Application of Audible Signals in Tool Condition Monitoring using Machine Learning Techniques

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Application of Audible Signals in Tool Condition Monitoring using Machine Learning Techniques

Submitted by,

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A Thesis Submitted in Partial Fulfillment of the Requirements for Master of Science in Mechanical Engineering

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Dedication

I dedicate this thesis to my family for nursing me with affections and love and their dedicated partnership for success in my life.
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I would like to thank all those involved with my research for their help, support and good times. I especially would like to thank Dr. Rui Liu for the opportunity to work under her guidance. There have been a lot of tough and uncertain times throughout the past year. I am grateful to Dr. Liu for providing motivation and encouragement throughout the whole process. His confidence and trust in me inspires me to do my best.

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Achyuth Kothuru
Abstract

Machining is always accompanied by many difficulties like tool wear, tool breakage, improper machining conditions, non-uniform workpiece properties and some other irregularities, which are some of major barriers to highly-automated operations. Effective tool condition monitoring (TCM) system provides a best solution to monitor those irregular machining processes and suggest operators to take appropriate actions. Even though a wide variety of monitoring techniques have been developed for the online detection of tool condition, it remains an unsolved problem to look for a reliable, simple and cheap solution. This research work mainly focuses on developing a real-time tool condition monitoring model to detect the tool condition, part quality in machining process by using machine learning techniques through sound monitoring.

The present study shows the development of a process model capable of on-line process monitoring utilizing machine learning techniques to analyze the sound signals collected during machining and train the proposed system to predict the cutting phenomenon during machining. A decision-making system based on the machine learning technique involving Support Vector Machine approach is developed. The developed system is trained with pre-processed data and tested, and the system showed a significant prediction accuracy in different applications which proves to be an effective model in applying to machining process as an on-line process monitoring system. In addition, this system also proves to be effective, cheap, compact and sensory position invariant. The successful development of the proposed TCM system can provide a practical tool to reduce downtime for tool changes and minimize the amount of scrap in metal cutting industry.
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Glossary

CIM   Computer Integrated Manufacturing
FMS   Flexible Manufacturing Systems
CNC   Computer Numerical Control
TCM   Tool Condition Monitoring
AE    Acoustic Emission
SSA   Singular Spectrum Analysis
SVD   Singular Spectrum Analysis Singular Value Decomposition
AI    Artificial Intelligent
ANN   Artificial Neural Networks
FL    Fuzzy Logic
ANFIS Adaptive Neurofuzzy Inference System
DENFIS Dynamic Evolving Neurofuzzy Inference System
TWNFIS Transductive Weighted Neurofuzzy Inference System
ES    Expert System
SVM   Support Vector Machine
BN    Bayesian Network
TSK   Takagi Sugeno Kang
VB1   Uniform Flank Wear
VB2   Non-Uniform Flank Wear
VB3   Localized Flank Wear
HSS   High Speed Steel
Chapter 1  Introduction

1.1.  Research Background

A cutting tool monitoring system is very critical in present day fully-automated manufacturing environment which needs instant detection of cutting tool condition and other influencing phenomena of tool that have potential advantages to be gained from reduced maintenance costs, increased productivity and increased machine availability. Typically, irregularities and decrease in efficiency of a machining process involves due to many occurrences like tool wear, tool chipping, tool breakage and tool failure. The above stated phenomenon has their effects on the stability of the process and the tool condition. To look for a reliable, simple and cheap solution, this study proposes a new tool condition monitoring system to detect the tool wear condition and the hardness variation of the workpiece material in machining process by using machine learning techniques.

Tool Condition Monitoring (TCM) is a kind of machine condition monitoring method where the condition of the cutting tool is diagnosed through sensing and analysis of process information such as tool sound, vibration, current, etc.
A Tool Condition Monitoring (TCM) is a kind of maintenance predictive system used for mechanical systems or machine tools that monitors the condition of a cutting tool in a machine through analyzing the data collected by a variety of sensing approaches such as vibration, sound and current of cutting tool. In this study, a reliable and compact model that involves combination of less explored sensing approach and decision-making scheme for TCM has been investigated. This approach helps in the development of a TCM system capable of on-line process monitoring utilizing machine learning techniques to analyze the sound signals collected during machining and predict the tool condition during machining.

In a study conducted by Abellan-Nebot and Subiro'n [1] concluded that most of the research works published in this field were mainly focused on methodologies with much less focused on stating the key issues in development of intelligent TCM systems. Many of these systems has not been successfully implemented in industrial applications primarily because of the approaches and techniques are intrusive, not compact and expensive. These limitations are mainly due to the complexity in methodologies behind the approaches, and especially the sensory techniques applied for TCM. Thus, this research work focuses on developing an effective on-line TCM system, which is cheap, compact and sensory position invariant. The successful development of the process monitoring systems can provide a practical tool to reduce downtime related with tool changes and minimize the amount of scrap in metal cutting industry.

1.2. **Motivation for the Development of TCM System**

The metal cutting process plays an important role in manufacturing history. As one of primary modern manufacturing processes, the metal cutting is required to achieve very high dimensional accuracy and almost the desired surface finish [2]. The regular metal cutting processes relied on
highly skilled labor until the mid-1950s, when automated machining began to replace human operators with more efficient, less costly automated machining processes. Industries has shown interest in automated machining in a very short period due to the capability of these systems in reducing production costs and product quality [3-5].

In the meantime, complex manufacturing processes must be implemented for the customer driven market which requires more individualistic and varied products. To attribute the advantages in economics of mass production to these complex manufacturing processes associated with small batch productions, a new technologies and methods should be introduced to overcome this situation [6, 2, 7]. For many of these problems, the development of CIM (Computer-Integrated Manufacturing) and FMS (Flexible Manufacturing Systems) seemed to be an ideal solution.

The combination of CIM and FMS has shown promising results in cost controlling solution to meet new demands. But, for these systems to achieve maximum efficiency, the ongoing process should not be interrupted, which, manufacturers have various reasons to interrupt the process to respond to process instabilities caused due to various process conditions deterioration, mainly, tool wear [8]. In addition, the technological developments in manufacturing systems have resulted in requirement of skilled labor. For the past few decades, manufacturing industry, especially the machining industry, has been facing a serious decrease in skilled labor. In a statistical study published by Dupress publications, it has been stated that there will be an increasing demand in skilled labor for manufacturing industry to 63% in next decade which is currently at 54%. Thus, developing an effective means to monitor parameters and components causing instabilities in machining processes has become one of the most important issues in automated metal cutting processes [9].
Cutting tool wear is one of the most critical issue, that should be monitored to avoid interruptions in any machining process. For an effective monitoring system, it should detect the tool wear level and predict the failures beforehand to take corrective actions in maintaining the process parameters of process to reduce the wear rate or prompt for effective tool change strategies [10]. Failure to detect the above stated abnormalities could result in poor surface quality, dimensional workpiece defects, and even machine defects [11].

Tool wear monitoring has opened to a new and active research field in machining process to control the surface finish and dimensional integrity of the workpiece, as well as vibration in the tool. Furthermore, the development of tool wear monitoring systems could help the manufacturers to reduce their machine down time and resulting in higher efficiency of the automation systems. These systems can be utilized to obtain information regarding the process parameters, which can be controlled during the process to compensate for tool wear, and the avoidance of catastrophic tool failure.

The use of readily available, reliable and inexpensive computing power has resulted in technological advancements in machining process. Despite the high level of technology built into every aspect of innovative metal cutting operations, the development of tool wear still limits the reliability and full automation of machining process, and the successful and effective TCM in automated machining systems remains an engineering challenge [12]. The developed systems often have limited ranges of performance; require significant training or setup time to function correctly [13]. According to Ghasempoor [14], a reliable online tool wear measurement system does not exist yet and research in this area is continuing. Metal cutting theory is a complicated phenomenon which has been researched for many years, still there is in lack of understanding the
process and automate the monitoring of cutting process [15]. Therefore, further research is needed towards improving the efficiency of TCM system.

1.3. **Scope of Thesis**

The scope of the proposed work is to develop a cutting process monitoring system using machine learning techniques to analyze the sound signals collected during machining. Explicitly, the research involves in developing a tool wear classification model that will have a different wear ranges of tool wear on cutting tools. In addition to that, non-uniform hardness work pieces are prepared using Jominy End quench test, and labeled the hardness variation into different classes. A classification model is derived with different types of chip formation for which sound signals are collected by performing experimental runs. Experimental tests of machining process are performed to collect the sound signals, and a dataset of sound signals is developed with the proposed cutting parameters model. A machine learning algorithm with SVM approach are formulated is trained after splitting the dataset into test and train datasets. The proposed different approaches are then compared for pre-processing performances and prediction accuracy for both in normal and non-uniform hardness milling operations. Further, system is tested for the sensory position independence to ensure the system capability for real-time application.

The study has been divided into three tasks. Following are the three different tasks.

- TCM for Wear Prediction in End-Milling Application
- TCM in End-Milling a Non-Uniform Hardness Work Material
- Tool Condition Monitoring in Gear Milling

The primary task involves study of proposed approach and methodology in training and testing the system for predicting tool condition through wear progression from good to failure. Secondary
task deals with the study of tool condition monitoring for non-uniform mechanical properties work piece machining. Third task involves in study of TCM system proposed in task-2 for application in gear milling.

1.4. **Research Objectives**

The goal of thesis is to develop a cutting process monitoring system with a less complicated sensory system approach to predict the tool wear and failure in normal and non-uniform hardness work-piece machining process along with detection of hardness variation. This will be done by employing a sound monitoring sensory approach from which the sound signals collected are used as input signals to train the proposed intelligent model for cutting process monitoring. The research questions that must be answered are:

- The proposed intelligent model will be able to predict the tool condition through sound monitoring
- The proposed model will be able to predict the hardness variation and corresponding tool condition in machining a non-uniform hardness work-piece.
- The proposed intelligent process monitoring model can be implemented to other machining processes.
- The proposed model will be capable of application in real-time with a compact set-up.

1.5. **Impacts of the Study**

The new approach proposed in this thesis may contribute to the improvement of TCM systems in industrial metal cutting machine tools. Contributions to knowledge from this thesis work are summarized below:
• From the analysis, it is observed that the sound pressure amplitude of emitted tool sound signal during milling, increases with the progress of tool wear and this relationship can be used for the development of tool condition monitoring.

• A new method is proposed for TCM by classification of tool wear which involves sensory approach by sound monitoring and classification by SVM suitably configured and trained. The performance of the method has been verified using emitted tool sound data collected from university lab and industries.

• By utilizing the developed in-process tool condition monitoring system, manufacturers can expect a dramatic reduction of machine downtime related with tool changes in turning operations.

• The in-process tool condition monitoring system developed in this study also promises full utilization of the machining tool. Since manufacturers use a tool change policy based on their experience or the suggestions of manufacturers, most of the time they cannot fully utilize a cutting tool due to downtime while the policy is being enacted. This practice leads to the tool being changed more frequently than is necessary. The system proposed in the current study will alleviate this downtime.

• Since there is a direct correlation between the tool change times, machine downtimes, and higher numbers of tools, a cut in direct manufacturing costs can be expected because of implementing the system developed in this study.
Chapter 2  Background & Literature Review

Several studies involving various methodologies and technologies were proposed in the past for development of tool condition monitoring systems. This chapter provides a brief review on cutting process in machining, tool wear mechanism, variation of work piece mechanical properties influences on tool wear and generic architecture of a Tool Condition Monitoring (TCM) system. Each of these topics are reviewed in different sections with corroborating past studies in the respective fields.

2.1.  Machining Processes

Machining processes are the techniques used for removing material from a workpiece in the form of chips by means of single or multiple wedge-shaped cutting tools. Generally, conventional machining process can be grouped into three categories of processes; Cutting process, Abrasive processes, and Nontraditional processes. This study focuses on cutting processes in which the process involves machining of an external surface with work-piece rotating, and this category includes machining process such as turning and milling. Turning is used for producing cylindrical, conical, or irregularly shaped internal or external surface components, and milling for producing flat or curved surfaces and prismatic shapes.
Thus, the scope of the present study on application of machine learning techniques in cutting process monitoring by analyzing sound signals is limited to turning and milling processes. The significance in choosing the milling and turning operation for this study is to show the proposed system capability in application of both continuous and discontinuous cutting process. Other studies by the authors [16] indicate that the cutting phenomenon involved in milling process is complex. The following distinctions deserve special mention.

- Milling process in metal cutting is a discontinuous, for which, the nature of cutting introduces two additional sources of sound signals at the tool entry and exit from the workpiece.
- The operating conditions and cutting forces at the tool flank edge surface varies which is resulted due to chip thickness variation throughout the cutting cycle, thereby causing variation in generated sound signal characteristics.
- The random variations in the level and characteristics of the signal are generated due to the carrying of chip build up at tool exit of previous cut onto the next cut.
- There can be a case where multiple sources for sound signals can be generated due to the reason for more than one cutting edge can be in contact at the same time in multiple tooth configuration.

In addition to the end milling, this study also focuses on gear milling as to study the feasibility in application of process monitoring system for gear cutting. One of the most important components in a gear machining system is the cutting tool. Cutting tool wear is the inevitable result of the gear cutting process caused by abrasion, plastic deformation, diffusion, and grain-pullout. Furthermore, gear cutting tools are always very expensive, and the common industrial practice by replacing or regrinding machining tools per a conservative schedule is not cost-effective.
2.2. **Tool Wear Mechanism & Types**

The state of a cutting tool is an important factor to define the efficiency of machining process and represents the economic significance of the manufacturing process as the tool failure will lead to unscheduled machine downtime [17]. Automation of this monitoring systems increase the usage of capital equipment and allows the human operators to perform higher level tasks than to monitor these machine tools [18]. Thus, an intelligent tool wear monitoring system is required to detect the tool wear in predicting the failures of cutting tools thereby avoiding machine down time.

Tool wear is a critical indicator of cutting tool life, as the wear on tool increases and leads to failure which is caused by a combination of various thermos-mechanical mechanisms. Generally, tools experience three stages of wear: break-in, steady state, and failure. Break-in is a stage where the first few minutes of use as cutting shape is established, whereas in steady state the cut quality gradually deteriorates with use, and finally, failure stage is a rapid deterioration that occurs as the tool reaches the end of its useful life. It has been realized that crater wear, flank wear, built-up edge, chipping and breakage are the main modes of tool wear [19], which are identified by their locations and geometry. These type of wear effects the dimensional accuracy, surface quality of finished component, increased tool interface temperatures, inefficient chip formation and flow and even process stability will be deteriorated.

Scheffer and Heyns [20] states that tool wear phenomenon is unpredictable based upon the observations from the experiences of the operators of machining. They have found that a tool could last for thousands of components, and at times it might wear out after a few hundred. This suggests in need for tool wear monitoring systems to avoid the possibility of damaging a part and to maximize the utilization of the tool life.
2.3. **Non-Uniform Hardness Materials**

Recently, one practical problem attracts the attention of many manufacturing companies that non-uniform mechanical properties of raw workpiece materials become very common due to the cost control or the improper heat treatment. The harmful impacts resulting from non-uniform mechanical properties, particularly hardness, is that it can cause expedited tool wear and unexpected tool breakage. To be specific, the specific type of cutting tool is designed for cutting certain types of materials within a range of hardness levels. The localized hard regions of the workpiece material may lead to the unexpected tool failure. In addition, the hardness variation also expedites the tool wear to shorten the tool life, which may cause unexpected tool change or influence the surface quality of products. Therefore, the key issue is how to detect the tool wear conditions accurately in machining of workpiece material having a non-uniform hardness with a reliable, efficient, and cost-effective way, which remains an open research question up to now.

The researchers have worked on many facets of machining of hardened steel using different tool materials and came up with their own recommendations. Many have tried to investigate the effects of cutting parameters, tool materials, different coatings and tool geometry on different machinability aspects like, the tool life, surface roughness, cutting forces, chip morphology, residual stresses and the tool–chip interface temperature under dry and/or semi-dry and/or flood cooling environment during turning of hardened steels while many of them have ventured to characterize the wear phenomenon. In the study [21], tool wear and cutting forces has been investigated with the variation of work piece hardness and cutting speed. The study has shown that the thrust force is the highest of cutting force components, and it is highly sensitive to work piece hardness, negative rake angle and tool wear evolution. In another study, Wardany [22] has proposed a stochastic model for predicting the tool failure rate in turning hardened steel with
ceramic tools. The results indicate the tool manufacturers to modify the quality control procedures to broaden the use of ceramic tools. Sadettin [13] has investigated the vibration amplitude to correlate the tool wear on milling a D3 cold work steel hardened to 35 HRC. In all the above studies, there has not been any study performed on detecting the hardness variation of work piece that resulted in acceleration of tool wear. Studies on this aspect are very limited to turning and grinding operation involving coated tools, in addition to this there has not been many studies proposed on implementing monitoring systems utilizing sound signals. Thus, this study would be one of the earliest to propose a monitoring system in detecting the hardness variation of work material along with wear state of the tool which alarms manufacturers to remodify the tool change cycles by avoiding damages of machining.

2.4. **Machining Process Monitoring**

The study of cutting behavior and parameters of these machining process has been considered as important field of research from the era of conventional machine tools to the present era of CNC machine tools. The prediction of cutting behavior of processes and optimization of machining parameters are much less tractable since theoretical and experimental methods on this study are still under development. In review of metal cutting analyses in 1956 [23], Finnie has pointed out that the basic relationship between the metal cutting process and various variables is not been completely clarified from the past and present attempts.

Nevertheless, the efforts to model machining process and their monitoring are still going on, as the process monitoring of these machining process has a large bearing on the economics of machining. The prediction of surface roughness, cutting force, and tool life in machining is a challenging task, but it is necessary for proper optimization of the cutting process. These general
needs have driven researchers over a period of more than fifty years to conduct experiments and develop models that could understand the behavior of cutting process through monitoring and predict the failures in machining processes.

The typical machining process monitoring system operates per the following rationale. In the cutting region, there are several process variables, such as cutting forces, vibrations, acoustic emission, noise, temperature, surface finish, etc., that are influenced by the cutting tool state and the material removal process conditions. The variables that are prospectively effective for machining process monitoring can be measured by the application of appropriate physical sensors. Signals detected by these sensors are subjected to analogue and digital signal conditioning and processing with the aim to generate functional signal features correlated (at least potentially) with tool state and/or process conditions. Sensor signal features are then fed to and evaluated by cognitive decision-making support systems for the final diagnosis. This can be communicated to the human operator or fed to the machine tool numerical controller to suggest or execute appropriate adaptive/corrective actions.

2.5. **Architecture of TCM System**

TCM system is a combination of information flow and processing system as shown in Fig. 1. According to the literature, a generic methodology for developing an TCM system for machining is composed of the three stages such as signal selection and acquisition, signal processing and features selection, and decision making. The decision making is based on the extracted features of the signal obtained from the system under investigation. A TCM consists mainly of two parts: hardware and software. Signal acquisition makes the hardware part while the
rest of the processes including signal analysis, interpretation, and tool state prediction come under the software part, as shown in Fig. 1.

**Fig. 1 Components of TCM system**

### 2.5.1 Sensory Systems for Tool Wear Estimation

Tool wear monitoring is a difficult task because many machining processes are non-linear time variant systems, which makes them difficult to model and secondly, it is extremely hard to measure the tool wear directly during the cutting process. Tool condition monitoring has been extensively studied by many researchers since the late 1980s to implement different types of monitoring systems to detect the tool wear and failure in advance to the occurrence of the actual event [24, 13, 25] by adopting different sensor functions to collect information. However, these attempts involving various sensing methodologies have different degrees of success in practical applications and it has also been reported that utilization of insufficient reliability sensing methods under varying cutting conditions limits the practical application of such systems. Therefore,
developing an automated tool monitoring system is a process-orientated problem where the selection of sensory system and modeling approach are closely related to the type of application.

2.5.1.1 Measuring Techniques

Measuring techniques are the basis of any sensing approach, and there are many process variables of machining process for which these measuring techniques has been applied to obtain the cutting tool condition information. Typically, these measuring techniques are categorized into direct and indirect approaches, based on the method of measurement technique. Direct approach consists of visual inspection, radioactive isotopes, laser beams and electrical resistance. These approaches involve measurement of the corresponding process variable through analysis by interrupting the process. Thus, these systems are confined to laboratory techniques and the processes are complex enough for usage in industrial applications. But, these approaches are considered to have higher degree of accuracy and applied in research labs to study the fundamental measurable phenomena behind the cutting process.

In-direct approach consists of systems that are flexible and mainly they are dependent upon secondary process parameters of machining process. These process parameters are found to be optimal for correlating the tool condition and especially in application for in-process tool condition monitoring systems [26]. Usually this approach has dynamometers, accelerometers, current sensors, and acoustic emission (AE) sensors. The dynamometer sensor is based on the measurement of cutting forces during machining process, and it has found to be the most reliable approach to monitor the tool condition [27]. As this approach is focused on cutting forces, which, are considerably sensitive as the frictional force changes with the wear on the cutting tool thereby resulting in decrease of the force. However, this approach has limitations in correlating the cutting
tool conditions during the collision and has restricted frequency range [28-30]. The major limitation for this approach is set-up costs during instillation onto the in-process monitoring systems. Vibration monitoring is another approach based on the variation in vibration amplitude with respect to the progressive flank wear during machining process. This method as monitoring approach is mainly seen in monitoring surface roughness [31, 32]. Although the use of this approach has been showed some interesting results [29, 33, 34], in fact, there are still some limitations involved in this method. The main and unique disadvantage compared to other in-direct sensors is that this approach is highly sensitive to the sensor position and the machine speed range [35]. Current measurement can be used to detect tool wear which is based on the motor current Proportionality with the torque of DC motor, which is, in turn, proportional to cutting forces. Although many studies [36, 37] have been performed to apply this method in tool condition monitoring systems due to its severity this approach has its own significant limitation. This system is not suitable for accurate sensing due to its relatively low sensitivity.

Acoustic emission approach is a sensing method by measuring different characteristics of acoustic (elastic) waves in solids, which corresponds to a large amount of useful information for monitoring the state of machining operation and identifying tool wear. Studies conducted in the past [38] pointed out acoustic emissions during the metal cutting process could be generated from various sources which exhibit different signal characteristics since the mechanisms by which AE is produced in these occasions are fundamentally different [39, 40]. Although some research works have recommended the use of AE sensors instead of dynamometers for tool-wear diagnosis [41], other researches argue that the use of AE sensors as an indicator of tool wear is inappropriate because they are more sensitive to noise and variations in cutting conditions than to the condition of the tool itself [42], and that they are only suitable as an additional sensor to increase reliability.
Sound monitoring is another indirect measurement approach for tool condition monitoring (TCM) in which the sound waves generated from the machining process can provide valuable information regarding the process and the condition of the cutting tool. There has been only a few studies to investigate the tool condition and failure monitoring through this approach. Weller et al. [43], one of the earliest works in this subject, considered sound measurement and analysis for determining the tool wear and observed a correlation between the features in sound signals and tool wear progression towards failure. Alonso and Salgado [44] used singular spectrum analysis (SSA) to extract information regarding flank wear from the measured sound signals. In another study [45], the emitted sound signals of cutting tools with different wear levels were processed by the singular value decomposition (SVD) analysis. The sound features obtained by SVD analysis correlated well with increasing flank wear. But the developed method was applicable only to the circumstances for which it was developed. Even though the above-stated research has been carried out in this approach, this field is less studied yet for industrial applications. Other studies conducted in this field [46, 47] considered the sound monitoring as a prime sensing approach for tool condition monitoring and concluded that the use of this method in the industrial floor is perhaps impractical due to high ambient noise. Anderson [48] patented an idea in which the background noise was sensed by a specific sensor and its effect on signals associated with tool wear could be reduced. Trabelsi and Kannatey-Asibu [49] obtained audible sound radiation from a microphone for tool wear and tool breakage detection in turning and determined tool conditions using pattern-recognition techniques. Delio, Tlusty, and Smith [50] concluded that audible sound is a good method for detecting chatter during the milling process. Tangjitsitcharoen and his peers have [51] carried out sound signal measurement along with force, vibration, and AE signal measurement to
utilize the sensor fusion approach. The energy spectral density parameters of sound and AE signals were found sensitive to tool wear.

2.5.2 Signal Processing Methods

The main difficulty hindering researchers from building an appropriate TCM systems is the nonlinear time-variant nature of the machining process itself. Also, the variation in the measured signal is due to many disturbances, and it is difficult to determine whether the change in the signal is due to tool wear or a change in the process conditions [52]. Hence, the measurement of signals is not as difficult as interpreting them for the correct tool wear state prediction. Thus, an appropriate signal processing strategy coupled with selecting/extracting sensory features is mandatory improve our understanding of information incorporated in the acquired signal. Signal processing is the main function of the information-driven TCM system, which includes feature extraction and feature selection. It involves two stages which are typically termed as signal pre-processing and feature extraction.

2.5.2.1 Signal Pre-Processing

Signal pre-processing is a mandatory stage in signal processing to increase the level of information associated with the corresponding sensory signal. In this stage, noises associated with signal that are generated due to high levels of mechanical, electrical and acoustic noises in industrial environments are eliminated to retain the actual information [53]. Generally, this stage consists two steps; analog preprocessing and digital preprocessing. Analog pre-processing involves digitization of acquired raw signal. During digital preprocessing, digitized signals are passed through digital filters such as low or band pass filters for filtration of signal for unwanted
frequencies, further, linearized and conditioned to reduce the noise and increase the level of information content [54].

### 2.5.2.2 Feature Extraction

Feature extraction stage involves extraction of the most appropriate features from the signal acquired after signal preprocessing, which correlate well with tool wear and not affected by process conditions. Mostly features are derived from any of the time, frequency, time–frequency domain. The techniques used in extracting from the above stated domains are used widely by the researchers which will be elaborated through references for each domain in following sections.

#### 2.5.2.2.1 Time domain

This technique is a basis methodology of feature extraction technique that generates the features not very informative as such, or at least it is very time consuming. Usually, cutting force signals are generally time-domain processed to extract features. Jong-Jin and Ulsoy [55], Lee [56], Ravindra [57], Dimla and Lister [58], Nadgir and Ozel [59], Koren  [60], Braun [61], Sikdar and Chen [62], Cakir and Isik [63], Sharma [64], Dimla and Lister [65], Balazinski [66], and Rao and Srikant [67] used time domain analysis for force signals. In all the above studies, features generated from time domain analysis has shown great correlation between force signals and tool condition. But, this method generates the features associated with disturbances, for which, requires supplementation of features from other processing domains.

#### 2.5.2.2.2 Frequency domain

There have been many studies on human hearing responses to sound frequencies [68]. Thus, analysis on frequency component of a signal can generate the features that can retain high information, typically, mathematical analysis of the frequency content of signals is called Fourier
analysis. The frequency content of a signal can be generated from Fourier transform, and its components are formed by a fast Fourier transform. Typically, this domain is well used for generating features of the vibration and sound signals. Weller [42] used the energy variation of sound signals in the frequency domain. Pandit and Kashou [69] and Jiang [70] used the spectral density plots for vibration signals. Rangwala and Dornfeld [24], Das [71], and Al-Habaibeh [63] used a FFT program to obtain the power spectrum representation of time domain signals. Haddadi [64] used frequency domain features for surface roughness and vibration signals. In their study, it has been found that an energy spectrum in the range of 0–3.5 kHz has shown a good indication of tool wear which was accompanied by an increase in the spectrum amplitude in 0–3.5 kHz frequency range. But, the major limitation of this technique is to identify the spectral bands that are sensitive to tool wear is not easy as always, and it is difficult to understand the cause for that specific frequencies influencing the tool wear.

2.5.2.2.3 Time–frequency domain

The time-frequency domain analysis utilizes the concept of wavelet transforms to generate features, which, describes the localization of a signal in the time domain and the frequency domain at the same time, and this process largely reduces the processing time. In a study [73], discrete wavelet transform has been used to perform time-frequency domain analysis to extract features from vibration signal and the dynamic characteristics of tool wear were extracted from wavelet coefficients. Chen et al. [74] applied wavelet filtering technique for his study in tool wear monitoring for turning process. Lee [75] used wavelet analysis for vibration and AE signals for feature extraction. In a review study conducted by Zhu et al. [76], it has been stated that wavelet transform has found to be more effective method in time-frequency analysis for non-stationary machining sensor signals due to sparsity and localization properties. On the other hand, wavelet
transform is time variant, short time delays in signal can cause large changes in the wavelet coefficients at fine scales [77], and this must be considered while designing a TCM system.

2.5.3 Decision-Making System

The decision-making scheme is to map the features of the signal to a proper class (tool wear states). The diagnostic tools employed for this part of TCM plays the important role of classifying the previously acquired and processed signals in a TCM system and taking quick and precise decisions about the extent of the tool wear. The output of the decision-making process includes either prediction or classification of tool conditions (such as fresh, slightly worn or severely worn etc.). For the past few decades researchers have been using Artificial-Intelligent (AI) techniques for the decision-making strategy of an TCM. In this context, several AI techniques have been widely used in the past for the diagnosis of tool wear. The main AI techniques applied for modelling and monitoring machining systems are artificial neural networks (ANN), expert systems called fuzzy logic systems and the AI technique that results from the hybridization of these two techniques, called neuro-fuzzy inference systems. Other AI approaches that belongs to machine learning techniques which is a subset of AI techniques, such as evolutionary algorithms or support vector machines have been less widely used, although they are gaining popularity in recent works.

2.5.3.1 Artificial Neural Networks

For an intelligent monitoring system, it needs to identify abnormalities and initiate corrective action without human intervention. This requires the system to have a decision-making ability, which can interpret information from sensors, learn from environment, align itself in
response to knowledge gained during the learning process, and decide on appropriate control action. One of the possible architecture for this purpose can be neural networks [78]. Neural networks are computational models similar to that of the human brain and made up of several processing elements known as neurons where each neuron relates to several other neurons [79]. Their ability to approximate continuous nonlinear functions well, and due to this reason, many publications have used them to model nonlinear dependencies between process parameters and tool wear.

In a study conducted by Rangwala and Dornfeld [24] for tool condition monitoring using AE and force signals, MLP neural networks were utilized to correlation between sensory information and tool condition through learning and pattern recognition system. Teshima [80] utilized image analysis with neural networks for tool wear and tool life prediction. Das [71] has done a comparative study to analyze the force signals, between three different models of three-layer backpropagation neural networks for the application of on-line tool condition monitoring system. Ghasempoor [14] utilized two feedforward neural networks in hierarchical architecture based on state space representation of a turning process by developing a methodology to determine the relationship between wear mechanisms and cutting force signals. In a study conducted by Balazinski [66], to estimate tool wear in turning, he utilized feedforward backpropagation neural network, fuzzy decision support system, and a neural network-based fuzzy inference system as decision-making method. But, these systems require intensive training for any change in process conditions.
2.5.3.2 Fuzzy-Logic

The application of this method has shown significant result in many different fields of applications. Especially, these systems have also been tried for tool condition monitoring systems. In a study conducted by Sokolowski [81] for machine tool and cutting process monitoring, he develops the system based on strategy that provides the system to be independent of wear factors from the cutting parameters through implementation of fuzzy-logic system. Similar approach has been followed by Rao and Srikant [67] that involves a comparative study between neural network, fuzzy logic, and Neurofuzzy classifiers by monitoring the radial force to predict tool wear. Lan [82] proposed a parameter optimization approach using the fuzzy Taguchi deduction optimization method to improve tool condition performance. Ren [83] conducted a study to develop tool wear condition monitoring system based on cutting force signals using TSK fuzzy model. Although the application of this method in monitoring systems results in faster response rates these systems have issues in selecting appropriate membership function for the respective application approach.

2.5.3.3 Neuro-Fuzzy

This technique combines the advantages in paradigms of fuzzy logic and neural networks, through which a simplified neural network model can be developed, and also providing the knowledge which has been mainly developed by a set of if-then rules of fuzzy-logic [84]. Balazinski [66] and Rao and Srikant [67] conducted a comparative study between artificial neural network, fuzzy logic, and Neurofuzzy classifiers. For which, Balazinski [66] concludes that neuro-fuzzy shows less training time compared to other models, and Rao and Srikant [67] concluded that this technique has shown significant results in comparison with others. In a study conducted by Sharma [64] to carry out wear estimation of the turning tool by analyzing cutting force, vibration
and AE signals, he proposed a decision-making model that involves development of a novel system; adaptive Neurofuzzy inference system (ANFIS), to estimate the tool wear. The system has shown an accuracy of 82.9% and it can only be functional in the cutting parameters that has been used for training. Gajate [84] performed a comparative study between various Neurofuzzy techniques that involves ANFIS, dynamic evolving Neurofuzzy inference system (DENFIS), and transudative weighted Neurofuzzy inference system (TWNFIS). He concluded that TWNFIS has shown in greater accuracy compared to others due to the advantages of transudative method of learning for the tool wear correlation.

2.5.3.4 Machine Learning (ML) Techniques

Nowadays, computer technology supports the development of maintenance strategy both in hardware and software. A recent developed method is using artificial intelligent (AI) techniques as tool for maintenance routine. Based on the idea performing an excellent and easy maintenance program; it leads the practical maintenance to create an intelligent maintenance system. Intelligent maintenance consists of parts (hardware and software), which are possible for the system to do maintenance routine in such a way like human being. Application of expert system (ES) as a branch of AI in maintenance is one of solution. The basic idea of ES is simply that expertise, which is the vast body of task-specific knowledge, is transferred from a human to a computer. This knowledge is then stored in the computer and users call upon the computer for specific advice as needed. The computer can make inferences and arrive at a specific conclusion. Then, like human consultant, it gives advice and explains, if necessary, the logic behind the advice [85].

Machine learning usually refers to the changes in systems that perform tasks associated with artificial intelligence (AI). Such tasks involve recognition, diagnosis, planning, robot control,
prediction, etc. The “changes” might be either enhancements to already performing systems or ab initio synthesis of new systems [86]. Machine learning is usually divided into two main types; Supervised and Un-supervised. In the predictive or supervised learning approach, the goal is to learn a mapping from inputs $x$ to outputs $y$, given a labeled set of input-output pairs $D = \{(x_i, y_i)\}_{i=1}^N$. Here $D$ is called the training set, and $N$ is the number of training examples. In the simplest setting, each training input $x_i$ is a $D$-dimensional vector of numbers, representing, say, the height and weight of a person. These are called features, attributes or covariates. The second main type of machine learning is the descriptive or unsupervised learning approach. Here we are only given inputs, $D = \{x_i\}_{i=1}^N$, and the goal is to find “interesting patterns” in the data. This is sometimes called knowledge discovery. This is a much less well-defined problem, since we are not told what kinds of patterns to look for, and there is no obvious error metric to use (unlike supervised learning, where we can compare our prediction of $y$ for a given $x$ to the observed value) [87].

2.5.3.4.1 **ML in Condition Monitoring**

In recent years, the field of machine learning has shown promising results in the application of its sophisticated Artificial Intelligence techniques in process monitoring of mechanical systems through image and signal analysis. Moreover, these techniques have been used in predicting the remaining tool life and fault detections. A study in this field [88] presented a hybrid Support Vector Machine (SVM)-Bayesian Network (BN) for predicting the thermal error; nonlinear deformation of machine tool resulted from flow of heat through the machine structure which is caused by varying temperatures in machine environment and in-between moving parts, in machine tool according to specific condition, which leads to a more generalized prediction model than the conventional method of directly mapping error and temperature irrespective of operating
conditions. Another research carried out by Sun [89, 90] classified tool wear using SVM based on manufacturing considerations and proposed a new performance evaluation function for TCM.

In recent years, the application of machine learning techniques in tool condition monitoring has been improved significantly. In [91], a real-time tool wear monitoring system has been proposed to perform wear classification of cutting tool in coroning process through acoustic emission monitoring. This study has proposed based on the concept of classifier fusion method which shows significant results in classification rate with unity weighting. In the other study published by Jinjiang [92], a virtual tool wear sensing technique based on multisensory data fusion is applied to develop an artificial intelligent model for tool condition monitoring. This method involves application of support vector regression model of machine learning. Conventional pattern recognition methods; other than SVM in machine learning techniques and artificial neural networks applications in this field of study has shown that the sample data needed to develop these algorithms is insufficient. Meantime, SVM can provide better generalization than ANN and other methods with small number of samples [93]. Since it is hard to obtain sufficient data in practice, SVM is introduced to have advantage of generating good results. With this approach, a tool is replaced or continued not only based on the tool condition alone but also the risk in cost incurred due to underutilized or overused tool.
Chapter 3  METHODOLOGY

An effective Tool Condition Monitoring (TCM) for any machining process results a significant advantage in decreasing production cost for industrial manufacturers. Methodologies proposed in the past are widely based upon indirect sensory approaches coupled with AI techniques. But, many of these methods and approaches have limitations to be applied on-line in shop floor environment. In addition, these methods have been restricted to operate in limiting cutting parameters and application scenarios of metal cutting process as the sensory information changes with respect to change in cutting parameters and other dependent factors such as tool and work piece materials and material properties of work piece etc. Thus, need for a reliable, efficient and compact TCM methodology is highly motivated for metal cutting process. This chapter begins with highlighting some of the limitations to the existing approaches for TCM in industrial applications before presenting the details of the proposed new approach.

3.1. The Existing Approach Limitations

In general, Tool Condition Monitoring (TCM) involves sensing and processing information of process variables of metal cutting process through various physical quantities measurements such as vibration, cutting force, acoustic emission and sound etc. These in-direct approaches have been
used by researchers in the past; as stated in chapter 2, to develop various methodologies for TCM’s. Although these methods have proven to be accurate in acquiring the sensory information, each of them has its own disadvantages.

For instance, cutting force measurement has considered to be the frequently used sensory approach for collecting accurate tool wear information where it also has disadvantages in application of metal cutting scenarios that varies with cutting parameters such as cutting speed, feed and depth of cut etc. Ren [83] considered cutting force measurement as the most reliable and accurate sensing method for online tool wear monitoring and used force measurements in a Takagi–Sugeno–Kang (TSK) fuzzy approach for tool wear monitoring. It was observed that such models were difficult in estimating the error of approximation and needed development to capture the uncertainty during turning process. In addition, sensory approaches like Acoustic Emission (AE) and vibration have also been applied and found disadvantages, in later approach (AE), Sensitivity to sensor location was studied by Haber [94] and Lan [95]. In their findings, it is observed that choosing a suitable position in which to place the AE sensors to sense sufficient AE signals is a necessary but contentious matter, and it requires an understanding of the AE transmission path [33]. Whereas in vibration sensory approach, it is very sensitive to changes in cutting parameters and the very dependent nature on these parameters has made it difficult in its application for various metal cutting scenarios. For example, Ertekin [34] tested the robustness of different sensor signal features from dynamometers, AE sensors and accelerometers using three different types of material. His results revealed that dynamometer and AE signal features are more robust than vibration signals for surface roughness prediction and dimensional accuracy estimation. For the current amplitude sensory approach, a major limitation is that the thresholds will vary greatly as the cutting conditions vary. Even a mere change in the radial or axial depth of
cut would require the trial cuts to be repeated [keep ref as review paper with imp notes]. For sound monitoring approach, Weller et al. [42] considered the sound of machine vibration as a source of information about the machining process, tool, and the machine and the techniques used by them as well as Sadat and Raman [46] for tool wear monitoring have been reviewed by Dan and Mathew [12], and it was proposed that use of this method in a typical shop-floor environment is perhaps impractical due to high ambient noise.

From the above stated limitations of existing approaches, it is evident that even though the indirect sensory approaches have their pro’s and con’s, at the end, these approaches should be utilized through a methodology that is practically possible to apply in industrial environments. Nonetheless, the final evaluation of these sensory approaches is to be against the application factors if these systems in industrial applications. Table 1 summarizes the evaluation of above stated sensors in machining monitoring systems for practical application in terms of cost, intrusive nature and reliability are also provided.
Table 1: Summary of evaluated sensors in machining monitoring systems

<table>
<thead>
<tr>
<th>Sensor Type</th>
<th>Cost-Efficiency</th>
<th>Accuracy</th>
<th>Flexibility</th>
<th>Non-Intrusive Nature</th>
<th>Reliability</th>
<th>Main Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cutting Force</td>
<td>★</td>
<td>★★★</td>
<td>★</td>
<td>★</td>
<td>★</td>
<td>Tool wear*, breakage, surf. roughness, chatter</td>
</tr>
<tr>
<td>Vibration</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>Surface roughness*, tool wear, chatter</td>
</tr>
<tr>
<td>Sound/Ultrasound</td>
<td>★★★</td>
<td>★</td>
<td>★★★</td>
<td>★★★</td>
<td>★★★</td>
<td>Tool wear*, breakage, chatter</td>
</tr>
<tr>
<td>Acoustic Emission</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>Tool wear, breakage*, chatter</td>
</tr>
<tr>
<td>Temperature</td>
<td>★</td>
<td>★</td>
<td>★</td>
<td>★</td>
<td>★</td>
<td>Tool wear*</td>
</tr>
<tr>
<td>Power</td>
<td>★</td>
<td>★</td>
<td>★★★</td>
<td>★★★</td>
<td>★★★</td>
<td>Tool wear*, breakage, chatter</td>
</tr>
<tr>
<td>Surface Roughness</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>★★</td>
<td>Tool wear*, breakage, surf. roughness*, chatter</td>
</tr>
<tr>
<td>Displacement</td>
<td>★★</td>
<td>★★</td>
<td>★</td>
<td>★★★</td>
<td>★</td>
<td>Tool wear*</td>
</tr>
</tbody>
</table>

From the above summarized table, it is noticeable that Sound monitoring shows a significant advantage in evaluation against key factors for industrial application. The major difficulty with gathering sensory information obtained from sound monitoring is that the signal-to-noise ratio of useful information about the tool wear is very poor [96, 97]. This problem can be solved by employing advanced process model to extract the features from the audible signals for tool wear identification or classification.

The other major lacking in the existing approaches for TCM is an application dependent system. The research evolving in this field so far has been developing the systems under constrained parameters of cutting theory. The unpredictability of the tool condition was affirmed by Scheffer and Heyns [20]. They observed from the experiences of the operators of machining that the wear rate has been unpredictable. The work piece properties, machining conditions and
type of machining would also affect the tool wear which in return affects the sensory information collected during machining. Recently, one practical problem attracts the attention of many manufacturing companies that non-uniform mechanical properties of raw workpiece materials become very common due to the cost control or the improper heat treatment. The harmful impacts resulting from non-uniform mechanical properties, particularly hardness, is that it can cause expedited tool wear and unexpected tool breakage. To be specific, the specific type of cutting tool is designed for cutting certain types of materials within a range of hardness levels. The localized hard regions of the workpiece material may lead to the unexpected tool failure. In addition, the hardness variation also expedites the tool wear to shorten the tool life, which may cause unexpected tool change or influence the surface quality of products. Therefore, the key issue is how to detect the tool wear conditions accurately in machining of workpiece material having a non-uniform hardness with a reliable, efficient, and cost-effective way, which remains an open research question up to now.

Although the research that has been developed in this field is successful with the application of advanced process models for TCM software part and multi-sensor fusion approaches for TCM hardware part, there is still limitation to apply these research in industrial environments. The practical application of this techniques and methodologies require huge capital investments and costs for maintenance procedures. The other important drawback in application of these methodologies is the complexity of set-up, position dependent of the sensor and intrusive nature of the system into the machining process. Thus, a tool condition monitoring system with a compact set-up, cost-effective and position invariant is in need with application of the above stated approaches and methodologies.
3.2. **The Proposed New Approach (Methodology)**

It was understood from the literature review that sensor based indirect methods, which can process nonlinear and non-stationary signals, are more suitable for an efficient TCM system. In this study, a machine learning technique with time-frequency domain analysis as signal processing method is proposed as advance process model to analyze the sensory information and predict the tool condition. The emitted tool sound from the turning operation is considered as the input signal.

The TCM system based on the proposed new approach consists of the following four stages;

- Input
- Features Extraction
- Classification and
- Output

The purpose and the function of each of them are explained in the following sub sections.

### 3.2.1 Input Stage

The signals in which the condition of the tool is determined are collected in this stage. The emitted tool sound is considered as input because the sound generated during machining is closely related to the system dynamics. Based on a review by Michaelletti [98] audible emissions is one of the easily measured quantities for sensor based indirect TCM. When the tool is gradually wearing, the surface of the flank becomes larger, making the contact surface between tool and work-piece to increase, and resulting in higher frictional forces. This induces vibration of the tool which, in turn, produces audible vibrational waves that are transmitted over the air. The principal benefits of audible sound for machining process monitoring are associated with the nature of the sensors employed in the acquisition of the signals. These are, in general, easy to mount on the machine
tool, near the machining point, with little or no interference with the machine, the tool, the workpiece, or the chip formation. Besides, these sensors, basically microphones, are easy to use in combination with standard phono meters or spectrum analyzers. These characteristics of audible sound sensors make the realization of the monitoring procedure quite straightforward. In addition, their maintenance is simple since they only require a careful handling to avoid being hit or damaged. Accordingly, they usually provide for a favorable cost/benefit ratio.

3.2.2 Feature Extraction Stage

This is one of the important stage which extracts the required features from the sound signal. Time frequency domain analysis is performed on the collected sound signals. At first, the collected sound signals are displayed in time domain and later transformed into frequency domain using Fast Fourier transform. This transformation of the digital signal into the frequency domain is performed for signal conditioning, and from which the feature generation and extraction phenomenon is carried out form the amplitude of sound signals. The frequency amplitudes form each data points of the signal and their average values are extracted as features. These extracted features will be used to feed a classifier in the proposed machine learning algorithm to monitor the tool conditions.

3.2.3 The Classification Stage

The purpose of the classification stage is to classify the condition of the tool into various states of tool condition from fresh to severely worn. A SVM is proposed as classifier to act as decision-making system. The reason behind choosing this method is explained as follows. Conventional pattern recognition methods; other than SVM in machine learning techniques and artificial neural
networks applications in this field of study has shown that the sample data needed to develop these algorithms is insufficient. Meantime, SVM can provide better generalization than ANN and other methods with small number of samples [93]. Since it is hard to obtain sufficient data in practice, SVM is introduced to have advantage of generating good results. With this approach, a tool is replaced or continued not only based on the tool condition alone but also the risk in cost incurred due to underutilized or overused tool.

3.2.4 The Output Stage

The output stage is simply an indicator which indicates the current state of the tool. In addition, the proposed approach is trained and tested with different microphones data for the system sensory position independency. Finally, with the application of this system, In the case of any machine tool without an automatic tool changer, the operator can start the tool change procedure after absorbing the indication. The tool changer may be activated automatically depending on the prediction, if the machine is equipped with automatic tool changer. In either case, it is possible to take the corrective action at the most appropriate time.
Chapter 4  Experimental Design & Setup

The goal of any TCM system is to find the appropriate information in the signal which links to the actual tool condition. Hence, the success of TCM system greatly depends on determining the best possible way to develop the experimental methodology from which the data collected for analyzing and training the decision-making system for real-time scenarios, the system should be accurate for correlating the sensory information with the actual cutting theory behind any machining process. This chapter introduces the experimental setup and design for the TCM system. The experimental setup encompasses the hardware and software systems and their setup, and shows the machining parameters and tool conditions considered in the experiments.

The initial part of this chapter explains the mechanism of tool wear and characterization of tool wear. It follows by explaining the chosen machining parameters for the whole scope of the study and followed by sensory set up involved in this study. The next part includes experimental design of for all the three tasks involved in scope and followed by data acquisition part. The remaining part of this chapter explains the signal processing strategy applied and classification methodology.
4.1. **Tool Wear Characterization**

Despite the high level of technology built into every aspect of modern metal cutting processes, the phenomenon of tool wear still affects the reliability and full automation of machining process. Ghasempoor [14] stated that the tool wear has a direct effect on dimensional precision, the quality of surface finish, and ultimately the costs of the parts produced. If the information about tool wear is obtained on-line, it can be used to set up tool change policy, economic optimization of machine cutting operations, adaptive control, and complete automation of machining operations.

Tool wear is a gradual process with severe shear and frictional forces in cutting process. When the tool is gradually wearing, the wear area on the flank surface keeps growing to increase the contact surface between tool and workpiece and result in higher frictional forces. In addition, tool wear also induces vibration to produce audible vibrational waves that are transmitted over the air. Per the standard ISO 8688 parts 1 and 2 (ISO 1989), one of the main wear patterns observed is flank wear. The flank wear is the loss of particles along cutting edge, observed on the clearance face of end milling tools. The measurements of flank wear are divided into three different types: Uniform flank wear (VB1), Non-uniform flank wear (VB2) and localized flank wear (VB3), shown in Fig. 2. In our study, flank wear has found to be predominant in all our observations.
Experiments conducted in all three tasks were conducted using high speed steel (HSS) end mills, and the number of flutes varies per each study depending upon the work piece characteristics. The state of the tool is determined by the amount of flank wear on the cutting edge of each flute, flank wear thickness is calculated by averaging different measurements within the cutting zone from cutting edge tool corner to the distance of axial depth of cut on cutting edge. The classification levels of tool states vary from task to task; explained elaborately in each task experimental design. Tool state classification levels are classified as per the observed wear ranges. The tool states levels are classified from good state; starts from 0 microns, to failure stage where tool reaches to dysfunctional state. Each tool state range boundaries are defined after conducting the experiments of preceding tool state and followed by observation of wear achieved on the tool. To maintain the tool wear in experimental runs of each tool state within the classified wear range, multiple cutting tools with same specifications are used and all the tools are labelled to keep track of wear.
observations and experimental runs data. In addition, each tool has been used in alternative cycle to avoid excess heat generated from same tool used for multiple experimental runs. The flank wear of the tools used in the experiments are measured using the dynamic profilometer.

### 4.2. Machining Parameters

The proposed TCM system in this study utilizes a TRACK K3 EMX milling machine, and the same machine has been used for all the three tasks. The machine can be operated in manual and semi-automatic modes. The machine is a vertical milling machine, and has a maximum spindle speed of 3200 rpm and 7.5 HP spindle motor power. Dry cutting conditions were used and face milling operation is performed for experimental runs in all three tasks. This study employed the straight cut (a major cutting type in milling operations).

Machining parameters are defined based on the combination of the workpiece material and cutting tool. Appropriate parameters are recommended by the machine tool manufacturer to ensure the quality of the product and the life of the machine. Cutting harder materials requires more power and generates more heat in the nose (hot spot) of the cutting tools. To operate the cutting tool without failure within the expected running time, the cutting speed must be kept under the recommended speed. This helps to maintain the cutting temperature within the limitations of the tool. For this reason, workpiece hardness is one of the critical factors to determine the proper cutting speed.

The cutting conditions are the combination of spindle speed, feed rate, and depth of cut during machining. Since each parameter has its limited range, based on the specifications of the machine, a proper combination of the parameters should be chosen before cutting. Selecting the appropriate cutting conditions also involves considering the service life of the tool. Tool life is defined as the
amount of time it takes for tool wear to reach certain, predetermined levels [99]. Therefore, optimizing the performance and life of the tool requires proper setup of the cutting conditions. Optimizing the machining condition requires considering the depth of cut based on the workpiece material, maximum power of the machine, and tool and machine rigidity [100]. Choosing a certain depth of cut allows the feed rate to be calculated within the limit of machine power. Spindle speed then can be decided to obtain the optimized life of the tool.

In this study, a general range of spindle speed and chip-load based on the recommended range for the optimal tool life of selected tool were chosen, and feed rate has been calculated by using the standard formula [provide ref for formula]. Depth of cut was kept constant for all the experimental runs. All the three tasks were followed the above stated method in determining machining parameters. Design of experiments for each task, based on this methodology are disused in subsection of experimental design.

4.3. Sensor Set-up & Data Acquisition System

In this study, the TCM system is employed with uni-directional microphones to capture the sound emitted due to the contact between the tool cutting edge and the work-piece. The same sensory setup scheme was followed for all the three tasks. Three microphones were used for the task 1 & 2 and four microphones were used for the task-3. The reason in selecting multiple number of microphones is to evaluate the proposed system for sensory position independence for real-time application purposes. All the microphones are placed in same plane with different angles and distances from the cutting zone, the details of the positions chosen for each study were discussed in sub-section of experimental design.
Additional instruments are necessary to obtain the signals from the microphones and transfer them to a personal computer for tool condition monitoring. A multi-channel audio interface device (Steinberg UR44) was employed for this study. It is an external module that can connect to the parallel port of a personal computer for data acquisition. It can handle up to 4 microphones simultaneously. Cubase AI 8, a Microsoft-Windows/Macintosh based software for the audio interface device, was used for control and data acquisition. The stream data were saved to a local disk drive so the data could be used for post-process data analysis and model development. The start position of data collection was set to a half inch after the end of workpiece, and the data collection is stopped as tool reaches the maximum length of cut of work-piece. Same methodology has been followed for all the three tasks for data acquisition.

4.4. **Experimental Design**

In the following sections, design of experiments and experimental methodology along with data collection details for each task of study is described in detail.

4.4.1 **Task-1: TCM for Wear Prediction in End-Milling Application**

This phase of study focusses on development of an intelligent tool condition monitoring system for end milling process. To realize this objective, a six-class tool wear classification was established by classifying different wear thickness ranges of two flute HSS end mill tools. A series of experiments were conducted using the six wear class tools under a wide range of cutting conditions (feed rate & spindle speed) for end milling process. The emitted sound signals during each cut were collected and further analyzed by a developed tool condition monitoring model using machine learning methods. The performance of proposed algorithm was analyzed by evaluating
confusion matrix and another performance metrics. The following sections provide a detailed explanation of experimental methodology and analysis on results for evaluating the performance of proposed system.

4.4.1.1  Experimental Set-up

All the experiments were conducted on a numerically controlled TRACK K3 EMX milling machine under dry, conventional end milling conditions. 6061 aluminum is used as workpiece for machining to all the experiments, and the cutting tool used is a non-coated high-speed steel two-flute end mill tool. For the sound signal collection, three professional EO-200 condenser microphones are positioned at 8, 12 and 15 inches and angled at 40°, 50° and 70° as shown in Fig. 3. Microphones are connected through a multi-channel audio interface device (Steinberg UR44) which is further connected to a computer for sound signal acquisition. Fig. 1 shows a picture of the whole experimental system.

![Schematic layout of experimental setup](image)

Fig. 3 Schematic layout of experimental setup
4.4.1.2 Design of Experiments

The type of milling operation performed in this study is a face milling with a straight cut done through the whole length of work piece which is a 6-inch long. Face milling was chosen to avoid the complications by increasing variables that can arise from other milling operations. To ensure the developed monitoring system can successfully detect the tool conditions irrespective of cutting conditions, in this study, the cutting conditions are selected over a wide range of cutting speed and chip load within the capability of the milling machine. More specifically, for each tool condition class, five spindle speeds were chosen, and for each spindle, three different feed rates were used to perform the experiments. Thus, overall during the experiment, 15 cutting cycles were performed for each tool condition class (explained below) that totals up to 90 cutting cycles for the whole experiment. Both the radial depth of cut (0.1875 inches) and the axial depth of cut (0.2 inches) were kept constant throughout the experiments. Different tools were prepared for each wear class in corresponding to the wear thickness assigned for respective class. Through this method, advancement of wear thickness on tool is avoided. For each test, the cutting tool was measured again after the cut to ensure the progression of wear within the specified wear thickness range. Tools used for each class were labeled with different numbers and alphabets.

4.4.1.3 Tool Condition Classes

In this study, cutting tool conditions are classified into six different classes with respect to various thickness ranges of flank wear lands on cutting edge of tools. Per the standard ISO 8688, flank wear thickness is calculated by averaging different measurements within the cutting zone from cutting edge tool corner to the distance of axial depth of cut on cutting edge as shown in Fig.
4. Table 2 summarizes the specification of each tool condition class per the level of average flank wear.

![Image of tool wear](image.png)

**Fig. 4 Observed wear on cutting edge**

<table>
<thead>
<tr>
<th>TOOL CONDITION CLASS</th>
<th>THICKNESS RANGE(µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0-20</td>
</tr>
<tr>
<td>Light Wear</td>
<td>20-40</td>
</tr>
<tr>
<td>Average</td>
<td>40-70</td>
</tr>
<tr>
<td>Advanced wear 1</td>
<td>70-100</td>
</tr>
<tr>
<td>Advanced wear 2</td>
<td>100-150</td>
</tr>
<tr>
<td>Failure</td>
<td>&gt;150</td>
</tr>
</tbody>
</table>

Table 2 Task-1: Tool wear classification

The tool wear was observed using optical microscope, and through which images of the wear regions were captured and displayed in the Fig.5.
Audio signals for each cutting cycle have been collected through three microphones. The length of the signal was considered from the start of actual metal removing until the point where cutting tool teeth edge leaves the workpiece. The sound signals were collected with a sampling frequency of 44100Hz. The sound signals collected for all the cutting cycles has been tabulated.
with different time stamps, different experimental conditions, cutting conditions, microphones positioning for each cutting cycle, and labeled with corresponding wear class. This table serves as an input data recognition file for the algorithm. From this file, algorithm categorizes every sound signal features into the corresponding wear class and other related conditions. Total of 270 samples of sound signals with corresponding experimental data had been collected and utilized for the development of the proposed tool wear prediction model. Table 3 summarizes the layout of spreadsheet with input parameters excluding time stamps that has been given to algorithm.

<table>
<thead>
<tr>
<th>TOOL CONDITION</th>
<th>SPINDLE FEED (RPM)</th>
<th>FEED RATE (IPM)</th>
<th>MICROPHONE NO.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>1800</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Good</td>
<td>1800</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>Good</td>
<td>1800</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Light wear</td>
<td>1700</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Light wear</td>
<td>1700</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>Light wear</td>
<td>1700</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>Average</td>
<td>1500</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>Average</td>
<td>1500</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>Average</td>
<td>1500</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Advanced wear1</td>
<td>1400</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>Advanced wear1</td>
<td>1400</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>Advanced wear1</td>
<td>1400</td>
<td>12</td>
<td>3</td>
</tr>
<tr>
<td>Advanced wear2</td>
<td>1300</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Advanced wear2</td>
<td>1300</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>Advanced wear2</td>
<td>1300</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Failure</td>
<td>2000</td>
<td>24</td>
<td>1</td>
</tr>
<tr>
<td>Failure</td>
<td>2000</td>
<td>24</td>
<td>2</td>
</tr>
<tr>
<td>Failure</td>
<td>2000</td>
<td>24</td>
<td>3</td>
</tr>
</tbody>
</table>

*Table 3 is an overview of actual datasheet with only a few data points per each class are displayed.

Table 3: Task-1 Experimental data cutting parameters*

*Table - 3 is an overview of actual datasheet with only a few data points per each class are displayed.
4.4.2 Task-2: TCM in End-Milling a Non-Uniform Hardness Work Material

This study involves implementation of redefined algorithm of the previously proposed model to predict the hardness variation during cutting process simultaneously with the tool state. To generate the experimental sound signals to train and test the developed system, specimens with hardness variation for gear milling were carefully prepared using the Jominy end-quench method, and the specimens were milled by four-flute end mills with different tool wear classes using the conventional milling machine. The emitted sound signals with respect to different tool wear classes and workpiece hardness levels were used to train the developed monitoring system. After that, the performance of the developed system was analyzed by evaluating confusion matrix.

4.4.2.1 Experimental Methodology

In this study, the experimental methodology involves building a dataset of sound signals with the features correlating variation in hardness of work-piece and wear of the tool. The study aims to prepare the work-piece specimens with variation in hardness across the length by Jominy End-Quench tests. A four-level hardness model is developed from the Rockwell hardness test results conducted on the specimens after end quenching tests. The progression of tool wear and failure is developed into a tool condition model by classifying the wear progression into three levels and failure as a final level. The following sections explain in detail of the overall structure of experimental methodology considered for this study.
4.4.2.2 Work-Piece Specimen

The work-piece material chosen for this study is an 8620-alloy steel, and the reason to choose this type of material is to have a hardness variation curve with in the gradual change in hardness with respect to distance. In this study, the work pieces are solid rods with the dimensions as per ASTM standards of Jominy End-quench test. The procedure followed for end-quench tests was performed same as described in ASTM standards with a change in water jet height of additional of 1 inch. After the end quench test, the hardness variation was observed by performing Rockwell hardness test C (HRC) along the length of the specimens. The hardness tests were duplicated three times to make sure the variations of hardness readings on every measurement points are less than 1%. The average hardness readings at different distances from the quench end are displayed graphically in the Fig.6. From the obtained results, a hardness variation model was developed by classifying the overall variation into four levels. The hardness variation model with specific range of hardness values for each level is shown in the Table 4.

Fig. 6 Task 2 Hardness variation of the specimen
Table 4 Task-2: Hardness level classification

<table>
<thead>
<tr>
<th>HARDNESS LEVELS</th>
<th>HARDNESS RANGE (HRB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>&gt; 30</td>
</tr>
<tr>
<td>Level 2</td>
<td>30-25</td>
</tr>
<tr>
<td>Level 3</td>
<td>25-20</td>
</tr>
<tr>
<td>Level 4</td>
<td>&lt; 20</td>
</tr>
</tbody>
</table>

The hardened specimens are solid circular rods which is not a suitable geometry to perform end milling operations on the specimens. Each specimen was machined to have a flat surface in the form of step geometry as shown in Fig. 7.

![Machined specimen for cutting tests](image)

**4.4.2.3 Tool Wear Classification Model**

Per the standard ISO 8688 parts 1 and 2 (ISO 1989), one of the main wear patterns observed are flank wear and chipping, flank wear is the loss of particles along cutting edge, observed on the clearance face of end milling tools. The measurements of flank wear are divided into three different types: Uniform flank wear (VB1), Non-uniform flank wear (VB2) and localized flank wear (VB3). In our study, the flank wear has found to be predominant in all our observations, and the uniform flank wear thickness is calculated by averaging different measurements on the teeth from cutting edge of teeth corner. The tool wear is observed using a Wyko NT1100 dynamic profiler for
accurate measurements of width of wear developed on tools. The width of wear is calculated from the 2-D surface profile drawn from cutting edge of tooth.

In order to reflect characteristics of tool wear and part hardness variation over the process, the multi-class classification technique was used to classify the tool wear conditions into different classes. Generally, a tool state is sharp during the initial stages and gradually tool wear occurs with respect to cutting time, and finally reaches the worn state. The progression of tool wear and failure is developed into a tool condition model by classifying the wear progression into three levels. Table 5 summarizes the specification of each tool condition class per the level of average flank wear.

<table>
<thead>
<tr>
<th>TOOL CONDITION CLASS</th>
<th>THICKNESS RANGE (µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0 - 60</td>
</tr>
<tr>
<td>Average</td>
<td>60-120</td>
</tr>
<tr>
<td>Advanced</td>
<td>120-180</td>
</tr>
<tr>
<td>Failure</td>
<td>&gt;180</td>
</tr>
</tbody>
</table>

### 4.4.2.4 Design of Experiments

To ensure the developed monitoring system can successfully detect the tool conditions irrespective of cutting conditions, in this study, the cutting conditions were selected over a wide range of cutting speed and chip load within the capability of the milling machine so that the developed system can be susceptible for analyzing tool condition over the wide range of cutting conditions. More specifically, for each tool condition class three spindle speeds were chosen, and for each spindle, three different feed rates were used to perform the experiments. Thus, overall during the experiment, 12 cutting cycles were performed for each tool condition class that totals up to 48 cutting cycles for the whole experiment. Different tools were carefully prepared for each
wear class in corresponding to the flank wear width assigned for respective class. For each test, the cutting tool was measured again after the cut to ensure the progression of wear within the specified wear thickness range.

4.4.2.5 Experimental Set-Up

All the experiments were conducted on a numerically controlled TRACK K3 EMX milling machine under dry, conventional end milling conditions. 8620 steel is used as workpiece for machining to all the experiments, and the cutting tool used is a non-coated high speed steel four-flute end mill tool. For the sound signal collection, three professional EO-200 condenser microphones were positioned at 8, 12 and 15 inches and angled at 40°, 50° and 70° as shown in Fig. 8. Microphones were connected through a multi-channel audio interface device (Steinberg UR44) which was further connected to a computer for sound signal acquisition.

![Fig. 8 Task 2 Schematic diagram of experimental layout](image_url)
4.4.2.6 Audio Signal Collection

Audio signals for each cutting cycle have been collected through three microphones. The length of the signal was considered from the start of actual cut until the point where cutting tool teeth edge leaves the workpiece. The sound signals were collected with a sampling frequency of 44 kHz. The sound signals collected for all the cutting cycles has been tabulated with different time stamps, different experimental conditions, cutting conditions, microphones positioning for each cutting cycle, and labeled with the corresponding wear class. This table serves as an input data recognition file for the algorithm. From this file, algorithm categorizes every sound signal features into the corresponding wear class and other related conditions. Total of 144 samples of sound signals with corresponding experimental data had been collected and utilized for the development of the proposed tool wear prediction model.

4.4.3 Task-3: Tool Condition Monitoring in Gear Milling

This work focusses on implementation of decision-making model developed through audible sound monitoring approach in gear milling, especially in milling of workpiece material with hardness variation. In order to realize this objective, the monitoring system was developed with two functions to detect the hardness changing of the workpiece in milling and the current cutting tool wear condition simultaneously based on the SVM algorithm as the decision-making support system. To generate the experimental sound signals to train and test the developed system, specimens with hardness variation for gear milling were carefully prepared using the Jominy end-quench method, and the specimens were milled by involute gear cutters with different tool wear classes using the conventional milling machine. The emitted sound signals with respect to different tool wear classes and workpiece hardness levels were used to train the developed monitoring
system. After that, the performance of the developed system was analyzed by evaluating confusion matrix.

4.4.3.1 Experimental procedures

In this study, the experimental methodology involves building a dataset of sound signals with the features correlating variation in hardness of work-piece and wear of the tool. All the details about the experimental procedures have been elaborated as follows.

4.4.3.1.1 Workpiece Preparation

In order to prepare the specimen with the hardness variation along the length, the workpiece material was heat-treated based on the Jominy end-quench method. For this study, the 1018 low carbon steel was selected as the workpiece material and was cut into cylinders 1 inch in diameter and 4 inches in length per ASTM A255.

After the end quench test, the hardness variation was observed by performing Rockwell hardness test B (HRB) along the length of the specimens. The hardness tests were duplicated three times to make sure the variations of hardness readings on every measurement points are less than 1%. The average hardness readings at different distances from the quench end are displayed graphically in the Fig. 9. In order accommodate to the machine learning techniques, the hardness variation was classified into three levels, which is also named as multi-class classification, as elaborated in Table 6, and displayed graphically in Fig. 9.
Fig. 9 Task 3 Hardness variation of work piece

Table 6 Task-3: Hardness level classification

<table>
<thead>
<tr>
<th>HARDNESS LEVELS</th>
<th>HARDNESS RANGE (HRB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>&lt;84</td>
</tr>
<tr>
<td>Level 2</td>
<td>84-90</td>
</tr>
<tr>
<td>Level 3</td>
<td>&gt;90</td>
</tr>
</tbody>
</table>

4.4.3.2 Cutting Tool Preparation

Based on the diameter of the specimen specified by Jominy end-quench method, No. 6 20° high speed involute gear cutter for milling (as seen in Fig. 10) was selected with diametrical pitch of 20 and 18 cutting teeth to rack per the standard formula as below.

$$OD = \frac{N + 2}{P}$$
Where $N$ is the number of cutter teeth, $P$ is the diametrical pitch of the cutter, and $OD$ is the outer diameter of the specimen.

Per the standard ISO 8688 parts 1 and 2 (ISO 1989), one of the main wear patterns observed are flank wear and chipping, flank wear is the loss of particles along cutting edge, observed on the clearance face of end milling tools. The measurements of flank wear are divided into three different types: Uniform flank wear (VB1), Non-uniform flank wear (VB2) and localized flank wear (VB3). In our study, the flank wear has found to be predominant in all our observations, and the uniform flank wear thickness is calculated by averaging different measurements on the teeth from cutting edge of teeth corner as shown in Fig. 11. The tool wear was observed using a Wyko NT1100 dynamic profiler for accurate measurements of width of wear developed on tools. The width of wear was calculated from the 2-D surface profile drawn from cutting edge of tooth.

To reflect characteristics of tool wear and part hardness variation over the process, the multi-class classification technique was used to classify the tool wear conditions into different classes. Generally, a tool state is sharp during the initial stages and gradually tool wear occurs with respect
to cutting time, and finally reaches the worn state. The progression of tool wear and failure was
developed into a tool condition model by classifying the wear progression into three levels. Table 7 summarizes the specification of each tool condition class per the level of average flank wear.

Table 7 Task-3 Tool wear classification

<table>
<thead>
<tr>
<th>TOOL CONDITION CLASS</th>
<th>THICKNESS RANGE(µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0 - 80</td>
</tr>
<tr>
<td>Average</td>
<td>80-140</td>
</tr>
<tr>
<td>Advanced</td>
<td>&gt;140</td>
</tr>
</tbody>
</table>

4.4.3.3 Design of Experiments

The approach employed for this study involves form-milling a tooth of involutes spur gear at varying feed and spindle speed on chosen workpiece material. Conventional type of milling was adopted for this study, and dry cutting approach was followed. The whole depth (HW) for each tooth was calculated per the standard formula for pitch number 20 and finer, which is shown below, and the obtained number is 0.112 inch.

\[ HW = \frac{2.2}{P} + 0.002 \], where \( P \) is diametrical pitch

To ensure the developed monitoring system can successfully detect the tool conditions irrespective of cutting conditions, in this study, the cutting conditions were selected over a wide range of cutting speed and chip load within the capability of the milling machine so that the developed system can be susceptible for analyzing tool condition over the wide range of cutting conditions. More specifically, for each tool condition class four spindle speeds were chosen, and for each spindle, four different feed rates were used to perform the experiments as shown in Table 8. Thus, overall during the experiment, 16 cutting cycles were performed for each tool condition class that totals up to 48 cutting cycles for the whole experiment. Different tools were carefully
prepared for each wear class in corresponding to the flank wear width assigned for respective class. For each test, the cutting tool was measured again after the cut to ensure the progression of wear within the specified wear thickness range.

Table 8 Corresponding feed rates(IPM) under different spindle speeds and chip loads

<table>
<thead>
<tr>
<th>CHIP LOAD (INCHES)</th>
<th>SPINDLE SPEED (RPM)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>110</td>
</tr>
<tr>
<td>0.00016</td>
<td>0.2</td>
</tr>
<tr>
<td>0.00064</td>
<td>0.8</td>
</tr>
<tr>
<td>0.00128</td>
<td>1.7</td>
</tr>
<tr>
<td>0.00152</td>
<td>2.0</td>
</tr>
</tbody>
</table>

4.4.3.4 Experimental Set-Up

All the experiments were conducted on a numerically controlled TRACK K3 EMX milling machine under dry, conventional end milling conditions. 1018 steel was used as workpiece for machining to all the experiments, and the cutting tools used were non-coated high speed steel involute cutters. For the sound signal collection, four professional condenser microphones were positioned at 8, 18, 12 and 12 inches and angled at 50°, 50°, 60° and 70° as shown in Fig. 12. Microphones 1 & 2 were positioned at same angles but with different distances, and microphones 3 & 4 were positioned with same distance and different angles. Microphones were connected

![Fig. 12 Schematic diagram of experimental layout](image)
through a multi-channel audio interface device (Steinberg UR44) which was further connected to a computer for sound signal acquisition, as shown in Fig. 12.

4.4.3.5 Audio Signal Collection

Audio signals for each cutting cycle have been collected through three microphones. The length of the signal was considered from the start of actual cut until the point where cutting tool teeth edge leaves the workpiece. The sound signals were collected with a sampling frequency of 44 kHz. The sound signals collected for all the cutting cycles has been tabulated with different time stamps, different experimental conditions, cutting conditions, microphones positioning for each cutting cycle, and labeled with the corresponding wear class. This table serves as an input data recognition file for the algorithm. From this file, algorithm categorizes every sound signal features into the corresponding wear class and other related conditions. Total of 192 samples of sound signals with corresponding experimental data had been collected and utilized for the development of the proposed tool wear prediction model.

4.5. Pre-Processing of Sound Signal

For good classification, data preprocessing is important step. A good data pre-processing can reduce the noise in the data and retains as much information as possible. From a clean data, the features (condition indicators) can be calculated and considered as patterns for fault diagnosis purpose. In the study [101], the necessity and importance of pre-processing step has been explained in detail.

The sound signals collected are transformed into a digital format which is non-stationary and often overlaps with other various sound sources, whose waveforms and arrival times are unknown.
In general, tool condition monitoring systems for machining apply signal processing as a pre-processing procedure to extract the physical parameters of interest that best correlate with the exact tool wear. Many signal processing methods have been proposed, and with the various approaches, to extract the features from sound signals for testing or monitoring [1].

The signals collected are very long representing a cutting cycle of an average duration of 35 seconds, and the signal length for each sound signal is around $10^6$ points due to reason that the sampling of signals are set at 44.1 kHz. At first, the collected sound signals are displayed in time domain and later transformed into frequency domain using Fast Fourier transform. This transformation of the digital signal into the frequency domain is performed for signal conditioning, and from which the feature generation and extraction phenomenon is carried out from the amplitude of sound signals. The frequency amplitudes from every data points of the signal and their average values are extracted as features. These extracted features will be used to feed a classifier in the proposed machine learning algorithm to monitor the tool conditions.

4.5.1 SVM in Condition Monitoring

Support vector machine (SVM) is a relatively new computational learning method based on the statistical learning theory and serves as an expert system. Typically, classical learning approaches such as neural networks, follows empirical risk minimization; an approach designed to minimize error on the training data set. In contrast, SVM is based on structural risk minimization principle based upon statistical learning theory. SVM has been noticed to be especially efficient in large classification problems due to its ability in handling very large feature spaces, and also benefit in faults classification, because the number of features to be the basis of fault diagnosis may not have to be limited.
Given a training set, the algorithm constructs a hyper-plane which maximizes the margin between two input classes. For example, consider linearly separable data with two classes. Plus, a sign indicates positive class samples and minus indicates negative class samples. There can be many hyper planes which separate two classes. SVM’s find the best hyperplane with a maximum margin of all the possible hyperplanes, where the margin is the distance between hyperplane and support vectors.

SVM can also be used in non-linear classification tasks with the application of kernel functions. Using kernels, nonlinear data is mapped into higher dimensional space to make it linearly separable. Kernel is a function that returns a dot product of the feature space mappings of the original data points. Working in the high-dimensional feature space enables the expression of complex functions, but it also generates the problem. Computational problem occurs due to the large vectors and the over fitting also exists due to high dimensionality. The latter problem can be solved by suing the kernel function. The selection of appropriate kernel function is very important, since the kernel defines the feature space in which training set examples will be classified. In this work, Gaussian Radial Basis Functions were evaluated and formulated.

The discussion above deals with binary classification where the class labels can take only two values. In our current problem, however, we have two classification levels with three classes which involves in application of multi-classification strategy.

In machine condition monitoring and fault diagnosis problem, SVM is employed for recognizing special patterns from acquired signal, and then these patterns are classified per the fault occurrence in the machine. After signal acquisition, a feature representation method can be performed to define the features, like the statistical feature of signal for classification purposes. These features can be considered as patterns that should be recognized using SVM.

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Based on the input data vectors that consist of representation of wear type observed during cutting, SVM will recognize these patterns. Usually, each wear type signal acquired produces special features as stated above which are considered as patterns. SVM is motivated to represent these patterns in a high dimension typically much higher than the original feature space. With an appropriate nonlinear mapping using kernel function to a sufficiently high dimension, data from two or more categories can always be separated by a hyper-plane.

In this research, Python 2.7 has been used to develop the algorithm and further the same platform has been used for all the simulations. Modeling process starts by reading the audio data from .WAV format in which the audio signal collected during machining is stored, into numpy array of the desired format. Further, the algorithm labels data with input and output data pairs where the cutting conditions, tool conditions are used as input parameters for labeling the data. In the next step, each audio signal is cut into variable window length; as given by the input for algorithm, which each cut signal is considered as data samples. A Fourier transformation on each sample is performed to transform the sound sample from time-domain to frequency-domain, and in this process, through transformation each data point has been generated as features that has been used as features for SVM.

A random pattern shuffling module is developed to divide the features data set into training and testing set. The training set is used for the learning purpose while the testing set is used to test the SVM performance. 70% of the whole data is used for training and remaining 30% for validation and testing, which are standard training and testing percentage values in machine learning techniques for an optimal performance of the classifier [102]. In this study, variable window length selected to unit 1 second which has found to be optimal window length with a reasonable amount of data points for analysis.
Chapter 5  Results and Discussion

After the training stage, a model function has been generated that will be used as functioning model to predict the tool condition. Further, this model is tested with test data set that has been set aside before training stage which the model algorithm has never seen before, to validate the model. To analyze the test results, firstly, the relationship between emitted tool sound and tool flank wear in three tasks are analyzed individually from the results obtained from the confusion matrix analysis of classifier predictions. Based on the proposed machine learning technique, tool wear predictions of each class can be analyzed from the evaluation of confusion matrix. A confusion matrix, also known as error matrix is a special kind of contingency table that is derived to evaluate the performance of a machine learning algorithm [103]. This analysis is facilitated by tabulating in a specific table layout in which a total number of samples is arranged in two dimensions, true (actual) and predicted, with an identical set of classes in both dimensions.

In this section, each task of study test results has been presented and discussed thoroughly about the performance of developed SVM algorithm. Within each task, confusion matrix is generated for test data set predictions, and further the results are analyzed and discussed for
algorithm performance in each tool condition class. Secondly this study also involves sensory position independence for task-1 and task-3. The system should be tested for sensory position independence to maintain the system’s capability in tool condition monitoring with comparable accuracy within a certain range. For the effective machining process monitoring system, one of the major concerns is the influence of the sensor position in the prediction accuracy. The specific requirements about the sensor position will greatly restrict the wide application of the monitoring system. To address this issue, this study used multiple microphones with different distances and angles, as mentioned in sensory setup section of chapter 4, with respect to the cutting zone to collect audible sound signals.

5.1. Results of Task-1: TCM for Wear Prediction in End-Milling Application

In this task of study, the test data set consists of random samples from the six tool condition classes. In the testing stage, random number of samples has been picked and their tool condition class is predicted by the model function generated from the training stage. The prediction results of these test samples into six tool condition classes were derived into confusion matrix. In this task, the test samples are predicted into each of the six class, and are evaluated against true values of the predicted samples in confusion matrix.
The confusion matrix is shown in Fig. 13; the number of samples bar represented in right shows the color intensity level based on number of samples and this color intensity has been displayed as predicted class of samples. Further, the proposed model has been evaluated for miss-classification (error) percentage and precision percentage of each wear class of test data set. These results are tabulated in Table 9.

Table 9 Task-1 Performance analysis of algorithm for each class

<table>
<thead>
<tr>
<th>WEAR CLASS</th>
<th>PRECISION (%)</th>
<th>ERROR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>99.37</td>
<td>0.63</td>
</tr>
<tr>
<td>Light</td>
<td>97.51</td>
<td>2.49</td>
</tr>
<tr>
<td>Average</td>
<td>90.75</td>
<td>9.25</td>
</tr>
<tr>
<td>Advanced Wear 1</td>
<td>92.44</td>
<td>7.56</td>
</tr>
<tr>
<td>Advanced Wear 2</td>
<td>98.51</td>
<td>1.49</td>
</tr>
<tr>
<td>Failure</td>
<td>97.00</td>
<td>3.00</td>
</tr>
</tbody>
</table>

In Table 9, the precision percentage is the predicted precision of actual wear class and other predicted wear classes of each specified wear class. Error percentage, also called as miss-classification percentage, is the percentage of total false predictions in each specified class. The
sample size for calculating these metrics is obtained from the confusion matrix, as number of predictions of each class from the total samples available in the test set percentage. In both precision and miss-classification, wear classes average and advanced wear 1 were found to be most affected in false predictions compared to other classes. Those increasing errors are mainly due to miss-classification of tool state from the actual wear class. To analyze in detail, the errors in average and advanced wear 1 classes are observed with respect to samples number and miss-classified cases in confusion matrix, and it has been found that most of the miss-classifications in a wear class of average are predicted as good, and most of the miss-classifications in a wear class of advanced wear 1 are predicted as light wear. The main reason for those errors is associated with the fact that the pre-processing methods applied are not sufficient to filter the noise, and those were classified into the respective signal characteristic wear range, thereby the chosen pre-processing methods must be improved, and more effective methods for better accuracy in signal conditioning are still needed.

For the furthermore performance evaluation of the proposed algorithm, a concatenation of randomly selected sound signals from all six wear classes that belongs to test data set was run through the algorithm to observe the accuracy in multi-wear classification simultaneously. The results of the above specified process are plotted into a graph, shown in Fig. 14.
In the above figure, a time-domain signal of the input concatenation signal is shown first, followed by the identification results of all six wear classes present in the signal. In the presented time-domain signal figure, the signal consists of actual wear classes, which can be observed from good to failure classes consecutively from the start to end. From the Fig. 8 (b), results show that the proposed algorithm has provided to accurately predict the progression of wear class from one to another and the transition between wear classes with slightly miss-classification. In contrast, most of the time, the developed algorithm has shown good accuracy in predicting the transition. The analysis has also shown that algorithm can predict tool wear class accurately in transition of sound signal to next class, although the amplitude shown in time-domain signal of test signal is same in transition stage of signal between the classes.

Fig. 14 Tool state prediction. (a) Time-domain signal composed of the sound signals collected from good to failure cutting tools under random cutting conditions. (b) Prediction results from proposed machine learning approach. (F - Failure, AW.2 - Advanced wear 2, AW.1 - Advanced wear 1, AVG - Average, LW - Light Wear, G - Good)
5.1.1 Study of Microphone Positioning

In this task of study three microphones were used with different distances and angles, as mentioned in experimental setup section of chapter 4, with respect to the cutting zone to collect audible sound signals. Different data sets were labeled into Mic-1 to Mic-3 with sound signals collected by the corresponding microphones. By varying the position and the number of microphones for training and testing the program, the prediction accuracies for three combinations of data sets have been set as shown in Table 10.

Table 10 Task-1 Position invariant prediction results

<table>
<thead>
<tr>
<th>Combination sets</th>
<th>Training data set&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Testing data set</th>
<th>Prediction accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Set-1</strong></td>
<td>Mic-1</td>
<td>Mic-2</td>
<td>90.6</td>
</tr>
<tr>
<td></td>
<td>Mic-2</td>
<td>Mic-1</td>
<td>90.6</td>
</tr>
<tr>
<td></td>
<td>Mic-3</td>
<td>Mic-1</td>
<td>92.0</td>
</tr>
<tr>
<td></td>
<td>Mic-1</td>
<td>Mic-3</td>
<td>92.0</td>
</tr>
<tr>
<td></td>
<td>Mic-2</td>
<td>Mic-3</td>
<td>89.1</td>
</tr>
<tr>
<td></td>
<td>Mic-3</td>
<td>Mic-2</td>
<td>89.1</td>
</tr>
<tr>
<td><strong>Set-2</strong></td>
<td>Mic-1, Mic-2</td>
<td>Mic-3</td>
<td>96.1</td>
</tr>
<tr>
<td></td>
<td>Mic-2, Mic-3</td>
<td>Mic-1</td>
<td>95.0</td>
</tr>
<tr>
<td></td>
<td>Mic-1, Mic-3</td>
<td>Mic-2</td>
<td>93.8</td>
</tr>
<tr>
<td><strong>Set-3</strong></td>
<td>Mic-1, Mic-2, Mic-3</td>
<td>Mic-1</td>
<td>96.0</td>
</tr>
<tr>
<td></td>
<td>Mic-1, Mic-2, Mic-3</td>
<td>Mic-2</td>
<td>95.1</td>
</tr>
<tr>
<td></td>
<td>Mic-1, Mic-2, Mic-3</td>
<td>Mic-3</td>
<td>97.0</td>
</tr>
</tbody>
</table>

<sup>a</sup> Mic-1/2/3 represents the data set of sound signals collected by the corresponding microphone

Firstly, within every set, the prediction accuracy varies with different combinations between the training data set and the testing data set. Among Set-3 with same training data set, the testing data set Mic-3 collected from the farthest place from the cutting zone displayed a higher accuracy due to reasons that the noise will be minimized by the longer distance between the microphone
and the machine and there is no work piece material between the microphone and the cutting zone to block the signals. In set-2, although the training data size has been decreased the testing mic positions 1 & 3 has shown significant prediction accuracy. Mic-2 position has shown least accuracy compared to other microphones position but has shown considerable prediction accuracy percentage that is closer to overall prediction accuracy. Further, for set-1, the prediction accuracies for has been decreased due to the reason that the data set size has been considerably decreased. Therefore, it is shown that the position of microphone really influences the prediction accuracy to a certain extent. However, this positional error can be minimized by having more training data from different locations as described below.

Generally, from Set-1 to Set-3, the prediction accuracies of developed program can be improved by increasing the number of data sets for training, which can be explained by the fact that training the program with more data sets collected from different positions can help separate the target signal features from the disturbances caused by the sensing position. However, this improvement of the prediction accuracy becomes insignificant as increasing the number of data sets. Besides the average value, the variation of the prediction accuracy also decreases from Set-1 to Set-3 as shown in Table 4. It is seen that the influence of the position for collecting the signals on the prediction accuracy can be reduced by using more training data sets collected from different positions. Expectedly, with adequate training, the system has proved that the developed monitoring system is not affected by positional variation within a certain range and independent of number of sensors.
5.2. **Results of Task-2: TCM in End-Milling a Non-Uniform Hardness Work Material**

In this task of study, the objective of this task is to test the proposed method and algorithm capability in predicting the tool condition under machining non-uniform hardness work piece material. In addition, the developed algorithm is trained to predict the hardness variation of work piece material.

Firstly, for tool condition prediction, during the training stage, a model function has been generated by the proposed algorithm that will be validated in testing phase with random samples of data set under non-uniform hardness machining. Secondly, the algorithm is trained with hardness variation labels of samples from the similar data set that has been used for tool condition prediction; in which the samples retain information of hardness variation, and various levels of hardness variation is defined through the given time stamps of each audio signal which is fed into algorithm through input excel sheet as discussed in experimental part; Chapter 4; 4.4.2. From this process, a model function has been generated which is used for hardness variation prediction of machining work piece.

For this task, the classification methodology followed for tool condition and hardness variation is a four-level multi-class system. Thus, the test data set results are derived into confusion matrices, separately for both prediction cases. In each of the case, the predicted results of test samples are evaluated against true values of samples to access the performance of generated model function from developed algorithm.
5.2.1 Tool Wear Prediction Analysis

In this section, confusion matrix is derived for tool wear classification. The matrix layout displays the number of samples predicted correctly with respect to actual labels, and it also shows the number of samples predicted incorrectly for each class, as shown in Table 11.

Table 11 Task-2 Confusion matrix layout

<table>
<thead>
<tr>
<th>ACTUAL CLASS</th>
<th>PREDICTED CLASS</th>
<th>Good</th>
<th>Average</th>
<th>Advanced</th>
<th>Failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>1383</td>
<td>107</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0</td>
<td>1218</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Advanced</td>
<td>0</td>
<td>0</td>
<td>522</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Failure</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1051</td>
<td></td>
</tr>
</tbody>
</table>

Performance analysis of the confusion matrix of proposed algorithm involves mainly evaluating miss-classification (error) percentage and precision percentage of each wear class of test data set. These results are tabulated in Table 12.

Table 12 Task-2 Performance analysis of algorithm for each class

<table>
<thead>
<tr>
<th>WEAR CLASS</th>
<th>PRECISION (%)</th>
<th>ERROR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>92.8</td>
<td>7.2</td>
</tr>
<tr>
<td>Average</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Advanced</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Failure</td>
<td>99.9</td>
<td>0.1</td>
</tr>
</tbody>
</table>

In Table 12, it is evident that the highest error percentage is for good tool condition, and in referring to these highest error percentage into the confusion matrix, and all the mispredictions have been observed in the average class. The potential reason behind these errors is due to the 107 samples that are miss predicted might be very close to the boundary of average class in classification model curve. Thus, the features generated in these samples have very close data
distribution to average class, which is associated with the fact that the pre-processing methods applied are not sufficient to filter the noise, and those were classified into the respective signal characteristic wear range. Therefore, the chosen pre-processing methods must be improved and more effective methods for better accuracy in signal conditioning need to be investigated.

### 5.2.2 Hardness Variation Prediction Analysis

In this section, confusion matrix is derived for hardness variation prediction. The matrix layout displays the number of samples predicted correctly with respect to actual labels, and it also shows the number of samples predicted incorrectly for each hardness level, shown in Table 13.

<table>
<thead>
<tr>
<th>MULTI-LEVEL CLASSIFICATION</th>
<th>PREDICTED LEVEL</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ACTUAL LEVEL</td>
<td>Level 1</td>
<td>Level 2</td>
<td>Level 3</td>
<td>Level 4</td>
</tr>
<tr>
<td>Level 1</td>
<td>2410</td>
<td>122</td>
<td>148</td>
<td>33</td>
</tr>
<tr>
<td>Level 2</td>
<td>266</td>
<td>234</td>
<td>119</td>
<td>16</td>
</tr>
<tr>
<td>Level 3</td>
<td>141</td>
<td>81</td>
<td>232</td>
<td>56</td>
</tr>
<tr>
<td>Level 4</td>
<td>61</td>
<td>20</td>
<td>72</td>
<td>179</td>
</tr>
</tbody>
</table>

Performance analysis of the confusion matrix of proposed algorithm involves mainly evaluating miss-classification (error) percentage and precision percentage of each hardness level of test data set. These results are tabulated in Table 14.

<table>
<thead>
<tr>
<th>HARDNESS LEVEL</th>
<th>PRECISION (%)</th>
<th>ERROR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>88.8</td>
<td>11.2</td>
</tr>
<tr>
<td>Level 2</td>
<td>36.9</td>
<td>63.1</td>
</tr>
<tr>
<td>Level 3</td>
<td>45.5</td>
<td>54.5</td>
</tr>
<tr>
<td>Level 4</td>
<td>53.6</td>
<td>46.4</td>
</tr>
</tbody>
</table>
In Table 14, it is evident that the hardness level 1 has shown highest precision compared to other three levels. Further, in the next three levels, Level 2 has shown the least precision compared to the Levels 3&4. Firstly, the variation in precision for each level can be mainly attributed to the uneven distribution of samples data among various hardness levels and miss-classification of hardness level from the actual level. To analyze in detail, the available signal lengths for different hardness levels are not equal. The signal length successively decreases from Level 1 to Level 4. This has resulted in decrease of samples for level 2, level 3 and further for level 4 thereby caused biasing of training function towards the hardness level with the largest data size. Thus, the system has leaned more towards the level 1 which consequently shows higher accuracy compared to other three levels.

Secondly, Level 2 precision has further decreased in comparison to level 3 & 4 which also shows a simultaneous decrease in number of total samples for predictions in those levels. Additionally, from the confusion matrix in Table 6, it is shown that false predictions in each level are considerably significant. The main reason for these errors is associated with the fact that the pre-processing methods applied are not sufficient to filter the noise, and those were classified into the respective signal characteristic wear range.

5.3. **Result of Task-3: Tool Condition Monitoring in Gear Milling**

In this task of study, tool condition prediction was tested under the gear milling of non-uniform hardness work piece material. During the training stage, algorithm was trained with samples of data set to generate a model function and further it is validated by testing with test data set samples. The tool condition and hardness variation classification methodology followed in this task of study is a three level multi-classification system. Thus, the algorithm is trained and tested in tool
condition and hardness variation cases separately to evaluate the performance of generated model in predicting the tool condition class and hardness variation level.

The test data set results are derived into confusion matrices, separately for both prediction cases. In each of the case, the predicted results of test samples are evaluated against true values of samples to access the performance of generated model function from developed algorithm.

### 5.3.1 Tool Wear Prediction Analysis

In this section, confusion matrix is derived for tool wear classification. The matrix layout displays the number of samples predicted correctly with respect to actual labels, and it also shows the number of samples predicted incorrectly for each class, as shown in Table 15.

<table>
<thead>
<tr>
<th>ACTUAL CLASS</th>
<th>PREDICTED CLASS</th>
<th>GOOD</th>
<th>AVERAGE</th>
<th>ADVANCED</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td></td>
<td>3949</td>
<td>17</td>
<td>44</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>393</td>
<td><strong>3421</strong></td>
<td>197</td>
</tr>
<tr>
<td>Advanced</td>
<td></td>
<td>158</td>
<td>61</td>
<td><strong>3792</strong></td>
</tr>
</tbody>
</table>

Performance analysis of the confusion matrix of proposed algorithm involves mainly evaluating miss-classification (error) percentage and precision percentage of each wear class of test data set. These results are tabulated in Table 16.

<table>
<thead>
<tr>
<th>WEAR CLASS</th>
<th>PRECISION (%)</th>
<th>ERROR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>98.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Average</td>
<td>85.3</td>
<td>14.7</td>
</tr>
<tr>
<td>Advanced</td>
<td>94.5</td>
<td>5.5</td>
</tr>
</tbody>
</table>
In Table 16, in both precision and miss-classification, wear class average was found to be most affected in false predictions compared to other classes. Those increasing errors are mainly due to miss-classification of tool state from the actual wear class. To analyze in detail, the errors in average class are observed with respect to the sample size and miss-classified cases in confusion matrix. It has been found that most of the miss-classifications in a wear class of average are predicted as good. The main reason for those errors is associated with the fact that the pre-processing methods applied are not sufficient to filter the noise, and those were classified into the respective signal characteristic wear range, thereby the chosen pre-processing methods must be improved or in need of effective methods for better accuracy in signal conditioning.

5.3.2 Hardness Variation Prediction Analysis

In this section, confusion matrix is derived for hardness variation. The matrix layout displays the number of samples predicted correctly with respect to actual labels, and it also shows the number of samples predicted incorrectly for each hardness level, shown in Table 17.

Table 17 Task-3 Confusion matrix layout

<table>
<thead>
<tr>
<th>MULTI-LEVEL CLASSIFICATION</th>
<th>PREDICTED LEVEL</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ACTUAL LEVEL</td>
<td>Level 1</td>
<td>2541</td>
<td>101</td>
<td>153</td>
</tr>
<tr>
<td></td>
<td>Level 2</td>
<td>179</td>
<td>441</td>
<td>56</td>
</tr>
<tr>
<td></td>
<td>Level 3</td>
<td>198</td>
<td>119</td>
<td>245</td>
</tr>
</tbody>
</table>

Performance analysis of the confusion matrix of proposed algorithm involves mainly evaluating miss-classification (error) percentage and precision percentage of each hardness level of test data set. These results are tabulated in Table 18.
Table 18 Task-3 Performance analysis of algorithm for each class

<table>
<thead>
<tr>
<th>HARDNESS LEVEL</th>
<th>PRECISION (%)</th>
<th>ERROR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>90.8</td>
<td>9.2</td>
</tr>
<tr>
<td>Level 2</td>
<td>65.2</td>
<td>34.8</td>
</tr>
<tr>
<td>Level 3</td>
<td>43.6</td>
<td>56.4</td>
</tr>
</tbody>
</table>

In Table 18, it is evident that the hardness level 1 has shown highest precision compared to other two levels. Level 3 precision has further decreased in comparison to level 2 which also shows a simultaneous decrease in number of total samples for predictions in those levels. These observed phenomena can be mainly caused due to the uneven distribution of sample data between the various hardness levels and miss-classification of hardness level from the actual level. The uneven distribution of sample data caused biasing of training function towards highest size data hardness level. Thus, the system has leaned more towards the level 1 which consequently shows higher accuracy compared to other two levels.

5.3.3 Sensory Position Independent Study

In this task of study, position independent study has been conducted for tool condition prediction, four microphones were used with different distances and angles, as mentioned in experimental setup section of chapter 4, with respect to the cutting zone to collect audible sound signals. Mic-1 and Mic-2 were varied with only distance but the angular position was kept same, and for Mic-3 & Mic-4; the distance was kept same and angular position was varied. This arrangement strategy was followed to observe the influence of sensor position by angle and distance from the cutting zone. Different data sets were labeled into Mic-1 to Mic-3 with sound signals collected by the corresponding microphones. By varying the position and the number of
microphones for training and testing the program, the prediction accuracies for three combinations of data sets have been set as shown in Table 19.

Table 19 Task-3 Position invariant predictions

<table>
<thead>
<tr>
<th>COMBINATION SETS</th>
<th>TRAIN DATA SET</th>
<th>TEST DATA SET</th>
<th>PREDICTION ACCURACY (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SET 1</strong></td>
<td>Mic1, Mic2, Mic3, Mic4</td>
<td>Mic1</td>
<td>99.2</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic2, Mic3, Mic4</td>
<td>Mic2</td>
<td>99.0</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic2, Mic3, Mic4</td>
<td>Mic3</td>
<td>98.4</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic2, Mic3, Mic4</td>
<td>Mic4</td>
<td>97.4</td>
</tr>
<tr>
<td><strong>SET 2</strong></td>
<td>Mic1, Mic2, Mic3</td>
<td>Mic4</td>
<td>87.6</td>
</tr>
<tr>
<td></td>
<td>Mic2, Mic3, Mic4</td>
<td>Mic1</td>
<td>91.5</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic3, Mic4</td>
<td>Mic2</td>
<td>87.3</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic2, Mic4</td>
<td>Mic3</td>
<td>88.2</td>
</tr>
<tr>
<td><strong>SET 3</strong></td>
<td>Mic1, Mic2</td>
<td>Mic3</td>
<td>90.3</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic2</td>
<td>Mic4</td>
<td>89.7</td>
</tr>
<tr>
<td></td>
<td>Mic2, Mic3</td>
<td>Mic1</td>
<td>92.7</td>
</tr>
<tr>
<td></td>
<td>Mic2, Mic3</td>
<td>Mic4</td>
<td>88.1</td>
</tr>
<tr>
<td></td>
<td>Mic3, Mic4</td>
<td>Mic1</td>
<td>92.6</td>
</tr>
<tr>
<td></td>
<td>Mic3, Mic4</td>
<td>Mic2</td>
<td>88.8</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic4</td>
<td>Mic2</td>
<td>71.1</td>
</tr>
<tr>
<td></td>
<td>Mic1, Mic4</td>
<td>Mic3</td>
<td>87.8</td>
</tr>
<tr>
<td><strong>SET 4</strong></td>
<td>Mic1</td>
<td>Mic2</td>
<td>74.2</td>
</tr>
<tr>
<td></td>
<td>Mic1</td>
<td>Mic3</td>
<td>84.8</td>
</tr>
<tr>
<td></td>
<td>Mic1</td>
<td>Mic4</td>
<td>88.2</td>
</tr>
<tr>
<td></td>
<td>Mic2</td>
<td>Mic1</td>
<td>92.6</td>
</tr>
<tr>
<td></td>
<td>Mic2</td>
<td>Mic3</td>
<td>89.4</td>
</tr>
<tr>
<td></td>
<td>Mic2</td>
<td>Mic4</td>
<td>87.9</td>
</tr>
<tr>
<td></td>
<td>Mic3</td>
<td>Mic1</td>
<td>90.2</td>
</tr>
<tr>
<td></td>
<td>Mic3</td>
<td>Mic2</td>
<td>88.1</td>
</tr>
<tr>
<td></td>
<td>Mic3</td>
<td>Mic4</td>
<td>89.0</td>
</tr>
<tr>
<td></td>
<td>Mic4</td>
<td>Mic1</td>
<td>93.6</td>
</tr>
<tr>
<td></td>
<td>Mic4</td>
<td>Mic2</td>
<td>73.9</td>
</tr>
<tr>
<td></td>
<td>Mic4</td>
<td>Mic3</td>
<td>89.1</td>
</tr>
</tbody>
</table>

*a* Mic-1/2/3/4 represents the data set of sound signals collected by the corresponding microphone

75
Firstly, within each set, for Set-1; Mic-1 position has shown significant prediction accuracy comparable to overall prediction accuracy. Mic-4 position has shown least among the four microphone positions. Thus, from this observation it can be said with significant training sample size the microphone position does not influence the prediction accuracy. Within Set-2 & Set-3, the prediction accuracies for the four microphone positions has been considerably decreased in comparison to Set-1. Overall, it is observed with the decrease in sample size for training data set the prediction accuracy has got decreased for which the microphone position doesn’t show considerable influence on prediction accuracy. In Set-4, due to the decrease of training samples size the overall prediction accuracies has been decreased significantly compared to Set-1. Although the data set size has been decreased the prediction accuracies of microphones position 1 and 4 hasn’t changed significantly compared to Set-2 & Set-3.

Secondly, in relation to the angular position, although, microphone 3 and 4 are placed at different angles and with same distance from cutting zone, from Set-1 to Set-4 it is evident that there is an insignificant change in accuracy. Thus, it is observed that change in angular position does not affect the prediction accuracy of the proposed system.

Further, it is observed that with the increase of training data set size through multiple microphones will improve the prediction accuracy. This can be due to the reason that with increased sensors with different positions, the data collected will help the classifier to train more effectively in developing model knowledge to identify the target features of signal. Overall, it is noticed that, with the increase in data set size provided the collection of data from different distances can reduce the influence of sensory position of the proposed system in real time application. Expectedly, with adequate training, the system has proved that the developed
monitoring system is not affected by positional variation within a certain range and independent of number of sensors.

5.4. **Summary**

Experiments were carried out with different applications coupled with variation in work piece hardness variation and cutting conditions to inspect the effect of emitted tool sound on tool wear classification. In all three tasks, the prediction of tool condition is maintained the significant accuracy rate thereby proving the proposed system feasibility for real-time application.

From the results of all three tasks, it can be concluded that:

- The proposed machine learning algorithm with SVM approach has shown the capability of predicting the tool conditions very accurately with an overall accuracy of 98%. These demonstrated the applicability of the proposed machine learning approach with sound monitoring for tool wear estimation.

- The proposed system can predict tool condition under work piece non-uniform hardness variation with a 98% accuracy for end-milling process and gear milling process.

- The proposed system can detect the hardness variation of the workpiece in machining with the reasonable prediction accuracy.

- The detection system demonstrated a very short response time to tool conditions. Total processing time is 0.0908 seconds for processing data points, identifying the tool conditions in SVM and sending/presenting the result to the computer. The high processing rate can reduce the risk of operating machine with the worn tool to damage the part.
• The proposed machine learning approach has shown favorable prediction in multi-class wear during the transition between different wear classes. Therefore, the proposed approach is more suitable for identifying the wear progression on same tool and machining operation.

• The system has capable of sensory position independency within the considerable range around the cutting zone which will have advantage of the proposed system in real time application.
Chapter 6 Conclusion

In this chapter, the final conclusions are discussed considering the different aspects of the study, namely the three tasks conducted with the application of proposed system in different scenarios of metal cutting processes. Recommendations for future research are also suggested based on the conclusions drawn from this study.

Tool condition monitoring remains to be a potential research field in developing intelligent monitoring systems to alert the failures and cutting process anomalies beforehand to minimize production losses. This study focused on proposing a tool condition prediction model with the application of machine learning techniques in end milling process based on the audible sound monitoring approach which can be employed to monitor the machining process for tool wear progression and failure. The results of proposed work have shown a promising prediction accuracy, especially in tool wear progression. Essentially, the key concept in the proposed tool condition monitoring model is to show the applicability of sound monitoring as sensing approach to correlate the tool condition and machine learning techniques for decision-making systems with high accuracy. In addition, the proposed system has also been made in capable of predicting tool condition during machining of non-uniform hardness metals and to display the capability of proposed system in replicating to various machining process. Further, this study explicitly
proposes a new methodology in analyzing the sound signals irrespective of type of noises associated with the signal to monitor and predict the condition of tool.

This study highlights two important aspects: the development of a systematic methodology to set up the cutting experiments, particularly allowing the proposed sensing approach for a better comparison of generated features in sound signal to correlate with the tool wear and application of machine learning techniques and the SVM approach as a classifier for the prediction of tool wear. The main shortage of this study has found to be pre-processing which involves signal conditioning. The signal conditioning methods used in this study are of basic methods in digital signal processing which have shown less capability in noise separation that has led to miss-classification in some cases. Thus, a sophisticated pre-processing method is required in predicting the tool wear with maximum accuracy. Another major drawback in this study has shown in decreased percentage of accuracy in hardness variation, compared to tool condition prediction, due to the non-homogeneous distribution of data in each hardness level. This can be addressed by improving the current input data processing method to consider the change in number of samples available per hardness level during classification to avoid the prediction biasing towards the class of highest samples available class.

6.1. Future Research

Further improvement in the application of this model in real-time involves in introducing effective pre-processing methods to increase the accuracy in feature generation and better correlation of tool wear for decision-making system. More importantly, the utilization of sound monitoring approach has shown feasibility of application in industrial applications with the help of machine learning techniques. However, the proposed approach is a data driven technique which
requires a significant amount of data from different scenarios of metal cutting theory to train the system.

The future study in this approach involves three aspects. Firstly, improving the prediction accuracy, in the case of non-uniformity in data size of classes, and application of other sophisticated concepts such as regularization for SVM to reduce the miss-predictions. In addition, to further optimize the prediction accuracy of SVM, a sliding window concept can be applied to study the transition of data characteristics from one state of tool condition to other thereby reducing the miss-predictions in prediction of tool wear progression.

Secondly, sophisticated machine learning techniques such as Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) that can perform signal separation to isolate the actual signal from the machine and other environmental noises will be implemented. Further to test the applicability of the proposed model and experimental methodology in further complex machining processes, study of various process variables of metal cutting theory to predict the tool condition in those variables variation and application of coated cutting tool monitoring in various machining process.

Finally, with the proposed sensory approach and methodology, sound monitoring and machine learning techniques, this study has shown the feasibility of developing a compact monitoring system for metal cutting machine tools. However, there is still a limitation to make the system capable of working under any unforeseen process variations in metal cutting processes. With the proposed methodology, system has to be re-calibrated for new scenario, which again is a repetitive and complicated process. To ensure the system to be universal for all the machining process under varying process variables, an advanced machine learning technique, such as deep learning, can be
introduced to develop a process model integrating cutting theory with machine learning to solve the above stated problem.
Bibliography


