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REVIEW ARTICLE

Conditioning and monitoring of grinding wheels: A state-of-the-art review

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ABSTRACT

Grinding wheel condition monitoring is an important step towards the prediction of grinding wheel faulty conditions. It is beneficial to define techniques to minimize the wear of the grinding wheels and finally enhance the life of the grinding wheels. Grinding wheel condition monitoring is done by two techniques such as (i) direct and (ii) indirect. Direct monitoring employs optical sensors and computer vision techniques, and indirect monitoring is done by signal analysis such as acoustic emission (AE), vibration, cutting force, etc. Methods implemented for grinding wheel monitoring in the published research papers are reviewed. The review is compiled in five sections: (a) process parameters measurement, (b) data acquisition systems, (c) signal analysis techniques, (d) feature extraction, and (e) classification methods. In today's era of Industry 4.0, a large amount of manufacturing data is generated in the industry. So, conventional machine learning techniques are insufficient to analyze real-time conditioning monitoring of the grinding wheels. However, deep learning techniques such as artificial neural network (ANN), convolutional neural network (CNN) have shown prediction accuracy above 99%.

Keywords: grinding wheel; condition monitoring; artificial neural network; convolutional neural networks

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1. Introduction

In the recent past, the demand for quality parts has been increased enormously. Grinding is a widely used precision finishing process. More than 70% high precision parts are manufactured using grinding process. It is used to produce very accurate dimensions and fine finishing for machined parts[1]. Grinding process is used in automobile, medical, marine, and aerospace industries. Grinding is an essential process as it is the final step in the manufacturing of any part. Any defect in this step can not only hamper the quality of the product but also the parts need to be scrapped. This causes a loss in production time and cost[2]. The main part of the grinding machine is the grinding wheel, which contains abrasive grains, bonding materials, and pores[3]. After a few cycles of grinding, the cutting ability of the grinding process deteriorates due to abrasive particle wear, bond material failure, and abrasive wheel loading and glazing of the grinding wheel[4]. This happens due to mechanical vibrations and friction with the part surface. Because of this wear on the grinding wheel, the accuracy of part dimensions and quality of the surface may get affected. So, monitoring of the grinding wheel is much needed to prevent excessive wear of grinding wheels[5,6]. Condition monitoring of the grinding wheels is usually done manually, which is an inefficient method[7]. Tool condition monitoring has become an essential field for monitoring various production process parameters due to significant developments in sensor and computing technologies in recent years[8]. It detects a change that indicates fault development. Tool condition monitoring is implemented for fault detection as well as predicting the healthy condition of machines[9]. Tool condition monitoring provides information about the state of the grinding wheel. By knowing the state of the grinding wheel, we can predict different failures and increase the grinding wheel life. Tool condition monitoring also helps in minimizing grinding wheel wear. During condition monitoring, different types of sensors and transducers are employed to monitor vibrations, acoustic emission, sound, motors, etc. to predict the condition of the grinding wheel. Moreover, different process parameters like acoustic emission, vibration, force, power, acceleration, and temperature are monitored in the grinding process[10].

2. Grinding processes

Grinding is used to manufacture high accuracy work pieces. The emerging field of automation in industry depends upon the high-quality parts[11]. In the grinding process, grinding wheel wear is more significant because it affects the accuracy and surface finish of the machined parts[12].

2.1. Types of grinding wheel

Many researchers have been carrying out experimentation in the past with different types of grinding wheels (**Table 1**). Lin and Wu have used a diamond abrasive grinding wheel for sapphire wafer grinding in the experimentation[13]. In the study conducted by Wang et al. for finishing of quarter glass, they have employed a grinding wheel of diamond material[14]. In the experimentation, aluminium oxide wheelswere used. These were used for grinding of ANSI 4140 steel alloy parts with hardness HRC45, HRC55[15]. Mahata et al. had performed grinding tests on a grinding wheel of aluminium oxide material. This was employed for grinding E31 workpiece with hardness HRC60[1]. Lee et al. have conducted experimentation by employing Monocrystalline aluminum oxide to grind carbon steel (S45C) work pieces[5]. Nguyen et al. used three silicon carbide vitrified abrasivegrinding wheels with external diameters 300, 350, and 400 for experimentation. The work piece material was Ti-6Al-4V alloy and the dimension of the work pieces were 100 (L) × 10 (T) × 20 (W) mm[16].

Table 1. Types of grinding wheel.

Sr. No.	Grinding wheel material	Workpiece material	Grinding wheel size	Author
1	Diamond abrasive grinding wheel	Sapphire wafers	External diameter 12"	Lin YK and Wu BF[13]
2	Diamond grinding wheel	quartz glass	20 × 20 mm (D, T)	Wang Y et al.[14]
3	Aluminum oxide	ANSI 4140 steel alloy	355 × 25 × 127 mm (D, T, H)	Zhang B et al.[15]
4	Aluminum oxide	EN 31	6" × 3/8" × 1–1/4" (D, T, H)	Mahata S et al.[1]
5	Monocrystalline aluminum oxide	Carbon steel (S45C)	355 × 38 × 27 mm (D, T, H)	Lee CH et al.[5]
6	Silicon carbide	Ti-6Al-4V alloy	External diameter 300, 350, 400 mm	Nguyen DT et al.[16]

2.2. Monitoring methods

Monitoring and prediction of grinding wheel wear is difficult because there is a lack of efficient methods to give real-time feedback during grinding (**Figure 1**). In the grinding process, mechanical vibrations and sound signals are observed. These signals are used for monitoring of grinding wheel conditions. Sound and vibration sensors are used for the collection of these signals[17]. In the recent past, new reliable and efficient tool monitoring methods are developed for accurate measurement of signals (**Figure 2**). These are classified into two categories (i) direct and (ii) indirect. Direct monitoring uses optical equipment such as CCD cameras, optical sensors, etc., and computer vision systems for identifying the state of the grinding wheels. These methods do not obstruct the grinding process. Direct methods achieve accurate measurement in ideal conditions. But these methods are unsuitable for manufacturing industry as the cost of equipment is very high. So, the use of these equipment increases the manufacturing cost. Moreover, due to the presence of cutting fluid/coolant and workpiece chips, the measurement accuracy gets affected. So, indirect tool monitoring methods are widely employed to predict grinding wheel conditions. These methods are less expensive compared to direct methods. In indirect methods, various signals are captured from different process parameters such as vibration, acoustic emission force, temperature, motor current, etc. These signals are used to monitor grinding wheel conditions[10]. Indirect methods are very beneficial for reducing the downtime of machines and increasing the quality of parts.

Indirect tool condition monitoring comprises of the following steps:

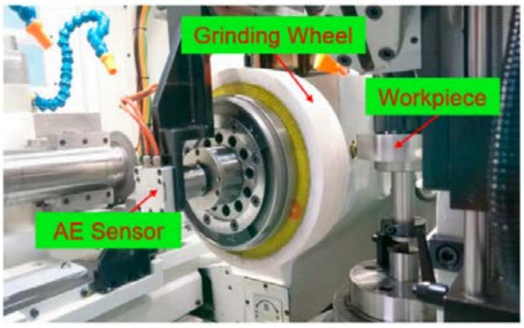
1) Sensor selection—suitable sensor for measuring process parameters is selected, such as AE sensor, accelerometer, etc.

2) Data acquisition—signals are acquired for different process parameters such as vibration, Acoustic Emission, temperature, etc.

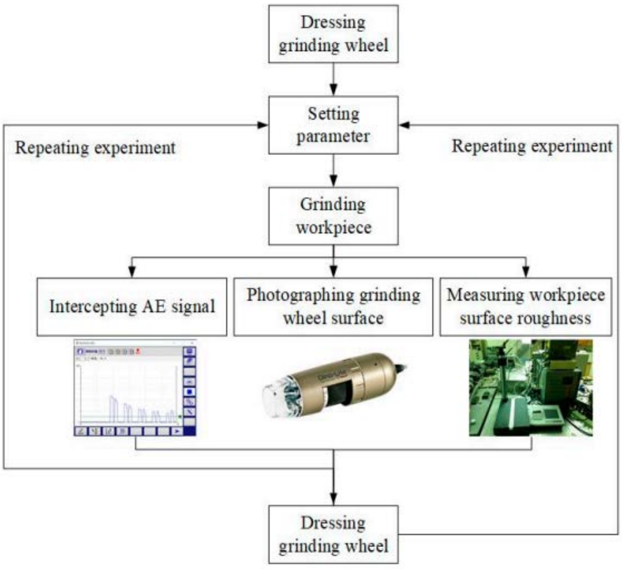
3) Signal conditioning on the collected signals is performed.

4) Feature extraction—this step involves the conversion of the original signal into significant features.

Decision making—grinding wheel condition is predicted using various decision making techniques such as support vector machine (SVM), Hidden Markov model (HMM), and artificial neural network (ANN)[18,19].

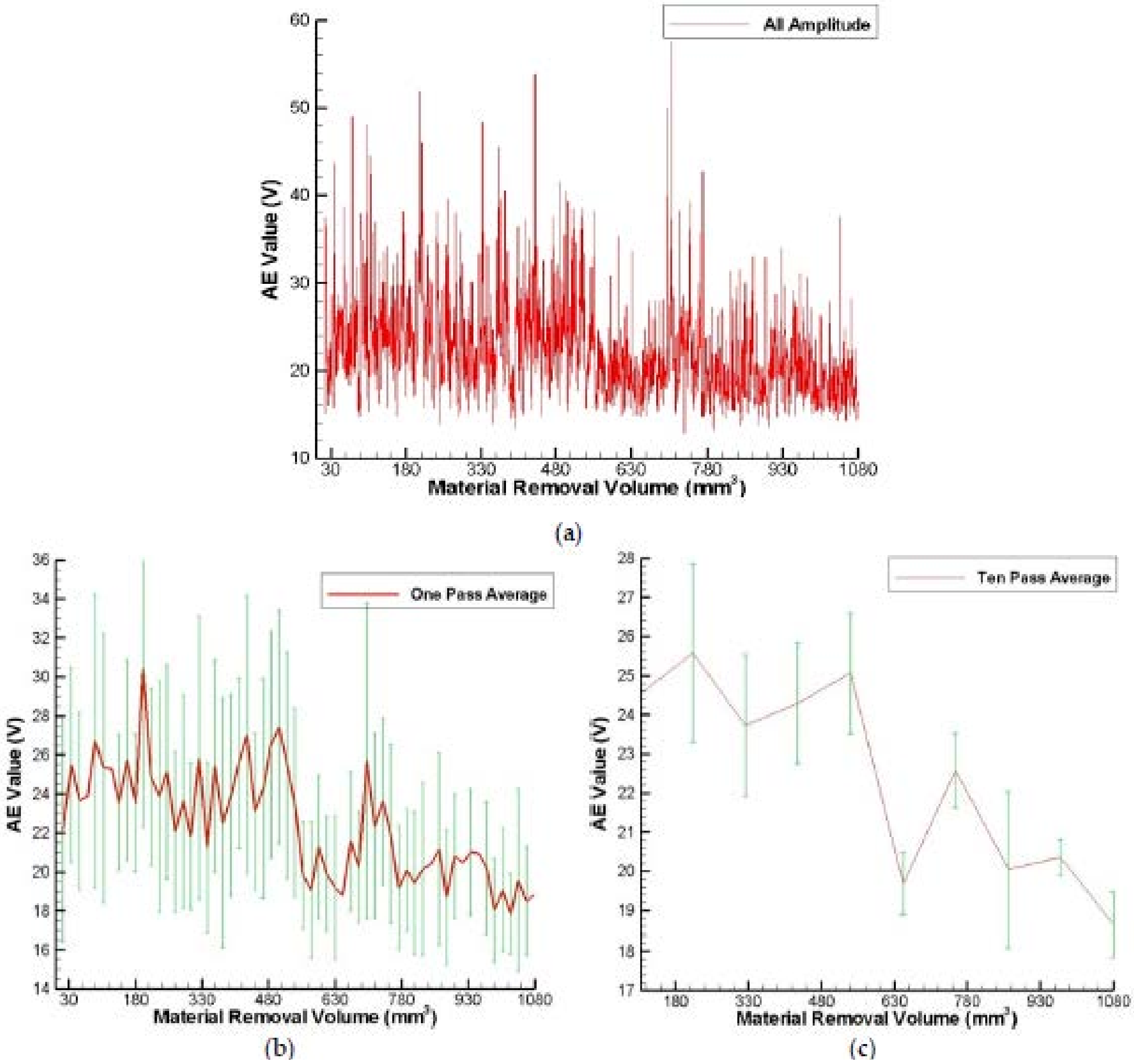


(i)



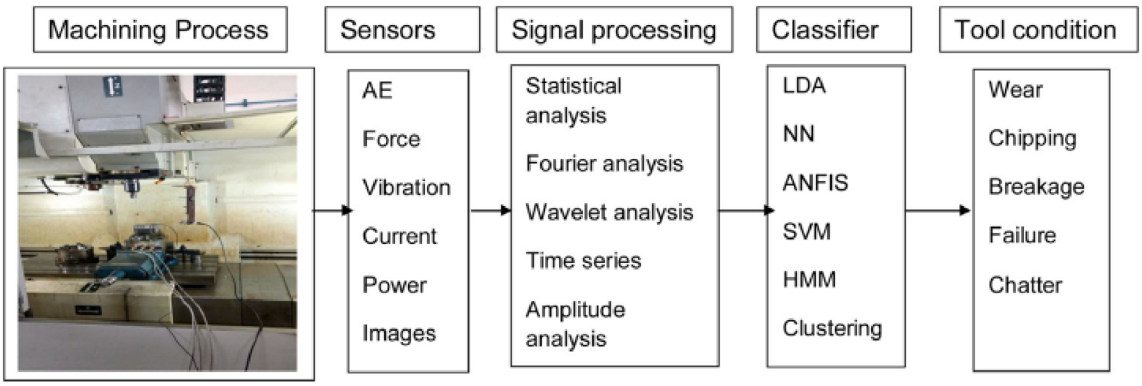
(ii)

Figure 1. (*Continued*).



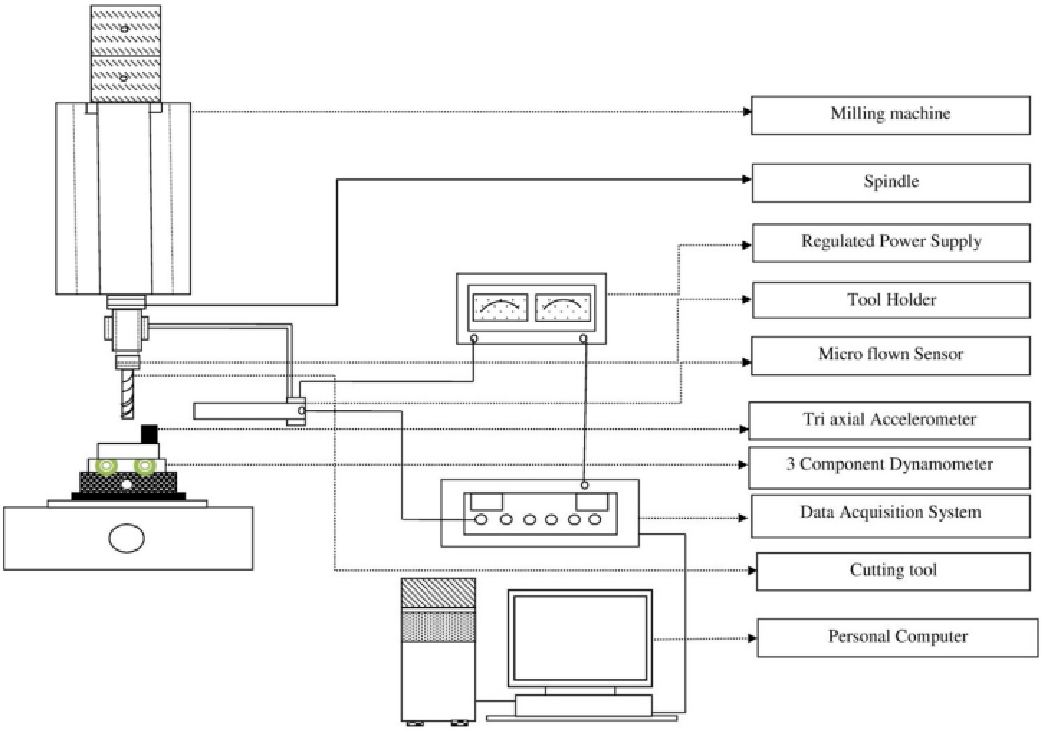
(iii)

Figure 1. Grinding wheel monitoring using AE and vibration signals[17]. **(i)** The gear grinding machine and workpiece; **(ii)** Overview of the grinding process; **(iii)** Measured AE signals less than 100 repeated trials: **(a)** original data, **(b)** one experiment on average, and **(c)** tenexperiments on average.



(a)

Figure 2. (*Continued*).



(b)

Figure 2. Tool condition monitoring[20]. **(a)** Framework of Tool condition monitoring; **(b)** An online tool condition monitoring system's concept.

3. Process parameter measurement

Grinding wheel condition monitoring is done by acquiring different signals from the grinding process. Vibration signals and acoustic signals are widely used for monitoring of grinding wheel conditions. Measurement of acoustic emission and vibration signals done by different researchers is discussed.

3.1. Acoustic emission

It is generated when the grinding wheel comes in contact with the work piece. Other causes of acoustic emission in grinding operation are crack generation and deformation in part due to the load applied while grinding dislocations, and phase transformations[10]. AE sensors are used in grinding wheel condition monitoring due to the following reasons (i) better accuracy and precision, (ii) higher sensitivity to machining parameters, (iii) the installation is simple, (iv) better real-time monitoring, (v) high frequency (1 kHz–1 MHz) signals can be acquired, (vi) higher signal to noise ratio, (vii) neural network prediction accuracy for grinding parameters increases[4–21]. Alexandre et al. conducted a study of AE signal frequency (25–40 kHz) for monitoring of grinding wheel dressing conditions and surface irregularities. The grinding wheel surface state was identified by a fuzzy model[11]. Liu and Ou used AE sensor (Model: VM25, Balance Systems, Make: MI, Italy) with sampling frequency 20 Hz to acquire AE RMS (AE root-mean-square) signal from Al_2O_3 grinding wheel condition of the gear grinding machine. The main outcome of this study is the use of AE signals for enhancing grinding quality[22]. In this study, an acoustic emission sensor was used to monitor aluminium oxide grinding wheels. Feature extraction is done using time-domain analysis. Support vector machine algorithm was implemented to identify the grinding wheel condition[10]. In this paper, the test was conducted on aluminum oxide grinding wheels and the workpiece material was 45 carbon steel with hardness 24 HRC. AE Sensor-SAEU2S, Make-Beijing Shenghua was used to collect grinding wheel signals. Classification of grinding wheel conditions was done by BP neural network[7]. In this study, AE signals from aluminium oxide grinding wheels were acquired by a piezoelectric AE sensor (**Table 2**). A neural network-multilayer perceptron type was trained with another algorithm (Levenberg-Marquardt) was used for the classification of the grinding wheel as a sharp, dull condition[23]. In this paper, the burn of aluminium oxide grinding wheel was monitored with an intelligent system. The study was conducted on a surface grinding machine and SAE 1020 workpiece material was used. AE sensor (Make-Sensis) is used to collect vibration and acoustic signals. Classification of the three conditions as burn, no burn, and high roughness value was done by a neural network-multilayer perceptron[17]. Feature extraction for burn was done by using different sensors like AE, voltage, accelerator, and current. A sensor system using motor current sensors, voltage sensors, accelerator, and acoustic emission sensor for grinding burn feature extraction. Signal processing for AE and accelerator signals is done by Hilbert-Huang transform (HHT) method to classify burn[24]. In this experimentation, first AE signals were acquired and autoregressive model is used for signal processing to extract the features. Ant colony optimization (ACO) and sequential forward floating were used to select the best features[25]. Acoustic emission signal of the diamond grinding wheel was measured by AE sensor-piezoelectric type with sample frequency 1.25 MHz. The sensor was mounted on mild steelwork pieces. FFT analyser was used for signal analysis of AE signals[26].

Table 2. Types of sensors and their temperature ranges.

Sr. No.	Sensor type	Sensor details			Authors
		Sensitivity (in dB)	**Frequency limit (in Hz)**	**Temperature limit (in ºC)**	
1	Hydrophone AE fluid sensor-Make-Balance Systems	-	10 kHz–1 MHz	-	Lin YK and Wu BF[13]
2	AE Sensor-Model-R50A–Make-Physical Acoustic Corporation	62	100–700 kHz	−65 to 177	Bi G et al.[27]
3	AE sensor Micro30 D-Make-Physical Acoustic Corporation	65	100–350 kHz	−65 to 177	Shivith K and Rameshkumar K[4]
4	AE Sensor-Model DM-42, Make-Sensis	-	up to 1 MHz	-	Lopes WN et al.[28]
5	AE Sensor-Model - R15-UG–Make-Physical Acoustic Corporation	69	50–200 kHz	−65 to 75	Zhang B et al.[6]
6	AE sensor Micro30 D-Make-Physical Acoustic Corporation	65	100–350 kHz	−65 to 177	Krishnan PS and Rameshkumar K[29]
7	AE Sensor-Model: VM25, Make-Balance Systems	-	20 Hz	-	Liu CS and Ou YJ[22]
8	AE Sensor-DITTEL (DittelMesstechnik GmbH, Landsberg am Lech, Germany)	-	-	-	Mirifar S et al.[21]
9	AE Sensor-Model DM-42, Make-Sensis	-	up to 1 MHz	-	Aulestia MA et al.[30]
10	Piezoelectric type, Model 7BB-20-6, Make-MURATA Inc., USA.	-	2.8 kHz	−20 ℃ to 70 ℃	Junior PO et al.[31]
11	AE sensor Micro30 D-Make-Physical Acoustic Corporation	65	100–350 kHz	−65 to 177	Arun A et al.[10]
12	Omni directional microphone	58 dB/mW + 2 dB	20–16 kHz	-	Sane NM and Tamboli M[32]

Table 2. (*Continued*).

Sr. No.	Sensor type	Sensor details			Authors
		Sensitivity (in dB)	Frequency limit (in Hz)	Temperature limit (in °C)	
13	AE Sensor-Model DM-42, Make-Sensis	-	up to 1 MHz	-	Alexandre FA et al.[11]
14	AE Sensor-SAEU2S, Make-Beijing Shenghua	-	80–1100 kHz	-	Ding N et al.[7]
15	AE Sensor-Model DM-42, Make-Sensis	-	Up to 300 kHz	-	Moia DFG et al.[23]
16	AE Sensor-Soundwel SR 150	-	Working: 40–400 kHz, Sample-2E 6 Hz	-	Yang Z et al.[24]
17	AE Sensor-Model DM-42, Make-Sensis	-	Up to 1 MHz	-	Liu CS and Ou YJ[17]
18	Acoustic emission sensor (R80D)	-	30 kHz–1 MHz	-	Devendiran S and Manivannan K[33]
19	AE sensor (Micro80), Make-Physical Acoustics Corp.	57	170–1000 kHz	−65 to 177	Feng J et al.[34]
20	Piezoelectric transducer sensor-Model WDI, Make-Physical Acoustics Corp	-	100–1000 kHz	-	Stephenson DJ et al.[35]
21	Piezoelectric transducer sensor-Model-S9225	-	Up to 100 kHz to 1.2 MHz	-	Mokbel AA and Maksoud TMA[26]
22	AE sensor	-	50–1000 kHz	-	Tönshoff HK et al.[36]

3.2. Vibration signal

In grinding, two types of vibrations are observed: forced and self-excited vibrations. Forced vibrations are caused by the misalignment of the grinding wheels and eccentricity. Self-excited vibrations are caused by the regenerative effect which is incurred due to the waviness of the grinding wheel[37]. These Vibrations can cause waviness on the surface of the part, higher surface roughness values, increased wear of the grinding wheel, and reduced machine life. Moreover, excessive noise is observed due to vibration. Online monitoring of vibration signals is very crucial to reduce grinding wheel wear and increase machine life (**Table 3**). Many researchers have monitored the grinding wheel using the vibration analysis technique[38]. In this study, the vibration signals of the cylindrical grinding process were acquired using two accelerometers. These are placed on the X and Y-axis of the tailstock spindle. Time-domain signal extraction is performed by empirical mode decomposition (EMD). Surface finish prediction is done by a gradient boosting algorithm[1]. In this paper, chatter in aluminium oxide and CBN grinding wheels were monitored using vibration signals. The accelerometer was used for the collection of these signals. Short-time Fourier transforms (STFT) and the ratio of power (ROP) statistic is used for signal processing[39]. Wheel loading is monitored by using secondary vibration signals. A piezoelectric sensor was used for the collection of secondary vibration signals. This sensor was mounted on the housing of the grinding spindle. Signal analysis was done by LabVIEW software. A regression model has used the prediction of grinding wheel loading. It was concluded that this method is very efficient in online grinding wheel monitoring in mass production[38]. In this study, the grinding burn was monitored by using AE and vibration signals. Experiments were conducted on an aluminium oxide grinding wheel and parts made up of SAE 1020 steel. Piezoelectric sensor–Model 353B03 (Make–PCB Piezotronic) was used for vibration signal measurement. An oscilloscope was used for signal acquisition with a sampling frequency 2 MHz. Burn, no burn, and surface roughness states were classified by using artificial neural network (ANN)[17]. Tool life and wear monitoring in a Micro-grinding process for ceramic materials were done in this experimentation. Vibrations on the workpiece and fixture were collected by using two accelerometers (PCB ICP-typed 352 A21). Signal extraction is done by using time-domain analysis. Feng et al. used RMS values of the signal for grinding wheel monitoring[34]. In this experimentation, tests were conducted on a grinding wheel of Aluminium Oxide material. Chatter in the grinding wheel was monitored by AISI 1045 steel workpiece material. Accelerometer was used to measure vibrations in the grinding wheel and workpiece. Signal acquisition was performed by using an oscilloscope with a sampling frequency 2 MHz. Chatter conditions are classified by spectral analysis using the Ratio of Power (ROP) parameter[40]. In this paper, two accelerometers are used for the measurement of radial and axial vibrations. Tests were conducted on 5–diamond grinding wheels used for machining of sapphire wafers. Classification of grinding wheels was performed by k-NN, ANN, SVM models and a comparative study was done[13]. In this paper, belt grinding tool wear was monitored by a polishing process. Vibration signals were collected by using a 3-axis accelerometer. It was attached to the tension arm of the grinder for the acquisition of vibration signals from mild steel specimens and belt. Vibration data was analysed for individual axes (X, Y, Z) as well as combinations of different axes such as XY, YZ, XZ. States of the grinding belt were classified by a convolutional neural network (CNN) algorithm[41]. In this experimentation, monitoring of double-sided grinding wheel was done by piezoelectric (IEPE) type accelerometers for vibration signal measurement. This type of sensor is suitable for dynamic temperature conditions. RMS feature is extracted from the vibration signal. It is used for the classification of the surface quality of the workpiece[2]. This study was conducted on a cylindrical traverse grinding machine and an aluminium oxide grinding wheel. Two PCB piezoelectric accelerometers were used for tangential acceleration and normal acceleration near the tailstock. These sensors are less costly and installation is easy. Feature extraction is done using time and frequency domain analysis for vibration signals. Fuzzy based network (basic function type) was used to classify grinding wheel wear[6].

Table 3. Types of sensors and their specifications.

Sr. No.	Sensor type	Sensor details			Authors
		Sensitivity (in mV/g)	Frequency limit (in Hz)	Temperature limit (in °C)	
1	Accelerometer–Model 786A–Wilcoxon Research	100	0.5 Hz–14,000 Hz	−55 to +120	Lin YK and Wu BF[13]
2	Triaxial accelerometer-Model-8763A500-Make-Kistler	100	1 Hz to 10 kHz	−54 to +121	Caesarendra W et al.[41]
3	Piezoelectric Accelerometer-Model-8703A50M1-Make-Kistler	100	0.5 Hz to 10 kHz	−55 to 165	Kumar S et al.[2]
4	Piezoelectric Accelerometer-Make PCB	-	0 to 5 kHz	-	Zhang B et al.[6]
5	Accelerometer-Model 3055B2-Make Dytran	1 to 500	1 Hz to 10 kHz	−62 to 163	Mahata S et al.[1]
6	Accelerometer-Model 353B03-PCB Piezotronics	10	1 to 7000 Hz	−54 to +121	Thomazella R et al.[39]
7	Piezoelectric accelerometer	100	1 Hz to 10 kHz.	−54 to +121	Baban M et al.[43]
8	Accelerometer-Model 353B03-PCB Piezotronics	10	1 to 7000 Hz	−54 to +121	Alexandre FA et al.[40]
9	Piezoelectric Accelerometer-Model S9225	-	-	-	Subbiah P et al.[38]
10	Accelerometer-Model 353B03-PCB Piezotronics	10	1 to 7000 Hz	−54 to +121	Liu CS and Ou YJ[17]
11	Accelerator, Kistler 8042	-	0 to 8 kHz.	-	Yang Z and Yu Z[42]
12	Accelerometer (PCB ICP-typed 352 A21)	10	1–10,000 Hz	−54 to +121	Feng J et al.[34]

4. Data acquisition system (DAQ)

Data acquisition system is an important element of tool condition monitoring system. In the data acquisition system, various types of sensors are used for measuring different types of signals. While monitoring the grinding process, acoustic emission signals, vibration signal, cutting force signal, surface roughness, and electric current, etc. are measured by using different types of data acquisition systems. It is used to sense, condition and transmission of these signals to the digital systems after further processing. In the tool condition monitoring, various types of DAQ systems are used, mainly NI instruments, oscilloscopes, fast Fourier transform (FFT) analysers, and Arduino based DAQs etc.

4.1. NI DAQ systems

NI DAQ systems are used mainly for the collection of acoustic emission, vibration, and power signals[1]. These systems have 2, 4, 8, and 16 input data channels to interface different sensors used for tool condition monitoring. NI DAQ cards are used along with LabVIEW software and MATLAB.These softwares are used for display, storage, and analysis of acquired signals[8,32,44]. These systems can be easily combined with different types of sensors. These are commonly used in tool condition monitoring.

4.2. FFT analyser

Fast Fourier transform is an essential tool used for the measurement and analysis of signals. FFT analyser is widely used for sound and vibration measurement and analysis. FFT analyser along with different software such as DEWE is used for signal processing. After the signal is acquired, the frequency content of the signal is measured by using FFT. FFT analyser is used to collect different Time-domain signals, converting it into frequency domain for display and analysis[5].

4.3. Oscilloscope

Oscilloscope is a data acquisition system used for measurement different types of signals such as vibration, sound, or acoustic emission signals. Moreover, the oscilloscope displays different signals graphically on its screen. Researchers can see the changes in the signal with respect to time. In the study conducted by Junior et al. Oscilloscope (Make-Yokogawa) was used to measure vibrations with a sampling frequency of 2 MHz[45]. Tomezella et al. used an oscilloscope for collection of vibration signals which were measured by Accelerometers[46]. In the experimentation done by Aulestia et al. acoustic emission and PZT raw signals were acquired with the use of Oscilloscope-Model-DL850-made–Yokogawa at sampling frequency 2 MHz[30].

4.4. MEMS sensor data collection

In tool condition monitoring, different types of MEMS sensors are interfaced with Arduino based data acquisition systems for signal collection. In the study conducted by Aswin et al., vibration signals are measured by a 3–axis accelerometer MEMS sensor. These signals are processed by Arduino nano microcontroller. Speed of the equipment is measured by reflective sensors. This signal is a processed by Arduino Pro-Mini Microcontroller[48]. Kanu et al. used two accelerometers (MEMS sensors) that are used for the acquisition of vibration signals[49]. In these systems, low-cost MEMS sensors and Arduino processors are used. So, the overall cost of the system is low compared to other DAQ systems (**Table 4**). Moreover, the optimal performance is achieved using these systems[50].

Table 4. Types of DAQs and their specifications.

Sr. No.	Name of DAQ	Specifications				Reference
		Operating temperature range [°C]	Signal range	No. of channels	Sample rate	
1	KistlerLabAmp 5165A	0–60	±10 V	4	-	[2]
2	PCI 2-Make-Physical Acoustic System	−5 to 45	±10 V	2	1 MHz	[28]
3	NI 9205	−40 to 70	±10 V	32 Single-Ended, 16 differential	67 Hz	[1]
4	VM25, Balance Systems	−20 to 65	±10 V	4	20 Hz	[22]
5	Oscilloscope-Picoscope 4424	0 to 45	±50 mV to ±100 V	4	1 MHz	[21]
6	Fast Fourier Transform (FFT)	-	-	-	300 Hz to 500 Hz	[5]
7	NI USB-6221	0 to 45	±11 V	8 differential or 16 single ended	250 kS/s	[32]
8	NI USB-6008	0 to 55	±10 V	8	10 kS/s	[16]
9	Oscilloscope-Model-DL850-Make-Yokogawa	5 to 40	±8 V	16	2 MHz	[45]
10	Oscilloscope-Model-DL850-Make-Yokogawa	5 to 40	±8 V	16	2 MHz	[46]
11	Oscilloscope-Model-DL850-Make-Yokogawa	5 to 40	±8 V	16	2 MHz	[47]
12	Siemens LMS data acquisition system-Vibration Signal	−20 to 55	±10 V	6 or 12	3200 Hz	[51]
13	Soundwel SAEU2S DAQ system-AE signal	−10 to 45	±10 V	200	2000 kHz	[51]
14	NI PCI-6111	0 to 45	±11 V	2	5 MS/s/ch	[8]
15	ADVANTECH USB-4711 card	0 to 60	±10 V	16	40 kHz	[52]
16	DAQ Card-PC 104	−40 to 85	±10 V	4	8 kHz	[53]
17	Digital DAQ	−10 t 55	±10 V	12	0–25.6 kHz	[54]
18	Advantech 6700L	−40 to 70	±10 V	4	100 kHz	[55]
19	DAQ Card-PC based-Make–ADLINK-2010	0 to 55	±10 V	4	2 kHz	[56]
20	NI PCI-6011	0 to 55	±10 V	8 differential or 16 single ended	2.5 MS/s	[44]
21	DAQ Card-PC based-Make–ADLINK-2010	0 to 55	±10 V	4	1 MHz	[57]
22	DAQ Card–Model 6036E-Make National Instruments	0 to 55	±10 V	16	200,000 samples/s	[58]
23	AEDSP-32/16 card (TMS320C40 Embedded)	0 to 85	−0.3 V to 7 V	6	-	[59]

Table 4. (*Continued*).

Sr. No.	Name of DAQ	Specifications				Reference
		Operating temperature range [°C]	Signal range	No. of channels	Sample rate	
24	NI PCI-6035E DAQ board	0 to 55	±10 V	8 differential or 16 single ended	2 KS/s	[60]
25	Dynamic Signal Acquisition module-DT9738B	0 to 55	±10 V	4	Up to 105.4 KS/s	[61]
26	NI9234	−40 to 70	±5 V	4	10,240 s/ch	[62]
27	NI9205	−40 to 70	±10 V	7	-	[63]
28	Arduino Pro Mini	NA	5–12 V	14	8 MHz to 16 MHz	[48]
29	Arduino Nano controller	NA	7–12 V	8	16 MHz	[48]

5. Signal analysis techniques

After data acquisition of different signals, these signals are analysed before further feature extraction is done. Time-domain analyses, frequency-domain analysis, time-frequency domain analysis, and Hilbert-Huang transform (HHT) are the main techniques used for signal analysis.

5.1. Time domain signal analysis

Time domain signal analysis is a basic technique used for signal analysis. Performance of this method is severely affected by the signal, process parameters under evaluation and the type of machining process. This approach is suitable for real-time applications since it allows fast signal processing[64]. This can be advantageous in some occasions. However, in some cases, this approach is incapable to identify substantial data inside the signal[65]. This is used for signal analysis of cutting force signals.

5.2. Frequency domain analyses

The Fourier series is used in frequency domain analysis. Every periodic function can be calculated using a Fourier series given in sine and cosines, according to the Fourier series. This denotes that each signal is represented by a set of cycles with different frequencies and amplitudes[66]. This domain is well suited for signal analysis for vibration and sound signals. In a study conducted by Alexandre et al. frequency domain signal analysis was done by Welch's approach for acoustic emission signals and frequency bands were selected to finely characterise this process. After frequency band selection, for diagnosis of the condition of grinding wheel, the counting statistic method was used[11]. Stochastic characteristic of the process was reflected by vibrations in the grinding. Frequency domain analysis is required to identify the pattern of signal behaviour. A Fourier transform can be used to generate the power spectral density (PSD), which shows how the signal's power is spread across all of its frequency components[45].

5.3. Time-frequency domain analysis

Wavelet packet transforms (WPTs) are used to generate features in time-frequency signal analysis. It refers to the simultaneous classification of the signal in time and frequency domain, which significantly lowers the processing time. Aulestia et al. applied time-frequency domain signal analysis for the extraction of features from acoustic emission signals to monitor the surface roughness of ceramic components during surface grinding[30]. Junior et al. monitored the dressing tool through electromechanical impedance (EMI) using wavelet analysis[31]. Pandiyan et al. used time-frequency domain signal analysis to extract features from AE signals and force signal to monitor abrasive belt wear conditions[19]. Kanu et al. applied wavelet packet transform for feature extraction of AE signals to identify grinding burns[67].

5.4. Hilbert-Huang Transform (HHT)

This is a recent method which is used in tool condition monitoring for time-frequency domain analysis. This is mainly used to analyse non-stationary and non-linear signals[68,69]. The main difference between HHT and other methods is HHT applies algorithm to the acquired signal data instead of theoretical tools. HHT method comprises of Hilbert spectral analysis and empirical mode decomposition (EMD). When signals consist of multiple oscillatory modes, Hilbert transform cannot be used because it is unable to produce complete frequency content. So, EMD is used to decompose signal data into intrinsic mode functions (IMF)[24]. Mahata et al. used Hilbert–Huang transform for the analysis of vibration and power signal for prediction of surface roughness[1]. In this paper, vibration and acoustic signals are measured using HHT for the analysis of grinding wheel conditions such as chatter and grinding wheel wear in cylindrical plunge grinding process[70]. Yang et al. used HHT for grinding burn detection from acoustic emission and vibration signals in a surface grinding process[24].

6. Feature extraction for grinding

Feature extraction is done after data acquisition and signal analysis in the monitoring of grinding wheel. Feature extraction is an essential issue in condition monitoring of any engineering system. Feature extraction is a process which converts the acquired signal into important features that can be used for giving input to the algorithms[71]. Various feature extraction techniques used are statistical analysis, histogram analysis, and wavelet transform. These techniques are briefly explained in subsections 6.1, 6.2, and 6.3.

6.1. Statistical feature extraction

Statistical feature extraction is a widely used feature extraction method. This is employed to extract statistical features from acoustic emission signal, vibration signals, and images. Various statistical features are mean, mode, median, bias, variance, standard deviation, kurtosis, skewness, etc. These features are sent to different algorithms for classification of grinding wheel conditions. Classification accuracy depends upon which type of statistical feature is selected for feature extraction[72–74].

6.2. Histogram feature extraction

Histogram technique separates the whole signal data set into different classes or subsets. This is used for the representation of numerical and discrete data which is acquired with defined time gaps. This technique is generally used for the representation of large signal data. It is also helpful in finding out outliers from the signal data. Histogram feature extraction is used for continuous signal data acquired using different sensors. This method is mainly used for the analysis of images of the grinding wheel during the process. Kanu et al. monitored and evaluated alumina grinding wheel wear and loading by using this technique. In this, images captured from the surface of a grinding wheel were observed and analysed[75]. Kanu et al. measured grinding wheel loading by grinding wheel image processing. Digital camera is used for taking images of the grinding wheels. During edge detection, grey pixel values along lines A-B are represented using a histogram[76]. In this study, grinding wheel loading analysis is done by processing of grinding wheel surface images. Grinding wheel surface images are captured by a microscope with 20 X magnification. Histogram of grey scale images of the fully loaded wheel was analysed and the threshold range was decided by considering the unloaded grinding wheel image[77].

6.3. Wavelet transform

Wavelet transform converts the time domain signals into time-frequency domain signals[78]. It is a technique which is used to decompose different types of signals to several lower resolution levels. Shifting and scaling factors of a single wavelet function are controlled to achieve this. The main reason to use wavelet transform is local spectral and temporal signals can be extracted simultaneously. The state of the grinding wheel is monitored by using continuous and discrete wavelet transform. These are also used for signal extraction[4]. In this study, feature extraction from the force signals is done by wavelet packet decomposition (WPD) for a micro grinding machine. These features were applied to back-propagation neural network for monitoring the state of the grinding wheel. Three grinding wheel surface statuses—dull, middle, and sharp are classified using BPNN[79]. In this study, feature extraction from acceleration signals was done using WPD technique to identify grinding wheel wear. Signals in the complete frequency band were decomposed to obtain specific decomposed components. In WPD, the time domain signal is converted to individual frequency bands. Then the extraction of band energies was performed and these are mixed with time-domain to get features. By using normalization, a typical energy ratio is extracted from the energy ratio. At the end, the final feature is extracted which can be used for grinding wheel wear monitoring[80]. In this paper, feature extraction is done from acoustic emission signals using wavelet transform. These features are applied to a genetic clustering algorithm for the classification of sharp and dull grinding wheel states. This method achieved 97% average clustering accuracy[81].

7. Classification methods for grinding

In the recent past, artificial intelligence-based classification methods have been increasingly used by researcher's tool condition monitoring. It is found that the performance of these methods can be improved easily. Moreover, modifications can be implemented easily compared to conventional methods. These classification methods are very adaptive for the new Industry 4.0 era. Artificial Intelligence methods are classified into two groups, (i) machine learning and (ii) deep learning.

7.1. Machine learning

Machine learning is the use of different computer algorithms which are used to make accurate diagnosis and prediction for different real-time situations and different actions of human beings. Machine learning algorithms learn from the past data and make improved decisions for the future. This artificial intelligence technique primarily focuses on prediction. SVM, genetic algorithm, random forest, linear regression are some examples of machine learning algorithms. A recent study on grinding wheel condition monitoring by using a machine learning algorithm is presented here. **Table 5** summarizes a few papers that deal with fault diagnosis of different grinding wheel conditions, signal extraction techniques, machine learning algorithms, and classification accuracy. In this, various feature extraction strategies like statistical feature extraction, time-domain analysis, frequency domain analysis, and wavelet transform were implemented. For fault classification, numerous algorithms were applied, including support vector machine (SVM), artificial neural networks (ANN), k-Nearest neighbour (KNN), ant colony optimization-random search (ACO-R) algorithm, ant colony optimization-sequential forward search (ACO-S) and genetic algorithm (GA). Some machine learning algorithms are discussed in subsections 7.1.1, 7.1.2, 7.1.3, and 7.1.4.

7.1.1. Artificial neural network (ANN)

This is a simplified model of the networks of neurons which occur naturally inside the brain. The ANN is constructed from three layers, namely, input, hidden, and output layers. Input layer is the layer which receives input information like text, images, pixels, etc. Hidden layers are in between input and output layers which process the information or data and the output layer is the layer which produces the result for the given initial information. ANN works with a training algorithm for study datasets which changes the weights of the neuron depending on the error rate between the target and the actual output[82]. ANN is a powerful tool for tool monitoring of grinding process. Relation between surface roughness parameters, AE signals, and forces due to the grinding process was explored by Mirifar et al. by using ANN[21]. ANN model is used for the estimation of the life of grinding wheels. By observing the results, it is seen that around 95% prediction accuracy is achieved by ANN to estimate the grinding wheel life[83].

7.1.2. Support vector machine (SVM)

It is a supervised machine learning algorithm which can be applied for classification and regression problems. It is mainly used for classification of tool conditions. Tool condition monitoring using SVMs is feasible and can ensure reliable production quality. Support vector machines-least square type (LS-SVM) can make good classification with a small amount of time and training data. It has been demonstrated that the performance of the grinding process can be monitored by using a LS-SVM algorithm[84]. Quadratic SVMs are used to perform the classification of the best tool conditions with the prediction accuracy of 94.7%. From this study, it is observed that SVMs can be used for monitoring of belt tool condition effectively[19].

7.1.3. Fuzzy logic

Fuzzy Logic is a thinking approach which resembles human reasoning. It predicts ‘yes’ and ‘no’ options. Recently, fuzzy logic has been utilized to monitor the states of different tools. Fuzzy inference is the process of formulating the mapping from the specified input to the output using fuzzy logic. Fuzzy inference process includes association functions, ‘If-then’ rules, and fuzzy logical operators. Fuzzy analysis is separated in three steps: (i) input value Fuzzification; (ii) rules-based reasoning; and (iii) defuzzification of output values[11]. States of grinding wheels are monitored by using fuzzy logic[15–32].

7.1.4. Adaptive neural fuzzy inference system (ANFIS)-Gaussian process regression (GPR) hybrid algorithm

ANFIS-GPR hybrid algorithm is used to increase the benefits of both ANFIS and GPR algorithms. This is implemented to solve approximation issues and nonlinear functions. By using this, the values of dependence functions can be altered manually the same as ANFIS model. It is used for online monitoring of grinding wheel wear and surface roughness during grinding. It gives the confidence intervals of the estimated results. The findings demonstrate that the technique is very intelligent and easily adapts to intelligent production conditions. It may offer a wide range of potential applications[16].

7.2. Deep learning

Deep learning is a technique that mimics the working of the human brain for data processing and pattern creation in order to make decisions. It is also called as deep neural learning or deep neural network. Traditional models of machine learning such as linear regression, Bayesian networks, SVM, logistic regression, and single-layer ANN do not predict the tool conditions effectively when the amount of training data is enormous (**Table 5**). Multi-layer neural networks and deep learning approaches, on the other hand, perform better for learning and prediction as the amount of training data is excessive[20]. Convolutional neural network (CNN), recurrent neural network (RNN), Generative adversarial network, Multilayer perceptron neural network, back propagation, and long–short-term memory is some of the deep learning algorithms. It is observed that recently different deep learning models were employed for monitoring different states of grinding wheel. TCM based on deep learning can be utilized for a variety of machining, including turning, milling, drilling, broaching, and grinding. Grinding wheel wear was monitored by using convolutional neural network (CNN) and spectrum analysis[5]. From this study, it has been observed that a deep learning algorithm named long short-term memory network (LSTM) was developed for the monitoring of grinding wheel wear. It is evaluated with a random forest algorithm. After observing the results, it is seen that even with fewer features, the long short-term memory model is able to forecast the wear of the grinding wheels more accurately[51]. Deep convolutional neural network (DNN) is employed for classifying vibration signals in gear grinding monitoring[85].

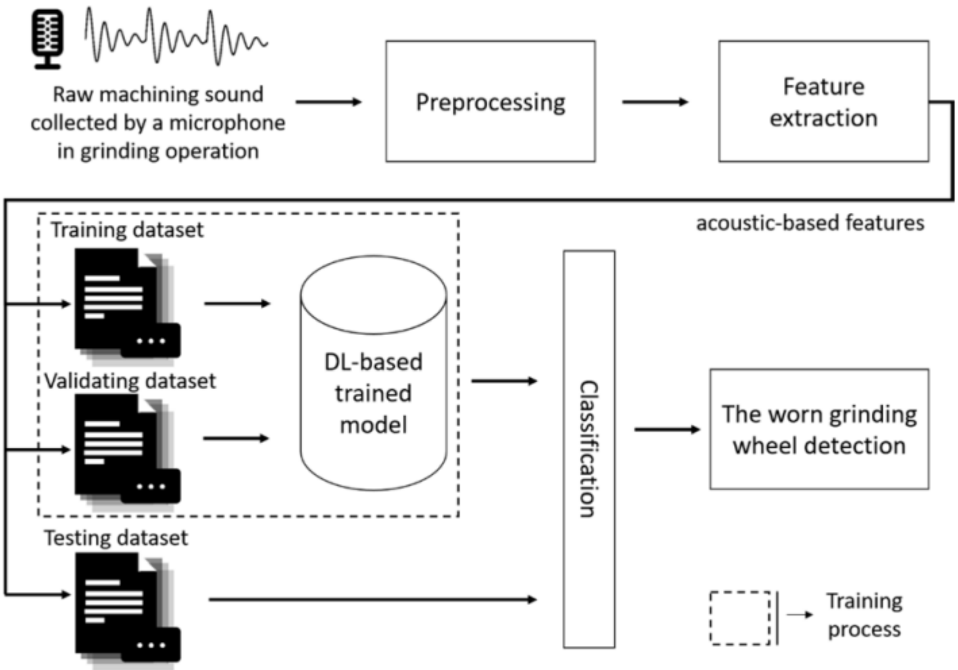
Table 5. Fault diagnosis technique.

Sr. No.	Fault detection	Signal processing/feature extraction system	Method	Classification technique	Accuracy (in %)	References
1	Grinding wheel wear	Time-frequency domain/Continuous wavelet domain, discrete wavelet transform	Machine learning	J48 and CART algorithm	97.06	[4]
2	Grinding wheel wear	Statistical analysis	Machine learning	Support vector regression model	95.90	[72]
3	Grinding belt wear	Short-time Fourier transform (STFT)	Deep learning	Convolutional neural networks (CNN)	94.23	[41]
4	Grinding wheel burn	Time-frequency domain/PSD, STFT, WPT, EEMD, and VMD	Machine learning	K-nearest neighbours (KNN) algorithm	99	[86]
5	Surface roughness	-	Machine learning	Gaussian process regression (GPR)	98	[87]
6	Grinding wheel burn	Time-frequency domain (HHT, CWT, STFT)	Deep learning	Convolutional neural networks (CNN)	99.40	[88]
7	Grinding belt wear	Time-frequency domain	Machine learning	Bayesian network model	85	[89]
8	Grinding burn, surface roughness	-	Machine learning	Bayesian network model	95	[90]
9	Surface roughness	Time-frequency domain	Deep learning	Long short-term memory (LSTM) network	-	[91]
10	Grinding belt wear	Time domain	Machine learning	Random forest algorithm, multiple linear regression (MLR)	90, 96	[64,92–94]
11	Grinding wheel wear	Statistical	Machine learning	Interval type-2-fuzzy basis function network (FBFN)	-	[6,95–97]
12	Grinding wheel wear	Empirical mode decomposition	Machine learning	Gradient boosting algorithm	88	[1,99–105]
13	Grinding wheel wear	Spectrum analysis	Deep learning	Convolutional neural network (CNN)	97.44	[5]
14	Surface roughness	-	Artificial neural networks (ANN)	Feedforward Bayesian backpropagation algorithm	99	[21]
15	Grinding wheel wear	Discrete wavelet transform	Artificial neural networks (ANN)	Fuzzy systems	-	[32]
16	Grinding wheel wear	Statistical	Artificial neural networks (ANN)	-	95	[83]
17	Grinding wheel wear	Taguchi method	Machine learning	Adaptive neural fuzzy inference system (ANFIS)-Gaussian process regression (GPR) hybrid algorithm	98	[16]
18	Surface Quality	MATLAB software-digital signal processing by time–frequency domain	Machine learning	Short-time Fourier transform (STFT)	-	[31]
19	Grinding wheel wear	Waveform data analysis (time and frequency domain)	Machine learning	support vector machine, genetic algorithm	94.7	[19]
20	Grinding wheel dressing condition	Frequency domain analysis	Machine learning	Fuzzy model	-	[11]

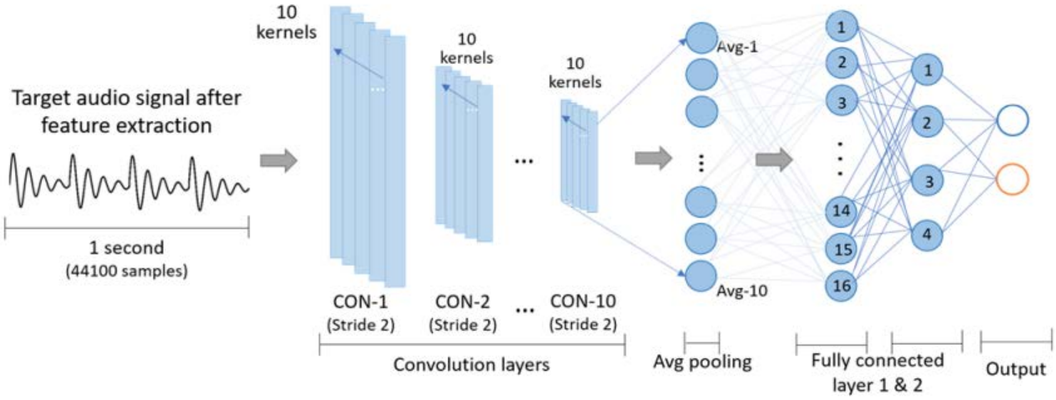
7.3. Case study: A deep learning-based and intelligent system for monitoring the condition of grinding wheels

The accuracy of the workpiece's surface during grinding is directly impacted by the immediate monitoring of the grinding wheel's conditions. This study uses artificial intelligence to try to learn the experience of auditory recognition of experienced operators because the variation in machining sound during the grinding process is essential for the field operator to judge whether the grinding wheel is worn or not.

As a result, researchers suggest an intelligent system based on deep learning and machining sound to identify the grinding wheel state. This work collects audio signals from the grinding process using a microphone integrated into the machine, and then utilizes spectrum analysis to extract the most differentiated features. To develop a deep learning-based training model for differentiating between the various conditions of the grinding wheel, the features will be entered into the specified CNNs architecture (**Figure 3**). The proposed method can obtain an accuracy of 97.44%, a precision of 98.26%, and a recall of 96.59% from 820 testing samples, according to the experimental results.

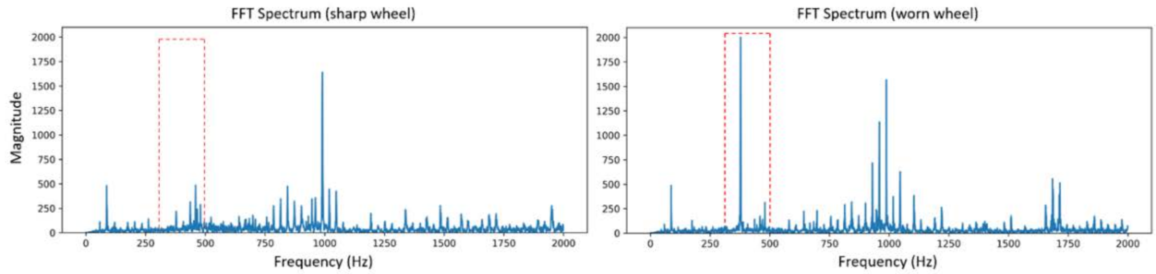


(a)

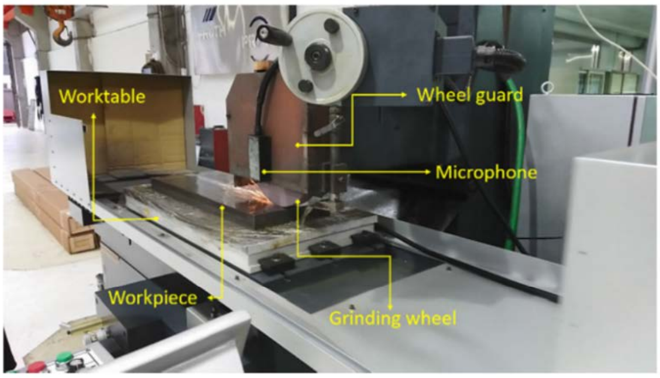


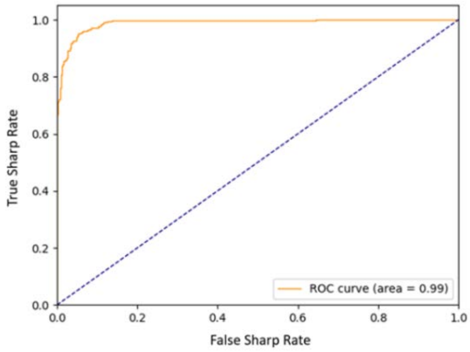
(b)

Figure 3. (*Continued*).



(c)





(d) (e)

Figure 3. A deep learning-based and intelligent system for monitoring the condition of grinding wheels[106]. **(a)** The layout of the suggested intelligent system for tracking grinding wheel condition; **(b)** The suggested architecture for CNNs; **(c)** two FFT machining sound spectrums recorded while using worn-out, sharp grinding wheels. The 300 Hz to 500 Hz range is shown by the red dotted line; **(d)** The grinding machine's experimental equipment configuration; **(e)** The proposed acoustic-based features' receiver operating characteristic (ROC) curve for classification results.

8. Conclusions

In the first section of the article, the need of tool condition monitoring is discussed. As a result of considerable advancements in sensor and computational technology over the past several years, tool condition monitoring has emerged as a crucial field for tracking numerous manufacturing process parameters. Monitoring tool condition is used to both identify faults and forecast the health of equipment. Grinding processes, types of grinding wheel, and the monitoring methods are highlighted in the second section. Because there are not any effective ways to provide real-time feedback while grinding, monitoring and predicting grinding wheel wear is challenging. Mechanical vibrations and acoustic signals are detected during the grinding process. The signals are used to monitor the grinding wheel's condition. Monitoring the state of grinding wheels involves gathering various signals from the grinding operation, including (a) acoustic output and (b) vibration signal (Section 3). Different types of data collecting systems are used to measure acoustic emission signals, vibration signals, cutting force signals, surface roughness, electric current, etc. while monitoring the grinding operation (Section 4). Different signals are acquired as data, and before further feature extraction is done, these signals are examined. The primary methods for signal analysis include the Hilbert-Huang transform (HHT), time-domain analyses, frequency-domain analyses, time-frequency analyses, and time-frequency analyses (Section 5). Data collection and signal analysis are completed following feature extraction in the monitoring of the grinding wheel. A crucial problem in engineering system state monitoring is feature extraction. The process of feature extraction transforms the obtained signal into significant features that may be used as input for the algorithms (Section 6). Recent years have seen a rise in the application of artificial intelligence-based classification techniques by researchers for tool condition monitoring. It has been discovered that these approaches' performance can be easily enhanced. In addition, adjustments are simpler to implement than with traditional techniques. The emerging Industry 4.0 age may easily adapt to these classification systems. Machine learning and deep learning are the two categories in which artificial intelligence techniques are discussed in Section 7.

Planning and motivation

Smart Manufacturing (CPS, IoT, and AI) for Industry 4.0, Smart Energy, and Smart Chemistry and Materials are the current areas of focus for the Journal. We aim to join hands for smart science in the future, which includes but not limited to Internet of Things (IoT), cyber-physical system (CPS), and Internet of Brain (IoB), artificial intelligence, advanced computing, smart machine/design, adaptive sensing, smart networks and information.

Conflict of interest

The authors declare no conflict of interest.

Additional information

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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