CHAPTER 1

TOOL CONDITION MONITORING

Tool Condition Monitoring (TCM) is a very important aspect to maintain quality of products manufactured in any machining process. This chapter presents a general overview of tool condition monitoring systems and techniques. Acoustic emission and surface roughness for tool condition monitoring are discussed in detail. The motivation for the proposed work and the statement of the problem concludes the chapter.

1.1 Introduction:

In recent years the manufacturing environment has undergone drastic changes. One of the most significant developments has been the trend towards cost savings through various means like reduction in staff numbers while at the same time desiring to improve product quality and reduce production time. The shift has been towards automation. It is the concept of Computer Integrated Manufacturing (CIM) that will lead us towards the unmanned factories of the future. Within the CIM philosophy the entire operation from design through production to marketing and service will be integrated together as a global system. As a subsystem of CIM, Flexible Manufacturing System (FMS) integrates machine tools and automated storage and retrieval system (AS/RS) to provide flexibility for meeting varied needs. Each of the machining centre within a machining cell is normally equipped with a tool magazine consisting of a large number of different tools for a variety of operations. Thus an FMS which may contain several of such machining cells deals with hundreds, sometimes thousands of tools. This has created a whole new area of what is called Tool Management System (TMS). The principal function of TMS is to ensure the availability of the right tool at the right time and at the right station for carrying out the required machining operation. The TMS itself includes tool condition monitoring (TCM). Fig. 1.1 shows TMS as an element of CIM [47].
In order to achieve the goal of automation-optimization, one of the major obstacles has been the ability to reliably detect tool wear or failure on-line. The condition of the cutting tool has to be monitored continuously in order to replace it at appropriate time, for which some indication is required. Traditionally, tool condition monitoring has been undertaken by machine operators themselves. Based on his/her experience or using some mathematical models of the cutting process, the operator would change the tool when he/she judged it to be no longer capable of performing satisfactorily. These methods were not able to detect any sudden failure of the cutting tool or the onslaught of any failure mechanism. And these methods did not take into account the complex and diverse nature of the metal cutting operation. Thus the cutting tools were either under utilized or over utilized [12, 47]. To avoid this problem various types of sensory signals have been used to evaluate the condition of the cutting tool.

1.2 Tool Wear/Failure:

Failure of a cutting tool has occurred when it is no longer capable of producing parts within required specifications. Every tool, when put to use is subjected to wear after certain machining time. This is called gradual or progressive wear of the tool. During gradual wear, the tool will reach its limit of life by either flank wear or crater wear. Flank wear involves wear on the nose and the primary cutting edge with its accompanying notch. These are classified as regular wear, as they are always present in a machining operation and have ‘regular’ cutting time related growth characteristics. The other types
of tool wear are classified as irregular tool wear phenomena and can generally be avoided by proper selection of tool material and cutting conditions. Breakage, fracture, chipping come under this category. Fracture occurs more easily in brittle tools under interrupted cutting conditions, causing not only a complete failure, but sometimes a small chipping of the cutting edge. The failure by wear can be treated by periodically changing the tool, but fracturing or chipping of the cutting edge cannot be treated that way because it generally occurs as a catastrophic process. Fig. 1.2 shows the major forms of tool wear/failure [3, 22].

![Fig. 1.2. Tool Wear/Failure](image)

1.3 Tool Condition Monitoring Systems:

The need for monitoring in a metal cutting process encompasses monitoring the machine and cutting process, cutting tools and workpiece to ensure optimum performance of the system. The lack of a tool condition monitoring system (TCMS) can lead to excessive power take-off, inaccurate tolerances and uneven workpiece surface finish, sometimes damage to the machine tool and also injury to the operator. Research is going on for the past several years for the development of a reliable TCMS. Teti (1995) compiled a database of research publications on TCMS from 1960-1995 [57]. The importance of TCM and different techniques of TCM for various machining operations and their applications have been reviewed by Cook (1979) [7], Lister and Barrow (1986) [30] and Dimla E. Dimla Snr (2000) [13]. Several factors have impeded advances in the development of TCMSs that include inappropriate choice of sensor signals and their utilization. One of the primary reasons for the lack of industrial application of TCMSs is due to the fact that these systems have been developed mainly based on mathematical
models, which require huge amounts of empirical data. The nature and characteristics of
the utilized sensor signals in general, tend to be stochastic and non-stationary and
therefore difficult to model [2]. It poses a practical problem, because of the complex
nature of a typical metal cutting process, limiting the precision and control of the cutting
process. There is a need for the TCMS to be capable of diagnosing and identifying the
fault and to possibly isolate or respond with remedial action within a prescribed response
time.

Many attempts have been made for developing intelligent TCMSs for various
operations like drilling, milling, turning etc. The application of condition monitoring
techniques to the detection of cutting tool wear and breakage during the milling process
are discussed by Prickett & Johns (1999) [41]. But one of the major reasons for the
unsuccessful implementation has been the non availability of sensors for on-line
monitoring of the cutting process. Traditionally operators have been using a combination
of sight, smell and sound for performing tool condition monitoring. It is almost
impossible to develop sensors to mimic exactly the human operator, who is subjective
and flexible, but inaccurate.

1.4 Tool Condition Monitoring Techniques:

The monitoring of tool wear and failure necessitates the development of very
sensitive, accurate and reliable methods, which may be classified as being either ‘direct’
or ‘indirect’ methods. Fig. 1.3 shows the various methods of tool wear monitoring.

![Fig. 1.3. Various Methods of Tool Wear Monitoring](image-url)

<table>
<thead>
<tr>
<th>Direct</th>
<th>Indirect</th>
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<tr>
<td>Electrical Resistance</td>
<td>. Cutting Edge</td>
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<tr>
<td>Optical</td>
<td>Temperature</td>
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<tr>
<td>Radioactive Sensing</td>
<td>Torque and Power</td>
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<td>Contact Sensing</td>
<td>Vibration</td>
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<td>AE</td>
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1.4.1 Direct methods:

These methods generally involve taking measurements associated with the volumetric loss of the cutting tool material. They tend to be 'off-line' techniques, since the measurement can only be taken when the tool is out of cut. The two major disadvantages associated with offline techniques are:

- They can be very time consuming from production rate standpoint and
- The onslaught of premature cutting edge failure while tool is actually in cut cannot be detected.

Hence there is a need for indirect techniques, which have the potential of eliminating these problem areas [2, 7, 30].

1.4.2 Indirect methods:

The shortcomings and difficulties in the implementation of direct methods have made researchers attempt to detect tool wear in-process by measuring parameters which can be closely correlated with tool wear. Some of the important indirect methods are briefly discussed below.

1.4.2.1 Acoustic Emission:

Acoustic emission (AE) has been used as a sensing alternative for tool condition monitoring since the late seventies (Iwata & Moriwaki, 1977) [19]. Research on AE signals from machining by Dornfeld & Kannatey-Asibu (1980, 1985) [33] has shown that the common sources of AE are plastic deformation in the shear zone and the tool/chip interface, rubbing of the tool on the tool/chip interface and the machined workpiece surface, chip breakage and entanglement, chipping and breakage of the cutting tool. AE refers to the elastic stress waves generated as a result of the rapid release of strain energy from within a material due to a rearrangement of its internal structure. Research has shown that AE has been successfully used to detect tool wear on-line in turning operations (Sampath & Vajapayee (1986, 1987) [46, 47]). Diei & Dornfeld (1987) [11] noted that in intermittent cutting processes like milling, there are several distinctions that can be made related to AE activity which are likely to distinguish them from continuous processes like turning. They also investigated the nature of AE during multi-tooth face
milling of steel, particularly the angle of engagement and disengagement, the varying chip thickness and the number of engaged teeth. The results showed good correlation between the RMS AE signal and the severity of contact conditions during chip formation at the tool entry and exit [9]. Carolan et.al (1997) studied AE monitoring of tool wear during face milling of steels and aluminium alloys using a fibre optic sensor [4, 5].

The use of AE sensing for tool condition monitoring has attracted lot of attention because of its non-intrusiveness, ease in operation and fast dynamic response. The acoustic emission sensor is small and easy to be positioned on workpiece or tools. It does not interfere with the cutting operation, thus allowing for continuous monitoring of the tool condition. The major advantage of using AE to detect the condition of the tool is that the frequency range of the AE signal is much higher than that of machine vibrations and environmental noises. Thus a relatively uncontaminated signal can be easily obtained by the use of a high-pass filter. The size and weight of the workpiece or tool do not have a strong bearing on the performance of the AE sensor. AE signals obtained are not influenced by the dynamic characteristics of the machine tool, implying that it is transferable from one machine tool to another. But due to its high frequency nature and sensitivity to micro-structural behavior of material, AE signals often have to be treated with additional signal processing schemes so that the most useful information can be extracted [31].

1.4.2.2 Surface roughness:

It is very well understood that the quality of the surface plays a very important role in the performance of machined parts. Surface quality significantly influences properties like fatigue strength, corrosion resistance etc. The condition of the cutting tool has a significant influence on the surface finish of a workpiece. In fact surface finish can be considered as the signature of the condition of the cutting tool. Therefore surface roughness is also used as one of the parameters for TCM. A large number of theoretical and experimental studies have been carried out evaluating the use of surface roughness as a tool condition monitoring technique. Venkatesh and Satchithanandam [28] examined the efficiency of using surface finish as a criterion and found that the crater index and
surface roughness $R_a$ are fairly reliable indicators of total tool failure. D.Yan et.al (1995) [62] developed a new optical approach based on a laser system which incorporates a charge-coupled-device (CCD) for real-time measurement of the maximum peak-to-valley roughness, $R_{max}$, produced during finish turning. Scott A.Coker and Y.C.Shin (1996) [48] used ultrasonic sensing for in-process monitoring and control of surface roughness during milling. These results have indicated that it is possible to maintain surface roughness within 10% of the target value for tool wear up to 0.3 mm.

The above literature survey very clearly establishes the wide use of Acoustic emission & surface roughness signals for tool condition monitoring applications. In this research work, AE & surface roughness data have been collectively utilized for tool wear monitoring in face milling operations. This data has been used as inputs along with the corresponding flank wear on the tool as output for training and testing with neural networks.

1.5 Tool Condition Monitoring using Artificial Neural Networks:

A new focus of the research in tool condition monitoring has been towards using information from several signals to better and more robustly characterize a process. This method is called ‘Sensor fusion’. The benefits of sensor fusion include –

(i) During measurement the signal gets distorted by noise and hence by using a variety of signals, maximum amount of information is made available for decision making process.

(ii) As more signals are considered, the certainty of the estimated parameter value improves. This benefit can be obtained not only by using a variety of signals, but also by using multiples of one type of signal [2, 16].

Artificial Neural Networks (ANN) have been widely used for sensor fusion in tool condition monitoring [12]. This is because the conventional mathematical models based on the sensory data are not successful enough to achieve the desired accuracy in TCM over numerous machining conditions for the resulting tool changing strategy in factories. Even though sensor fusion using various signals provide increased sensitivity to tool
wear, the variations of these signals with the progress of tool wear are non-linear and non-monotonic, in that some features in the sensor signals are correlated with certain levels of tool wear but not with others. Also sensor signals are distorted due to the effects of other parameters and noise. Hence due to this inherent complexity and variability, the underlying distributions are unknown or not very clearly understood [29]. ANNs require no knowledge of the underlying distribution or any other assumptions in order to estimate how outputs functionally depend on inputs. They can be considered as model-free estimators and they learn from meaningful data without any prior assumptions. The functional relationship between the sensed signals and the levels of tool wear is estimated adaptively using training data via a learning algorithm. The abstracted knowledge that is obtained from the training process in the massively parallel interconnected structure is generalized for interpretation of novel sensor signals in terms of level of tool wear. This generalization capability of the neural network makes correct interpretation possible even when the information residing in the sensor signals is noisy and incomplete, which is really advantageous in a manufacturing environment in a shop floor [12, 29].

1.5.1 Brief overview of ANNs:

ANN is a new computational model that has one or more layers of processing elements called ‘neurons’. Generally there are three layers – an input layer, which receives information from the external world, a hidden layer, which processes the information and an output layer which presents the output to the external world. The arrangement of neurons in each layer is entirely dependent on the user, which depends on the problem to be modeled and studied. The investigations on ANNs started in the early 1950’s with the goal of discovering an alternative computing model to the sequential computers. Initial results were very encouraging with the announcement of a new computational model known as “Perceptron” by Rosenblatt (1957). But Minsky (1960) showed that perceptrons have limited scope and that they can solve only linearly separable problems. The research on ANNs virtually came to a standstill till 1986. Hinton and others discovered a learning algorithm for Multi Layer Perceptrons (MLP) and called it Back Propagation (BP) algorithm. This is one of the most popular algorithm used in all fields of science and engineering [69]. ANNs can be classified into two types –
Supervised learning neural networks
Unsupervised learning neural networks

Supervised learning involves the presentation of both input and corresponding output patterns to the neural network during training. The network learns all the patterns at the end of training and then the network is tested for its performance using patterns that are not used for training. BP algorithm is a powerful supervised learning algorithm. In unsupervised learning, only input patterns are presented to the network. The network learns the similarity in the input data, which will be obtained using any unsupervised learning algorithm. Kohonen's Self-Organising Map is an example for an unsupervised ANN [75, 76].

1.5.2 Benefits of ANN:

a) Neural networks are adaptive and fault tolerant, which can reduce error apparent in the sensor signal to a low level and concentrate on recognizing tool wear state. They have specified training algorithms, where weight factors between nodes are adjusted until the desired performance is obtained.

b) They can manage large amounts of data that is generated during a cutting process.

c) They are massively parallel so that each node operates independent of others. Each node encodes only a microfeature of the overall input-output pattern. Because of this parallelism, they have a better filtering capacity and perform better even when the data is noisy or incomplete.

d) They are truly multiple-input and multiple-output (MIMO) systems i.e., they can map many independent variables to many dependent variables as needed[64,65].

In the next section a review of the reported work on the application of ANNs for tool condition monitoring is presented.

1.5.3 Previous work:

Tool condition monitoring is a real time problem and the diagnostic system used must be reliable and accurate. The complexity of tool wear phenomenon and its dependence on various factors have led to the use of new intelligent systems like neural
networks. Dornfeld (1990) [44] fused signals of acoustic emission, cutting forces and spindle motor current and used the output from this fusion as inputs to a MLP neural network in a turning operation. The superior learning and noise suppression abilities of these networks enabled high success rates for recognizing tool wear under a range of machining conditions. Following the pioneering work of Dornfeld, researchers have attempted TCM with various kinds of neural networks and have reported encouraging results [12]. Chryssolouris and Domroese (1988) also showed a superior performance of neural networks trained by BP in comparison with statistical sensor fusion methods in tool wear monitoring [29]. Das et.al (1995) [8] used a simple three layer MLP neural network with a 5-3-1 architecture for cutting tool wear monitoring based on the cutting force components. The results of the neural network show close matching between the model output and the directly measured flank wear. Kumudha et.al (1996) [26] used acoustic emission technique and cutting force in monitoring the tool status and they reported that ANNs can take correct decision about the tool status in face milling operation. Researchers have also used unsupervised learning ANN with limited success in tool condition monitoring. Burke (1989) used unsupervised neural network on cutting forces and AE data. Unsupervised networks are autonomous whereby the network uses the presented data to embark on finding some underlying properties in the data. This is then used as the basis for its future classification. Burke and Rangwala (1991) together assessed the advantages of using an unsupervised method compared to supervised one. They concluded that both methods achieved nearly the same level of output success and accuracy of classification rate when tested. Elanayar & Shin (1995) proposed a unified method of flank and crater wear estimation using radial basis functions (RBF) neural networks. The input patterns have been derived from the cutting forces components. They investigated three different basis functions (third-order, Hardy multiquadrics and thin plate splines) for this purpose and reported their performance to be satisfactory [12]. C.S.Leem et.al (1995) [29] developed a customized neural network for sensor fusion of acoustic emission and force in on-line detection of tool wear. The network had been trained by unsupervised Kohonen’s Feature Map procedure followed by an Input Feature Scaling so that the resulting decision boundaries of the neural network approximate those
of error minimizing Bayes classifier. The customized neural network achieved high accuracy rates in the classification of levels of tool wear.

In summary the review revealed the following:

a) MLP is the most widely applied neural network architecture. The error prediction levels and its rate of convergence has been found to be adequate for TCM applications. The differences in MLP architecture in terms of topology have been widely investigated.

b) Dimla et.al (1997) [12] have presented a critical review of neural networks for tool condition monitoring. It is clear from the study that both supervised and unsupervised neural network architectures have been applied in the TCM problem with fairly similar results being achieved. Among unsupervised neural network types Restricted Coulomb Energy (RCE) networks. (Tansel et.al (1993), Choi et.al (1991) & Yao &Fang(1993)) and Kohonen’s Self-Organizing Maps have been used widely after MLP for tool condition monitoring.

1.6 Observations & Motivations:

The following observations have been made after careful analysis of the previous works reported in the literature.

i) Tool Condition monitoring is very important in any machining operation. The condition of the tool has a significant bearing on the quality of the workpiece machined, machine downtime and safety of the machine tool and personnel. Various signals have been investigated for tool wear monitoring, which have a correlation with wear status on the tool.

ii) Acoustic emission is one of the most widely used signals for tool condition monitoring. The advantage is that the signal is generated by the basic mechanisms of machining operations like plastic deformation, fracture and tool wear. AE has been widely used in continuous machining process like turning. The application of AE to milling is rather restricted. AE in face milling involves some additional sources of AE. Various researchers have used different signal processing
methodologies to extract the various signal features for evaluating the condition of the tool [4, 5, 9, 10, 11].

iii) Surface roughness has also been used for tool condition monitoring to a limited extent. The signal parameters like $R_a$, $R_t$ or $R_{qt}$, $R_z$ and $R_{max}$ are the most widely used.

iv) Application of Neural networks to tool condition monitoring is viewed as a pattern classification problem. The output of the system indicates whether the tool is good or bad. The neural networks are trained using input data only for unsupervised learning and using both input and output data for supervised learning. ANNs which are generally applied to low dimensional problems have been extended to high dimensional problem like tool condition monitoring (TCM).

v) MLP trained using Back Propagation algorithm is the most widely used neural network. The acceptable error prediction levels and its rate of convergence have been found to be adequate for TCM applications. The learning algorithm basically performs gradient descent in the weight space in order to find global minima. During backward pass it computes the derivative of the error with respect to each weight in the weight space. The dimension of the weight space increases with the size of the training data and hence the algorithm becomes very slow which is an inherent limitation of the BP algorithm.

vi) MLP networks trained using BP algorithm are of fixed architecture type. In other words the number of hidden units have to be fixed prior to training. A number of trials are required to fix the optimum number of hidden units. There exist no established rules to determine the optimum number of hidden units for a given problem. Thus it is a trial and error process and works fine with small size training data and low dimensional problems.

vii) The training of MLP networks with BP algorithm for high dimensional training patterns takes lot of time. The algorithm requires the learning rate parameter and momentum coefficient to be fixed before learning can start. A change in the values of these parameters will make one to wait for the network to converge. Thus for high dimensional problems like tool wear monitoring, the training of
MLP is a very tedious process and sometimes can be frustrating. The need to find an optimal architecture with BP algorithm involves exploring all possible combination of different parameters that meets the desired error level that is a serious limitation of the algorithm.

It is clearly evident that Multi-Layer Perceptrons have been widely used for TCM application. However MLPs have certain limitations such as fixing the size of the network, local minima and large training time. Thus there is a need to explore suitable neural network architectures that will overcome the limitations of BP algorithm for tool wear monitoring.

1.7 Problem Formulation:

The increase in training time with the increase in input dimension and size of the training data set makes MLP trained using BP algorithm less efficient for practical applications. Hence we propose to investigate the suitability of new neural network models that build their architecture themselves during learning and develop an optimal architecture at the end of learning. An optimal architecture is very much essential for good generalization. Radial Basis Function neural networks are new classes of neural network models, which have not been widely applied in the area of tool wear monitoring. The thesis mainly focuses towards the creation of efficient learning algorithms for RBF neural networks for tool wear monitoring in face milling operations. The RBF architecture must meet the following objectives.

1. The algorithm must construct the neural network architecture during learning.
2. The algorithm must generate an optimal architecture.
3. The learning process must be fast.
4. The algorithm should result in a neural network architecture, which is able to estimate tool wear accurately i.e., it must exhibit good generalization.

The performance characteristics of these algorithms have been compared with MLP trained using BP algorithm.