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A Comparative Study of Measurement Systems Using Machine Learning Techniques for Tool Fault Di-agnosis During Metal Removal in the Milling Process

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Abstract

Despite significant advancements in both measurement systems and machine learning techniques, the integration of these technologies for real-time tool fault diagnosis in milling processes remains under developed. Existing studies tend to focus on a comprehensive comparative analysis that bridges these two areas machine learning algorithms or the application of specific measurement sys-tems. There is also a gap in evaluating the cost-effectiveness and practicality of different measurement systems when integrated with machine learning models for industrial applications. This study addresses these gaps by conducting a detailed comparative analysis of multiple measurement sys-tems and their performance with machine learning techniques in a real-world milling context, aim-ing to provide practical recommendations for industry adoption. Using both traditional and Artificial Intelligence (AI) to define and exploit sensory systems in the milling process, as well as various (direct and indirect) monitoring approaches, are summarised in this study. Machine learning tech-niques SVM, KNN, DT performs better and provide higher accuracy and in feature extraction clas-sification techniques statistical features, wavelet transform with the Holder Exponent (HE) having higher accuracy for diagnosing the tool faults.

Keywords: *Artificial Intelligence, Cutting Tool, Direct and Indirect Methods , Feature Extraction, Milling Process, Machine Learning,Tool Fault Diagnosis*

1.0 Introduction

Milling, being among the most adaptable methods of machining, has been extensively used for the metal removal of flat, curved, and spatially complex surfaces in the automotive and aerospace industries[1]. There has been a lot of scientific interest in the areas of tool flaws, tool life, and machinability; most of this study has been focused on milling processes. This is because the discontinuous nature of the operation and the chip thickness fluctuation during the cut make milling methods challenging. Tool wear in cutting tools is a very complex phenomenon that is affected by many different factors and cutting conditions. Tool-life is crucial in any assessment of machining economics and final product quality since the kind and degree of wear a tool experience ultimately defines its total usefulness[2]. The most vulnerable part of a machine tool system to wear and waste during production is the milling tool, which is the last tool used in the cutting process. The state of it directly affects the cost of manufacturing, production efficiency, and work piece surface quality[1]. The unpredictability of

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tool conditions has become one of the hurdles limiting the improvement of machining precision and reliability as processing technology and machining equipment have advanced[3]. High-speed manufacturing, as well as complexity, characterize highly automated machining centers. Operational problems include tool breakage, improper tool clamping, and chip jamming are brought on by harsh environmental conditions and rapid processing[4]. Tool Wear Monitoring (TWM) is a subset of the TCM area that monitors tool wear as the object of the monitoring process. Tool wear is a physical ailment that develops on the surface of the tool, especially near the cutting edge. For macro and micro-milling, a number of image-based Tool Condition Monitoring (TCM) systems have already been created[5,6]. The development of surface layers as a result of Inconel 718's roughing and polishing, and the prediction of machined surface integrity using machine learning techniques. It is noteworthy to emphasize that roughing was done with a ceramic tool, which increases productivity but also degrades the surface layer[7]. The incorporation of historical data into simulation models, as well as the collecting and analysis of the resulting data, may enable for the research and prediction of prospective problems. Machine Learning (ML) methodology advancements provide improved data measurement analysis using statistical techniques[8]. Machining flaws, such as tool wear, may have an impact on the machined part's durability and dimensional accuracy. For example, the steady increase in tool wear during machining leads to overall process failure and machine tool damage, in addition to large scrap yields and product quality difficulties[9]. As a result, keeping an eye on machine condition is essential to increasing machining process efficiency, which results in a better and more reliable production schedule for the whole manufacturing floor[9-11]. TCM is divided into two groups: Tool wear measurement done directly and indirectly. Temperature, vibrations, acoustic emission, and forces and moments of force are the most often used phenomena for tracking the state of the art. It is possible to extract appropriate features and identify the tool's status based on these signals[12]. Front panels for control systems and housing parts for electrical and electronic components are the major components made from thin sheets of aluminum alloys, which need a significant share of milling in the manufacturing process. Dimensional and surface quality are critical factors of production for these components, especially if the machined surface is also intended to serve as a heat or radiation shield. Blank (semi-finished) products with minor machining allowances are frequently utilized in the manufacturing process of aluminum alloy components to save costs[13]. The fast advancement of artificial intelligence algorithms and sensor technology has made the live monitoring of the cutting process a focus for research. As a significant factor in metal cutting, the wear state of cutting tools directly affects processing quality and production efficiency[14]. In order to profit from larger-scale monitoring, a modular retrofitting kit was created that allows many data sources to be combined and utilized for different types of monitoring tasks[15]. Machinability concerns like surface roughness, MRR, cutting forces, and tool wear are affected by a variety of cutting factors such speed, depth of cut, feed, as well as reinforcing particle type, size, weight percentage, kinematics of milling process[16,17]. Based on the recorded acceleration data from the sensory milling tool, a machine learning approach is described that can predict the surface roughness of the component. A CNN is created to calculate surface roughness[18]. Five separate sensors were attached to a lathe to collect data in order to determine each sensor's ability to reflect tool wear. Temperature, current, vibration, cutting forces, and sound emission were all measured while turning AISI 5140 with coated carbide tools. Using a graphical analysis, the effectiveness of the sensors in identifying growing flank wear and tool breakage was assessed[19-21]. By employing different machine learning techniques to track flank wear and extracting the Hoelder's exponent as a feature, wavelet analysis will be used to forecast tool condition. A Tungsten carbide insert was utilized for the test, and specific cutting settings were applied. The prediction model was developed using the vibration signals that were received. Hoelder's exponent, statistical properties, and wavelet coefficients were extracted from the vibration signals. These features were employed in machine learning techniques including SVM, KNN, Kernel Bayes, Multilayer Perceptron, and Decision trees to forecast flank wear[22-27]. Classification and tool condition prediction would be aided by the application of the "Machine Learning" (ML) technique. An ML-based method for tracking the condition of multipoint tool

inputs is presented in this paper. Four insert tools were face milled on a Vertical Machining Center (VMC), and the time-domain vibration response of each tool was recorded for a variety of problematic and defect-free configurations. Additional statistical data was extracted using an event-driven approach in Visual Basic Environment (VBE). Of all the recovered attributes, the traits shown in the Decision Tree (DT) produced by the J48 algorithm are the most significant, hence they were selected for additional categorization[2]. Using the suggested evaluation methodology, four unique classifiers are empirically compared under increasingly challenging generalization tasks: KNN, SVM, Random Forest, Bayes classifier, and One-Dimensional Convolutional Neural Network, K-star algorithms are some of the algorithms used[28-32]. The Holder Exponent (HE) index was used to quantitatively characterize the variation of vibration waveforms using the singularity analysis method based on wavelet transform. To extract effective, HE characteristics from the HE indices that correlate with the varied tool circumstances, the probability density distribution and statistical analysis were used[33]. Wavelet analysis provides a range of optional characteristics, such as wavelet coefficients, scaling coefficients, and wavelet domain statistics, due to its superior time-frequency analysis capacity. Among these, wavelet-based singularity analysis has excellent potential for estimating various tool conditions[34]. A TCM milling cutting condition is demonstrated via vibration singularity analysis. An experimental study's findings indicate that the parameters most closely associated with tool conditions are the means of the HE values and the number of singular points of feed direction vibration components[35]. Consequently, indirect monitoring techniques-which gauge the condition of a tool using signal analysis from one or more sensors-have proliferated in production environments. Numerous characteristics, including as cutting force, vibration, motor current, and Acoustic Emission (AE), can be reflected in these signals. The signal analysis used a range of approaches, such as those based on the time domain, frequency domain, Wavelet Transform (WT), Empirical Mode Decomposition (EMD), and multi-domain analysis, in an attempt to extract meaningful features from a signal that are suggestive of tool condition. Lastly, retrieved feature parameters from a pattern recognition technique like an Artificial Neural Network (ANN), Hidden Markov Model (HMM), or Support Vector Machine (SVM) could be used to assess the cutting tool condition. Indirect methods are more cost-effective and better suitable for

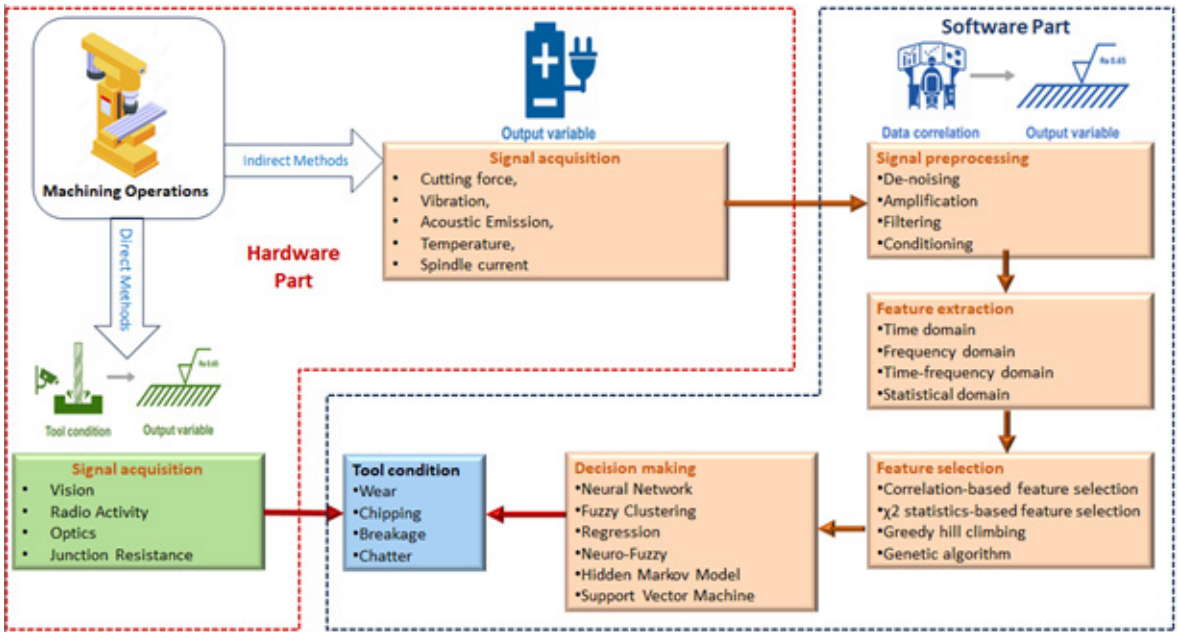


Figure 1. Basic tool fault diagnosis process flow in milling processes.

real-world applications than direct approaches[36,37]. The quick learning feature of a PNN is used to create a breakage detection system that is highly accurate and real-time self-learning tool[38]. As illustrated in Figure 1, indirect TCM is data-driven and comprises two components. Three components comprise the model training step: Feature extraction, sensor configuration, and model monitoring. A sensor signal is generated by the sensor configuration module, features pertaining to tool condition (such as wear, damage, and breakage) are extracted from the sensor signal by the feature extraction module, and an online monitoring decision support model is created by the monitoring model module. Three components comprise the online monitoring phase: Data collecting, decision making, and online sensor monitoring. The sensor configuration utilized in the model training phase is the basis for and generally identical to that employed during online monitoring. However, the online monitoring phase will not consider unnecessary sensors when evaluating tool status if the sensor configuration is modified (which is feasible when using many sensors at first).

The decision-making module's sensor signals are first put through an equivalent feature extraction process to that employed in the model training phase. After that, the cutting tool condition may be assessed in real time using the trained monitoring model that was acquired during the model training phase. This paper is organized as follows discusses (Section 2) Methodologies for TCM, (Section 3) Data acquisition and feature extraction and (Section 4) Decision-making algorithms and (Section 5) outlines a few of the shortcomings in the TCM research that is currently being applied to milling operations, and concluding remarks for the same.

The primary aim of this study is to evaluate and compare the effectiveness of various measurement systems in diagnosing tool faults during the metal removal process in milling operations using machine learning techniques.

The novelty of this research lies in its comprehensive comparative analysis of measurement systems integrated with advanced machine learning techniques specifically for tool fault diagnosis during the milling process in metal removal. While traditional methods for fault detection primarily rely on conventional signal processing and expert systems, this study introduces a novel approach by systematically evaluating and contrasting various measurement systems through the lens of machine learning.

2.0 Methodology of TCM and Tool Fault Diagnosis System

Additional statistical data was extracted using an event-driven approach in visual basic. One of the most important characteristics of a system's machinability

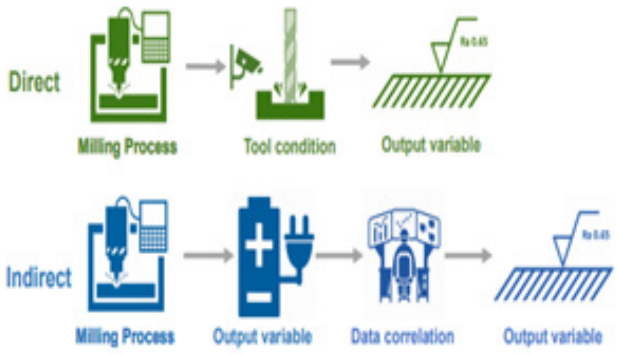


Figure 2. Assessment of tool faults by direct and indirect method[39].

is tool condition, which corresponds with production parameters like setup time and expenses, machining conditions like cutting forces, and cutting parameters like tool geometry and speed.

For this reason, keeping an eye on tool wear is essential to increasing a machining operation's sustainability and efficiency[39,40]. In terms of how the algorithms affect the output of CNC

machining operations, the study looks at a variety of ML and AI applications in CNC machining. We take into consideration lowering machine downtime, optimizing CNC machine tools, predicting cutting tool wear, modelling cutting force, maintaining.

CNC machine tools, keeping an eye on machining operations, predicting surface quality, and energy prediction systems in order to review the applications of ML and AI in CNC machining operations. To highlight the gaps in the literature, the advantages and drawbacks of employing ML and AI to boost the productivity of CNC machining operations are explored. Lastly, research directions for the future are suggested in order to create

ML and AI applications for raising CNC machining operations productivity[41].

As depicted in Figure 2, there are two approaches to monitoring tool conditions: Direct monitoring and indirect monitoring. However, the following rule will be used in this work to draw distinctions. When data is gathered directly from a tool in response to chip production, it is considered direct monitoring; when data is gathered from a response outside of the actual cutting interface, it is considered indirect monitoring. As mentioned earlier, the direct monitoring procedure monitors the output variable directly at the machining interface of the machined surface. The main purpose of machine vision is to obtain data immediately from a tool's reaction during the process[39].

2.1 Direct Sensor System for Tool Fault Diagnosis

The primary advantage of applying digital image processing or machine vision techniques is that there is no mechanical interaction between the cutting interface and the measurement equipment that could affect the system's rigidity. The main disadvantage is that the online monitoring process is usually less predictable because of the high machining rates. High-speed cameras are expensive and generate massive volumes of data, which requires a lot of processing power on the computer[6,42]. The Motor current and the power is utilized to identify tool failure. With its optimal ratio of noise to signal and spin power, this signal could be used to predict tool wear[43-46]. Image acquisition, the initial phase in machine vision monitoring, typically uses complementary metal oxide semiconductors or charged coupled devices, the first possessing greater sensitivity and the second, a greater pace of acquisition[47]. The current endeavor aims to measure tool temperature directly while drilling and milling at high spindle rotation frequencies. The techniques outlined are predicated on a special tool holder that ensures wireless communication between a data collection computer and a rotating tool that has a K-type thermocouple mounted in it. A 9265B Kistler dynamometer table is used to measure axial force and torque separately from temperature using this method. High-speed data collection is made possible by the signal collected by the thermocouple implanted in the tool being transmitted to the tool holder and sent to an amplifier via a radio frequency antenna near the tool holder and a transmitter integrated within the tool holder[48,49]. Cutting forces measured with a dynamometer, tool temperature measured with thermocouples, thermographic cameras, vibration, acoustic emission, force sensor and electric energy consumption are a few examples of indirect tool monitoring approaches. Vibration sensors are widely used for tool failure detection because they are inexpensive, easy to install, and produce a periodic signal form similar to that of the cutting force[50-53]. The amount of tool wear has a direct impact on machined surface texture. To assess it, tool wear classification using the HMM technique is applied[54].

2.2 Indirect Sensor System for Tool Fault Diagnosis

As it can keep an eye on tool conditions while requiring little to no assistance during the cutting process, indirect tool condition monitoring is being used more and more in the industry. The approaches often have a lesser

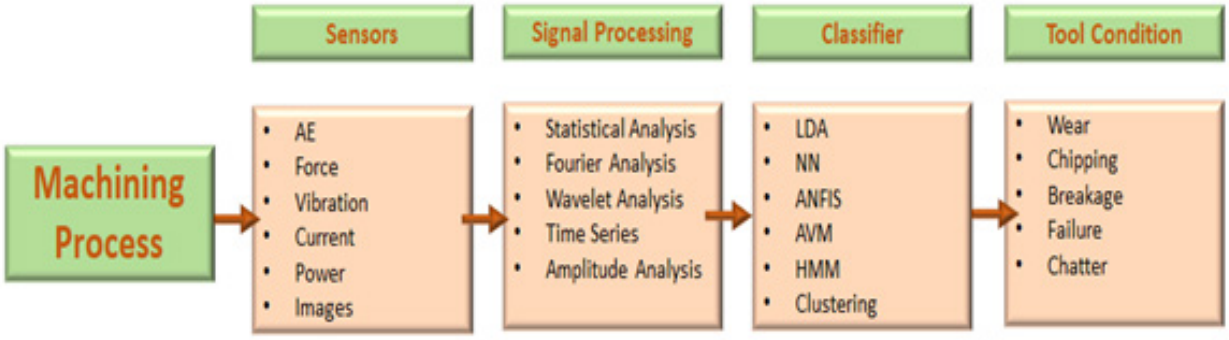


Figure 3. An overview of tool fault diagnosis system for milling[43].

accuracy than direct monitoring since they depend on the machine tool's reaction to the cutting process, though they typically off set this lower accuracy with reduced implementation costs. Because there is less uncertainty propagated from the chip creation to the output data, cutting force monitoring typically delivers the most precise analysis in regard to tool condition[39]. Due to the significant amount of frictional heat generated at the interface between the tool and work piece, the temperature of the cutting tool rises as the cutting speed, feed rate, and depth of cut are increased[43]. To enhance part quality and lengthen the lifespan of microtools, a unique configuration of a machine vision system for online tool condition monitoring is described. The automatic on-machine vision inspection performed by the vision system is dedicated to tracking the rate of wear. To reduce imaging mistakes, this inspection system employs a telecentric lens with a light source and a camera[47,55]. Table 1 and 2 shows previous work on tool fault diagnosis and representative summary of direct and indirect system for tool fault diagnosis. In Figure 3, an overview of indirect tool fault diagnosis is shown.

3.0 Data Acquisition Method and Feature Extraction

Getting data is a technique for gathering the signals, archiving the information for later use and analysis. The signals were obtained using a variety of sensors, including dynamometers, microphones, accelerometers, ultrasonic sensors, spin power sensors, and sensors for spindle current. From the recorded signals, time, frequency, and time-frequency domain features were extracted. During feature extraction, the most pertinent features that are not inflated by cutting conditions and have a strong correlation with tool wear were recovered from the acquired signals[43]. To monitor tool condition continuous wavelet, transform and blind source separation techniques are also used for feature extraction[56].

3.1 Analysis in the Time and Frequency Domain

The response was shown to be a time function in the time domain analysis. The majority of time-domain features for cutting force and AE signals have been established[57]. A deterministic model is one that generates precise calculations. However, due to the influence of several elements throughout the machining process, very few dynamic systems were fully deterministic. Using distinct samples of data from a physical systems input and output, a stochastic model was constructed using a time-series modelling technique. In this way, the behavior of experimentally obtained data can be used to study fundamental system physics[43]. Frequency domain analysis had the advantage over time-domain analysis in that it could quickly identify and separate the

Table 1. Previous work on tool fault diagnosis for various machining process using machine learning techniques

Tool	Defect Area	Signals	Signal Analysis Techniques	Technique of AIML and Sub Technique	Feature Extraction Classification Techniques	References
Milling cutter	Tool flank wear	Vibration signals and triaxial cutting forces	Time-frequency domain, wavelet packet denoising	hybrid ML technologies, SVR and algorithm for particle swarm optimization	Extraction of multi-domain features Fusion of features using KPCA	1
Multipoint tool insert	tool wear, face milling	Time-domain vibration	Vibration signals	ANN, SVM	In order to extract statistical features, an event-driven algorithm was created	2

Three ball-nose carbide tools	Tool wear monitoring	Sensory signals Vibration Signals force sensor signals	Sensor signal acquisition	MPAN is proposed SVR	LSTM dual-frequency attention model hand-crafted features extracted	3
4-axis horizontal CNC machining	Presents a benchmark dataset	Data from Bosch CISS sensors' accelerometers	An IoT infrastructure and a benchmark data set for process monitoring of milling machines based on acceleration data were provided	MEMS Sensor Signals	Generic feature extractor	4
Ceramictool	Surface integrity prediction	Sensory tool holder	MATLAB software was used to process each signal from the sensing tool holder separately during the roughing and finishing phases.	KNN	Using Pareto Chart	7
Rolling	Rolling Mill, gearbox bearing' defects	Accelerometer, Temperature & pressure Sensors	A technique of real-time and DT simulation	The use of a Digital Twin Model in conjunction with ML	XG Boost model uses boosting algorithms rather than normal decision tree methodology.	8
Milling, face mill cutter	Machine fault detection	Signals of audio and vibration	FFT and Principal Component Analysis	3 Classifiers KNN, CNN and SVM and two repressor SVR and NNR	The Hilbert-Huang transformation and wavelet analysis	9
A tool holder with wireless vibration sensor	Tool wear condition	Signal - triaxial vibrations	To assess dynamic performance, a pulse test and modal analysis were performed.	Support Vector Machine algorithm	Singularity analysis and HE characteristics for characterizing tiny changes in signal waveforms	12

Milling cutter made of carbide and diamond	The edge tool	AE- signals	Acoustic Signals	SVM, KNN and NN algorithm	fuzzy, statistical, approximation, neural networks, and distance classifiers (like k-nearest neighbours)	14
DMC 60H machining centre, Face mill	Surface roughness	Vibration signals	Kit for retrofitting based on a machine's internal edge device	DWT	Wavelet packet transform	15
End milling tool	Surface roughness	Acceleration signals	High-performance test system PXIe	CNN, KNN, SVM, ANN	Trained using lab view and python algorithm	18
Lathe machine, AISI 5140 coated tools	Tools wear	measurements of the cutting forces, vibration, temperature, current, and acoustic emission	Using sensor fusion to produce high-quality products with extended tool lives	fuzzy logic based prediction	Fuzzy logic	19
Tungsten carbide insert	Flank wear	Vibration signals	Vibration signals	Decision trees, Multilayer Perceptrons, Kernel Bayes, SVM, and KNN	HE, wavelet coeff. and statistical feach.	22
Sigle Point Cutting Tool	Tool tipping, tool wear	Vibration signals	Vibration singularity analysis.	KNN, SVM, DT, EL	Statistical analysis, wavelet transform with the Holder Exponent (HE)	33
Multi Point Cutting Tools	Tool life on a CNC m/c	Vibration signals	Cutting force singularity analysis	Support Vector Machine (SVM)	Fisher's Discriminant Ratio (FDR) is used, and the HE were chosen as the index of singularities.	34

Sigle Point Cutting Tool	Cutting condition	Vibration signals	Vibration singularity analysis.	Models of the TPIM and SVM	To estimate the singularity, HE are selected as the index, and wavelet basis selection	35
End milling	Tool wear	Vibration signals , sound signals	vibration signal analysis	ANN, WNN	MLP, RBFNN	43
Milling Tool	Cutting edges	The following are all regarded as sensors: force, vibration, sound, emission, current and power, and image thermal.	Cutting Force, Vibration, AE, Temp. spindle Current	Neural Network, Fuzzy clusturing, Regression, Neuro Fuzzy, HMM, SVM	Time domain Frequency domain Wavelet packet transform	39
Coated tungsten carbide inserts (CNC lathe m/c)	Vibration data acquired by robus	Triaxial piezoelectric dynamometer and accelerometer	Cutting forces, temperature and vibration data acquired	NN and SVM. Machine learning based models are developed	Random Forest, Gaussian Process Regression	57

particular frequency components that are relevant. The first principle of spectrum analysis is to examine all or specific frequency components that are of interest. The wavelet analysis focuses on features in the time-frequency domain. The majority of researchers used time-frequency domain analysis[57].

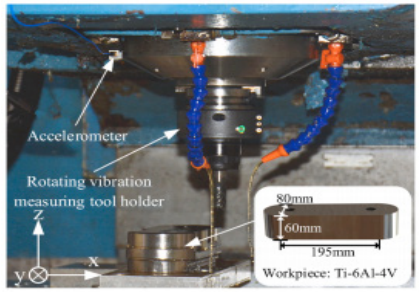
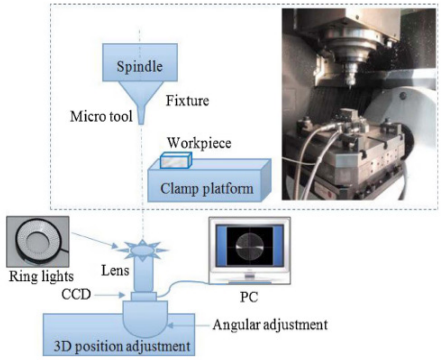
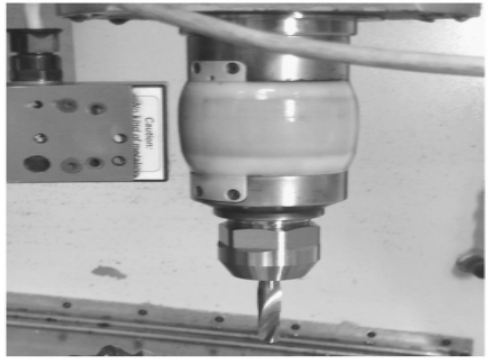
4.0 Decision Making Algorithms

Different time domain, statistical data, and time-frequency domain features were extracted from the experimental data. Tool condition was predicted using multiple decision-making methods based on the obtained information. An important part of the development of TCMs in tool fault diagnosis is the decision-making algorithm. Artificial neural networks, fuzzy logic, genetic algorithms, support vector machines, probabilistic neural networks, fuzzy logic, and pattern recognition are only a few of the methods that have been taken into consideration to automate the TCMs for tool fault diagnosis. Recently, researchers predicted the tool condition using the Decision trees, ANFIS and the Hidden Markov-model.

5.0 Discussion

While the machine is running monitoring variables like roughness, vibrations, stresses, and tool wear, *etc.* is essential. For this reason, the literature has used both direct and indirect monitoring for tool malfunction diagnoses. While executing machining operations, direct techniques, sometimes referred to as online methods, keep an eye on tool wear. However, this technique works effectively with single point-cutting tools because just one edge was utilized for the cutting process. Because of the numerous edges it includes and the potential for inconsistent results between measured and seen results, this method is not advised for complex processes like milling. Depending on the applications, a variety of machining settings and milling operations are offered. Because so many factors affect toll defect identification in milling, including cutting circumstances, work piece material, and process parameters, it is an extremely challenging procedure. The tool condition was assessed using sensor data, selected features, and decision-making algorithms. One of the indirect methods is the use of different sensors, such as vibration sensors,

Table 2. Representative summary of direct and indirect system for tool fault diagnosis

Types of Measurement	Schematic Illustration	Specification or Illumination	Authors	Machining Process Involved	Remarks
Vibration measurement-Indirect measurement system		Wireless vibration sensing tool holder, Accelerometer	Chang'an Zhou[14]	Milling	It is capable of identifying the current tool wear statuses and can correctly distinguish the tool wear state with an accuracy of 86.1%.
Vision inspection module- Direct sensor system		Microscopic ring LED illumination for image aquisition	Yiquan Dai[47]	Micro-Milling	Once every 60 seconds or when there is visible damage or condition variation, the tool wear will be assessed. The degree of tool wear will be determined.
Measuring temperature-Indirect measurement system		Thermocouple, Transmiter, RF Antenna,	G. Le Coz[48]	MQL drilling and dry milling -rotating cutting tools	For all feed rates more than 0.10 mm/rev, the slight increase in cutting speed from 30 to 35 m/min causes a temperature increase, illustrative of the monitoring system's sensitivity.

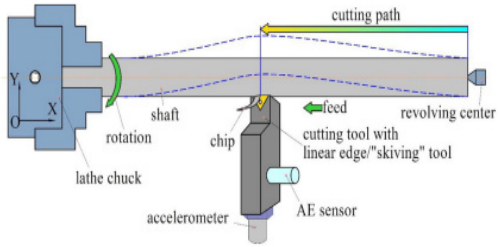
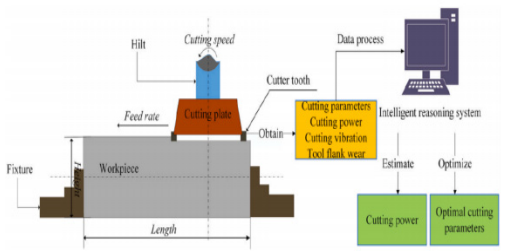
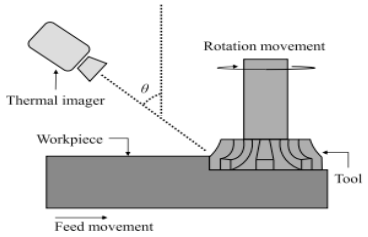
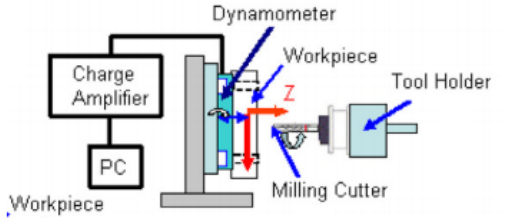
Vibration and acoustic emission-Indirect measurement system		Accelerometer and AE Sensor	A.V. Filippov[57]	Lathe turning operation	The spectrum properties of the AE signal were found to be responsive to chatter mode vibrations in both experimental and MD simulations.
Current and power sensors-Indirect measurement system		3-component piezoelectric dynamometer Kistler 9257 B	Longhua Xu[56]	milling process	In comparison to normal CBR and other intelligent models, the estimation accuracy of the ICBR is up to 91.7%.
Thermal imager -Indirect measurement system		Thermal imager in the direction of a preset zenith emission angle (θ), which in this study is equal to 37°	Matheus de Oliveira Moreira[59]	milling	The temperature variation between the various methodologies was as high as 41%, proving how significantly the temperature estimating process affects the outcomes.
Force sensor measurement-Indirect measurement system		Dynamometer	M.Kious[60]	milling operation	Proven that the evolution of flank wear was related to the variance variation and the first harmonic amplitudes. These variables exhibit the tool wear state's optimal behavior.

Table 3. Using machine learning approaches, a comparison of tool fault diagnosis results

Authers	Tool	Defect Area	Measurement System for Acquiring Signals	AIML Technique	Feature Extraction Classification Techniques	Accuracy Result
Abhishek Dhananjay Patange[2]	Multipoint tool inserts	Tool wear, face milling	Time-domain vibration	ANN, SVM	An event-driven algorithm was created	According on the comparative analysis, the best first tree classifier has a 97% classification accuracy.
V. Kryzhanivskyy[7]	Ceramic tool	Surface integrity	Sensory tool holder	KNN	Using pareto chart	Based on the validation through confusion matrix, the prediction accuracy for many tests varied between 64.7% and 84.9%.
Sotirios Panagou[8]	Rolling tool	Rolling mill, bearing defects	Accelerometer, temperature and pressure sensors	The use of a Digital Twin Model in conjunction with ML	XGBoost model	The training set's overall accuracy was 0.99.
Paweł Twardowski[12]	Milling cutter made of carbide and diamond	The edge tool	AE - signals	SVM, NN and KNN algorithm	NN distance classifiers statistical, approximation, fuzzy	The adopted strategy utilising a decision tree allowed the tool condition class prediction error to be less than 6%.
Chang'an Zhou[14]	A tool holder embedded wireless vibration sensor	Tool wear condition	Signal - triaxial vibrations	SVM	HE features,	accuracy of 86.1%
H. C. Mohring[18]	End milling tool	Surface roughness	Acceleration signals	CNN, KNN, SVM, ANN	Trained using LabView and python algorithm	Over the 1000 cycles, the test displays an accuracy of 80%.
T. Mohanraj[12]	Tungsten carbide insert	Flank wear	Vibration signals	SVM, KNN, KB, multilayer perceptron and DT	HE, wavelet coefficient and statistical feach.	The results showed that SVM and DT had the highest accuracy, with 99.86% and 100%, respectively.

Authers	Tool	Defect Area	Measurement System for Acquiring Signals	AIML Technique	Feature Extraction Classification Techniques	Accuracy Result
Thomas Walter Rauber[28]	Bearing	Bearing fault diagnosis	Vibration signals	KNN, SVM, Random Forest and One-Dimensional CNN	Four distinct classifiers are experimentally compared,	Accuracy 90.65%
Chang An zhou[33]	Single point cutting tool	Tool tipping, tool wear	Vibration signals	KNN, SVM, DT, EL	Statistical analysis, wavelet transform with the Holder Exponent (HE)	The SVM model built on the chosen HE features performs best in terms of training and classification accuracy, with 99.4% and 98.7%, respectively.
Changan Zhou[34]	Multi point cutting tool	Tool life on a CNC milling m/c	Vibration signals	SVM	FDR is used, and the HE was chosen as the index of singularities.	The SVM model's accuracy is 94.9%.
Pauline Ong[43]	End milling	Tool wear	Vibration signals, sound signals	ANNs, WNN	MLP, RBFNN	ANN-based tool wear monitoring is at least 10% more precise than RSM.
Mariane Prado Motta[58]	Inserts-tungsten carbide (CNC lathe machine)	Surface roughness	Triaxial dynamometer and accelerometer	NN and SVM	Random Forest Gaussian Process Regression & Tech	It is found that GPR produces better and more consistent results than RF for training sets that make up 67 to 90% of the dataset.

thermal and acoustic emission sensors, power and energy sensors, image sensors, and dynamometers for measuring cutting forces. These sensors are expensive, and measuring the results requires both a highly competent operator and sophisticated equipment. For instance, the cutting forces were previously measured using sensors and transducers, but the findings were not very accurate. The measurements in another type of measurement, known as offline methods, were made following machining processes. The quality of the work piece has been evaluated once the machining operation is complete, for instance, and surface roughness measures are taken into account in this category. Although there has been significant advancement in the identification of tool problems for the milling process, Table 3 compares the outcomes of tool fault diagnosis utilizing machine learning techniques. The following problems still need to be resolved.

- In the framework of sustainable manufacturing, measuring energy consumption, acoustic emissions, vibrations, image processing measurements, *etc.,* is critical. The use of these sensor systems in conjunction with artificial intelligence techniques is now being researched.

- A variety of AI techniques, including machine learning, and ANN, will be used in the construction of sensors, making CNC machine tool structures smarter than those of traditional machines.
- In the field of contemporary manufacturing, a new word called Artificial Intelligence assisted machine shop needs to emerge.
- Conventional lathes, CNC lathes, milling machines, tool fault diagnostics on VMC with associated failure modes, as well as other vibration-based condition monitoring techniques, are the subjects of the majority of research.

6.0 Concluding Remarks

The many approaches like direct and indirect approaches for tool defect diagnostics in milling processes are included in the current comprehensive overview. The conclusions are as follows:

- When there is a limited range of machining parameters and no cooling conditions, direct TCM procedures are often the optimum method for certain cutting conditions.
- These days, indirect TCM techniques are preferred since they enable the measurement of machining reactions in real time. Controlling the machining responses in accordance with shop floor needs is made easier by the online monitoring system
- Vibration sensors are an excellent choice for use in machining operations since it's crucial to monitor vibrations so that the entire machine tool structure may be created in accordance with them.
- Vibration sensors can also be used to forecast the work piece's surface finish. For instance, more vibration in a machine tool results in more rough surfaces, and less vibration results in smooth surfaces.
- It can be inferred from this that the monitoring system for tool fault detection is extremely beneficial in identifying tool wear, surfaces, vibrations, and other tool problems, *etc.* during machining processes.
- As depicted in Table 3, machine learning techniques SVM, KNN, DT performs better and provide higher accuracy and in feature extraction classification techniques statistical features, wavelet transform with the Holder Exponent (HE) having higher accuracy for diagnosing the tool faults.

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8.0 References

1. Huang Z, Shao J, Guo W, Li W, Zhu J, Fang D. Hybrid machine learning-enabled multi-information fusion for indirect measurement of tool flank wear in milling. Int J. Meas. 2023; 206:112255. https://doi.org/10.1016/j.measurement.2022.112255
2. Patange AD, Jegadeeshwaran R, *et al.* A machine learning approach for vibration-based multipoint tool insert health prediction on Vertical Machining Centre (VMC). Int J Meas. 2021; 173:108649. https://doi.org/10.1016/j.measurement.2020.108649
3. Guoa H, Zhanga Y, Zhua K. Interpretable deep learning approach for tool wear monitoring in high-speed milling. Comput Ind. 2022; 138:103638. https://doi.org/10.1016/j.compind.2022.103638
4. Tnani MA, Feil M, *et al.* Smart data collection system for brownfield CNC milling machines: A new benchmark dataset for data-driven machine monitoring. Procedia CIRP. 2022; 107:131-136. https://doi.org/10.1016/j.procir.2022.04.022
5. Christiand, Kiswanto G, *et al.* Micro eye : A low-cost online tool wear monitoring system with modular 3D-printed components for micro-milling application. HardwareX. 2022; 11(e00269). https://doi.org/10.1016/j.ohx.2022.e00269
6. Mikolajczyk T, Nowicki K, Bustillo A, Pimenov DY. Predicting tool life in turning operations using neural networks and image processing. Mech Syst Signal Process. 2018; 104:503-513. https://doi.org/10.1016/j.ymssp.2017.11.022
7. Kryzhanivskyy V, Saoubi RM, *et al.* Machine learning based approach for the prediction of surface integrity

in machining. Procedia CIRP. 2022; https://doi.org/10.1016/j.procir.2022.03.084

8. Panagou S, Fruggiero F, *et al.* Feature investigation with digital twin for predictive maintenance following a machine learning approach. IFAC Papers OnLine. 2022; 55(2):132-137. https://doi.org/10.1016/j.ifacol.2022.04.182
9. Han S, Mannan N, *et al.* Classification and regression models of audio and vibration signals for machine state monitoring in precision machining systems. J Manuf Syst. 2021; 61:45-53. https://doi.org/10.1016/j.jmsy.2021.08.004
10. Guo Z, Xu Q, Jiang S , Li M, Shen Y, Jiang G, XiaoB. Nonlinear dynamic analysis and vibration reduction of two sandwich beams connected by a joint with clearance. Mech Syst Signal Process. 2024; 223:111828. https://doi.org/10.1016/j.ymssp.2024.111828
11. Yin H, Xu H, Fan W, Sun F. Fault diagnosis of pressure relief valve based on improved deep residual shrinking network. Measurement. 2024; 224:113752. https://doi.org/10.1016/j.measurement.2023.113752
12. Twardowski P, Tabaszewski M, Wiciak M. Identification of tool wear using acoustic emission signal and machine learning methods. Precis Eng. 2021; 72:738-744. https://doi.org/10.1016/j.precisioneng.2021.07.019
13. Chuchala D, Dobrzynski M, *et al.* Surface roughness evaluation in thin EN AW-6086-T6 alloy plates after face milling process with different strategies. Mater. 2021; 14(11):3036. https://doi.org/10.3390/ma14113036
14. Zhou C, Guo K, Sun J. An integrated wireless vibration sensing tool holder for milling tool condition monitoring with singularity analysis. Mater. 2021; 14:109038. https://doi.org/10.1016/j.measurement.2021.109038
15. Barton D, Federhen J, *et al.* Retrofittable vibration-based monitoring of milling processes using wavelet packet transform. Procedia CIRP. 2021; 96:353-358. https://doi.org/10.1016/j.procir.2021.01.099
16. Patil SP, Waware SY, *et al.* Characterization and machinability studies of aluminium-based hybrid metal matrix composites – A critical review. J Adv Res in Fluid Mech Thermal Sci. 2023; 101(2). https://doi.org/10.37934/arfmts.101.2.137163
17. Pereira RBD, Brandao LC, *et al.* A review of helical milling process. Int J Mach Tools Manuf. 2017; 120: 27-48. http://dx.doi.org/10.1016/j.ijmachtools.2017.05.002
18. Mohring HC, Eschelbacher S, *et al.* Machine learning approaches for real-time monitoring and evaluation of surface roughness using a sensory milling tool. Procedia CIRP. 2021; 102:264-269. https://doi.org/10.1016/j.procir.2021.09.045
19. Kuntoglu M, Saglam H, *et al.* Investigation of signal behaviors for sensor fusion with tool condition monitoring system in turning. Measurement. 2021; 173:108582. https://doi.org/10.1016/j.measurement.2020.108582
20. Bhuiyan MSH, Choudhury IA, Dahari M, Nukman Y, Dawal SZ. Application of acoustic emission sensor to investigate the frequency of tool wear and plastic deformation in tool condition monitoring. Measurement. 2016; 92:208-217. http://dx.doi.org/10.1016/j.measurement.2016.06.006
21. Caposciutti G, Marracci M, Trigona C. A temperature measurement method based on time parameters associated to CoFeSiB microwire magneto-thermal behavior. Measurement. 2024; 224:113963. https://doi.org/10.1016/j.measurement.2023.113963
22. Mohanraj T, Yerchuru J, Krishnan H. Development of tool condition monitoring system in end milling process using wavelet features and Hoelder's exponent with machine learning algorithms. Measurement. 2021; 173:108671. https://doi.org/10.1016/j.measurement.2020.108671
23. Navneet Bohara, Jegadeeshwaran. R, and Sakthivel G. Carbide coated insert health monitoring using machine learning approach through vibration analysis. Int J Progn Health Manag. 2020; 8(2). https://doi.org/10.36001/ijphm.2017.v8i2.2635
24. Dimla DE. The correlation of vibration signal features to cutting tool wear in a metal turning operation. Int J Adv Manuf Technol. 2002; 19:705–713. https://doi.org/10.1007/s001700200080
25. Amichai Painsky, Saharon Rosset. Cross-validated variable selection in tree-based methods improves predictive performance. IEEE Trans Pattern Anal Mach Intell. 2016; 39(11):2142-2153. PubMed ID: 28114007. https://doi.org/10.1109/TPAMI.2016.2636831

26. Sharma A, Sugumaran V, Devasenapati SB. Misfire detection in an IC engine using vibration signal and decision tree algorithms. Measurement. 2014; 50:370-380. http://dx.doi.org/10.1016/j.measurement.2014.01.018
27. Gangadhar N, Kumar H, Narendranath S, Sugumaran V. Fault diagnosis of single point cutting tool through vibration signal using decision tree algorithm. Procedia Materials Science. 2014; 5:1434-1441. https://doi.org/10.1016/j.mspro.2014.07.462
28. Rauber TW , Loca ALS, *et al.* An experimental methodology to evaluate machine learning methods for fault diagnosis based on vibration signals. Expert Syst Appl. 2021; 161:114022. https://doi.org/10.1016/j.eswa.2020.114022
29. Elangovan M, Ramachandran KI, Sugumaran V. Studies on Bayes classifier for condition monitoring of single point carbide tipped tool based on statistical and histogram features. Expert Syst Appl. 2010; 37(3):2059-2065. https://doi.10.1016/j.eswa.2009.06.103
30. Madhusudana CK, Kumar H, Narendranath S. Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal. Eng Sci Technol. 2016; 19(3):1543-1551. http://dx.doi.org/10.1016/j.jestch.2016.05.009
31. Karandikar J, McLeay T, Turner S, Schmitz T. Tool wear monitoring using naive Bayes classifiers. Int J Adv Manuf Technol. 2014; 77:1613–1626. https://doi.org/10.1007/s00170-014-6560-6
32. Painuli S, Elangovan M, Sugumaran V. Tool condition monitoring using K-star algorithm. Expert Syst Appl. 2014; 41(6):2638-2643. http://dx.doi.org/10.1016/j.eswa.2013.11.005
33. Zhou C, Jiang Z , Sun C, Zhu Z. The monitoring of milling tool tipping by estimating holder exponents of vibration. IEEE Access. 2020; 8: 96661-96668. https://doi.org/10.1109/ACCESS.2020.2996607
34. Zhou C, Guo K, Sun J, Yang B, *et al.* Tool condition monitoring in milling using a force singularity analysis approach. Int J Advanced Manuf Tech. 2020; 107: 1785-1792. https://doi.org/10.1007/s00170-019-04664-4
35. Zhoua C, Yang B, *et al.* Vibration singularity analysis for milling tool condition monitoring. Int J Mech Sci. 2020; 166:105254. https://doi.org/10.1016/j.ijmecsci.2019.105254
36. Liu Y, Guo L, Gao H, You Z, Ye Y, Zhang B. Machine vision based condition monitoring and fault diagnosis of machine tools using information from machined surface texture: A review. Mech Syst Signal Process. 2021; 164:108068. https://doi.org/10.1016/j.ymssp.2021.108068
37. Su Y, Liu C, Zhang Y, Liu S, Wang J, Xie S. Indirect measurement method for high frequency response of complex structure based on statistical energy analysis. Measurement. 2024; 225:113970. https://doi.org/10.1016/j.measurement.2023.113970
38. Huang PB, Ma CC, Kuo CH. A PNN self-learning tool breakage detection system in end milling operations. Appl Soft Comput. 2015; 37:114-124 http://dx.doi.org/10.1016/j.asoc.2015.08.019
39. Pimenov DY, Gupta MK, Silva LRR, *et al.* Application of measurement systems in tool condition monitoring of milling: A review of measurement science approach. Int J Meas. 2022; 199:111503. https://doi.org/10.1016/j.measurement.2022.111503
40. Ahmad MAF, Nuawi MZ. Development of tool wear machining monitoring using novel statistical analysis method, I-kaz. Procedia Eng. 2015; 101:355-362. https://doi.org/10.1016/j.proeng.2015.02.043
41. Zhou Y, Xue W. Review of tool condition monitoring methods in milling processes. Int J Adv Manuf Tech. 2018; 96: 2509-2523. https://doi.org/10.1007/s00170-018-1768-5
42. Qian Q, Zhang B, Chuan Li C, Mao Y, Qin Y. Federated transfer learning for machinery fault diagnosis: A comprehensive review of technique and application. Mech Syst Signal Process. 2024; 223:111837. https://doi.org/10.1016/j.ymssp.2024.111837
43. Ong P, Lee WK, Lau RJH. Tool condition monitoring in CNC end milling using wavelet neural network based on machine vision. Int J Adv Manuf Tech. 2019; 104: 1369–1379. https://doi.org/10.1007/s00170-019-04020-6
44. Drouillet C, Karandikar J, *et al.* Tool life predictions in milling using spindle power with the neural network technique. J Manuf Process. 2016; 22:161-168. http://dx.doi.org/10.1016/j.jmapro.2016.03.010
45. Seemuang N, McLeay T, Slatter T. Using spindle noise to monitor tool wear in a turning process. Int J Adv

Manuf Technol. 2015; 86: 2781-2790. https://doi.org/10.1007/s00170-015-8303-8

46. Amarnath M, Sugumaran V, Kumar H. Exploiting sound signals for fault diagnosis of bearings using decision tree. Measurement. 2013; 46(3):1250-1256. http://dx.doi.org/10.1016/j.measurement.2012.11.011
47. Daia Y, Zhua K. A machine vision system for micro-milling tool condition monitoring. Precis Eng. 2018; 52: 183-191. https://doi.org/10.1016/j.precisioneng.2017.12.006
48. Coz GL, Marinescu M, Devillez A , Dudzinski D, Velnom L. Measuring temperature of rotating cutting tools: Application to MQL drilling and dry milling of aerospace alloys. Appl Therm Eng. 2012; 36:434-441. https://doi.org/10.1016/j.applthermaleng.2011.10.060
49. Chung TK, Yeh PC, Lee H. An attachable electromagnetic energy harvester driven wireless sensing system demonstrating milling-processes and cutter-wear or breakage-condition monitoring. Sensors. 2016; 16(3):269. https://doi.org/10.3390/s16030269
50. Wang G, Yang Y, Li Z. Force sensor based tool condition monitoring using a heterogeneous ensemble learning model. Sensors. 2014; 14(11):21588-21602. https://doi.org/10.3390/s141121588
51. Isavand J, Kasaei A, Peplow A. A reduced-order machine-learning-based method for fault recognition in tool condition monitoring. Measurement. 2024; 224:113906. https://doi.org/10.1016/j.measurement.2023.113906
52. Bhat NN, Dutta S, Pal SK, Pal S. Tool condition classification in turning process using hidden Markov model based on texture analysis of machined surface images. Measurement. 2016; 90:500-509. http://dx.doi.org/10.1016/j.measurement.2016.05.022
53. Dimla DE, Lister PM. On-line metal cutting tool condition monitoring force and vibration analyses. Int J Mach Tools Manuf. 2000; 40(5): 739-768. https://doi.org/10.1016/s0890-6955(99)00084-x
54. Benkedjouh T, Zerhouni N, Rechak S. Tool wear condition monitoring based on continuous wavelet transform and blind source separation. Int J Adv Manuf Tech. 2018; 97: 3311–3323. https://doi.org/10.1007/s00170-018-2018-6
55. Filippova AV, Nikonova AY, Rubtsova VE, Dmitrieva AI, Tarasov SY. Vibration and acoustic emission monitoring the stability of peakless tool turning: Experiment and modeling. J Mater Process Technol. 2017; 246: 224-234. http://dx.doi.org/10.1016/j.jmatprotec.2017.03.030
56. Xu L, Huang C, Li C, Wang J, Liu H, Wang X. A novel intelligent reasoning system to estimate energy consumption and optimize cutting parameters toward sustainable machining. J Clean Prod. 2020; 261: 121160. https://doi.org/10.1016/j.jclepro.2020.121160
57. Motta MP, Pelaingre C, *et al*. Machine learning models for surface roughness monitoring in machining operations. Proc CIRP. 2022; 108: 710-715. https://doi.org/10.1016/j.procir.2022.03.110
58. Kiswanto CG. Digital twin approach for tool wear monitoring of micro-milling. Proc CIRP. 2020; 93:1532-1537. https://doi.org/10.1016/j.procir.2020.03.140
59. Moreiraa MO, Abrao AM, Ferreiraa RAM, Portoa MP. Temperature monitoring of milling processes using a directional-spectral thermal radiation heat transfer formulation and thermography. Int J Heat Mass Transfer. 2021; 171:121051. https://doi.org/10.1016/j.ijheatmasstransfer.2021.121051
60. Kious M, Ouahabi A, Boudraa M, Serra R, Cheknane A. Detection process approach of tool wear in high speed milling. Measurement. 2021; 43(10):1439-1446. https://doi.org/10.1016/j.measurement.2010.08.014

Abbreviations

AI	:Artificial Intelligence
AE	:Acoustic Emission
ANN	:Artificial Neural Network
CNN	:Convolutional Neural Network
DT	:Decision Tree
HE	:Holder Exponent
HMM	:Hidden Markov Model
KNN	:Effective work
ML	:Machine Learning
PNN	:Probabilistic Neural Network
SVM	:Temperature or Celsius temp. scale
TWM	:Tool Wear Monitoring
TCM	:Tool Condition Monitoring
VMC	:Vertical Machining Center
VBE	:Visual Basic Environment
WNN	:Wavelet Neural Network
WT	:Wavelet Transform