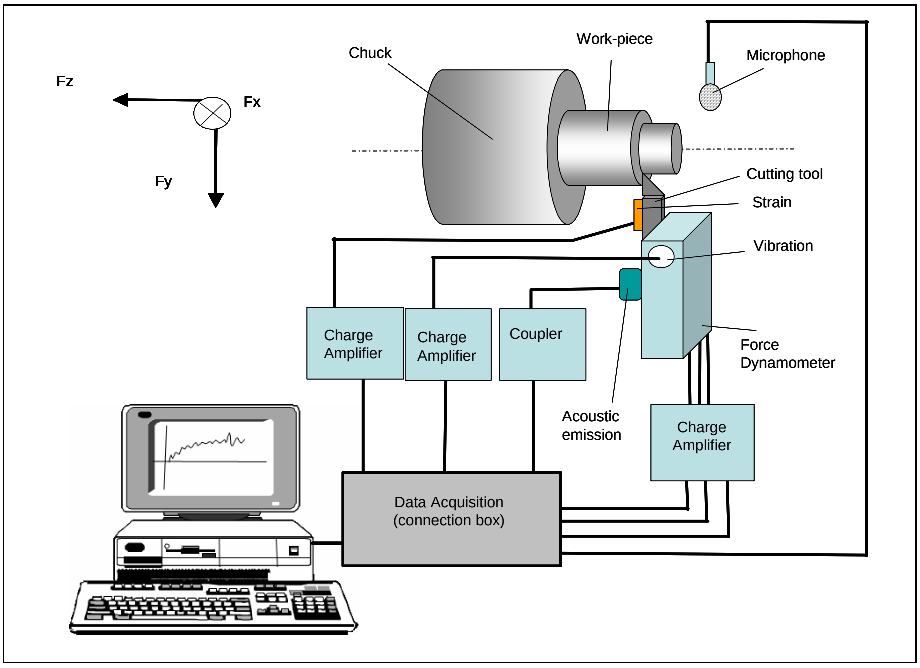

Figure 11.1: Schematic diagram of the complete monitoring system.

11.3 Signal Simplifications

The Associated Matrix (ASM) for this test has a size of 8x33, and embodies 264 features. These features are divided into 26 different systems each system contains 10 features. The features are arranged in descending order so that the system number 1 containing the features of maximum sensitivity while system number 26 contains the feature of minimum sensitivity. As mentioned in Chapter 9, section 9.4, the suggested number of features in every system, 10, is based on previous implementation of the ASPS in end-milling. However, any other number could be used based on the applications.

The level of tool wear is visually monitored in this experimental work and it shows that wear increases with machining time. Figure 11.2 and 11.3 show, respectively, examples of the raw machining signals of a fresh and worn tool during the turning process.

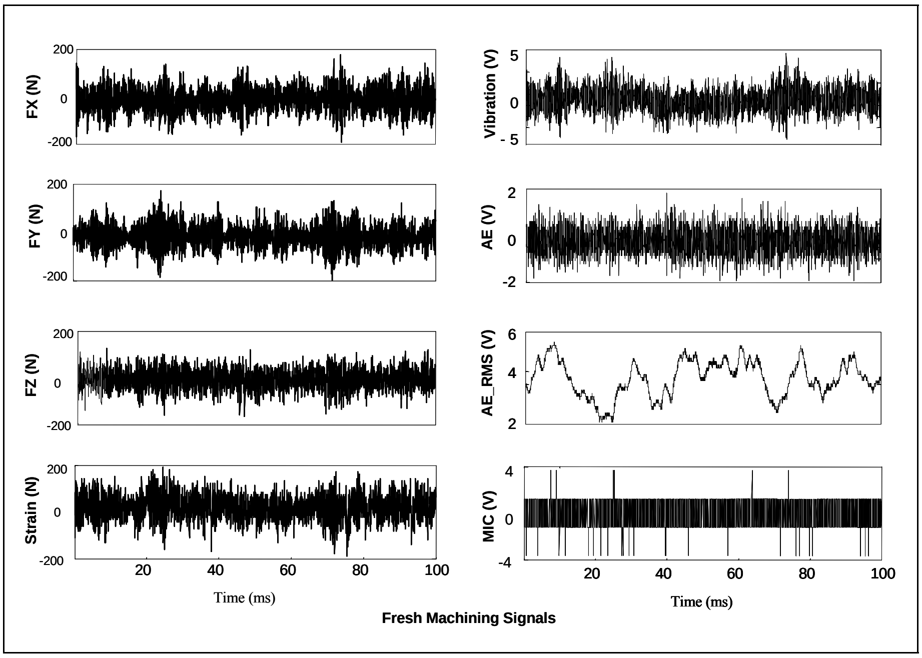

Figure 11.2: Machining signals of the fresh tool.

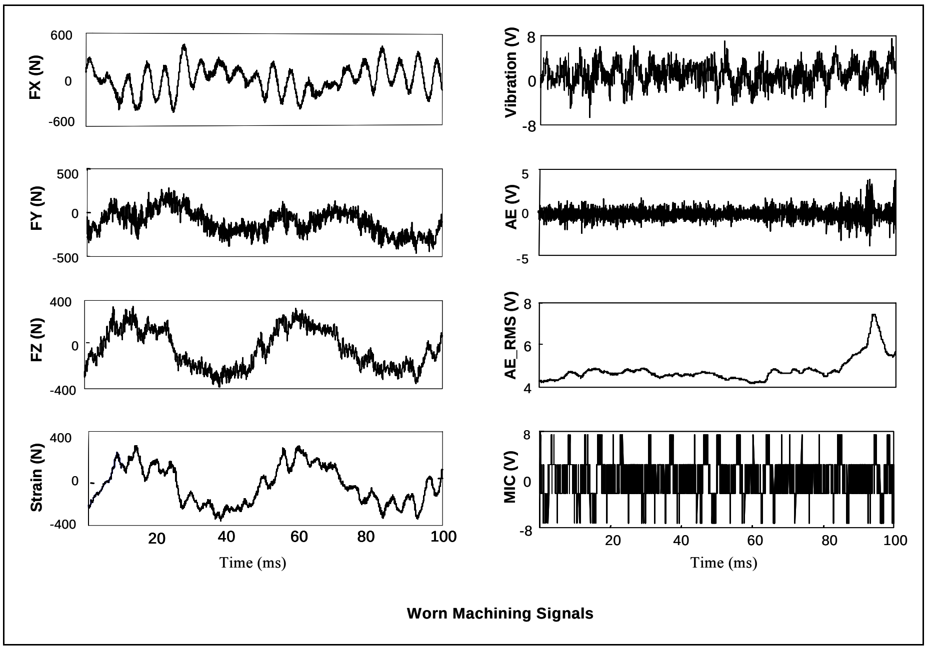

Figure 11.3: Machining signals of the worn tool.

Looking at Figures 11.2 and 11.3, it can be observed that the cutting forces, strain and AE_RMS signals include more vibration noise. For example, the AE signal level is relatively low, forces Fz and Fy are high and vibration is low. On the other hand, the vibration level of some signals has decreased for the worn tool, as in the acoustics emission and cutting forces signals. In addition, the level of some sensory signals has changed such as in the sound and strain signals.

In Chapter 9 and 10, the SCFs are visually inspected and compared with the utilisation of the automated detection method. The results prove that using visual (manual) inspection is time consuming and the automated method can give better and more accurate detection because the turning process has complex machining signals and there are too many features, 264 SCFs, in this experimental work. The signals cannot easily be interpreted to find the most appropriate signal or sensor for the detection of tool wear conditions. Therefore, it has been found difficult to predict the most sensitive signals to tool wear manually. From the above discussion it is concluded that visual inspection of the monitored signals is time consuming and should be automated. In this chapter, the implementation of the ASPST for tool wear detection in turning processes will be tested using several sensory signals and signal processing methods to automate the system. Therefore, this experimental work should provide a basis for the evaluation of the ASPST approach in designing a condition monitoring system to detect tool wear in turning processes which develop massive data.

The detection of the sensitivity of the SCFs should be automated in order to develop a rapid and structured methodology of selecting sensors and signal processing methods. Any method can be used as long as it can indicate a change in the average level of the SCF as a function of time and show a reason for change in the process condition. It is basically a detection of change in the SCF level forming a specific trend with time. The following statistical methods are utilised in this Chapter to find the best method to detect sensitivity:

1. The Range Value (RV) method.
2. The Linear Regression Slope method.
3. The Sudden Change In Value (SCIV) method.

11.3.1 Range Value (RV) Method

The range value (RV) method is used in this test to calculate the sensitivity of every feature to the wear of the tool. In this method, the range value is the difference between maximum and minimum values in the SCFs. Hence, features which have high values mean high sensitivity and low values mean low sensitivity. Figures 11.4 and 11.5 show two examples of features with high sensitivity to tool wear according to the range value method.

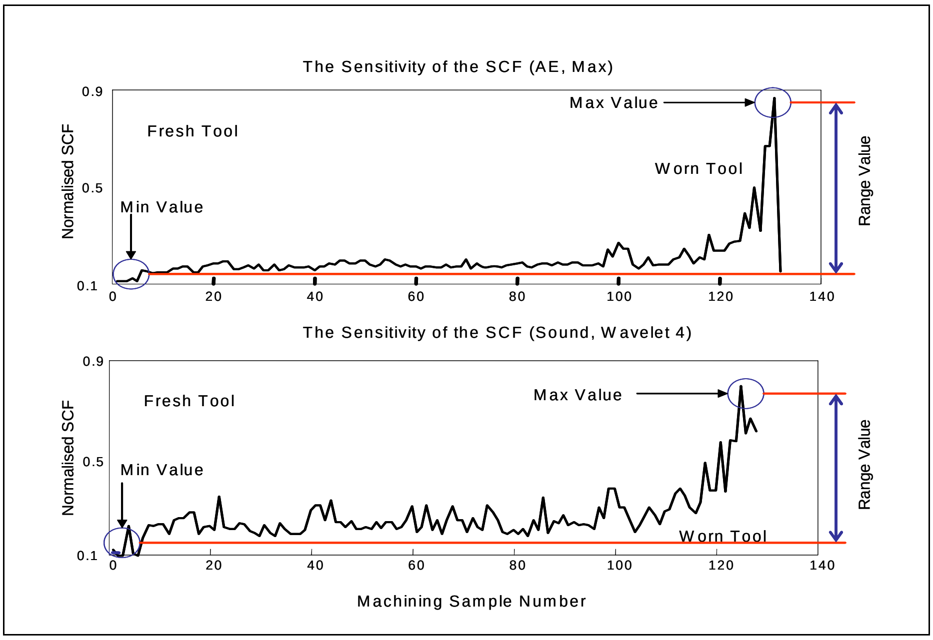

Figure 11.4: Example of SCFs with high sensitivity using range value method.

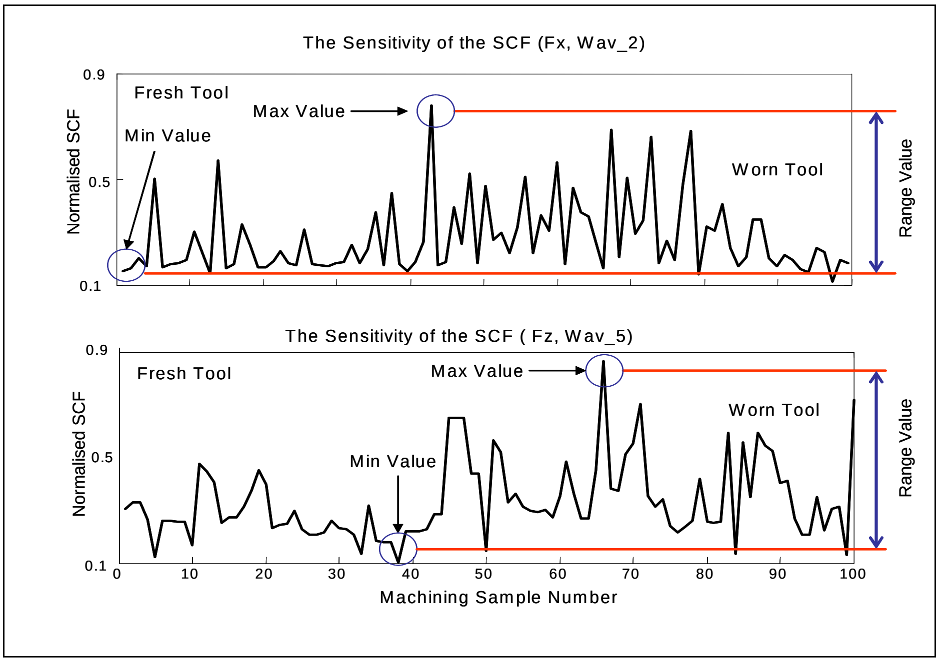

Figure 11.5: Example of SCFs with high sensitivity using range value method.

Looking at Figure 11.4, it can be noticed visually that applying the range value method is significant. On the other hand, Figure 11.5 shows high sensitivity features when applying the range value method. But, in fact, when testing the features manually it shows that these features have low sensitivity. Therefore, the Range Value (RV) method is found insignificant method to detect the sensitivity of the SCFs of tool wear in turning processes, which means it is not an appropriate analysis method to be utilised in the ASPST approach. For more analysis verification, Figure 11.6 shows an image of the SCFs using the range value method.

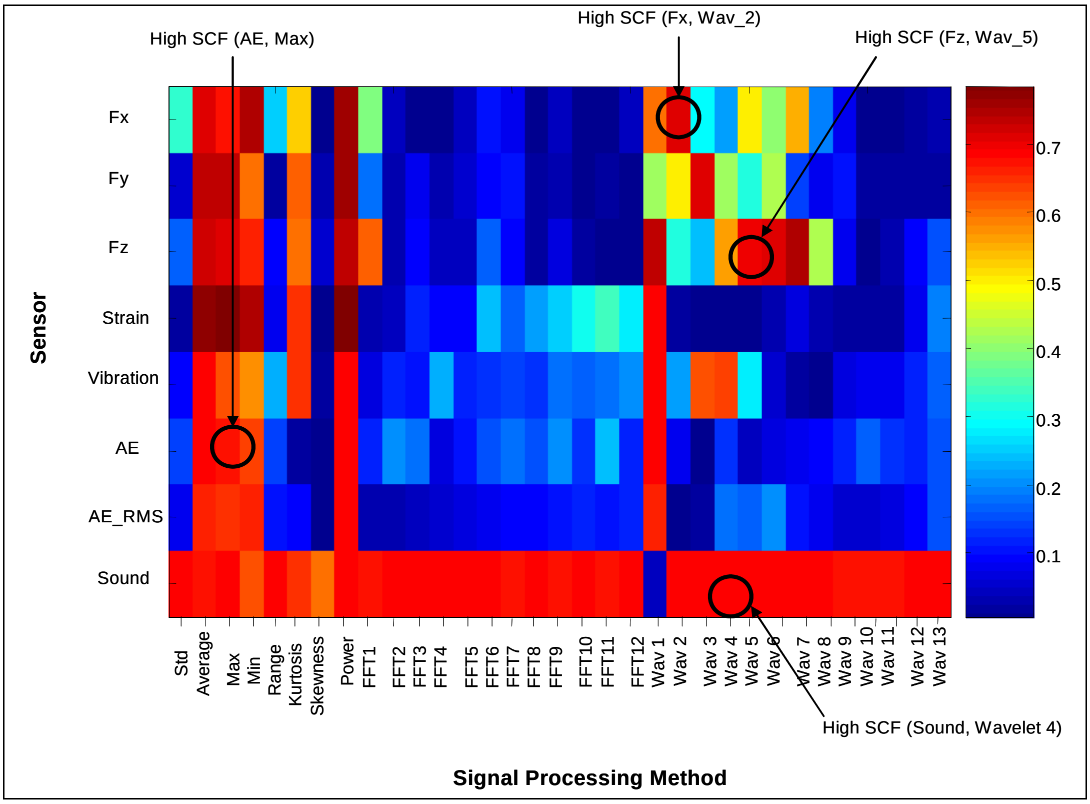

Figure 11.6: Example of the result for all the SCFs using range value method.

It can be observed from Figure 11.6, that the SCF (sound, wavelet_4) has high sensitivity. This means that it is reflecting the real feature when investigated manually. On the other hand, the SCF of (Fx, wavelet_2) does not reflect the real features when it is investigated manually, where it shows low sensitivity when investigated visually and high sensitivity when utilising the range value method. Figure 11.6 confirms that implementing the range value method in not accurate.

Therefore, this confirms that the range value method is not suitable for the ASPST approach as an automated sensitivity detection method due to unconfirmed output.

11.3.2 Linear Regression Slope Method

The linear regression method is used to find the linear equation which best represents the linear relationship between two variables. The first variable is the independent variable which could be the degree of cutter wear, etc. The second variable is the dependent variable and this variable is a sensory characteristic feature which changes according to the change in the independent variable. The line is obtained by using the least squares straight line fitting. This section presents the utilisation of the linear regression method as a sensitivity detection method for the ASPST approach to detect tool wear in turning processes. For more information, see Chapter 7, section 3.3. Figures 11.7 and 11.8 show examples of two features with high sensitivity and two features with low sensitivity to tool wear respectively according to the linear regression analysis method.

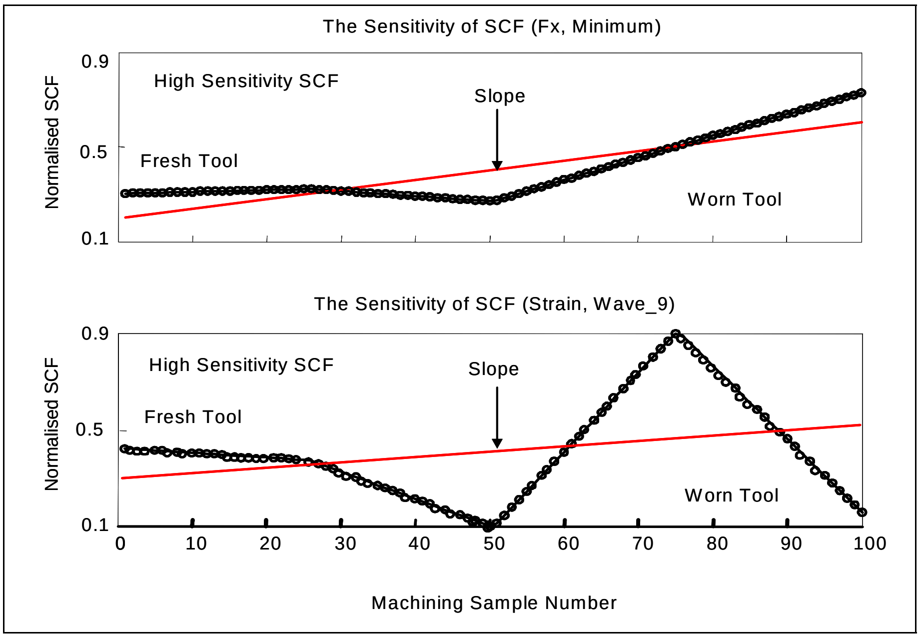

Figure 11.7: Example of two features with high sensitivity using linear regression.

Investigating these features manually, it can be noticed that the SCF (Fx, Minimum) shows high sensitivity to tool wear. On the other hand, the second feature (Strain, Wave_9) shows low sensitivity to tool wear but it shows high sensitivity when utilising the linear regression to detect the sensitivity in turning.

In addition, Figure 11.8 shows two SCFs with low sensitivity when utilising the linear regression method. It can be seen from the features in Figure 11.8, that the (AE, FFT_9) shows low sensitivity which is the same as visual investigation. But, the other feature (Sound, Wave_8) shows visually high sensitivity to tool wear. It can be concluded that the result from the linear regression method does not provide the real sensitivity level of tool wear in turning processes.

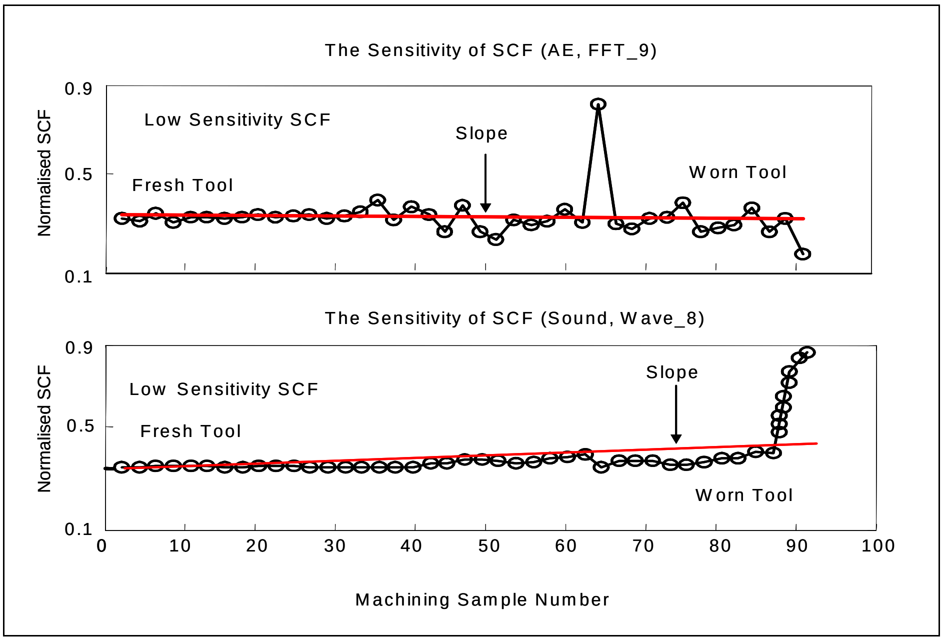

Figure 11.8: Example of two features with low sensitivity using linear regression.

Figure 11.9 shows the images of the SCFs with the linear regression method. This is used as additional proof to confirm that the linear regression methods are not an appropriate method to detect tool wear in turning processes. This contradicts the milling result found in [20].

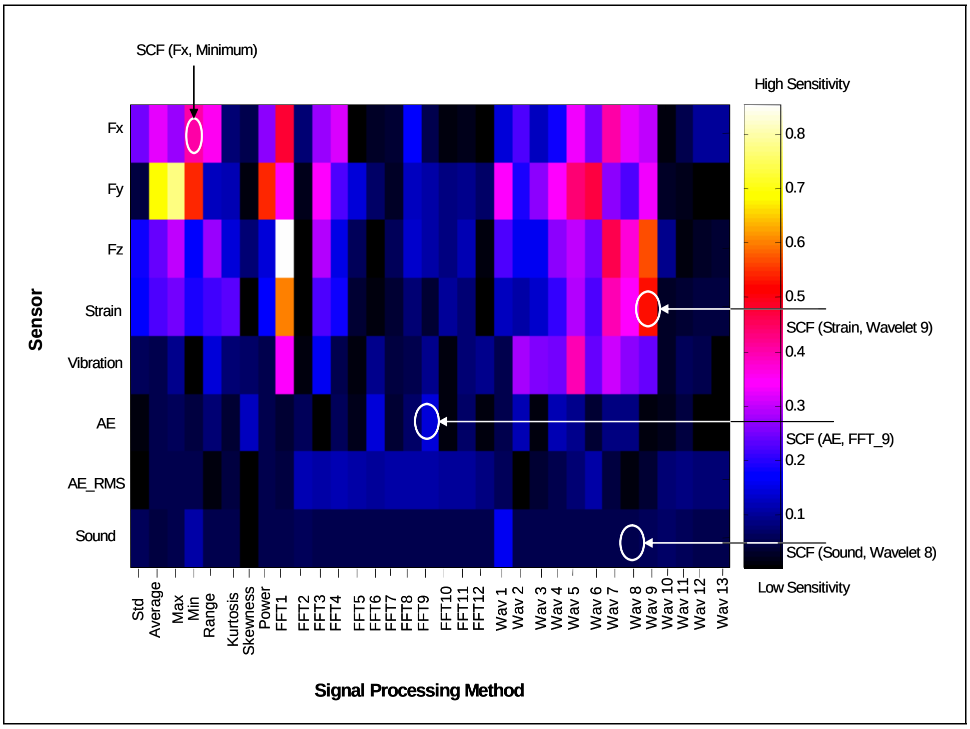

Figure 11.9: Example of the result for all the SCFs using linear regression.

It can be noticed from Figure 11.9, that the SCF of (AE, FTT_9) and (sound, wavelet_8) appear in navy which means low sensitivity. But the SCF of the (sound, wavelet_8) shows high sensitivity in its real feature. This confirms that the linear regression slope method is not an appropriate method to be utilised in the ASPST approach as an automated detection method to detect tool wear in turning processes.

11.3.3 Sudden Change In Value (SCIV) Method

In order to automate the sensitivity detection of the systems and to keep the automated measurements simple for a complex machining process such as turning, it has been found that the SCIV method is a significant method to be used in this research as a sensitivity detection method. The details of SCIV method are presented in Chapter 7, section 7.3.3. Figures 11.10 and 11.11show examples of two features with low sensitivity and two features with high sensitivity to tool wear respectively.

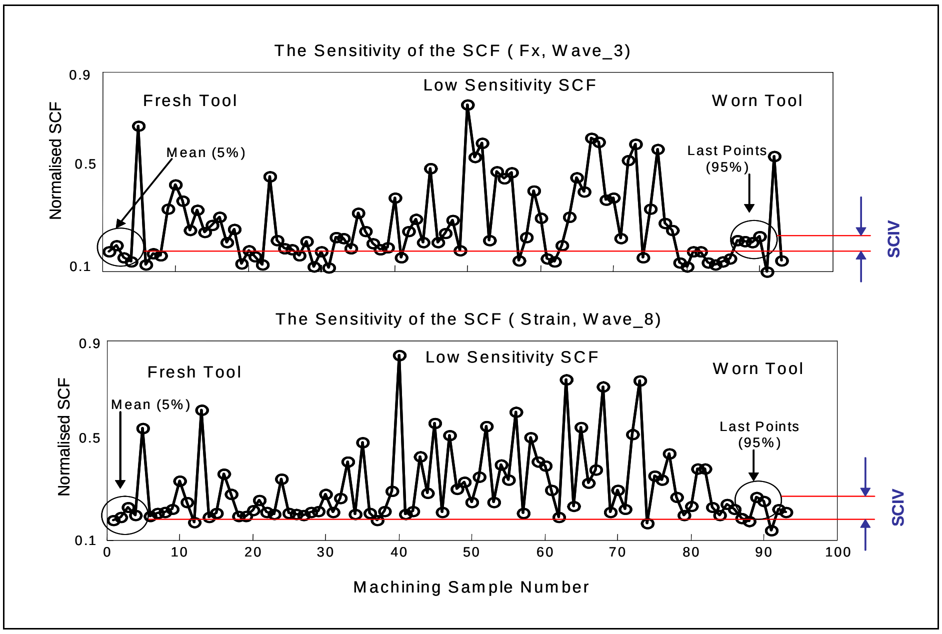

Figure 11.10: Example of two features with low sensitivity using SCIV.

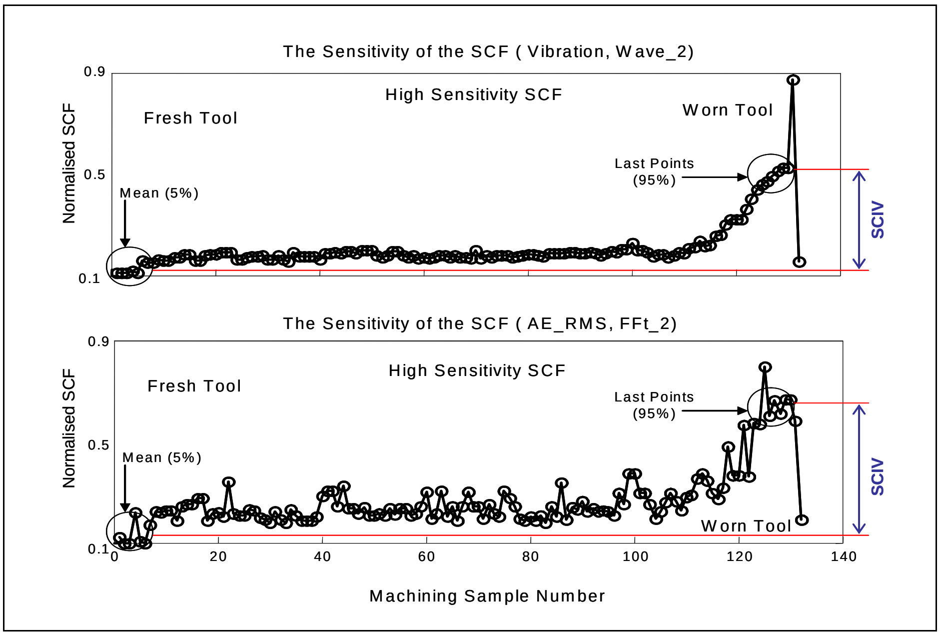

Figure 11.11: Example of two features with high sensitivity using SCIV.

As can be observed from the above figures, the absolute value of the Sudden Change In Value (SCIV) method presents a good indication of how sensitive a sensory feature is to tool wear.

Table 11.1 shows a part of the ASM matrix for this particular tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised features.

Table 11.1 Part of the ASM matrix (using SCIV).

	Std	Avg.	Max	Min	Range	Kurtosis	Skewness	…
FX	0.72121	0.72611	0.73879	0.72975	0.7397	0.68131	0.53461	…
FY	0.69115	0.77365	0.73003	0.77532	0.73343	0.58857	0.10311	…
Fz	0.10487	0.72975	0.75149	0.71418	0.1027	0.56133	0.61405	…
Strain	0.60758	0.73975	0.77648	0.72336	0.70702	0.602	0.60318	…
Vibration	0.58458	0.69316	0.74036	0.49323	0.53379	0.75149	0.7464	…
AE	0.53687	0.59562	0.73369	0.72311	0.73343	0.27331	0.50736	…
AE_RMS	0.60253	0.64621	0.64673	0.64959	0.6648	0.24121	0.10217	…
Sound	0.69565	0.59557	0.5657	0.58393	0.69536	0.64988	0.59012	…

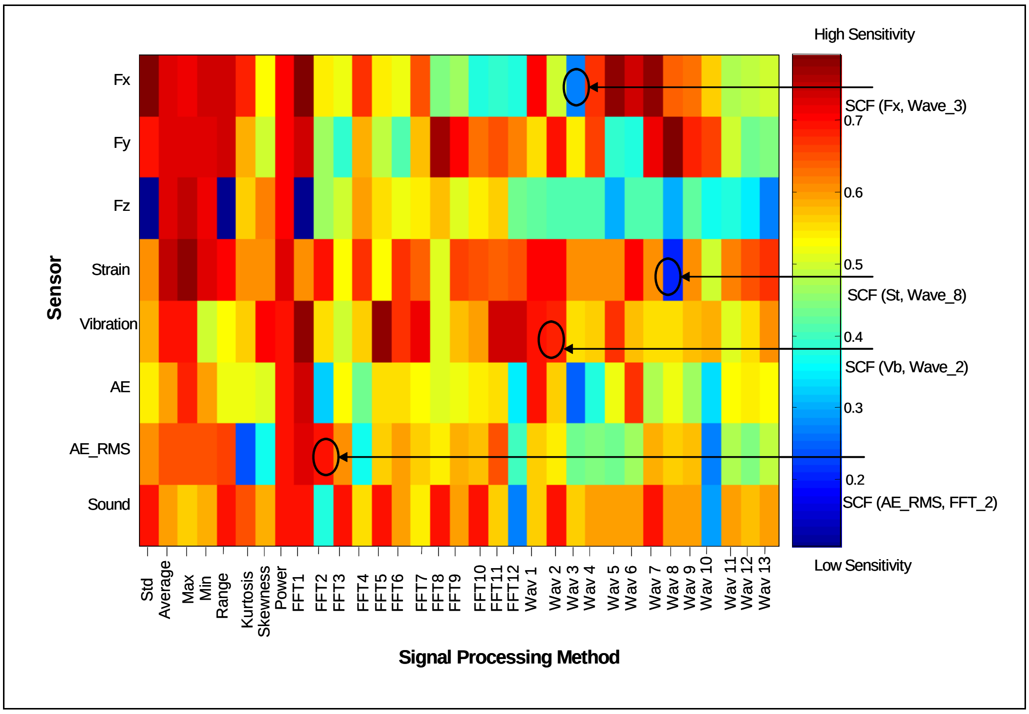

Figure 11.12: Example of the result for all the SCFs for one tool (SCIV).

Figure 11.12 shows the result of using the Sudden Change In Value (SCIV) method. It can be noticed from Figure 11.10 that the SCFs of (strain, wavelet_8) and (Fx, wavelet_3) are not sensitive to tool wear. Looking at the result in Figure 11.12, it is noticed that when utilising the Sudden Change In Value (SCIV) method it indicates that both have low sensitivity as indicated manually. In addition, looking at Figure 11.12 it can be observed that the SCFs of (AE_RMS, FTT_2) and (vibration, wavelet_2) are very sensitive to tool wear with high sensitivity. Therefore, the Sudden Change In Value (SCIV) method is an appropriate method to use as an automated detection method with the ASPST approach. From the above figures, it is concluded that the Sudden Change In Value (SCIV) method is a good indicator of the automated sensitivity detection. In addition, the SCIV method indicates the same result when it is used as an automated sensitivity detection method and gives accurate result when it is applied to the massive data of the SCFs. Therefore, the Sudden Change In Value (SCIV) method is an excellent method to detect sensitivity and to keep measurement automated and simple.

11.4 Selection of Sensory Characteristics Features (SCFs)

From the results and the discussion in section 11.3 and the previous chapter, it can be concluded that the Sudden Change In Value (SCIV) method shows excellent results as an automated sensitivity detection method compared with the range value and linear regression methods. The result shows that the range value method is not suitable as an automated method to detect sensitivity in turning processes. In addition, the linear regression method shows good results with some features but is insignificant with others. This section presents the selection of the sensory characteristics feature (SCFs) using the SCIV method to confirm that the utilisation of the SCIV method can also show excellent results in the optimisation of the system. To enable the classification system to be fast and to give a good classification, it was decided to base the implementation and the design of the ASPST condition monitoring system of this test on a set of 10 SCFs. The sensory characteristic features are grouped into 26 systems, 10 features each. A Matlab computer program is utilised to arrange the ASM features according to the absolute Sudden Change In Value (SCIV) to arrange every 10 as a separate system. All systems have the average sensitivity as shown in Figure 11.13. It can be observed from that the first system has the most sensitivity features for tool wear detection compared to the other systems.

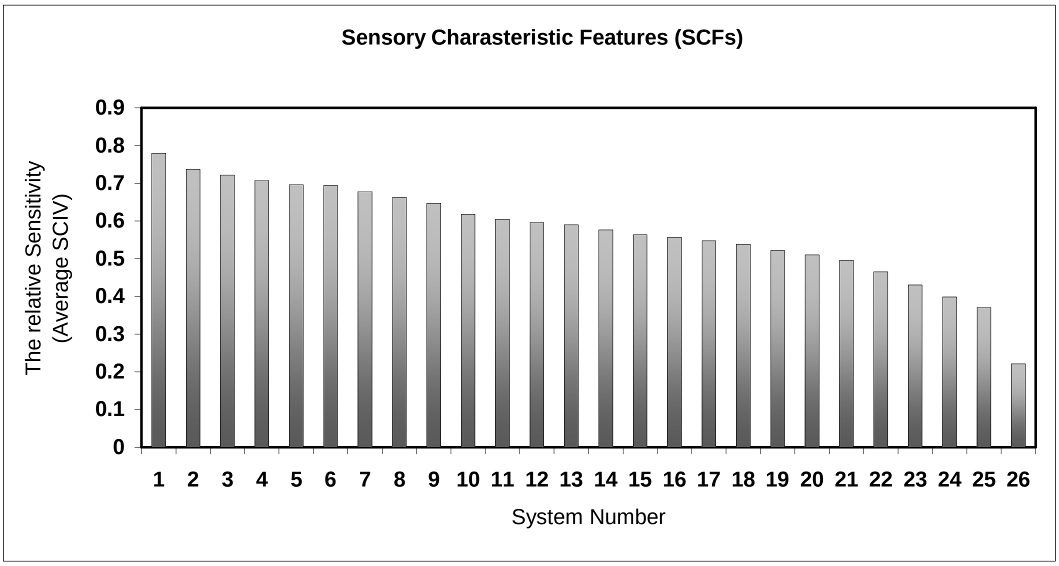

Figure11.13: Comparison between the 26 systems according to their sensitivity.

The first system which includes the most sensitive 10 features is shown in Table 11.2. In addition, Tables 11.3 and 11.4 show the next 10 features and Table 11.5 shows the least sensitive 10 feature to tool wear. The first system is found to have relative sensitivity (SCIV average of 0.7797) which is more than the average sensitivity of the second (0.7372). In addition, system number 26 is found to have the lowest sensitivity for the detection of the tool wear (0.2210). The following tables are examples of the first three systems and system number 26.

Table 11.2: First system with the SCFs sensitivity.

Sensory Signal	**Signal Processing Methods**	**Sensitivity (SCIV)**
Fy	Wavelet_3	0.79668
Fy	Wavelet_4	0.79635
Strain	Wavelet_1	0.78646
Fx	Power	0.78141
Vibration	Wavelet_5	0.78058
Fy	Power	0.77813
Vibration	Wavelet_1	0.77648
Fy	Minimum	0.77532
Fy	Average	0.77365
Vibration	Kurtosis	0.75149
	Average	**0.7797**

Table 11.3: Second system with the SCFs sensitivity.

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
Vibration	Skewness	0.74646
Fy	Wavelet_6	0.74039
Vibration	Maximum	0.74036
Strain	Average	0.73975
Fx	Maximum	0.73879
Sound	Wavelet_4	0.73633
AE	Maximum	0.73369
AE	Range	0.73343
Fy	Wavelet_2	0.73245
Strain	Wavelet_6	0.73003
	Average	**0.7372**

Table 11.4: Third system with the SCFs sensitivity.

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
Fx	Minimum	0.72975
Strain	Wavelet_8	0.72747
Sound	Wavelet_5	0.72611
Strain	Wavelet_5	0.72496
Fx	Wavelet_7	0.72336
AE	Minimum	0.72311
Vibration	FFT_1	0.72209
Fz	Wavelet_1	0.71475
Sound	Wavelet_7	0.71418
Strain	Wavelet_9	0.71273
	Average	**0.7219**

Table 10.5: System 26 with the SCFs sensitivity.

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
Fx	FFT_1	0.30635
Fy	Wavelet_5	0.29562
AE	Kurtosis	0.27331
Fx	Wavelet_12	0.26596
Fz	FFT_1	0.26562
Vibration	Wavelet_2	0.25142
Fx	Std	0.24121
Fx	Wavelet_3	0.10487
Fy	Skewness	0.10311
AE_RMS	Skewness	0.10217
	Average	**0.2210**

The details of the first few SCFs structure can be used to optimise the systems cost without significantly affecting performance.

11.5 Cost and Performance

The costs of condition monitoring systems are essential in industrial application. The aim is not only to produce a successful condition monitoring system, but also to keep the system as cheap as possible in order to be economically justifiable. In order to keep the monitoring system as cheap as possible, the utilisation of sensors in the system should be kept relatively high. The overall Average Sensor Utilisation factor for a system, SUA, is defined as the average value of the SU of all the sensors used in a system. It has been found that the SU factor is useful in reducing the cost of the system by removing the least utilised sensors in the monitoring system. The changeable supposed cost of each system is calculated and compared with the attempt to optimise the performance of the system relative to its cost. The cost reduction process theory is discussed in Chapter 6, section 6.5. This section explains and evaluates the cost reduction process with the aid of the tool wear experimental work.

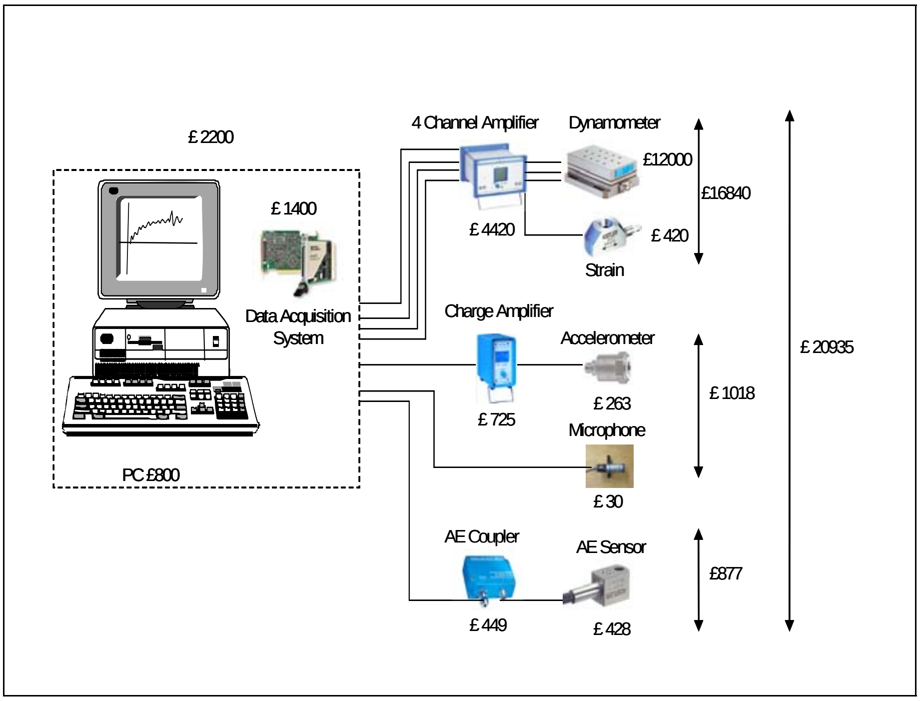

Figure 11.14: The sensor set-up used to calculate the cost of the system.

Figure 11.14 shows the complete sensor set-up used to calculate the cost of the monitoring system for the experimental work in this chapter. The analysis is done using the variable cost of the system, i.e. the cost of the sensors. The cost analysis is based on using the same equipment shown in Figure 11.14. The fixed costs such as the PC, data acquisition card, and the software should be added to the supposed variable cost to obtain the total cost of the system. The variable supposed cost of each system is calculated and compared in an attempt to optimise the performance of the system relative to its cost. In this research work, the term "cost" means the supposed variable cost of the monitoring system since the aim is to compare systems. The sensory characteristics features are grouped into 26 systems, 10 features each. Figure 11.15 shows the cost of the 26 systems.

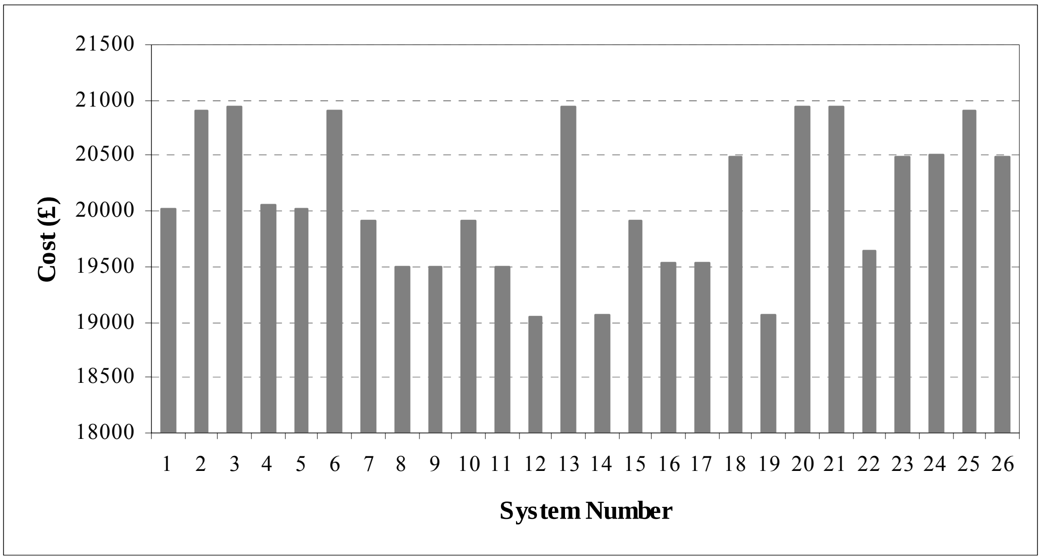

Figure 11.15: Comparison between the 26 systems according to their cost.

11.5.1 System Optimisation

The same method used previously to optimise the system is used here again. From Table 11.2 and 11.3, it can be observed that there is no big difference in the average sensitivity for both systems. But it can still be optimised by increasing system utilisation. By replacing the sensory characteristic features of the strain sensor from the first system with the vibration sensor signals from the second system, the cost can be reduced and the sensitivity maintained.

Table 11.6: Sensor optimisation.

Sensors	U 1st System	U 2nd System	Optimised System
Dynamometer	20%	10%	20%
Strain	10%	20%	-------
Vibration	30%	20%	40%
AE	-----	20%	-------
Sound	------	10%	-------
UA Utilisation Average	**20%**	**16%**	**30%**
System Cost	**£20028**	**£20935**	**£18883**
Average Sensitivity	**0.7797**	**0.7372**	**0.7757**

Table 11.7: The optimised system (form 1st and 2nd systems).

Sensory Signal	Signal Processing Methods	Sensitivity (SCIV)
Fy	Wavelet_3	0.79668
Fy	Wavelet_4	0.79635
Fx	Power	0.78141
Vibration	Wavelet_5	0.78058
Fy	Power	0.77813
Vibration	Wavelet_1	0.77648
Fy	Minimum	0.77532
Fy	Average	0.77365
Vibration	Kurtosis	0.75149
Vibration	Skewness	0.74646
Average		**0.7757**

Table 11.6 shows sensor utilisation of system numbers 1 and 2, and the optimised system (from systems 1 and 2). It can be observed from Table 11.6, that the overall average utilisation has increased in the first system from 20% to 30%, from 16% to 30% in the second system and the cost is reduced by 10% from £20935 to £18883. In addition, the average sensitivity of the system has not significantly changed as can be seen in Table 11.7. In fact the average sensitivity has increased to 0.7757 compared with 0.7372 in the second system. From the previous discussion, it has been found that the force and vibration sensors are the most appropriate sensors to monitor tool wear based on the ASPST approach.

Figure 11.16 shows a comparison between the cost and the sensitivity of systems 1, 2 and the optimised system.

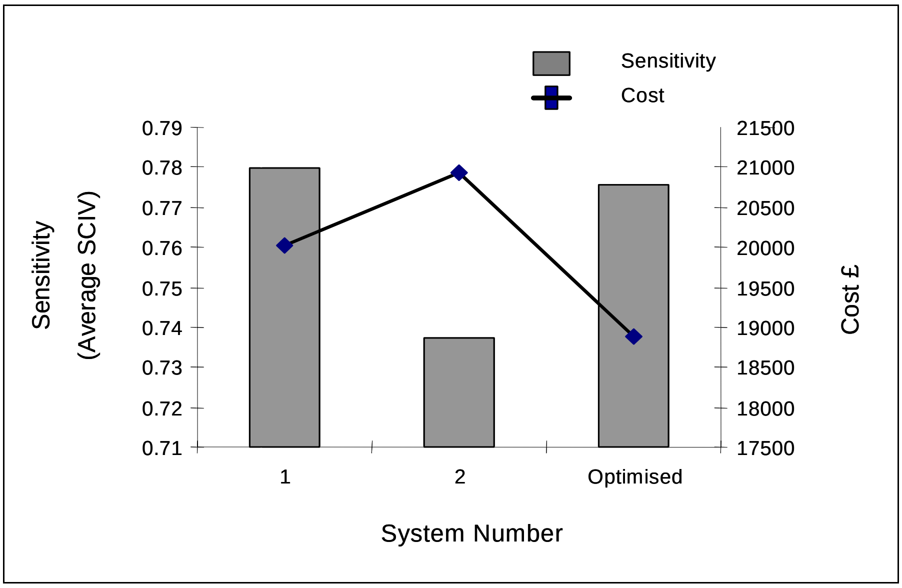

Figure 11.16: A comparison between the cost and the sensitivity.

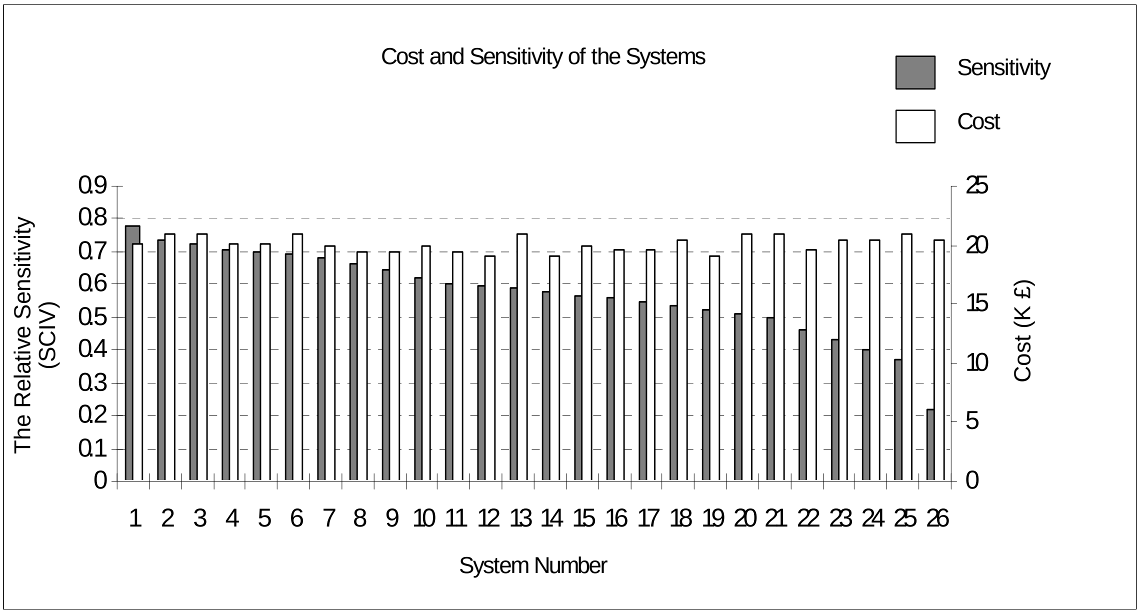

Figure 11.17: A comparison between the sensitivity of the systems and their cost.

Figure 11.17 shows a comparison between the cost and the relative sensitivity (Average SCIV) of the 26 systems. From Figure 11.17, it can be seen that system 12 has the lowest cost of £19040 and has a sensitivity level of 0.5958. On the other hand, system 3 has a sensitivity level of 0.7219 but it has a high cost of £20935. By comparing systems 12 and 3, it can be noticed that an improvement in sensitivity of 0.126 has caused an increase in the system cost of £1895. Therefore, it is essential to compromise between cost and sensitivity of the systems if a cheaper system with relatively acceptable sensitivity is needed.

11.5.2 System Evaluation

The same method used in Chapter 10 to evaluate the system is used here again. To evaluate the effectiveness of the condition monitoring system elements (sensors and signal processing methods) the ASM matrix could be used based on the sensitivity of every sensor and signal processing method to the faults which are included in the ASM matrix.

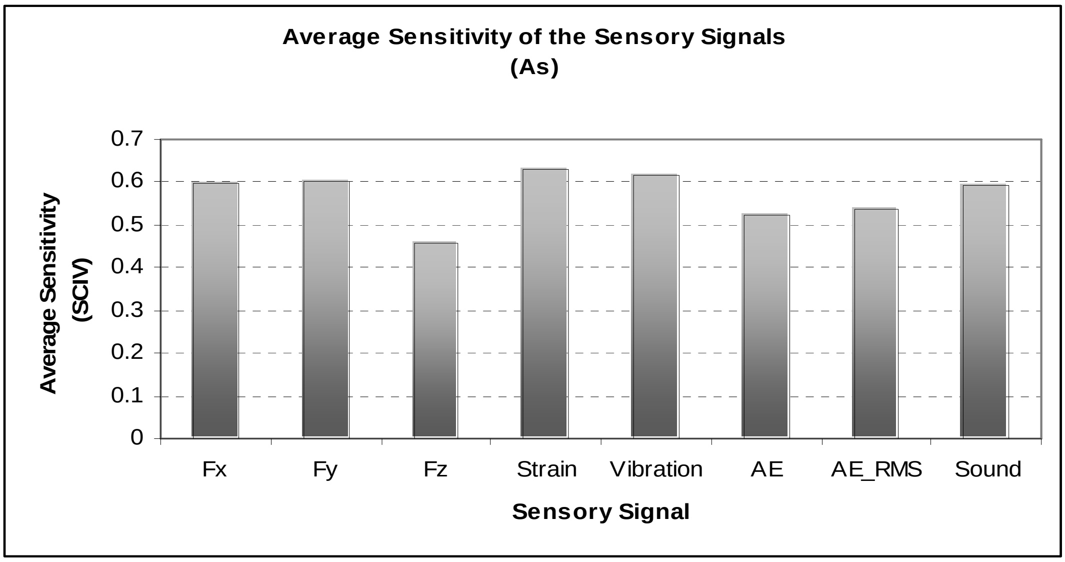

Figure 11.18: As values for the sensory signals.

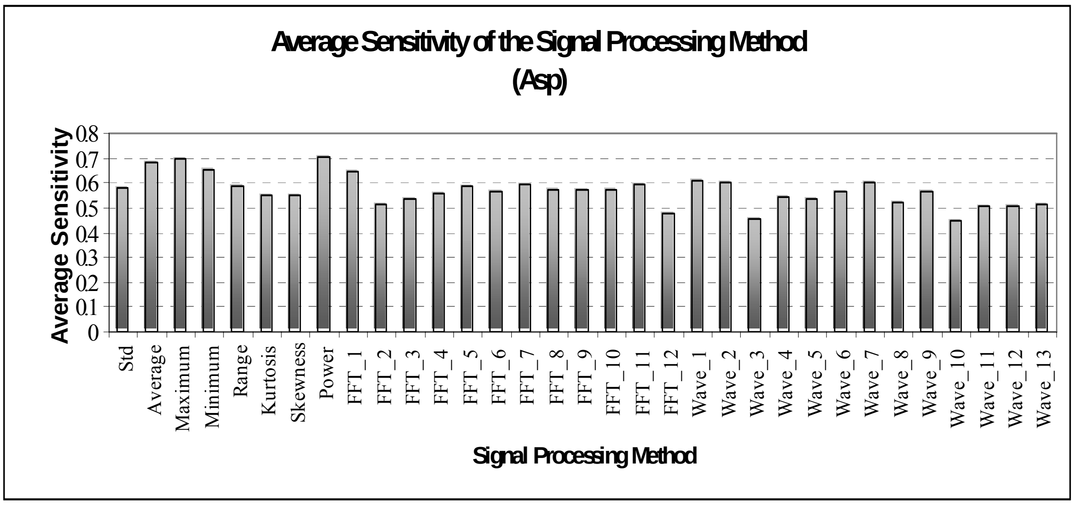

Figure 11.19: Asp values for the signal processing methods.

The Ac factor of this system is found to be 0.56. However, to find out the effectiveness of the selection of the utilised sensors and signal processing methods, the evaluated values can be compared with other systems. The high A_c value means a high sensitivity level and meaning high information and low Ac means low sensitivity level and less information. But low Ac values could include features with high sensitivity.

From the results from the first and second investigation and from the previous discussions, it can be concluded that the ASM matrix can be helpful to evaluate how significant a sensor or a signal processing method is to a monitoring system. In addition, it can be employed to evaluate and compare the sensitivity of the monitoring system compared with other similar monitoring systems.

11.6 The Performance of the Pattern Recognition Systems

The sensitivity of a sensory characteristics feature to detect tool wear in turning processes for all the tools is investigated automatically using the automated Sudden Change In Value (SCIV) sensitivity detection method for the 8 sensors and 33 signal processing methods which represent the 264 SCFs. Two tools are selected arbitrarily for the analysis and the training of pattern recognition systems and testing the 20 tools. It is noticed that the sensitive characteristics features will indicate a fault by a significant change in their values. In order for the ASPST approach to be a useful methodology, the sensory characteristics features which are assumed to have a higher sensitivity to tool wear should result in better identification when it is tested by a pattern recognition system. On the other hand, the sensory characteristics features which are assumed to have a lower sensitivity to tool wear should result in poorer identification when they are tested by a pattern recognition system. For this purpose two pattern recognitions are used to test the system:

1. Learning Vector Quantisation (LVQ).
2. Novelty Detection Algorithm.

The details of the two pattern recognitions are briefly explained in Chapter 7, section 7.4. The parameters used in both pattern recognitions, LVQ and Novelty Detection, are selected to given a practical response. Nevertheless, it is significant to note that neither pattern recognitions are optimised for this application since the target here is to evaluate the systems to select the most suitable sensor and signal processing method. The implemented LVQ and Novelty Detection systems used in this research are programmed using Matlab toolbox.

11.6.1 Learning Vector Quantisation (LVQ) using High Sensitivity SCFs

The advantage of using LVQ is that it learns to classify input vectors into target classes chosen by the user. However, the learning rules are done according to the competitive layers depending on the distance between the input vectors and the weight and, unlike back propagation neural networks, not according to the error between the output and the target. Hence, there is no mechanism in the network to dictate whether or not any two input vectors belong to the same category. LVQ has an input layer, a competitive layer, and a linear output layer. The competitive layer learns to classify the input vectors to subclasses while the output linear layer transforms the competitive subclasses into the desired target classes. The parameters used are a learning rate 0.05, hidden layer size 50, training iteration 500 and bias time constant 0.99. The parameters are chosen in order to give a reasonable response. However, it is important to point out that the neural networks are not optimised for this application since the objective in this research is to compare systems in order to select the most appropriate sensors and signal processing methods. For more details see Chapter 7 section 7.4. Two tools are selected arbitrarily to train the LVQ neural networks. In addition, using one tool for the analysis and the training of the neural networks could be sufficient to give an excellent result, but in this test the purpose of using two tools is due to the mass of production in the industrial environment. Therefore, this will confirm that the ASPST approach is suitable for real industrial implementation purposes.

The SCFs from all tools are fed to the neural networks for testing. Figures 11.20 - 11.23 present the results of using the LVQ for detecting tool wear for all tools. For example, in Figure 11.20, the arrows show the maximum number of cuts for each tool (i.e. tool-life) until complete wear or failure. The number 0 means that the tool is in normal condition where 1 means that the tool is in worn condition. For example, for tool 2 the LVQ neural networks has identified that cut/sample 27 is the start of tool failure. However, the actual tool failure happened at 40 cuts/samples, as shown in Figure 11.24. For tool 3, the maximum number of cuts is 60, and failure is identified at sample 59. In addition, the maximum numbers of cuts in tool 19 are 87, and failure is identified at sample 86, as shown in Figure 11.25. The number of cuts/samples needed to produce a worn tool is significantly different for each tool. This proves that using statistical methods is not a suitable option. Also the system is successful in detecting tool wear before the end-of-life of the tool. The ASPST approach has been found successful in detecting tool wear. However, for tool 2, there has been early warning regarding the end of its life. When examining the signals, it has been found that there is less stability on the nature of the signal for tool 2. In addition, when examining the insert this explains the early warning. In some cases, unexpected wear or tool breakage does occur. However, the subsequent machining cuts could re-sharpen the tool and extend its life for a specific period before total failure. Because this approach presented in this work uses the ‘black-box’ concept (i.e. looking at the process signals and outputs without studying the intermediate tool conditions), it is difficult to confirm the conditions of the tool at every stage of the process.

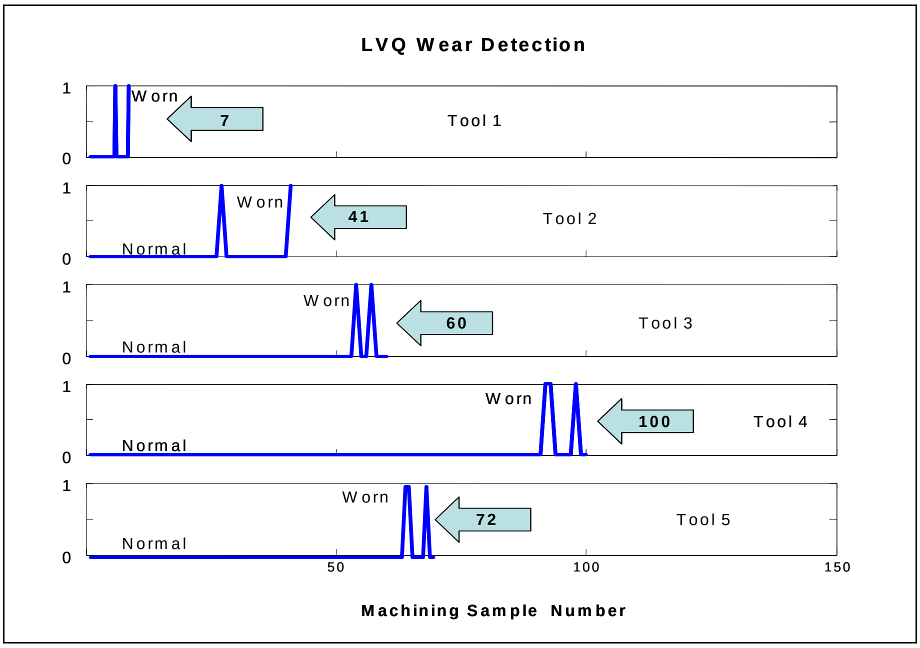

Figure 11.20: The result of the LVQ to detect tool wear (tools 1-5).

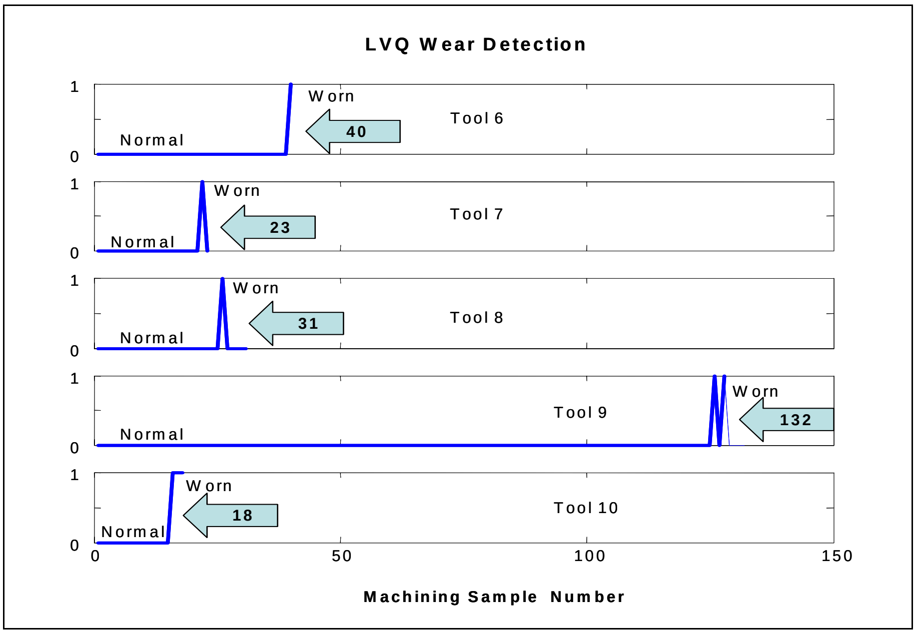

Figure 11.21: The result of the LVQ to detect tool wear (tools 6-10).

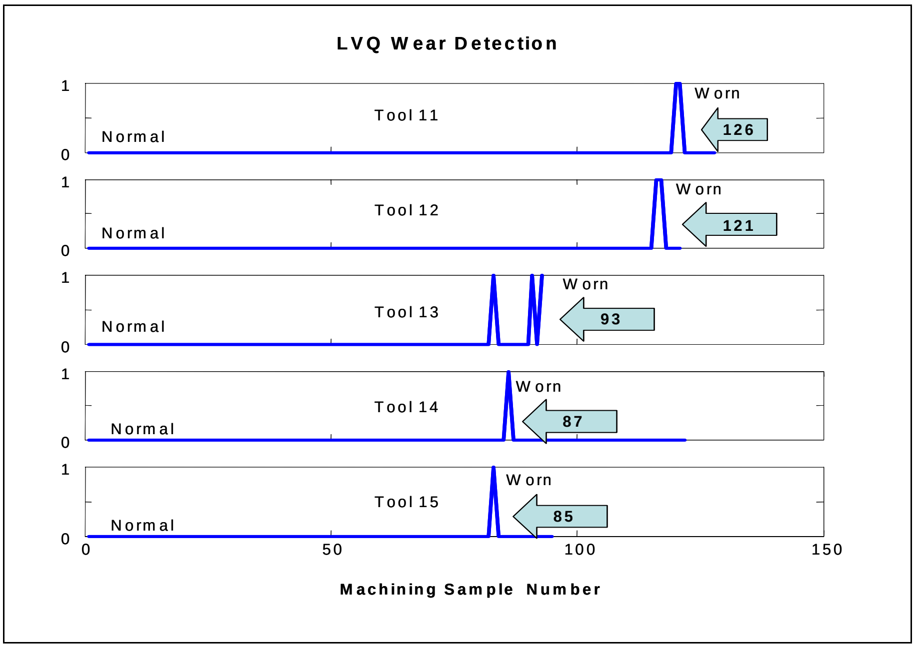

Figure 11.22: The result of the LVQ to detect tool wear (tools 11-15).

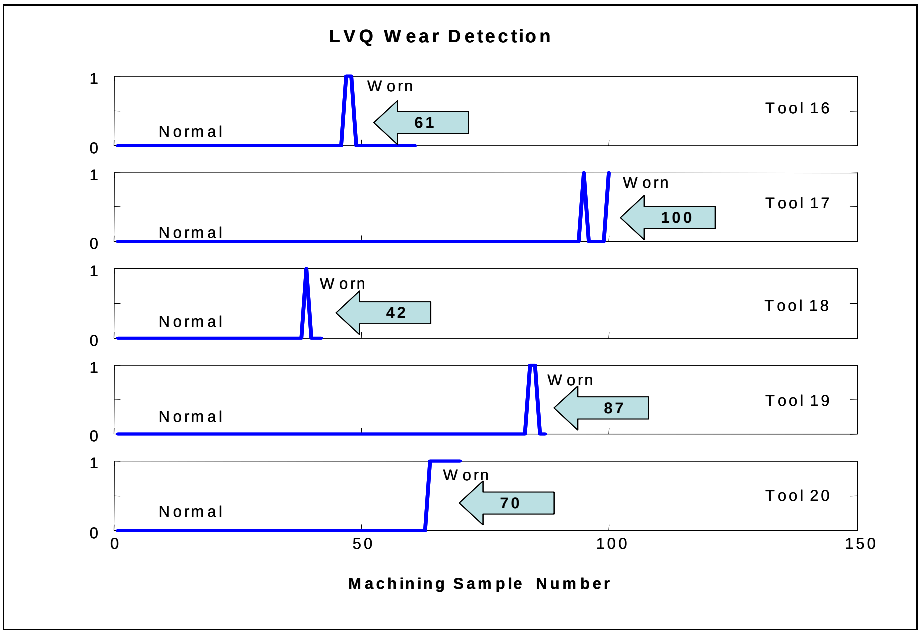

Figure 11.23: The result of the LVQ to detect tool wear (tools 16-20).

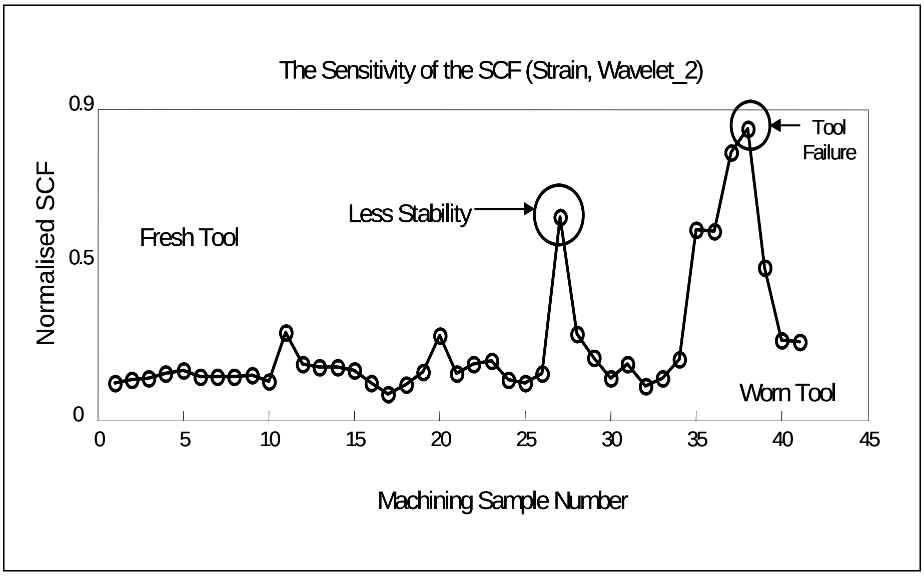

Figure 11.24: Sensory Characteristic Features of tool 2.

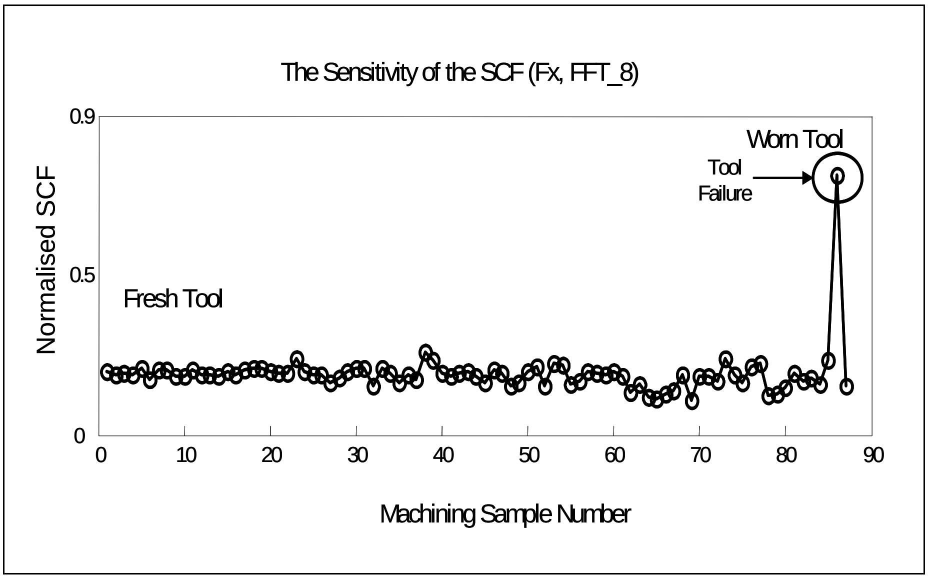

Figure 11.25: Sensory Characteristic Features of tool 19.

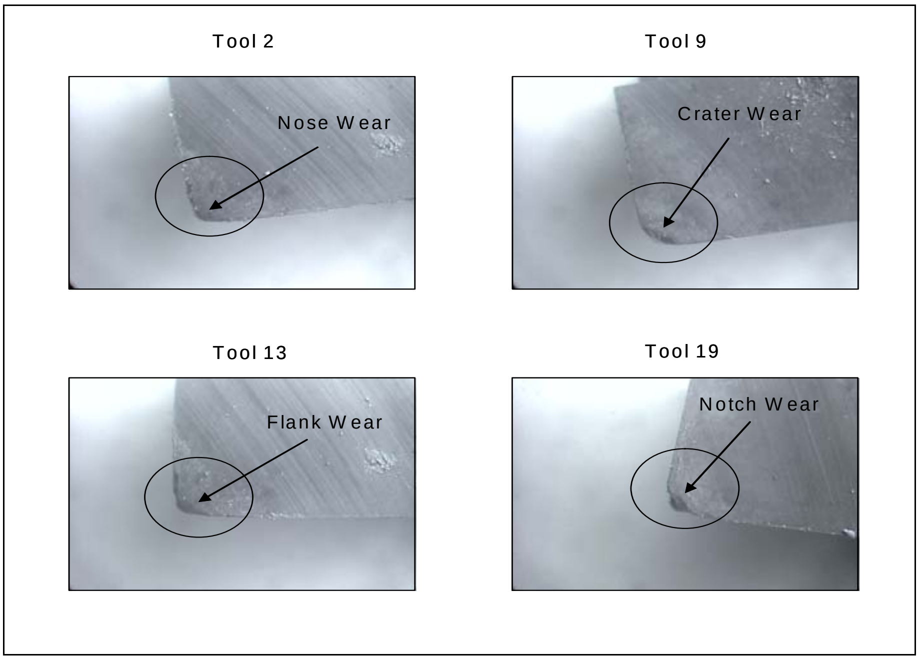

Figure 11.26: Top view of worn tool edges.

Figure 11.26 shows images of wear modes of four tools out of twenty as an example. It can be seen from the images that there are different wear modes. Nose wear and notch wear are the main failure modes for tools 2 and 19. Crater wear is the predominant failure mode for tool 9 and flank wear for tool 13. From the analysis and the images, it is concluded that the mode of the wear could play a major role in the result of the sensitivity level. In addition, the mode of the wear could affect the sensitivity of the feature as in tool 2 where there is less stability and re-sharpening of the tool. In addition, tool wear processes generally occur in combination with the predominant wear mode dependant upon the cutting conditions, workpiece and tool material and tool insert geometry. Therefore, the early detection could be due to tool geometry or chipping which is not an element of wear detection as are the rest of the cuts.

Looking at the above figures, it can be noticed that systems with high sensitivity levels produce better identification and less error. In addition, a system with high sensitivity levels will be steadier and have less average variation. Thus, it can be concluded that the higher the sensitivity level of the system, the better and more stable, the classification of the pattern recognition system. Therefore, the ASPST approach is found very useful in predicting the behaviour of condition monitoring systems. The result of the LVQ neural networks has proved that high sensitivity means better information for the neural networks.

11.6.2 Novelty Detection using High Sensitivity SCFs

Novelty detection is used in this work as a self-learning approach to characterise the "fresh" or normal state of the cutter. Novelty detection is a classification technique that recognises presented data as novel (i.e. new) or non-novel (i.e. normal). The details of the Novelty Detection are briefly explained in Chapter 7, section 7.4. The SCFs of all the 20 tools are then fed into a novelty detection algorithm to investigate the capability of the ASPST approach and the complete monitoring system. NETLAB software is used for the implementation of the novelty detection. The response of the Gaussian kernels ϕ_j is defined by a covariance matrix (a spherical matrix in this case) and a centre (i.e. the centroid of the input clusters). A single variance parameter for each Gaussian component is calculated using 6 centres in the mixture which has been found to be a suitable structure that gives a relatively quick learning process and consistent results.

Figure 11.27 shows the novelty detection result for tool 2. It can be seen that there is an early warning before tool wear detected. By comparing this with the results from the LVQ and SCFs of tool 2 as shown in Figure 11.20 and Figure 11.24, it can be seen that both systems show same detections. This proves that the utilisation of the SCIV automated method in ASPST approach is successful.

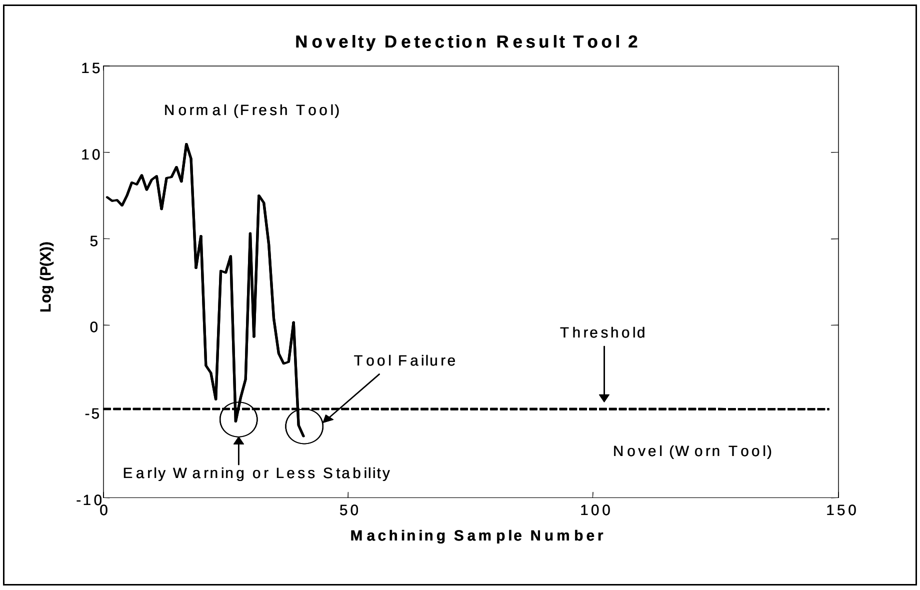

Figure 11.27: The result of the Novelty Detection of tool 2.

In addition, Figure 11.28 shows the novelty detection result for tool 19. Looking at Figures 11.23, it can be observed that the result of the LVQ shows gradual tool wear detection as well as the Novelty Detection result for the same tool (tool 19). Moreover, Figure 11.25 shows the SCFs of tool 19 which prove the results of the novelty detection.

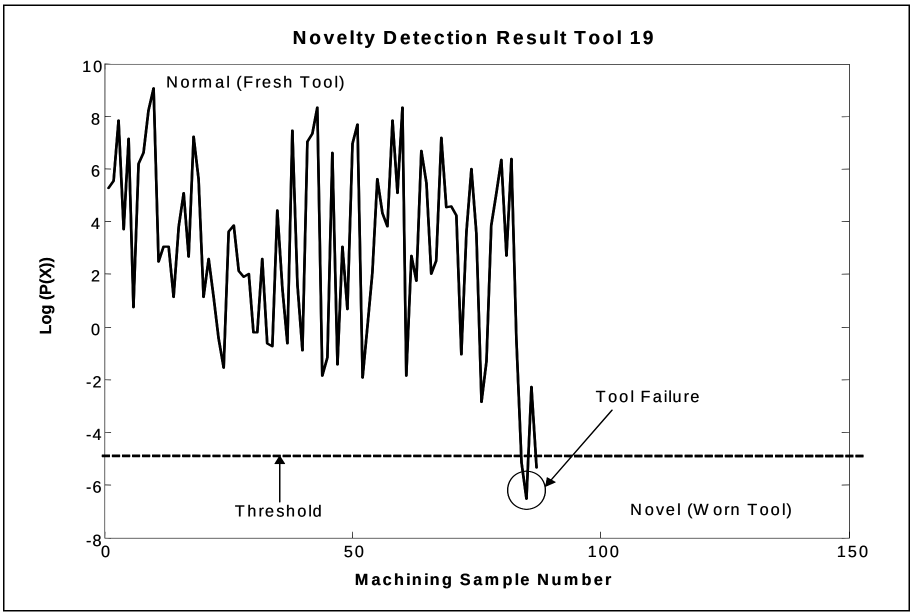

Figure 11.28: The result of the Novelty Detection of tool 19.

The above figures present examples of the Novelty Detection results that verify the utilisation of the Sudden Change In Value (SCIV) method in the ASPST approach, Figures 11.29 – 11.33 show the novelty detection results and include an analysis of the first 5 tools based on the sensory characteristics features for each system where the top 10 features are used. The tools used for analysis and training are tools 6 and 10 as for the LVQ neural networks. By selecting a suitable threshold value the success of the novelty detection algorithms is found 100%. Moreover, the threshold value could be selected for efficient wear prediction before the actual tool wear occurs. Figure 11.34 shows the novelty detection results for tools (1-5). The novelty detection results of tools 6-20 are shown in Appendix (B).

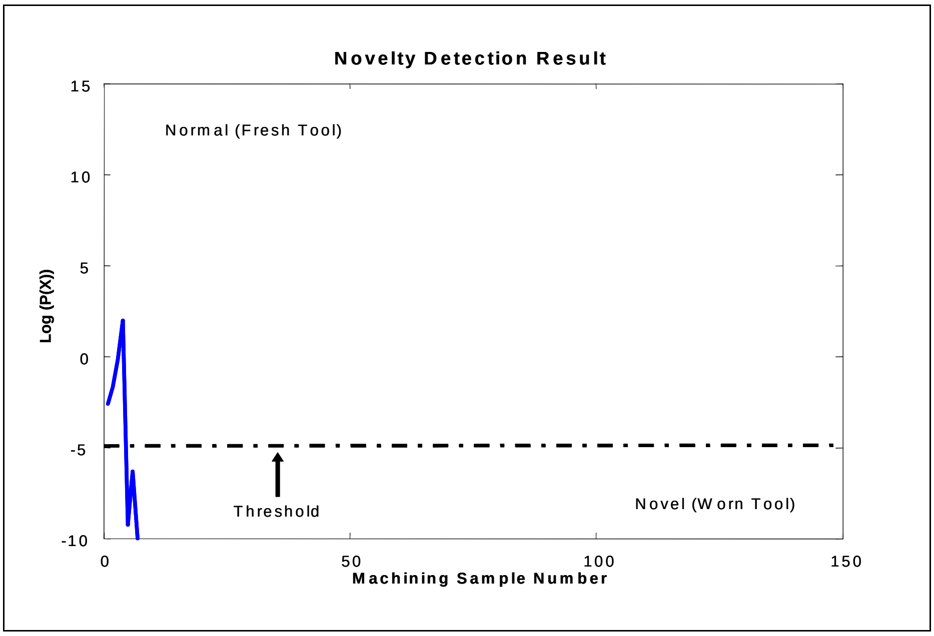

Figure 11.29: The result of the Novelty Detection (tool 1).

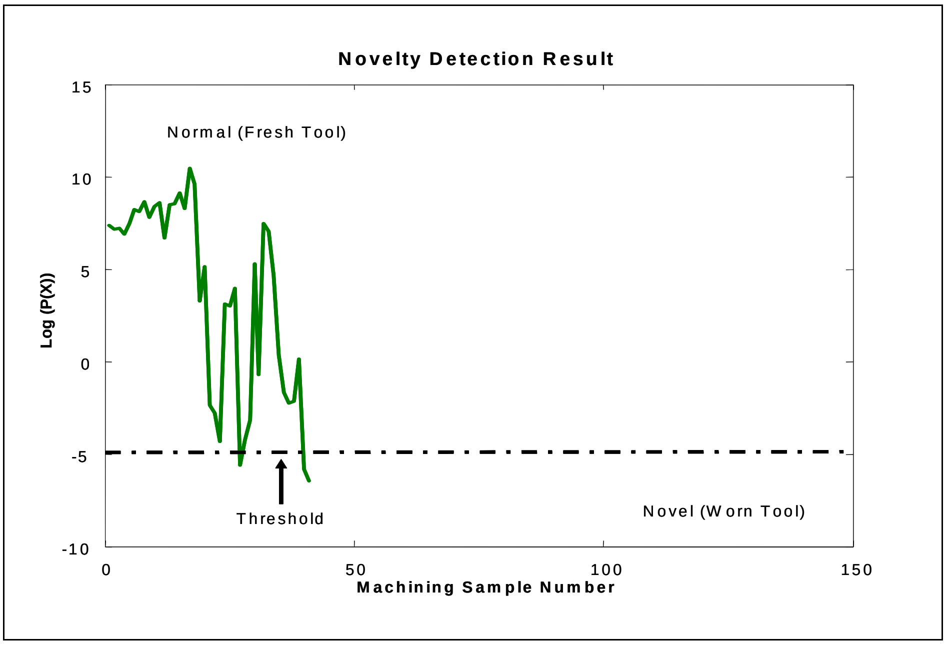

Figure 11.30: The result of the Novelty Detection (tool 2).

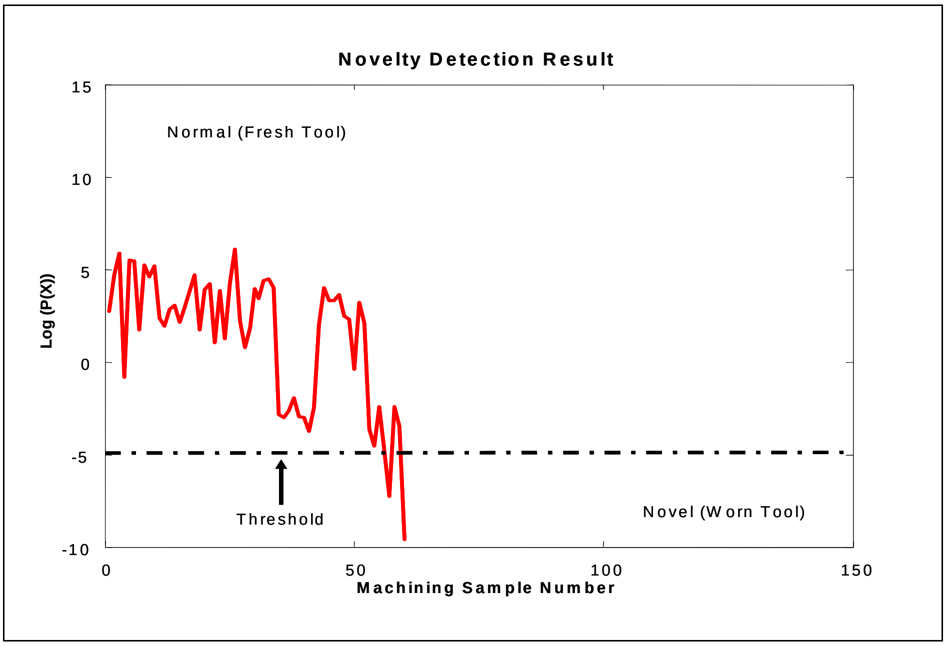

Figure 11.31: The result of the Novelty Detection (tool 3).

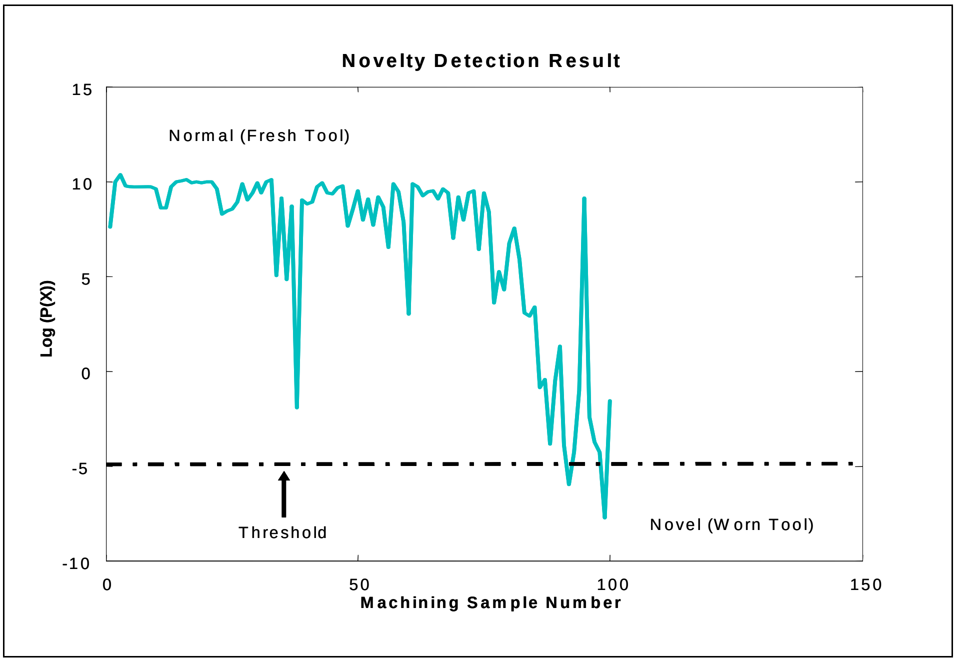

Figure 11.32: The result of the Novelty Detection (tool 4).

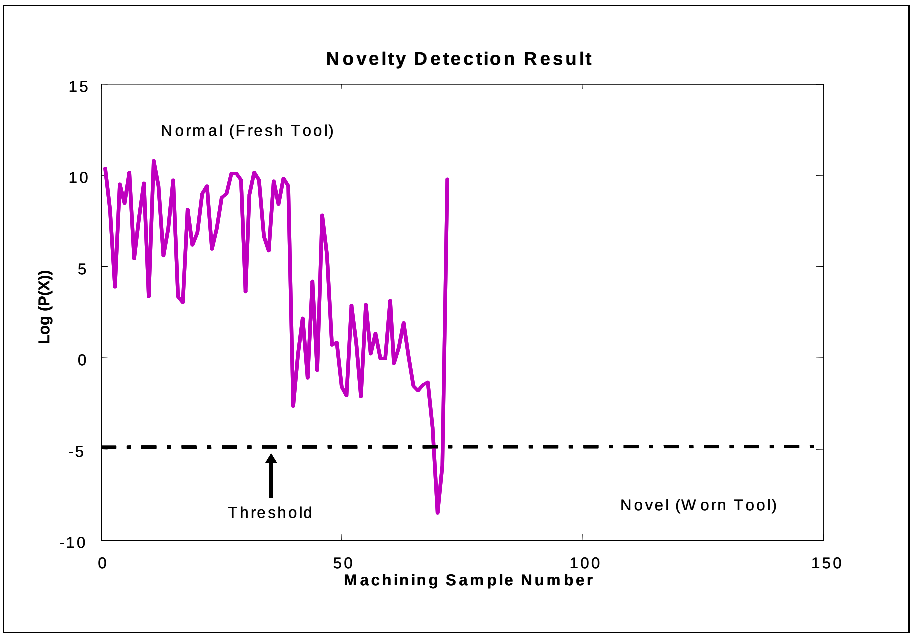

Figure 11.33: The result of the Novelty Detection (tool 5).

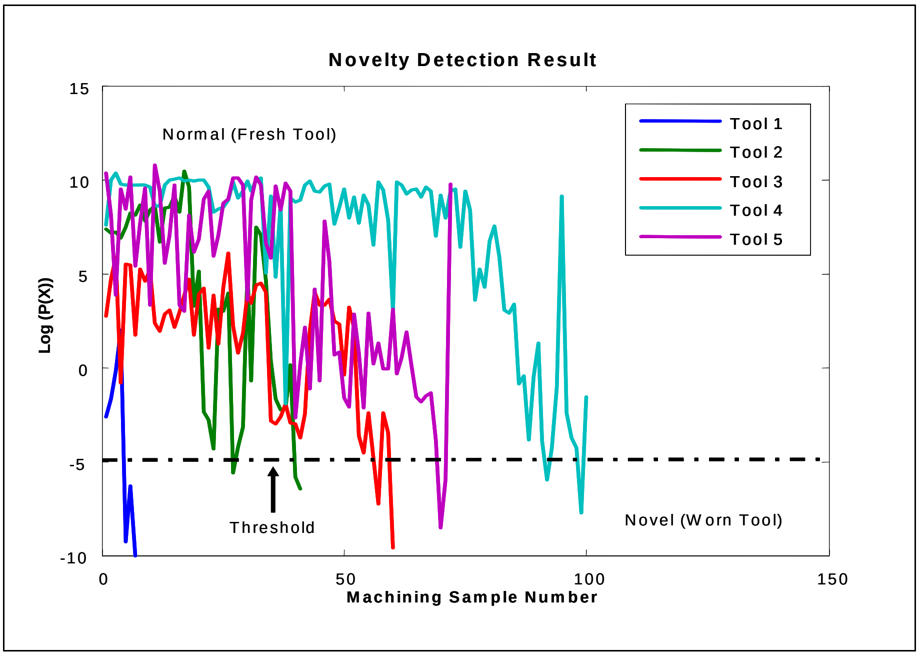

Figure 11.34: The result of the Novelty Detection (tools 1-5).

11.6.3 Learning Vector Quantisation (LVQ) using Low Sensitivity SCFs

The same method used in section 11.6.1 to test the neural networks is used here again. From the previous section, it is concluded that the sensory characteristics features with high sensitivity on the tool wear resulted in better identification when they are tested by LVQ neural networks. In this section, the sensory characteristics features from all tools with low sensitivity to tool wear are fed to the neural networks for testing. Figures 11.35 -11.38 present the results of using the LVQ for detecting tool wear for all tools. They include an analysis of all the 20 tools analysis based on 10 sensory characteristics features for each system where the last 10 features are used. The tools used for analysis and training are tool 6 and 10.

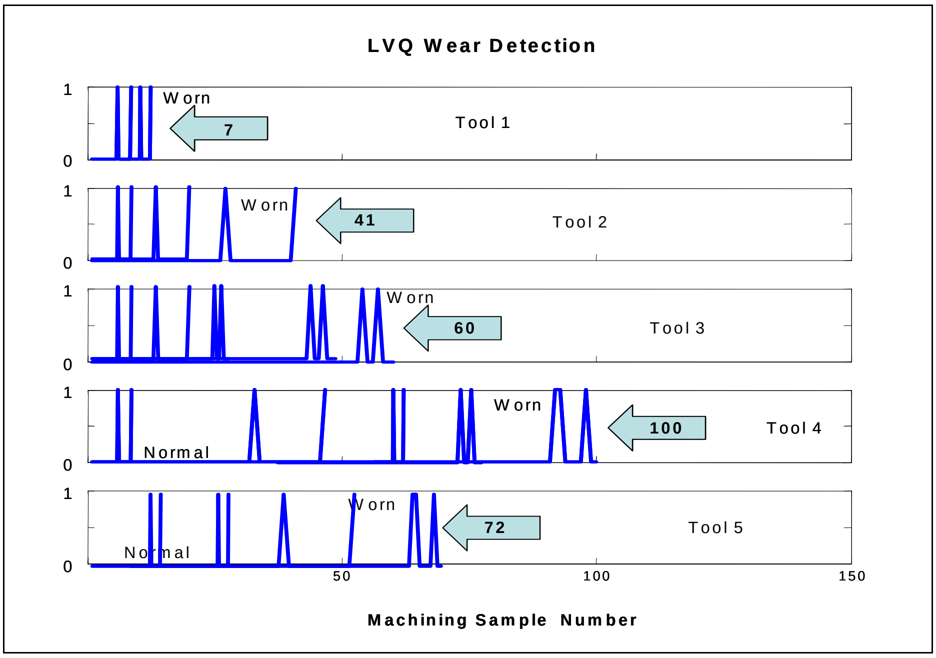

Figure 11.35: The result of the LVQ to detect tool wear (tools 1-5).

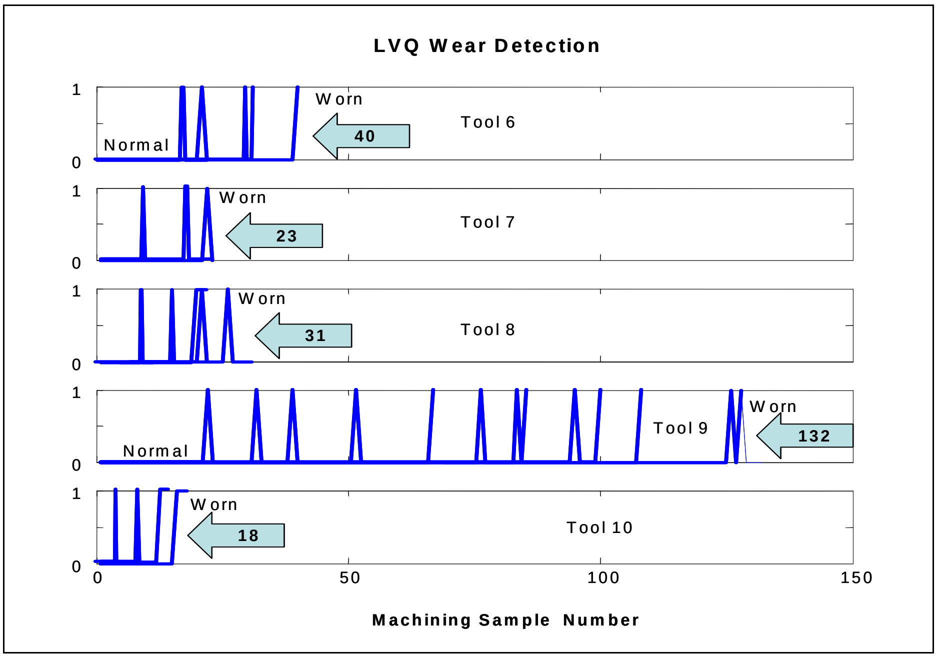

Figure 11.36: The result of the LVQ to detect tool wear (tools 6-10).

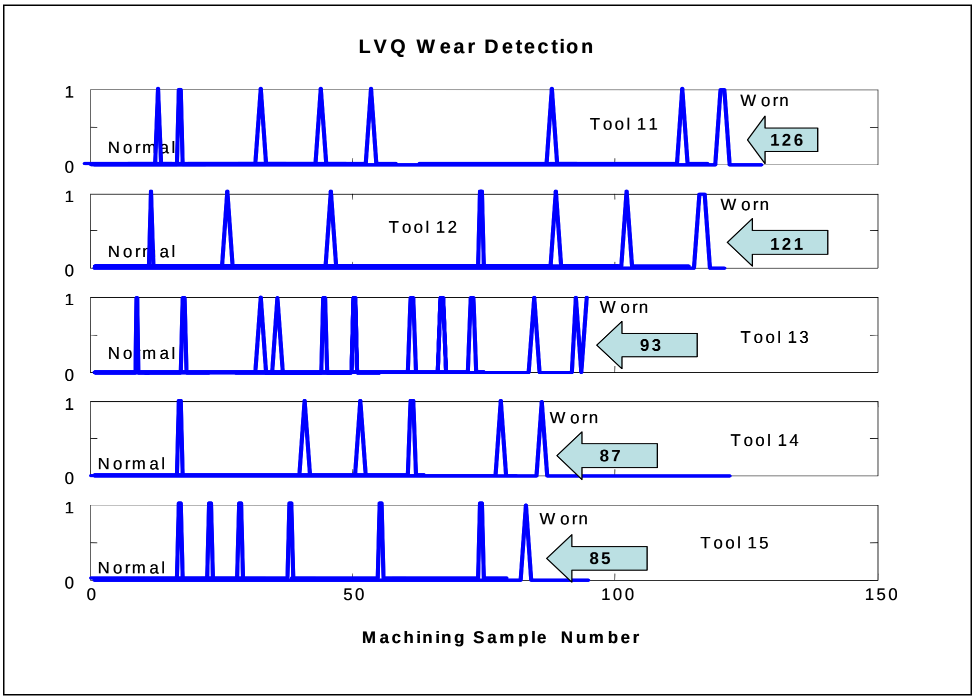

Figure 11.37: The result of the LVQ to detect tool wear (tools 11-15).

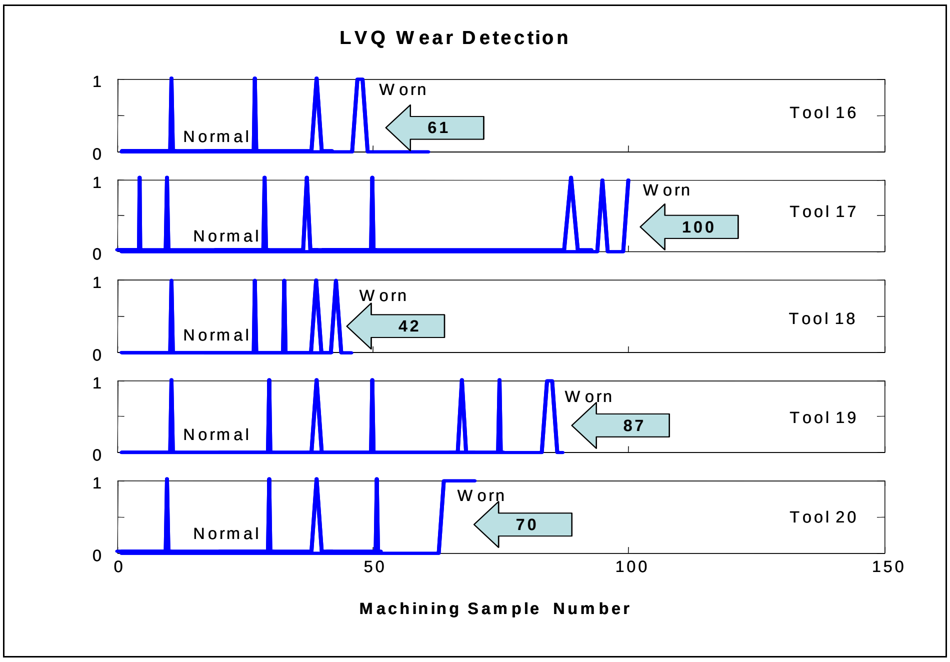

Figure 11.38: The result of the LVQ to detect tool wear (tools 16-20).

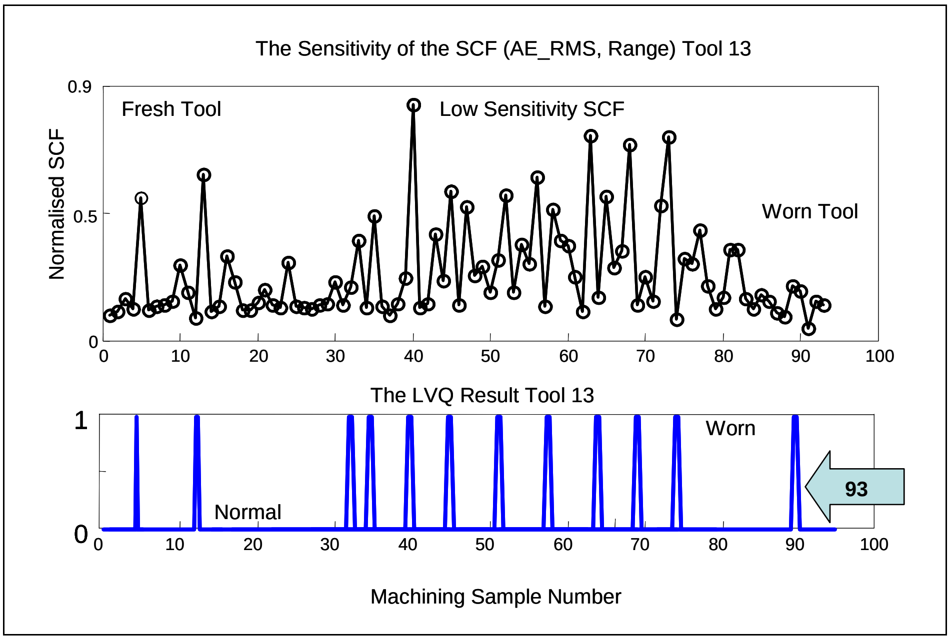

Figure 11.39: Comparison between low sensitivity SCF and LVQ result.

Figure 11.39 shows the comparison between the behaviour of the SCF (AE_RMS sensory signal and the range signal processing method) and the LVQ result for tool 13. This verifies that the utilisation of the Sudden Change In Value (SCIV) method as an automated detection method in the ASPST approach and the performance of the LVQ neural networks.

It can be concluded from the above figures, that systems with low sensitivity level produce bad recognition and more error. Furthermore, a system with low sensitivity levels will be unsteady and have more variation. Therefore, it can be concluded that the lower the sensitivity level of the system, the worse and less stable the classification of the pattern recognition system. Therefore, the ASPST approach is found very useful in predicting the behaviour of condition monitoring systems. The result of the LVQ neural networks has proved that low sensitivity means worse information for the neural networks.

11.6.4 Novelty Detection using Low Sensitivity SCFs

Figures 11.40 – 11.44 shows the novelty detection results. They include an analysis of the first 5 tools based on the sensory characteristics features for each system where the last 10 features are used. The tools used for analysis and training are tools

6 and 10 as for the LVQ neural networks. The previous figures are an example of the Novelty Detection results that verify the utilisation of the Sudden Change In Value (SCIV) method in the ASPST approach. Figure 11.45 shows the result of the Novelty Detection for tools (1-5). The novelty detection results for tools 6-20 are shown in Appendix (B).

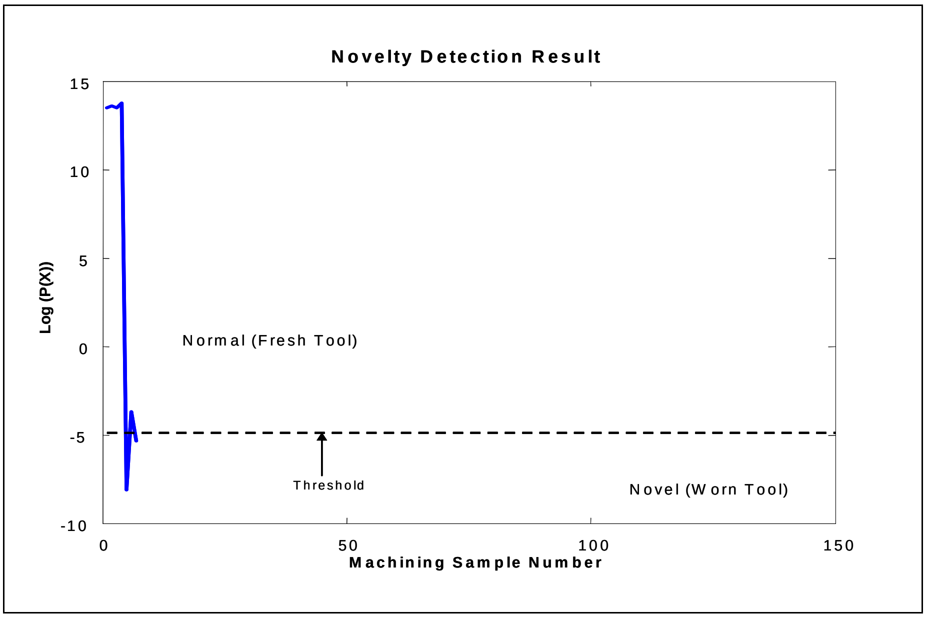

Figure 11.40: The result of the Novelty Detection for tool 1.

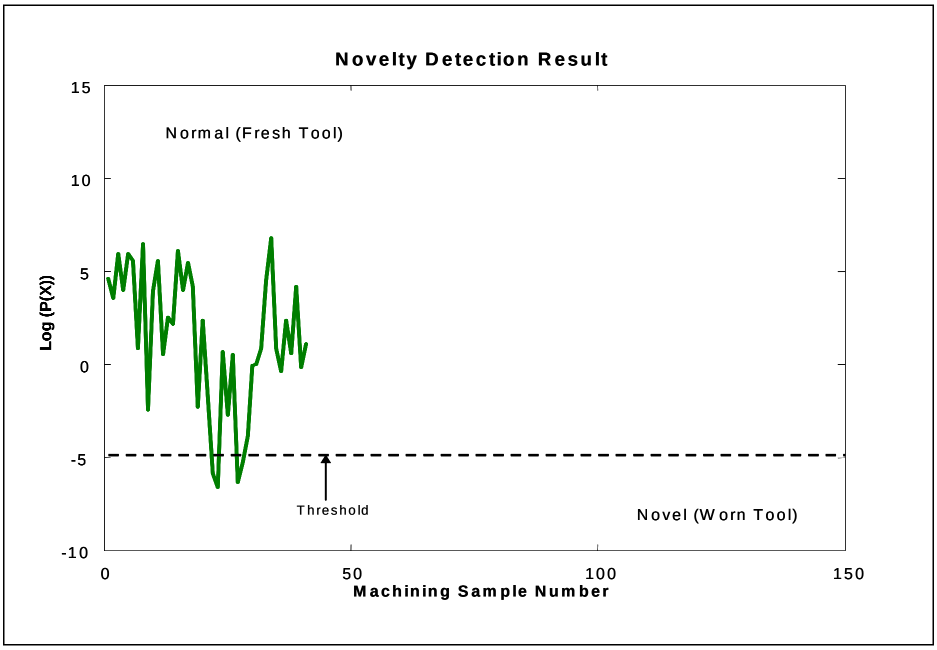

Figure 11.41: The result of the Novelty Detection for tool 2.

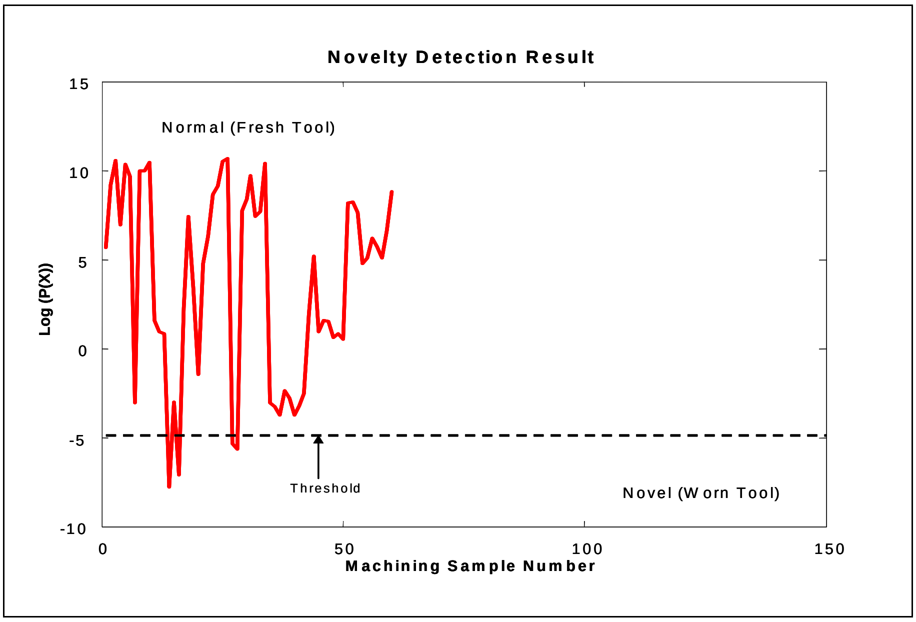

Figure 11.42: The result of the Novelty Detection for tool 3.

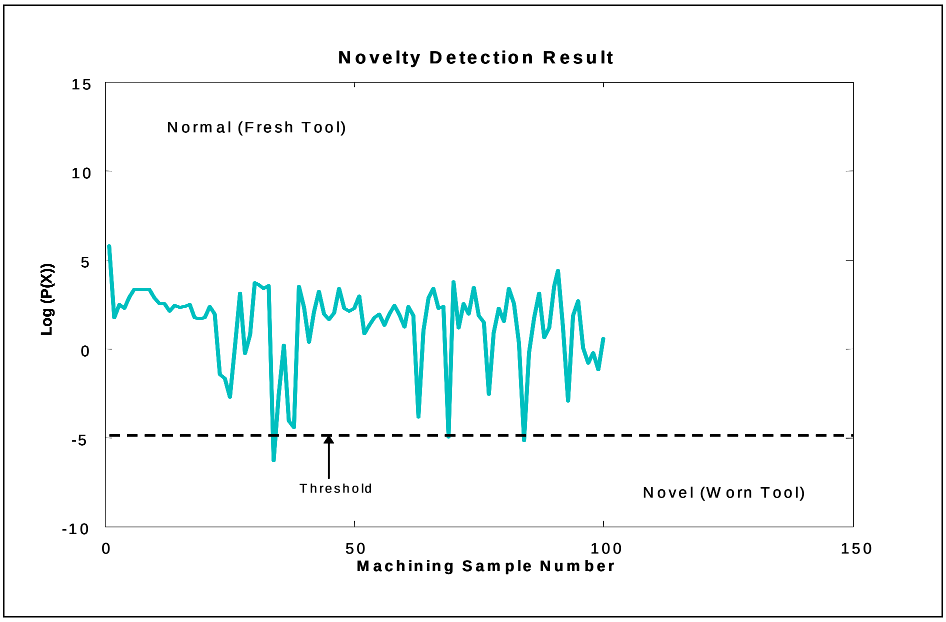

Figure 11.43: The result of the Novelty Detection for tool 4.

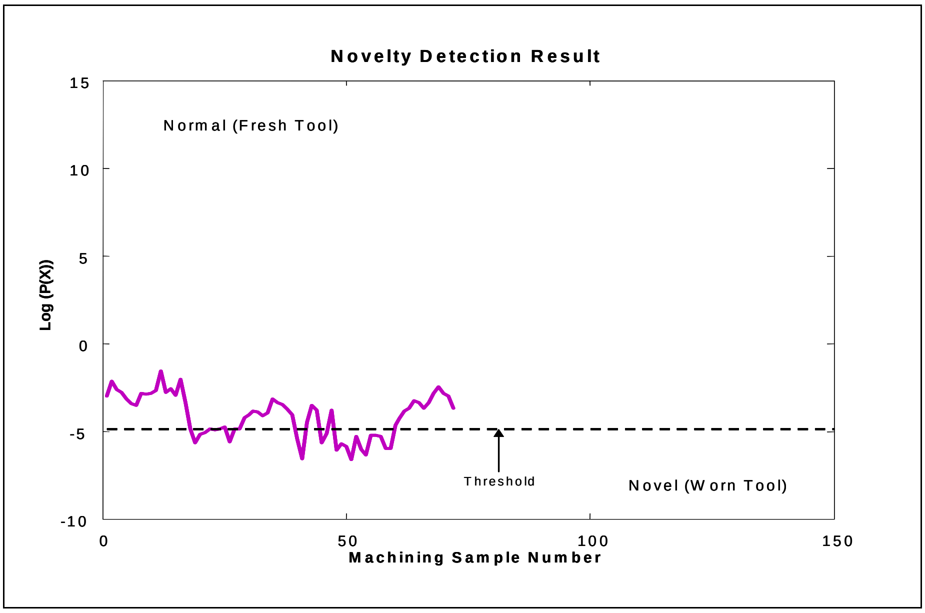

Figure 11.44: The result of the Novelty Detection for tool 5.

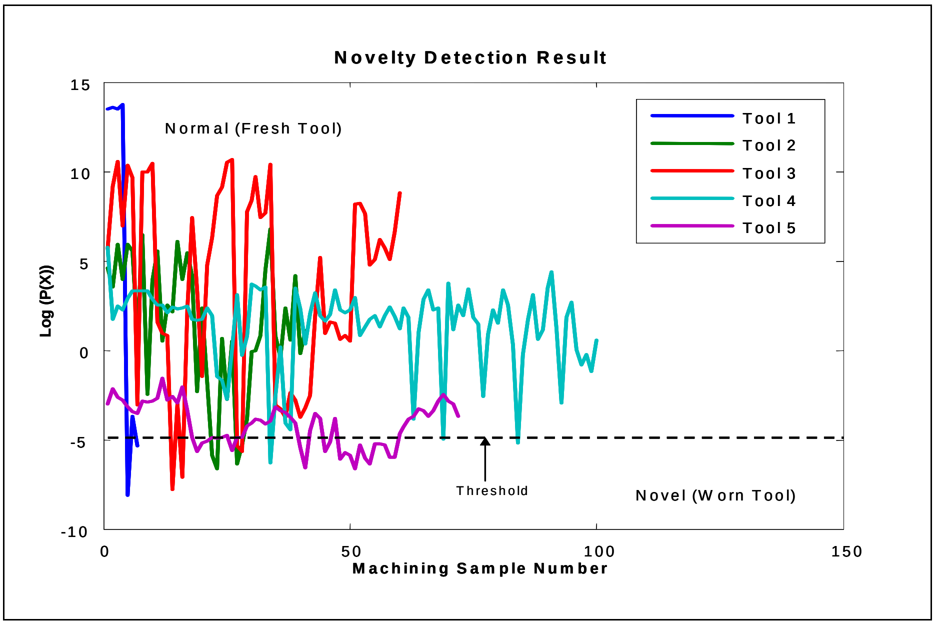

Figure 11.45: The result of the Novelty Detection for tools (1-5).

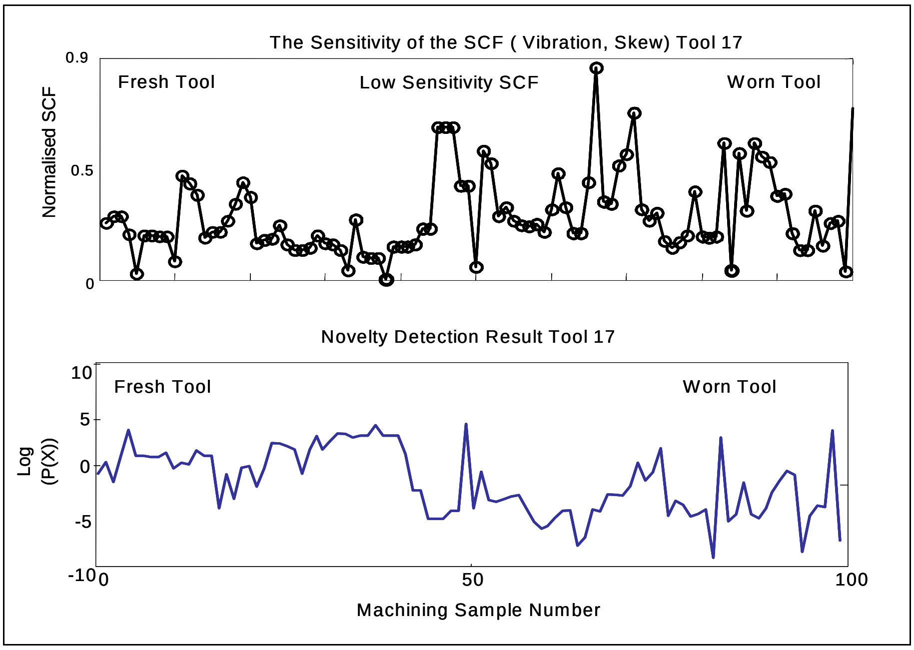

Figure 11.46: Comparison between low sensitivity SCF and ND result.

In addition, Figure 11.46 shows the novelty detection result for tool 17. The above figure is an example of the Novelty Detection results that verify the utilisation of the Sudden Change In Value (SCIV) method in the ASPST approach and the pattern recognition performance.

As shown in previous LVQ and Novelty Detection results, there is a clear trend that systems with high sensitivity values produce better identification, better information, and less error. In addition, systems with low sensitivity values produce worse identification, worse information and more error. Furthermore, for systems with high sensitivity the results are steadier. Therefore, it can be concluded that the higher the sensitivity of the SCFs, the better, and more stable, the classification of the pattern recognition system; and the lower the sensitivity of the SCFs, the worse, and less stable, the classification of the pattern recognition system. Therefore, the ASPST approach is found very useful in predicting the behaviour of condition monitoring systems. The results of the LVQ neural networks and Novelty Detection Algorithm have proved that high sensitivity means better information and low sensitivity means worse information for the neural networks. In general, the behaviour of LVQ neural networks and Novelty Detection has shown similar results for the twenty tools for both high and low sensitivity. Since the behaviour of both systems is found relatively similar, any one of them can be chosen for further analysis since it shows a stable and average performance.

11.7 Conclusion

This chapter has proved the full capability of the proposed ASPST approach. It has been used in this chapter to design a relatively effective and cheap system to monitor tool wear in turning processes. A wide range of sensor and signal processing method applications to evaluate the ASPST approach for turning processes has been presented. The sensors have been carefully chosen to evaluate the generality of the ASPST approach (i.e. dynamometer, strain, vibration, sound and AE). The presented work has included using a lathe machine to detect wear in a cutting tool when machining stainless steel workpiece.

The Associate Matrix (ASM) is constructed to choose the most sensitive sensory characteristic features to detect tool wear in turning processes based on a Sudden Change In Value (SCIV) analysis of the sensory characteristic features. Neural networks (LVQ) and Novelty Detection Algorithm are used to test and prove the capability of the ASPST approach.

System evaluation and cost analysis have been performed on the tool wear test to reduce the cost of the monitoring system without significantly affecting its predication capability based on the average sensitivity of the monitoring system. Based on the utilisation of sensors and the overall SCFs sensitivity it is possible to reduce the cost of the system.

The results presented in this chapter show that the proposed ASPST approach can be utilised to design a condition monitoring system in turning processes. In addition, the experiments show that the methodology described in this work can be used to reduce the complexity of condition monitoring systems and reduce the number of sensors required for tool wear in turning processes without compromising the systems ability to detect tool wear.

Chapter 12

Discussion and Conclusions

12.1 Introduction

This thesis has developed an effective sensor-fusion model for turning processes using a cost-effective methodology with reduced experimental work. Figure 12.1 shows a summary of the overall structure of the thesis. Chapter 1 presented an introduction to the research work. Chapters 2, 3, 4 and 5 presented the literature review for the problem domain under investigation. The scope of investigation, the aim of the thesis, the suggested ASPST approach and the elements of the implemented condition monitoring systems, were presented in Chapters 6 and 7. Chapter 8 described the general experimental set-up and the details of the ASPST approach and its implementation for turning processes were presented in Chapters 9, 10 and 11.

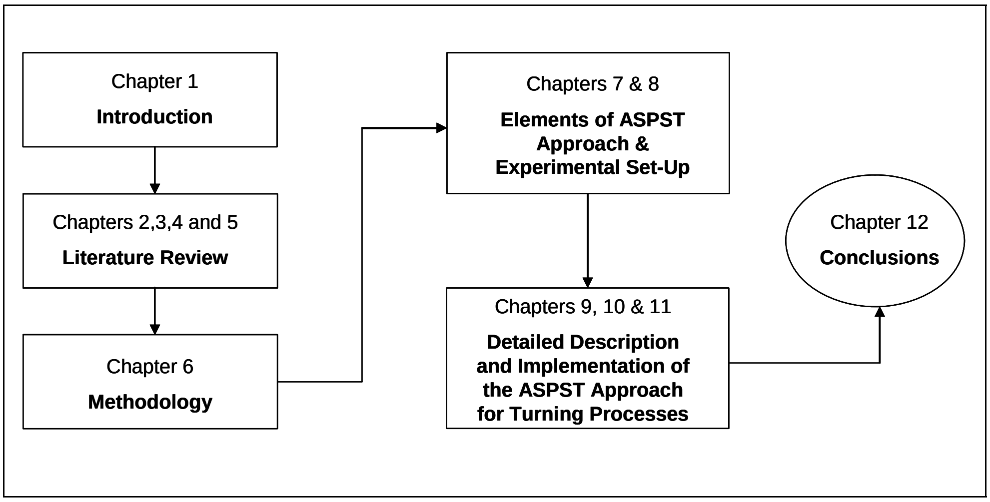

Figure 12.1: Summary of the overall structure of the thesis.

This chapter provides a summary of the thesis and a discussion of the results obtained in this work. It describes how new knowledge has been produced and tested. It contains the contribution to knowledge, outstanding problems, testing and findings. Moreover, it presents general conclusions and suggested further work.

12.2 Quantifiable Objectives

The aim of this research is to develop an effective sensor-fusion model for turning processes using a cost-effective methodology with reduced experimental work. This aim has been accomplished by the selection of the most effective and suitable sensors and signal processing methods and achieved by the following steps:

- Simplification of complex signals by transferring the complex sensory signals automatically into simplified forms (Sensory Characteristic Features, SCFs).
- Automated sensitivity detection by assessing the extracted SCFs automatically for their quality of information.
- The selection of a specific number of sensors and signal processing methods based on their associated SCFs to produce the required monitoring system.
- Reducing the cost of the monitoring system by eliminating any sensor which comparatively contributes to a limited number of SCFs compared with other sensors used in the system.

The above steps has been performed with taking into consideration the industrial environment of self learning or by using reduced experimental tests; and the design of the process is based on the inputs and outputs of the system rather than by studying the mechanics of the process.

12.3 Discussion

The applicability of the suggested approach has been demonstrated with respect to the condition monitoring of turning processes. A wide range of sensors were installed to investigate the applicability and capability of the ASPST approach for turning processes. Force, strain, acceleration, acoustic emission and sound sensory signals were used to design and develop the condition monitoring systems. The signal processing methods used included: standard deviation; range; mean; maximum; minimum; power; kurtosis value; skew value; Fourier transformation; and wavelet analysis. For more details of the experimental tests, see Chapters 9, 10 and 11.

The main steps to verify the ASPST approach were explained and verified in Chapter 9. Furthermore, Chapters 10 and 11 provided more experimental tests and analysis in order to confirm the capability of the ASPST approach. This methodology is based on ASPS [47] approach, but it has been implemented in turning taking into consideration all the required modifications and improvements.

12.3.1 Automated Simplification Method

Simplification was introduced by processing all the sensory signals produced within a period of time by using a wide range of signal processing methods to produce an adequate number of sensory characteristic features (SCFs) automatically. The signal processing and simplification techniques were selected so that the SCFs produced real numbers. The simplification process was successfully implemented for all sensory signals using the selected signal processing method. The SCFs were placed in a three-dimensional matrix called the Sensory Feature Matrix (SFM), where every two dimensional parts presented the SCFs of a machining sample. Figure 12.2 presents a schematic diagram of the automated simplification process.

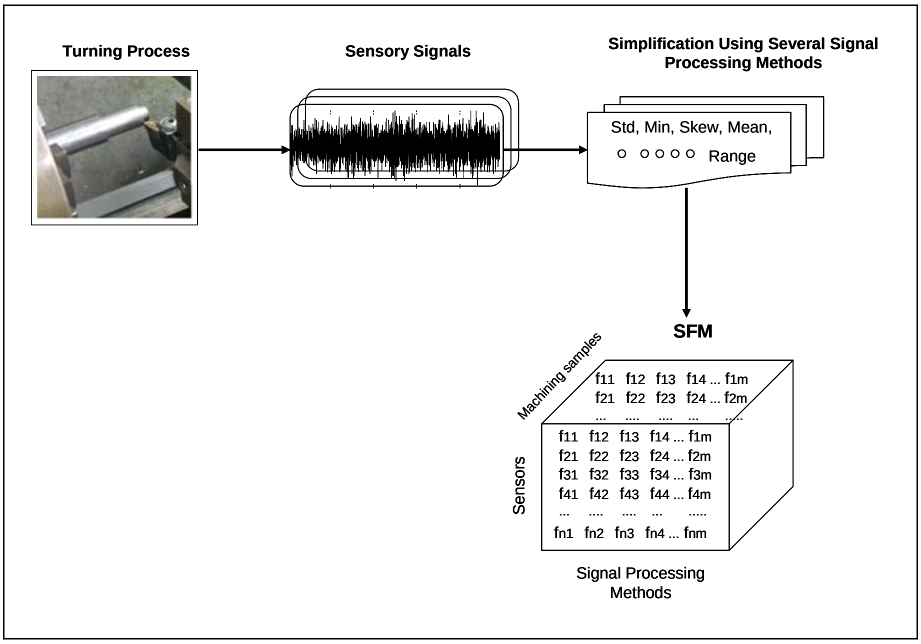

Figure 12.2: The automated simplification process.

This stage has successfully moved the complex signals into more simplified SCFs to look for the required information for the condition monitoring system. The SCFs were extracted for all the experimental tests. For more details of the simplification method, see Chapter 9 section 9.3.

12.3.2 Automated Sensitivity Detection Method

The research shows that the Sudden Change In Value (SCIV) analysis method is a useful automated method for detecting the sensitivity of the SCFs contained in the SFM matrix. In Chapter 9, the sensitivity of SCFs to the gradual tool wear was inspected visually and compared with the Sudden Change In Value (SCIV) analysis method. It shows that sensitive SCFs which show significant change in their levels due to gradual tool wear, have relatively high value with the Sudden Change In Value (SCIV) method. Similar results for the other experimental tests were introduced in Chapters 10 and 11. The sensitivity of the SCFs of all experimental tests was visually tested to confirm that the Sudden Change In Value (SCIV) method is an appropriate method to measure the sensitivity of SCFs. The reader has been provided with a limited number of low sensitivity and high sensitivity SCFs of every test due to the high number of SCFs produced in all the experiments.

12.3.3 The Selection of Sensors and Signal Processing Methods.

Sensor and a signal processing method were used to produce a SCF. When a SCF is found sensitive to a fault it can be concluded that its related sensor and signal processing method should be chosen for the monitoring system. The sensitivity coefficients were used to make another matrix, named the Association Matrix (ASM). The ASM is a two dimensional matrix which includes the sensitivity values of all the SCFs obtained using the initial sensors and signal processing method. The SCFs with high sensitivity should be selected for the design of a condition monitoring system. The most sensitive 10 SCFs were selected to form the foundation of the monitoring system. Therefore, the related sensors and signal processing methods could be chosen as the most sensitive and appropriate tools to design and develop the monitoring system.

12.3.4 Cost Reduction

The cost of the monitoring systems, based on the previous step, was calculated by adding the costs of the selected sensors and their conditioning devices. Cost reduction was performed based on removing sensors which contribute to a relatively small number of SCFs into the system. A limited number of SCFs was removed from the selected system of SCFs and exchanged with other sensitive SCFs from the sensors which were already in the system. The Sensor Utilisation factor (*SU*) is found helpful in identifying the least utilised sensors within the monitoring system for the removal process. The cost reduction step was found useful in all the experimental tests in reducing the cost of the system without significantly affecting the sensitivity of the monitoring system.

12.3.5 System Evaluation

The Association Matrix (ASM) matrix can be used for evaluation, based on the sensitivity values, the overall sensitivity of the set-up and the average sensitivity of every sensor and signal processing method. It was found that the ASM matrix includes useful general information to rapidly compare signals and signal processing methods and to evaluate how useful they can be to a condition monitoring system. See Chapter 11, section 11.5 as an example.

12.4 Contribution to Knowledge

It is a difficult task to find an on-line monitoring method which exactly determines tool condition during turning operations. The use of ASPST approach for continuous monitoring seems to have as a real-time and data trainable system that does not require any mechanical or mathematical model of the machine tool. The main contribution of this thesis is in developing a structured and effective sensor-fusion model for turning processes with reduced cost and experimental work. The development of the approach includes several conceptual and technical contributions. These contributions can be summarised as follows:

12.4.1 Conceptual Contributions:

The suggested approach includes the following conceptual contributions for the development of condition monitoring systems for turning processes:

1. The ASPST approach has been suggested which takes the ASPS [47] approach into a new dimension and different application.
2. The flexibility and generality of the suggested methodology is based on the inputs and outputs of the turning process rather than an investigating the

mechanics of the process and fault mechanisms. Thus it is possible to apply this methodology to turning processes.

3. The sensor fusion concept had been broadly investigated in previous research in condition monitoring and confirms that the implementation of more than one sensor could increase the detection reliability of the system. This thesis justifies the previous research by affirming the sensitivity concept of the features and the average sensitivity of a system.
4. The suggested approach does not require any manual or visual examination of the sensory signals searching for information. An automatic search for information has been proven to be achievable by using automated sensitivity detection techniques.
5. The proposed tool wear estimation method, ASPST approach, is generic general enough to extend its application to other sensor-based monitoring problems in manufacturing.

12.4.2 Technical Contributions:

The ASPST approach consists of several new or modified techniques for implementing the design methodology:

1. An automated simplification technique has been implemented for turning in this thesis to transfer complex signals into a group of simplified SCFs. This simplification technique which uses a wide range of signal processing methods enables an automated search for information by calculating the sensitivity values.
2. Automated sensitivity detection has been introduced by using the novel Sudden Change In Value (SCIV) analysis method. The Association Matrix (ASM), which includes the sensitivity values of the SCFs to machining faults are used to simplify the analysis and systematically select sensitive sensors and, a signal processing method for the design of a condition monitoring system.
3. The utilisation and comparison between the following automated detection methods:

- The Range Value method (RV).
- The Linear Regression Slope method.
- The Sudden Change In Value methods (SCIV).

4. Comparison between high sensitivity and low sensitivity systems.
5. A novel approach using dynamic threshold is utilised to improve the accuracy of the novelty detection system:

$$\bar{X}_t = \frac{1}{n}\sum_{i=0}^{n-1}(x_t - i)$$

6. The sensor utilisation factor was implemented in turning to reduce the cost of monitoring system. It has been used to evaluate the contribution of every selected sensor in the monitoring system and to eliminate sensors with a relatively limited contribution.
7. The system has been implemented in real-time and several extensive experiments were conducted to verify and validate the performance of the ASPST approach.
8. In this research a wide range of the state-of-the-art sensors, force, vibration, strain, acoustic emission and sound, are proposed and installed as the sensors for on-line monitoring system
9. The ASPST approach uses novelty detection and LVQ neural networks as they require less training time compared to other neural networks and has been tested with satisfactory results.

12.5 Final Conclusion

The main aim of this research work is to develop an effective sensor-fusion model for turning processes using a cost-effective methodology with reduced experimental work. This has been achieved and successfully tested. A systematic approach, named ASPST (Automated Sensor and Signal Processing Selection System for Turning), has been introduced to develop an effective sensor-fusion model for turning processes. This system will help to find the most sensitive sensors and signal processing methods for use in a condition monitoring system. The approach does not use any theorises methods in developing the system and it is also combined with a new procedure to reduce the cost of the system without significantly affecting its prediction consistency. The experimental results of this research work have shown, with clear consistency, that this approach has been successful in developing a condition monitoring system for turning processes without the need for involvement in the actual mechanics of the process or the mechanism of the faults.

12.6 Research limitation and Further Work

Due to the time limitation involved in completing this research, further work is still needed. It is believed that the following areas need to be considered in more detail in developing an ASPST approach:

1. The suggested methodology has been only tested for one type of fault (gradual tool wear). More experimental estimations of the approach for other industrial faults such as breakage, collision, and chatter could be done.
2. Fixed cutting conditions were selected during the evaluation of the approach. Thus, several cutting conditions could be selected for a more complete evaluation of the approach.
3. The suggested approach has been only tested for one type of insert and one type of material. Different inserts and material types could be tested using the ASPST approach.
4. Limited numbers of sensory signals were utilised. The approach could be evaluated using more signal processing methods types and other of sensors such as infrared sensors.
5. Limited numbers of pattern recognition systems have been implemented and greater investigation on optimising pattern recognition systems and performance comparisons are still needed. This could lead to changing the proposed number of SCFs in the designed system.

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Appendices