CHAPTER 1

Introduction

1.1 Background

Economic forces drive the need for high availability of machining equipment, and demands high quality of machined parts. Tool Condition Monitoring (TCM) is a means to this end. Through the optimised use of cutting tools and process monitoring, TCM supports this trend of economic forces. A spin off of TCM is of course the potential for substantial cost savings in terms of less scrapped parts and more efficient use of expensive machine tools. The lack, on the other hand of a proper TCM may include excessive power take-off, inaccurate tolerances, serrations and an uneven workpiece surface finish. This may eventually lead to machine tool and/or machine peripheral damage, according to Dimla (2000). Research into these systems has been continuing for some time now and as sensor and computing technology have advanced, their presence is starting to be felt in industry. To quote Byrne et al. (1995):

> *Despite the huge amount of research, not many of these strategies for TCM have found their way into commercial products. This is mainly due to the following:*
>
> - *The nature of machining processes, which can be complex and chaotic.*
> - *Non-linear relationships between tool wear and process parameters.*
> - *Changes in sensor signals due to tool wear are very small in some cases.*
> - *An adequate sensor that can satisfy all the requirements for TCM does not exist yet.*
> - *A number of different tool wear modes exist which cannot always be monitored with the same strategy.*

The above quote is given from an international perspective. In a small country like South Africa this lack of TCM is even more apparent. According to Scheffer (2003), South Africa does not have any commercial tool condition monitoring systems currently installed anywhere in the country. The reason for this is that manufacturers consider the currently available systems still too unreliable and/or too expensive. The need for cheap and efficient TCM systems is clear. Scheffer et al. (2003) developed such a system and have proved it to be both effective and cheap. As research progresses, more and more techniques become available for process modelling and monitoring. This forces us to review our current methods and explore new options that are made available as time progresses. This dissertation will do just that, and explore TCM using hidden Markov models.

The methods used in this dissertation belong to the continuous, indirect methods of TCM. There exist a number of philosophies on how TCM should be done. The first two schools of thought are continuous and intermittent TCM. The former advocates that monitoring should be done continuous, while the latter encourages monitoring at intervals (e.g surface finish of every 10th component manufactured). The next level of separation is that of the type of monitoring scheme used, direct or indirect. Direct monitoring is concerned with volumetric loss at the tool tip. This may be done by electrical sensing methods or visually. Indirect methods seek patterns in sensor data from the process, e.g. torque on spindle increasing when a cutting tool becomes blunted. A taxonomy is presented in figure 1.1, which should give a brief overview of some methods in TCM. Most research in TCM have gone into continuous systems and only the continuous branch is expanded in the figure.

Various authors (Byrne et al. (1995); Scheffer and Heyns (2001) and Leem and Dornfeld (1996)) state that the establishment of a TCM system can be divided into a number of stages:

1. Sensor selection and deployment
2. Generation of a set of features indicative of tool condition
3. Classification of the collected and processed information to determine the amount of tool wear.

In the next three subsections, these stages will be elaborated on.

1.1.1 Sensor selection and deployment

Byrne et al. (1995) has described the requirements for a tool condition monitoring system. This is listed in table 1.1 on the selection and deployment of sensors for TCM.

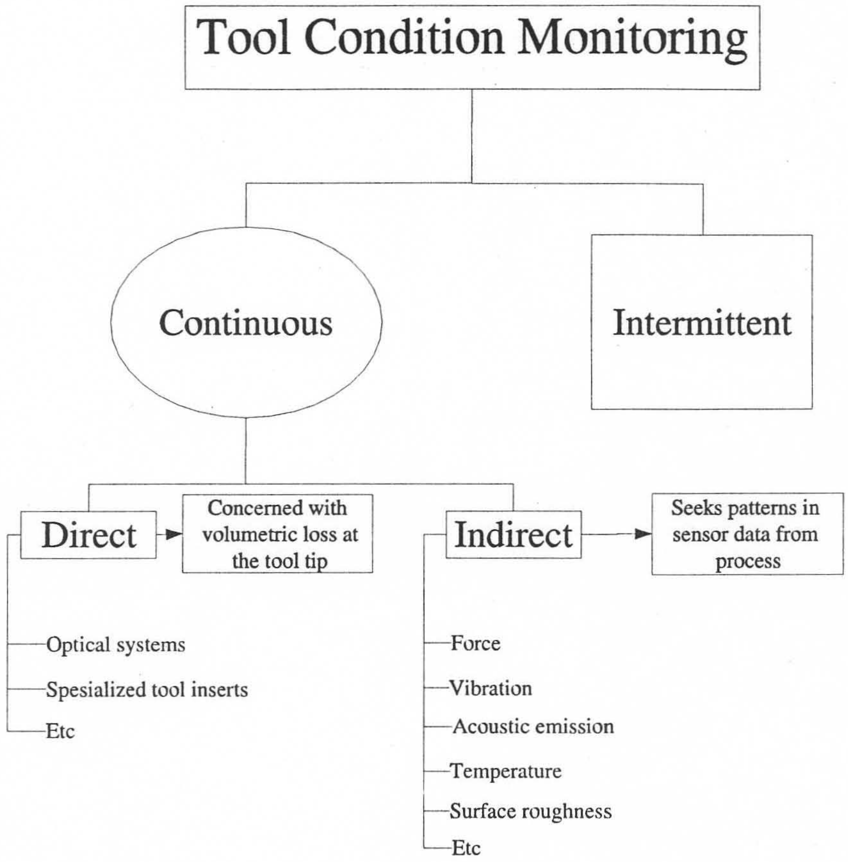

Figure 1.1: A taxonomy of continuous tool condition monitoring systems

Table 1.1: Requirements of a TCMS

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

Table 1.1 puts in full view what is ideally expected of a sensor and how it should be employed. A real sensor system will always end up as a trade-off between performance and cost.

1.1.2 Generation of features sensitive to tool wear

This subsection deals with the generation of suitable features that are indicative of tool wear and will be continued in the next chapter on the theory of feature extraction and selection. Features are also referred to as monitoring indices. This requires that one keeps in mind the disadvantages of using certain sensors on a TCM-system (e.g. the reduction in stiffness of the tool holder when using a dynamometer). Some common monitoring indices are listed in table 1.2

Table 1.2: Common features for TCM

Common Features
Mean
Variance
Root mean squares (RMS)
Skewness
Kurtosis
Crest factor
Power in a specific frequency band
Auto Regressive (AR) and Auto Regressive Moving average (ARMA) coefficients
Wavelet packet energy

Sensor fusion is also applied in order to get the most from the measured data. During sensor fusion the signals from different sensors are combined. According to Dimla (2000), sensor fusion serves the following purposes:

- Enhances the richness of the underlying wear-level 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 another.

1.1.3 Classification of signals to establish tool wear

In this stage a signal model classifies the features from the collected data to obtain a useful conclusion about the tool life. This is a decision making technique. There are a variety of methods, which include trending, threshold and force ratios methods. One such is by Choudhury and Kishore (2000) who used different force ratios. Artificial intelligence (AI) approaches, however are arguably the most popular method currently used for signal classification. Park and Kim (1998) provide an introduction and a review of the use of AI. Broadly, the methods of classification can be put into two categories:

1. Weighting methods. Which include:
    - Neural networks (NN). This seems to be the most popular method because of its robustness to noise and its ability to handle more than one simultaneous input and to extract underlying information. An excellent review of online and indirect tool wear monitoring methods with artificial neural networks was done by Sick (2002).
    - Fuzzy logic. Fuzzy systems have the advantage of being able to directly encode structured knowledge. A number of fine articles can easily be found on the web. One such is by Li and Elbestawi (1996).
2. Decomposition methods. These are:
    - Signal understanding. Signal understanding is a technique based on the blackboard system, which was an artificial intelligence technique created in the 1980's. Du (1999) gives an application of signal understanding in tool condition monitoring.
    - Decision trees
    - Knowledge-based expert system (KBES)

These decision making techniques are often combined, so as to ensure a more robust output from the decision making algorithm. An excellent example of this is the work done by Balazinski et al. (2002). In this work, a fuzzy inference system and a backpropagation network were compared with an Artificial Neural Network Based Fuzzy Inference System (ANNBFIS). The neuro-fuzzy system was found to be quite adequate for wear prediction because of its short training time.

The three stages highlighted above are also given in a schematic form in figure 1.2. This is the generic form of a TCM setup.

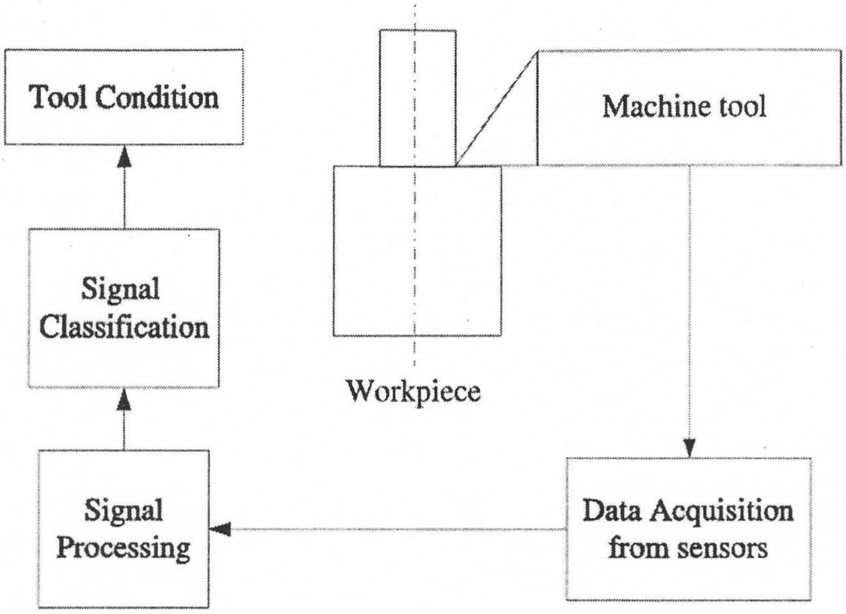

Figure 1.2: A generic TCM system setup

1.2 Complexity

An important issue which must be addressed is that of complexity. Does a TCM system really have to be so complicated, could similar results not be achieved by a simpler system? The answer to this is negative. There are numerous reasons for this; the non-linear nature of the machining process and the information lost in sensing and the signal processing corrupts the monitored indices. Measured signals are also not only correlated with tool wear, but also with machining conditions. On the other hand, monitoring tool indices that are only related to tool wear (methods of direct monitoring) are very expensive. Another reason is that the definition of tool condition is typically vague. There are also a number of different tool wear patterns, each with its own characteristics. Condition indices are also usually very small changes in processes with very wide dynamic ranges, which make them very hard to track. This, as Byrne et al. (1995) has stated, is why TCM has not yet properly found its way into commercial systems.

1.3 Some trends in tool condition monitoring

According to Sick (2002) the most popular method for tool condition monitoring in turning operations are methods that use neural networks. One reason for this is because of the emphasis that has been placed on online, indirect methods for TCM. Another reason is that usually during monitoring, several process parameters have to be measured and evaluated. Neural networks provide a very natural way to do this.

Sick (2002) also states that the most popular sensor signals are cutting force signals and the second most popular are vibration signals. Most of these sensor signals are from the cutting force and almost as much from the feed force. The reason why the monitoring of cutting forces is effective is because it provides a direct link to the cutting tool and workpiece interaction.

Also clear from the literature survey from Sick (2002), is the fact that most research into online and indirect tool wear monitoring has gone into systems that only classify wear. The author states that systems that use only two states may be sufficient to establish a practical tool monitoring strategy.

Currently (as previously mentioned) in TCM, neural networks that use a feature set generated from fused signals from the process have become the "state of the art." Because the understanding of cutting processes and neural networks has increased, the way in which neural networks are applied has moved toward the continuous wear estimation. Practical systems have recently achieved by Scheffer et al. (2003) and Balazinski et al. (2002). Scheffer et al. (2003) used a neural network configuration proposed by Ghasempoor et al. (1999) and reviewed by Sick (2002). Balazinski et al. (2002) used a neuro-fuzzy system and compared it to plain neural and plain fuzzy techniques.

The reason why practical continuous wear estimation has only recently been achieved is provided by Leem and Dornfeld (1996). The authors have also identified that the main problem with on-line systems is the problem of feature selection and suggest an unsupervised method. Indeed the greatest problem with most classification systems or methods are that they are sensitive to cutting conditions. Scheffer et al. (2003) also suggest that research into TCM using NNs be focused on this area.

Silva et al. (1998) has shown that there exists a zone of influence where NNs are insensitive to a change in cutting parameters. The network recognition then performs adequately for system conditions for which it was not trained. This zone is small but usable according to the authors. The authors experimented using Adaptive Resonance Theory (ART) and Self Organising Maps (SOM) network paradigms.

In answer to this problem, methods for various force ratios have been proposed by Choudhury and Kishore (2000), Novak and Wiklund (1996), Lee et al. (1998). Empirical formulae were created by Choudhury and Kishore (2000) and Novak and Wiklund (1996) for the prediction of tool life. Lee et al. (1998) continues from the force ratios to train an 1-step-ahead ANN predictor to forecast tool wear.

1.4 Document overview

The document is divided into the following sections.

1. Introduction. An overview on TCM and the associated problems.

2. Literature. Trends in TCM as well as presentation of work done on measuring equipment, specifically tool holders. Work done on hidden Markov models as mechanical fault identification is also shown. Based on this the scope of the research is defined.

3. Theory. Basic knowledge on hidden Markov models is supplied as well as the process of feature selection and extraction.

4. Experiment. This elaborates on the detail of the equipment used in the experiment as well as the operating parameters.

5. Results. The results of the applications of the theory on the experimental data are presented.

6. Conclusion. The results are discussed and suggestions are made with regard to future directions which the research might take.