Journal of Modern Mechanical Systems and Machining
Volume 3, Issue 2, July-December 2020

Tool Condition Monitoring using Machine Learning and Sensor Fusion

Sukanya Mahajan[1], Pawan Chaudhary[2], Kunal Deshmukh[3], Amrender Joshi[4]
Associate Professor, Assistant Professor
Department of Manufacturing Engineering
Sunrise College of Technology, Bhopal, India
Email: *Sukanyamahajan09@rediffmail.com[1], pawanchaudhary747@gmail.com[2], kunal4deshmukh@yahoo.com[3]*

Abstract

Tool wear and unexpected tool failure are major issues in modern machining industries because they directly affect product quality, machining cost, and machine downtime. Traditional tool inspection methods depend mostly on manual checking or scheduled tool replacement which is not always efficient and can lead to unnecessary cost. Tool Condition Monitoring (TCM) has emerged as an important solution for predicting tool wear and detecting tool failure during machining operations. With the advancement of sensors, data acquisition systems and artificial intelligence, machine learning based monitoring methods are widely used. Sensor fusion further improves monitoring accuracy by combining signals from multiple sensors such as vibration, acoustic emission, cutting force and temperature.

This paper reviews the concept of Tool Condition Monitoring using Machine Learning and Sensor Fusion techniques. It discusses the working principle, different sensors used for monitoring, data processing techniques and machine learning algorithms applied in TCM systems. The paper also highlights benefits, challenges and future research directions in this field. The study shows that integrating multiple sensors with machine learning models can significantly improve tool wear prediction accuracy and machining process reliability. However, challenges such as data quality, sensor noise, and model generalization still exist and require further research.

Keywords: *Tool Condition Monitoring, Machine Learning, Sensor Fusion, Tool Wear Prediction, Smart Manufacturing, CNC Machining*

INTRODUCTION

Machining processes such as milling, turning and drilling are widely used in manufacturing industries to produce high precision components. During machining, the cutting tool is continuously subjected to high temperature, mechanical stress and friction. Due to these conditions, the cutting tool gradually wears out. If the tool wear is not detected at the right time, it may lead to poor surface finish, dimensional inaccuracies, and even sudden tool breakage.

Traditionally, tool condition is monitored using scheduled replacement or manual inspection. In many workshops, operators check the tool visually after a fixed time of operation. This method is not efficient because sometimes the tool may still be usable, while in other cases tool failure may occur before the inspection time. Therefore intelligent monitoring techniques are required to detect tool wear in real time.

Tool Condition Monitoring (TCM) refers to the use of sensors and data analysis techniques to monitor the health of cutting tools during machining operations. Modern TCM systems rely on signals collected from sensors such as vibration sensors, acoustic emission sensors, cutting force sensors, and temperature sensors. These signals provide useful information about the machining process and tool wear condition.

In recent years, machine learning techniques have become popular for analyzing sensor data and predicting tool wear. Machine learning models are able to identify patterns in large datasets and make predictions about tool condition. Sensor fusion is another important concept in TCM where information from multiple sensors is combined to obtain more reliable monitoring results.

This paper presents a review of tool condition monitoring using machine learning and sensor fusion methods. The objective is to discuss different sensors, data processing methods, machine learning algorithms and their applications in machining process monitoring.

TOOL WEAR MECHANISMS IN MACHINING

During machining processes such as turning, milling, and drilling, the cutting tool is subjected to severe mechanical and thermal loads. High cutting speed, friction between tool and workpiece, and elevated temperature in the cutting zone cause gradual deterioration of the cutting edge. This deterioration is generally known as **tool wear**. Tool wear not only reduces tool life but also affects surface finish, dimensional accuracy and overall machining performance.

In most metal cutting operations, several wear mechanisms may occur simultaneously. The type and rate of wear depend on many factors such as tool material, workpiece material, cutting speed, feed rate, cutting environment and lubrication conditions. Understanding these mechanisms is important because different wear types produce different sensor signals, which can later be used for tool condition monitoring systems.

The most commonly observed wear mechanisms in machining include abrasive wear, adhesive wear, diffusion wear and oxidation wear. These wear types may occur independently or in combination depending on the cutting conditions.

1. Abrasive Wear

Abrasive wear is one of the most common wear mechanisms observed in machining processes. It occurs when hard particles present in the workpiece material or produced during cutting slide across the surface of the cutting tool and gradually remove tool material.

In machining operations, the workpiece material may contain hard inclusions such as carbides, oxides or other hard compounds. When these particles come into contact with the cutting tool, they act like microscopic cutting edges and scratch the tool surface. As the cutting process continues, these scratches gradually deepen and result in material removal from the tool.

Abrasive wear usually appears as **flank wear** on the clearance face of the cutting tool. The flank face rubs against the newly machined surface of the workpiece, and if hard particles are present, they continuously scratch the tool surface. Over time this leads to formation of a wear land along the flank of the tool.

The severity of abrasive wear depends on several factors:

- Hardness difference between tool and workpiece materials
- Cutting speed and feed rate
- Presence of hard inclusions in the workpiece
- Surface finish of the cutting tool
- Cutting environment and lubrication

For example, when machining hardened steels or composite materials containing ceramic particles, abrasive wear becomes more dominant. Tools made of carbide, ceramic or cubic boron nitride are generally preferred for such applications because they offer higher hardness and wear resistance.

Abrasive wear can also generate increased vibration and cutting force due to gradual tool dulling. Therefore vibration sensors and cutting force sensors are often used to detect abrasive wear during tool condition monitoring.

2. Adhesive Wear

Adhesive wear occurs when strong bonding takes place between the cutting tool material and the workpiece material during machining. At the tool–chip interface, extremely high pressure and temperature exist, which causes small portions of the workpiece material to weld or adhere to the cutting tool surface.

When the chip flows along the rake face of the tool, these adhered fragments may break away. Sometimes they carry small particles of the tool material along with them. This repeated sticking and breaking process gradually removes material from the cutting tool.

One of the common results of adhesive wear is the formation of a **Built-Up Edge (BUE)**. Built-up edge occurs when layers of workpiece material accumulate near the cutting edge. This built-up material periodically breaks off and exposes a fresh surface of the tool. Although BUE may temporarily protect the tool surface, its repeated formation and removal can cause tool chipping and irregular cutting conditions.

Adhesive wear is commonly observed when machining ductile materials such as aluminum, copper, and mild steel. It is more likely to occur under the following conditions:

- Low cutting speeds
- High cutting pressure
- Poor lubrication
- High chemical affinity between tool and workpiece materials

The effects of adhesive wear include fluctuating cutting forces, irregular chip formation and poor surface finish of the machined component. Because adhesive wear causes sudden variations in machining signals, it can often be detected using acoustic emission sensors and force sensors in tool monitoring systems.

Proper selection of cutting tool materials, use of cutting fluids and maintaining appropriate cutting speeds can help reduce adhesive wear.

3. Diffusion Wear

Diffusion wear becomes significant when machining at high cutting speeds and elevated temperatures. In such conditions, the temperature at the tool–chip interface can reach several hundred degrees Celsius. At these high temperatures, atoms from the cutting tool material may diffuse into the workpiece material or the flowing chip.

Diffusion is a process in which atoms move from a region of higher concentration to a region of lower concentration. In the context of machining, this means atoms from the tool gradually migrate into the chip material due to chemical interactions and high thermal energy.

This process weakens the cutting tool structure because essential elements from the tool material are lost. For example, in carbide tools, cobalt binder may diffuse away, leading to weakening of the tool matrix. As a result, the cutting edge becomes brittle and more susceptible to fracture.

Diffusion wear is most commonly observed on the **rake face** of the cutting tool where the chip slides at high velocity. It often leads to formation of a **crater wear** region on the rake face. The crater gradually grows deeper and may eventually weaken the cutting edge.

Factors affecting diffusion wear include:

- High cutting temperature
- High cutting speed
- Chemical affinity between tool and workpiece materials
- Tool composition and coating

Coated cutting tools such as TiN, TiAlN or Al_2O_3 coatings are often used to reduce diffusion wear because these coatings act as thermal and chemical barriers.

In monitoring systems, diffusion wear may be detected indirectly through temperature measurement and changes in acoustic emission signals.

4. Oxidation Wear

Oxidation wear occurs due to chemical reactions between the cutting tool material and oxygen present in the surrounding environment. When machining operations are performed at high temperatures, the tool surface can react with oxygen and form oxide layers.

These oxide layers are generally brittle and weaker compared to the original tool material. During cutting, the flowing chip and workpiece contact may easily remove these oxide layers. Once removed, the fresh tool surface becomes exposed to oxygen again, leading to repeated oxidation and removal cycles.

This repeated formation and removal of oxide layers gradually leads to loss of tool material. Oxidation wear is more common in high temperature machining processes such as high speed cutting or dry machining.

Some of the main factors influencing oxidation wear include:

- High cutting temperature
- Presence of oxygen in the cutting environment
- Tool material composition
- Absence of protective coatings

Oxidation wear often occurs together with diffusion wear because both mechanisms are temperature dependent. It can contribute to crater wear and flank wear depending on where the oxidation reactions occur.

To reduce oxidation wear, manufacturers often use protective coatings on cutting tools. These coatings act as a barrier against oxygen diffusion and help improve tool life.

SENSORS USED IN TOOL CONDITION MONITORING

Sensors are the most important part of a Tool Condition Monitoring (TCM) system because they collect real-time information from the machining process. During cutting operations many physical phenomena occur such as vibration, heat generation, force variation and acoustic emission. These phenomena change as the cutting tool gradually wears out. By measuring these changes through sensors, it becomes possible to evaluate the condition of the cutting tool while the machining process is still running.

In modern CNC machining environments, sensors are usually connected to data acquisition systems that continuously record signals during cutting. These signals are then processed using signal analysis techniques and machine learning algorithms to detect tool wear or predict tool failure.

Different types of sensors are used in TCM systems depending on the machining operation, required monitoring accuracy and cost considerations. Some sensors measure mechanical parameters like vibration and force, while others monitor thermal or acoustic signals. The most commonly used sensors in tool condition monitoring include vibration sensors, acoustic emission sensors, cutting force sensors and temperature sensors.

1. Vibration Sensors

Vibration sensors are among the most widely used sensors in tool condition monitoring systems. During machining operations, vibrations are generated due to interaction between the cutting tool and the workpiece material. These vibrations contain useful information about cutting conditions, tool wear, and machine stability.

When the cutting tool is sharp and in good condition, the machining process is usually stable and vibration levels remain relatively low. However, as the cutting edge becomes worn or damaged, the cutting process becomes less stable and vibration amplitude tends to increase.

Therefore vibration signals can be used as an indirect indicator of tool wear.

The most commonly used vibration sensor in machining is the **accelerometer**. Accelerometers measure acceleration in one or more directions and convert mechanical vibrations into electrical signals. These sensors are usually mounted on the machine spindle, tool holder, or workpiece fixture to capture vibration data during machining.

Vibration signals can be analyzed in both **time domain** and **frequency domain**. Time domain features include parameters such as root mean square (RMS), peak value, and standard deviation of vibration amplitude. Frequency domain analysis, usually performed using Fast Fourier Transform (FFT), helps identify dominant frequencies associated with tool wear or machine chatter.

Vibration sensors offer several advantages in tool monitoring systems:

- They are relatively low cost and easy to install.
- They provide continuous monitoring without interrupting the machining process.
- They can detect tool wear, tool breakage, and machining instability.

However, vibration signals can sometimes be affected by external disturbances such as machine structural vibration or environmental noise. Therefore, proper signal filtering and processing techniques are required to obtain reliable results.

2. Acoustic Emission Sensors

Acoustic Emission (AE) sensors are another important type of sensor used in tool condition monitoring. Acoustic emission refers to the high-frequency stress waves produced when materials undergo plastic deformation, friction, or crack formation. These waves propagate through the machine structure and can be detected by sensitive sensors.

During machining operations, several events generate acoustic emission signals, including:

- Plastic deformation of the workpiece material
- Friction between tool and chip
- Micro-cracks in the cutting tool
- Tool chipping or breakage

AE sensors are particularly useful because they are capable of detecting very small changes in the cutting process. Even minor tool damage or micro-chipping can generate detectable acoustic signals. This makes acoustic emission sensors highly sensitive and effective for early detection of tool wear.

Typically, AE sensors operate in a high-frequency range, often between **100 kHz and 1 MHz**. These sensors convert stress waves into electrical signals that can be analyzed using specialized signal processing methods.

Acoustic emission signals are usually characterized using parameters such as:

- AE count rate
- RMS value of acoustic signal
- Energy of acoustic bursts
- Frequency spectrum of AE signals

An increase in acoustic emission activity often indicates increased friction or crack formation in the cutting tool. Therefore AE sensors are commonly used for monitoring sudden tool failure or breakage in automated machining systems.

One limitation of acoustic emission sensors is that they require proper mounting and signal amplification to capture weak signals. Additionally, AE signals may be affected by background noise from machine components, so advanced filtering methods are often necessary.

3. Cutting Force Sensors

Cutting force sensors are widely used to measure the forces generated during machining operations. These forces occur due to resistance offered by the workpiece material as the cutting tool removes material from its surface.

The magnitude and direction of cutting forces depend on several factors including cutting speed, feed rate, depth of cut, and tool condition. As the cutting tool gradually wears out, friction between the tool and workpiece increases. This results in higher cutting forces and greater energy consumption during machining.

Cutting force measurement provides a direct indication of tool condition because it reflects the mechanical interaction between tool and workpiece. When the tool is sharp, cutting forces remain relatively stable. As wear progresses, forces gradually increase and may fluctuate due to irregular cutting.

The most commonly used instrument for measuring cutting forces is a **dynamometer**. A dynamometer is a device equipped with strain gauges or piezoelectric sensors that measure forces in multiple directions, usually along three axes:

- Cutting force (main force)
- Feed force
- Radial force

These force components provide detailed information about the cutting process and can help identify abnormal machining conditions.

Force signals are often analyzed using statistical features such as mean value, RMS value, and force variance. Sudden spikes in cutting force may indicate tool breakage or severe wear.
Although cutting force sensors provide accurate measurements, they can be relatively expensive and may require modifications to the machine setup. Therefore they are more commonly used in research laboratories and advanced manufacturing systems.

4. Temperature Sensors

Temperature is another important parameter in machining operations. During cutting, a large amount of heat is generated due to plastic deformation of the workpiece material and friction between tool, chip and workpiece surfaces. The temperature in the cutting zone can sometimes exceed several hundred degrees Celsius.

Excessive temperature can accelerate tool wear mechanisms such as diffusion wear and oxidation wear. Therefore monitoring temperature is important for understanding the thermal behavior of the cutting process and predicting tool life.

Several types of temperature sensors are used in machining applications. These include

thermocouples, **infrared sensors**, and **thermal cameras**.

Thermocouples are widely used because they are simple and capable of measuring high temperatures. A thermocouple consists of two different metal wires joined together at one end. When this junction experiences a temperature difference, it generates a small electrical voltage that can be measured and converted into temperature.

In machining operations, thermocouples can be embedded in the cutting tool or placed near the cutting zone to measure temperature variations during cutting.

Infrared sensors and thermal cameras provide a non-contact method of temperature measurement. These devices detect infrared radiation emitted from hot surfaces and convert it into temperature readings. Non-contact temperature measurement is useful when direct sensor placement near the cutting zone is difficult.

Temperature signals can provide useful information about tool wear because worn tools often generate higher friction and therefore higher temperature. Monitoring temperature also helps prevent overheating of tools and improves machining efficiency.

However, measuring temperature accurately in machining processes can be challenging due to rapid heat generation and limited access to the cutting zone.

Table 1: Common Sensors Used in Tool Condition Monitoring

Sensor Type	Measured Parameter	Application
Accelerometer	Vibration	Detect chatter and tool wear
Acoustic Emission Sensor	High frequency waves	Detect micro cracks and breakage
Dynamometer	Cutting force	Monitor tool load
Thermocouple / Infrared Sensor	Temperature	Identify thermal wear

SENSOR FUSION IN TOOL MONITORING

Using a single sensor sometimes gives incomplete information about the machining process.

Sensor fusion combines signals from multiple sensors to obtain more reliable monitoring results.

Sensor fusion can be classified into three main levels.

1. Data Level Fusion

In this approach raw data from different sensors is directly combined before processing. This method requires synchronized data acquisition systems.

2. Feature Level Fusion

Features are first extracted from each sensor signal such as mean, variance, RMS value, or frequency components. These features are then combined into a single dataset for machine learning models.

3. Decision Level Fusion

In this method each sensor signal is analyzed separately and individual decisions are generated. The final decision is obtained by combining these outputs using voting or weighted rules.

Sensor fusion improves monitoring accuracy because different sensors capture different aspects of the machining process.

MACHINE LEARNING TECHNIQUES FOR TOOL CONDITION MONITORING

Machine learning algorithms are widely used to analyze sensor data and predict tool wear condition. These algorithms learn patterns from historical data and make predictions for new data.

1. Artificial Neural Networks (ANN)

Artificial neural networks are inspired from biological neural systems. They consist of multiple interconnected layers which learn relationships between input signals and tool wear conditions. ANN models are widely used in TCM because they can handle nonlinear relationships between sensor signals and tool wear.

2. Support Vector Machines (SVM)

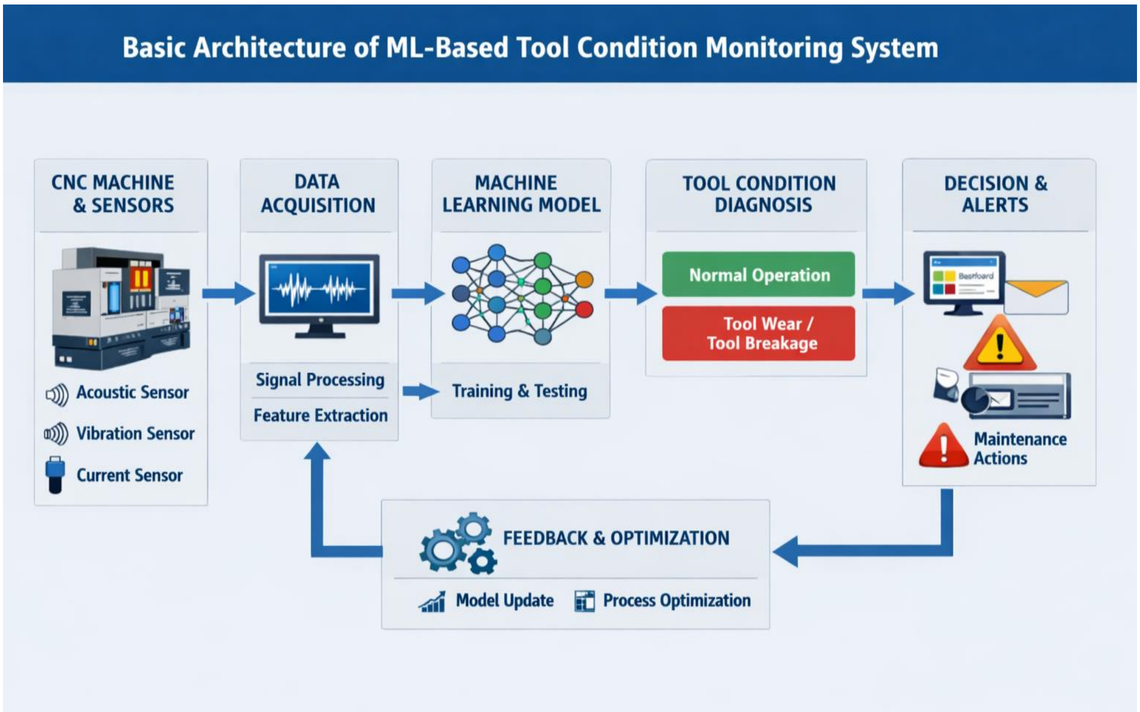
Support Vector Machines are supervised learning algorithms used for classification and regression problems. In tool monitoring applications, SVM can classify tool condition into categories such as healthy, worn or failed.

3. Random Forest

Random forest is an ensemble learning technique based on multiple decision trees. It improves prediction accuracy by combining outputs from several trees.

4. Deep Learning Methods

Deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are also used in advanced TCM systems. These models are capable of automatically extracting important features from sensor signals.



DATA PROCESSING FOR SENSOR SIGNALS

Raw sensor data collected from machining operations usually contains noise and unwanted signals. Therefore data preprocessing is necessary before applying machine learning algorithms.

1. Signal Filtering

Filtering techniques such as low-pass and band-pass filters are used to remove noise from sensor signals.

2. Feature Extraction

Important features are extracted from signals to represent the condition of the tool. Commonly used features include:

- Root Mean Square (RMS)
- Standard deviation
- Kurtosis
- Skewness
- Frequency spectrum components
-

3. Dimensionality Reduction

When large number of features are extracted, dimensionality reduction methods like Principal Component Analysis (PCA) can be used to reduce complexity while retaining important information.

APPLICATIONS IN MODERN MANUFACTURING

Tool condition monitoring systems are increasingly being implemented in modern smart manufacturing environments.

1. CNC Milling

In milling operations, vibration and acoustic emission signals are commonly used to detect flank wear and tool breakage.

2. Turning Operations

Force sensors and vibration sensors help in monitoring tool wear during turning processes.

3. High Speed Machining

High speed machining requires accurate monitoring because tool wear occurs faster. Sensor fusion combined with machine learning helps maintain process stability.

4. Industry 4.0 Integration

Modern manufacturing systems integrate TCM with cloud computing and IoT platforms. Sensor data from multiple machines can be collected and analyzed centrally for predictive maintenance.

ADVANTAGES OF MACHINE LEARNING BASED TCM

Machine learning based monitoring systems offer several benefits compared to traditional approaches.

- Real time detection of tool wear
- Reduction in machine downtime
- Improved product quality
- Lower production cost
- Automatic decision making without human intervention

These advantages make intelligent monitoring systems highly valuable for automated manufacturing environments.

CHALLENGES AND LIMITATIONS

Although machine learning based TCM systems provide many benefits, there are still several challenges that need to be addressed.

1. Data Quality

Machine learning models require large datasets for training. Poor quality or insufficient data can reduce prediction accuracy.

2. Sensor Noise

Sensor signals may contain noise due to machine vibration or environmental conditions which makes signal analysis difficult.

3. Model Generalization

Models trained for a specific machine or cutting condition may not perform well for other machines or materials.

4. Cost of Sensors

Installing multiple sensors and data acquisition systems can increase system cost which may not be affordable for small industries.

Future research should focus on developing cost effective monitoring systems with improved reliability.

FUTURE RESEARCH DIRECTIONS

Several research opportunities exist in the field of intelligent tool condition monitoring.

1. Development of advanced deep learning models for automated feature extraction
2. Integration of edge computing for real time monitoring
3. Use of digital twin technology for predictive maintenance
4. Development of low cost wireless sensor networks
5. Standardization of datasets for benchmarking algorithms

Advancements in these areas will further enhance the effectiveness of machine learning based monitoring systems.

CONCLUSION

Tool Condition Monitoring has become an essential component of modern manufacturing systems. Conventional monitoring methods based on manual inspection are inefficient and often lead to increased production cost and machine downtime. The integration of sensors with machine learning algorithms provides an intelligent solution for real-time monitoring of tool wear.

Sensor fusion techniques significantly improve monitoring accuracy by combining information from multiple sensors such as vibration, acoustic emission, cutting force and temperature. Machine learning algorithms including Artificial Neural Networks, Support Vector Machines and Random Forest models are widely used for analyzing sensor data and predicting tool condition.

Although significant progress has been made in this field, challenges such as data quality, sensor noise and model generalization still remain. Future research should focus on developing more robust and cost effective monitoring systems suitable for industrial applications.

Overall, the combination of machine learning and sensor fusion provides a promising approach for intelligent machining and smart manufacturing systems.

REFERENCES

1. Teti, R., Jemielniak, K., O’Donnell, G., Dornfeld, D. (2010). Advanced monitoring of machining operations. CIRP Annals.

2. Byrne, G., Dornfeld, D., Denkena, B. (2003). Advancing cutting technology. CIRP Annals.
3. Sick, B. (2002). On-line and indirect tool wear monitoring in turning. IEEE Transactions on Industrial Electronics.
4. Jemielniak, K., Arrazola, P. (2008). Application of AE and cutting force signals in tool condition monitoring.
5. Scheffer, C., Heyns, P. (2001). Wear monitoring in turning operations using vibration signals.
6. Dimla, D. (2000). Sensor signals for tool wear monitoring in metal cutting operations.
7. Li, X. (2002). A brief review of machine learning algorithms for tool condition monitoring.
8. Zhou, Y., Xue, W. (2018). Review of tool condition monitoring methods in machining.
9. Kuntoğlu, M., Sağlam, H. (2021). Intelligent tool wear monitoring systems.
10. Liu, C., Wang, G. (2019). Machine learning approaches for predictive maintenance in manufacturing.