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Sensors for in-process and on-machine monitoring of machining operations

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ABSTRACT

Machining is extensively used for producing functional parts in various industries such as aerospace, automotive, energy, etc. There is a growing demand for improved part quality and performance at lower costs from increasingly difficult-to-machine materials. Whilst modern machine tools are equipped with sensors for closed loop control of their axes' movements and position, they provide minimal information regarding the cutting performance and tool condition. The integration of additional sensors into cutting tools, machine tools and/or their components can provide an insight into the machining performance. It also provides an opportunity to improve the machining process and reduce the need for post-process inspection and rework. This paper presents a comprehensive analysis of various sensors utilised for in-process and on-machine measurement and monitoring of machining performance parameters such as cutting forces, vibrations, tool wear, surface integrity, etc. Data transfer and communication methods, as well as power supply options for sensor-integrated systems are also investigated. Sensor integrated machining systems can potentially improve machining performance and part quality by early detection of errors and damages, maximising tool usage and preventing machining and tool wear induced damages. A combination of sensor data collection and intelligent sensor signal processing can further increase the capabilities of sensor integrated systems from process monitoring to active process control.

1. Introduction

Machining is a key manufacturing process for producing functional components with the required accuracy and surface finish. The ever-increasing demand for higher product quality, productivity, and performance, while simultaneously achieving lower cost and environmental impact, requires improved process monitoring and control in manufacturing processes. However, whilst post-process offline inspection can ensure part quality, it offers an inefficient and costly option for process optimisation. Statistical process control and deterministic modelling can converge to high quality solutions. However, they are challenged by random and time dependent errors which can occur during manufacturing. In machining operations, these factors necessitate the addition of sensors to monitor and measure various parameters during the process beyond the relative position between the cutting tool and workpiece. The sensor data enable informed decision marking for process control and increased machining performance and applying process control.

Many sensors have been used for on-machine and in-process measurement and monitoring of various quantities on a machine tool. These quantities include cutting forces, torque, power, temperature, acoustic emissions, vibration (e.g., displacement, velocity, and acceleration), surface and subsurface properties as well as the geometry of the part and the cutting tool. Fig. 1 illustrates different types of sensors used for process monitoring in machining and the type of variable (measurand) that can be measured/detected using these sensors. Depending on the

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sensor type, the machining process, and the intended parameter to be controlled, these additional sensors can be positioned on (i) the machine tool structure, such as the spindle or table; (ii) the cutting tool assembly, e.g., tool or tool holder; or (iii) the fixture. The outputs from the machine tools' built-in sensors can also be accessed through the controller for further processing. Additionally, spindle power and encoder feedback can be accessed through the controller and used to extract information regarding machining performance.

Fig. 2 illustrates the potential sensor locations on a typical three-axis milling centre. Sensor signals have been used for measuring, monitoring, and detecting the tool wear or damage, also termed tool condition monitoring (TCM), investigating and monitoring the surface integrity of the machined parts, improving cutting performance, avoiding chatter, and ensuring geometric accuracy of the parts.

The structure of the paper is shown in Fig. 3 and is divided into three main categories of sensor types based on various measurement phenomena in machining, sensor integration into machining processes depending on the location of the sensors and the sensors' functional requirements for power and data transmission. This paper provides a detailed analysis of the sensors used for in-process and on-machine measuring and monitoring of various machining performance parameters such as cutting forces, power consumption, tool wear, part geometry and surface integrity. Additionally, specific methods, benefits, and limitations when employing sensors on various components of a machining system are analysed. This includes sensor-integrated tools and tool holders, sensor integration on the machine tool structure and fixturing, and employing the existing sensors on a machine tool for further data collection. This is followed by an overview of different methods for powering sensors and collecting data from the sensors. The paper is concluded by an in depth discussion on the findings and highlighting the future research directions.

2. Measurement types and sensors

In this section different sensors used for collecting data during machining have been identified and their application is reviewed. They are categorised based on the machining measurand to be monitored as shown in Fig. 1.

2.1. Cutting forces, torque, and power

Cutting forces and torque are significant parameters in tool condition and machining process monitoring. They are typically measured using commercial or research dynamometers. Commercial table-type dynamometers consisting of piezoelectric sensors, such as those provided by Kistler [1], offer high stability, accuracy, repeatability, and sensitivity. However, they have high cost and complexity and have limited work holding space which can restrict their industrial application. The Kistler rotating dynamometer is another type of piezoelectric dynamometer which is spindle mounted. This can provide more flexibility in terms of workspace, but they are still expensive and increase the dynamic flexibility of the machine tool since it is mounted between the spindle and cutting tool. As a result, they are mostly used in research and development environments as opposed to production scenarios.

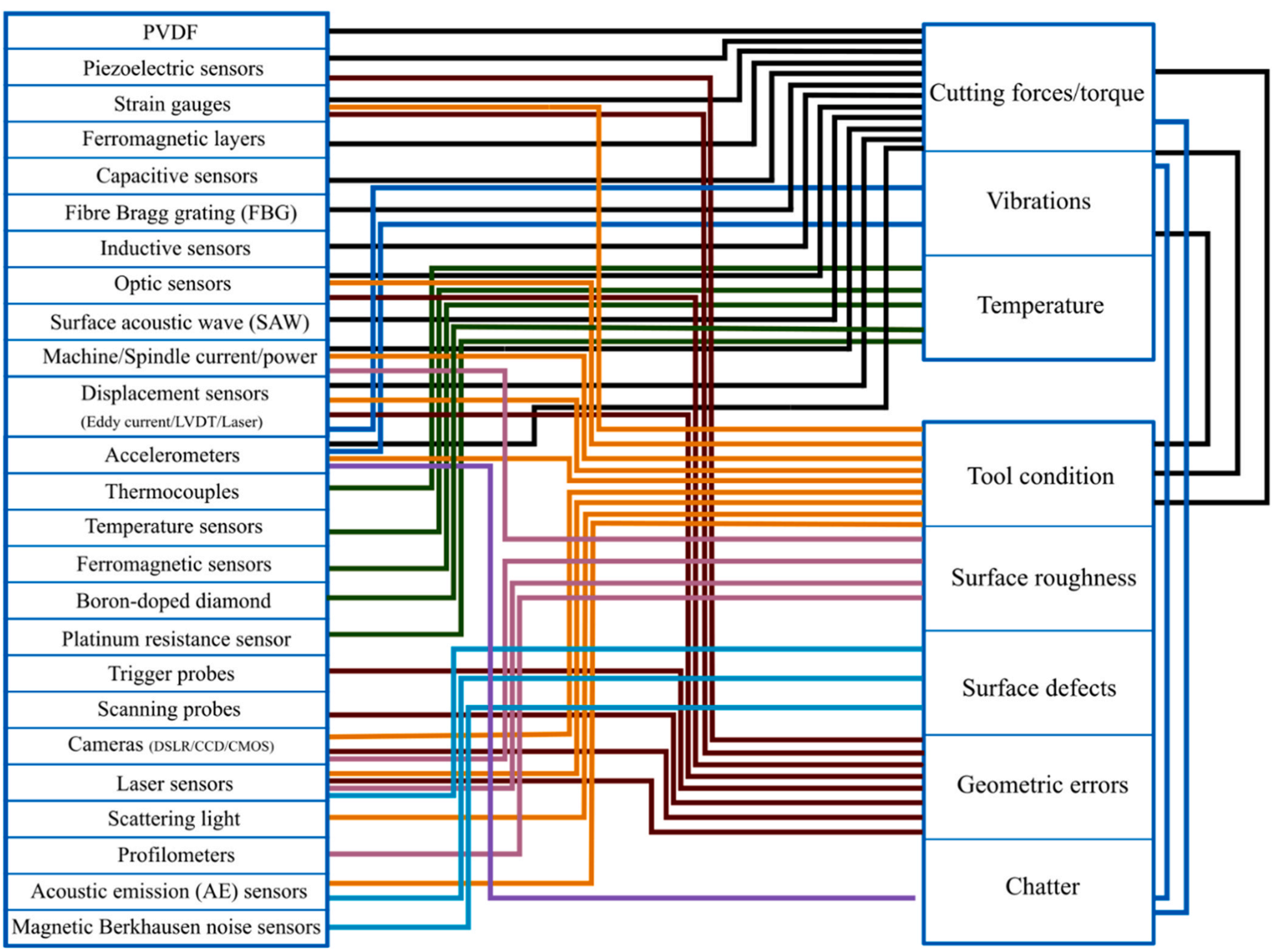

Fig. 1. Summary of the types of sensors discussed in this paper for direct and indirect measurement and monitoring of various parameters during machining.

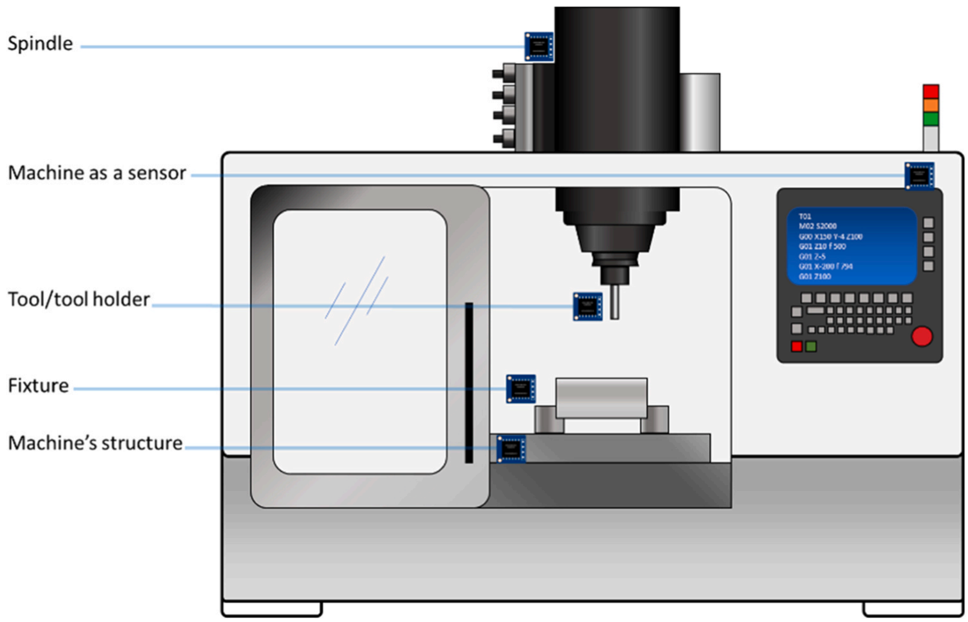

Fig. 2. Potential sensor locations for on-machine in-process monitoring and measurement.

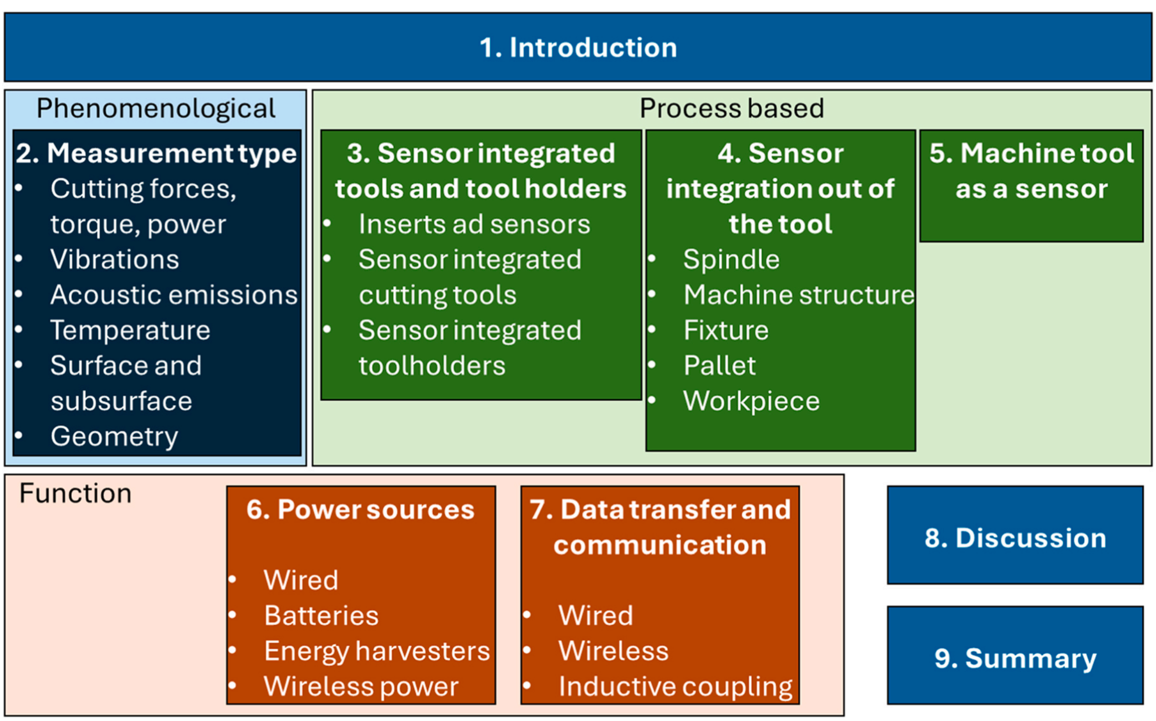

Fig. 3. Paper structure.

To overcome the drawbacks of commercial dynamometers, alternative methods have been widely investigated. Byrne and O'Donnell [2] integrated piezoelectric force rings onto a spindle for drilling and highlighted their higher bandwidth in comparison to spindle power monitoring. Beyond cutting force measurement, the system can be used for monitoring the spindle condition and detecting traverse motions of the spindle. Totis et al. [3] placed a triaxial force sensor between the modular cartridge and the cutter body in a face mill to measure cutting forces from each cutting edge. The cutting tests indicated the entrance and exit cutting edges, multiple cutting teeth cutting, and runout. Totis et al. [4] built a plate dynamometer to measure cutting forces in high-speed millings with small cutting tools using three triaxial piezoelectric force sensors. Despite their capability in detecting dynamic forces, piezoelectric sensors are not suitable for measuring static forces [5,6]. Piezoelectric sensors tend to leak current under static load leading to an exponential reduction in the output charge. In addition, piezoelectric sensors are susceptible to temperature drift making them unsuitable for conditions where high temperature gradients are expected. To overcome this limitation, Rezvani et al. [7] integrated both piezoelectric sensors and strain gauges into a work-holding vice. They reported measurement errors of 11%, 17% and 6% for dynamic forces in x, y and z directions and 19% error for static clamping force.

Different types of sensors, such as strain gauges, surface acoustic wave sensors, fibre Bragg gratings, and optical sensors, have been applied to detect cutting forces and torque. The majority of these have been integrated into tool/tool holder, fixture/work table, or spindle. These are discussed in more detail in the following Section 3 and 4.

Due to their low cost and ease of applications, strain gauges have been extensively used for monitoring cutting forces. However, they typically have lower sensitivity than piezoelectric sensors. Therefore, they require significantly larger deformation which compromises rigidity and accuracy required in machining. This also impacts the natural frequency of the setup limiting the applications in machining. Yaldiz et al. [8] built a milling dynamometer to measure the cutting forces and torque using strain gauges placed on octagonal rings. Subasi et al. [9] developed a triaxial dynamometer based on a monolithic flexural component using photo-interrupters. The analysis showed that the dynamometer can only reliably measure forces with harmonics of less than 500 Hz. Luo et al. [10] implemented PVDF piezoelectric thin film sensors on the side and bottom faces of a table on which the workpiece is mounted for measuring cutting forces in milling. Whilst the system indicated capability to detect forces, its sensitivity was significantly lower than that of a Kistler dynamometer. Gomez and Schmitz [11–14] presented a constrained-motion dynamometer based on a flexure design that used optical knife edge sensors to determine force from dynamic displacement measurements which was successfully tested for stability evaluation. Furthermore, the cutting forces and torque were indirectly measured by using accelerometers [15,16], displacement sensors [17,18] and active electro-magnetic bearings [19] mounted or integrated on the spindle. The results from these methods were reportedly similar to the measurements from conventional methods such as dynamometers in specific machining scenarios.

2.2. Vibrations

Vibrations can be detected through the measurement of acceleration, velocity or displacement. This has led to a myriad of different sensors for measuring and detecting vibrations. In addition, sound pressure can be correlated to the vibrations during machining. Acoustic emissions are covered in Section 2.3. Historically, strain gauges or sensors based on the coupling of vibration velocity and electrical induction have been used. More recently, capacitive and piezoresistive accelerometers are used for vibration measurements on machine tools. Capacitive microelectromechanical system (MEMS) sensors have a lower frequency and dynamic range. Their relevance for monitoring machining processes is therefore limited. The vibrations during machining can range from low frequency (~1 Hz) due to structural vibrations and imbalances to medium range frequency (~100 Hz to 1000 Hz) due to the bearings and spindle rotation, chatter and tooth passing frequency to high frequency range (>1 kHz) due to and bearing ball passing, chatter, wear and material cutting. There is no accelerometer or vibration sensor that has a wide enough bandwidth and sensitivity across the ranges experienced during machining. Thus, for monitoring various phenomena during machining, multiple sensors with varying bandwidths and sensitivities are required. Acoustic emission sensors are more suited for higher frequency ranges that are difficult to be captured by MEMS or piezoelectric accelerometers. Tsai et al. [20] integrated three analogue MEMS accelerometers namely, i) an ADXL001 with 22 kHz bandwidth and 25 mV/g sensitivity, ii) an ADXL203 with 5.5 kHz bandwidth and 1000 mV/g sensitivity and iii) an ADXL327 with 1.6 kHz bandwidth and 420 mV/g sensitivity to form a system capable of monitoring high, medium and low frequency vibrations during machining.

The advantage of piezoelectric accelerometers is their low weight and high resonant frequency due to the high stiffness and low inertial mass providing a wide bandwidth up to tens of kHz. Piezoelectric sensors have high output impedance and generate small values of electrical charge, typically 0.004 - 1000 $pC/m{\cdot}s^{-2}$ [21]. However, high-impedance (i.e., charge) sensors place high demands on cabling and installation care. To limit these negative effects, modern accelerometers are often equipped with an integrated charge amplifier. Such sensors are referred to as Integrated Electronics Piezoelectric (IEPE) accelerometers. An integrated charge amplifier converts the high-impedance charge signal into a low-impedance signal, typically 100 Ω. The low-impedance signal has the advantage that it does not require special low-noise cables and can be transmitted over long distances without significant loss of signal quality. Most IEPE sensors work at a constant current between 2 mA and 20 mA; a common value is 4 mA. However, charge output sensors are still being produced. They are especially suitable for high temperatures, very low frequencies, extremely large dynamic range, energy savings, or miniature design applications. In general, the weight of the accelerometer should not be greater than 1/100 of the weight of the object to be measured (exceptionally 1/10), in order not to adversely affect the measured vibrations [22]. Compensation for the accelerometer mass can also be applied using the inverse Receptance Coupling Substructure Analysis [23].

Accelerometers are used for direct chatter detection or indirect tool wear monitoring. Dimla [24] tested the correlation of vibration signal features to cutting tool wear in EN24 carbon steel turning by evaluating the signals in the time-domain and frequency-domain. The sum total power (STP) in the time-domain and the amplitude at specific frequency in the frequency-domain increased with the progressive flank wear. Similar trends of the time-domain signal were presented also by Sharma et al. [25]. Haber et al. [26] also presented the correlation between vibration signals and tool wear in both time and frequency domain in high-speed milling. TCM was also investigated using an accelerometer integrated into a tool holder [27,28]. Suprock et al. [29] incorporated an electret condenser in an indexable end mill. They devised and tested an experimental method for detecting chatter during machining with the aim of reducing the number of machining experiments for identifying a suitable combination of cutting speed and depth of cut.

Vibrations can also be detected by measuring the microscopic displacement of the workpiece, cutting tool or the machine tool spindle. High resolution eddy current sensors [30], optical interferometers [31] and linear variable differential transformer (LVDT) sensors [32] can be used to detect mechanical displacement due to vibrations. A comprehensive overview of the signal processing techniques and decision making algorithms based on sensor data are provided in Teti et al. [33] and Serin et al. [34].

2.3. Acoustic emissions

Acoustic emission (AE), also referred to as stress wave emission (SWE), is based on the build-up and propagation of elastic stress waves in solids. Stress waves are primarily generated by the dynamic release of mechanical stress within a material, such as dislocation movements, phase transformation, friction mechanism, crack formation, and extension. AE signals may be burst-type emission or continuous. In the case of burst-type, it is a discrete emission event. The onset, threshold crossing, and duration can be clearly defined. A continuous signal consists of a sequence of emission events for which a beginning and an end cannot be detected easily. The local process that produces the emission events is called the emission source. For mechanical engineering, the practical usable bandwidth is in the range of tens of kHz to a few MHz which may be reduced depending on the specific application.

AE sensors are based on several physical principles. Traditional AE sensors use the piezoelectric effect [35]. Recently, however, sensors using capacitive and piezoresistive principles have gained popularity. These sensors are often manufactured as micro electromechanical system (MEMS) sensors [36].

Acoustic emission (AE) sensors are used in machine tools and in-process measurement to detect and diagnose issues such as tool wear and breakage [37], machine condition monitoring and rolling bearing failure [38]. Twardowski et al. [37] used a Kistler 8152 C AE sensor, with the measurement range of 100–900 kHz, attached to the workpiece for tool wear monitoring. They applied feature extraction and trained a series of machine learning algorithms for TCM. In their analysis, decision tree algorithm resulted in only 6% error in detecting tool condition. To be effective, AE sensors must have a wide frequency range with a flat frequency response, high sensitivity, and high reproducibility [39]. They should also be resistant to low-frequency noise, electric and magnetic fields, and be able to withstand harsh industrial environments.

AE reflect and decay as they bounce against various surfaces within the machine tool. This usually result in noise in the measured signal. As such, a primary consideration is the location for AE sensor placement. This is typically determined experimentally using the quality of the measured signal [40].

AE research was intensive during 1980 s and 1990 s. Dornfeld [41, 42], Inasaki [43], and Jemielniak [44] reviewed AE monitoring methods for tool deterioration (tool wear, edge chipping), edge fractures, and chatter detection. These included tool wear monitoring of single tip operations (turning), a time-domain RMS calculation of the signal is sufficient to track the tool wear, and others. The situation is more complex for analysis of processes with interrupted cutting such as milling.

Guo and Ammula [45] used an AE sensor from Physical Acoustics Corporation which was mounted on a cutting tool holder for monitoring machined surface in hard turning. They noted that the frequency of the AE signal can be correlated with the presence of white layers and surface roughness. For milling operations, Marinescu and Axinte [46,47] used a Kistler 8152 A AE sensor with 50–400 kHz frequency response for detecting surface defects during machining by applying advanced signal processing methods such as Choi–Williams distribution (CWD), Zhao–Atlas–Marks distribution (ZAMD). For force, vibration and AE signal analysis, the implementation of appropriate time, frequency and time and frequency response signal processing methods are important for successful process monitoring. As in the case of vibrations, recent papers [33,34] covering the signal processing, and feature evaluation methods are recommended for further details.

2.4. Temperature and cutting temperature

Heat is generated and dissipated during the cutting process, which varies with the material, machining parameters, tool design, tool condition, and other process variables. The cutting temperature measurement is therefore critical to revealing the process condition. There are two major categories of sensing techniques for measuring cutting temperature: contact thermocouples and non-contact infrared pyrometer/thermography [48,49].

Based on the location of the thermocouple, contact methods for process monitoring can be categorised into (i) tool-work thermocouples [50] and ii) thermocouples integrated into the cutting tools [51], as shown in Fig. 4. The former assumes the temperature along the workpiece is linearly distributed so that the measured temperature can be used to estimate the temperature at the cutting location. This approach is less accurate, not sensitive to dynamic process changes, and requires a complex calibration procedure. The latter provides more accurate cutting temperature measurement because the thermocouple can be placed as close as possible to the cutting surface; a limitation is the negative impact of sensor placement on tool strength and performance. Additionally, the thermocouples can be embedded into the workpiece for measuring the cutting temperature. However, this requires drilling holes into the workpiece to house the thermocouples making this method redundant beyond scientific studies and not suitable for industrial applications.

Non-contact infrared sensing, on the other hand, measures the surface radiation temperature, improving measurement flexibility and

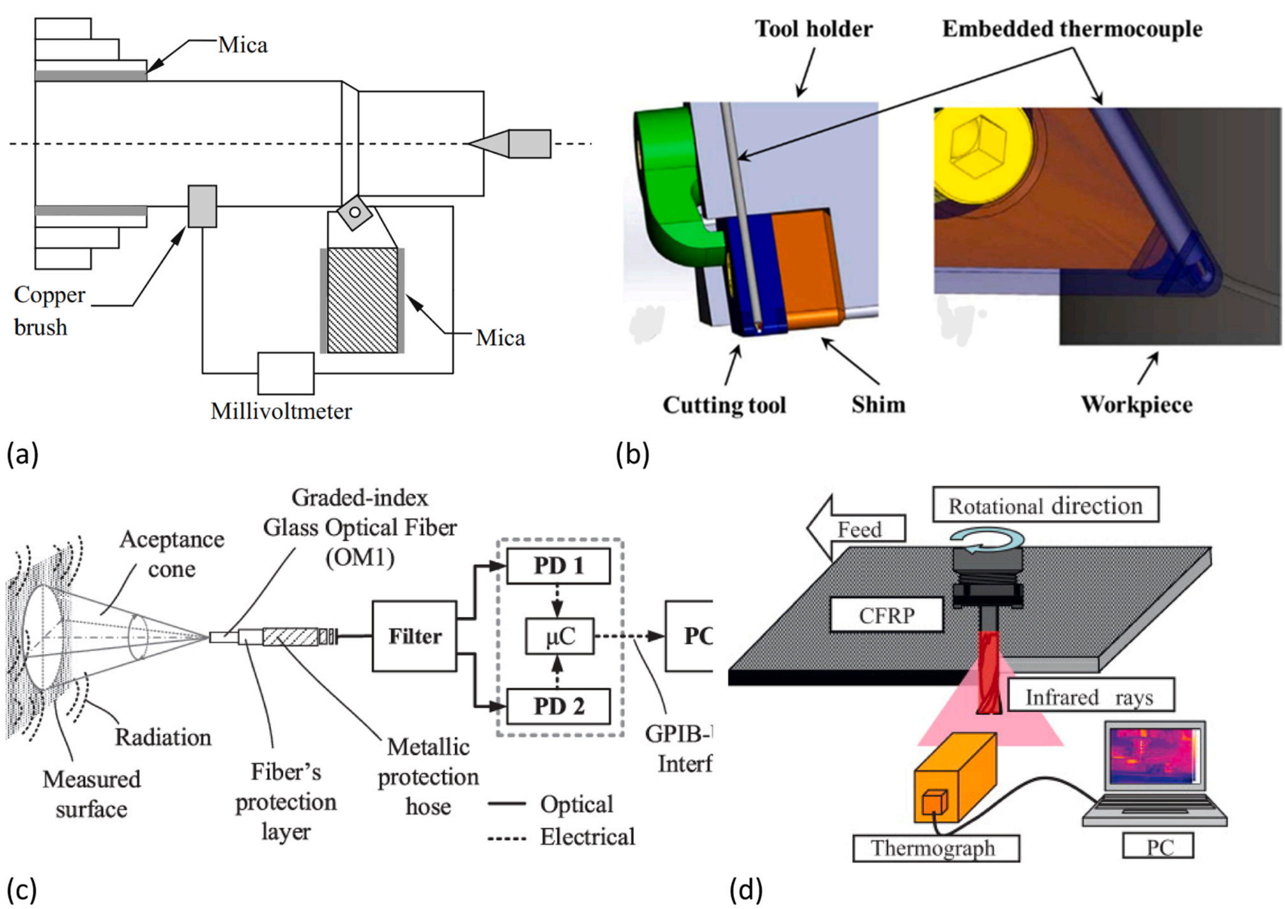

Fig. 4. Example sensor placement/configuration of (a) tool-work thermocouple [50], (b) embedded thermocouple [51], (c) infrared pyrometer [52], and (d) infrared camera/thermograph [53] for cutting temperature measurements.

reducing interference of sensor placement in the cutting process/performance. Infrared sensing provides both point temperature measurement using an infrared pyrometer [52] and field temperature measurement using an infrared camera [53,54]. Example setups are shown in Fig. 4(c)-(d). Compared to the infrared pyrometer, an infrared camera is more suitable for measuring the surface temperature distribution in the cutting zone and evaluating the heat flow. Both methods require line of sight access to the surfaces and the measurements are affected by the emissivity of the target limiting their industrial application.

Cutting temperature can also be indirectly estimated using "soft sensors" by measuring other process variables. The three-dimensional partial derivative heat diffusion equation, solved using Green's function, can be used for estimating the cutting temperature in milling, based on the measured cutting forces [55,56]. Ning and Liang [57] compared three analytic models that separately quantify the heat input at the primary and secondary shear zones in orthogonal cutting using a modified chip formation model, Komanduri-Hou two heat source model [58] and Ning-Liang material flow model. Komanduri-Hou model resulted in the closest temperature estimation for the primary shear zone whilst Ning-Liang model performed best in estimating the temperature at the secondary shear zone compared to experimental results from the literature.

Cutting temperature measurement can reveal the tool-workpiece interaction and be used for part quality prediction and cutting tool wear evaluation. For example, many empirical tool wear and tool life models, such as Takeyama and Murata's model [59] and Usui's model [60], consider the effect of cutting temperature on tool wear propagation.

2.5. Surface and subsurface

Cutting forces, torque, vibration, acoustic emission, and temperature can be correlated to tool wear, surface roughness, and other surface and subsurface information. However, it is also possible to directly measure tool and machined surfaces. Beemaraj et al. [61] used a DSLR camera to take images of turned surfaces and applied an adaptive neuro-fuzzy inference to classify images based on surface roughness. They reported a 98% accuracy using the system. However, visible light has limited capability in detecting and measuring features with high accuracy. Li and Nee [62] applied adaptive resonance theory neural networks integrated with fuzzy classifiers to detect tool wear based on the laser light scattering from turned surfaces. Shahabi and Ratnam [63] and Kumar and Ratnam [64] proposed a method to measure surface roughness in turning operations using a silhouette of the edge of the machined surface captured by a camera. They used moment-based edge operators to detect the profile of the machined surface, which were used for surface roughness calculations. Shahabi and Ratnam [63] used a CCD camera with 25 fps to capture images of stationary parts. The measurements showed only 10% difference in the average roughness compared to measurement made by a stylus.

Magnetic Barkhausen noise has been used for characterising subsurface microstructure and residual stresses in ferromagnetic materials. Jedamski et al. [65] used a Stresstech Rollscan 300 to assess residual stresses in a AISI 4820 workpiece and correlated the results with X-ray diffraction and subsurface microhardness. Bottger [66] used a 3MA-II magnetic transmitter/receiver sensor and analyser to characterise the Barkhausen noise, incremental permeability, and the tangential magnetic field strength, as well as eddy current impedance. The micromagnetic parameters can detect white layer formation in AISI 4041 workpiece surface after machining compared to before machining. Persson [67] developed an instrument based on light scattering using a He-Ne laser with a wavelength of 632.8 nm. They highlighted the limitations of this method for measuring low surface roughness values smaller than 1 μm Ra. Shiraishi [68] designed a system based on light scattered from turned surfaces using a He-Ne laser and photodiode detector for evaluating surface roughness. The system was further developed [69] to assess both surface roughness, surface defects, and part dimension. Fuh et al. [70] designed a system based on laser light scattering using a 4.5 mW laser with 635 nm wavelength for surface roughness measurement. They used a laser power meter sensor for detecting the scattered light and found that the measured peak power has an over 99% correlation coefficient with average surface roughness, Ra, measured by a contact profilometer. In addition to non-contact methods, the company Blum-Novotest [71] has developed an on-machine system termed Roughness Gauge for on-machine contact surface profilometry. The system can be integrated into the machine tool to perform surface roughness measurement in-between processes and prior to the part removal.

The existing methods for monitoring surface and sub-surface parameters require uninterrupted access to the machined surface and thus are performed in dry cutting or in-between cutting processes. Currently, there is no method that can effectively assess the machined surface quality directly during the cutting process. Instead, indirect methods based on vibration and AE signals have been used for estimating the surface anomalies and average surface roughness as highlighted in Sections 2.2 and 2.3.

2.6. Geometry

Many contact and non-contact methods have been developed for on-machine and in-process assessment of the geometrical accuracy of the parts as well as the dimensions and wear state of the cutting tools. In this section an overview of these methods is provided for analysing the workpiece and the cutting tool.

2.7. Workpiece

A number of methods have been used to measure geometries of the workpiece and cutting tool in machining. These can be broadly categorised into i) touch trigger probe sensors and ii) optical sensors. The concept of on-machine measurement (OMM) has been applied to measure machined part geometric accuracy during machining or prior to part removal from the machine tool [72]. The majority of this research used a touch trigger probe, otherwise used for part setting. In this method, the machining process is interrupted and a touch trigger probe is used to locate features on a machined part [73]. If an anomaly is detected, corrective machining actions are used to bring the part geometry within the required tolerance. Ibaraki et al. [74] implemented OMM with a touch trigger probe to measure a test workpiece and calibrate the rotary axis location errors for five-axis machining. OMM provides an alternative to using a coordinate measuring machine (CMM) for post-process, off-machine measurement or comparators before the part is removed from the fixtures with the aim of reducing setup errors. Choi et al. [75] demonstrated that error compensation by OMM can bring machining errors to less than 10 μm.

Touch trigger probes have limited capability in assessing complex geometries and freeform surfaces. An alternative is using scanning probes such as Renishaw's Sprint, Blum Novotest and Marposs' WRSP60 probes which enable on-machine scanning of machined profiles and surfaces [76]. However, the accuracy and repeatability of the measurements are heavily reliant on the accuracy and repeatability of the machine tool and the touch trigger probe [75]. This makes this method more suited for measuring tool wear and, tool and workpiece deflection induced errors.

Selak and Bracun [77] and Bracun and Salek [78] highlighted the time consuming process of measuring and setting up large polymer composite parts using contact touch trigger probes and proposed using optical systems instead. They developed a system based on the principles of laser triangulation integrated into a machine tool and achieved 0.2 mm measurement uncertainty [78] and approximately 30% increased machine utilisation [77]. They noted that part surface reflectivity, presence of contaminants on the surface such as coolants and environmental conditions, and external light sources can impact the quality of the measurements. Zhang et al. [79] developed a vision system for rapid 3D modelling of machining setup. Two CCD cameras were used to generate a stereo view of the machining volume which is used to develop a 3D representation of the machine setup, including the workpiece and the fixturing arrangement. Kondo et al. [80] used a Keyence LK-H022 laser displacement head for on-machine measurement of the ridge profiles of the vane tip for radio-frequency quadrupole cavities. The LK-H022 sensor was attached to the machine tool spindle to scan the profile before and after each machining pass. The proposed method achieved an accuracy of 6 μm and 15 μm in measuring longitudinal and traverse profile, respectively. Nishikawa et al. [81] mounted a laser displacement sensor into a milling tool holder (Fig. 5) for non-contact measurement of turbine blade freeform surfaces and validated the measurement results against that of a CMM showing significant reduction in inspection time from 1.5 per point to 0.008 s. Similarly, Ko et al. [82] used a Keyence LK-031 laser displacement sensor for noncontact OMM of the workpiece. A comparison with measurements from a CMM indicated deviations of 10–20 μm. The proposed method specifically performed poorly in measuring steep surfaces.

2.8. Tool

Many methods for tool setting and direct measurement of wear on cutting tools have been presented. Touch trigger methods have been used for setting the tool length and diameter prior to machining. In this method, the system is calibrated against an artefact with known length and diameter. The cutting tool to be evaluated contacts the probe in different directions and the tool length and diameter are calculated in comparison to the reference artifact. Optical methods using vision and laser line have also been used for measuring the tool length and diameter. In non-contact laser systems, the tool is positioned between the transmitter and receiver and the interruption of the laser beam is used to determine the cutting tool geometry [83]. The measured length and diameter are used as a reference for detecting tool breakage and wear.

Both touch trigger and laser-based systems rely on the machine tool's positioning accuracy and repeatability for assessing the cutting tool geometry. Szafarczyk and Chrzanowski [84] developed a tool probing system based on a linear variable differential transformer (LVDT) touch trigger sensor to measure the X-coordinate and wear of a turning cutting tool. Valino et al. [85] proposed using the touch trigger probe in turning for setting the cutting tool. Liu and Zhu [86] used a fibre optic sensor consisting of a light emitter and a receiver to develop a tool setter for micro-milling applications. The receiver detects the intensity of the light from the emitter which can be correlated to the position of the tool within the light beam. The authors noted that a repeatability of 0.6 μm and an accuracy of 2 μm could be achieved.

Traditionally, tool makers' microscopes have been used for measuring tool wear on cutting tools. Similar microscopes can be integrated into the machine tools to directly measure tool wear inside the machine tool. Due to the limitations posed by cutting chips and coolant and lubricants, however, the majority of these methods are considered as off-line processes in which the cutting process is interrupted to perform tool wear measurement. Charge coupled devices (CCD) and complementary metal-oxide semiconductors (CMOS) are the two sensor types for digital image capture in machining [87]. While CMOS and CCD sensors have a fundamentally different architecture, they both have pixels made of metal oxides which generate a charge when exposed to light. In CMOS sensors, each pixel transforms the charge to a voltage. In CCD sensors, the charge from each pixel is read sequentially and digitised. For further details, readers are referred to Durini [88]. There is no comparative study between CCD and CMOS sensors in tool wear detection and both sensor types have been implemented successfully for static imaging. CMOS sensors commonly have a rolling shutter which may result in image distortion when imaging moving tools. However, there are many CMOS sensors available with a global shutter which allows for high speed imaging.

In optical tool wear measurement, the cutting tool is positioned in front of a camera inside the machine tool and an image is taken at a predetermined angle. Kurada and Bradley [89] proposed using edge detection to identify the boundaries of wear on a cutting tool for automated tool wear measurement. The presence of cutting fluids on cutting tool surfaces results in noisy scattering for on-machine optical assessment of tool wear. Giusti et al. [90] also highlighted the importance of lighting for tool wear geometry detection based on the wear position on the flank or rake faces of the cutting tool. Bagga et al. [91] used a camera with an 18 MP CMOS sensor and a ring light for capturing images of a cutting tool. You et al. [92] proposed using a CCD camera equipped with a telecentric lens to develop a wide field of view vision system for on-machine tool wear assessment. The aim was to overcome the issue of small field-of-view and costs associated with high resolution microscopic systems. Hou et al. [93] developed a setup consisting of a CMOS camera equipped with a telecentric lens for measuring tool wear on the auxiliary flank face of milling tools as shown in Fig. 6. They used a machine vision algorithm for reproducing the expected location of the cutting edge from the worn tool and reported a maximum error of 57 μm. Takaya et al. [94] noted that irradiating cutting fluid covered cutting tools with focused laser light can excite the cutting fluid to emit fluorescence light with uniform intensity irrespective of the irradiation direction. The emitted fluorescence light can then be used for on-machine assessment of tool wear using a fluorescence confocal microscope. The research in direct measurement of tool wear and cutting tools is mainly focused on image processing and machine vision and there is less justification for the camera, optics, and lighting selection.

Ryabov et al. [95] developed a system consisting of a scanning laser to measure the distance between the sensor and a rotating milling tool and the intensity of light reflected from the cutting tool to measure tool wear and detect chipping. They used a 670 nm wavelength laser with a spot size of 40 × 20 μm and a distance resolution of 50 μm. The system was used to reconstruct a 3D model of the cutting tool and was capable of detecting flank wear down to 40 μm. Jeon et al. [96] proposed using

Fig. 5. laser displacement sensor for freeform profile measurement [81].

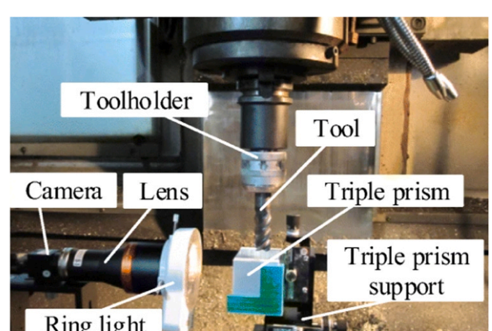

Fig. 6. Vision system for on-machine tool wear measurement [93].

knife edge interferometry for assessing the wear on cutting tools. The fringes generated as a result of interferences between a transmitted and a diffracted wave to and from a cutting tool were detected using a photodetector and correlated with abrasive and attrition wear at the cutting edge.

Instead of directly measuring the wear geometry, Evans et al. [97] proposed assessing the impression of the tool in plunge cutting using laser interferometry for measuring the tool wear in diamond turning. In this method, plunge cuts were made in a reference part using a new and worn tool and the difference was calculated to eliminate the non-zero slope bias with white light interferometry. Hocheng et al. [98] used the scattered light from the machined surface to assess the condition of the tool in diamond turning. While this method is applicable to precision machining processes, such as diamond turning, its suitability is limited for general machining processes [99]. Cerce et al. [100,101] developed an on-machine tool wear measurement system by using a Keyence LJ-G015 2D laser displacement sensor. The data were then used to generate a 3D model of the worn cutting tool as shown in Fig. 7. A comparison of the measurement results with data obtained from an Alicona IF-Edge Master with 5 μm lateral resolution indicated an accuracy of 8 μm.

3. Sensor integrated tools and tool holders

Sensor integration into tool systems have been realised for inserts, tools (end mills, face mills), and tool holders (rotating or stationary). Stationary cutting tools include turning and boring operations. Sensors are integrated into either inserts [102–104] or stationary tool holders [105,106]. Rotating cutting tools include milling, drilling, tapping, reaming, and others. There are two ways of sensor integration: i) the sensor is located on the tool and the data acquisition unit is placed on the tool holder; and ii) the sensor and data acquisition unit are integrated in the tool holder.

3.1. Inserts as sensor

Li et al. [102,103] developed an array of embedded thin-film thermocouples (TFTCs) arranged along the rake face of solid carbide inserts, as shown in Fig. 8, to enable cutting temperature measurement. The integration required micro-grooves on the rake face of solid carbide inserts where TFTCs were inserted to protect them from the abrasive flowing chips. The TFTCs exhibited a sensitivity of 20 μV/°C and a response time of less than 1 μs. However, they weakened the tool coating at the tool-chip interface and accelerated its delamination.

Temperature sensing integrated in coatings is a transformative technology for developing smart cutting tools. This technology can prevent intrusive modifications to the cutting insert design while enabling temperature measurement at the cutting zone using high sensitivity and high spatial resolution sensors. Chromium nitride (CrN_x)

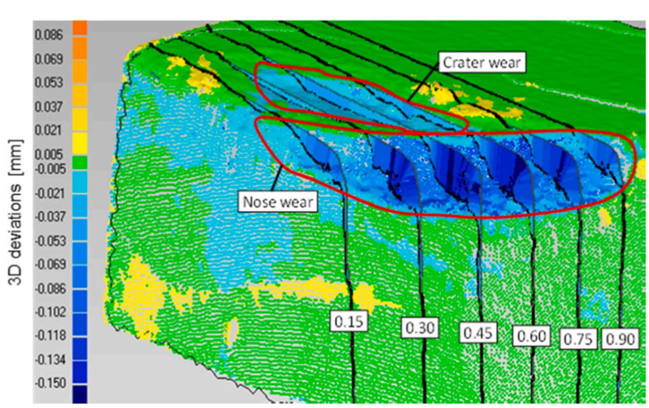

Fig. 7. Reconstructed 3D model of a worn cutting edge [100].

has exhibited promising performance as a wear-resistant coating material that possesses sensing capabilities [104,107]. Plogmeyer et al. [108] developed a wear-resistant thin-film temperature sensor integrated directly on the surface of a cutting tool. The sensor was built by direct deposition of the layers, shown in Fig. 9, on the rake face of an uncoated cutting insert. The sensor showed fast response to temperature changes, high reproducibility of signals, and maintained sensor functionality in the cutting tests despite the development of crater wear on the rake face.

Seemann et al. [109] presented a novel ferromagnetic sensor that detects the change in the magnetic properties of a ferromagnetic material layer with temperature rise. The sensor reduces the magnetic effect and the eddy current interactions of the ferromagnetic and conductive WC-Co substrate. This was achieved by the sensor layers, shown in Fig. 10, including the (SiO_2 and/or Ti-Al-N) between the Fe-Co-Hf-N sensing layer and the WC-Co substrate. The sensor was capable of detecting high gradient temperature rises that corresponded to wear and failure. Chen et al. [110] presented a multilayer wear sensor system (Fig. 11), comprising two layers of conductive nanocrystalline diamond and one non-conductive nanocrystalline diamond layer in-between that acted as the capacitor's plates and the dielectric, respectively. A multilayer wear sensor system was implemented on WC-Co dummy cutting tools, where the sensor provided an efficient protection of the cutting tool body and the sensor returned signals that indicated its own wear condition.

A novel approach was demonstrated by Uhlmann et al. [111], which used the boron-doped diamond's semi-conducting behaviour to measure the temperature during cutting. Fig. 11 shows the assembly of the integrated boron-doped diamond cutting insert into the tool shank along with the data conditioning and acquisition system. The experimental investigation included calibrating the sensor using a known heat source. The boron-doped diamond sensor was then used to measure cutting temperatures during the machining of polymethyl methacrylate (PMMA) at different cutting depths and cutting speeds. A high repeatability of temperature measurements and trends were achieved within a range of average cutting temperatures of 20 °C to 100 °C.

3.2. Sensor integrated cutting tools

Sensors integration into cutting tools requires small size, such as thin film polyvinylidene fluoride (PVDF), piezoelectric thick film, thermocouple, or strain gauge. Thermocouples have been embedded near the cutting edge of inserts in multiple studies for measuring cutting temperatures. However, with their geometric and size limitations, the key limitation is the proximity between the thermocouple wires and cutting edge to ensure non-intrusive and reliable temperature sensing during cutting. For instance, Campidelli et al. [112] embedded a K-type thermocouple with a sensitivity of 41 μV/°C into the inserts of a rotating milling tool integrated with a HC-06 Bluetooth module to enable data transmission to an external PC at a sampling rate of 450 Hz. Although the overall evaluation showed reasonable temperature measurements under different cutting speeds, no reliable solution was reported for measured temperature uncertainty evaluation. Wegert et al. [113] used three platinum resistance sensors for temperature measurement in the cutting zone in single lip deep hole drilling. They also placed two more sensors on the drill head's side to measure the temperature changes induced by friction and forming processes on the bore hole surface.

Ma et al. pasted PVDF sensors on the body of a solid carbide end mill and placed data logging electronics on the tool holder to measure feed and transverse forces [114] as well as torque [115] as illustrated in Fig. 12. The PVDF sensors were examined for chatter detection. The investigations indicated that microphone and accelerometer have superior performance in detecting chatter compared to the PVDF sensor and dynamometer. A similar PVDF sensor was tested in robotic milling by Cen et al. [116]. The signal from the PVDF sensor was coupled with mechanistic models of the operation and used as a closed-loop feedback to compensate for the errors caused by the flexibility of the robotic arm.

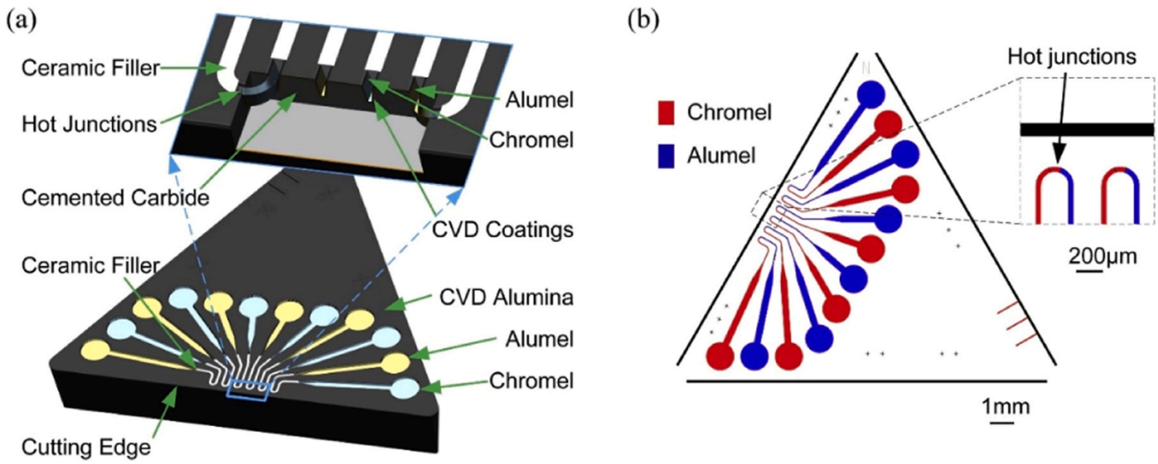

Fig. 8. (a) Schematic of the embedded distributed pattern of thin-film thermocouples and (b) its horizontal view [103].

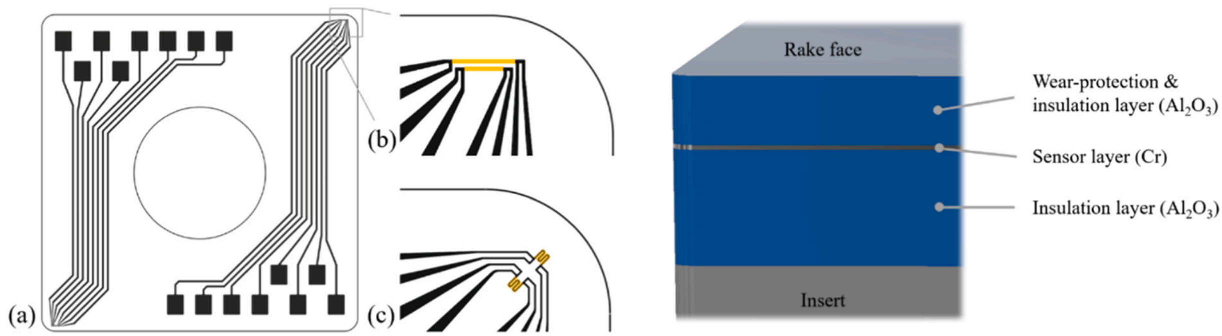

Fig. 9. Direct deposition of the layers in the sensor on the rake face of the uncoated cutting tool [108]: (a) overview of the sensor, (b, c) sensing zones.

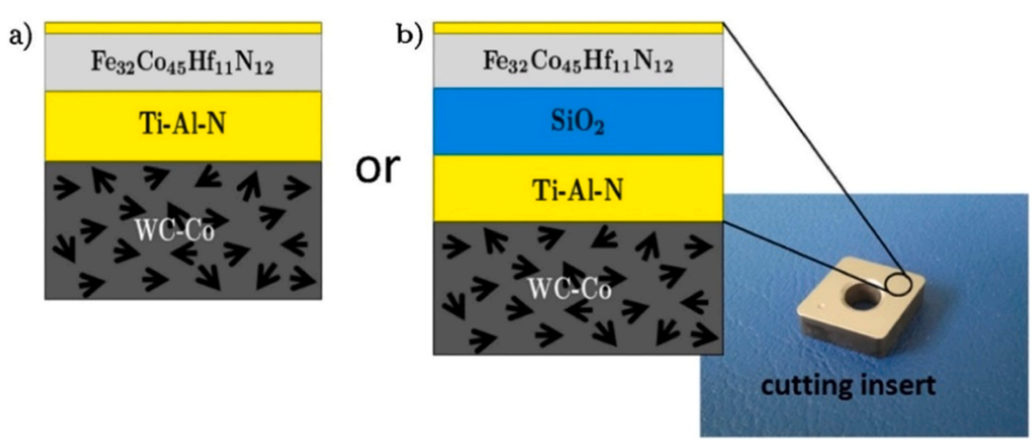

Fig. 10. Sensor layers consisting of SiO_2 and/or Ti-Al-N between the Fe-Co-Hf-N sensing layer and the WC-Co substrate [109].

The proposed method indicated over 70% improvements in dimensional accuracy of the machined geometry. Another study using thin film PVDF integrated into a solid carbide end mill was presented by Ting et al. [117]. The analysis indicated 3–19% error in cutting force measurement in comparison with that of a Kistler dynamometer. They highlighted the need for enhancing the signal-to-noise ratio in the system to be able to reliably measure cutting forces.

Conventional dynamometers do not typically separate the cutting force for each of the cutting edges individually. To enable this level of visibility into the process performance, Drossel et al. [118] instrumented each insert on an indexable cutting head using piezoelectric thick film sensors mounted below the inserts as shown in Fig. 13. Experimental testing demonstrated a good correlation between the forces measured with the new sensor system and dynamometer with a maximum discrepancy of 7% at the peak force. The system limitation was its inability to measure different components of the cutting force. Luo et al. [119], embedded PVDF sensors into the seat of cutting inserts and decoupled the measured forces to triaxial force at each tooth, as displayed in Fig. 14. They reported a maximum of 10% error in cutting force measurement compared to dynamometer.

Suprock et al. [120] placed strain sensors into an inserted tool for measuring torque. An amplifier and wireless Bluetooth transmission were placed on a tool holder as depicted in Fig. 15 (a). Furthermore, an embedded tool design was presented for tool tip vibration testing by

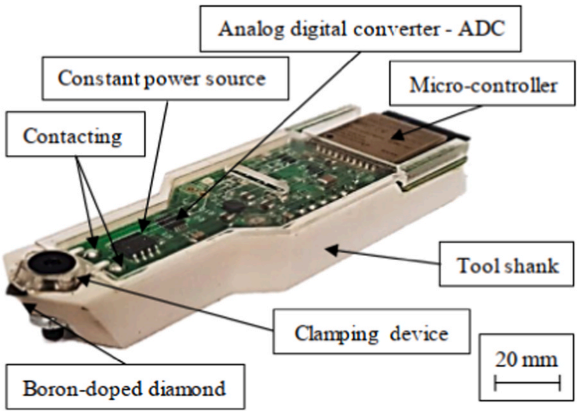

Fig. 11. A nanocrystalline diamond-based multilayer wear sensor system [111].

Suprock et al. [121], as shown in Fig. 15 (b). The authors showed that the developed design can be effectively used for chatter detection to define the stable spindle speeds with in-cut stability estimation.

Möhring et al. [122] discussed the potential technologies for self-optimising machining systems (SOMS), including embedded sensor technologies that enable effective and nonintrusive data acquisition. Maier et al. [123] designed and fabricated a sensory milling tool with indexable inserts that integrated six strain gauges to measure cutting forces as shown in Fig. 16. K-type thermocouples and a MPU6050 MEMS accelerometer and gyroscope were also included to detect the insert temperature, rotational speed, vibrations, and possible impacts. The sensor signals were transmitted wirelessly using a Bluetooth low energy module. Totis et al. [3] mounted a Kistler 9251 A triaxial force sensor between the insert and cutter body of a modular milling tool. They integrated an inductive telemetry device onto the tool holder, which could measure the tooth-dependent triaxial force in face milling with a sampling rate of 13 kHz as illustrated in Fig. 17. They reported a maximum 6.6% error relative to the cutting force measurements from a Kistler dynamometer. Möhring et al. [124] developed an experimental machining test setup equipped with an on-tool integrated uniaxial vibration sensor to measure accelerations at a sampling rate up to 20 kHz. The sensors integrated in the tool had the advantage of being close to the cutting area, so were more sensitive to the cutting process. However, this integration method limited the size of the cutting inserts or tools, resulting in poor flexibility. To overcome this shortcoming, the method of sensor integrated tool holder has been proposed by many researchers which is discussed in the following section.

3.3. Sensor integrated tool holders

Many researchers and commercial systems have proposed integrating sensors and data acquisition systems into the tool holder instead of the cutting tool. This method takes advantage of the larger dimensions and hence space available within the tool holders. In addition, tool holders are not considered as consumables within production scenarios. In this section, sensor integration is categorised into (i) rotating tools and (ii) stationary/non-rotating tools.

3.3.1. Rotating tool holders

One of the early examples of sensor integrated tool holders for milling is that of Ohzeki et al. [125]. They utilised ferromagnetic layers on a rotating shaft in a tool holder to measure cutting torque by monitoring the change in magnetic permeability. The cutting tests showed a maximum of 2% deviation in measured torque between the tool holder and a dynamometer. The authors also noted the difference between the torque signal from the tool holder when a new tool was used compared to a worn tool and highlighted the possibility of using the tool holder for TCM.

Smith et al. [126] developed a sensing element with the circumferential groove based on strain gauges, which can be attached to the tool holder without any modification, in order to measure the cutting torque in milling. Wu et al. [127] and Dini and Tognazzi [128] modified the

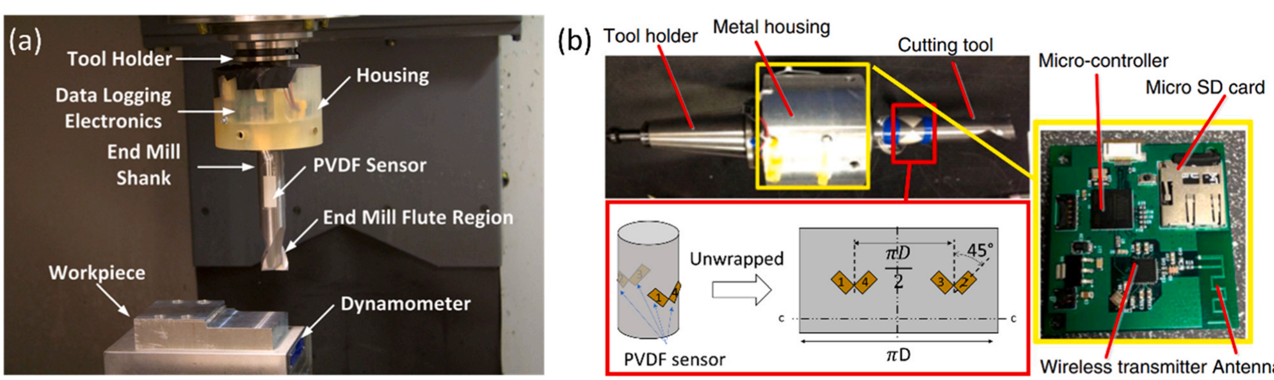

Fig. 12. Tool integrated sensor system proposed by Ma et al. [114,115] for the measurement of (a) feed and transverse forces; (b) cutting torque.

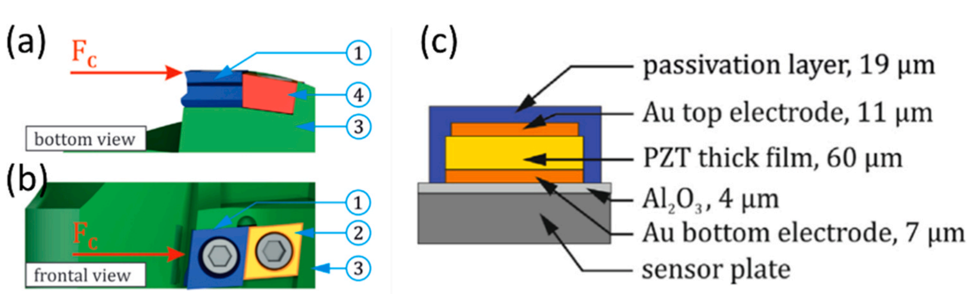

Fig. 13. Indexable cutting head with a piezoelectric thick film sensor adjacently mounted below an insert [118]: (a) bottom and (b) front view of the sensor consisting of (1) insert, (2) piezoceramic thick film, (3) milling tool, and (4) sensor plate; (c) layers of the sensor.

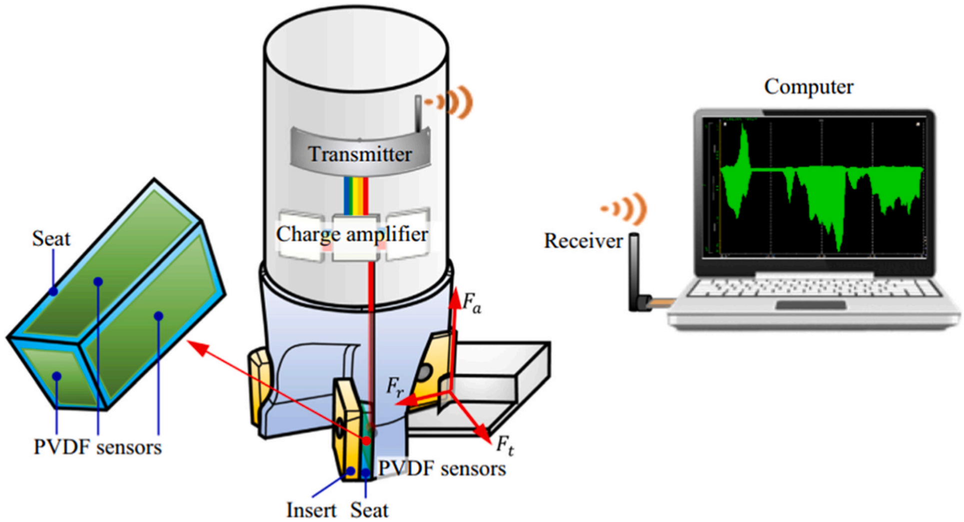

Fig. 14. Embedded PVDF sensors into the seat of each cutting insert developed by Luo et al. [119].

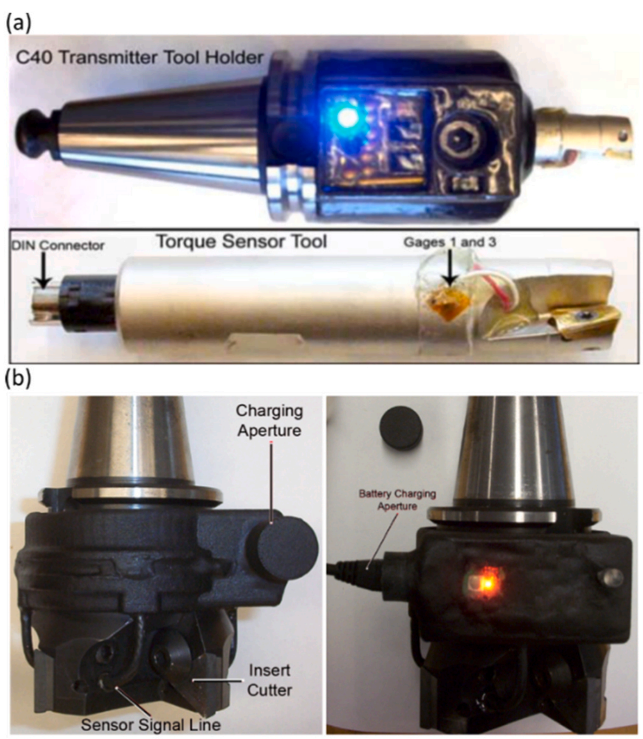

Fig. 15. (a) Cutting torque and (b) tool tip vibration measuring system [120,121].

standard tool holder to form an annular groove and place the strain sensor for measuring torque. The experimental results showed good indication to detect the tool breakage and excessive wear. Rizal et al. [129] designed an integrated tool holder in the form of a symmetrical cross beam type with 24 strain gages to measure three-component force. The tool holder had a sensitivity in the range of 4.23×10^{-4} – 8.53×10^{-4} mV/N and a cross sensitivity error of approximately 4%. Moreover, a PCB Piezotronics 352C67 single-axis accelerometer with a maximum range of 50 g and a K-type thermocouple were added to this integrated tool holder by Rizal et al. [28]. Due to the use of foil strain gauges, the stiffness of the tool holder was reduced. The tests showed the sensitivity of the force measurement to temperature as shown in Fig. 18 (a). It could reliably detect the tooth passing frequency as compared to a Kistler dynamometer as displayed in Fig. 18 (b).

Zhang et al. [130] developed a tool holder embedded with a force sensor which was composed of eight semiconductor strain gauges as shown in Fig. 19 (a). The analysis indicated that the addition of the sensor system reduced the natural frequency of the tool holder from 515 Hz and 529 Hz in the F_x and F_y directions to 477 Hz and 488 Hz, respectively. Comparison of the cutting forces and torque measured during machining is provided in Fig. 19 (a) and (b) indicating less than 10% deviations between the forces measured by the tool holder and that from a dynamometer. Qin et al. [131] designed a sensing unit to place eight MEMS strain gauges for measuring axial force and torque during milling as illustrated in Fig. 20 (a). In addition, Qin et al. [132] designed a thin-walled cylinder tool holder to arrange four MEMS strain gauges for measuring torque as shown in Fig. 20 (b). Since both MEMS strain gauges and semiconductor strain gauges are composed of a semi-conductor silicon strip, the sensitivity of force sensor and stiffness are increased. However, semiconductor sensors are sensitive to temperature. If the sensor does not include temperature compensation, the measurement accuracy will be reduced.

Xie et al. [134] modified a commercial tool holder to provide force sensing. The design included four vertical deformation beams and four horizontal deformation beams to place six capacitive sensors as shown in Fig. 21 (a). However, the nonlinearity of capacitive sensor leads to a reduction in force measurement accuracy. Furthermore, Xie et al. [135] modified a commercial tool holder to install an axial vibration sensor, which required the sensor axis to coincide with the rotational axis of the tool holder as displayed in Fig. 21 (b). They applied Continuous Hidden Markov model to the sensor signal for TCM and reported successful classification of the tool wear into initial, medium and severe. Later, Xi et al. [136] combined the force-sensing element and the axial accelerometer in a tool holder to enhance the performance of the system for TCM. The cutting forces and acceleration signals collected in the experiments were fused and processed using the Hidden Markov model to monitor tool condition. The results indicated 95% average accuracy for the detection of severe tool wear. Liu et al. [137] developed an integrated rotating dynamometer based on fibre Bragg grating (FBG), which consists of two mutually perpendicular octagonal rings. Due to the cutting fluid and chips in the cutting process, FBGs cannot be practically applied in production scenarios. The key point in the sensing elements based on strain measurement is that there is a trade-off between the stiffness of the tool holder system and the sensitivity. High sensitivity without weakening the stiffness can be possible with the use of high sensitivity sensors or micro sensors that can be placed into small notches [138,139]. Reducing the stiffness for the sake of sensitivity in high

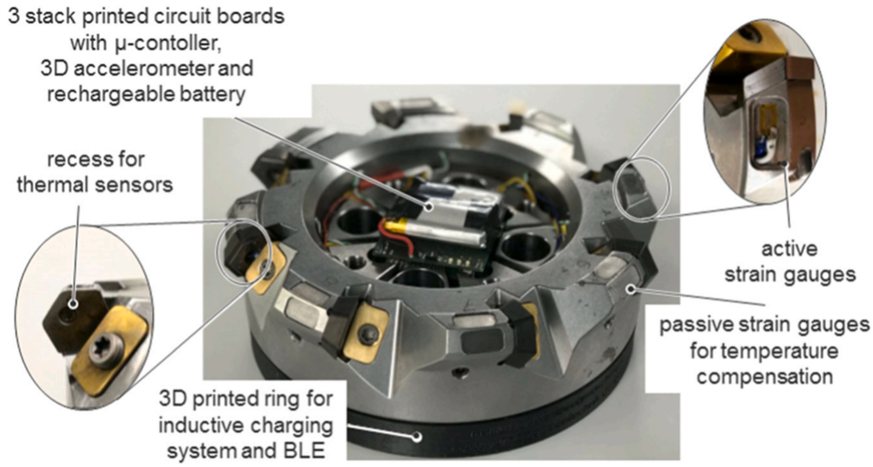

Fig. 16. A prototype milling tool integrated six strain gauges, K-type thermocouples, an MEMS accelerometer and position sensor [123].

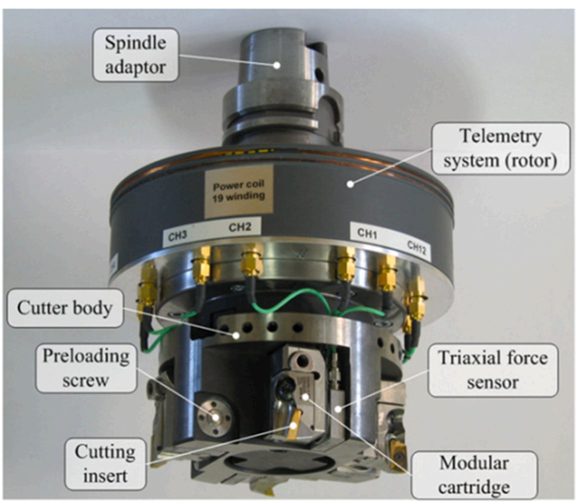

Fig. 17. Rotating dynamometer proposed by Totis et al. [3].

frequency applications, such as milling, limits the tool holder operational range for high speed cutting.

Tognazzi et al. [140] studied a special tool holder with two slotted discs, which enabled the measurement of the cutting torque through the changing phase difference between two inductive sensors. The inductive sensors were placed closed to the slotted discs and the phase difference between the upper and lower discs due to the torque acting on the tool holder was analysed to predict the torque.

Bleicher [141] integrated a uniaxial MEMS accelerometers into a milling tool holder as shown in Fig. 22. They noted a change in the sensor signal when a tool edge chipping occurs. They reported that feature extraction from the sensor signal and machine learning can be used for detecting tool edge chipping during machining. This tool holder was later commercialised as “iTendo” by Schunk [142]. Zhou et al. [27] integrated a three-axis accelerometer on the tool holder for tool wear detection as displayed in Fig. 23. In the cutting tests, they estimated the tool conditions with an accuracy of 86.1% employing the Support Vector Machine with the integrated accelerometer. Although the three-axis accelerometer enabled both axial and radial acceleration measurement, the speed was low in the test process. Uhlman and Holznagel [143] used a rotating AE attached to the tool holder for machining process monitoring. The AE sensor consisted of two parts: the stator from which the data is transferred to the control card through inductive transmission; and the rotor that rotates with the tool holder. The attached AE sensor was successfully utilised in the cutting tests for the

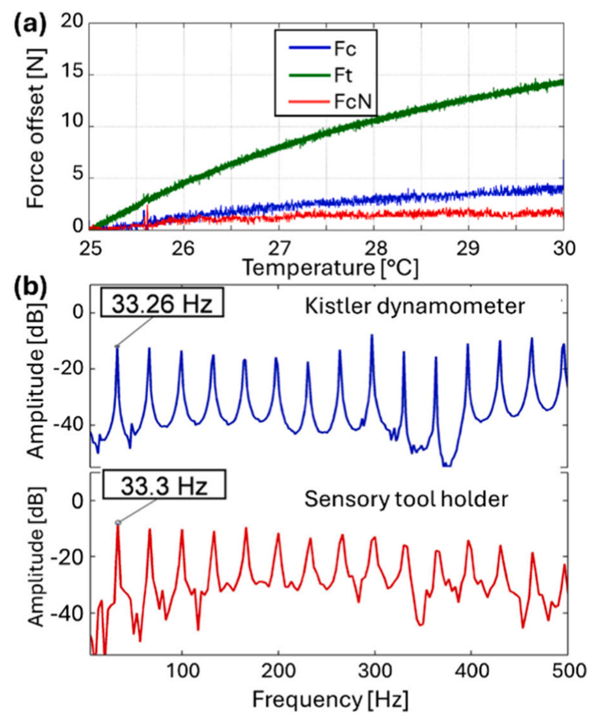

Fig. 18. (a) Impact of temperature on the force measured by the multi-sensor integrated tool holder [129] and (b) comparison of forces measured by a Kistler dynamometer with multi-sensor tool holder [28].

detection of tool wear condition, coating failures and workpiece damages in the milling of carbon fibre-reinforced plastics. Different setups and sensor types have been integrated into cutting tools and tool holders. In so far, the aim has been to replicate the results from a dynamometer or detect tool wear and chipping by analysing the sensor signals. The capabilities of these systems can be extended to part geometry and surface integrity monitoring and decision making in the future.

Numerous sensor-integrated tool holders have been developed for monitoring machining processes, with several commercially available options on the market. In addition to iTendo [142], which was previously discussed, another noteworthy example is the Spike [144], a sensory tool holder developed by Promicron. Both of these systems show the increasing potential of integrating sensors into tool holders for improved process monitoring and control. Additionally, Kistler has

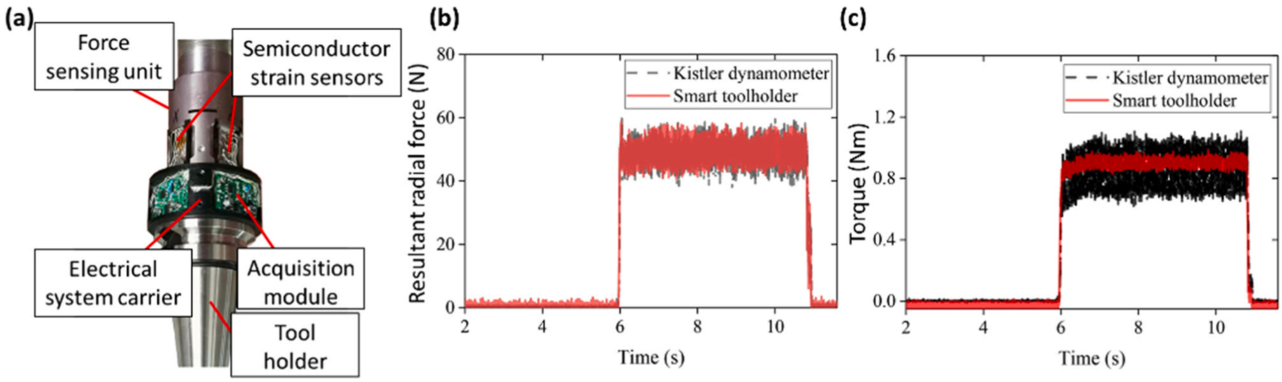

Fig. 19. (a) smart tool holder with semiconductor strain gages and a comparison of (b) resultant radial force and (c) torque measured by the tool holder and Kistler dynamometer [130].

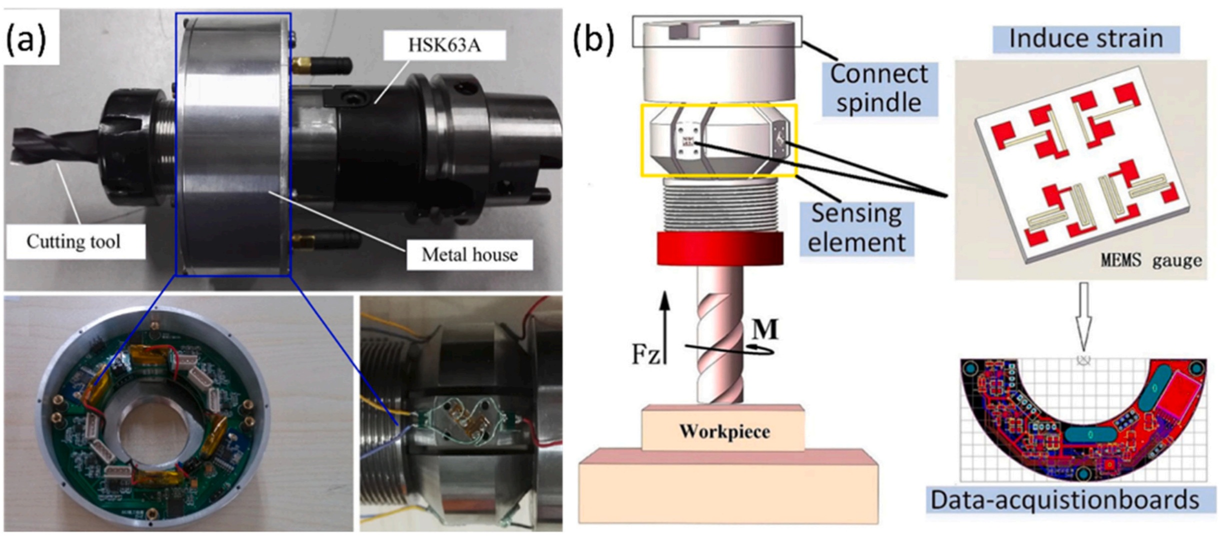

Fig. 20. MEMS strain gauges integrated in the tool holder to measure (a) axial force and torque [131] (b) torque [133].

introduced several piezoelectric rotary dynamometers based on the piezoelectric effect [1]. Although they have high stiffness, they are bulky and expensive making them unsuitable for industrial use.

3.3.2. Stationary/non-rotating tools

Non-rotating tools include turning tools, boring holders, saws, broaching tools, etc. The majority of research in this area have been focused on sensor integration into turning tool holders. Rao et al. [145] used a piezoelectric force sensor placed between the shank end of tool and tool holder to improve workpiece geometrical accuracy in turning operations. Totis et al. [146] integrated a piezoelectric force ring into a commercial tool holder to measure triaxial orthogonal force in the turning process, as shown in Fig. 24. However, the piezoelectric force ring caused the volume of the turning tool to be large. Therefore, the piezoelectric film was proposed by Xiao et al. [106] and Wang et al. [147] to assemble on the turning tool holder and measure the three-axis force, but the low-frequency signal was not evaluated in detail.

Because of its small size and relatively low cost, strain gauges have been utilised by many researchers for force measurement. Scheffer and Heyns [148] used strain gauges to form three half-bridges in order to establish a tool wear estimation system. The signal from the sensors was used for estimating tool wear using feature extraction and neural networks. They reported an RMS of 5 μm. Zhao et al. [149] designed two octagonal ring turning tool holders instrumented with 12 strain gauges into Wheatstone full bridge circuits to sense triaxial cutting forces acting on the tool. Thangarasu et al. [150] built a full bridge circuit based on the strain gauge to measure the cutting force and compared it with the cutting force predicted by an analytical model. The strain gauge that they used had low sensitivity and the stiffness of tool holder was sacrificed to improve sensitivity.

Zhao et al. [151,152] employed high-sensitivity semiconductor strain gauges (Fig. 25a) and MEMS strain sensor (Fig. 25b) on two octagonal ring turning tool holders to measure two-component cutting forces. Zhang et al. [153] proposed a turning dynamometer with high strain sensitivity, which combined with thin-film resistive grids to form three Wheatstone bridges to measure triaxial cutting forces, as shown in Fig. 26 (a). Cheng et al. [154] placed a thin-film strain sensor inside the turning tool to measure unidirectional cutting force as displayed in Fig. 26 (b). Although the sensitivity of the sensor is improved while ensuring the stiffness, the structure was complex and interfered with the normal clamping process limiting the practical application. In addition, only static cutting forces could be measured and dynamic forces were not tested.

Stoney et al. [155] employed four surface acoustic wave (SAW) strain sensors attached to four sides of the tool holder to measure cutting force and feed force as shown in Fig. 27 (a). Each differential sensor pair had a frequency response of frequency response of 433.42 and 434.42 MHz. Machining tests indicated the potential of the setup in measuring cutting forces as shown in Fig. 27 (b). Wang et al. [156] used two SAW strain sensors installed at the top and side of the turning tool to measure cutting force and feed force, and applied them in machining hybrid dissimilar material [157]. However, the cross-talk (20%) and

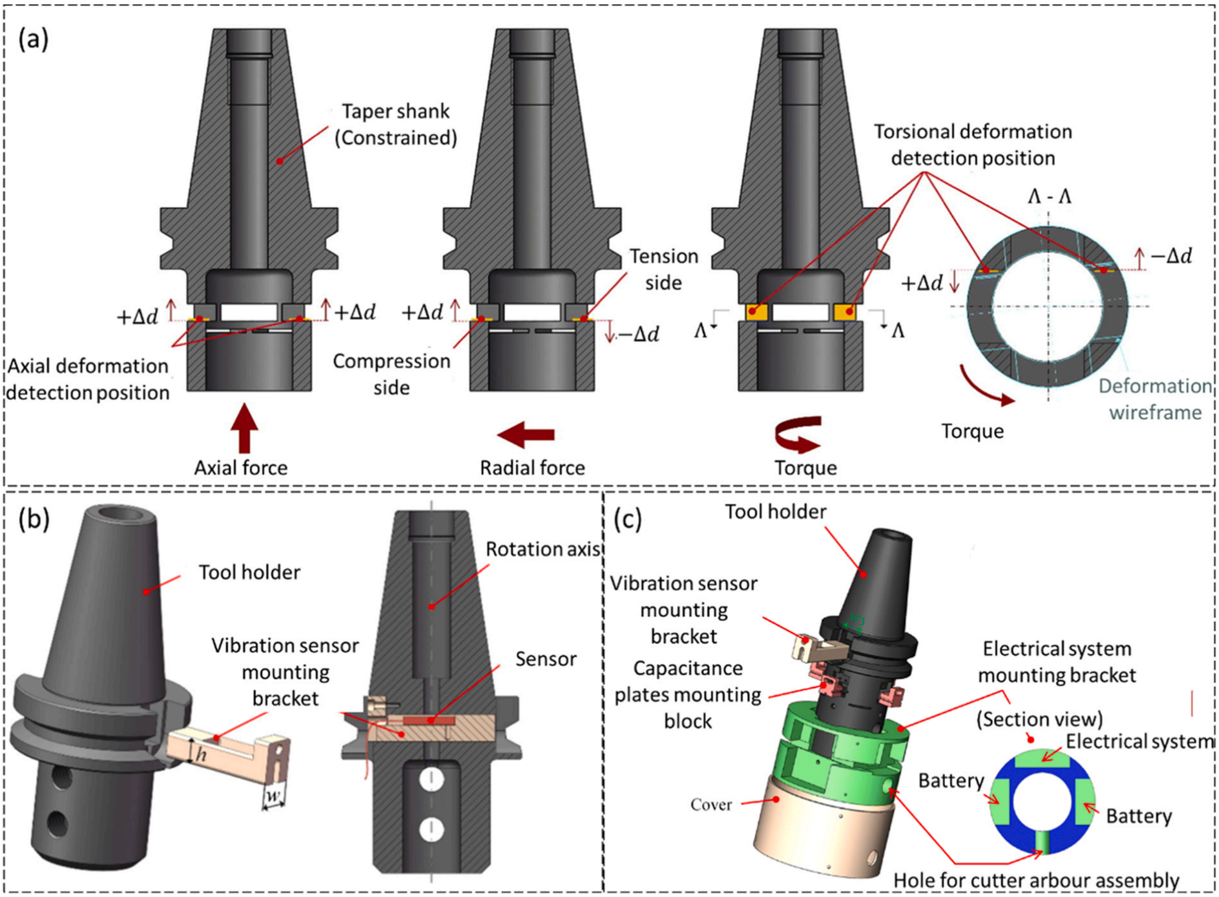

Fig. 21. Modified tool holder by Xie et al.:(a) cutting force sensors [134]; (b) cutting vibration sensor [135]; (c) multi-sensor [136].

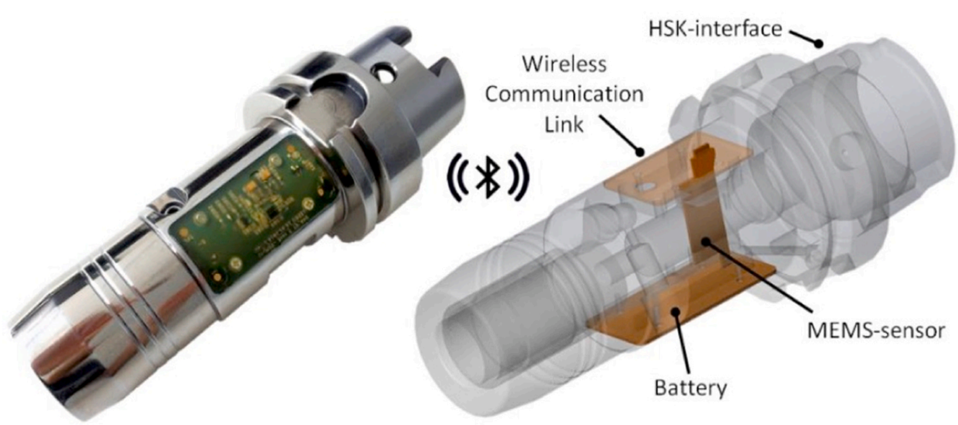

Fig. 22. Uniaxial MEMS accelerometer in tool holder developed by Bleicher et al. [141].

hysteresis (7%) of the instrumented tool were higher than a Kistler dynamometer. The high cross-talk where a single SAW sensor is used for each direction, indicated the advantages of differential mode SAW sensor setup. Jin et al. [158] employed an optical sensor mounted on the tool post to estimate the cutting forces from the tool shank's displacement without the need for extra space and reduced stiffness. Huang et al. [159] presented an instrumented turning tool to measure triaxial force based on optical fibre sensor in the turning process. The authors reported that cutting experiments demonstrated a close agreement with the reference dynamometer but only qualitative measure of inaccuracies was provided.

Hassan et al. [160] integrated an AE and vibration sensors into a turning tool holder interfaced with an advanced time-frequency analysis to detect tool failure in intermittent turning processes. Östling et al. [161] integrated a MEMS accelerometer with strain gauges into a boring bar for cutting force monitoring and chatter detection. In the cutting tests, gradually increasing vibration due to chatter was detected with the MEMS accelerometer.

At present, the sensor integrated tool holder is developing towards high sensitivity, high stiffness, small volume, and low cost for high fidelity data collection in real time. Moreover, the instrumented tool holder is non-invasive to machining processing and is not considered a consumable making it a more suitable solution for industrial applications. The various types of sensors integrated into tools and tool holders

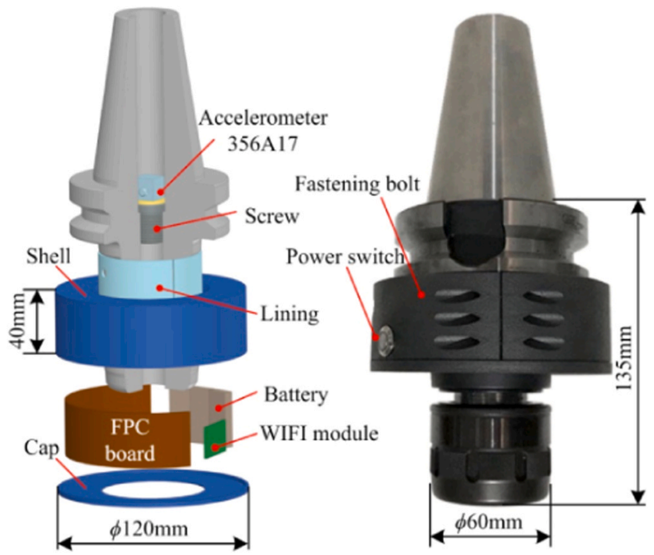

Fig. 23. Three-axis accelerometer in the tool holder designed by Zhou et al. [27].

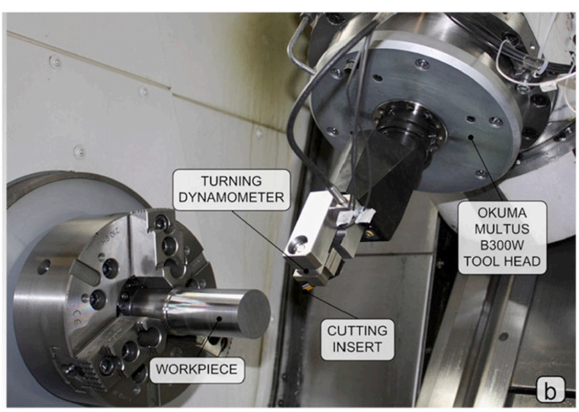

Fig. 24. A piezoelectric force ring assembled on the turning tool holder [146].

are discussed in the following subsection.

3.4. Sensor types for integration in tools

Sensor integrated machines and cutting tools are one of the foundations towards achieving intelligent machining [162]. Sensor integrated or instrumented tools are generally targeted for measuring temperatures, cutting forces, vibrations and acoustic emissions. Bleicher et al. [163] provided an overview of sensor integration in tools and explained the principles for measuring force, displacement and temperature during machining. The temperature near the cutting zone has been measured as an important indicator to analyse the wear condition. K-type thermocouples have been integrated in tools to measure the tool temperature in many studies [164,165]. Thermocouples offer a broad temperature range with low cost but have relatively low accuracy and high latency. Another temperature sensor types include resistance temperature detectors [113]. These offer higher accuracy and linearity over a wide temperature range. Moreover, ferromagnetic film sensors [109] and boron-doped diamond [111] have been considered for temperature measurement in the cutting zone.

Cutting force is one of the most important signals that can be used for tool condition and machining process monitoring. Two types of sensor that are commonly employed for cutting force measurement are strain gauges [126,128–132,149,150–152,166] and piezoelectric-based sensors [1,3,145,146]. Ceramic piezoelectric sensors offer high stiffness and high frequency range, but they are expensive and have current leakage issues. They also have limitations in measuring static forces. Strain gauges on the other hand can deliver high accuracy and low cost. However, there is a trade-off between structural stiffness and resolution in strain gauge-based force measurement. The structural stiffness is mostly sacrificed in order to increase the sensor resolution [28,127,129,131,132,136]. Instead of foil strain gauges, semiconductor [130,151] and MEMS strain gauges [131,132,152] have also been employed to improve the sensitivity of force sensors. Another cost-effective and high-fidelity sensor is PVDF piezoelectric sensors, which has been integrated into rotating cutting tools in milling for cutting forces and torque measurements [105,114–116,119]. Moreover, other sensor types such as capacitive sensors [132,136], fibre Bragg gratings [43], SAW strain sensors [155,156], and optical sensors [158,159] have been applied to measure deformation/strain and correlated to cutting forces.

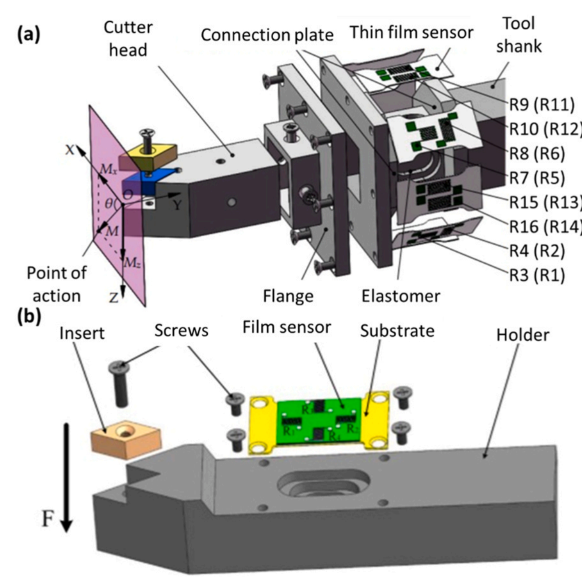

Fig. 26. Thin-film strain sensors integrated in the turning holder: (a) Zhang [153]; (b) Cheng [154].

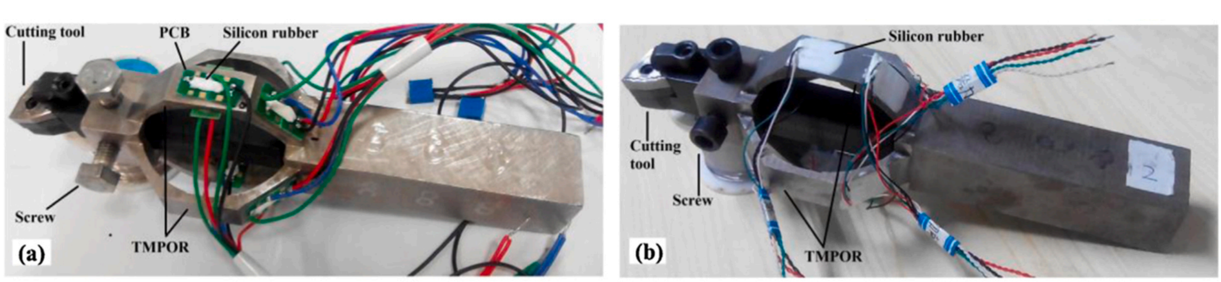

Fig. 25. High-sensitivity strain gages used by Zhao [151,152]: (a) semiconductor strain gauges; (b) MEMS strain gages.

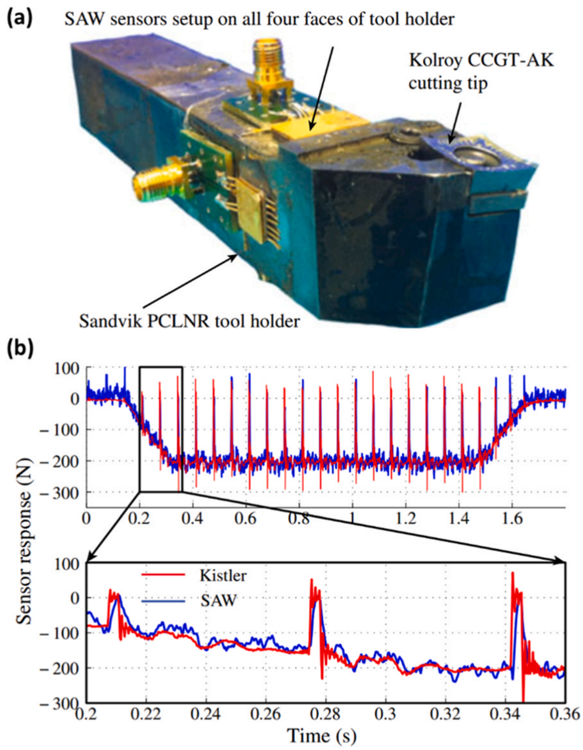

Fig. 27. (a) SAW strain sensor integrated in the turning tool holder and (b) example cutting force signal from the tool holder compared with Kistler dynamometer in dual axis oblique interrupted cutting [155].

Vibrations during machining can also provide a quality signal which can be used for process monitoring (e.g., chatter detection, tool wear monitoring). Vibration can be measured as acceleration, velocity, or displacement. The most commonly employed accelerometers in the literature are piezoelectric [27,28,135] and MEMS [136,161] accelerometers. The majority of these sensors can detect vibrations up to 10–15 kHz and measure either uniaxial or triaxial directions, but higher frequencies can also be measured. Whilst MEMS accelerometers can provide the form factor required for integration into tooling at lower costs, they are susceptible to noise at high frequencies. In the absence of machining-specific sensors, off the shelf generic sensors have been used by various researchers which often limits the frequency and bandwidth range.

AE sensors are capable of measuring frequencies up to a few MHz. The high frequency range that can be detected by AE sensors provides detailed information about tool wear condition and workpiece surface integrity. Furthermore, AE signal can be filtered to attenuate the frequencies induced by machine tool and environmental noise. However, the high frequency range requires a high sampling rate, which increases the data acquisition cost. Also, high computational times required to process large datasets collected from the sensor which can hinder its use in real time applications [167].

4. Sensor integration out of the tool

In practice, the cutting forces act on the entire workpiece-tool-machine tool system. Therefore, the process forces and vibrations can be sensed and measured in places other than the cutting edge. The key issue is the appropriate balancing between the sensor stiffness, the overall system stiffness, the optimal measurement sensitivity of the sensor and the tolerable level of noise. Sensors have been integrated into various elements of machine tools, such as the spindle, structure, linear guideway carriage, workpiece fixture, workpiece, and pallet. The measured signal is processed and used for a machining process monitoring or as an input signal for an actuator to achieve a corrective activity. Sensory systems have been used for force monitoring, vibration monitoring, tool or workpiece deflection estimation, and surface quality estimation. An overview of sensory components and corrective actions is provided by Möhring et al. [122].

4.1. Sensory spindles

The spindle is a machine tool component that is tightly coupled to the cutting process. It is also the main source of power for the cutting process, and its high stiffness and high precision make it an ideal choice for sensor integration. A preferred sensor placement is the mechanical connection between the spindle housing and spindle body. One of the pioneers in integrating sensors in the machine tool spindle is Jan Jeppsson of Boeing [168]. Jeppsson integrated strain gauges on the casing of a spindle in order to measure and control the bending of the cutting tool [169]. Altintas and Park [170] integrated a Kistler force sensor into a spindle (Fig. 28) to measure cutting forces up to 300 Hz with an enhanced sensor bandwidth of 50–1000 Hz due to signal dynamic compensation using the disturbance Kalman filter. In the Adaptronic spindle system, AdSpin, presented by Denkena [171] and Will [172], piezoelectric force sensors were integrated in the spindle mount as illustrated in Fig. 29. The spindle front end was supported with three piezo actuators in a parallel kinematic configuration arranged around a conventional design milling spindle. The sensor-actuator system provided dynamic positioning of the spindle end with a frequency up to 2000 Hz and a range of $\pm$ 0.1 mm. This enabled active stabilization of the machining process [173].

A spindle with an integrated displacement sensor was presented by Brecher [174], which is shown in Fig. 30. The spindle has an integrated sensory ring with eddy current sensors measuring the radial and axial displacement of the spindle shaft front end against the spindle housing. The deflection signal was conditioned before the cutting force was calculated. The run-out errors and static and kinematic deviations were synchronized with the rotary encoder signal for correction of the displacement signal. Finally, the spatial position of the spindle shaft was multiplied by the frequency response function (FRF) identified for force excitation at the end of the shaft and response on the sensory ring. The system was applied for virtual workpiece quality estimation and was validated by comparison with CMM part measurements after machining operation.

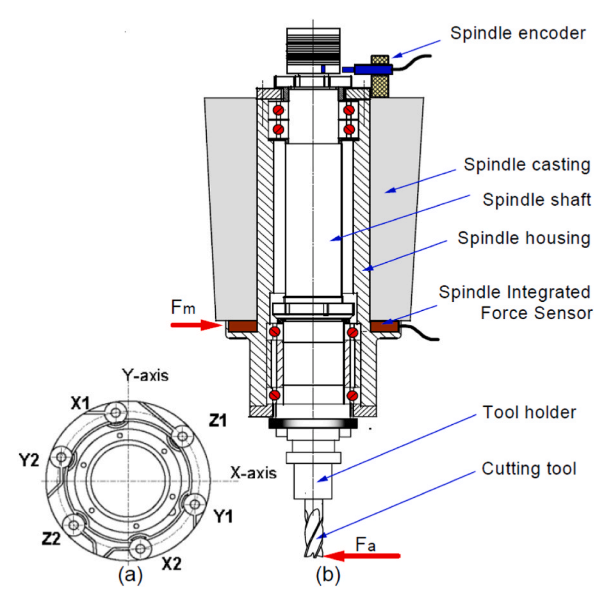

Fig. 28. Assembly of the force sensors between the spindle and the spindle stock: (a) top view, (b) schematic cross section [170].

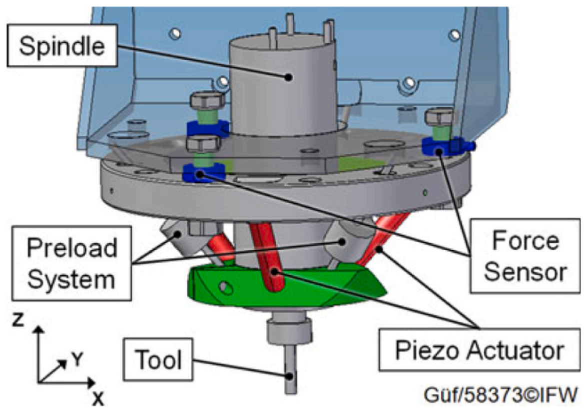

Fig. 29. Adaptronic spindle system (AdSpin) [173].

4.2. Structure bodies with integrated sensors

Cutting forces and vibrations can also be detected away from the cutting zone on the machine tool structure. One such method is to use strain gauges to measure the deflection of the machine tool's structure. As with sensor integrated tools, the key issue for strain gauge application is the trade-off between sensitivity and structure stiffness. Denkena et al. [175] presented miniature strain sensors attached in small notches on the Z-slide body of a machine tool located in four positions (P) as shown in Fig. 31. These notches had little influence on the body stiffness. Laser structured strain gauges (L-SG) and micro strain gauges (μ-SG) based on a flexible polymer substrate were tested. After calibration, the sensors could also be used for vibration measurement. The maximum sampling frequency was limited to 500 Hz and the measurement range was up to 200 Hz. This technology was used for detection of the tool deflection in 2.5D milling [139,176].

The same approach was also used to design "the feeling lathe turret" by Bergmann and Witt [177]. Finite element (FE) structural sensitivity analysis was used to identify optimal sensor positions [139,177]. Krampert et al. [178] presented force measurement using the carriage of the linear guideways. The measurement was based on the piezoresistive diamond like carbon (DLC) coating called DiaForce®. The sensory coating is placed on the steel inlay integrated to the carriage. The rolling elements ran directly over this inlay as shown in Fig. 32. Whilst sensor integration into the machine tool's structure can broadly eradicates the issues such as form factor, wiring and data collection associated with sensor integrated tools, it is achieved at the expense of lower signal to noise ratio and the data can be skewed due to wider environmental conditions.

4.3. Sensory workpiece fixture

The workpiece fixture provides another possibility for sensor integration. The goal is to locate a sensor as close to the cutting process as possible for high fidelity monitoring. Strain gauges, accelerometers and AE sensors have been investigated. Denkena et al. [179] presented a study of dynamic multi-sensor systems. They demonstrated the need for a combined system to provide a high measurement frequency range. Strain gauges have higher sensitivity in lower frequency ranges whilst

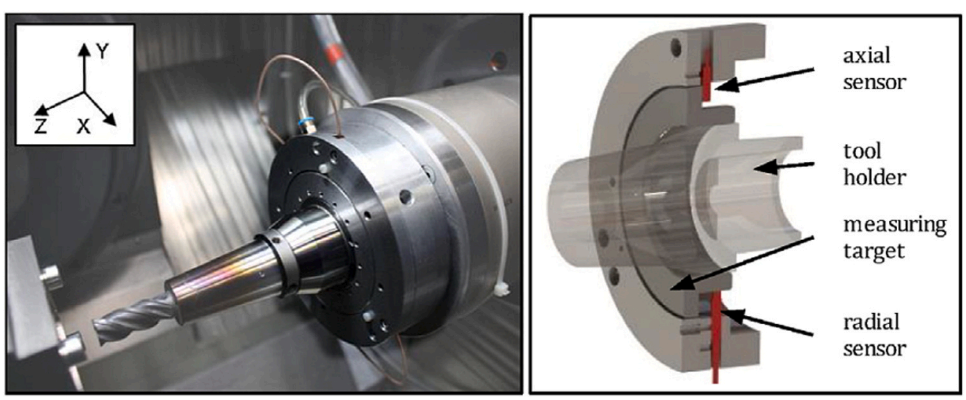

Fig. 30. Integration of the sensory ring with eddy current sensors into the electrospindle design [174].

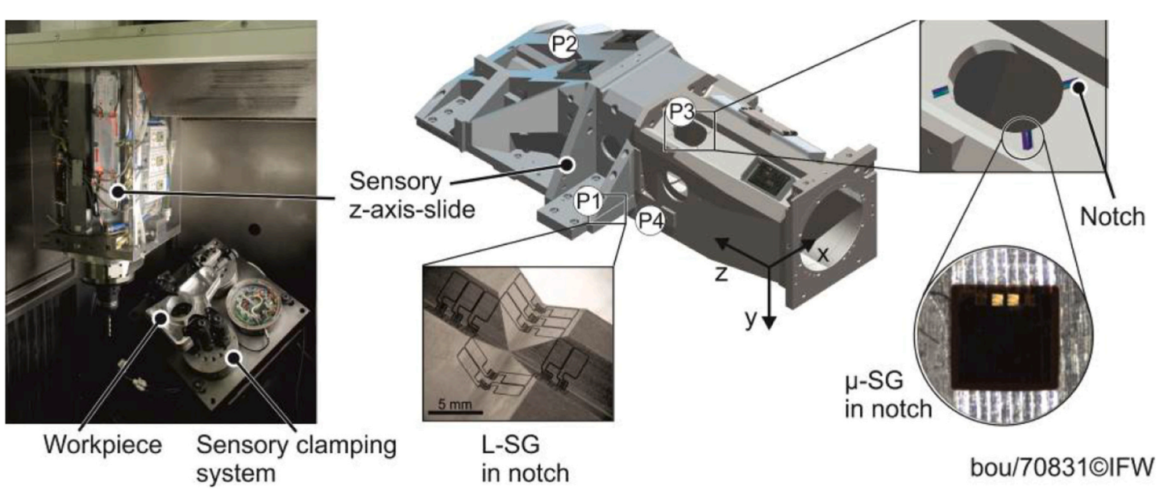

Fig. 31. Example of the Z-slide of a vertical milling centre with integrated strain gauges located in four positions (P) [175].

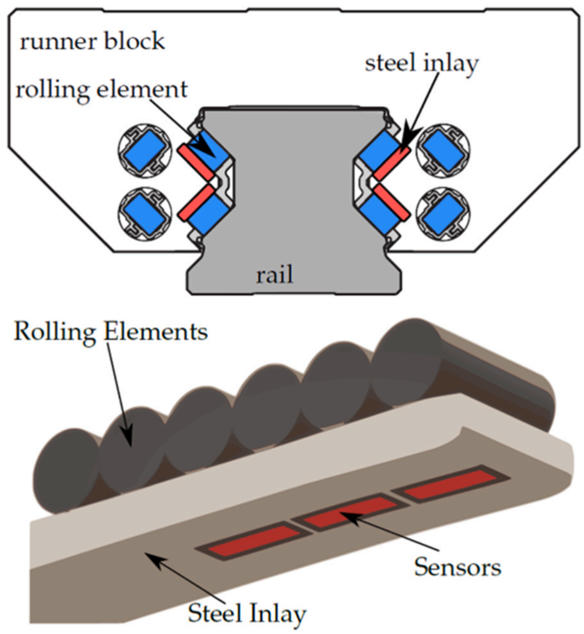

Fig. 32. Position of steel inlays (red) below the rolling elements (blue) inside the linear guideway carriage and sketch of the sensor position on the steel inlay [178].

accelerometers are more sensitive in higher frequency ranges. The authors proposed integration of the strain gauges and accelerometer sensor in the fixture clamping system and the supporting pin as shown in Fig. 33.

This system, when combined with an adaptive spindle system, offers self-calibration ability [180]. The sensor signal fusion is based on Kalman filters. Two calibration approaches are possible. The "calibration by colliding" approach is based on the spindle smooth movement against the workpiece and measurement of the contact force with both systems: spindle and fixture. The measurement is done at multiple workpiece positions and machine directions. The sensor transfer matrix is then

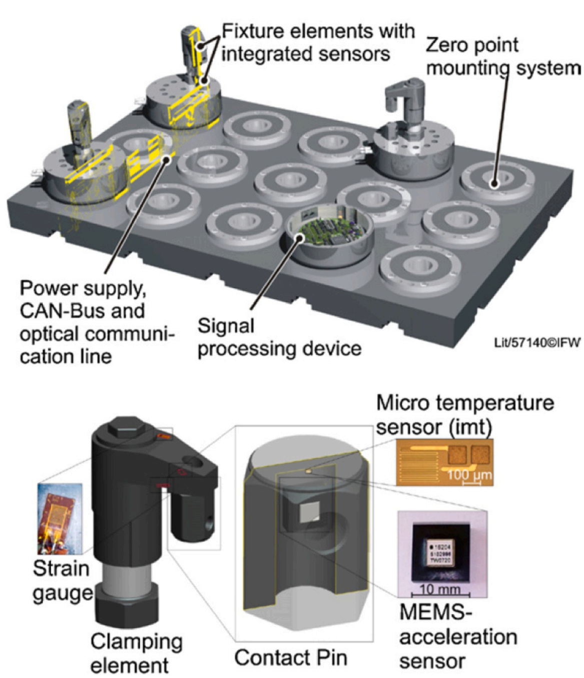

Fig. 33. Sensory fixture with strain gauges and MEMS accelerometer integrated in the clamping element [180].

calculated by least squares regression analysis. The "in-process calibration" approach is based on the system excitation by the process force. The machining is done for a set of cutting conditions in various system directions. The reference signal is measured by the spindle. Using this reference, the dynamic forces measured on the fixture are identified.

4.4. Sensory pallets for workpiece clamping

The workpiece pallet is an ideal machine tool component for sensor integration. The instrumented pallet can replace the existing non-sensory pallet if the same clamping interface is used. Therefore, integration into the machine tool is not invasive. In addition, pallets are large, stiff bodies enabling integration of sensors as well as actuators for corrective measures. Essentially, conventional plate dynamometers can be seen as sensory pallets. Rashid and Nicolescu [181] presented a pallet with integrated active vibration control shown in Fig. 34. The vibration was detected by a piezoelectric force sensor and used as an input for an actuator which provided corrective vibrations. A similar integrated sensor and actuator was presented by Möhring and Wiederkehr [182] for a rotational active chuck used in the production of blisks.

4.5. Additional sensors for workpiece implementation

Thermocouples and acceleration sensors have been integrated into workpiece by researchers to measure cutting temperatures and vibrations during machining. The application of thermocouples often requires drilling housing holes into the workpiece [183]. In production, this can add unnecessary operations or even damage the part [184]. In contrast, accelerometers can be surface mounted on the workpiece using adhesives that can be removed after machining. Nevertheless, they add to the setup time. Denkena et al. [185] proposed integrating a low-cost strain gauges into the workpiece to measure thermal and mechanical load on the workpiece during machining, shown in Fig. 35. The sensing system can be based on one or more sensors that communicate within a network. This method requires optimal sensor placement in the part to ensure the viability of the measurements. The advantage is that the workpiece becomes an active unit enabling process monitoring on multiple machining centres. Consideration of the machining processes at the design stage and if the sensors can be part of the component in operation or if they need to be removed after manufacturing should also be taken into account.

5. Machine tool as a sensor

Machine tools can be used as a force sensor using the control system data. Force monitoring can be realised by reading signals from numerical control units (NCUs), whose working frequency is about 1000 Hz

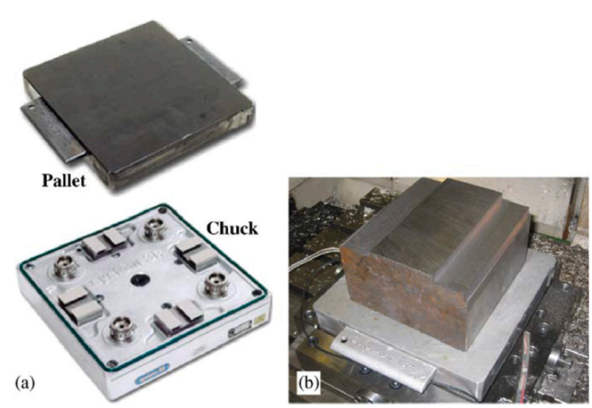

Fig. 34. Sensory pallet with active vibration avoidance: a) the pallet (upper), chuck permanently fixed a machine table (lower); b) the pallet system equipped with a steel workpiece [181].

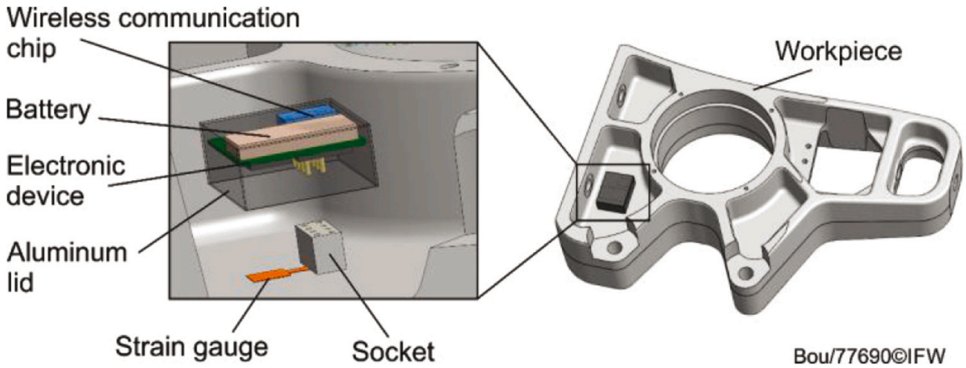

Fig. 35. Concept of the low-cost sensor for integration to the workpiece [185].

(integrated control loops can reach higher frequencies). The producers of CNC controllers such as Siemens, Fanuc, Heidenhain, etc. offer individual solutions and tools for direct reading of the control system data. Having access to the main variables per movement axis and spindle allows for analysing the drive load, drive positions set value, and drive position actual value. The drive load value is obtained from the drive current signal and includes passive forces, dynamic forces, and process forces. The drive load acquired during constant machining conditions (constant feed, constant engagement, constant cutting speed) is used to identify the baseline data for a specific drive. It is used to determine in-process data for varying working conditions. The drive position actual value defines the true tool centre position where the specific drive loads occur. The difference between the position set value and the position actual value determines the workpiece dynamic shape error caused by the feedback loop control of the axes' movements. The combination of these signals acquired from the machine tool control system enables estimation of the cutting forces loading the machine tool structure including its drives and drive feed loop control.

The spindle current signal is directly dependent on the cutting process torque and tangential cutting force. The segregation of the cutting and passive torque has to be identified before the spindle is used as a measuring device. Dunwoody [186] proposed a procedure for indirect identification of tangential cutting force coefficients from the spindle cutting torque by estimating the spindle torque as being linearly proportional to the spindle drive current. The power losses of the spindle motor current are measured during air cutting. The overall method is simple and effective. However, it neglects other potential power losses during machining such as the friction losses of the bearings depending on spindle speed and load. Aggarwal et al. [187] presented a detailed analysis of the spindle power losses composed of various components of the mechanical losses (load-related friction in spindle bearings, spin-related friction, friction due to lubricant viscosity, and windage friction) and the electrical losses (rotor and stator copper loss, iron loss, and stray losses) as shown in Fig. 36. The cutting torque is calculated as the difference between the total measured torque and the power losses estimated by the model. The cutting and edge components of the specific tangential cutting force are calculated using a mechanistic cutting force model based on measured data acquired during milling with multiple feed per tooth values. The analysis indicated that the losses increase with the spindle speed and can reach up to 20% of the spindle power consumption.

Janota et al. [188] presented a method for identification of the tangential component of the specific cutting force during milling. The specific cutting force value is calculated as a ratio between the machining power and the metal removal rate (MRR). The machining power is a difference between the spindle total power mean value and the spindle idle run mean value. The proposed method was tested with two cases where a good agreement with the reference dynamometer with an error of 5% was achieved. Kolar et al. [189] used this method for on-machine estimation of the specific cutting force as a part of semi-virtual testing of the machine tool usable spindle power.

In these methods, the mean value of the spindle current is used in order to avoid local deviations of the measured signal. There are also strategies for time-invariant identification of the cutting forces based on the machine tool drive inputs. Denkena et al. [190] compared the model-based approach with the method for reconstruction of process forces based on the drive current, position, velocity, and acceleration signal using long short-term memory neural network (LSTM). Compared to other artificial neural network (ANN) approaches, the LSTM approach is based on the machine tool data only without any further information on engagement condition. Fig. 37 demonstrates a comparison between the measured cutting forces and reconstructed forces using LSTM. Whilst the model shows potential for reconstructing cutting forces, further research is necessary to improve the accuracy of the results.

Using the model-based approach, tool deflection can be estimated using the machine tool data and the tool stiffness [191]. The system bending stiffness is measured using a so-called soft collision. The drive forces and the movement axis position are measured during multiple contacts between the workpiece and tool. The current difference between the idle run and collision run is used for system identification. The experiment results, presented in Fig. 38, show that the tool load can be identified from the drive signal using this approach. Based on this estimation, two correction approaches were successfully tested: feed override control and the position-based control for tool path correction in the direction perpendicular to the feed direction.

Machine tool data, including energy measurement, has been

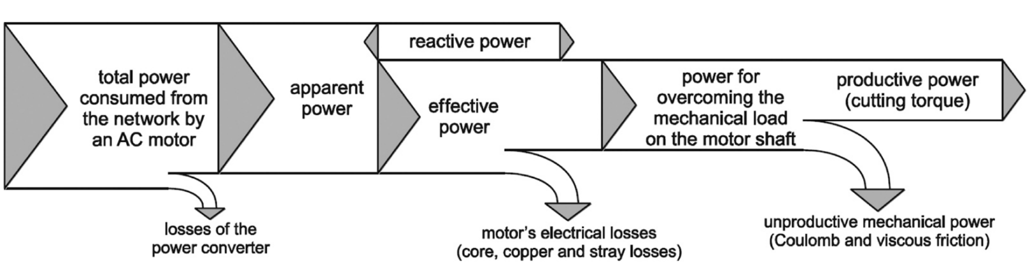

Fig. 36. Power flow in a motorized spindle – an overview of various types of power losses [187].

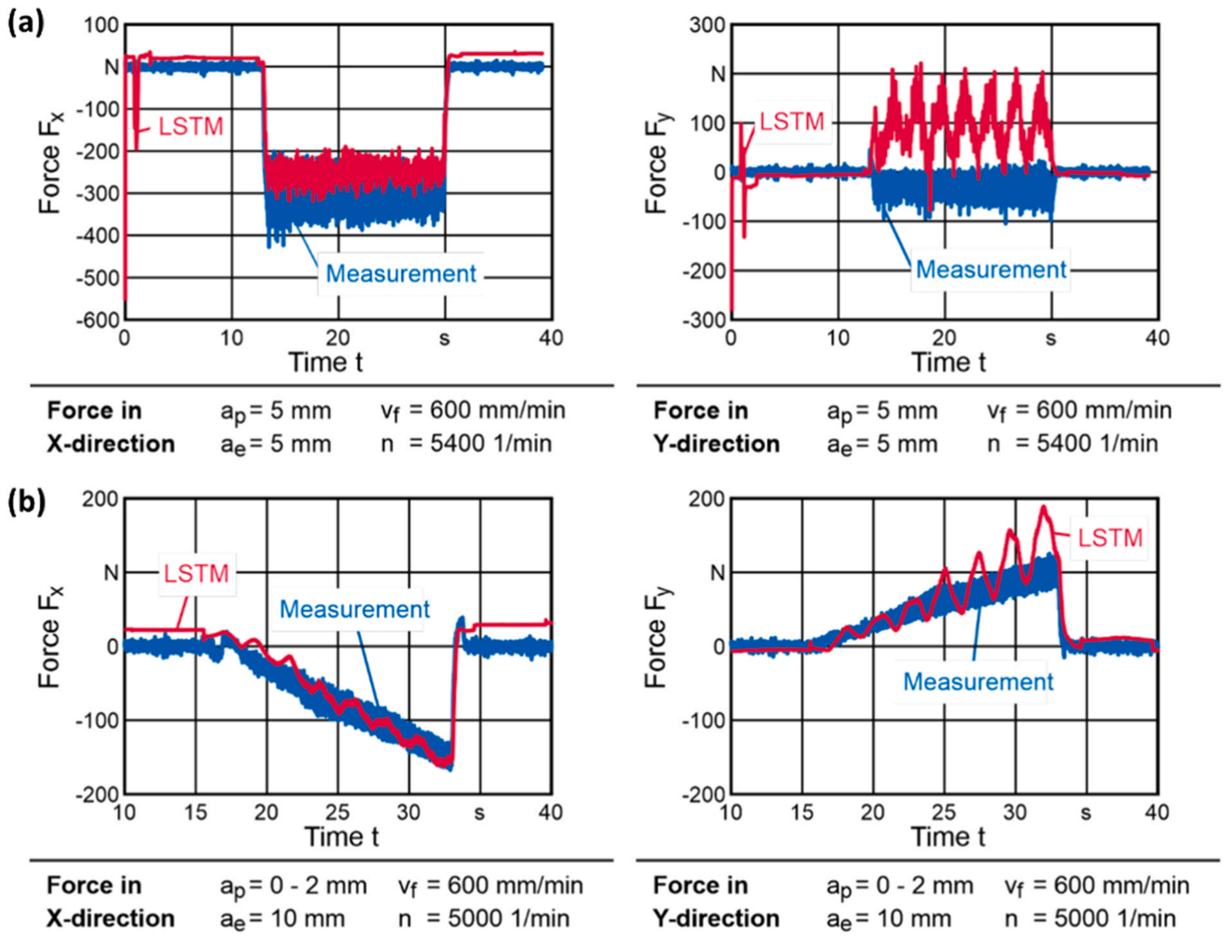

Fig. 37. Measured cutting forces in x and y direction against predicted values using LSTM for two machining scenarios: (a) side milling in negative X direction and (b) ramp milling in negative Y direction and positive Z direction.

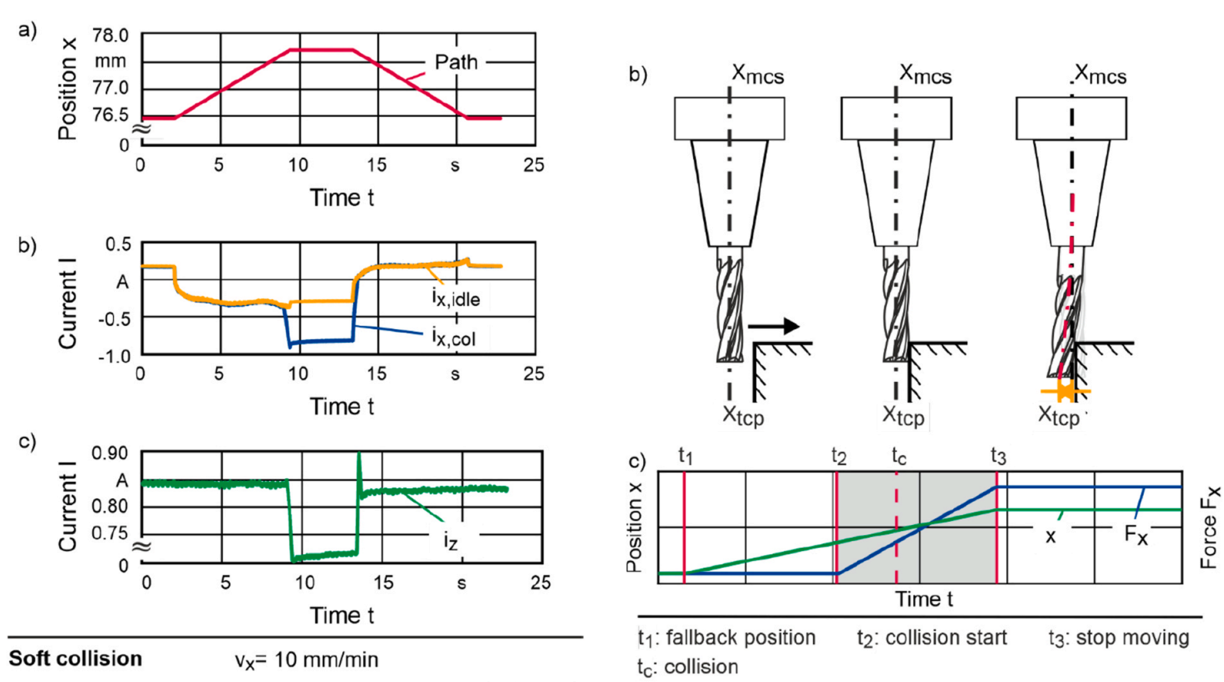

Fig. 38. Principle of the system stiffness identification using the drive current and axis position measurement [191].

investigated for tracking tool wear and part surface quality. Specific cutting energy controls chip formation and surface generation, which governs surface integrity of the machined part. An experimental study indicated that a decrease in process energy increases the surface roughness [192]. In a follow-up study [193], it was demonstrated that specific cutting energy could reflect the relationship between the internal thermomechanical loads and surface integrity, as shown in Fig. 39 [193]. Because the tool-wear-power profile-surface roughness relationships are nonlinear and not easily modelled analytically, a hybrid neural network structure was used to model the relationships between the tool wear, surface roughness and power consumption [194].

Whilst the aforementioned methods were solely based on the machine tool data, there is a possibility to combine them with material removal simulation models. Altintas and Aslan [195] and Aslan and Altintas [196] presented a method for time-domain machining process monitoring based on the machine tool drive currents and the virtual machining model. The cutting forces were predicted as linearly proportional to the measured drive currents. Kalman filters were used for compensation of the dynamic properties of the monitored feed axes. This system compensation allowed force monitoring bandwidth to be increased to 200 Hz. The system estimated the spatial components of the cutting forces after calibration. The cutting forces based on the machine tool monitored current signals were compared with the cutting forces calculated by the virtual model using the MACHpro Virtual Machining System [197]. Tool failure was identified if the deviation between the measured and simulated force was larger than a threshold value.

Hanel et al. [198,199] presented a method to determine cutting forces based on process planning data and process data acquired from the machine tool. Since the recorded data are used for offline processing, this method can be characterized as a post-process digital twin. Information on the tool centre point position was used for the material removal simulation. The tool engagement parameters were outputs from this simulation. The spindle passive torque was subtracted from the total spindle current signal using air cutting tests [186,187]. The corrected spindle signal and the simulated engagement parameters were used for calculation of the cutting force coefficients. These coefficients could be visualized along the tool path with period of 1 ms (based on the Siemens Edge device acquisition rate) for detailed workpiece quality control based on the acquired machine tool data. This is the so-called cyber-physical approach for predictive quality control used mainly for part production in demanding industries such as in the aerospace or space industries [200].

Schmucker et al. [201] presented a system architecture for process monitoring using the machine tool data. The machine tool used the real-time operating system Siemens 840Dsl. The edge computer (in this case, IPC Beckhoff C6640, with Windows 10 operating system, 32 GB RAM and Intel i7–7700 3.6 GHz processor) with a real-time operating system (Beckhoff TwinCAT3.1) was connected to the machine tool controller through a wired network connection (real-time Ethernet). This IPC provides a so-called inner control loop working with minimal time delay which is dedicated to time-critical tasks such as chatter detection, tool wear monitoring, and collision avoidance. The IPC integrates also inputs from external sensors with higher data acquisition frequency than the typical numerical control system (500 Hz to 2000 Hz). The data pre-processed by the edge computer were stored on the cloud for offline processing as illustrated in Fig. 40. The whole schema enabled real-time, on-line and off-line processing of the acquired data. Using this monitoring schema, Schmucker et al. [202,203] presented identification of the instantaneous cutting force coefficients using Bayesian optimisation and dexel-based process force simulation. Dynamic time warping (DTW) of the signal was used for comparison of both (measured and simulated) non-synchronized cutting force time series.

6. Power sources

Sensor integrated tools and tool holders incorporate sensors and components with the electric circuits (e.g., amplifier, signal conditioner, analogue-to-digital converter, data and power transmissions and data acquisition). It is necessary to supply the required power for these components without restricting the functionality of the tool/tool holder. Power transmission for sensor integrated tools and tool holders can be provided via wires, batteries, energy harvesters or wireless power transmission systems. Bleicher et al. [163] categorised power source systems for rotary tool holders into inductive power transfer, energy storage systems, energy harvesting and slip rings. However, they highlighted that the latter suffers from excessive wear during operation.

6.1. Wired

Wired power sources are convenient to implement. They have been mostly applied to supply energy for applications where sensors were mounted on a non-rotating component of the machine [106,159,161,204]. However, the harsh environment, the use of coolant/lubricant, and high voltages in machining operations can damage wire connections or have undesirable effects on the performance of the sensor-integrated tools/tool holders. Therefore, high-cost protection for the installation of wired connections could be required. Also, they are inapplicable for rotational tools or tool holders. Slip rings and brushed systems can provide an alternative to wired connections and can be employed for

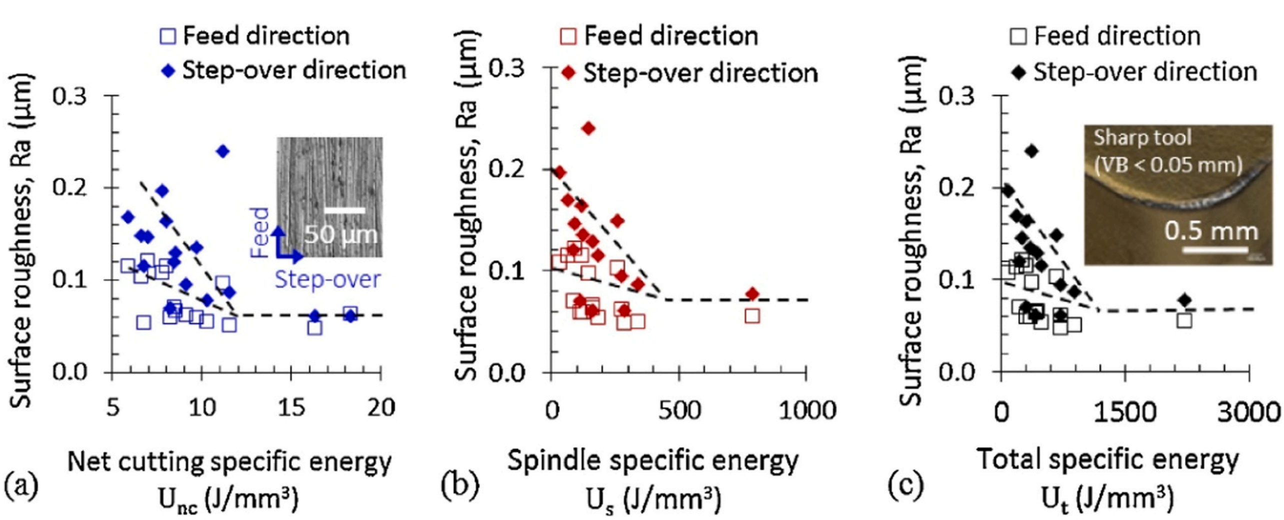

Fig. 39. Coherence of surface roughness with (a) specific cutting, (b) spindle, and (c) total specific energy by milling with a sharp tool (VB < 0.05 mm) [193].

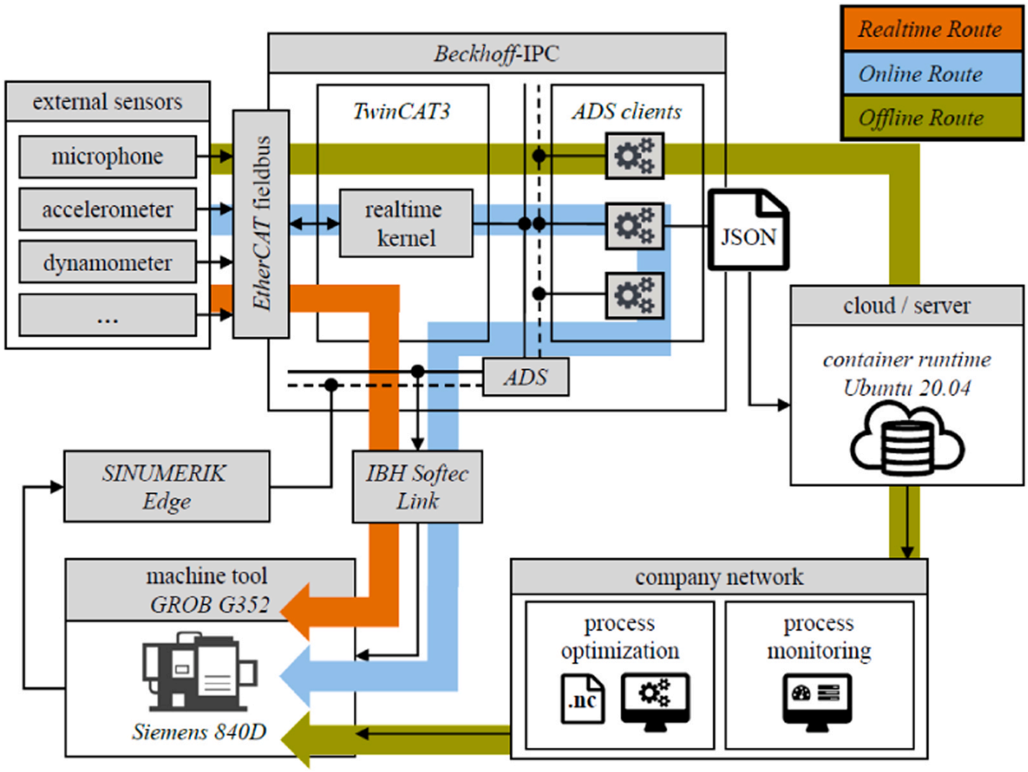

Fig. 40. Process monitoring and control platform with highlighted real-time, on-line and off-line processing routes [203].

non-stationary parts. Zhang et al. [130] utilised a high-speed slip ring for both data transmission and energy supply of a smart tool holder.

6.2. Batteries

Batteries require a wired connection from the energy source to the electrical circuit, but the energy source can be mounted on the rotating part. The batteries are commercially available in a wide range of energy density and capacity. Most researchers have used lithium-ion batteries to supply power to the electrical circuits and sensors [27,116,120,123]. They are generally mounted in the tool holder together with the electrical circuit/board. It has been reported that the operational time of the sensor integrated tool holder with batteries can reach more than 10 h [136] or even up to 17 h [123] depending on the power consumption of the electronics system and the battery capacity. However, they have a limited lifetime and, thus, replacement or charging operations are needed, which leads to interruption of the cutting operation. In addition, there are health and safety requirement specifically for Lithium based batteries. The major considerations beyond delivering the necessary voltage for selecting appropriate batteries for machining are the volumetric energy density and the life span of the batteries. Fig. 41 provides an overview of the volumetric and gravimetric energy density of different batteries.

6.3. Energy harvesters

Energy harvesters used in sensor integrated tools transform the mechanical energy in the form of vibration or rotation into the electrical energy. This energy can be used for the power supply of the electrical components. Ostasecivius et al. [206,207] employed piezoelectric transducers for energy harvesting from tool vibrations to charge a capacitor to supply power for wireless data transmission and auxiliary electronics. Moreover, the capacitor load rate was used for the evaluation of the TCM. The rotation of the spindle has more potential for energy harvesting than the tool vibration. Therefore, Chang and Lee [208] developed a sensing node whose power is supplied by rotation of the

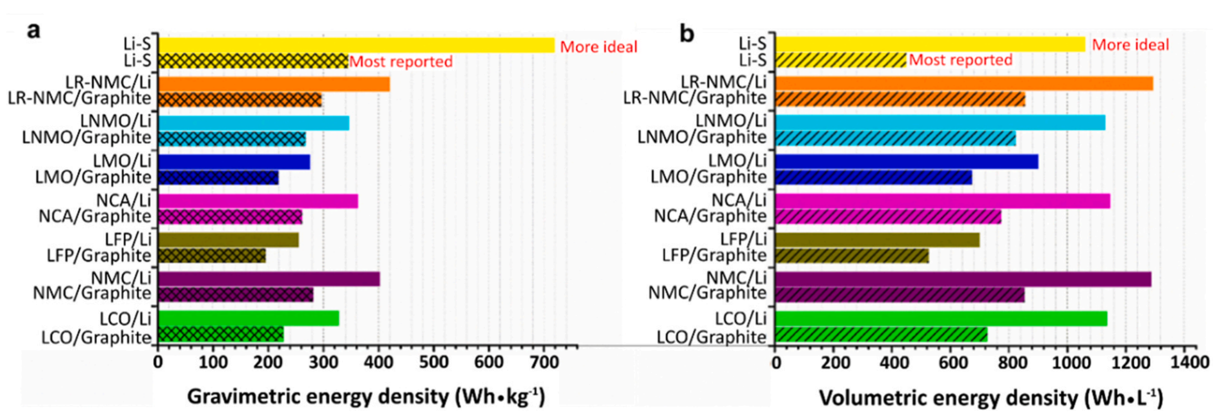

Fig. 41. a) Gravimetric and b) volumetric energy density of various batteries [205].

spindle. However, this method requires modifications to be made to the spindle. Chung et al. [209] proposed an electromagnetic energy harvester consisting of four permanent magnets on the spindle and inductance fixed to the machine to supply energy for the sensors and auxiliary systems at 1650 rpm and higher spindle speeds. However, the need for an external energy supplier to power the system for lower speed restricts the operational range of the energy harvester. Fuchs et al. [210] combined photovoltaic (PV) cells with a LiPo battery integrated with an energy management circuit for powering a sensory milling tool holder. The PV cells convert the ambient light into electrical energy which is stored in the LiPo battery.

6.4. Wireless power transmission

Wireless power transmission has frequently been employed to eliminate wired connections that are not applicable for non-stationary parts of the machine tool. Inductive coupling has been mostly employed to transfer the power to the electrical system (sensors and circuit) for rotating systems [3,28,129,164,211]. Totis et al. [3] used a telemetry system consisting of a rotor on the tool holder and a fixed stator to inductively supply the power as well as cutting force data transmission. Kerrigan et al. [164] employed a similar telemetry system which used an inductive power supply. Similarly, Rizal et al. [28,129] used inductive telemetry transmitter units for sensor integrated tool holders. Two transmit coils around the cover of the tool holder and two receive coils mounted on a nearby fixture were used. Due to the number of coils and the close placement of the static part to the tool holder, these telemetry units required a large volume. To reduce the system complexity, Zhu and Tao [211] developed a wireless transmission system where the power and data was transferred over a single pair of coils. However, the data transfer rate was low. To increase the wireless power transfer distance, Lee et al. [212] used an electromagnetic coupled resonance system on a rotating spindle. However, this technology has not been applied for the sensor-integrated tool holders. The use of inductive power transmission systems increases the likelihood of noise in the sensors and signal conditioning, transmission and acquisition systems.

Some researchers applied RFID technology to wirelessly supply the sensor power. Stoney et al. [155] used passive wireless SAW strain sensor whose energy was supplied via radio frequency signal. Drossel et al. [118] employed PZT thick film sensor under the cutting insert to measure the cutting forces. The power and data transmissions for the sensor were completed using RFID technology.

7. Data transfer and communication

The data made available by sensors integrated into either the tool/tool holder or off the tool is transferred to a data acquisition device (possibly being conditioned, amplified, or converted to digital signal) and is then transferred to a computer/laptop/microcontroller to be post-processed and/or stored. Depending on machining conditions and collected data properties (e.g., size and sampling rate), the data transfer method and communication can require special considerations.

7.1. Wired connection/coupling

Data transmission via wired connection are commonly used for relatively straightforward plug and play data acquisition applications. Kurfess et al. [213] described the seven layers of an Open Systems Interconnection (OSI) communication model [214,215], where the first, physical layer contains the electrical components of the network, such as the cable used for data transfer between the machine and the data acquisition device. The authors also pointed out that various communication protocols are used on analogue and digital data acquisition devices to collect data from sensors and communicate with edge devices through wired connections. This explains the second layer of an OSI model which deals with the different protocols by which data is shared within a network, such as Ethernet, point-to-point protocol (PPP), switch, etc.

Urbikain et al. [216] used Labview© to monitor machining processes and tool condition via data acquisition. The software also included simulation capabilities for teaching metal cutting mechanics using practical lessons. They used Bayonet Neill-Concelman (BNC) cables to connect their sensors and input/output (I/O) modules. However, wired connections for data transmission for sensors integrated into rotating tools/tool holders in milling and workpieces in turning are not applicable.

Multiple protocols and devices can coexist at the same physical interface at the same time. Modbus, an automation communication protocol, can communicate over several types of serial communication protocols such as RS232 and RS485. RS485 is an upgraded version of RS232, and is a communications bus for connecting multiple devices at once and transmitting at 10 Mbits/s, while RS232 is limited to 20 Kbits/s. RS485 allows a maximum cable length of 1219 m (4000 ft) and can handle up to 32 connected devices on a single multidrop network via wire couplings, while RS232 is limited to a maximum cable length of 15 m (50 ft) and a single device at a time. RS485 serial communications are also less susceptible to electrical noise than RS232 serial communications.

7.2. Wireless communication

Wireless communication technologies such as Bluetooth [217] and ZigBee [218] are commonly used in Internet of Things (IoT) applications for machining data acquisition and communication. Bluetooth's low energy requirement is preferable where battery management is important [213]. Choudhury et al. [219] proposed a data acquisition system that collects data from sensors to a control device through a ZigBee network capable of transmitting data as far as 100 m. The system then transferred the collected data from the control device to smart devices and computers through a Bluetooth network capable of transmitting data as far as 9 m (30 ft). Their ZigBee and Bluetooth networks operated at 9600 baud rate and 2.4 GHz frequency in the ISM (industrial, scientific, and medical) radio band. They used an Arduino microcontroller to measure data from various sensors for temperature, gas sensor, motion, and sound. While ZigBee has low power consumption, it is limited to 250 kbps data transfer rate. Higher data transmission rates of 1 Mbps and 2 Mbps can be achieved using Bluetooth low energy 4.2 (BLE4.2) and BLE5. However, the actual data transfer rate for sensor signals will be lower due to the protocol overheads and limitations, packet size and acknowledgement schemes, etc. [220].

Another option for wireless communication is Wi-Fi. It is based on a serial standard of IEEE 802.11 for time-sensitive networking capabilities that support low latency and ultra-reliability, thereby advancing IoT technologies [221]. Wi-Fi generally works in the 2.4 GHz and 5 GHz frequency bands and can achieve significantly higher data transfer rates than Bluetooth. Zhu et al. [27] developed a wireless sensor integrated tool holder as shown in Fig. 42. They used a STM32 microcontroller for data collection and a ESP8266 Wi-Fi microcontroller for transferring data. They reported that the system can achieve a maximum of 40 kHz sampling rate thanks to the use of Serial Peripheral Interface (SPI) protocol. Xing et al. [222] proposed a low-cost, vision-based monitoring system involving image processing, IoT, and cloud computational tools for monitoring the positioning performance of a five-axis CNC machine tool. Their system's hardware included a camera for capturing images and a Wi-Fi router for transferring the collected images to a computer or other smart devices via a Wi-Fi network. Multiple users of the machine tool could remotely access the collected data with their devices as long as they were connected to Wi-Fi and stayed in range of the signal. Nor and Yusof [223] conducted research on developing STEP-NC (Standard for the Exchange of Product model data for Numerical Control) communication and control of a machine tool using an Android

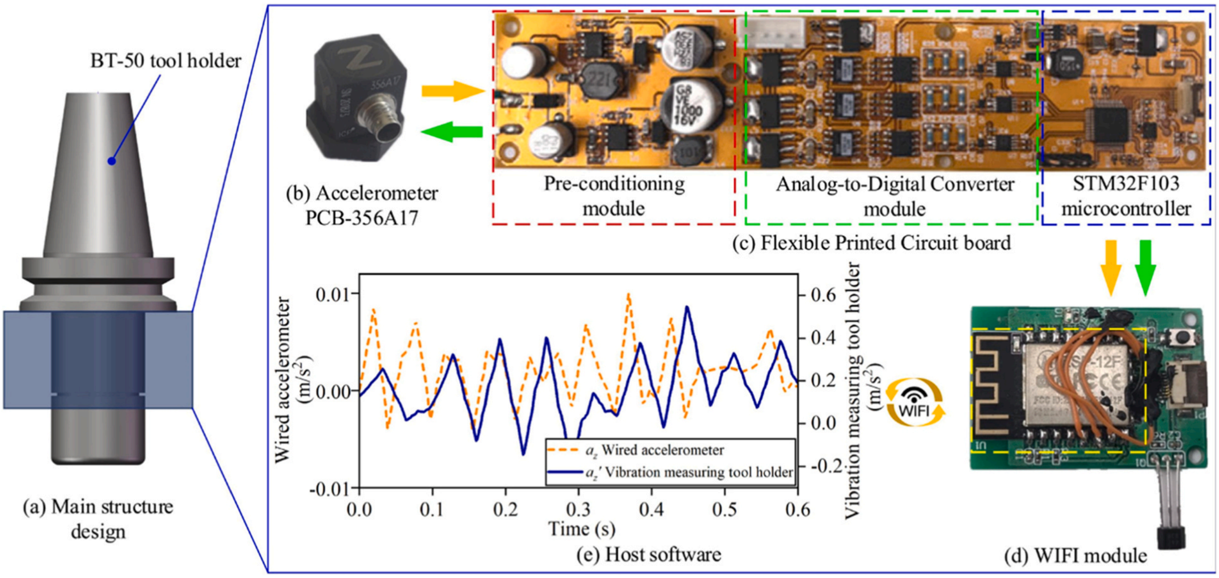

Fig. 42. Wireless communication for a tool holder using STM32F103 microcontroller and a WIFI module [27].

application via Wi-Fi communication.

LoRa is another alternative method that can be used for wireless data transmission. It is specifically suited for low power extra-long range data transmission [224]. However, its low data rate (up to 27 kbps) makes it only suitable for applications where low sampling rates are required [225]. Bleicher et al. [163]provides an overview of various wireless communication protocols that can potentially be used for wireless sensor systems in machining.

7.3. Inductive coupling

Data and power transmission can be provided via inductive couplings. For example, Hiraga et at. [226] described an approach to industrial manufacturing systems using inductive transmission of power and data for motion controls. They designed a system made up of a high frequency inverter for power transmission, a controller (programmable logic controller or numerical controller) for high speed data transmission, power converters, mount-on actuators, and associated drivers. These features comprised their "Integrated Power and Data Transmitting Unit (IPDTU)" or high frequency inductive coupler. Motion control and sensing were achieved rotationally, linearly, and in a separable attach-detach mode. Therefore, the inductive coupling performance was achieved based on the air gaps between the various coil cores in the rotatable unit, the linear unit, and the separable unit of the IPDTU.

Sanftl et al. [227] presented an approach for simultaneous inductive power transfer (IPT) and communication in one system, with the objective to transmit sensor data free of noise and error. They explained the concept of IPT, where power is transmitted from a primary to a secondary coil over an air gap. Their communication system was connected to a 20 W IPT system and featured digital signal processing operations implemented with 16 Bit fixed-point algorithms at a sampling rate of 64 kHz. It also featured 12 Bit A/D (analogue to digital) and D/A (digital to analogue) converters and achieved an optimum carrier frequency of 8 kHz from the coupling filter passband.

Mora et al. [228] presented a methodology for the design of an electro-spindle to be mounted on an anthropomorphic robot for milling operations. Using inductive displacement sensors integrated close to the spindle nose (front sensor location in Fig. 43) and close to the rear bearing unit (rear sensor location in Fig. 43), the spindle shaft deflection was measured to determine the cutting force.

8. Discussion, gaps and opportunities

This paper contributes to advancing sensor integration for machining process monitoring by offering a thorough examination of various sensors employed for on-machine and in-process monitoring of machining operations. The understanding obtained from this evaluation can aid in attaining increased productivity, reduced manufacturing costs, superior performance, and higher part quality within the machining industry by ultimately achieving adaptive machining. In addition, potential future research directions in sensor integration and optimisation of machining process have been highlighted.

Many companies, industries, organizations, and governments are involved in designing, defining, and promoting the next generation of digital manufacturing and enterprise capabilities associated with the Industry 4.0 concepts. The speed and variety of breakthroughs occurring

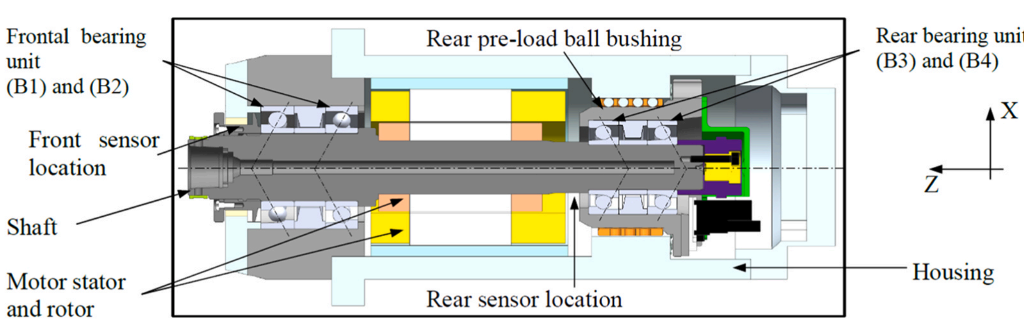

Fig. 43. Electro-spindle components (without tool and tool holder) [228].

are unprecedented and have a global impact. The goal is creating new strategies and methods for agile, connected, and robust manufacturing environments. The sharp cost reduction, variety, and availability of digital technologies over the last two decades has made it possible for companies to get a greater return on their investments and implement developments that would have been prohibitively expensive, or even technically impossible, before. One of the most rapidly growing trends associated with digital manufacturing is the use of monitoring and data collection systems that provide visibility and actionable information with respect to the machines and process condition. A key element of such systems are the sensors, technology residing at the edge, converting physical phenomena into measurable quantities that can be processed and used for decision making.

There have been many decades of research and development in applying sensors in machining towards the goal of autonomous machine tools capable of monitoring and controlling their movements but also the cutting condition. There are many sensors already incorporated into modern CNC machine tools. However, these sensors are targeted for monitoring and control of the movements and positioning of the machine tool components, as well as ensuring the health of the machine tool and safety of the users. This has led to the need for expert knowledge during the machining and costly post machining verification and validation of machined parts and surfaces. The lack of sensory systems within the machine tool for monitoring and controlling of the cutting performance has resulted in a large interest within the research and industry community for embedding additional sensor systems into machining processes. These have been mainly applied for monitoring the cutting tool condition [229,230], the surface integrity of the machined parts [46,231] and the geometric quality of the parts beyond machine tool positioning [232]. The investigations have shown that single quantity measurements cannot provide a complete monitoring system for machining condition. Different quantities can indicate a specific machining performance metric or detect specific anomalies during machining. For instance, while cutting forces/torque/power can indicate tool wear, they fail to distinguish chipping and flank wear or detect the surface roughness of the part. This necessitates the development of sensor networks for monitoring different machining performance parameters.

Various types of sensors have been used for measuring cutting forces, torque and temperatures, vibrations, acoustic emissions, power consumption, surface integrity, etc. in order to get an insight into the machining condition. In many instances, sensors are positioned away from the cutting location and represent an indirect method to determine the characteristics of a machining process. In an effort to increase accuracy and fidelity of the measurements, as well as to provide better input for the feedback control loops, sensors have been embedded in the cutting tool itself [113–124,164,165,166,233], in the tool holders [125–130], or in workpieces [179,180]. For similar reasons, critical machine tool subsystems such as the spindle [171,174], pallets [181], or fixtures [182] have been instrumented with sensors. There have also been efforts to exploit data from the existing sensors within the machine tools to provide high fidelity data necessary for monitoring cutting conditions [178,187].

Although, there are machining specific sensors available commercially, it has been found that they are mostly suitable for laboratory and research environments. On the other hand, while using low-cost off the shelf sensors can provide an insight into cutting performance, they often fail to provide the necessary bandwidth, response rate, and accuracy required for machining processes. The need for low-cost sensors fine-tuned for machining operations have been identified as a research gap which will require multidisciplinary research in the future. Correspondingly, research efforts in the developments of such sensors (with low cost) will benefit “smart manufacturing”, as it provides big data needed for decision-making via artificial intelligence algorithms. Quantum sensors have also been identified as a growing area of research with potential applications in machining processes [234,235]. Whilst optical systems based on photonics have been used for improving positioning accuracy and measuring 3D surfaces, there are further opportunities to enhance data collection from machining processes using these sensors.

Although most laboratory systems rely on wired connections for power and data transfer, wireless systems are increasingly required in order to enable wide industrial adoption. Given the high capital investments required in machining industries, wireless systems are favoured for retrofitting existing machine tools. This highlights the need for reliable wireless power and data transfer systems that can be readily integrated into machine tools. The majority of the existing systems rely on off the shelf electronics for data transfer and data acquisition. Given the high processing speed in machining operations and the need for integrating multiple sensors for monitoring and measuring various incidents during machining, lossless high sampling rate data transfer systems at scale are required. Existing systems currently can provide up to 10 kHz sampling rate on a single channel or 2.5 kHz in multi-channel systems such as the Spike and iTendo sensory tool holders. However, higher sampling rates may be required in case of higher cutting speeds and number of cutting edges. Embedded intelligence and edge devices as well as smart sensors can reduce the need for high fidelity data transfer. These technologies can pre-process the data prior to transfer, perform signal conditioning, and make decisions at the point of data collection. However, this has significant impact on the power consumption and form factor. These are specifically important for sensor integrated tools and tool holders with geometrical constraints. Transferring data wirelessly can also raise issues with data security which may require further considerations in terms of wireless protocols and frequencies used which can affect the data transfer rate.

Beyond sensors and data transfer, the issues of data collection, storage, security, processing and decision making should be resolved. Collecting high fidelity data at high sampling rate requires capabilities for safe storage of the data. High sampling rates also pose a challenge for real time processing and decision making and further investigations are necessary to realise sensor-based monitoring and control systems for on-machine and in-process systems. Table 1 summarises the research gaps identified in this paper and provides the future research direction in sensor integrated systems for machining.

The ultimate goal of using sensor for machining is to gain an insight into the machining condition that can be used for decision making and controlling the process for autonomous machining. Selecting appropriate sensors and collecting data is only the first step towards this goal. Sensor integration into machine tools or their components enables the utilisation of sensor-based modelling for predicting the machining behaviour, anomaly detection and decision-making in real time. Whilst analytical models are helpful in understanding the machining process, they fail to account for stochastic events during machining and variations in the material properties, and geometries. Acquiring data via sensory instrumentation and extracting useful features from the data enables decision making in real time based on the machining condition. Advanced signal processing techniques such as time, frequency and time-frequency methods combined with machine learning methods have proven to be able to predict various parameters during machining and detect anomalies and incidents. The detailed information regarding machining condition cannot be effectively extracted manually from a large amount of data collected from multiple sensors. Machine learning algorithms can be trained on machining data to predict machining performance and detect various incidents such as chipping of the tool or damage to the workpiece. Sensor data collection and machine learning models have shown to be capable of detecting tool wear and tool chipping as well as predicting part surface roughness in specific scenarios. Future work will need to focus on generalising these models and integration into machine tool controllers. Detecting and predicting the machining performance would not be sufficient for achieving autonomous machining. In effect, expert users would still be required to make decisions, process plan the parts and select the cutting parameters.

Table 1
Summary of research gaps and opportunities for sensor integration for on-machine and in-process monitoring of machining.

Research Gap	Future Directions
Sensors' precision and reliability	Development of advanced sensor technologies with increased precision and reliability Investigation of environmental factors' impact on sensor performance such as temperature and vibration effects in harsh machining environments Sensors with wide/adjustable frequency band suitable for monitoring machining
Data processing and transfer	Integration of edge devices such as FPGA for pre-processing data and decision making on the edge Advanced signal processing approaches and artificial intelligence methods to maximise the utilisation of collected data and decision-making Real-time monitoring methods with emphasis on low-computational algorithms and hardware Seamless and lossless data transfer and processing hardware and protocols
Sensor integration	Miniaturisation of sensors Smart machine tool components with embedded sensors Formulating sensor locations for improved accuracy and performance Smart parts: Integrated sensors in the parts with functional application during machining as well as in service
Power supply	Energy harvesting technologies to power sensors and other devices Wireless energy transmission New battery technologies and structural batteries with improved the lifespan

Multi-objective optimisation methods can be beneficial in decision making where optimising one parameter may lead to deterioration of another, such as trade-offs between cutting speed and tool life or productivity and surface integrity. Further developments in sensor data collection, intelligent data processing, machine tool control, process planning and CAM and the integration of these systems is required for successful implementation of adaptive machining in which the machine tool can predict machining condition and adapt the cutting parameters and process plan to ensure part quality and productivity.

9. Summary

This paper provided a comprehensive review of the state of the art in the types and application of sensors for monitoring of cutting performance in machining processes. The sensors have been classified into the type of variables that they can measure in the context of machining: force, torque, power, vibrations, acoustic emissions, temperature, surface and subsurface properties and part geometry. These can be further divided into direct and indirect methods where the parameter measured is correlated to a cutting performance metrics such as tool wear or surface integrity. It has been shown that a network of different sensors collecting different quantities are necessary in order to monitor various machining performance metrices. Generally, the sensors can be positioned on the workpiece, integrated into the cutting tool assembly, integrated into the work holding system or on the critical components of the machine tool. Additionally, data can be collected from the machine tool controller such as the spindle power or the electrical current and voltage used for operating the machine tool. The sensors can be also integrated into the cutting tool and tool holder where the signal-to-noise ratio is higher providing a better insight into the machining condition. As a result, sensor integrated tools and tool holders has received significant attention in recent years. The major limitations for sensor integrated tool holders are due to the form factor requirements for the sensors, data processing units and data transmission systems. This has limited the types of sensors used, the processing capabilities within the tool/tool holder and the sampling rate from the sensors. As such, no *smart* cutting tools or tool holders exists that can perform substantial data processing or decision making within the tool.

Once the data is collected, it needs to be transferred for further processing. Various wired and wireless data transfer systems have been identified and reviewed. There is an increasing need for zreliable lossless wireless data transfer and acquisition systems within industrial systems. Specifically for machining, systems with high sampling rates are necessary to enable real time monitoring and decision making in order to be able to predict machining performance and prevent costly damages to the workpiece, cutting tool and the machine tool. The data collected from sensors can be potentially correlated with various machining performance parameters such as tool wear, cutting forces, workpiece surface integrity and geometry. Machine learning algorithms and multi-objective optimisation methods are best suited for processing a large amount of data collected from multiple sensors in order to achieve real time data analysis and decision making during machining.

CRediT authorship contribution statement

Alborz Shokrani: Conceptualization, Formal analysis, Data curation, Methodology, Investigation, Project administration, Visualization, Supervision, Writing – review & editing, Writing – original draft. **Hakan Dogan:** Formal analysis, Data curation, Methodology, Investigation, Visualization, Validation, Software, Writing – original draft, Writing – review & editing. **David Burian:** Formal analysis, Data curation, Methodology, Investigation, Visualization, Validation, Software, Writing – original draft, Writing – review & editing. **Tobechukwu D. Nwabueze:** Formal analysis, Data curation, Methodology, Investigation, Visualization, Validation, Software, Writing – original draft, Writing – review & editing. **Petr Kolar:** Formal analysis, Data curation, Methodology, Resources, Investigation, Visualization, Validation, Software, Writing – original draft, Writing – review & editing. **Zhirong Liao:** Formal analysis, Data curation, Methodology, Investigation, Visualization, Validation, Software, Writing – original draft, Writing – review & editing. **Roberto Teti:** Writing – review & editing. **Peng Wang:** Methodology, Investigation, Writing – original draft. **Radu Pavel:** Conceptualization, Formal analysis, Data curation, Methodology, Investigation, Resources, Visualization, Validation, Software, Writing – review & editing, Writing – original draft. **Ahmad Sadek:** Formal analysis, Investigation, Data curation, visualisation, Writing – original draft. **Tony Schmitz:** Formal analysis, Data curation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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