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ORIGINAL ARTICLE

Machine monitoring system: a decade in review

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Abstract

In recent years, significant advancements have been achieved in the domain of machine monitoring as witnessed from the beginning of the new industrial revolution (IR) known as IR 4.0. This new revolution is characterized by complete automation, and an increase in the technological deployments and advanced devices used by various systems. As a result, considerable advancement has been reported by researchers and academia around the world by adopting and adapting the new technology related to the machine condition monitoring problem. For these reasons, it is important to highlight new findings and approaches in machine condition monitoring based on the wireless sensor solution and machine learning signal processing methodology that are relevant to assist in advancing this new revolution. This article presents a comprehensive review on tool condition monitoring (TCM), tool wear, and chatter based on vibration, cutting force, temperature, surface image, and smart label monitoring parameters from signal acquisition, signal processing methodology, and decision-making, particularly for the milling process. The paper also provides a brief introduction to the manufacturing industries and computer numerical control (CNC) machine tool demand and a review of machine monitoring and countries involvement in machine monitoring, as well as the approaches and a survey of machine monitoring. The aim is to contribute to this rapidly growing field of machine condition monitoring research by exploring the latest research findings on the solution approach for milling machine process monitoring, to help expedite future research, and to give some future direction that needs to be considered as a path to produce a standardized CNC machine platform.

Keywords Machine monitoring · WSN · Milling monitoring

1 Introduction

Manufacturing industries around the globe are currently experiencing a significant transformation known as Industrial Revolution 4.0 (IR 4.0), which was introduced in 2011. The aim of IR 4.0 is to produce product models that are very flexible in terms of production and services [1]. To achieve this aim, communication in real time with surroundings, people, machines, devices, and products during production must be outstanding. It is important for every country to adopt and adapt the IR 4.0 trend by meeting the challenges and capitalizing on the advantages of the economic globalization opportunities. This is followed by the need to enable communications among different countries in the same language to achieve the aim of the slogan "Design Anywhere, Build Anywhere, and Service Anywhere" (DABASA) [2, 3].

In manufacturing industries, conventional machining operations, such as turning, milling, drilling, and grinding, are classified as the most common activities in production environments. With the rapid development of computer applications and technology, conventional machining has been gradually transformed into modern machining operations with efficient support for large scale manufacturing. Although many of these advancements in machining have been implemented based on the programming language known as G-code (ISO 6936), it is a low-level programming language with a limited amount of information and is unable to provide data feedback.

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As a result, CNC machines have limited capabilities in terms of their movement. They follow the programmed input even if unsuitable machining parameters are assigned. Furthermore, in the absence of a monitoring system, these scenarios may result in machine tool downtime. Machine downtime is defined as a certain duration of time during which no machining operation can be done on the workpiece [4], and can be divided into two—unavoidable and avoidable. The former occurs due to machine maintenance or any replacement of machine components, while the latter is due to disturbances during machining processes, which include overloading of spindle torque, excessive cutting force, chatter, tool wear, and other constraints [5]. The problem does not end at the machining process as it could typically lead to a major problem of product quality deterioration [6]. Machine downtime due to tool breakage has been estimated to average 6.8% [7], but can be up to 20% [8]. One of the main principles of eliminating these issues is by automating the current machining process condition monitoring [9–12] and applying a high-level programming language known as standard for the exchange of product data (STEP-NC) to control the machining process [2, 13–16]. This can be achieved by the integration of wireless sensor network (WSN) information and STEP-NC programming language with machine tools. Adopting this for the current machining process system will have a major influence on the production lines in terms of increased productivity and savings of up to 50% and 40%, respectively [4, 17].

Numerous studies have been conducted regarding the automation of machine condition monitoring to produce high-quality products the first time, effectively, and efficiently, without any waste [18–20]. This was proven by the results based on the data gathered from various databases. Based on the search, a total of 1306 journal articles were found from a variety of multidisciplinary studies. The first serious discussions and analyses of machine condition monitoring emerged in 1969 by the McDonnell-Douglas Corporation, as reported by Hillman [21]. The proposed system was based on graphic cathode ray tube terminals for three significant purposes, namely to reduce flight test development time, certification time, and the costs of data processing. Furthermore, the system was unequally developed to enable time-sharing into real-time data of up to 2 million bits per second of the total bandwidth.

From the 1306 journal articles found, unreliable articles were excluded, and the authors came to the conclusion that the research on machine condition monitoring can be divided into two sections, namely machine condition monitoring and machine process monitoring. Machine condition monitoring includes the monitoring of machine components, such as gears and bearings [22, 23], while machine process monitoring includes the monitoring of cutting tools and workpieces [6, 13, 24]. Both types of research aim to realize the adoption and adaption of the automated machine monitoring system. This review focuses on machine process condition monitoring and a total of 60 journal articles were found to be related to this topic.

Through the screening process of all 60 articles, the research can be divided into three major categories, namely chatter, tool wear, and tool condition monitoring (TCM). The respective quantities of publications are illustrated in Fig. 1. Most research has been conducted on tool wear and tool condition monitoring, because excellent tool conditions are vital to produce good quality products and to eliminate vibrations causing chatter problems. This is particularly so for cases where the CNC machine itself is in good condition

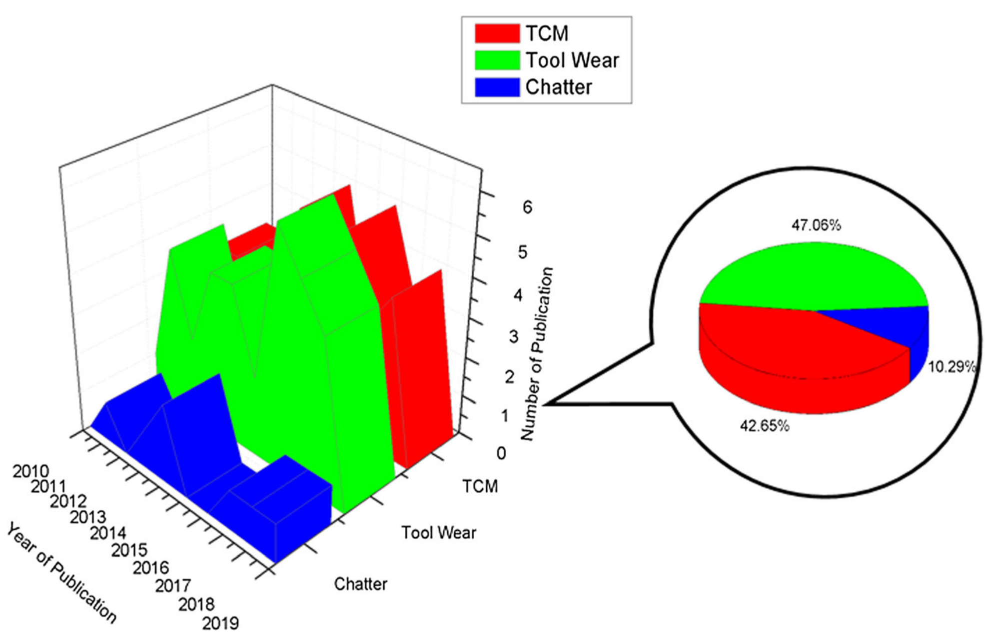

Fig. 1 Publication trend of machine process condition monitoring

and all the components, such as the cutting tool, the tool holder, and the workpieces, are perfectly positioned without any misalignment. The information about tool vibrations should provide details in terms of the periodic shape that resembles the cutting force, tool conditions, robustness, reliability, and applicability, at low cost, and be easy to measure without any modifications to the machine tools; as previously stated by Sevilla-Camacho et al. [25]. Furthermore, studies on machine condition monitoring have increased in number over the past year due to the vision of the world manufacturing industry for the automation system and the need to fulfill IR 4.0 requirements. Figure 2 shows the countries involved in machine process condition monitoring research.

The aforementioned review articles have provided an interesting review on the topic of machine condition monitoring, such as TCM, tool wear, and chatter. The combination of TCM, tool wear, and chatter was found to be relevant in the milling process; as cited by many studies [12, 24, 26–29]. Due to the considerable amount of work in the area of machine condition monitoring, several review articles were found between 2000-2015, such as by Rehorn et al. [4], Li [30], Lauro et al. [31], and Quintana and Ciurana [32], most of which focused on the techniques to solve signal acquisition and signal processing methodologies. However, since 2015, considerable advancement on signal acquisition and signal processing methodologies has occurred due to the emergence of new technologies, such as WSN, Internet of Things (IoT), and machine learning. Furthermore, the reflection of the IR 4.0 paradigm for smart manufacturing must also be considered. Therefore, a new review is required to cover the advancements and rapidly growing field of machine condition monitoring research. The main motivation is to explore the latest technology and research findings on the signal acquisition and signal processing methodologies based on wireless sensor solution and machine learning signal processing methodology,

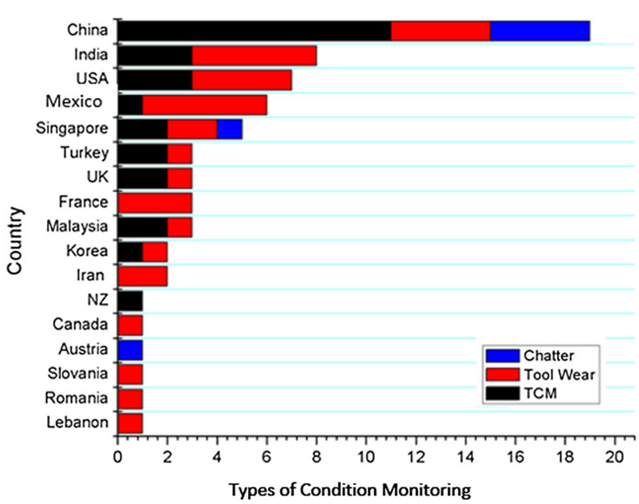

Fig. 2 Number of publications by country and type of condition monitoring

respectively. This article presents a comprehensive review of TCM, tool wear, and chatter based on vibration, cutting force, temperature, surface image, and smart label monitoring parameters from signal acquisition, signal processing methodology, and decision-making, particularly for the milling process. Finally, conclusions and future suggestions for machine process condition monitoring based on WSN were made as a plan to adopt and adapt IR 4.0 in the manufacturing industry. In this article, a review of the research work for the decade from 2010 to 2019 is presented. The design of this article includes a review of machine monitoring covering the past and present approaches, and a methodology survey on machine process condition monitoring.

2 Approaches applied for machine process condition monitoring

The machine process condition monitoring methodology is divided into two categories past and present as depicted in Fig. 3.

2.1 Past methodology

As the manufacturing industry has experienced several revolutions, from IR 1.0 to IR 4.0, the methods of collecting the monitored data from real machine conditions have also changed tremendously, as evidenced by the studies reported yearly by researchers since 1974. Despite the changes in the data collection methods over the years, the past method of machine monitoring remains the same. The first step in machine process condition monitoring is signal acquisition. Different signals, including vibration, temperature, cutting force, and others, are used for different purposes in the monitoring system. Previously, milling process signals were collected based on a wired system direct to the personal computer. Due to the rapid development of technology and IR 4.0 transition, the old technique has slowly changed into WSN. Based on the reviews conducted in this study, particularly for milling operations, Rizal et al. [18] were the first authors who set up a WSN-based signal acquisition system. The next step in monitoring the machine process condition monitoring was the signal filtering process. During machine rotation, the machine itself produces different types of noise. Since the noise comes from different sources, the raw signals need to be filtered by a feature extraction method. There are different types of signal filtering methods, which include time domain analysis, frequency domain analysis, and wavelet analysis. The different methods of signal filtering analysis suit different signal filtrations and the detection or classification is applied to finally get the condition of the machining process. Previously, most condition detections applied statistical approaches. However, with the passage of time and the development of

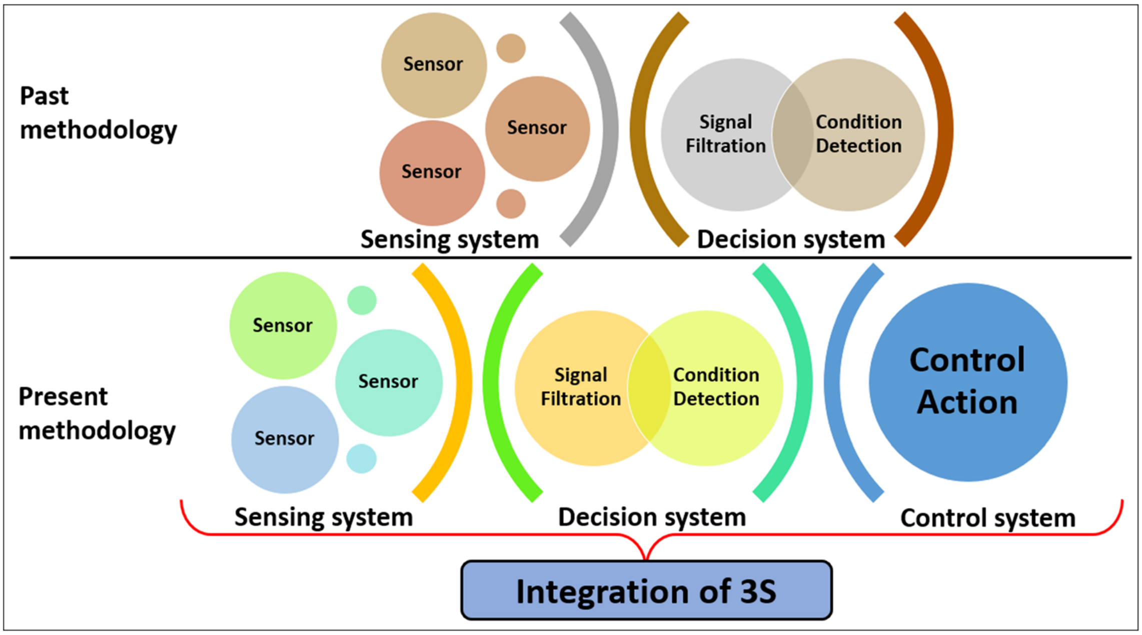

Fig. 3 Methodology of past and present machine process condition monitoring

different software and computer applications, most researchers have turned to applying machine learning algorithms to develop robust decision-based models.

2.2 Present methodology

The key to building smart factories is by turning the traditional machines into modern machines. Figure 3 illustrates the integration of 3S, representing the sensing system, decision system, and control system for present and future machine process condition monitoring. WSN is integrated into traditional machines to enable wireless data collection and data transfer. Signal filtration and signal processing are done based on the machine learning algorithms. Machine learning enables data to be processed intelligently, with robust and fast responses without human intervention. The final and next important stage is to control the current bad conditions of the machining process, to either stop the machining process, fix the loose part/component, or self-adjust the cutting parameters to manufacture products and to achieve the best product quality.

3 Survey on machine process condition monitoring methodology

Machine process condition monitoring research has been widely explored. In this section, the methods introduced by each researcher for milling operations since 2010 are comprehensively discussed. Based on the survey made on the reported articles, it was found that machine process condition monitoring methodology could be divided into two major sections—data acquisition methodology and signal processing methodology.

3.1 Data acquisition methodology

In this section, detailed explanations are provided of the five most usable monitoring parameters for data acquisition methodology, which includes vibration monitoring, cutting force monitoring, temperature monitoring, motor and spindle monitoring, and smart label monitoring.

1. Cutting force monitoring

The cutting force is the force produced due to the material properties of the cutting tool and workpiece, cutting tool geometry, material shearing force, and the friction force between the cutting tool and the chip [8, 17, 33]. It reflects the real situation of the machine conditions during the machining process and is the most widely used measurement parameter due to its high accuracy of measurement. Through the observations made of the existing research, most researchers opted for the dynamometer for the cutting force measurement due to its accuracy [12, 24, 34]. However, measurements using a dynamometer are incompatible with industrial environment applications due to their low capability and high cost [6, 17]. Moreover, table-type dynamometers and customized dynamometer-based strain gauges are only applicable to certain sizes of workpiece [35, 36]. Therefore, Rizal et al. [6] and Luo et al. [17] proposed the indirect cutting force measuring technique by embedding a cutting force measurement system. The introduction of the cutting force measurement by embedding a strain gauge inside the spindle housing was invented by Rizal et al. [6] while Luo et al. [17] proposed cutting force measurement by using working tables integrated with PVDF Thin-Film Sensors. Both approaches were validated, and the measurement of the cutting force matches the dynamometer measurement. Most researchers have applied wired signal acquisition sensor data transfer while Rizal et al. [6] and Zhong et al. [19] applied WSN. Table 1 summarizes the findings of the cutting force monitoring introduced by several researchers from 2010 to 2019. Based on the table, it was concluded that the information from the cutting force monitoring is applicable to monitoring TCM, tool wear and chatter, and is suitable to be used with face milling and end milling operations.

2. Vibration monitoring

Vibration is the second signal commonly measured to propagate and predict TCM, tool wear, and chatter. Table 2 presents a solution for vibration monitoring, which was invented as an alternative to the cutting force for machining process monitoring. It was the most favored indirect measurement parameter for monitoring, and was proposed by most researchers as the vibration signal offers better characteristics (periodic shape) similar to the cutting force and rich tool condition information, as well as being robust, reliable, widely applicable, low cost, and easy to install without any modification to the current machine [25]. Vibration signals can be detected directly using a piezoelectric accelerometer or via an indirect measurement technique (laser or embedded systems). Previous scholars reported that vibration sensors could be placed on the workpiece, CNC table, spindle housing, vise jaw, or embedded inside spindle housing [6, 52, 57]. Vibration sensors placed on the spindle housing or embedded offer more accurate signals compared with those on the workpiece. Vibration sensors placed on the workpiece are often unstable due to the potential relative movement of the tool holder during the machining [6, 28, 54, 65]. From 2014 onward, some

Table 1 Cutting force monitoring

Author	Milling operation	Purpose	Measuring technique	Measuring device	Signal acquisition
[6]	Face milling	Tool wear	Indirect	Strain gauge	WSN
[37]	Face milling	Tool wear	Direct	Kistler piezoelectric dynamometer	Wired
[38]	Face milling	Tool wear	Direct	Quartz dynamometer (3D)	Wired
[33]	Face milling	Tool wear	Direct	Kistler piezoelectric dynamometer	Wired
[39]	Face milling	TCM Tool wear	Direct	Cutting force signal	Wired
[40]	Face milling	Tool wear	Direct	Kistler rotating dynamometer (3D)	Wired
[12]	End milling	Chatter	Direct	Kistler dynamometer	Wired
[17]	End milling	TCM	Indirect	PVDF thin film	Wired
[24]	End milling	TCM	Direct	Kistler quartz dynamometer (3D)	Wired
[34]	End milling	Tool wear	Direct	Kistler quartz dynamometer	Wired
[41]	End milling	Tool wear	-	-	Wired
[35]	End milling	Tool wear	Direct	Kistler dynamometer	Wired
[42]	End milling	TCM	Direct	Kistler dynamometer	Wired
[36]	End milling	Tool wear	Direct	Kistler mini dynamometer	Wired
[43]	End milling	Tool wear	Direct	Kistler dynamometer	Wired
[44]	End milling	Tool wear	Direct	Kistler 9265B quartz dynamometer (3D)	Wired
[45]	End milling	TCM	Direct	Dynamometer (3D)	Wired
[46]	End milling	TCM	Direct	Kistler dynamometer	Wired
[47]	End milling	Chatter	Direct	Kistler dynamometer	Wired
[48]	End milling	Chatter	Direct	Kistler dynamometer (3D)	Wired
[49]	End milling	TCM Tool wear	Direct	Dynamometer (3D)	Wired
[50]	End milling	Tool wear TCM	Direct	Kistler dynamometer (3D)	Wired
[51]	End milling	TCM	Direct	Kistler dynamometer	Wired
[52]	End milling	Tool wear	Direct	Kistler dynamometer	Wired
[19]	Milling	TCM	Direct	Force	WSN

Table 2 Vibration monitoring

Author	Milling operation	Purpose	Measuring technique	Measuring device	Signal acquisition
[6]	Face milling	Tool wear	Indirect	Piezoelectric accelerometer	WSN
[37]	Face milling	Tool wear	Direct	Kistler piezoelectric accelerometer	Wired
[53]	Face milling	TCM	Direct	Triaxle piezoelectric accelerometer	Wired
[54]	Face milling	TCM	Direct	Tri-axial IEPE accelerometer	Wired
[25]	Face milling	TCM	Direct	ADXL321 accelerometer	Wired
[38]	Face milling	Tool wear	Direct	Piezo accelerometer	Wired
[30]	Face milling	Tool wear	Direct	Kistler Piezo accelerometer (3D)	Wired
[55]	Face milling	TCM	Direct	Vibrational signal (3D)	Wired
[56]	Face milling	TCM Tool wear	Indirect	Laser Doppler vibrometer	Wired
[24]	End milling	TCM	Direct	Kistler piezoelectric accelerometers (3D)	Wired
[57]	End milling	Chatter	Indirect	Microelectromechanical system	WSN
[34]	End milling	Tool wear	Direct	Kistler Piezo accelerometers	Wired
[28]	End milling	TCM Tool wear	Direct (fixed in the machine spindle)	Piezoelectric accelerometer micro 30D	Wired
[41]	End milling	Tool wear	-	-	Wired
[58]	End milling	Tool wear	Direct	Triaxle accelerometer	Wired
[59]	End milling	TCM Tool wear	Indirect	Triaxle accelerometer (3D)	WSN
[35]	End milling	Tool wear	Direct	Tri-axial accelerometer (3093B13)	Wired
[42]	End milling	TCM	Indirect	Triaxle accelerometer Kistler 9257BA	Wired
[60]	End milling	TCM	Direct	Biaxial ADXL321 accelerometer	Wired
[61]	End milling	Chatter	Direct	PCB 352C65 accelerometer (2D)	Wired
[62]	End milling	TCM	Direct	PCB356A15 accelerometer	Wired
[18]	End milling	Tool wear	Indirect	Piezoelectric accelerometer (MT32-ICP)	WSN
[63]	End milling	Tool wear	Direct	Vibration signal	Wired
[64]	End milling	Tool wear	Direct	Accelerometer (3D)	Wired
[65]	End milling	TCM	Direct	Triaxial piezoelectric accelerometer	Wired
[51]	End milling	TCM	Direct	Kistler piezoelectric accelerometer 8692C50	Wired
[52]	End milling	Tool wear	Direct	Piezoelectric accelerometer Kistler 9257A	Wired
[66]	Milling	TCM	Direct	–	WSN
[20]	Milling	TCM	Direct	ADXL 345	WSN
[19]	Milling	TCM	Direct	Vibration	WSN

studies switched to utilize WSN for signal acquisition purposes [6, 18–20, 57, 59, 66]. The researchers believed that WSN enables real-time monitoring anytime and anywhere, and the infrastructure of the monitoring system requires less cabling, is low in cost, and requires shorter deployment time compared with wired sensors. Furthermore, the machine downtime due to maintenance can be controlled for increased production efficiency and product quality, together with a reduction in labor cost and human error.

From the findings, vibration monitoring is suitable for TCM and tool wear as well as chatter for both face and end milling operations. It was also found that only 20% of the research proposed applied indirect measuring techniques while others applied direct. Besides that, monitoring by a WSN was only applied by 23% of the researchers. Utilization of vibration monitoring enables easy installments, is low in cost, and offers low power consumption compared with a dynamometer.

3. Motor and spindle monitoring

Another indirect sensory device that is applicable for reflecting the real situation of machine conditions during a machining process after cutting force and vibration is the spindle or motor power. Table 3 presents the motor and spindle-based monitoring approaches that have been proposed recently. As discussed earlier, although cutting force is the best measurement device in terms of accuracy, it is expensive and not compatible for use in the industrial environment, while the vibration signal produces a different value depending on where it is

Table 3 Motor and spindle monitoring

Author	Milling operation	Purpose	Measuring technique	Measuring device	Signal acquisition
[67]	Face milling	Tool wear	Indirect	CTA 213 spindle current sensor	Wired
[68]	Face milling	TCM	Indirect	Power sensor (CE-P41) spindle power signal	Wired
[58]	End milling	Tool wear	Indirect	Spindle power	Wired
[69]	End milling	TCM	Indirect	Universal power cell	Wired
[70]	End milling	TCM	Indirect	Current transducer	Wired
[62]	End milling	TCM	Indirect	Honeywell CSNP611 (3-phase) (current)	Wired
[71]	End milling	TCM	Indirect	Keyence eddy current	Wired
[72]	End milling	TCM	Indirect	Feed motor current signal	Wired
[50]	End milling	Tool wear TCM	Indirect	Spindle rotary encoder	Wired
[51]	End milling	TCM	Indirect	Spindle power	Wired
[20]	Milling	TCM	Indirect	SCT013	WSN

mounted. Thus, the application of the spindle or motor power is more suitable in industrial environments. Ammouri and Hamade [70] mentioned that the spindle or motor power was proportional to and correlated with the torque and cutting forces, respectively. Besides that, the spindle or motor power signal can be acquired easily as the installation does not interrupt the current machine tool structure [51, 58, 69]. Apart from that, the spindle or motor current has proven to provide a better tool condition monitoring signal compared with the spindle or motor power. Several studies proposed machine condition monitoring based on the spindle or motor current [20, 25, 27, 62, 70–73]. Based on observations, most researchers have applied a wired current sensor [20].

It is observed that motor and spindle-based monitoring is more applicable in replacing the cutting force and vibration monitoring for tool wear and TCM monitoring for any milling operation as it offers the same advantages as vibration monitoring, is easy to install, and does not interrupt any machine structure.

4. Temperature monitoring

Temperature is another parameter that has received considerable attention [18–20, 66, 74], as shown in Table 4. Researchers have agreed that high temperatures will contribute and create abnormalities in the cutting process. The increase in temperature during machining may cause tool wear, degradation of workpiece quality, and increased tool cost [18–20, 66, 74]. In terms of the measurement of cutting, the temperature is complicated and difficult due to its scalar field, which is different throughout the system and cannot be described at a point. However, the success of measuring temperature results in maintaining the cost of the cutting tool, workpiece, and total production cost. Based on the review, it was found that all the researchers introduced a contact type temperature measuring technique. In 2013, Sivasakthivel and Sudhakaran [74] applied temperature sensor by inserting the K-type thermocouple inside the hole at the back of the workpiece with the signal acquisition via a wired system. Rizal et al. conducted a series of work in 2014 [18] and 2018 [6] by embedding a K-type thermocouple in the cutting tool and an applied wireless telemetry system for signal acquisition. As the IoT became widespread, Zhong et al. [19], Zedong and Azman [20], and Deng et al. [66] introduced the application of WSN temperature acquisition nodes by deploying the sensor on various components to enable direct temperature monitoring. Based on author review, none of the research proposed a non-contact temperature measuring technique and, except

Table 4 Temperature monitoring

Author	Milling operation	Purpose	Measuring technique	Measuring device	Signal acquisition
[6]	Face milling	TCM	Contact	Type-K thermocouples	WSN
[18]	End milling	TCM	Contact	Type-K thermocouple	WSN
[74]	End milling	Tool Wear	Contact	Type-K thermocouple	Wired
[66]	Milling	TCM	Contact	Temperature sensor	WSN
[20]	Milling	TCM	Contact	DS18B20	WSN
[19]	Milling	TCM	Contact	Temperature sensor	WSN

Sivasakthivel and Sudhakaran [74], almost all of the researchers shifted to a WSN signal acquisition method until 2018. Besides that, only Sivasakthivel and Sudhakaran [74] proposed machining parameter optimization using a mathematical model and genetic algorithm for machining process control activity while others only focused on temperature monitoring activity.

5. Surface image monitoring

Surface image monitoring could be another important parameter to describe the current condition of the machining process. It is mainly applied for tool wear or chatter monitoring. From the review, surface image monitoring approaches were proposed by several researchers for different purposes, as summarized in Table 5. These studies applied two types of surface monitoring approach, namely direct and indirect sensing. In direct sensing, surface images are retrieved directly by capturing the surface image of the workpiece or cutting tool using a microscope, charge couple device (CCD) camera, electrical resistances, radioactive isotopes, and others. The captured images are evaluated by using image analysis technology while indirect sensing measures the auxiliary in-process quantities, such as cutting force, vibration, sound, acoustic emission, temperature, spindle power and displacement, and the status of the workpiece or cutting tool are evaluated by analyzing the collected information. Numerous studies have applied indirect sensing in their research [12, 24, 28, 30, 34, 35, 41, 43–46, 56, 63, 67, 76, 78]. They also applied direct sensing approaches to verify the performance of the indirect sensing approaches. Besides that, there are two ways of measuring tool wear, which are contact and non-contact measuring techniques. Usually, in the contact measuring technique, a Leica MZ 12.5 stereo microscope, Olympus tool makers microscope, digital microscope, or microscope is used to observe the tool wear value. For the non-contact measuring technique, most researchers utilize a CCD camera, single-lens reflex camera, optical microscope, and three-dimensional (3D) laser scanning microscope. Only Yang et al. [12] and Ritou et al. [74] made their own imaging mechanism to enable flank wear or tool wear shape and value observation. Almost all studies applied time domain analysis to observe the tool wear shape and value. Jennings et al. [33] and Wang and Wang [55] applied surface topography and statistical methods while Sun et al. [75], Liukkonen and Tsai [79], and Dutta et al. [77] applied their own image processing techniques.

Table 5 Surface image monitoring

Author	Milling operation	Purpose	Measuring technique	Measuring device	Signal acquisition
[11]	Face milling	Tool wear	Non-contact	Machine vision system	Wired
[67]	Face milling	Tool wear	Contact	Microscope	Wired
[37]	Face milling	Tool wear	Contact	Leica MZ12	Wired
[38]	Face milling	Tool wear	Non-contact	Optical microscope	Wired
[33]	Face milling	Tool wear	Contact	Digital microscope	Wired
[30]	Face milling	Tool Wear	Contact	Microscope	Wired
[56]	Face milling	TCM Tool wear	Non-contact	CCD camera microscope	Wired
[41]	Face milling	Tool wear	-	-	Wired
[12]	End milling	Chatter	Contact	Microscope	Wired
[27]	End milling	Tool wear	Non-contact	Machine vision system	Wired
[75]	End milling	Chatter TCM	Non-contact	Single-lens reflex camera	Wired
[34]	End milling	Tool wear	Contact	Leica MZ12 microscope	Wired
[28]	End milling	TCM Tool wear	Non-contact	CCD camera (non-contact)	Wired
[35]	End milling	Tool Wear	Non-contact	Optical microscope	Wired
[36]	End milling	Tool wear	Non-contact	3D laser scanning microscope (non-contact)	Wired
[43]	End milling	Tool wear	Contact	Olympus microscope	Wired
[44]	End milling	Tool wear	Contact	Leica MZ 12.5 stereo microscope	Wired
[45]	End milling	TCM	Contact	Olympus tool makers microscope	Wired
[63]	End milling	Tool wear	Contact	Digital microscope	Wired
[46]	End milling	TCM	Contact	Microscope	Wired
[76]	End milling	Tool wear	Contact	Leica MZ12.5 stereo microscope	Wired
[77]	End milling	Tool wear	Non-contact	Optical microscope	Wired

By considering the findings in Table 5, surface image monitoring is mostly applied to observe the flank wear value offline. Nevertheless, it is also used to verify the performance of the indirect sensing approach, such as vibration and cutting force monitoring for comparison purposes. Furthermore, to enable online surface image monitoring, a non-contact mechanism should be considered.

6. Smart label monitoring

Product barcode or product labelling is included as an important part of a monitoring system. Through product barcode or labelling, a product can be traced easily. In the past, a barcode system was used for labelling in the entire manufacturing environment for resource identification [79]. However, there are some drawbacks to barcode application, and it is not practical for use in a manufacturing environment, especially on the shop floor because it is easily polluted by dust and oil, which makes it difficult for scanning. Since World War II, radio-frequency identification (RFID) technology has been used by the British Defense Department for aircraft detection [80]. In this technology, digital data is encoded in RFID tags and a RFID reader is captured through radio waves. RFID has its working mechanism similar to that of a barcode, but with many more advantages. It works as an automatic object identification, where it collects data and sends it directly to the computer system without any human intervention. RFID is beneficial for workpiece or part monitoring activity, as it enables products to be traced automatically and adds value to the intelligent machine monitoring. Based on the review conducted, Zhong et al. [19] have been the only researchers who applied RFID technology in their milling process monitoring system since 2010. The researchers applied a wireless RFID tag and Reader on each workpiece thereby enabling it to be traced anywhere on the shop floor or even after finishing the machining process as a complete product.

3.2 Signal processing methodology

This sub-section explains the steps for the signal processing methodology and discusses in detail the method applied by several studies to process the uncooked signal into a valuable signal that can be used to make a conclusion or any decision regarding tool condition monitoring.

1. Feature extraction and statistical approach

Several steps need to be taken before any decision can be made. The first step is cleaning, filtering the raw signal by the pre-processing process. The next important step is feature extraction, since the signal acquired from the cutting process is assumed to be nonlinear and nonstationary, and to contain information about the condition of the process. The three most important signal processing methods are time domain, frequency domain, and time frequency domain. Generally, the types of features extracted from the time domain signal are arithmetic mean, average, magnitude, root mean square (RMS), standard deviation, skewness, kurtosis, signal power, peak to peak, crest factor, ratios of signals, and signal increments for statistical method and auto-regression (AR), autoregressive moving average (ARMA), time domain averaging (TDA), and other information for time series analysis [24, 81]. The frequency domain is the signal obtained from the time domain signal, which is transformed to the frequency domain via fast Fourier transform (FFT). The frequency domain signal only consists of frequency amplitude without time information, such as power spectrum, peak-to-peak amplitude, and tooth frequency [24]. Both time domain and frequency domain assume that the signal is stationary. To enable the availability of both types of information, the frequency domain needs to be transformed to the time-frequency domain via wavelet transform. Wavelet transform enables the wave to be transformed into a wavelet and enables the hidden information regarding the condition of the tool to be extracted. Furthermore, to extract a wavelet coefficient using the wavelet transform method, discrete wavelet transform, continuous wavelet transform, and wavelet packet transform are utilized to reflect the tool states [82]. Discrete Fourier transform and statistical analysis using linear least squares is applied to the vibration signal to track the magnitude of the energy at the tooth pass frequency under a 40-Hz band and to trace the tool condition consistently including any drastic changes that occur in the tool's life [65]. Tool wear appearance is found by monitoring the variation in rotational frequency and observing tool breakage by the sudden variation in the frequency amplitude [50]. The power signal is analyzed by wavelet packet transform together with the independent component analysis and short-time Fourier transform (STFT) to detect tool breakage but is unable to detect minor breakage [68], while Sevilla-Camacho et al. [72] proposed tool breakage monitoring based on the motor current signal by wavelet packet transform and statistical methods to compare with a normal cutting threshold to detect tool breakage efficiently. Other researchers that applied statistical methods are Rizal et al. [6], Luo et al. [17], Zedong and Azman [20], Sevilla-Camacho et al. [25], Zhu et al. [45], Aghazadeh et al. [52], and Friedrich et al. [57]. Nevertheless, the time domain and frequency domain, time-frequency domain, and statistical analysis contain a huge number of features, and executing analysis for each available feature is time consuming, and may contain redundant information that will affect the final result if irrelevant features are selected. Therefore, it is important to select the most relevant information and eliminate redundant information from the available features by feature fusion/reduction method or feature selection method.

2. Feature fusion and feature selection

The feature fusion/reduction method or feature selection method is able to reduce the time complexity of the signal processing algorithm, especially in the machine learning model. In the feature reduction method, a set of multidomain feature parameters is set by linear or nonlinear mapping to obtain a new parameter. This new parameter is then used as an input to the monitoring model. For example, Li [30] used multi-class support vector machine recursive feature elimination (SVM-RFE) to remove less and irrelevant features from the pre-set features to identify the tool wear status. The researcher selected 8 out of the 213 original features and the 8 features provided the same accuracy as the 213 original features. Another dimensional reduction algorithm used by Wang et al. [63] is locality preserving projection (LPP) for feature vector reduction. Recursive maximum likelihood estimation (MLE) is applied to update the feature parameters based on an aperiodic monitoring interval [43]. Madhusudana et al. in their series of work [53, 54] proposed the decision tree (J48), for their feature selection method by classifying tool condition into four types of tools which include healthy, flank wear, chipping, and breakage. Madhusudana et al. [54], mentioned that they reduced 30 histogram features to 7 features. The kernel principle component analysis (KPCA) algorithm for feature reduction was utilized for a total of 65, which included time domain, frequency domain, and wavelet domain features [34]. Based on the review of the available research reporting on the feature fusion/reduction methods, it shows that the feature fusion method is more comprehensive and allows involvement of all the pre-set features during the feature reduction process. Nonetheless, the involvement of all of the pre-set features in the training phase for online monitoring will increase the computation time, increase the maintenance costs, and affect the performance of monitoring [24, 34, 35, 53]. Different from the feature fusion method, the feature selection method only applies the dominant features from the pre-set features to be analyzed next in the monitoring model. Based on studies by Cho et al. [51], the researcher applied the entropy correlation algorithm to select 25 features out of 135 features from the multisensory signal. Another researcher Hsieh et al. [64] selected five features through class mean scatter criteria and reduced the spectral signal bandwidth from 120 to 30 Hz for feature selection. Zhang et al. [59] utilized the Pearson's Correlation Coefficient (PCC) algorithm to select the most relevant feature for tool wear values. Out of 144 feature parameters, 13 were selected based on the algorithm. The minimal redundancy and maximal relevance (mRMR) algorithm was utilized to select the most signification feature for online monitoring [46]. By comparing the feature fusion and feature selection methods, the feature selection method was able to reduce the number of input parameters to the monitoring model and only input features that had a strong correlation with the tool status. Moreover, it was also able to improve the computing efficiency. However, the feature selection method does not consider the influence of the selected parameter on the prediction accuracy [24, 34]. Therefore, it is important to consider the optimization method to select the most relevant combination of the feature parameters that result in high prediction accuracy. The reviews by Zhou and Xue [24] and Wang et al. [34], utilized the optimization method in their feature combination selection approach using the Genetic Algorithm and Differential Evolution, respectively. Using their approach enables high prediction accuracy, improves computing efficiency, and also minimizes the maintenance cost.

3. Decision-making based machine learning algorithm

Machine Learning is a subset of artificial intelligence, it is a technique that enables prediction or making decisions based on a set of data [83]. Machine Learning enables a computer to learn and react like humans. Machine Learning is competent for dealing with complex mechanical issues like prognostics due to the degradation process and which are difficult to study using statistical methods. Hence, machine learning decision-making techniques have become the choice for machine tool condition monitoring. Machine Learning can be divided into two main types based on the training characteristics, which include supervised learning and unsupervised learning. Supervised learning is a type of machine learning that works under supervision; its prediction is based on a labelled data set. Supervised machine learning can be divided into two typical tasks—regression and classification. Classified machine learning assigns a category to each data image; for example, the category of two types of tool—healthy tool and worn tool, while regression predicts a value for each instance; for example, determining the relationship between the temperature and tool wear. The types of supervised machine learning algorithm used for the classification task are support vector machine (SVM), decision trees, *k*-nearest neighbor (KNN), and naïve Bayes, while the algorithms for the regression task include linear regression and polynomial regression. Supervised machine learning for classification could be divided into two—classic machine learning (SVM, decision tree, KNN, naïve Bayes) and deep learning (convolutional neural network (CNN), recurrent neural network (RNN), artificial neural network (ANN)). Unsupervised machine learning is a type of machine learning that works without supervision and is the opposite of supervised machine learning. It recognizes patterns of unlabeled data sets and groups them according to the similarities. Types of unsupervised machine Learning are clustering and dimension reduction. The clustering algorithm includes *k*-mean clustering, hidden Markov model (HMM), and latent Dirichlet allocation (LDA), while the dimensions for the reduction algorithm include Principle Component

Analysis. Based on the observations and review work, the machine learning methods applied by various researchers since 2010 until now are as follows:

i. ANNs, similar to the human brain, mimic the working structure of the human brain. They comprise numerous nodes that are connected to the other in a complex layer [84, 85]. ANNs have been the most popular artificial intelligence technique applied in the area of machine condition monitoring since 1940 [86]. By training multi-layer networking, ANNs are effective at learning complex nonlinear relationships. Tool wear estimation based on the ANN model was tested on 25 different cutting conditions and time intervals and demonstrated 99.2% correlation between the actual and the experiment value [40]. The backpropagation neural network was applied for tool wear monitoring using spindle vibration and a 100% classification rate was obtained by improving the bandwidth size of the spectral signals [64]. Cus and Zuperl [49] utilized ANNs, together with the adaptive neuro-fuzzy inference system (ANFIS) method to classify tool breakage and tool wear in their research. ANFIS connects the nonlinear relationship between sensor data and tool wear in ANNs to estimate the tool flank wear. The application of ANFIS together with ANNs provides an extension to the level of transparency, which was not applicable to the single application of ANNs. Even though ANNs perform best for complex nonlinear relationships, the generalization ability of ANNs is reduced due to random initialization of the parameters in the ANNs structure. Moreover, the application of ANNs for high quality and large amounts of data to enable training is not suitable for industrial applications.

ii. The neuro-fuzzy system is a technique that couples the neural networks and fuzzy logic paradigm to achieve modelling simplicity and provide explicit knowledge, respectively [87]. A comparison between NN and the neuro-fuzzy model was carried out for tool condition monitoring and remaining useful life prognostics [59]. Based on the experiment, it was found that the neuro-fuzzy model performed best with the smallest MSE and MAPE and the biggest R^2 compared with the NN model. A sequential fuzzy clustering based dynamic fuzzy neural network (SFCDFNN) was utilized to enable fault diagnosis and prognosis in a complex system [42]. Based on other available models, SFCDFNN is easy to implement and suitable for industrial applications. Nonetheless, the two paradigms are coupled together, as the neuro-fuzzy model still requires an amount of high-quality data for training the data.

iii. The HMM has been broadly used for speech recognition with established computing performance and strict data structures in the field of condition monitoring and fault diagnosis [39, 88]. HMM performs better than ANN with easy interpretation ability, and is applicable for small sample, nonlinear, complex regressions, and classification [84, 88]. Moreover, HMM has the ability to outperform ANNs and the Neuro-fuzzy model in an industrial environment [39, 85]. The continuous hidden Markov model (CHMM) analysis to diagnose tool wear status followed by the Gaussian regression model was utilized to predict the remaining useful life of the cutting tool [39]. Based on the analysis from the diagnosis, CHMM is capable of diagnosing tool wear status with 97.6% accuracy. Wang and Wang [39] also claimed that the proposed approach is suitable for applications in small and medium enterprises with a small set of data and is capable of predicting the remaining life of the cutting tool accurately using the Gaussian regression model. Other research on HMM was proposed by Geramifard et al. [44] for tool wear monitoring. The research was done on the basis of improving the flexibility of the original HMM and to deal with complicated tool state switching strategies and various weighting schemes by applying the multi-model HMM. Hong et al. [35] proposed tool wear monitoring states by the combination of the Wavelet Packet Transform and Fisher's Discriminant and found that the monitoring approach was applicable for determining the normal wear and premature failure accurately. However, the HMM application is limited to the Markov Property assumption, which may affect the results in real situations.

iv. The SVM is a well-known statistical-based learning theory that was introduced in the 1990s [86]. SVM requires high dimensional features to yield optimal solutions. The SVM approach was broadly used for the purpose of classification and regression. SVM for classification has gained high research interest, which was based on its excellent generalization capability and efficient computational capability compared with other machine learning algorithms [89]. Multiclass SVM has been used to classify and estimate tool wear, tool breakage, and chipping detection based on a multi fusion sensory data set [51]. Based on their research, SVM outperforms the neural network approach due to its nature of structural risk minimization. The integration of SVM with kappa statistics uses a confusion matrix to perform tool condition classification [28]. The research also studied the performance of the final result by applying two different kernels. It was found that different kernels give different performance results based on each kernel objective. LS-SVM provides better resistance impatient capacity and minimum operation speed. Based on the practical experiment, LS-SVM has greater generalization capability and a good error of estimation compared with neural networks. Samix Dutta et al. [77] performed the support vector machine regression model to predict progressive tool flank wear based on surface image analysis. SVMR requires less training data set based on its generalization capability. SVMR effectively predicts the type of tool flank wear degradation with 94.8% average correlation between the measured and predicted value of tool wear. Nevertheless, SVM is not able to provide a probabilistic prediction. It is only able to provide point prediction [90]. Therefore, Tipping [91] proposed an extended version of SVM by formulating RVM, which is capable of providing complete predictive distribution. The application of the RVM based multicategory tool wear monitoring construct is by binary classifier and multi nominal function [33]. Through evaluation of the SVM and RVM performance, RVM provides stronger generalization performance together with higher accuracy and is less time consuming. After generalization performance, the speed capability and sample size issue, another important aspect that needs to be considered in SVM and RVM application and performance is the kernel function selection because different kernel functions have different levels of performance. Therefore, a standard need to be established to select the most suitable kernel function for specific issues.

4 Discussion

This section wraps up the findings from all the 60 journal articles reviewed in the previous section. The graphical representation of the signal acquisition method, statistical, and machine learning approaches for signal processing methodologies and machine learning algorithm percentage distribution during 2010 to 2019 are summarized in Fig. 4. Based on the authors' observation, signal acquisition is done through both wired and wireless mechanisms. Based on the graphical representation in Fig. 4, only 13% of the researchers applied wireless sensor networks, while 87% of the researchers applied a wired mechanism for signal acquisition. Even though the percentage is small, nowadays, the usage of a wireless sensor network has become more popular in the era of IR 4.0 and to take advantage of the Internet revolution. Moreover, WSN is the key driver to enable data transfer anytime anywhere without boundaries and enables the realization of automated systems. Furthermore, between 2010 and 2014, most of the studies 57% conducted focused on the time domain, frequency domain, statistical, threshold, and observation method for signal processing solution and were based on machine learning algorithms, only a few, about 43% of the researches were found. Meanwhile, between 2015 and 2019, the signal processing methodology using the machine learning algorithm was slightly higher than the other approaches with the percentage being 59% and 41%, respectively. Machine learning enables intelligent decision-making, prediction, and estimation with very short time computation time and the highest prediction accuracy of about 99%. Through review and observation, the SVM/RVM application is higher than other machine learning algorithms with 43% of the application popularity. Moreover, SVM and RVM outperform other machine learning algorithms based on the performance accuracy and capability.

Most of the reviewed articles focused on signal acquisition, signal filtration, and selection and signal processing mechanisms. Only Friedrich Bleicher et al. [57]focused on integrating the signal processing with machine tool control system to enable automated control. Furthermore, to the best of the authors' knowledge, Deng et al. [66] and Zhong et al. [19] were the only researchers who proposed machining process monitoring under the STEP-NC machining program, which

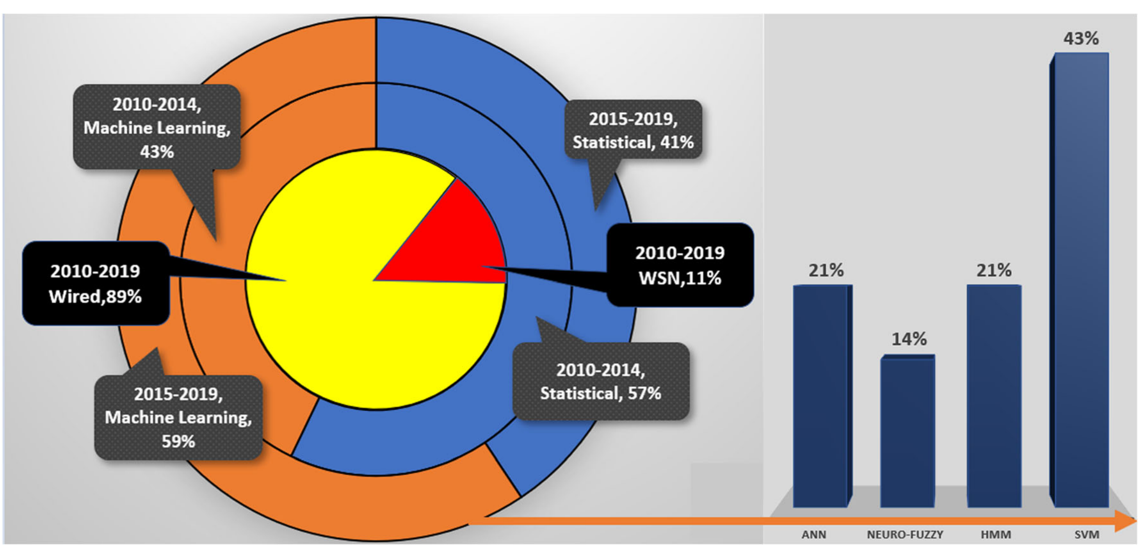

Fig. 4 Graphical representation of research findings

enables two-way communication, intelligent control, and updates on the machining parameters during the machining process. However, the integration between signal processing and the control system to develop an intelligent machine monitoring system is still new and is considered to be a new direction for future implementation.

5 Conclusion

Machine monitoring plays an important role in the future CNC machine tool system due to its effects on the production quality and production cost. Therefore, the need for machine monitoring is always there in future CNC machine tool systems. In this article, an attempt was made to provide a comprehensive review on tool condition monitoring, tool wear, and chatter based on vibration, cutting force, temperature, surface image, and smart label monitoring parameters from signal acquisition, signal processing methodology to decision-making in the milling process in the past and present. The article presents a review of machine monitoring from 2010 to 2019. A total of 60 journal articles were reviewed. The authors believe that this article provides a big picture and will help future researchers to address the past and present of machine monitoring for enhanced industrial growth and development.

From the review, it has been found that most of the machine monitoring works carried out on the machining process resolve the issue of machine monitoring. This is done by selecting the best parameters for signal acquisition by either the direct or indirect approach. Some of the parameters or approaches discussed include cutting force, temperature, vibration, surface image, spindle motor signal, feed motor signal, and application of wired or WSN sensor type as well as the sensor location. Others are signal processing methodology from feature extraction using time domain, frequency domain, time frequency domain, statistical analysis, feature selection, or feature fusion using a specific algorithm and decision-making via the machine learning algorithm to obtain the highest accuracy of decision-making and control system.

From the review, the authors conclude that cutting force is the most important signal to trace any undesirable machine process condition. However, other indirect monitoring signals exist, which may mimic or are proportional to the cutting force signal output, such as vibration signal, motor and spindle signal, and temperature signal. Indirect monitoring signals are more compatible for application in the industrial environment. Moreover, they are easily installed on the current machine tool without interrupting the machine structure and are low in cost. Besides cutting force, smart labelling is another monitoring parameter that needs to be included in machine monitoring. Smart manufacturing requires every single resource to be connected to the world. With smart labelling, operators are not only alerted to the machining process status, but information on the operators as well as the part being machined is captured.

In the future, a standardized and all in one CNC machine mechanism needs to be considered to achieve interoperability, connectivity, and seamless data transfer between cyber and physical systems. Next, exemplifying a solution on how to fully utilize machining information for evaluation of machining performance, quality assessment, benchmarking, and service purposes. Besides that, optimization based on real-time machining process information, data visualization platform, and control based on any smart device are additional future works that need to be considered. By comparing the most popular machine learning algorithm applied in decision-making SVM and RVM perform best in terms of generalization capability, fast response, and high accuracy. However, another important aspect that needs to be considered in SVM and RVM application and performance is the kernel function selection because different kernel functions have different performance capabilities. Therefore, a standardized model needs to be established to select the most suitable kernel function for specific issues as a new direction for advanced signal processing methodology.

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References

1. Y. Yusof, A. Adam, M. Iliyas, and Y. Saif, “Review on Manufacturing for Advancement of Industrial,” vol. 2011, no. 2018, pp. 93–98, 2018.
2. Yusof Y, Tan NZZ, Kassim N (2009) Exploring the ISO 14649 (STEP-NC) for Intelligent Manufacturing System. Eur J Sci Res 36(3):445–457
3. Cha J-M, Suh S-H, Hascoet J-Y, Stroud I (2016) A roadmap for implementing new manufacturing technology based on STEP-NC. J Intell Manuf
4. Rehorn AG, Jiang J, Orban PE (2005) State-of-the-art methods and results in tool condition monitoring: a review. Int J Adv Manuf Technol. 26(7–8):693–710
5. Ridwan F, Xu X, Liu G (2012) A framework for machining optimisation based on STEP-NC. J Intell Manuf 23(3):423–441
6. Rizal M, Ghani JA, Nuawi MZ, Haron CHC (2018) An embedded multi-sensor system on the rotating dynamometer for real-time condition monitoring in milling. Int J Adv Manuf Technol. 95(1–4): 811–823
7. Yeo SH, Khoo LP, Neo SS (2000) Tool condition monitoring using reflectance of chip surface and neural network. J Intell Manuf 11(6): 507–514
8. Kurada S, Bradley C (1997) A review of machine vision sensors for tool condition monitoring. Comput Ind

9. Elias DM, Yusof Y, Minhat M (2013) CNC Machine System Via STEP-NC Data Model and Lab VIEW Platform for Milling Operation, pp 27–31
10. Latif K, Yusof Y, Nassehi A, Latif QBAI (2017) Development of a feature-based open soft-CNC system. Int J Adv Manuf Technol. 89(1–4):1013–1024
11. Zaretalab A, Haghighi HS, Mansour S, Sajadieh MS (2018) A mathematical model for the joint optimization of machining conditions and tool replacement policy with stochastic tool life in the milling process. Int J Adv Manuf Technol 96(5–8):2319–2339
12. Yang K, Wang G, Dong Y, Zhang Q, Sang L (2019) Early chatter identification based on an optimized variational mode decomposition. Mech Syst Signal Process 115:238–254
13. Zhao YF, Xu X (2010) Advanced engineering informatics enabling cognitive manufacturing through automated on-machine measurement planning and feedback. Adv Eng Informatics 24(3):269–284
14. Yusof Y, Latif K (2014) Survey on computer-aided process planning. Int J Adv Manuf Technol. 75(1–4):77–89
15. Latif K, Kadir AZA, Yusof Y (2019) The importance of STEP-NC in the IR 4.0 manufacturing systems. 8(4):1568–1570
16. Xu X (2017) Machine Tool 4.0 for the new era of manufacturing. Int J Adv Manuf Technol 92(5–8):1893–1900
17. Luo M, Chong Z, Liu D (2018) Cutting Forces measurement for milling process by Using working tables with integrated PVDF thin-film sensors. Sensors (Basel) 18(11)
18. Rizal M, Rizal M, Ghani JA, Nuawi MZ, Che Haron CH (2014) A wireless system and embedded sensors on spindle rotating tool for condition monitoring. Adv Sci Lett 20(10–12):1829–1832
19. Zhong RY, Wang L, Xu X (2017) An IoT-enabled real-time machine status monitoring approach for cloud manufacturing. Procedia CIRP 63:709–714
20. Zedong Z, Azman MA (2017) Towards Industry 4.0: sensorizing CNC machine. Singapore Polytechnic
21. Hillman JB (1969) Graphic time-sharing with real-time data bases. In: Proceeding ACM '69 Proceedings of the 1969 24th national conferenceg, pp 443–457
22. Holub M, Bradac F, Pokorny Z, Jelinek A (2018, 2018) Application of a ballbar fordiagnostics of cnc machine tools. MM Sci J (December):2601–2605
23. I. O, Olalere MD (2018) Early fault detection of elevators using remote condition monitoring through IoT technology. South African J Ind Eng 29(December):17–32
24. Zhou Y, Xue W (2018) A multisensor fusion method for tool condition monitoring in milling. Sensors 18(11):3866
25. Sevilla-Camacho PY, Robles-Ocampo JB, Muñiz-Soria J, Lee-Orantes F (2015) Tool failure detection method for high-speed milling using vibration signal and reconfigurable bandpass digital filtering. Int J Adv Manuf Technol. 81(5–8):1187–1194
26. Rabah B, Benkedjouh T, Said R (2019) Tool wear condition monitoring based on blind source separation and wavelet transform. Lect Notes Electr Eng. 522:377–389
27. Dai Y, Zhu K (2018) A machine vision system for micro-milling tool condition monitoring. Precis. Eng. 52:183–191
28. Krishnakumar P, Rameshkumar K, Ramachandran KI (2018) Machine learning based tool condition classification using acoustic emission and vibration data in high speed milling process using wavelet features, vol 1, pp 1–18
29. Huang YX, Liu X, Liu CL, Li YM (2018) Intrinsic feature extraction using discriminant diffusion mapping analysis for automated tool wear evaluation. Front Inf Technol Electron Eng 19(11):1352–1361
30. Li W (2013) Study on feature selection and identification. Int J Smart Sens Intell Syst 6(2):448–465
31. Lauro CH, Brandão LC, Baldo D, Reis RA, Davim JP (2014) Monitoring and processing signal applied in machining processes - a review. Meas J Int Meas Confed. 58(December):73–86
32. Quintana G, Ciurana J (2011) Chatter in machining processes: a review. Int J Mach Tools Manuf 51(5):363–376
33. Wang G, Yang Y, Xie Q, Zhang Y (2014) Force based tool wear monitoring system for milling process based on relevance vector machine. Adv Eng Softw 71:46–51
34. Wang J, Xie J, Zhao R, Zhang L, Duan L (2017) Multisensory fusion based virtual tool wear sensing for ubiquitous manufacturing. Robot Comput Integr Manuf 45:47–58
35. Hong YS, Yoon HS, Moon JS, Cho YM, Ahn SH (2016) Tool-wear monitoring during micro-end milling using wavelet packet transform and Fisher's linear discriminant. Int. J. Precis. Eng. Manuf. 17(7):845–855
36. Oliaei SNB, Karpat Y (2016) Influence of tool wear on machining forces and tool deflections during micro milling. Int J Adv Manuf Technol. 84(9–12):1963–1980
37. Jennings C, Terpenny J, Gao RX (2017) Cloud-based parallel machine learning for tool wear prediction. J Manuf Sci Eng (c)
38. W. Yang, Q. Zhou, and K. Tsui, "Differential evolution-based feature selection and parameter optimisation for extreme learning machine in tool wear estimation," vol. 7543, no. December, 2015.
39. Wang M, Wang J (2012) CHMM for tool condition monitoring and remaining useful life prediction. Int J Adv Manuf Technol. 59(5–8):463–471
40. Kaya B, Oysu C, Ertunc HM (2011) Force-torque based on-line tool wear estimation system for CNC milling of Inconel 718 using neural networks. Adv Eng Softw 42(3):76–84
41. Javed K, Gouriveau R, Li X, Zerhouni N (2016) Tool wear monitoring and prognostics challenges : a comparison of connectionist methods toward an adaptive ensemble model. J Intell Manuf.
42. Torabi Jahromi A, Er MJ, Li X, Lim BS (2016) Sequential fuzzy clustering based dynamic fuzzy neural network for fault diagnosis and prognosis. Neurocomputing 196:31–41
43. Yan HC, Zhou JH, Pang CK (2015) Gamma process with recursive MLE for wear PDF prediction in precognitive maintenance under aperiodic monitoring. Mechatronics
44. Geramifard O, Xu J-X, Zhou J-H, Li X (2014) Multimodal hidden Markov model-based approach for tool wear monitoring. IEEE Trans Ind Electron 61(6):2900–2911
45. Zhu K, Vogel-Heuser B (2014) Sparse representation and its applications in micro-milling condition monitoring: noise separation and tool condition monitoring. Int J Adv Manuf Technol 70(1–4):185–199
46. Wang G, Yang Y, Li Z (2014) Force sensor based tool condition monitoring using a heterogeneous ensemble learning model. Sensors (Switzerland) 14(11):21588–21602
47. Abbas J, Al-Habaibeh A, Su DZ (2013) Investigating the design of condition monitoring systems to evaluate surface roughness under the variability in tool wear and fixturing conditions. Key Eng Mater 572:467–470
48. Bagci E (2011) Monitoring and analysis of MRR-based feedrate optimization approach and effects of cutting conditions using acoustic sound pressure level in free-form surface milling. Sci Res Essays 6(2):256–277
49. Cus F, Zuperl U (2011) Real-time cutting tool condition monitoring in milling. Stroj Vestnik/Journal Mech Eng 57(2):142–150
50. Girardin F, Rémond D, Rigal JF (2010) A new method for detecting tool wear and breakage in milling. Int J Mater Form. 3(SUPPL. 1):463–466
51. Cho S, Binsaeid S, Asfour S (2010) Design of multisensor fusion-based tool condition monitoring system in end milling. Int J Adv Manuf Technol. 46(5–8):681–694
52. Jauregui JC, Resendiz JR, Thenozhi S, Szalay T, Jacso A, Takacs M (2018) Frequency and time-frequency analysis of cutting force and vibration signals for tool condition monitoring. IEEE Access 6(c):6400–6410

53. Madhusudana CK, Budati S, Gangadhar N, Kumar H, Narendranath S (2016) Fault diagnosis studies of face milling cutter using machine learning approach. J Low Freq Noise Vib Act Control 35:128–138
54. Madhusudana CK, Kumar H, Narendranath S (2016) Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal. Eng Sci Technol An Int J 19(3): 1543–1551
55. Bisu CF, Zapciu M, Cahuc O, Gérard A, Anica M (2012) Envelope dynamic analysis: A new approach for milling process monitoring. Int J Adv Manuf Technol. 62(5–8):471–486
56. M. M. S. D. B. Srinivasa Prasad*, a (2011) Analysis of face milling operation using acousto optic emission. Jordan J Mech Ind Eng. 5(6):509–519
57. Friedrich B, Schorghofer P, Habersohn C (2018) In-Process Control with A Sensory Tool Holder to Avoid chatterc. J Mach Eng. 18(3):16–27
58. Harris K, Triantafyllopoulos K, Stillman E, McLeay T (2016) A multivariate control Chart for autocorrelated tool wear processes. Qual. Reliab. Eng. Int. 32(6):2093–2106
59. Zhang C, Yao X, Zhang J, Jin H (2016) Tool condition monitoring and remaining useful life prognostic based on awireless sensor in dry milling operations. Sensors (Switzerland) 16(6)
60. Sevilla-Camacho PY, Robles-Ocampo JB, Jauregui-Correa JC, Jimenez-Villalobos D (2015) FPGA-based reconfigurable system for tool condition monitoring in high-speed machining process. Meas J Int Meas Confed.
61. Li H, Jing X, Wang J (2014) Detection and analysis of chatter occurrence in micro-milling process. Proc Inst Mech Eng Part B J Eng Manuf. 228(11):1359–1371
62. Liu H, Lian L, Li B, Mao X, Yuan S, Peng F (2014) An approach based on singular spectrum analysis and the Mahalanobis distance for tool breakage detection. Proc Inst Mech Eng Part C J Mech Eng Sci 228(18):3505–3516
63. Wang GF, Yang YW, Zhang YC, Xie QL (2014) Vibration sensor based tool condition monitoring using ν support vector machine and locality preserving projection. Sensors Actuators, A Phys 209:24–32
64. Hsieh WH, Lu MC, Chiou SJ (2012) Application of backpropagation neural network for spindle vibration-based tool wear monitoring in micro-milling. Int J Adv Manuf Technol 61(1–4):53–61
65. Milner JL, Roth JT (2010) Condition monitoring for indexable carbide end mill using acceleration data. Mach Sci Technol. 14(1):63–80
66. Deng C, Guo R, Zheng P, Liu C, Xu X, Zhong RY (2018) From open CNC systems to cyber-physical machine tools: a case study, vol 72, pp 1270–1276
67. Aghazadeh F, Tahan A, Thomas M (2017) Tool condition monitoring using spectral subtraction algorithm and artificial intelligence methods in milling process. Int J Mech Eng Robot Res 6(6):30–34
68. Shao H, Shi X, Li L (2011) Power signal separation in milling process based on wavelet transform and independent component analysis. Int J Mach Tools Manuf. 51(9):701–710
69. Drouillet C, Karandikar J, Nath C, Journeaux AC, El Mansori M, Kurfess T (2016) Tool life predictions in milling using spindle power with the neural network technique. J Manuf Process. 22: 161–168
70. Ammouri AH, Hamade RF (2014) Current rise criterion: a process-independent method for tool-condition monitoring and prognostics. Int J Adv Manuf Technol. 72(1–4):509–519
71. Ritou M, Garnier S, Furet B, Hascoet JY (2014) Angular approach combined to mechanical model for tool breakage detection by eddy current sensors. Mech Syst Signal Process. 44(1–2):211–220
72. Sevilla-Camacho PY, Herrera-Ruiz G, Robles-Ocampo JB, Jáuregui-Correa JC (2011) Tool breakage detection in CNC high-speed milling based in feed-motor current signals. Int J Adv Manuf Technol. 53(9–12):1141–1148
73. Aghazadeh F, Tahan A, Thomas M (2018) Tool condition monitoring using spectral subtraction and convolutional neural networks in milling process. Int J Adv Manuf Technol.
74. Sivasakthivel PS, Sudhakaran R (2013) Optimization of machining parameters on temperature rise in end milling of Al 6063 using response surface methodology and genetic algorithm. Int J Adv Manuf Technol. 67(9–12):2313–2323
75. Sun W, Chen B, Yao B, Cao X, Feng W (2017) Complex wavelet enhanced shape from shading transform for estimating surface roughness of milled mechanical components. J Mech Sci Technol. 31(2):823–833
76. Zhou JH, Pang CK, Zhong ZW, Lewis FL (2011) Tool wear monitoring using acoustic emissions by dominant-feature identification. IEEE Trans Instrum Meas 60(2):547–559
77. Dutta S, Pal SK, Sen R (2016) Progressive tool condition monitoring of end milling from machined surface images. J Eng Manuf.
78. Roth JT, Djurdjanovic D, Yang X, Mears L, Kurfess T (2010) Quality and inspection of machining operations: tool condition monitoring. J Manuf Sci Eng 132(4):041015
79. Liukkonen M, Tsai TN (2016) Toward decentralized intelligence in manufacturing: recent trends in automatic identification of things. Int J Adv Manuf Technol. 87(9–12):2509–2531
80. Domdouzis K, Kumar B (2007) Radio-frequency identification (RFID) applications : a brief introduction, vol 21, pp 350–355
81. Bhattacharyya P, Sengupta D, Mukhopadhyay S (2007) Cutting force-based real-time estimation of tool wear in face milling using a combination of signal processing techniques. Mech Syst Signal Process. 21(6):2665–2683
82. Zhu KP, Wong YS, Hong GS (2009) Wavelet analysis of sensor signals for tool condition monitoring: a review and some new results. Int J Mach Tools Manuf
83. Zhang JM, Harman M, Ma L, Liu Y (2020) Machine learning testing: survey, landscapes and horizons. IEEE Trans Softw Eng.: 1–1
84. Siddhpura A, Paurobally R (2013) A review of flank wear prediction methods for tool condition monitoring in a turning process. Int J Adv Manuf Technol.
85. Lei Y, Li N, Guo L, Li N, Yan T, Lin J (2018) Machinery health prognostics: a systematic review from data acquisition to RUL prediction. Mech Syst Signal Process. 104(December 2017):799–834
86. Boutaba R et al (2018) Comprehensive survey machine learning. J OfInternet Serv Appl 9(16):99
87. Gajate A, Haber R, Del Toro R, Vega P, Bustillo A (2012) Tool wear monitoring using neuro-fuzzy techniques: a comparative study in a turning process. J Intell Manuf. 23(3):869–882
88. Miao Q, Huang HZ, Fan X (2007) A comparison study of support vector machines and hidden markov models in machinery condition monitoring. J Mech Sci Technol.
89. Bhat NN, Dutta S, Vashisth T, Pal S, Pal SK, Sen R (2016) Tool condition monitoring by SVM classification of machined surface images in turning. Int J Adv Manuf Technol. 83(9–12):1487–1502
90. Bishop CM, Tipping ME, Cb C (2000) Variational relevance vector machines. In: Uncertainty in artifical intelligence proceedings 2000, pp 46–53
91. Tipping ME (2001) Sparse Bayesian Learning and the relevance vector machine. J Mach Learn Res. 1(3):211–244