Monitoring Tool Condition with Acoustic and Vibration Signals Using IoT

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Abstract - This article reviews the recent advances in the field of monitoring tool condition using acoustic and pulse signals. Specifically, the research focuses on the development and application of signal processing techniques to extract valuable information from acoustic and pulse signals generated by cutting tools during machining operations. To this end, the literature is reviewed with emphasis on the signal acquisition and analysis techniques used in the field. Additionally, the article presents a comprehensive overview of the existing methods and techniques used to monitor tool conditions, including signal analysis techniques, feature extraction techniques, and classification techniques. Furthermore, the article discusses the challenges associated with acoustic and pulse-based TCM, including signal noise and impurities, signal acquisition, feature extraction, and classification. The review concludes with a discussion of the possible future directions in the field. The use of acoustic and pulse signals to monitor the condition of cutting tools has become increasingly popular in recent years. In order to extract useful information from the signals generated by cutting tools, sophisticated signal processing techniques are required. In this article, a comprehensive review of the existing methods and techniques used to monitor tool conditions is presented. Various signal acquisition and analysis techniques are discussed, as well as feature extraction and classification methods. Additionally, the article delves into the challenges associated with acoustic and pulse.

Keywords - Acoustic and Pulse Signals, TCM, Signal Processing, Signal Analysis, Feature Extraction, Classification, Signal Acquisition, Signal Noise and Impurities.

I. INTRODUCTION

The Internet of Things (IoT) has revolutionized the way we interact with the physical world and has enabled the development of novel applications that combine physical and digital processes. One of the most promising applications of IoT is the monitoring of tool condition [1]. TCM is a process of collecting and analyzing data from sensor readings to detect and diagnose any wear or damage in the cutting tools used in industrial machining. This paper reviews the available literature on TCM using acoustic and pulse signals obtained from the IoT [2]. The various techniques used to detect tool wear, their advantages and limitations are discussed. The paper also provides an overview of the current trends in IoT-based TCM. The use of cutting tools in industrial machining is an essential part of many manufacturing processes. The performance of these tools is directly related to the quality of the machined parts and the overall productivity of the process. However, the cutting tools wear out over time, resulting in reduced productivity and poor quality of the parts. In order to maintain the performance of the tools, regular maintenance and inspection of the tools is required [3]. This process is known as TCM. TCM is a process of collecting and analyzing data from sensor readings to detect and diagnose any wear or damage in the cutting tools used in industrial machining. It involves the use of sensors to measure the parameters that indicate tool wear, such as pulse, temperature, acoustic emission, etc [4]. The data collected from the sensors is then analyzed using various algorithms to detect any tool wear or damage. The development of IoT has provided new opportunities for the implementation of TCM in industrial processes. IoT-based TCM involves the use of IoT-enabled sensors to monitor and detect the condition of the tools in real-time. The data collected from the sensors is analyzed using cloud-based analytics to provide insights into the condition of the tools [5]. This helps in minimizing the downtime due to tool wear and maximizing the efficiency of the manufacturing processes. The majority of the existing research on TCM using IoT has focused on the use of acoustic and pulse signals. Acoustic and pulse signals are generated when the cutting tool interacts with the workpiece during machining. These signals can be used to detect the onset of tool wear [6]. Various techniques, such as pattern recognition, wavelet transform, and artificial neural networks, have been used to analyze the acoustic and pulse signals in order to detect tool wear. The use of IoT in TCM also enables the use of other techniques, such as machine learning, to analyze the data collected from the sensors. Machine learning algorithms, such as support vector machines and deep neural networks, can be used to identify the patterns in the data and detect the onset of tool wear [7]. The current trends in IoT-based TCM include the use of wearable sensors and the integration of artificial intelligence (AI) for online monitoring of the tools. Wearable sensors can be used to directly measure the parameters that indicate tool wear and send the data to the cloud for analysis. AI-based algorithms can be used to analyze the data in real-time and detect the onset of tool wear. In conclusion, the use of IoT in TCM is a promising approach to improve the efficiency of the manufacturing processes. The various techniques used to detect tool wear, their advantages and limitations are discussed in this paper. The current trends in IoT-based TCM are also discussed [8]. The types of signal processing are exhibited in **Table 1**

Table 1. Signal Processing Techniques

Technique	Description
Acoustic Signal Analysis	Analysis of sound waves generated by cutting tools during machining operations
Pulse Signal Analysis	Analysis of pulse signals generated by cutting tools during machining operations
Signal Noise Reduction	Techniques to reduce noise and impurities in the acquired acoustic and pulse signals
Signal Preprocessing	Preprocessing techniques such as filtering, normalization, and resampling of the signals
Time-Domain Analysis	Analysis of the signals in the time domain, including statistical analysis and waveform analysis
Frequency-Domain Analysis	Analysis of the signals in the frequency domain, including Fourier transform and spectral analysis
Time-Frequency Analysis	Techniques to analyze the signals in both time and frequency domains, such as wavelet transform and spectrogram

II. SIGNAL ACQUISITION AND ANALYSIS TECHNIQUES

The development of sophisticated monitoring and control systems has enabled manufacturers to identify and control the condition of their machinery in order to improve production and maintain a safe working environment [9]. By monitoring the condition of tools and machinery, operators can detect potential problems before they cause costly damage or downtime. Acoustic and pulse signals are widely used in the industry as one of the most effective ways to monitor tool condition [10]. As the Internet of Things (IoT) emerges, there are opportunities to implement these methods more effectively and efficiently. This paper will review the use of acoustic and pulse signals in the context of IoT and discuss the latest advancements in signal acquisition and analysis techniques. Background Acoustic and pulse signals are widely used in industry to monitor the condition of tools and machinery. Acoustic signals are generated by the friction of two surfaces and can be used to detect changes in the wear of cutting tools, such as drills, taps and reamers. Pulse signals are generated by the motion of rotating or reciprocating parts and can be used to detect changes in the bearing condition of machinery [11]. Both acoustic and pulse signals contain information about the condition of the tool or machinery, and can be used to detect potential problems before they cause costly damage or downtime. Signal Acquisition The acquisition of acoustic and pulse signals is an important step in monitoring tool condition with IoT. The quality of the signal acquired will affect the accuracy of the condition monitoring system, so it is important to use the appropriate signal acquisition equipment [12-15]. This equipment typically includes microphones, accelerometers or strain gauges which are connected to a data acquisition system. The signal is then digitised and stored on a computer or other device for further analysis. The signal acquisition system must be designed to capture the relevant frequency range for the application, for example the range of frequencies associated with cutting tools or the range of frequencies associated with bearings [16]. The signal should also be recorded with sufficient accuracy and resolution for the analysis to be accurate and meaningful. This can be achieved by using an appropriate sampling rate and signal-to-noise ratio. Signal Analysis Once the signal has been acquired, it can be analysed to identify changes in tool condition. Several techniques can be used for this purpose, including spectral analysis, time-frequency analysis, statistical analysis and artificial intelligence (AI) [17]. Spectral analysis is used to identify the frequency components in a signal and can be used to identify changes in cutting tool wear or bearing condition. Time-frequency analysis can be used to analyse the dynamics of the signal over time, allowing for the detection of gradual changes in tool condition [18]. Statistical analysis can be used to identify patterns in the signal and to detect changes in the characteristics of the signal. AI techniques such as neural networks, fuzzy logic and genetic algorithms can be used to identify changes in the signal which may not be detectable by other methods. Acoustic and pulse signals are widely used in industry to monitor the condition of tools and machinery [19]. The different types of data extraction techniques are exhibited in **Table 2.**

Table 2. Data Extraction Techniques

Technique	Description

Statistical Features	Extraction of statistical measures from the signals, such as mean, variance, skewness, and kurtosis
Time-Domain Features	Extraction of features based on time-domain characteristics, such as peak amplitude and duration
Frequency-Domain Features	Extraction of features based on frequency-domain characteristics, such as spectral centroid and bandwidth
Wavelet Transform	Transformation of the signals using wavelet basis functions to extract time-frequency information
Spectral Analysis	Extraction of features from the frequency spectrum, such as spectral peaks and harmonics
Energy Features	Extraction of features based on signal energy, including total energy and energy distribution

The development of IoT has enabled more effective and efficient acquisition and analysis of these signals. This paper has reviewed the use of acoustic and pulse signals in the context of IoT and discussed the latest advancements in signal acquisition and analysis techniques. These techniques can be used to detect changes in tool condition before they cause costly damage or downtime [20].

III. FEATURE EXTRACTION TECHNIQUES

In the past few decades, the industrial world has seen an immense transformation in terms of the level of automation and the way in which machines are monitored and managed [21]. In this context, the internet of things (IoT) has emerged as a revolutionary technology that has enabled the connection of various physical objects to the internet, allowing them to be monitored and controlled remotely. This has resulted in improved efficiency, safety, and cost savings for industrial and manufacturing processes. One of the key components of IoT is the ability to monitor and predict the condition of machines and tools using acoustic and pulse signals. This article reviews the existing literature on acoustic and pulse signal-based TCM using IoT [22]. Background TCM (TCM) is a method of monitoring the performance and condition of tools and machines in a manufacturing or production environment. This can be done using a variety of methods, including manual visual inspection, temperature and pressure measurements, or pulse and acoustic signal analysis. The use of pulse and acoustic signals for TCM is particularly beneficial because it allows for the detection of subtle changes in the machine or tool condition that may not be visible with manual inspection techniques. This is especially useful in the case of rotating machines, such as motors, turbines, and pumps, which generate pulses that can be used to detect changes in the machine's condition [23]. Similarly, acoustic signals can be used to detect changes in the tool condition, as well as potential problems such as tool wear, misalignment, and breakage. Using the IoT, it is possible to collect, process, and analyze acoustic and pulse signals in order to detect changes in the condition of tools and machines. This has become increasingly important as the complexity of manufacturing processes has increased and the need for accurate and timely monitoring of machine conditions has become critical. The use of acoustic and pulse signals for TCM is also beneficial because it allows for the detection of subtle changes in the machine or tool condition that may not be visible with manual inspection techniques [24]. Feature Extraction Techniques Feature extraction is a key step in the process of acoustic and pulse signal-based TCM using IoT. This involves extracting important characteristics of the signals that can be used to detect changes in the tool condition. These features can be broadly categorized into two types: time-domain features and frequency-domain features. Time-domain features are based on the characteristics of the signal over time, such as the shape of the signal, the amplitude, and the duration of the signal [25]. These features can be used to detect changes in the machine or tool condition, such as changes in the alignment, wear, or breakage of the tool. Frequency-domain features are based on the characteristics of the signal in the frequency domain, such as the power spectrum and the spectral density of the signal. These features can be used to detect changes in the pulse or acoustic characteristics of the tool, such as changes in the resonant frequency or the harmonics of the signal. In addition to these time-domain and frequency-domain features, other types of features can also be used for TCM. These include wavelet-based features, which are based on the wavelet transformation of the signal, and time-frequency-based features, which are based on the analysis of both the time and frequency characteristics of the signal. These features can be used to detect changes in the pulse or acoustic characteristics of the tool. This article has reviewed the existing literature on acoustic and pulse signal-based TCM using IoT. In particular, the article has discussed the various feature extraction techniques that can be used for TCM, including time-domain features, frequency-domain features, wavelet-based features, and time-frequency-based features. These features can be used to detect changes in the pulse or acoustic characteristics of the tool, as well as changes in the alignment, wear, or breakage of the tool. The use of acoustic and pulse signals for TCM is beneficial because it allows for the detection of subtle changes in the machine or tool condition that may not be visible with manual inspection techniques. The use of IoT for TCM is therefore becoming increasingly important as the complexity of manufacturing processes increases and the need for accurate and timely monitoring of machine conditions becomes more critical [26].

IV. CLASSIFICATION TECHNIQUES

Classification techniques are a powerful tool in the field of machine learning that can be used to accurately identify objects in a given dataset. Classification techniques are used to group data into distinct categories based on certain characteristics, enabling machines to recognize patterns and make predictions. In the context of monitoring tools condition with acoustic and pulse signals using IoT, classification techniques can be used to identify objects based on their acoustic and pulse signals. Classification techniques can be divided into two main categories: supervised learning and unsupervised learning. Supervised learning involves training the model on labeled data in order to develop the algorithm. This type of learning is used when the desired output is known in advance, and the purpose is to generate an algorithm that can accurately predict the output. Unsupervised learning, on the other hand, does not require labeled data and is used when the desired output is not known in advance. This type of learning is used to identify patterns in the data without the need for prior knowledge. In the context of monitoring tools condition with acoustic and pulse signals using IoT, supervised learning techniques can be used to accurately detect the presence of certain features in the acoustic and pulse signals. For example, supervised learning techniques can be used to identify the presence of a specific tool in the signal by training the model on labeled data of known tools. Unsupervised learning techniques can then be used to identify the condition of the tool based on the signal, without prior knowledge of the tool. This can be used to detect anomalies in the signal, such as a decrease in the tool's performance, or to detect a change in the tool's condition. This can be used to identify potential issues with the tool before they become a major problem. Overall, classification techniques are important tools in the field of machine learning that can be used to accurately identify objects in a given dataset. In the context of monitoring tools condition with acoustic and pulse signals using IoT, classification techniques can be used to identify the presence of certain features in the signal, detect anomalies, and identify changes in the tool's condition. Another type of classification technique that can be used in the context of monitoring tools condition with acoustic and pulse signals using IoT is deep learning. Deep learning is a subset of machine learning that uses artificial neural networks to learn from large datasets. Deep learning can be used to detect subtle changes in the acoustic and pulse signals that may be indicative of a change in the tool's condition. The types of Machine learning used for prediction of machine behaviour is exhibited in **Table 3**.

Table 3. Types of Machine Learning Techniques for Machine Behaviour Prediction

Technique	Description
Supervised Learning	Classification algorithms trained on labeled data to classify the tool condition, such as SVM and KNN
Unsupervised Learning	Clustering algorithms to group the signals based on similarity, such as k-means and DBSCAN
Deep Learning	Neural network models for automatic feature learning and tool condition classification
Ensemble Methods	Combination of multiple classification models to improve performance, such as random forests and boosting
Hybrid Approaches	Integration of multiple techniques, such as combining supervised and unsupervised learning
Online Learning	Techniques that adapt the classification model over time as new data is acquired

By leveraging the power of classification techniques, it is possible to accurately monitor the condition of tools in real time, enabling efficient maintenance and preventing costly downtime. The literature on tool condition monitoring are summarized in **Table 4** as follows.

Table 4. Literature Summary on Tool Condition Monitoring Using IOT

Reference	Techniques Used	Findings
Denkena et al., 2021	Bio-inspired manufacturing, gentelligent processes	Explores the use of bio-inspired manufacturing systems for condition monitoring and anomaly detection, combining vibration sensors and IoT architecture to enhance manufacturing processes.
Aruquipa and Diaz, 2022	IoT architecture, vibration sensors	Presents an IoT architecture based on controlling a bio-inspired manufacturing system using vibration sensors for anomaly detection. The system aims to enhance manufacturing processes by identifying deviations from normal operating conditions.
Cooper et al., 2020	Acoustic signals, convolutional neural network (CNN)	Utilizes a CNN-based approach to monitor tool condition in vertical milling operations using acoustic signals. The study demonstrates the effectiveness of the proposed method in detecting tool wear and identifying tool breakage.

Cheng et al., 2019	Abrasive belt grinding, deep convolutional neural network (DCNN)	Proposes a DCNN-based in-process tool condition monitoring technique for abrasive belt grinding. The method enables real-time monitoring and classification of tool conditions, assisting in timely tool change decisions and improving the grinding process.
Huang et al., 2021	Milling, vibration signals, short-time Fourier transform (STFT), deep convolutional neural network	Introduces a tool wear monitoring method for milling operations using vibration signals. The proposed approach combines STFT and deep convolutional neural network to accurately detect and predict tool wear, facilitating proactive tool replacement and optimization of machining processes.
Huang et al., 2019	Multisensory signals fusion, reshaped time series convolutional neural network (ResTS-CNN)	Presents a tool wear prediction method that fuses multisensory raw signals using ResTS-CNN in manufacturing processes. The fusion of signals from various sensors enhances the accuracy of tool wear prediction, enabling timely tool replacement and reducing production downtime.
Cao et al., 2019	Translation-invariant wavelet frames, convolutional neural network (CNN)	Proposes an intelligent tool wear state identification approach using translation-invariant wavelet frames and CNN. The method effectively classifies tool wear states based on acquired sensor data, aiding in the decision-making process for tool replacement and maintenance.
Wu et al., 2018	Cloud-based parallel machine learning, tool wear prediction	Introduces a cloud-based parallel machine learning approach for tool wear prediction. By leveraging the power of cloud computing, the method facilitates real-time monitoring and prediction of tool wear, enabling proactive maintenance and reducing production interruptions.
Li et al., 2022	Audio sensors, ensemble deep learning model	Proposes an ensemble deep learning model for cutting tool wear monitoring using audio sensors. The model effectively analyzes audio signals captured during machining processes, enabling accurate detection and prediction of tool wear.
Balachandar and Jegadeeshwaran, 2021	Vibration signals, Random Forest algorithm	Investigates friction stir welding tool condition monitoring using vibration signals and a Random Forest algorithm. The approach demonstrates the effectiveness of machine learning techniques in accurately identifying tool conditions, contributing to improved tool maintenance and process control.
Lutz et al., 2020	Image segmentation algorithms, benchmarking	Conducts a benchmark study on automated machine learning algorithms for tool condition monitoring using image segmentation techniques. The evaluation highlights the performance and suitability of various algorithms, aiding in the selection and implementation of image segmentation algorithms in the context of tool condition monitoring.
Nazir and Shao, 2021	Sensor fusion, ultrasonic metal welding	Presents an online tool condition monitoring approach for ultrasonic metal welding using sensor fusion and machine learning techniques. The method enables real-time monitoring of tool conditions, facilitating proactive maintenance and improving welding quality.
Zhou et al., 2020	Milling, two-layer angle kernel extreme learning machine (TAKELM), binary differential evolution	Proposes a tool condition monitoring method for milling operations using a two-layer angle kernel extreme learning machine and binary differential evolution. The approach effectively detects and predicts tool wear based on vibration signals, enabling timely tool replacement and optimization of milling processes.
Sossenheimer et al., 2019	Condition-based energy monitoring, machine learning	Presents a sensor-reduced machine learning approach for condition-based energy monitoring in machine tools. The study aims to identify the energy consumption pattern associated with tool condition, contributing to energy-efficient manufacturing processes.
Caggiano et al., 2018	Principal component analysis (PCA), artificial neural network (ANN)	Applies PCA for dimensionality reduction of sensorial features and ANN machine learning in tool condition monitoring during CFRP drilling. The method effectively classifies tool conditions based on extracted features, enhancing drilling process control and tool maintenance.
Patange and Jegadeeshwaran,	Milling, tool condition classification, machine	Provides a review of tool condition classification approaches in milling using machine learning techniques. The study examines

2021	learning	various machine learning algorithms and their effectiveness in accurately classifying tool conditions, facilitating improved tool management and process control.
Jin et al., 2022	Edge trimming of carbon fiber reinforced polymer, machine learning with instantaneous parameters	Investigates tool wear prediction in edge trimming of carbon fiber reinforced polymer using machine learning techniques. The study utilizes instantaneous parameters to develop a predictive model for tool wear, enabling proactive tool replacement and optimization of trimming processes.
Zhu et al., 2023	Super-resolution, machine vision	Proposes an online tool wear monitoring method based on super-resolution using machine vision techniques. The approach enhances the resolution of acquired images, enabling accurate detection and prediction of tool wear during manufacturing processes.

V. CHALLENGES IN TCM

TCM is a critical part of any successful manufacturing operation, as it enables the efficient and reliable operation of machines and tools. However, while it is important, it is also a complex process, and one that can bring with it a number of challenges. In this article, we will explore some of the common challenges associated with TCM, as well as some considerations for overcoming them. The first challenge associated with TCM is the detection of faults. This includes the detection of wear on cutting edges, as well as the detection of broken tools or other defects. For example, if a tool is broken or worn out, it is important to detect this quickly so that it can be replaced. However, this can be difficult to do, as it often requires manual inspection of the tools. Another challenge associated with TCM is the selection of appropriate sensors and systems for monitoring. This includes selecting the right type of sensor for the application, as well as the right type of system for monitoring. For example, a sensor may be used to measure the pulse of a tool and then a system is used to analyze the data and detect any abnormalities. The type of sensor and system chosen will depend on the application, as different tools and materials require different types of sensors and systems. A third challenge associated with TCM is the interpretation of the data. This involves analyzing and interpreting the data collected by the sensors and systems, and determining if there is a fault or an anomaly. This can be difficult to do, as the data can often be noisy and difficult to interpret. In addition, it may be difficult to determine the cause of any anomalies, as the data may not provide enough information to determine the root cause. Finally, TCM can be time-consuming and expensive. This is because it requires the ongoing use of sensors and systems, as well as the manual inspection of tools. This can be especially challenging for small and mid-sized operations, as they may not have the resources to invest in the necessary equipment and personnel. Fortunately, there are a number of ways to address these challenges. For example, when selecting sensors and systems for monitoring, it is important to consider the application and the environment in which the tool will be used. This will help to ensure that the right type of sensors and systems are used, as well as that they are robust enough to withstand the environment. In addition, there are a number of software solutions available that can help to automate the process of TCM. These solutions can help to reduce the amount of time and effort required for manual inspection, as well as to aid in the interpretation of data. Finally, it is important to consider the use of predictive maintenance solutions [30]. These solutions can help to identify potential problems before they occur, allowing for proactive maintenance and repair of tools. This can help to reduce the amount of time and effort required for TCM, as well as to reduce the risk of unexpected downtime. In conclusion, TCM can present a number of challenges, including the detection of faults, the selection of sensors and systems, the interpretation of data, and the time and cost associated with the process. However, by considering the application and environment, utilizing automation solutions, and implementing predictive maintenance solutions, these challenges can be addressed and overcome.

Currently, there are various legislations and standards in place relating to tool condition monitoring to ensure workplace safety, quality control, and efficient manufacturing processes. One such standard is ISO 13399, which provides guidelines for the representation of cutting tool data and information exchange between manufacturers, suppliers, and users. This standard promotes interoperability and accurate tool condition monitoring across different systems and platforms. In terms of legislation, occupational health and safety regulations, such as those set by the Occupational Safety and Health Administration (OSHA) in the United States or the Health and Safety Executive (HSE) in the United Kingdom, require employers to implement measures for ensuring the safety of workers using tools and machinery. These regulations often include provisions for regular tool inspections, maintenance, and monitoring to prevent accidents and injuries. Additionally, there may be specific regulations or guidelines in certain industries, such as aerospace or automotive, that outline the requirements for tool condition monitoring to maintain quality standards and ensure reliable manufacturing processes. It is crucial for organizations to stay informed about these legislations and standards, incorporating them into their tool condition monitoring practices to promote a safe and productive working environment.

VI. SIGNAL NOISE AND IMPURITIES

TCM is an important part of any manufacturing process as it is used to detect any potential problems or faults in the machinery used. The aim of TCM is to make sure that the tools are in good working condition and that any potential problems are addressed before they become critical. This can be done through various methods such as pulse analysis, ultrasonic inspections, and visual inspections. One of the main challenges with TCM is that the data collected can be prone to signal noise and impurities. Signal noise and impurities are disturbances that can be picked up by the sensor during the monitoring process. These can be caused by the environment, such as interference from other machinery, or they can be caused by the tools themselves, such as pulses from the tool cutting. This noise and impurities can distort the data that is collected, leading to incorrect or incomplete results. To ensure accurate monitoring results, it is important to minimize the effect of signal noise and impurities. This can be done in a variety of ways. First, the sensors used for the monitoring process should be of a high quality and should be designed to minimize the effect of external noise. Additionally, the environment should be monitored for any disturbances that could affect the results. This can be done through regular inspections and through the use of pulse dampening materials. Another way to minimize the effect of signal noise and impurity is through the use of data processing techniques. Data processing techniques can be used to filter out any disturbance that is picked up by the sensors. This can help to reduce the amount of noise that is present in the data and can help to ensure that the results are accurate and reliable. Finally, it is also important to ensure that the tools themselves are in good condition and are not contributing to the signal noise and impurity. This can be done through regular maintenance and inspections of the tools, as well as through the use of maintenance strategies such as pulse analysis. By minimizing the effect of signal noise and impurity, TCM can be more accurate and reliable. This can help to ensure that any potential problems with the tools are identified and addressed before they become critical. This can help to reduce downtime and ensure that the manufacturing process is running smoothly and efficiently.

VII. SIGNAL ACQUISITION

Signal acquisition in TCM is the process of collecting and analyzing data from an array of sources in order to assess a tool's performance and health. This data is used to identify signs of wear and tear, defects, or other problems that could lead to failure or breakdown of the tool. The process is essential for predictive maintenance, which helps reduce downtime and keep machines running in optimal condition. Signal acquisition in TCM involves the use of various types of sensors, such as pulse sensors, temperature sensors, and pressure sensors. These sensors are typically placed on or near the tool and connected to a data acquisition system. The data acquisition system then collects, stores, and processes the data from the sensors. It is important for the data acquisition system to accurately measure the signals from the sensors in order to ensure the accuracy of the data. Once the data is collected, it can be analyzed to identify any potential issues with the tool. There are a variety of methods used to analyze the data, such as signal processing, statistical analysis, and machine learning. These methods are used to identify patterns and trends in the data that may indicate a problem with the tool [35]. For example, a sudden increase in pulse levels or high temperatures may be indicative of a mechanical issue. The data can also be used to make predictions about future performance of the tool. By understanding the patterns in the data, predictive models can be created that can help predict when a tool is likely to fail or require maintenance. This helps prevent unexpected breakdowns and allows maintenance to be scheduled in advance. Finally, the data can also be used to improve the design of the tool. By understanding the signals that indicate problems with the tool, manufacturers can make design changes to improve its performance. This can help reduce tool failure and improve overall efficiency. Signal acquisition in TCM is a powerful tool that helps maintain the health and performance of tools. By collecting and analyzing data from a variety of sources, it is possible to identify problems with a tool before they become serious, predict future performance, and make design changes to improve efficiency. This helps reduce downtime and improve the overall efficiency of the machine. A Typical Tool condition monitoring condition in machining of super alloy is exhibited in **Fig 1**

The costs associated with signal acquisition and analysis techniques in tool condition monitoring can vary depending on several factors. Traditional signal acquisition methods, such as using dedicated sensors or transducers, generally have upfront costs for purchasing and installing the necessary hardware. These costs can include the sensors themselves, cabling, amplifiers, and data acquisition systems. Additionally, there may be costs involved in integrating these sensors into the existing machinery or equipment. On the other hand, newer technologies like IoT-based systems may require investments in wireless connectivity, edge computing devices, and cloud storage for data analysis, which can incur additional expenses.

The analysis of acquired signals also carries its own costs. Traditional signal analysis methods, such as statistical analysis or basic signal processing algorithms, often require skilled personnel and specialized software tools, which may have associated licensing fees. However, these costs can be relatively lower compared to more advanced techniques like machine learning or deep learning. Implementing machine learning or artificial intelligence algorithms for signal analysis may require more significant investments in terms of computational resources, software development, and training data collection.

It is essential to consider the long-term costs of maintaining and updating the tool condition monitoring system. This includes expenses related to system calibration, sensor maintenance, software updates, and ongoing data storage and analysis. It is worth noting that while advanced techniques may involve higher initial costs, they can potentially offer more accurate and automated tool condition monitoring, leading to cost savings in terms of reduced downtime, improved productivity, and enhanced quality control. Tool condition monitoring (TCM) relies on various underlying technologies and concepts to assess the health and performance of tools used in industrial processes. One fundamental technology is sensor technology, which involves the deployment of sensors to collect data on parameters such as vibration, temperature, acoustic emissions, and cutting forces. These sensors provide real-time information about the tool's condition, enabling the detection of anomalies and potential failures [38]. Another important concept is data analytics, which involves the processing and analysis of the sensor data using techniques such as machine learning and statistical modeling. By leveraging these analytics methods, patterns and trends can be identified, allowing for predictive maintenance and proactive tool replacement. Additionally, Internet of Things (IoT) plays a crucial role in TCM by connecting sensors and tools to a network, enabling continuous monitoring, data transmission, and remote access for diagnostics and decision-making. Overall, TCM combines sensor technology, data analytics, and IoT to optimize tool performance, minimize downtime, and enhance productivity in industrial settings.

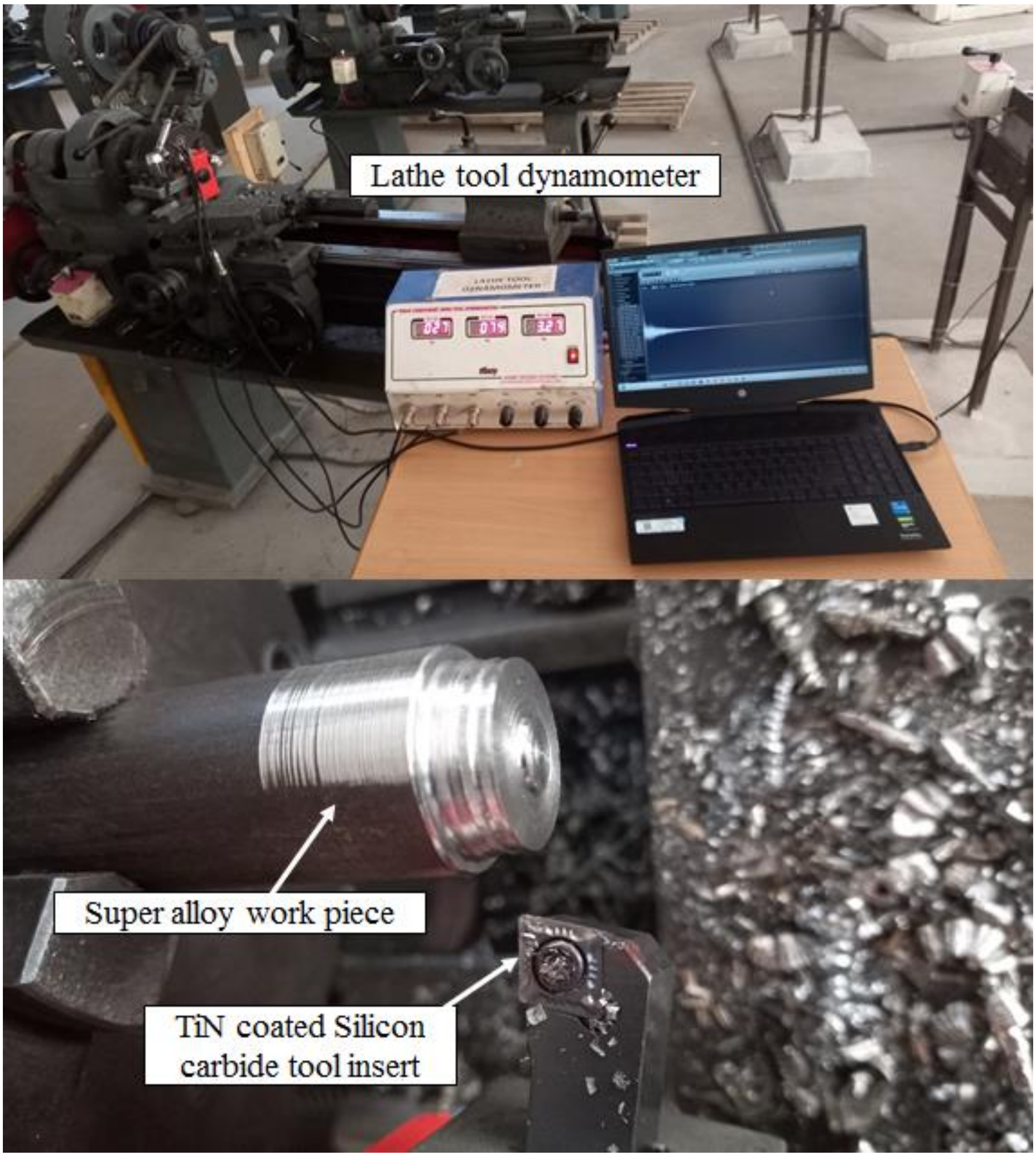

Fig 1. A Typical Experimental Condition for Tool Condition Monitoring in Machining of Super Alloy.

VIII. CONCLUSION

In conclusion, monitoring tool condition using acoustic and pulse signals is an important and growing field of research. The recent advancements in the field have provided us with novel methods and techniques for extracting valuable information from the acoustic and pulse signals generated by cutting tools during machining operations. The signal processing techniques used to analyze and classify the signals are complex and require sophisticated algorithms. Moreover, the challenges associated with acoustic and pulse-based TCM, such as signal noise and impurities, signal acquisition, feature extraction, and classification, must be addressed in order to ensure the accuracy of the results. With the increasing importance of TCM, more research is necessary in order to improve the current methods and to develop new techniques that can accurately and reliably monitor tool condition.

References

[1]. B. Denkena, M.-A. Dittrich, S. Stamm, M. Wichmann, and S. Wilmsmeier, "Reprint of: Gentelligent processes in biologically inspired manufacturing," CIRP Journal of Manufacturing Science and Technology, vol. 34, pp. 105–118, Aug. 2021, doi: 10.1016/j.cirpj.2021.06.006.

[2]. G. Aruquipa and F. Diaz, "An IoT architecture based on the control of Bio Inspired manufacturing system for the detection of anomalies with vibration sensors," Procedia Computer Science, vol. 200, pp. 438–450, 2022, doi: 10.1016/j.procs.2022.01.242.

[3]. C. Cooper et al., "Convolutional neural network-based tool condition monitoring in vertical milling operations using acoustic signals," Procedia Manufacturing, vol. 49, pp. 105–111, 2020, doi: 10.1016/j.promfg.2020.07.004.

[4]. C. Cheng, J. Li, Y. Liu, M. Nie, and W. Wang, "Deep convolutional neural network-based in-process tool condition monitoring in abrasive belt grinding," Computers in Industry, vol. 106, pp. 1–13, Apr. 2019, doi: 10.1016/j.compind.2018.12.002.

[5]. Z. Huang, J. Zhu, J. Lei, X. Li, and F. Tian, "Tool Wear Monitoring with Vibration Signals Based on Short-Time Fourier Transform and Deep Convolutional Neural Network in Milling," Mathematical Problems in Engineering, vol. 2021, pp. 1–14, Jun. 2021, doi: 10.1155/2021/9976939.

[6]. Z. Huang, J. Zhu, J. Lei, X. Li, and F. Tian, "Tool Wear Predicting Based on Multisensory Raw Signals Fusion by Reshaped Time Series Convolutional Neural Network in Manufacturing," IEEE Access, vol. 7, pp. 178640–178651, 2019, doi: 10.1109/access.2019.2958330.

[7]. X.-C. Cao, B.-Q. Chen, B. Yao, and W.-P. He, "Combining translation-invariant wavelet frames and convolutional neural network for intelligent tool wear state identification," Computers in Industry, vol. 106, pp. 71–84, Apr. 2019, doi: 10.1016/j.compind.2018.12.018.

[8]. D. Wu, C. Jennings, J. Terpenny, S. Kumara, and R. X. Gao, "Cloud-Based Parallel Machine Learning for Tool Wear Prediction," Journal of Manufacturing Science and Engineering, vol. 140, no. 4, Feb. 2018, doi: 10.1115/1.4038002.

[9]. Z. Li, X. Liu, A. Incecik, M. K. Gupta, G. M. Królczyk, and P. Gardoni, "A novel ensemble deep learning model for cutting tool wear monitoring using audio sensors," Journal of Manufacturing Processes, vol. 79, pp. 233–249, Jul. 2022, doi: 10.1016/j.jmapro.2022.04.066.

[10]. K. Balachandar and R. Jegadeeshwaran, "Friction stir welding tool condition monitoring using vibration signals and Random forest algorithm – A Machine learning approach," Materials Today: Proceedings, vol. 46, pp. 1174–1180, 2021, doi: 10.1016/j.matpr.2021.02.061.

[11]. B. Lutz et al., "Benchmark of Automated Machine Learning with State-of-the-Art Image Segmentation Algorithms for Tool Condition Monitoring," Procedia Manufacturing, vol. 51, pp. 215–221, 2020, doi: 10.1016/j.promfg.2020.10.031.

[12]. Q. Nazir and C. Shao, "Online tool condition monitoring for ultrasonic metal welding via sensor fusion and machine learning," Journal of Manufacturing Processes, vol. 62, pp. 806–816, Feb. 2021, doi: 10.1016/j.jmapro.2020.12.050.

[13]. Y. Zhou, B. Sun, and W. Sun, "A tool condition monitoring method based on two-layer angle kernel extreme learning machine and binary differential evolution for milling," Measurement, vol. 166, p. 108186, Dec. 2020, doi: 10.1016/j.measurement.2020.108186.

[14]. J. Sossenheimer, J. Walther, J. Fleddermann, and E. Abele, "A Sensor Reduced Machine Learning Approach for Condition-based Energy Monitoring for Machine Tools," Procedia CIRP, vol. 81, pp. 570–575, 2019, doi: 10.1016/j.procir.2019.03.157.

[15]. A. Caggiano, R. Angelone, F. Napolitano, L. Nele, and R. Teti, "Dimensionality Reduction of Sensorial Features by Principal Component Analysis for ANN Machine Learning in Tool Condition Monitoring of CFRP Drilling," Procedia CIRP, vol. 78, pp. 307–312, 2018, doi: 10.1016/j.procir.2018.09.072.

[16]. A. D. Patange and R. Jegadeeshwaran, "Review on tool condition classification in milling: A machine learning approach," Materials Today: Proceedings, vol. 46, pp. 1106–1115, 2021, doi: 10.1016/j.matpr.2021.01.523.

[17]. F. Jin, Y. Bao, B. Li, and X. Jin, "Tool wear prediction in edge trimming of carbon fiber reinforced polymer using machine learning with instantaneous parameters," Journal of Manufacturing Processes, vol. 82, pp. 277–295, Oct. 2022, doi: 10.1016/j.jmapro.2022.08.006.

[18]. K. Zhu, H. Guo, S. Li, and X. Lin, "Online tool wear monitoring by super-resolution based machine vision," Computers in Industry, vol. 144, p. 103782, Jan. 2023, doi: 10.1016/j.compind.2022.103782.

[19]. K. A. Ajayram, R. Jegadeeshwaran, G. Sakthivel, R. Sivakumar, and A. D. Patange, "Condition monitoring of carbide and non-carbide coated tool insert using decision tree and random tree – A statistical learning," Materials Today: Proceedings, vol. 46, pp. 1201–1209, 2021, doi: 10.1016/j.matpr.2021.02.065.

[20]. Y. Liu, L. Guo, H. Gao, Z. You, Y. Ye, and B. Zhang, "Machine vision based condition monitoring and fault diagnosis of machine tools using information from machined surface texture: A review," Mechanical Systems and Signal Processing, vol. 164, p. 108068, Feb. 2022, doi: 10.1016/j.ymssp.2021.108068.

[21]. P. Twardowski, M. Tabaszewski, M. Wiciak – Pikuła, and A. Felusiak-Czyryca, "Identification of tool wear using acoustic emission signal and machine learning methods," Precision Engineering, vol. 72, pp. 738–744, Nov. 2021, doi: 10.1016/j.precisioneng.2021.07.019.

[22]. A. Fertig, M. Weigold, and Y. Chen, "Machine Learning based quality prediction for milling processes using internal machine tool data," Advances in Industrial and Manufacturing Engineering, vol. 4, p. 100074, May 2022, doi: 10.1016/j.aime.2022.100074.

[23]. V. Nasir, S. Dibaji, K. Alaswad, and J. Cool, "Tool wear monitoring by ensemble learning and sensor fusion using power, sound, vibration, and AE signals," Manufacturing Letters, vol. 30, pp. 32–38, Oct. 2021, doi: 10.1016/j.mfglet.2021.10.002.

[24]. H.-C. Möhring, S. Eschelbacher, and P. Georgi, "Machine learning approaches for real-time monitoring and evaluation of surface roughness using a sensory milling tool," Procedia CIRP, vol. 102, pp. 264–269, 2021, doi: 10.1016/j.procir.2021.09.045.

[25]. M. P. Motta, C. Pelaingre, A. Delamézière, L. B. Ayed, and C. Barlier, "Machine learning models for surface roughness monitoring in machining operations," Procedia CIRP, vol. 108, pp. 710–715, 2022, doi: 10.1016/j.procir.2022.03.110.

[26]. G. Gokilakrishnan, S. Ganeshkumar, H. Anandakumar, and M. Vigneshkumar, "A Critical Review of Production Distribution Planning Models," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), Mar. 2021, doi: 10.1109/icaccs51430.2021.9441879.