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REVIEW

Supervision of Milling Tool Inserts Using Conventional and Artificial Intelligence Approach: A Review

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ABSTRACT

Due to continuous cutting tool usage, tool supervision is essential for improving the metal cutting industry. In the metal removal process tool, supervision is carried out either by an operator or online tool supervision. Tool supervision helps to understand tool condition, dimensional accuracy, and surface superiority. For downtime in the metal cutting industry, the main reasons are tool breakage and excessive wear, so it is necessary to supervise tool which gives better tool life and enhance productivity. This paper presents different conventional and artificial intelligence techniques for tool supervision in the processing procedures that have been depicted in writing.

KEYWORDS

Tool supervision system; data acquisition and extraction; decision algorithm; artificial intelligence

1 Introduction

A Tool Condition Monitoring (TCM) is a predictive maintenance system used for mechanical systems or machine tools that monitors the condition of a cutting tool in a machine. By analyzing the data collected by various sensing approaches such as vibration, sound, cutting force, acoustic emission, and current of a cutting tool. Additionally, in the modern manufacturing process, tool condition monitoring is essential for reducing machining tool downtime. Due to lowering machining tool downtime, the productivity level of the manufacturing process increases. At the time of enhancing the life of tool and machine, condition monitoring is necessary. Tool condition monitoring (TCM) aims to implement an equivalent sensor signal processing technique to monitor and envisage the cutter's condition to decrease losses due to tool wear. For improvement in machining accuracy, product quality, and productivity, powerful tool condition monitoring is required. In tool condition monitoring (TCM), different sensors are used to acquire the data, including vibration, acoustic emission, cutting force, sound energy, temperature, a current signal, etc. The raw signal of this sensor uses a different extraction technique to extract the data. The artificial methods use this extracted data to monitor the cutting tool under various cutting tools' fault conditions. Compare the actual data and predicted data to check the accuracy of tool supervision. TCM plays a vital role in manufacturing industries due to the prevention of downtime and the optimization of tools [1].

1.1 The Architecture of Tool Condition Monitoring

Fig. 1 shows the framework, i.e., the architecture of tool condition monitoring. Tool condition monitoring comprises hardware and software parts to achieve signal processing, feature extraction, feature selection, and decision making. Tool supervision includes direct and indirect measurement of tool wear.

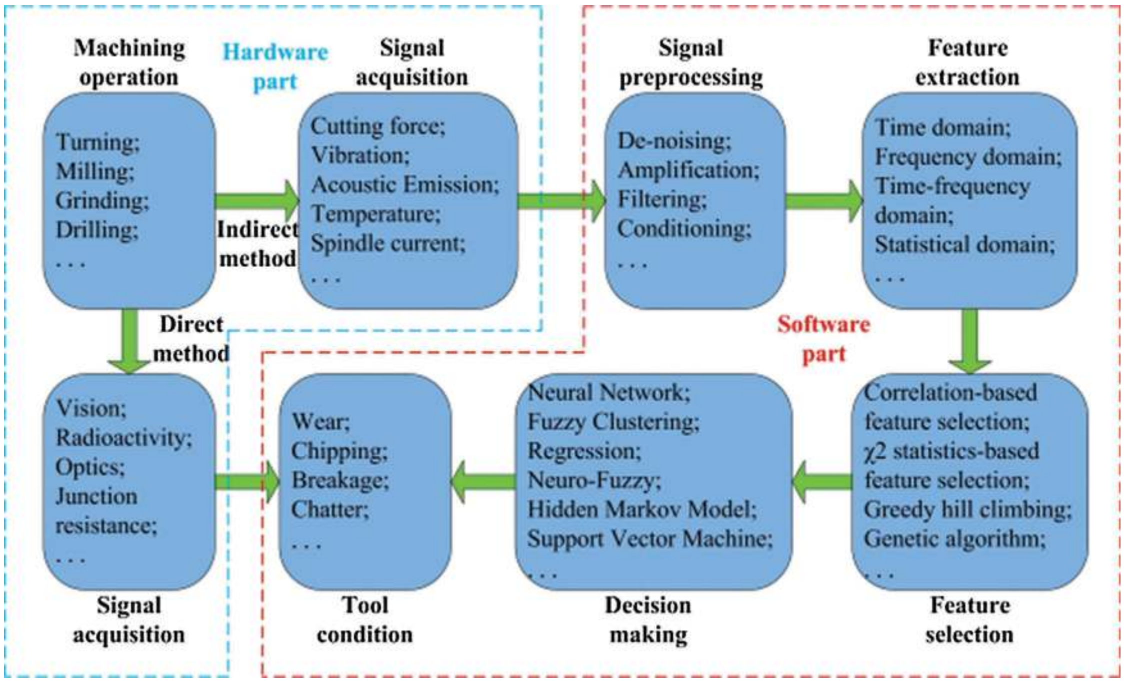

Figure 1: The framework of tool condition monitoring [2]

1.1.1 Direct Measurement Method

Direct measurement gives precise information about the physical wear of the machining tool. In the direct measurement, a Charge-coupled device (CCD), laser displacement sensor, optical sensing technique, surface profiler, vision inspection used to monitor the machining tool under different conditions. This method is vulnerable compared to indirect measurement. Only in a few situations, direct measurement provides exemplary accuracy. This method is generally executed offline manner. The accurate dimension of tool wear monitoring is not possible with the direct measurement method [2].

1.1.2 Indirect Measurement Method

In indirect measurement, different signal acquired, namely vibration, acoustic emission, cutting force, temperature, spindle current, and signal processing. In signal processing, denoising, amplification, filtering, conditioning done under the software part. In feature extraction, time, and frequency domain extracted. This obtained signal's relevant feature is extracted with different data extraction techniques, including statistical, histogram, and wavelet feature extraction. In feature classification, different classifiers were used to classify the fault of the tool. The feature selection includes correlation-based, statistical-based, genetic algorithm-based. The decision making carried out with a neural network, fuzzy clustering, neuro-fuzzy, support vector machine, regression, and hidden Markova model [2]. Based on the decision-making, tool condition monitoring is carried out under different machining tools' fault conditions. This method is easy to install and easy to implement online in real-time. Hence indirect measurement is more suitable for tool condition monitoring [2].

In this paper Section 2 presents the tool supervision system, which includes the indirect measurement techniques of TCM. Data acquisition and feature extraction are described in Section 3, followed by the decision making algorithms technique in Section 4. The artificial intelligence study for TCM is presented in Section 5. Discussion and summary of the milling tool's condition monitoring incorporated in Section 6 and Section 7.

2 Tool Supervision System

In manufacturing industries, cost-saving and productivity improvement playing a crucial role. The manufacturing industries utilize computer numeric control machine using automatic tool change and generally focuses on the automatic tool change process. From the 1980s to the 1990s, cutting tools changed based on the cutting tool's condition. In different ways, tool wear is a problematic phenomenon [3]. The dramatic change happened in the manufacturing environment in recent years for cost-saving methods. Therefore sensor and signal processing-based tool condition monitoring is accepted in manufacturing industries. In meeting process requirements, conventionally cutting tools changed for manufacturing machining processes. Hence online tool condition monitoring is required to detect precise wear of cutting tool [4]. Therefore tool supervision is essential to reduce low dimensional accuracy, poor surface finish, more power consumption, tool breakage, an inappropriate selection of sensors, and their operation, which affects the whole condition monitoring system [3]. The proper selection of sensor signal processing techniques helps predict tool states accurately to reduce tool breakage [5]. The information of tool condition monitoring is dependent on the tool wear. In tool supervision, generally acquired signals are vibration, acoustic emission, torque, power, and cutting force [6]. Hence to reduce the downtime, there are two techniques to supervise tool conditions: direct and indirect measurement methods. The direct method is carried out with an optical microscope, tactile sensor, and machine vision system. In indirect measurement tools, wear monitored with the use of different sensors [7]. Here significant problems and challenges discussed tool condition monitoring include the type of sensors, data acquisition, and extraction, prediction methods [8]. This paper describes the conventional and artificial techniques used for tool supervision. Below, the indirect measurement technique of tool condition monitoring has been described.

2.1 Acoustic Emission

Acoustic emission is used since 1977 to monitor the tool condition [9–10]; it has utilized electrical power to supervise the tool's condition. The power of the running spindle motor was nullified. The only energy required to drill in mild steel specimens only recorded this differential power monitoring method is more effective than the conventional power monitoring method.

During high-speed machining processes, the acquired AE signals were analyzed in frequency and time domains [11] for a useful tool wear monitoring system. Sensor information from multiple sensors has been compared [12]. Fig. 2 represents different kinds of sensor uses for different control parameters and levels of precision. The boundary denotes the estimated range of usage, with the shaded zone highlighting the essential application range. Investigations of acoustic emission from metal cutting have frequently been restricted to orthogonal machining or two-dimensional due to the easiness of chip flow and geometry [12]. Studied acoustic emission sensing range and signal characteristics are shown in Fig. 3 and Fig. 4 [12,13]. Suggested a sensor fusion model based on neural networks for tool supervision. Features extracted from the signals acquired during machining by force, vibration, and sound sensors. They are fused to estimate the flank wear of the tool advances in signal processing technique, which helps in finding the correlation between signal feature and tool condition. Acoustic Emission (AE) is the wonder of radiation of acoustic waves in a material that happens when exposed to twisting, metal cutting, or break. It is commonly acknowledged Acoustic Emission (AE) is the marvel of radiation of acoustic waves in material that happens when exposed to disfigurement, metal cutting or break. It is commonly acknowledged that AE is connected to plastic miss happening process during formation of chip, because of the interface among workpiece and cutting apparatus.

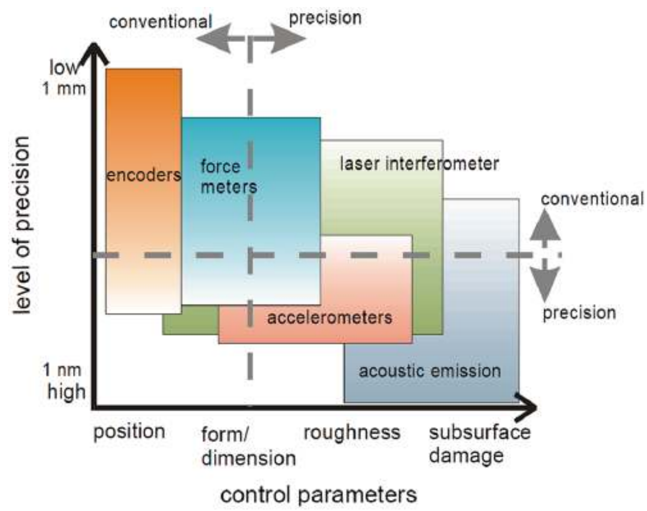

Figure 2: Sensor applications *vs.* level of precision and error control [12]

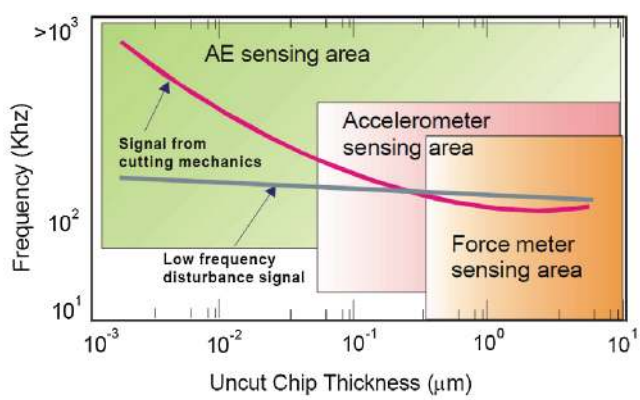

Figure 3: Acoustic emission sensing range [12]

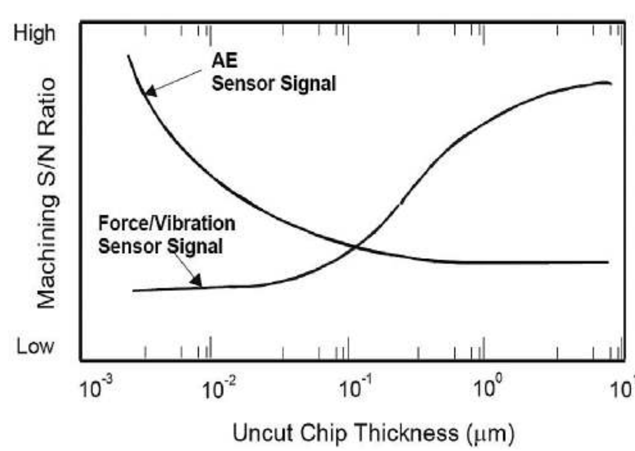

Figure 4: Signal characteristics of AE [12]

In machining, acoustic emission is promising to be a better approach for evaluating machine tool state and workpieces malfunctions [14,15]. Studied the correlation between acoustic emission characterization parameters like ASL, energy, duration, and RMS in predicting the failure or damage [16]. They also found that the quantification of these characteristics will help predict the failures.

A Power Spectral Density (PSD) methodology [17] for the finding of wear mechanisms and tool lifespan is implemented in the turning of hardened AISI4340 steel by the AE sensor. Both uncoated and coated cemented carbide tools have been used. The rise in flank wear of the tool resulted in a higher PSD value.

In a recent study, the acoustic emission (AE) sensor was used to acquire a signal for wear generation of the H13 steel. For the prediction of the tool wear state, an AE signal was used. After analyzing the AE signal, the study found that cutting speed is more influencing than a feed of operation. Also, a low feed rate is hazardous for the cutting tool [18]. Additionally, the AE signal was analyzed, and wear measured after 3 min of machining with a stereomicroscope. For statistical analysis of the AE signal probabilistic neural network (PNN) approach was studied. The PNN gives 91% of the result for this study. This study concluded that the AE signal is good for monitoring the tool [19]. Tool wear state studied with empirical mode decomposition and independent component analysis with the acoustic signal acquisition. The experiment was conducted with four conditions of a tool with a cutting sound signal. The broken insert was successfully separated and detect tool breakage. This method with the AE signal provides an effective solution to real-time industrial applications [20]. Subsequently, in high-speed machining of titanium alloy, AE signals were captured under different fault conditions of a tool, and discrete wavelet transform wavelet features were extracted. The tool state's prediction study was carried out with a decision tree, naïve bays, Support vector machine, and ANN after AE signal analysis. SVM provides 99.26% accuracy, which is superior to other algorithms with an analysis of the AE signal [21]. In this study, the AE signal acquired and detected tool condition with a machine learning classifier. A comparative study of artificial neural network support vector machine, decision tree, and naïve bays was carried out in tool fault classification. SVM gives more accuracy (99.48%) than others after analyzing the AE signal [22].

Additionally, AE signals provide information about tool state regarding crack propagation, flank wear, and severe adhesive wear. With the adding of a large amount of chip on the surface, a burst of AE with enormous amplitude occurred in finishing. Two-dimensional plot of roughing, semi-finishing, and finishing were studied [23]. With duration time, rise time energy, and peak frequency, AE burst signals clustered.AE burst signal was identified in 3 categories: plastic deformation, fracture, and Minimum quantity lubrication (MQL) [24]. In the machining process, the application of acoustic emission (AE) is discussed [25].

In the high-speed milling process, an artificial neural network algorithm based online tool supervision has completed. Here AE based technology proved tool condition monitoring with AE is good. Taguchi's design of the experiment was used to conduct Experiments. Interfacing artificial neural networks and AE with flank wear can increase the online tool condition monitoring [26]. C4.5 decision tree algorithm was used to study the flank wear. The AE sensor was used to acquire a signal with a frequency operating range of 100 kHz to 2 MHz. In detecting tool breakage, peak to peak amplitude found. It found that to study flank wear AE technique is superior [27]. Subsequently, two flute end mills were used for machining AISI steel. A Physical acoustic corporation (PAC) based acoustic signal was used to acquire an acoustic signal during the machining process. In two frequency bins, the AE signal was divided, 1.5 MHz sampling rate has selected in the AE signal. Machine learning algorithms comparison were carried out to detect the tool state [28]. After analytical modeling, the AE sensor signals are used to monitor the peripheral milling process [29]. It was found that AE signal was used for analysis purpose and Tin coated insert used in milling cutter for machining of mild steel, also with toolmakers microscope, flank wear is measured. Flank wear *vs.* time study has been carried out. The occurrence of the tool wears captured with the AE sensor. An AE technique is used for tool supervision and chip form supervision [30]. An acoustic sensor directly measures acoustic particle velocity. Compared with the traditional method, the use of particle velocity sensors is more advantageous [31]. Tab. 1 review has been carried out based on the type of acoustic sensor used during experimentation and sensor specification, including sensitivity, frequency of range, and operating temperature of a particular sensor. Tab. 2 represents cutting parameters used during experimentation, including workpiece material, depth of cut, speed, feed, type of cutter used, etc.

Table 1: Acoustic emission sensor application in milling machining process

Sr. No.	Type of Sensor	Sensor Specification			Authors
		Sensitivity	Frequency Range	Temperature Range	
1	Acoustic emission Kistler sensor (8125B)	48 (dB ref 1 V (m/s))	100–900 kHz	−40 to 140°F	[18]
2	Piezoelectric Acoustic emission sensor	48 (dB ref 1 V (m/s))	100–230 kHz	−40 to 140°F	[19]
3	Electric microphone MPA201	−46 to 42 dB (dB = 1 V/1 Pa)	20 to 20000 Hz	−20 to 70°C	[20]
4	Micro 30D	31 mV/Pa (−30 dBV)	20 Hz to 20 kHz	−10 to 55°C	[21]
5	Micro 30D	31 mV/Pa (−30 dBV)	20 Hz to 20 kHz	−10 to 55°C	[22]
6	piezoelectric AE sensor (Murakami-giken AE-1)	8 (dB ref 1 V/(m/s))	100–230 kHz	−40 to 140°F	[23]
7	AE sensor WSA and AE sensor ISR3CA-HT	55 (dB ref 1 V/(m/s))	100 to 1000 kHz	−65 to 175°C	[24]
8	Piezoelectric Acoustic emission sensor	48 (dB ref 1 V/(m/s))	100–230 kHz	−40 to 140°F	[26]
9	FAC 500Piezoelectric transducer	48 (dB ref 1 V/(m/s))	100–230 kHz	−40 to 140°F	[27]
10	Physical Acoustic Corporation (PAC)AE Sensor	80 (dB ref 1 V/(m/s))	200 to 850 kHz	−35 to 80°C	[28]
11	Piezo-electric Material (PTZ)	48 (dB ref 1 V/(m/s))	100–230 kHz	−40 to 140°F	[30]

Table 2: Machining parameter (acoustic signal acquisition) during milling process

Sr. No.	Work piece material	Type of cutter used	Cutting parameters			Authors
Speed	Feed	Depth of cut mm				
1	H13 mould steel	Indexable end mill (25 mm dia.)	170–230 m/min	200 to 300 mm/min	2	[18]
2	Martensitic Stainless Steel VP80	Cemented carbide tool	151 m/min	0.08 mm/tooth	1	[19]
3	Q235 steel	Cemented carbide Number of teeth: 4	160 rev/min	262 mm/min	0.2	[20]
4	Alloy of Titanium (Ti-6Al-4V)	4 flute coated carbide end mill cutter	225 m/min	300 mm/min	0.3	[21]
5	Titanium Alloy	tungsten carbide and cubic boron nitride (Cutting tools)	150 to 350 m/min	300 mm/min	0.3	[22]
6	block of 3.5 % Ni Steel	Firtree milling tools	190 to 220 rpm	12 to 15mm/min	–	[23]
7	Inconel 182 overlays	Milling cutter with four teeth	160 mm/min	0.2 mm/tooth	1	[24]
8	Aluminium Alloy	2 Flute titanium aluminium nitride coated solid carbide milling cutter	376 to 678 m/min	2000to 6000 mm/min	0.05 to 0.25	[26]
9	C45 steel	Rough turning grade of TK35	110 to 300 m/min	0.05–0.5 mm/rev	1.5	[27]
10	AISI 4340 steel	Carbide two flute end mill	122 to 152 m/min	0.08 mm/tooth	2.4, 3.56	[28]
11	Mild Steel	TiN coated insert	90 rpm	16 mm/min	0.3	[30]

2.2 Cutting Force Signal

In the indirect measurement method, cutting force measurement has been utilized to monitor the cutting apparatus in different conditions [32]. It found that in milling, by changing the magnitude of cutting harmonics, flank wear monitored. Cutting force harmonics is altered based on the number of teeth on the cutter and immersion ratio. Additionally, for online tool condition monitoring, harmonics of cutting force signals have been used [33]. The study carried out using cutting force signals and neural networks to supervise the cutting apparatus condition. Training neural network model input was given as workpiece geometry, cutting force, and cutting parameter.

Additionally, the regression model had utilized to monitor the tool wear state [34]. For apparatus (tool) wear estimation, cutting force signal, and neural network used. During the machining process, constantly cutting force variation increased. It was found that cutting edge tool lost their effectiveness and worn out [35]. For the milling process, the artificial neural network and the cutting force signal is used to envisage surface roughness and flank wear. The result confirmed that with tools, wear cutting force signals were increased [36]. The face milling tool wear had monitored using the Normalized Cutting Force indicator (NCF) and Torque Force Distance indicator (TFD). Subsequently, the result confirmed that the TFD was superior to NCF. The cutting parameter and its interaction consequences on TFD are not significant [37]. The coated carbide inserts had been used in machining of 'Inconel 718', the experiment conducted using cutting force variations and tool wear propagation. The result shows that the breakage tool occurred due to flank wear. For the up milling operation, tool flank wear propagation was faster than down milling operations [38]. Continuous hidden Markova model (CHMM) and cutting force signal had been utilized to supervise the cutting apparatus state in the milling process. Results confirmed that CHMM for tool supervision requires less training samples and time. It also produces outcomes very quickly [39]. Tool conditions were monitored in the milling process by tracing radial and tangential cutting force coefficients. This coefficient behavior is to not depend on cutting conditions plus correlated through the cutting apparatus condition. This type of analysis was used for tool supervision [40]. An adaptive network-based fuzzy inference system (ANFIS) and cutting force signal were used at the end milling process to supervise the cutting apparatus condition for Glass Fiber Reinforced Plastic (GFRP) Composite. It found that a superior prediction of tool condition had been observed with feed force data using ANFIS predictor [41]. In the frequency and time domain, cutting force signals were analyzed. With a rise in flank wear and cutting speed, result confirmed that the amount of cutting force in the frequency domain was decreased and increased during the time domain [42]. For online force, modeling and tool condition monitoring milling force, and flank wear were studied. In TCM cutting force signals affected by cutting conditions. With the help of cutting force model tool condition predicted with an accuracy of 98.5% [43].

The framework of the implemented model is presented in Fig. 5. In micro milling, Hidden Markova Model (HMM) was used to supervise the tool state. Also, both cutting state and cutting time was considered [44]. In the milling process, cutting force signals were acquired, and the status of the tool was predicted with an artificial neural network. It was found that tool wear state is linked with cutting force signal [45]. Tab. 3 review has been carried out based on the type of cutting force sensor used during experimentation and sensor specification, including sensitivity, frequency of range, and operating temperature of a particular sensor. Tab. 4 represents cutting parameters used during experimentation, including workpiece material, depth of cut, speed, feed, and type of cutter used, etc.

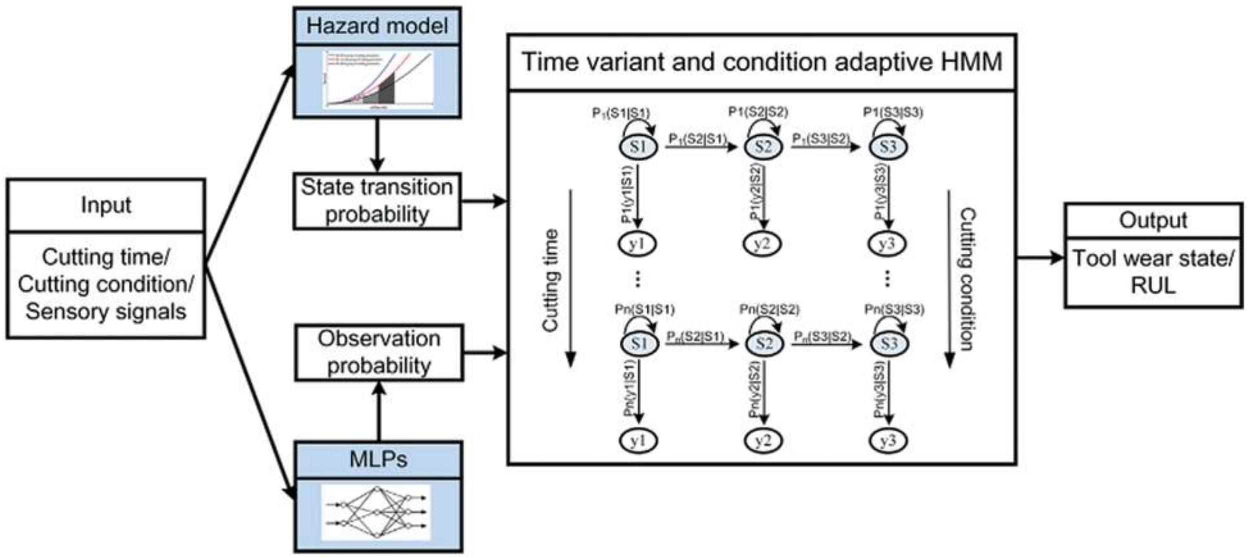

Figure 5: Time-varying and condition adaptive HMM for tool state monitoring [44]

Table 3: Cutting force sensor application in milling machining process

Sr. No.	Type of cutting force sensor	Sensor specification			Authors
		Sensitivity	Frequency range	Temperature range	
1	Kistler 9263 Dynamometer	−7, 8 pC/N	−20 to 20 kN	−20 to 70°C	[32]
2	Piezoelectric Dynamometer	−6 to −9 pC/N	−15 to 15 kN	0 to 60°C	[33]
3	Kistler 9255B Dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[34]
4	Kistler 9257B Dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[35]
5	Kistler 9265B Dynamometer	0, 5/5 mV/N	−5 to 5 kN	0 to 70°C	[36]
6	Kistler 9123C Dynamometer	−7 pC/N	−20 to 20 kN	0 to 60°C	[37]
7	Kistler Type 9254 quartz	−7, 9 pC/N	−30 to 30 kN	−20 to 70°C	[38]
8	Kistler 9257B dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[39]
9	Kistler Dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[40]
10	Piezoelectric Dynamometer	−6 to −9 pC/N	−15 to 15 kN	0 to 60°C	[42]
11	Kistler Dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[41]
12	Kistler 9265B Dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[43]
13	Kistler9256A 3-channel Dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[44]
14	Tool Dynamometer	−7 pC/N	−5 to 5 kN	0 to 70°C	[45]

2.3 Vibration Signal

In rotating machinery, vibration analysis is widely used to supervise the tool condition. An online-based monitoring system to detect tool breakage [46] was developed using a vibration sensor to supervise the tool state during the end milling operation. Vibration Signal collected during end milling was analyzed together in a frequency domain and time domain. Conversion from the time domain to the frequency domain was completed by the Fast Fourier Transform (FFT) to acquire the signal's frequency values. Most of the tool monitoring systems have not been successfully implanted because of the inadequate machining process models and sensor information, which does not reveal the process's difficulty [47]. Online monitoring requires quick and reliable responses from sensors. A better tool supervision system needs to accommodate the machining and mechanism of the tool wear process.

Table 4: Machining parameter (cutting force signal acquisition) during milling process

Sr. No.	Workpiece material	Type of cutter used	Cutting parameters			Authors
			Speed	Feed	Depth of cut	
1	C, 1040 steel	carbide inserts (Mitsubishi)	0.09–0.90 m/min	0.12–0.71 mm/min	0.14–0.86 mm	[32]
2	AISI 1020 steel and Aluminium alloy	HSS end mills	–	0.055, 0076, 0.110 and 0.152 mm/tooth.	2.54 mm	[33]
3	Aluminum and steel	carbide end mill	45,000, 15,000 rev/min	5 in./min	0.015 in.	[34]
4	CSRPR 2525	TiN–AL_2O_3–TiCN coated sintered carbide insert	–	0.1 mm/rev	–	[35]
5	Inconel Alloy 718	3-flute ball-nose end milling tools is tungsten carbide	8000–30000 rpm	10-50 µm/tooth	0.15–0.3 mm	[36]
6	Ck45	Kieninger 3D-MSC HK-E P20 inserts	250, 300 and 350 m/min	0.08, 0.1 and 0.12 mm	–	[37]
7	T6061 Aluminium alloy	Carbide inserts (SECO S25M)	–	0.05, 0.1 and 0.15 mm/tooth	–	[38]
8	ASSAB718HH	milling cutter, EGD 4440R	800 rpm	32 mm/min	0.5 mm	[39]
9	Steel 1018	Sandvik Mill390 uncoated carbide inserts	1500–4500 rpm	0.38 -9.31 mm/sec	–	[40]
10	GFRP composites	End mill	110–230 m/min	0.16–0.32 mm/rev	2 mm	[41]
11	Steel	Single insert coated tungsten carbide	200&370 m/min	0.2 mm/rev	0.6 mm	[42]
12	Inconel Alloy 718	3-flute ball-nose end milling tools is tungsten carbide	8000–30000 rpm	10–50 µm/tooth	0.15–0.3 mm	[43]
13	Steel T4	CS2008-0200 with 2 flutes	18000–30000 rpm	0.5–6 µm/tooth	60–100 µm	[44]
14	Aluminum Alloy hybrid metal matrix composite	Three-flute TiN coated cemented carbide	1999 rpm	0.08 mm/tooth	1 mm	[45]

In rotating machinery, vibration analysis is widely used to supervise the tool condition. An online-based monitoring system to detect tool breakage [46] developed using a vibration sensor to supervise

During tool supervision in milling, a microscope was utilized to capture the flank wear. Vibration signals were acquired with two accelerometers. The vibration signal was obtained with a new tool and some distance of cutting the mild steel workpiece. During increment of tool wear, spectra of vibration signal plotted. With the rise of flank wear amplitude of vibration signal increasing. With scalogram and its mean frequency vibration signal were acquired [48]. Additionally, to monitor tool condition in end milling, a three-axis accelerometer was used to obtain the vibration signal, and a data acquisition system based on a microcontroller is used. Subsequently, the vibration signal had acquired in the X, Y, and Z ways. Vibration *vs.* sample graphs has plotted. Hence vibration signal is necessary to monitor the tool condition [49]. It was found that spectrum analysis was carried out for the vibration signal in different tool conditions. Vibration signals had been captured for three states of tool condition. Time-domain acceleration signals sampled at a rate of 10 kHz [50]. The TCM investigated with a fractal analysis of the vibration signal. Subsequently, the time *vs.* acceleration graph plotted for different tools, and fractal dimension calculation carried out. Hence the fractal theory is utilized to supervise the milling tool condition [51]. During tool supervision in micro-milling, the three-axis Kistler (8141A) type accelerometer was used to acquire pulsation signals. The frequency and time domain had analyzed with a vibration signal. A combination of X, Y, and Z direction used during vibration signal acquisition [52]. In tool condition monitoring, titanium alloy workpiece used and acquired vibration signal. The flank wear study had been conducted on the digital microscope.

Figs. 6 and 7 shows the experimental arrangement and tool wear around flank wear. Additionally, vibration signals had acquired with new, small, medium, and severe wear conditions. In monitoring the tool condition, C-SVM and ν-SVM were used to understand the tool classification [53]. During tool supervision, a multipoint milling cutter is used. The piezoelectric accelerometer was used to acquire vibration signals for the different tool states. After the vibration signal acquisition, the histogram technique provides the extraction of features. K Star algorithm is applied to predict the cutting tool situation [54]. In milling tool supervision, Variational Mode Decomposition (VMD) and Backpropagation Neural Network (BPNN) were used. The genetic algorithm was used for tool condition classification.

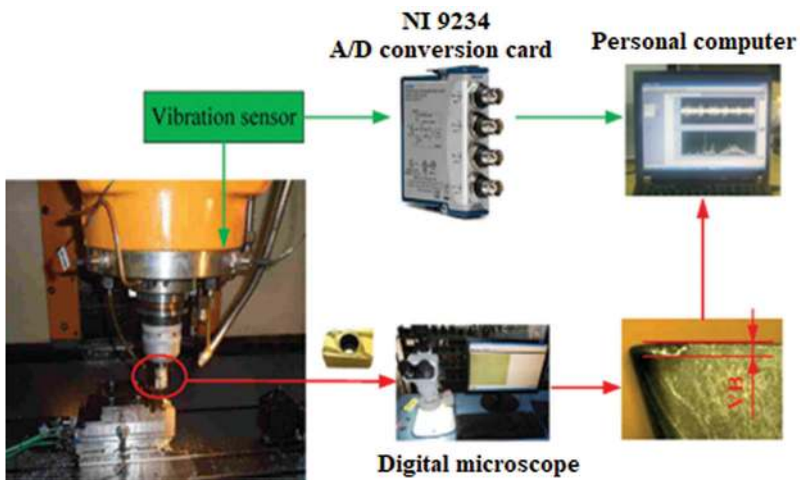

Figure 6: Layout of experimental setup [53]

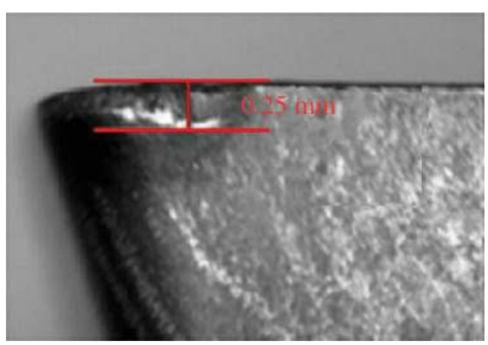

Figure 7: Tool wear morphography and measurement [53]

For chatter detection above model is developed. A milling cutter with six teeth used to acquire vibration signals under a different state of the tool. During monitoring chatter detection, a hybrid health monitoring system is used [55]. For monitoring the tool condition, a conventional machine was used with a vibration sensor. A vibration signal and an artificial neural network utilized to predict tool conditions [56]. In the milling process for monitoring, spindle shaft vibration flank wear measured. It was found that with an increase in tool wear frequency component also increased [57]. In Tab. 5 summary is carried out based on the type of vibration sensor used during experimentation and sensor specification, including sensitivity, frequency of range, and operating temperature of a particular sensor. Similarly, Tab. 6 shows the cutting parameter used during experimentation, including speed, workpiece material, depth of cut, feed, type of cutter, etc.

Table 5: Vibration sensor application in milling machining process

Sr. No.	Type of sensor	Sensor specification			Authors
		Sensitivity	Frequency range	Temperature range	
1	1 Axis 2 Piezoelectric accelerometer	9 mV/g	5000 g	–50 to 120°C	[48]
2	Low cost 3 axis accelerometer	230 to 282 LSB/g	±2 g/±6 g	–40 to 85°C	[49]
3	1 axis Accelerometer, Kistler 8752A50	100 (±5) mV/g	±50 g	–55 to 120° C	[50]
4	1 Axis Piezoelectric accelerometer IV9898	9 mV/g	5000 g	–50 to 120° C	[51]
5	3 Axis Accelerometer, Kistler 8141A	100 mV/g	±50 g	–55 to 90° C	[52]
6	1 Axis Piezoelectric accelerometer	9 mV/g	5000 g	–50 to 120° C	[53]
7	Triaxial IEPE Accelerometer (7132A)	10 mV/g	±2000 g	–55 to 125° C	[54]
8	1 Axis Accelerometer 356A16 PCB	100 mV/g	50 g	–54 to 80° C	[55]
9	1 Axis Accelerometer BMA280	4096 LSB/g	±2 g	–40 to 85° C	[56]

Table 6: Machining parameter (vibration signal acquisition) during milling process

Sr. No.	Work piece material	Type of cutter used	Cutting parameters			Authors
			Speed	Feed	Depth of cut	
1	Mild steel	4 Flute standard end mill	600 rpm	0.3 mm/s	1.5 mm	[48]
2	Mild steel	End mill	1200–2250 rpm	12–36 in/min	0.08 in/min	[49]
3	C45 steel	TiN coated CNMG carbide insert type	196–310 m/min	0.2–0.6 mm/rev	0.5–1 mm	[50]
4	Thermal refining 45 steel	High speed end milling cutter diameter (14 to 20 mm)	8.792–21.98 m/min	20–35 mm/min	2–5 mm	[51]
5	SK2 steel	Micro end mill	50,000 rpm	0.8 μ/rev	0.2 mm	[52]
6	Titanium alloy	APMT1604PDER-H2 VP15TF inserts	597 r/min	–	1 mm	[53]
7	42CrMo4/1.1225 steel alloy	Carbide insert	128 m/min	0.12 mm/insert	0.5 mm	[54]
8	Titanium alloy Ti6A14V	Hard alloy milling cutter with 6 teeth	3000–12000 rpm	0.1 to 0.3 mm/rev	0.2 mm	[55]
9	Steel block S235JR	Two cylindrical end mill P45355501	4245 1/min	680 mm/min	18 mm	[56]

2.4 Sensor Fusion Techniques

The sensor fusion is the combination of multisensory used to acquire the data and compare the results. In the face milling operation, tool condition monitoring was studied using cutting and acoustic emission (AE) signals [58–59]. Result confirmed that the flank wear is connected with cutting and AE signals. Additionally, in the machining process, sensor fusion is studied with a tool wear sensing system. In tool condition monitoring use of multiple sensors enhance the performance [60]. In milling tool condition monitoring vibration and cutting force signals used. For Combine extracted feature, different data fusion techniques used, such as Indices Multiplication and Division Group (IMDG), Comparison Group (CG), Indices Summation Group (ISG), Index Multiplication Group (IMG), Vector in Mapping Space Group (VMSG). For the classification of the tool condition, a neural network had used. It found that IMG and IMDG data fusion techniques enhanced classification accuracy [61]. During the high-speed machining method, cutting force, vibration, and Acoustic emission (AE) signals were achieved. Analysis of frequency and time domain carried out. It was found that AE signals were more sensitive for tool condition monitoring compared with other signals [11]. In tool condition monitoring, indirect sensor (Force) and direct sensor (vision) combined. In flank wear monitoring, vision measurement, and self-organization map used. It was found that force and vision measurement techniques overcome single sensor-based tool condition monitoring [62]. In tool condition monitoring, spindle current, spindle vibration, sound pressure, and cutting forces signals were captured. The feature was extracted from these signals. This signal was combined to evaluate the average flank wear of the main cutting side. Result confirms that for tool supervision, a sensor fusion model was developed based on a neural network [13]. In the micro-milling manufacturing process, cutting force and AE signals were acquired to supervise the tool in different conditions. In tool supervision, it was found that AE signals have a short response time for a tool to get in contact with the workpiece. Result confirmed that the better result is obtained with cutting force and AE signal [63]. The tool supervision was completed by acquiring signals from an accelerometer, dynamometer, microphone. Acquired signals are vibration, cutting force, and cutting sound. These signal from various sensor gives input to the fuzzy inference system (FIS). In the sensor fusion model, the input is given as a FIS output, and sensor fusion model output gives tool wear estimation [64]. In developing an online tool supervision system, vibration, AE, cutting force, and torque signals were obtained. The statistical technique of feature extraction was used to extract data from these signals; for support vector machine training, these data were utilized and monitored tool condition. The genetic algorithm was used to choose a feature that gives necessary information, and hence accuracy was 89 and 100%, respectively [65].

Fig. 8 shows the sensor installation for implemented TCM. Additionally, Tool supervision was carried out by using cutting sound and AE signals. In the prediction of tool condition, the Support Vector Machine (SVM) decision-making algorithm was used. It was found that a combination of two signals was superior to single sensor-based tool condition monitoring [66]. In milling tool supervision, vibration, AE, and cutting force signals are acquired, plus support vector regression was utilized to envisage the cutting tool state [67]. For online tool supervision and fault detection, various clustering methods were employed during the high-speed milling process. Results confirmed that the fuzzy clustering method achieves superior to additional clustering techniques [68]. The tool condition monitoring had been carried out by acquiring spindle drive current and acceleration signals. Pattern recognition system and Degree regression models were utilized to predict tool wear conditions [69]. Newly tool conditions were monitored by acquiring spindle vibration, spindle current, cutting force, and cutting sound signals. In the fuzzy inference system, these received signals were combined, and decisions were made to monitor the tool condition [70]. In milling, power, cutting force, and vibration signals had utilized to predict wear [71]. In tool supervision, cutting force and vibration signals were used. Multiscale principle component analysis (MSPCA) and Principle component analysis (PCA) were used to supervise tool state [72].

Figure 8: : Close-up view of sensors installation [66]

2.5 Thermal Imaging

During the micro-end milling, infrared thermography was used to supervise tool fault. It was found that with an increase in cutting tool temperature, the rise in speed, depth of cut, and feed happened. Similarly, heat generation takes place due to contact among the workpiece and tool [73]. Hence by increasing cutting speed, cutting tool temperature increases [74]. Additionally, an infrared camera was utilized to obtain the other side of the cutting edge's temperature for monitoring temperature range. Results confirmed that there is a relation between the increase in temperature and cutting direction, depth of cut feed, and speed [75]. In high-speed machining of bronze alloy infrared sensor with developed software was used to evaluate heat transmitted to the workpiece. It was found that this system reduced the number of tests required and enhanced accuracy [76].

In the machining process, to avoid tool failure, online supervision of tool temperature is necessary. For monitor tool and workpiece temperature monitoring, various non-contact and contact methods were used [77,78]. The direct contact method has many limitations; therefore, a non-contact method of measurement is superior to direct contact measurement. In the non-contact mode, an infrared pyrometer was used to supervise the cutting apparatus's temperature. It was found that the infrared pyrometer temperature measurement method was superior to the conventional thermocouple temperature measurement technique [79]. The infrared thermal imaging arrangement was utilized to measure the cutting temperature signal. It was found that cutting force increases with rising in tool edge radius; hence, the micro cutter's mean cutting temperature decreases slightly [80]. Infrared thermography (IRT), a non-contact type temperature measurement technique, was used. Using Stephan Boltzmann's law, the body's hotness was obtained with radiated rays [81]. The use of IR and IRT cameras were discussed [82]. In the indirect contact temperature measurement method, IRT is more economical and reliable [83]. Tab. 7 summary is carried out based on which type of monitoring device or camera is used for tool supervision. Similarly, the experimentation includes depth of cut, workpiece material, feed and speed, type of cutter utilized, etc., described in the below table.

Table 7: Thermal imaging sensor application in milling machining process

Sr. No.	Workpiece material	Type of cutter used	Cutting parameters			Monitoring camera/ device	Authors
			Speed	Feed	Depth of cut		
1	Aluminium Alloy Al6061, AISI 4340 steel	Double-flute micro-end cutting tools	3140-6280 r/min	5-15 mm/min	0.06–0.1 mm	Agema Thermovision-550 infrared camera	[73]
2	P-20 Mold Steel	Uncoated Carbide Tool	4010 rpm	0.100 mm/tooth	–	–	[74]
3	Aluminum 7050	End mill Model R216.33-20040-AC38U	314 to 628 m/min	0.10 to 0.25 m/rev	15 mm	FLIR infrared camera model	[75]
4	Thin Cu–Zn40–Al12 plates	Face 7 Inserts	min 200 m/min max-1800 m/min	1.4 mm/rev	3 mm	Infrared cameras, infrared pyrometer	[76]
5	2A12- T4 Aluminium Alloy	Micro–Cutter	67.9, 135.7, 226.2, 339.3 m/min	8, 12, 15, 20, 25, 35, 50 µm/rev	–	Data acquisition device (NI-USB 6215)	[77]
6	Annealed Carbon Steel (AISI 1045)	Silicon Nitride Tool Insert (SNG 433)	60 to 600 m min^{-1}	–	0.025 mm	IR pyrometer	[79]
7	Aluminium Alloy Al2024-T6	Tungsten-carbide (WC) Micro-Cutters	–	1,00,000 to 1,60,000 rpm	–	Infrared thermal imaging system	[80]

2.6 Miscellaneous Method

Different methods are used in tool condition monitoring, such as surface roughness, workpiece dimension measurement, stress-strain measurement, optical measurement, and ultrasonic sound, torque, and chip formation measurement method [84].

2.6.1 Stress Measurement Method

For tool failure monitoring, stress analysis of 3-dimensional loading attempted. For predicting the location and mode of tool failure, finite element analysis was used [85].

2.6.2 Vision System Method

In recent years, tool condition monitoring with machine vision gaining popularity. Additionally, machine vision is applied to acquire tool conditions for online tool supervision. Before and after the machining process, the tool wear image captured. Tool wear was assessed based on detected wear edge points. Results compared with microscope measurements [86]. The turned surface images and the image texture analysis technique used to monitor flank wear. Voronoi tessellation method was used to study the machined surface's surface quality, later drawing the 'Voronoi diagram' [87]. For monitoring, flank wears Voronoi tessellation, gray level co-occurrence matrix, and discrete wavelet transform is used to extract several features. Finally, the support vector machine (SVM) model was used to monitor the tool state [88]. In tool condition monitoring, surface images of machined surfaces study were carried out using the image processing method [89]. Additionally, tool states were measured and monitored by a Charge-coupled device (CCD) camera [90]. Tool state images were acquired and analyzed. It was found that the percentage of a white pixel is applied to envisage the tool fault condition [91].

2.6.3 Motor Current and Power Method

For online tools state detection, the power consumption of tool drives was used. Results confirmed that the tool drives' electrical power consumption was the best choice for online tool supervision [92]. In monitoring tool wear, the spindle portion of the AC and DC taken. It was found that the adaptive procedure can quickly detect the tool wear [93]. In tool breakage monitoring, spindle signals were acquired. A Support Vector Machine (SVM) was used to classify tool breakage. Result confirms that a combination of the spindle power signal and SVM model can accurately detect tool wear [94].

2.6.4 Chip Formation and Workpiece Dimension

In the milling manufacturing process, tool state, cutting force, and chip morphology were revealed. In the face milling process, chips were obtained and analyzed for their texture and shape. Result confirms that during the cutting condition, chip morphology was not changed [95].

3 Data Acquisition and Feature Extraction

3.1 Data Acquisition

The data acquisition system (DAQ) needs to develop to obtain signals from a different sensor such as Accelerometer, AE, Microphone, Dynamometer, spindle current, spindle power, ultrasonic sensor, etc., and received signal is like Vibration, Cutting force, and sound. There are various types of data acquisition systems based on the application to be used [96].

3.2 Feature Extraction

The feature extraction phase involves extracting the maximum suitable features from the signal acquired after signal pre-processing, which relate fine using apparatus condition also not affected by process situations. Generally, features are resulting from any of the time-frequency, frequency, and time domain. The techniques used in extracting from the above-stated domains are used widely by the researchers. With the help of acquired signals from different sensors, frequency domain [52], time domain [45], and frequency-time domain [5] features were extracted.

3.2.1 Time Domain

This technique is a basic methodology of feature extraction technique that generates the features not very informative as such, or at least it is very time-consuming. Usually, cutting force signals are generally time-domain processed to extract features [32,97–100] and utilized a time-domain study for the force signals. In all the above studies, features generated from the time-domain study have shown a great connection between force signals and tool conditions. This method generates the features associated with disturbances, which requires supplementing features from other processing domains. A time series was used to make the stochastic model, and from experimental behavioral data, crucial system physics can be studied [101]. The model of time series comprises statistical feature time-domain Moving Average (MA) and Auto-Regressive (AR) [102,103].

3.2.2 Frequency Domain

There have been many studies on human hearing reactions to sound frequencies. Thus, the frequency component of a signal can generate the features that can retain high information; typically, a mathematical study of the frequency data of signals is known as Fourier 20 study. Additionally, frequency data of a signal can be generated from the Fourier transform. Also, a fast Fourier transform forms its components. Typically, this domain is well used for generating features of the vibration and sound signals [60,104] and used Fast Fourier transform (FFT) to get the time-domain signals power spectrum illustration [97] used frequency domain features for surface roughness and vibration signals [98]. But, the major limitation of this technique is to classify the spectral bands that are sensitive for tool condition is not easy as always, and it is difficult to understand the cause for that specific frequency influencing the tool wear. The features of vibration and sound signals were extracted using a frequency-domain study [105].

3.2.3 Time-Frequency Domain

The time-frequency domain study utilizes the concept of wavelet transforms to generate features. It describes the identification of a signal in the frequency domain and time domain simultaneously, and this process largely reduces the processing time. In a study, a discrete wavelet transform has been used to perform a time-frequency domain study to extract features from vibration signal, and the dynamic characteristics of tool wear extracted from wavelet coefficients [106]. Chen et al. applied the wavelet filtering technique for his study in tool wear monitoring for the turning process [107]. Lee used wavelet analysis for vibration and AE signals for feature extraction [108]. A review study has stated that the wavelet transform has been a more effective method in time-frequency analysis for non-stationary machining sensor signals due to localization and sparsity properties [5]. The other techniques were used for signal processing such as Hilbert Transformation (HT), Empirical Mode Decomposition (EMD) [109–110], and continuous wavelet transform. These techniques can be used for feature extraction [111].

3.2.4 Feature Extraction Methods

In feature extraction, it is necessary to extract features from an acquired signal. The different methods are available to extract features from these signals, such as statistical feature extraction, Histogram feature extraction, Wavelet feature extraction [96].

Statistical Feature Extraction

In statistical feature extraction, descriptive statistical features such as Mean, Median, Mode, Skewness, Minimum, Range, Maximum, Kurtosis, Standard error, Standard Deviation, Variance, Sum, Count is applied as input to train the model [112]. According to the selection of a number of statistical features, classification accuracy is varying [112].

Histogram Feature Extraction

In histogram feature extraction, the bin width and bin range need to select based on the maximum and minimum values of the signals belonging to all tool conditions, and each bin is considered a feature. Different sets of histogram features need to extract from the acquired signals. Each set of features needs to consider input to the classifier, and the classifier's outcomes need to be analyzed [113].

Wavelet Feature Extraction

In wavelet feature extraction, wavelet transforms are hierarchic, therefore support fine tuning [114]. The wavelet coefficients are efficient at identifying the discontinuity or singularity. Sudden transitions in signal generate enormous absolute wavelet coefficients. The wavelet decomposition coefficient needs to use as features for the machine learning model [115].

4 Decision-Making Algorithms

The decision-making system is to map the signal features to a proper class (tool condition). The decision-making algorithms output, i.e., tool condition prediction. For the past few decades, researchers have been using Artificial-Intelligent (AI) techniques for a TCM decision-making strategy. For tool supervision, various AI techniques have been used. The crucial technique for modeling and supervision of tools is the fuzzy logic system and artificial neural network, and a combination of these two techniques known as the neuro-fuzzy inference system. Other AI approaches that belong to machine learning techniques and deep learning are AI techniques, tool condition monitoring, decision algorithms playing a crucial role, and various decision algorithm techniques to predict tool conditions. Different methods available in decision algorithm are support vector machine [65], support vector regression [67], probabilistic neural network [19], Artificial neural networks [115,116], Hidden Markov model [39], Fuzzy logic [117,118], decision tree [119], Adaptive neuro-fuzzy inference system [41] convolutional neural network, recurrent neural network, Backpropagation, multilayer perceptron neural network, Deep belief network, etc.

4.1 Artificial Neural Network (ANN)

ANN is a new computational model with one or multiple layers of processing elements known as 'neurons.' The ANN comprises the input layer, hidden layer, and output layer. The first, i.e., the input layer, obtain information from the outer world, middle, i.e., hidden layer process data, and last, i.e., the output layer gives output to the outer world. The neurons' structure depends on the operator, which depends on the problem to be modeled and studied. The investigations on ANNs started in the early 1950s, intending to discover an alternative computing model to the sequential computers. ANN study was carried out in tool condition monitoring, and it was found that ANN gives better performance [120,121]. Few limitations include in ANN are it needs a huge number of training samples, selection of neurons numbers in the hidden layer, and hidden layers numbers [122,123].

4.2 Support Vector Machine (SVM)

The support vector machine is a machine learning technique that analyses data for regression and classification analysis. The SVM, which utilized to classify and predict the tool condition. In recent years SVM playing a crucial role in monitoring the tool condition [53,65]. It was found that condition monitoring for SVM tool monitoring is superior to ANN-based tool condition monitoring [28,54]. Additionally, the limitation is selecting the kernel function, and its parameter is based on a trial and error method [124,125]. But, it is hard to get adequate data in practice; SVM is presented to have the advantage of generating good results. With this study, it is possible to monitor and replace tools.

4.3 Hidden Markov Model

It is a statistical model in which the system being modeled is expected to be a Markov process with a hidden state. In this HMM model, the state of the system is not dependent on all other states. It is influenced by only an earlier state that is constant with the tool state's progression [44]. The limitation of HMM is that it needs a huge amount of training data and time. It is used to monitor tool conditions.

4.4 Fuzzy Logic

Fuzzy logic is a human-like reasoning system that involves intermediate possibilities between 'YES' and 'NO.' In recent years, it was used to supervise tool conditions, i.e., tool state. The fuzzy inference system (FIS) comprises input and output membership function, fuzzy logic operator, and If-Then rules. The fuzzy logic working comprises three steps fuzzification input, fuzzy rule, and defuzzification output. Based on fuzzy logic operator 'if then' rules were developed [126]. Fuzzy logic was implemented to monitor the tool condition [68,99].

4.5 Adaptive Network-Based Fuzzy Inference System (ANFIS)

ANFIS is ANN like technique based on Takagi-Sugeno fuzzy inference system. Both fuzzy logic and ANN are incorporated into this system. ANFIS aims to combine the best feature of the fuzzy system and neural networks. Additionally, ANFIS is substantial than ANN, and it is taking extra time for data processing [45]. In the machining process, the ANFIS study was carried out to monitor the tool condition [100].

5 Artificial Intelligence Approach for Tool Condition Monitoring

Artificial intelligence is widely used in recent years for tool condition monitoring. Artificial intelligence techniques, such as machine learning and deep learning, are used to predict the tool condition in different states. Additionally, several algorithms of a machine and deep learning are used for tool condition monitoring. It was found that artificial intelligence is the best choice for tool condition monitoring study.

5.1 Machine Learning Approach

Machine learning is an artificial intelligence technique that gives a system that automatically learns from data and provides the prediction. Based on the acquired data machine learning algorithm, build a mathematical model for prediction purposes. Machine learning mainly emphasizes prediction. The machine learning algorithm includes linear regression, SVM, naïve bays, decision tree, random forest, gradient boosting algorithms, and dimensional reduction algorithms. In Section 4, a few machine learning algorithm is given. Here recent study was carried out on milling tool supervision using a machine learning method. Tab. 8 summarizes a few papers based on fault diagnosis cutters, extraction techniques, algorithms, and classification accuracy. It was found that different feature extraction techniques, including statistical feature extraction technique, histogram feature extraction technique, and wavelet transform technique, etc. Different algorithms, including J48, support vector machine, kernel, decision tree, CNN, K Star, and naïve Bayes, were used for fault classification.

5.2 Deep Learning

Deep learning is a machine learning technique that deals with algorithms motivated by the brain's structure and function; it is also called a 'deep neural network' or 'deep neural learning'. The algorithms that include in deep learning are Multilayer perceptron neural network, Deep belief network, convolutional neural network (CNN), recurrent neural network, Generative adversarial network, long short-term memory, and Backpropagation. It was found that deep learning algorithms were used to monitor tool conditions in recent years.

The chatter detection in the milling process carried out using a deep convolutional neural network (CNN) and a scalogram of continuous wavelet transform (CWT) [138]. Combination multisensory fusion and deep learning were used. It was found that the long short-term memory neural network (LSTM), integrated CNN, and deep residual networks (DRN) were used to monitor tool conditions. Result confirmed that the planned model is more precise [139]. For surface roughness monitoring, convolutional neural networks were used from the digital image of surface textures. Predicted and actual value of surface roughness were compared [140].

Table 8: Artificial intelligence approach for milling tool supervision

Sr. No.	Fault diagnosis	Extraction system	Technique	Algorithm	Accuracy	Reference
1	face milling cutter	Statistical	Machine Learning	Naïve Bayes, K star	Classification accuracy 96.9%	Madhusudan et al. [1]
2	Milling cutter with stages	Statistical	Machine learning	Kernel extreme	–	Zhou et al. [127]
3	Carbide milling tool	Statistical	Machine learning	Support vector machine	Classification accuracy 96.7%	Niu et al. [128]
4	Ball nose cutter	Wavelet	Machine learning	decision tree, k nearest, Support vector machine	Classification accuracy 97.1, 94.8, 92.5%	Zhou et al. [129]
5	ML Coated tool	–	ANN	ANFIS	–	Zhou et al. [130]
6	Ceramic coated cutter	PCA	Machine learning	Support vector machine	100%	Pedro et al. [131]
7	Face mill(6inserts)	–	Deep learning	LR, SVR, CNN	–	Cai et al. [132]
8	Carbide end mill	Wavelet	Machine learning	Support vector machine	90.8%	Yang et al. [133]
9	face milling cutter	CCWT	Machine learning	IELM	–	Soufiane et al. [134]
10	3 Edge tungsten milling cutter	–	Machine learning	Kernel extreme	93.28%	Lei et al. [135]
11	Single point cutting tool	Wavelet	Machine Learning	J48	Classification accuracy 96%	Gangadhar et al. [136]
12	face milling cutter	Wavelet	Machine Learning	J48, Support vector machine	Classification accuracy 94.5%	Madhusudan et al. [137]

5.3 Artificial Intelligence Techniques Used in Recent Years for Milling Tool Supervision

- In this study, support vector machine (SVM), k-nearest neighbor, decision tree, and ensemble training like machine learning algorithms were used to classify the milling tool's fault. The classification accuracy obtained with this algorithm is 97.1%, 94.8%, 92.5%, and 94.9%, respectively. Holder exponents feature given input to these algorithms. The obtained classification accuracies from these algorithms provide help for tool change [129].
- The paper presents chatter detection in the milling process established on the scalogram of continuous wavelet transform and deep convolutional neural network (CNN) model. The scalogram images are given input to the deep CNN. The CNN model was used to classify the state of the milling tool. The implemented CNN model provides better classification accuracy. With training and testing data, classification accuracy obtained 99.67% and 99.12%. The present technique was successfully implemented for chatter detection in the milling process [138].
- In this paper, tool condition monitoring is carried out in the end milling process. The experiment was conducted on a titanium alloy. A kernel-based support vector machine algorithm was used for classification. In the Kernel-based SVM classification, 70% of sample data used for training, and 30 % of sample data used for testing purposes. In the classification part, accuracy, precision, recall, and FI-Measure values were calculated [141].
- The paper presents the condition monitoring of cutting tools in the micro-milling process. In experimentation, vibration and sound signals were acquired in different conditions of the tool. In support vector machine algorithm, input features were selected by the recursive feature elimination method. In cutting tool, wear monitoring, support vector machine algorithm classification accuracy was 97.54% [142].
- The paper investigated tool wear condition centered on the order analysis and stacked sparse autoencoder (SSAE). Three-phase current signals were analyzed in the present study. SSAE neural

network was utilized to supervise the tool state, and it gives 96.411% training and 98.78% testing accuracy. The computation time for this classifier was 16.934 s. The classification accuracy of the SSAE neural network classifier is compared with different classifiers such as extreme learning machine, backpropagation neural network, support vector machine, radiofrequency-neighbor, etc. The results obtained by SSAE neural network show better performance than other methods [143].

- In the milling process, tool tipping monitoring was carried out. The holder exponents feature has been given input to model training. The different machine learning models, such as support vector machine, k-nearest neighbor, decision tree, and ensemble training, were used to calculate classification accuracy. The different kernel parameters were selected while calculating classification accuracy. The support vector machine model gives the highest classification accuracy than other machine learning models [144].
- The flank wear of cutting tool study was carried out with a convolutional neural network (CNN) model in the present study. A tool microscope took images of the cutting tool. These captured images are given as input to the CNN model. The CNN model was used to supervise the tool and envisage the tool life. The CNN model provides 87.26% classification accuracy for the remaining tool life prediction [145].
- In this study, milling multipoint milling tool inserts study had been investigated. The vibration signals were acquired in a different fault condition. The statistical features extraction method was used to extract the features. The statistical features are given as input to the machine learning model. Different machine learning classifiers like J48, Logistic model tree, random forest, Best first tree, Functional tree, and Simple cart was used to classify the milling tool insert's fault. According to the number of statistical features, the classification had been calculated. The training and testing accuracies were calculated for all classifiers. The best tree classifier gives the highest classification accuracy. Also, the time required to build the model calculated [112].
- In this paper, the combination of multifractal detrended fluctuation (MFDFA) and support vector machine learning algorithms was used to monitor the tool wear. The result displays that the implemented MFDFA and SVM approaches can classify the different tool wear stages fine, and the accuracy extends up to 95.6% [146].
- This paper investigated tool condition with complex continuous wavelet transform (CCWT) and improved extreme learning machine (IELM). The CCWT features as the input given to the IELM. In IELM From this method, it is possible to make the decision about complicated tool wear conditions [134].
- This paper had used an intrinsic timescale decomposition (ITD) with kernel extreme learning machine (KELM) for milling tool supervision. According to the data indicators extracted from the selected proper rotation (PR) components in time and frequency domains, a series of features sets had been constructed. At last, this set of features is an input given to KELM, which gives the fault classification. In the milling process, an experimental investigation was carried out in three stages of tool wear. With this method, 98.28% classification accuracy is obtained. Also, a comparison of achieved classification accuracy completed with another four methods, namely ITD based SVM, Ensemble empirical mode decomposition (EEMD) based KELM, Variational mode decomposition (VMD) based KELM, and KELM [135].
- This paper presents a deep learning approach for tool wear prediction in milling. Tool wear has been categorized into three stages, namely initial, normal, and severe wear. Tool wear prediction models were established by convolutional bi-directional long short-term memory networks (CNN + BILSTM) plus a convolutional bidirectional gated recurrent unit (CNN + BIGRU) [147]
- In the milling of titanium alloy, multisensory data were used to monitor the tool wear. Multisensor such as vibration, cutting force, and the cutting sound was used to acquire signals in a different

state of the tool. A support vector machine algorithm was used to classify the wear of the cutting tool. The classification accuracy was 96.7% [128].

- The paper presents a short time Fast Fourier transform (SFFT) and Support vector machine (SVM) method to detect the tool failure in the milling process. Acoustic emission (AE) signals were acquired in a different state of the tool. The SVM model gives 91.18% accuracy for tool failure detection. Here True positive rate (TP rate) and False positive rate (TP rate) were considered to evaluate the model [148].
- The paper investigated chatter prediction using machine learning algorithms. The vibration signals were acquired in different tool conditions using an accelerometer.The statistical features were extracted from these received signals. Decision tree, Artificial neural network, and support vector machine algorithms were used to predict chatter in milling tools. ANN algorithm gives 100% classification accuracy [149].
- The paper implemented a TCM system with acoustic sensor signals appropriate features and a two-layer angle kernel extreme learning machine. The two-layer network construction is used to enhance the learning of features connected by means of difficult nonlinear data. Two angle kernel functions without hyperparameters were employed. In avoiding the complications associated with preset hyperparameters in conventional kernel functions [150].
- This paper presents a multipoint milling tool supervision using an artificial neural network approach. The vibration signals were acquired in a different state of the tool. The statistical feature was extracted, and a decision tree selected the best features. An artificial neural network-based multilayer perceptron (MLP) classifier was used to classify the fault. The MLP classifier gives 97.33% classification accuracy [151].
- Fig. 9 shows a tool wear monitoring method for complex part milling based on deep learning. This method was implemented to monitor tool wear during complex part milling. The implemented deep learning model gives high accuracy for monitoring tool wear [152].

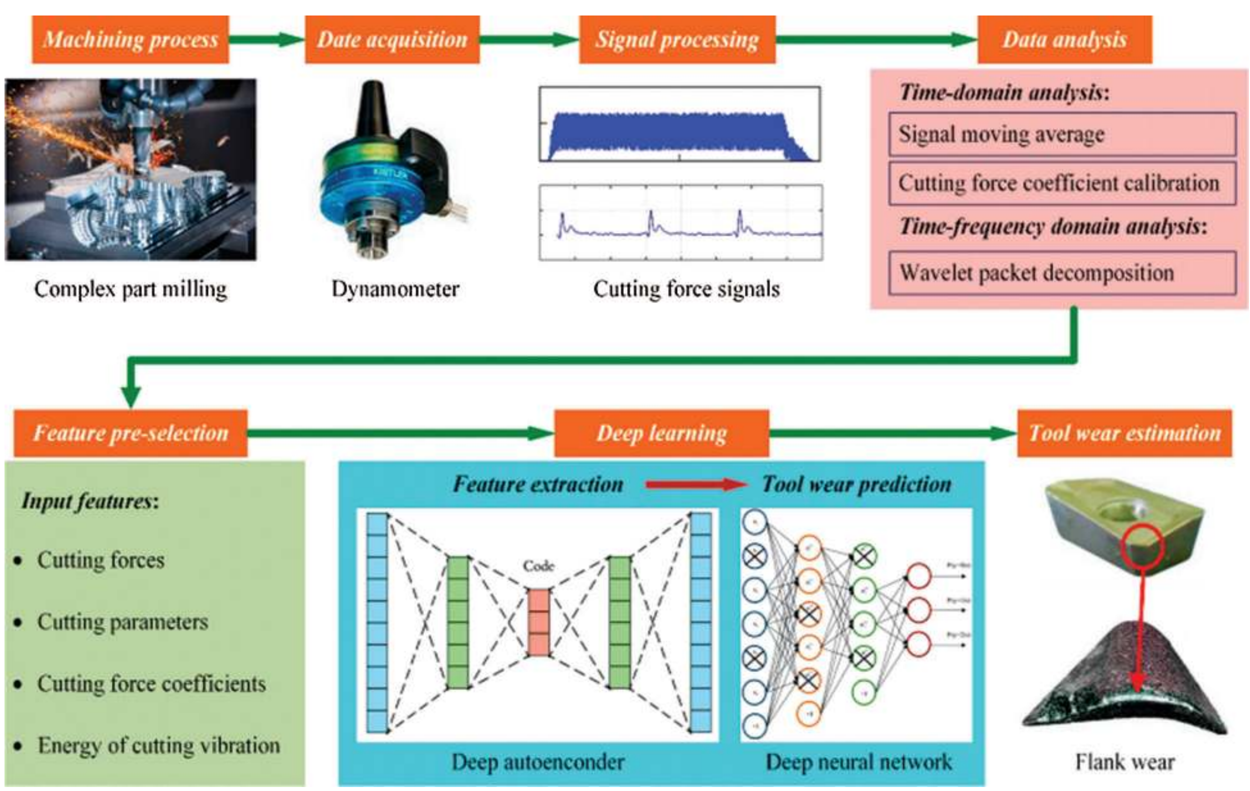

Figure 9: Tool wear monitoring method for complex part milling

6 Discussion

Tool supervision is difficult in the milling process due to workpiece material, cutting conditions, and process parameters. The tool condition monitoring was carried out by signal acquisition, feature selection, and decision-making algorithms [153,154]. In TCM, the condition of the tool was predicted by using decision-making algorithms. In TCM, conventional and artificial intelligence methods are used to monitor the tool state. Additionally, a conventional TCM graphical diagram is used, and in an artificial intelligence method, machine and deep learning algorithms are used to envisage tool fault. TCM in milling a lot of work has been carried, but some following problems have to be solved.

- The tool condition monitoring cost is more due to sensors, data acquisition systems.
- During signal acquisition, environmental and electrical noise should remove with the help of filters.
- In the sensor fusion technique, signal processing is a complex that decreases accuracy; hence, proper selection of significant features is necessary to enhance results.
- Therefore, it is necessary to enhance sensor fusion signal acquisition techniques.
- In decision-making algorithms, reduce misclassification in prediction, deep learning, and machine learning algorithms were used, such as convolutional neural network, recurrent neural network, deep belief network, multilayer perceptron neural network, naïve bays, decision tree, random forest, and the random tree.
- In TCM, the envisage of tool wear was carried out. Hence, in the upcoming year, the prediction of the tool's lifetime can be made.
- A lifetime of tool prediction is better than the tool wear prediction, i.e., up to how much period tool is useful for operation.

7 Summary

In manufacturing industries, tool wear is a significant problem. There are two techniques to supervise tool wear, such as indirect and direct measurement of tool wear. The direct measurement method reduces productivity, production rate, and machine idle time; hence indirect TCM is necessary to avoid this problem. In indirect measurement, various signals such as vibration, AE, cutting force, cutting sound, and spindle motor current need to acquire. The different feature extraction methods are available such as Statistical, Histogram, and Wavelet from which need to extract the features from these acquired signals. The decision-making algorithms provide the decision of tool condition; from this decision, it is possible to find classification accuracy. From classification accuracy it is possible to predict the health of tool condition. The artificial intelligence approach plays vital role to envisage the tool wear. Therefore, tool condition monitoring cost has increased due to various sensors for signal acquisition, data acquisition systems, etc.

In future, Onboard tool condition monitoring to be done by interfacing the software and hardware.

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