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Advanced monitoring of machining operations

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ABSTRACT

CIRP has had a long history of research and publication on the development and implementation of sensor monitoring of machining operations including tool condition monitoring, unmanned machining, process control and, more recently, advanced topics in machining monitoring, innovative signal processing, sensor fusion and related applications. This keynote follows a recent update of the literature on tool condition monitoring and documents the work of the cutting scientific technical committee in CIRP. The paper reviews the past contributions of CIRP in these areas and provides an up-to-date comprehensive survey of sensor technologies, signal processing, and decision making strategies for process monitoring. Application examples to industrial processes including reconfigurable sensor systems are reported. Future challenges and trends in sensor based machining operation monitoring are presented.

1. Introduction

Previous comprehensive surveys published by CIRP on the subject of sensor monitoring of machining operations were by Micheletti et al., in 1976 [1], on tool wear monitoring in metal cutting; Tlusty and Andrews [2], in 1983, on sensors for unmanned machining; Tönshoff et al. [3], in 1988, covering monitoring and control; Byrne et al. [4], in 1995, as an issue of the activities of the CIRP STC-C Working Group on Tool Condition Monitoring (TCM WG). A further issue of the TCM WG was the publication of "A Review of Tool Condition Monitoring Literature Data Base" by Teti et al. [5] that was updated in 2006 with 500 new publications in the time frame 1996–2006 to comprise >1000 classified references. This 2010 CIRP STC-C Keynote Paper on Advanced Monitoring of Machining Operations has been developed on the basis of a large number of contributions by CIRP members, non-CIRP researchers and CIRP Annals papers review, emphasising the continuance and expansion of the CIRP interest in this highly innovative production engineering research area.

The typical machining process monitoring system operates according to the following rationale. In the cutting region there are several process variables, such as cutting forces, vibrations, acoustic emission, noise, temperature, surface finish, etc., that are influenced by the cutting tool state and the material removal process conditions. The variables that are prospectively effective for machining process monitoring can be measured by the application of appropriate physical sensors. Signals detected by these sensors are subjected to analogue and digital signal conditioning and processing with the aim to generate functional signal features correlated (at least potentially) with tool state and/or process conditions. Sensor signal features are then fed to and evaluated by cognitive decision making support systems for the final diagnosis. This can be communicated to the human operator or fed to the machine tool numerical controller in order to suggest or execute appropriate adaptive/corrective actions.

The sequence of activities in sensor monitoring of machining process conditions can be surmised as follows (in parenthesis: paper sections where they are dealt with): process variables → sensorial perception (Sections 2 and 3) → data processing and feature extraction (Section 4) → cognitive decision making (Section 6) → action (Sections 5, 7 and 8).

2. History of sensorial perception and knowledge acquisition

In the cognitive sciences, sensorial perception is the process of attaining awareness or understanding of sensory information. It is a task far more complex than was imagined in the '50s–19s', when it was predicted that building perceiving machines would take about a decade, a goal which is still very far from fruition.

2.1. Historical/philosophical background of sensorial perception

Since the times of early ancient Greek philosophy, a number of interesting considerations concerning Sensorial Perception (SP), knowledge achievement and truth identification have emerged. The diverse concepts, views and theories regarding SP and knowledge acquisition may be grouped into a few categories that, along with the predominant cultural tendency in the course of epochs, attribute to SP a higher or lower role (Table 1).

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Table 1
Concepts of sensorial perception (SP) and its role in knowledge acquisition and truth identification during the different epochs.

SP role	Authors of concepts/theories of SP in the course of epochs
Trivial, minor or no value	Heraclitus (535–475 B.C.); Parmenides (515–450 B.C.) and the Eleatics; Pyrrho (360–320 B.C.) and the Sceptics
Initiates cognition	Empedocles (490–430 B.C.); Democritus (460–370 B.C.) and the Atomists
Supports cognition	Plato (427–347 B.C.); Plotinus (205–270 A.D.); St. Augustine (354–430 A.D.); Hegel (1770–1831) and the Idealists
Indispensible for cognition	Aristotle (384–322 B.C.); St. Thomas Aquinas (1221–1274); Ockam (1280–1349); Spinoza (1632–1677); Leibniz (1646–1716); Locke (1632–1704) and the Empyrists; Kant (1724–1804); Peirce (1839–1914) and the Pragmatists
Basis of all knowledge acquisition	Epicurus (341–270 B.C.); Zeno (334–262 B.C.) and the Stoics; L. da Vinci (1452–1519); Telesio (1509–1588); Galilei (1564–1642); F. Bacon (1561–1626); Newton (1642–1727); Descartes (1596–1650) and the theory of passive perception; Condillac (1714–1780) and the Sensists; Stuart Mill (1806–1873), Comte (1798–1857) and the Positivists
Continuous adaptation of sensing to environment	Darwin (1809–1882), Avenarius (1843–1900), Mach (1838–1916) and the Empiriocriticists; Dewey (1859–1952) and the Instrumentalists; Bergson (1859–1941); Gregory [6–8] and the theory of active perception

2.2. Modern theories of sensorial perception

Passive perception, initially conceived by R. Descartes and surmised as a "static" sequence of events: surrounding → input (senses) → processing (brain) → output (reaction), is still supported by mainstream philosophers, psychologists, neurologists and scientists. However, it is a theory nowadays largely losing momentum. The theory of active perception has emerged from extensive research of sensory misapprehensions, most notably the works of Gregory [6,7]. This theory, which is increasingly gaining experimental support, can be surmised as the "dynamic" relationship between description (in the brain) ↔ senses ↔ surrounding, all of which holds true to the linear concept of experience. For more information on the implications of active perception theory for science and technology see [8].

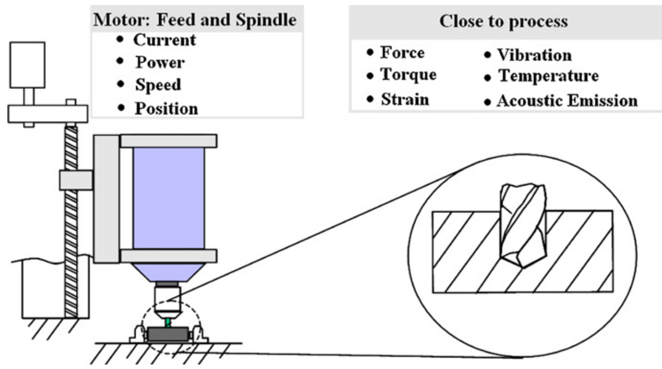

Fig. 1. Measurable phenomena for online sensor monitoring.

3. Sensors and sensor systems for machining

The measuring techniques for the monitoring of machining operations have traditionally been categorised into two approaches: direct and indirect. In the direct approach the actual quantity of the variable, e.g. tool wear, is measured. Examples of direct measurement in this case are the use of cameras for visual inspection, radioactive isotopes, laser beams, and electrical resistance. Many direct methods can only be used as laboratory techniques. This is largely due to the practical limitations caused by access problems during machining, illumination and the use of cutting fluid. However, direct measurement has a high degree of accuracy and has been employed extensively in research laboratories to support the investigations of fundamental measurable phenomena during machining processes.

Through indirect measurement approaches, auxiliary quantities such as the cutting force components can be measured. The actual quantity is subsequently deduced via empirically determined correlations. Indirect methods are less accurate than direct ones but are also less complex and more suitable for practical applications. In contrast to the traditional detection of tool conditions, the approach is that machining processes are being continuously monitored via sensing devices to quantify the process performance or provide information for process optimisation using sensors. Sensors that are commonly used for online measurement are summarised in Fig. 1.

3.1. Motor power and current

Electric drives and spindles provide the mechanical force necessary to remove material from the part. By the measurement of motor related parameters such as motor power or current, both process power and, more recently, measures of the machine tool and drive condition can be realised. The major advantage of motor related parameters to detect malfunctions in the cutting process is that the measurement apparatus does not disturb the machining. The capacity to measure power already exists in the drive controller as part of the drive control loop or can be readily retrofitted and is suitable for use in production environments [4].

3.1.1. Power and current measurement technology

Retrofit power measurement solutions are an economical monitoring solution for many machining operations. However, the latest modern open control systems allow access to internal signals in the numerical controller such as motor power and motor current [9]. Software can be seamlessly integrated into the CNC control and provides the user with a dedicated monitoring interface via the Human Machine Interface (HMI) [10]. Over the last decade, this technology has become commonplace in industry. A logical extension of this approach is the adaption of control parameters based on internal control signals. Adaptive Control Optimise (ACO) and Adaptive Control Constraint (ACC) based algorithms have been developed and implemented using both internal control signals and additional sensors [11,12]. An emerging and interesting direction for power monitoring research is to undertake the monitoring directly in the drive control (Fig. 2). Pritschow and Kramer [13] proposed a methodology for increased openness in drive controls demonstrating high quality signal information for process and drive condition monitoring. Systems based on power measurement technology have been applied in production, but there are ongoing requirements to investigate the sensitivity of internal signals and the compensation for drive characteristics: e.g. the motor and drive train dynamics are determined and removed from the power and current signals [14,15].

3.1.2. Power monitoring signal features

Motor current and power sensing use the motor itself as an indirect sensor of cutting force. Thus, when using sensor systems based on motor current or power, it is crucial that the relationship between input current/power and output force/torque is linear and understood. The signal features and uses of current/power

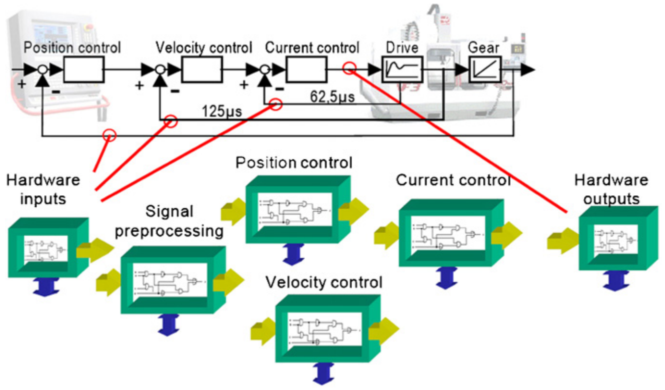

Fig. 2. Modular architecture for power monitoring on drive controller [13].

monitoring face a number of issues, including [4,16]: (i) the amount of spindle power required for material removal may be a very small part of total power, e.g. for small diameter drilling and finish machining; (ii) the spindle motor power is proportional to the resultant cutting force, the least wear sensitive parameter; (iii) temperature rises inherent in electrical motors influence power consumption; (iv) drive motors are highly dependant on the axis lubrication state, transverse rate and axis condition.

The performance of indirect sensors, such as motor current/power, can be improved by developing a model of the distortion introduced by the sensor within the mechanical/electro-mechanical system. A number of studies provided a better understanding of signal features for various spindles and drive systems [15,17–20]. Mannan and Broms [19] carried out investigations into the temperature dependence of motor current measurements, finding that input current increased with motor temperature from 4 to 9%. The temperature in permanent magnet feed motors is governed by magnetic material properties and errors from 1 to 15% can be expected over the tool life duration. Also, increases in current from 15 to 20% were required to maintain torque and this was attributed to magnetic losses. Laboratory investigations by Ketteler [16] found a 12% variation in spindle power between the machine start up time and when the machine was warm following a period of operation.

An important outcome of the models developed by researchers is the quantification of the sensitivity and dynamic bandwidth of the motor power/current sensing loop. Stein and Wang [15] related the sensitivity of the current drawn by the spindle and feed drive motors to the cutting forces and noted that the currents were very sensitive to the presence of Coulomb and viscous friction. The bandwidth of the spindle drive was between 2 and 18 Hz, and for the feed drive it was approximately 80 Hz. Prickett and Johns [21] noted that the bandwidth of feed drives used in milling was typically under 100 Hz, although Jeong and Cho [22] reported in their experimental trials a current sensor bandwidth of 130 Hz. The dynamic characteristics of the current feedback control loop of the feed drive system determine the bandwidth of the current sensing system for indirect cutting force measurements [17,23,24]. This feature is prevalent in milling, where the signal from the tooth passing frequency can be 400 Hz for certain operations. This would render power and current monitoring ineffective for some machine configurations and monitoring operations, or it would seriously reduce the sensory information quality. The high bandwidth of linear motors as feed drive motors is beneficial in this context, as these motors have no losses due to friction, although magnetic losses can be notable.

3.2. Force and torque

Any cutting operation requires a certain force to separate and remove the material. The monitoring of cutting forces in machining for the validation of analytical process models, the detection of tool failure, etc., has been used extensively by researchers [25]. This is due to the high sensitivity and rapid response of force signals to changes in cutting states. Torque sensors, like force sensors, also consist of a mechanical structure that responds to a deformation but in this case the applied load is torsional. The underlying force measurement technology is often identical but the application of torque sensors and the method of signal transmission from rotating tool holders are different.

3.2.1. Force and torque measurement technology

Force and torque sensors generally employ sensing elements that convert the applied force or torsional load into deformation of an elastic element. The two main sensor types used are piezoelectric based and strain based sensors.

3.2.2. Piezoelectric sensors

Direct force measurement using piezoelectric sensors is possible when the force transducer is mounted in line with the force path. In cases where more measurement flexibility is required, multi-component force transducers have been developed and are used extensively in lab based applications. Rotating cutting force dynamometers are also available that contain the force sensing elements capable to measure 3 components of force and torque. The data is transmitted from the rotating part of the sensor to a stator via telemetry. Rotating cutting force dynamometers can operate at speeds of up to 20,000 rpm and have been used for high speed milling of aerospace materials. Developments like the integration of force sensors into the machine structure have taken place over the last 10 years with concepts developed for drilling [26] and milling [27]. Fig. 3 shows sensors integrated into the main force flux of the motor spindle. These concepts have been slow to transfer into practice because the spindle or structure itself must be characterised and strategies to isolate process phenomena from spindle and machine dynamics must be developed [28–32].

3.2.3. Strain gauges

Strain gauge force transducers, consisting of a structure that deforms under a force, offer reasonably high frequency response and long-term stability. Kim and Kim [30] developed a combined tool dynamometer utilising the best features of strain gauge and piezoelectric sensor types: strain sensing for static force measurements and a piezoelectric thin film accelerometer for dynamic force measurements. The total cutting force could be obtained by the summation of the static and dynamic forces. Korkut [31]

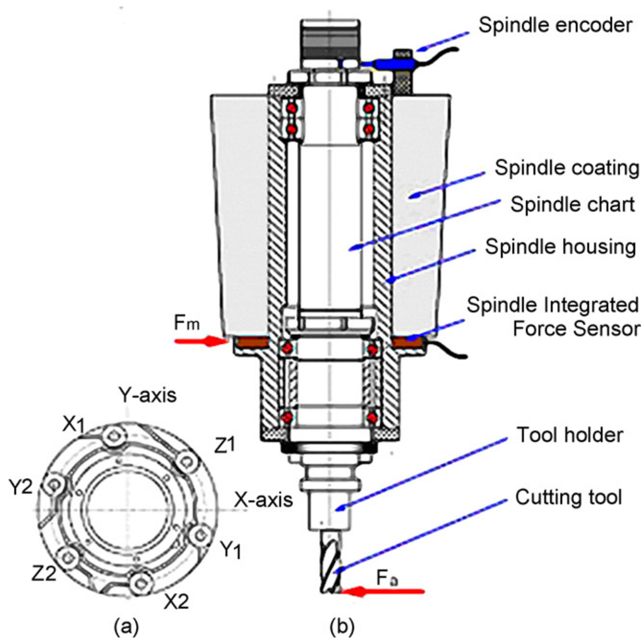

Fig. 3. Integrated force sensors in motor spindle [27].

developed a strain based force measurement platform to measure 3 cutting force components during milling. The dynamometer consisted of four elastic octagonal rings, on which strain gauges were mounted, clamped between upper and lower plates forming a platform. The precision of the strain based dynamometer was 5 N, with bandwidth 192 Hz and maximum loading 1500 N. Smith et al. [32] designed a strain based sensor to fit between tool and holder on conventional milling tooling. The sensor provided virtually distortionless torque measurement over a bandwidth DC – 2000 Hz for a 100 mm diameter face-milling cutter. A compensating filter with the reciprocal response of the sensor accounted for the frequency response distortion due to vibrational modes of the integrated sensor spindle assembly. An air core transformer operating at 10 kHz was used to couple power to the electronics rotating with the spindle. Opto-electronic devices in the form of light emitting diodes and photo-detectors were used to establish two way digital communications.

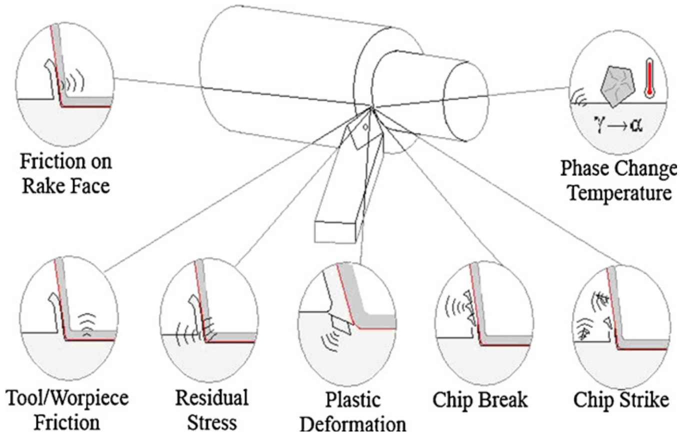

Fig. 4. Sources of AE in machining [11].

3.2.4. Other force sensor types

The ongoing development of silicon micro fabrication technology has facilitated the realisation of micro force sensors [33]. Good results have been reported indicating measurement ranges from as low as 1 mN. Surface Acoustic Wave (SAW) sensors have significant potential as passive strain sensors where wireless interrogation eliminates the need for the sensor to have power [34]. The properties of ferromagnetic materials have been investigated for use in force sensor technology. One approach is to fix a soft magnetic amorphous ribbon to the shaft under load and measure the resulting magnetic flux density. Aoyama and Ishii [35] used the Villari effect to detect cutting forces, cutting torque and tool deflection. The Villari effect is based on changes in material magnetic properties with applied load. A magneto-strictive film was deposited on a cutting tool shank and a detection system was developed where impedance changes in pick-up coils indicated a strain. Initial results indicated that both axial loading and torque could be measured, while further work was necessary to improve accuracy in comparison to piezo based force measurement systems. However, the techniques cited can offer advantages over the piezoelectric effect in that no direct contact is required to the structure surface, making it ideal for torque or force measurements during shaft rotations.

The new era in cutting force dynamometry using piezoelectric transducers has made the accurate measurement of cutting forces possible. However, instead of having a straightforward signal that can be easily decoded using a static calibration curve, signals now contain contributions from dynamic unevenness of machine fixture, cutting tool and environmental noise. Methods for online compensation of force measurement errors can be broadly arranged into two classes. In the first class, there are the systems that attenuate the impact of forces caused by vibration of the dynamometer and mass; this is accomplished by the estimation of the errors caused by inertia and the subtraction of these errors from the recorded signal [36]. In the second class of online methods, the compensation is accomplished by means of adaptive filtering [27,37–39].

3.3. Acoustic emission measuring technology and sensors

Piezoelectric sensor technology is particularly suitable for measuring acoustic emission (AE) [40,41] in machining process monitoring. With very wide sensor dynamic bandwidth from 100 to 900 kHz, AE can detect most of the phenomena in machining, though significant data acquisition and signal processing is required [11] (Fig. 4). This presents problems for signal processing and bandpass filters usually provide great flexibility for AE detection by selecting appropriate frequency ranges. The output signal from the AE sensor is fed through a preamplifier that has a high input impedance and low output impedance. A root mean square (RMS) converter, gain selection unit and filters are also typically contained within the preamplifier housing. The capacitance principle can also be used for detecting AE, as the capacitance of two parallel plates changes with the distance between plates. The accuracy of this AE detection method is higher than many other techniques and capacitance based AE sensors are used for calibrating other AE sensors. However, capacitance type displacement sensors for AE are very sensitive to sensor position and surface mounting. Thus, they are not suitable for machining process monitoring where the operating environment is often quite severe on the sensor [42].

Another sensing method for AE detection is the application of a piezoelectric thin film sensor deposited on a shim and located between cutting insert and tool holder. The coating materials can be AlN or ZnO. The sensor is reported to have advantages over commercially available AE sensors: it is located close to the cutting process and is characterised by a very large frequency bandwidth. Good signal quality has been reported, particularly in the high frequency range, with less interference and lower geometrical propagation loss and absorption rate [43]. An alternative approach using fibre optics was investigated in [44,45]. This sensing method has reported advantages over conventional AE sensors such as a broader bandwidth, flat frequency response and absolute calibration. More significantly, the fibre optic interferometer is a non-contacting method of signal transmission from source to sensor. The latter two methods have largely only been developed in the laboratory and have not been significantly used in industrial applications.

3.3.1. AE signal transmission and sensor location

The high frequency and low amplitude nature of AE means that signal transmission via a coupling fluid is possible. By the location of the AE sensor on the coolant supply nozzle, the coolant can be used as transmission path [46]. Hutton and Hu [47] used a non-intrusive coupling fluid to couple the AE sensor to the spindle drive shaft, similar to Li et al. [48]. These signal transmission methods had a distinct advantage for rotating tools such as in milling and drilling. Various other methods of signal transmission from AE sensor to AE coupler/signal processor are common to other sensing applications, including slip rings, inductive coupling, and radio frequency transmission [46,49]. Jemielniak [50] investigated aspects of AE signal processing in machining and proposed that in the machine tool environment the AE signal is repeatedly reflected from the inner surfaces of the structure where the sensor is mounted. This resulted in prolonged duration of the signal recorded by the sensor.

AE sensor mounting requires a couplant between sensor and material surface. The latter should be free from dirt, paint, and any other barrier that may influence the acoustic coupling. The farther the sensor is placed from the AE source, the greater the signal attenuation. This has significant implications for measuring AE during machining. If the AE sensor is mounted on the workpiece side, the changing distance between sensor and source during machining is a factor that requires consideration. This sensor location also presents difficulties regarding sensor mounting, e.g. should the AE sensor be located on the workpiece or on some stationary part of the machine tool [51].

3.4. Vibration and other sensor types

A large variety of sensing principles are used for sensing vibration. However, piezoelectric transduction is the most common type in vibration sensing of machining operations.

Vibrations that occur during metal cutting can be divided into two groups: (i) dependant and (ii) independent of the cutting process. The two groups are not mutually exclusive. Vibration independent of metal cutting include forced vibration caused by other machines or machine components, e.g. vibration transmitted through foundations, unbalance of rotating parts, inertia forces of reciprocating parts and kinematic inaccuracies of drives. Vibration dependant on metal cutting can demonstrate a number of characteristics as a function of the process, e.g. interrupted cutting. The varying cutting forces that occur during metal cutting may result from non-homogeneity and properties variations in the work material. Tool engagement conditions during machining play a notable role in the vibration produced. The self excited vibration characteristic known as chatter is the most renowned type of vibration in machining and is detrimental to surface finish and tool life. Chatter mainly occurs due to the waviness regeneration caused by the interaction between material surface and tool at particular spindle rotational frequencies, and by mode coupling where relative vibration between workpiece and tool occurs concurrently in two directions in the plane of cut.

3.5. Other sensor types

Many other sensor types have been the subject of research including the use of micro sensors such as the integration of temperature sensors into the tool insert [52–54]. Temperature measurement in machining has been extensively reviewed by Davies et al. [55]. The use of vision systems for monitoring tool condition has been comprehensively reviewed by Kurada and Bradley [56]. As in many applications using machine vision, object illumination notably impacts the process and for industrial applications can lead to process unreliability. Ryabov et al. [57] used lasers to examine the profile of the cutting edge of milling cutter inserts. A 3D tool image was realised using this technique. The tool condition was assessed using a histogram method for signal pre-processing of noisy input signals and a hybrid technique for detection and measurement of tool failures. Various researchers used multi-phenomenon sensing to detect tool conditions. Some of the lesser used techniques include the monitoring of sound and image analysis by Mannan [58], and the use of strain and temperature by Shinno and Hashizume [59]. The use of displacement to examine the workpiece dimension and surface quality in relation to tool wear has been a theme for a number of researchers. The techniques used were bifurcated optic fibre with reflected light intensity measurement [60], laser light with reflected light intensity measurement [61] and capacitive sensing [62]. The use of ultrasonics has also been attempted by Abu-Zahra and Yu [63], and by Nayfeh et al. [64]. These applications were limited to turning and the sensor/tool interface considerations and calibration techniques were topics for future work. The use of capacitance sensors to detect the spindle shaft displacement due to cutting load was investigated by Albrecht et al. [65]. A capacitive displacement sensor was integrated into the spindle to measure the static and dynamic variations of the gap between sensor head and rotating spindle shaft under load. A Kalman filter based scheme was used to compensate for spindle dynamic effects. Capacitance sensing allowed the observation of roundness error, spindle unbalance and spindle shaft dilation due to temperature variations. Auchet et al. [66] used the measured command voltages of magnetic bearings in the motor spindle to indirectly determine the cutting forces. The spindle was treated as a black box where the

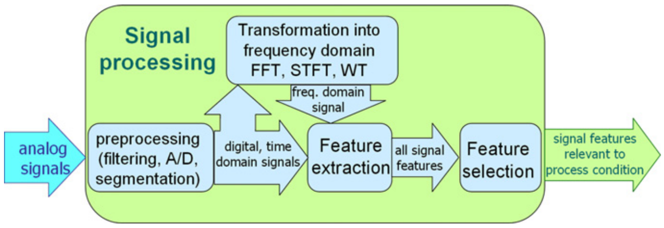

Fig. 5. Signal processing logical scheme.

transfer function linking the unknown cutting forces was experimentally established. The cutting forces calculated from the command voltages were found in good agreement with platform dynamometer force measurements. The bandwidth of the indirect force measurement using active magnetic bearings (4 kHz) was found to be notably in excess of that available with dynamometer based solutions. Further work was deemed necessary to deal with gyroscopic influences.

4. Advanced signal processing

It is generally acknowledged that reliable process condition monitoring based on a single signal feature (SF) is not feasible. Therefore, the calculation of a sufficient number of SFs related to the tool and/or process conditions [67–70] is a key issue in machining monitoring systems. This is obtained through signal processing methods that comprise the stages shown in Fig. 5.

First, pre-processing (filtering, amplification, A/D conversion, and segmentation) including, on occasion, signal transformation into frequency or time–frequency domain (Fourier transform, wavelet transform, etc.). The next stage is the extraction of signal or signal transform features changing with tool or process conditions. There are many diverse descriptors from different sensor signals, but most cannot be easily related with the process being monitored. Thus, feature selection is of critical importance and the identified relevant features are finally integrated into the tool or process condition diagnosis system.

4.1. Signal pre-processing

The analog signal from the sensor usually cannot be connected directly to the A/D converter but needs pre-processing by a conditioner specific to the sensor (piezotron coupler, charge amplifier, etc.). For example, a typical procedure of analog AE signal pre-processing follows the pattern schematically shown in Fig. 6.

The piezoelectric AE sensor is usually placed as close as possible to the cutting zone, e.g. on the tool shank, the tool post, the head stock or the spindle. Because of its high impedance, the sensor must be directly connected to a buffer amplifier which converts the charge signal from the sensor into a proportional voltage signal. This is typical also of other piezoelectric sensors such as dynamometers or accelerometers. The analog signal should be filtered to keep it within the range of the frequency response of the sensor, suppress high frequency noise or continuous biases. The filtered signal is then subjected to further processing and/or recording. The frequency range of the raw AE reaches 1 MHz (typically 80–700 kHz) so dealing with it requires a high sampling frequency (>1 MS/s) and large memory resources with high computing costs. Thus, in many cases the AE signal is demodulated to RMS (AE_{RMS}) to obtain a low frequency variable, which can be further processed with less expensive signal processing devices.

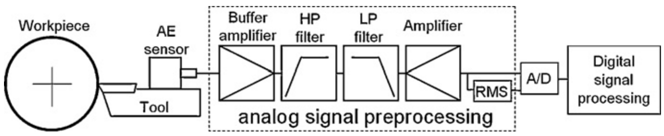

Fig. 6. Typical measuring chain for AE detection during machining.

The integration time constant of the RMS converter should be carefully selected, depending on the subsequent SF extraction. Signal averages can be calculated with other features such as burst rate, event counts, etc. In such cases, the integration time constant should be 10 times shorter than the typical burst duration, which is approximately 2 ms [50].

The AE energy from the cutting zone can be considerable. Because of the pre-processing units characteristics, these high amplitude signals may cause overloading of the buffer amplifier and signal saturation. High-pass filtering of saturated signals results in temporal vanishing of the signal value [71]. This can often result in misleading data evaluation. It should be noted that this signal distortion cannot be detected in the AE_{RMS} signal and, in this case, such signals must be considered completely distorted and useless. To avoid these problems, the gain of the buffer amplifier should be as small as possible and any further necessary amplification should be done after signal filtering. This is critically important when AE_{RMS} is used instead of AE_{raw} [71].

Just before conversion into digital form, for the highest possible accuracy, the signal is usually amplified so that the signal maximum voltage range equals the maximum input range of the A/D converter. The digital signal is often subjected to further pre-processing. Digital filtering reduces frequency bands not correlated with the monitored process or extracts information necessary for specific pattern recognition stages. For example while using a spindle-integrated force sensor system on a machining center, the cutting force signals are distorted when the spindle speed harmonics coincide with the spindle natural modes. Kalman filters eliminate the influence of structural modes on force measurement and significantly increase the frequency bandwidth of the force measurement system [72]. Scheffer and Heyns [73] investigated possible SFs related to tool wear in interrupted cutting. They applied digital filters to separate two frequency ranges of cutting force signals: the low frequency range was an indication of static cutting forces and the high-frequency range of the natural frequencies of the toolholder which resulted from the excitation of the cutting operation. Jemielniak [74] used low-pass filtering of cutting force signals for catastrophic tool failure detection in turning based on the detection of sudden force value changes. The filtering allowed a much lower tolerance band on the limit set on force value. In many applications, a digital signal is filtered to prevent high frequency noise and signal oscillations due to transient mechanical events [75,76].

Another sensor signal pre-processing method is segmentation. Signal information should be extracted when the tool is actually removing metal in a steady state, since only this signal portion contains information about process or tool conditions [77,78]. Dong et al. [79] calculated SFs from force samples in one spindle rotation, instead of one tooth period, to reduce the influence of run-out. Similarly in [80], where tool failure detection in interrupted turning was analyzed, the data points taken into consideration contained the AE data from at least one full workpiece revolution. Jemielniak et al. [81] noted that, despite constant cutting conditions in single micro-milling cut, AE was not constant; thus, separate SFs were calculated for all the cut and for the 1st and the 2nd third of the cut.

4.2. Feature extraction

4.2.1. Time domain

4.2.1.1. General purpose time domain features. From the sensor signal, SFs need to be derived that can describe the signal adequately and maintain the relevant information about the process or tool conditions. There are several SFs that can be extracted from any time domain signal. The most common are: (i) arithmetic mean, average value, magnitude [69,75,79,82–89]; (ii) effective value (root mean square – RMS) [69,75,83–85,87,89,90]; (iii) variance (or standard deviation) [75,79,82–84,86,90,91]; (iv) skewness [79,83–87,91]; (v) kurtosis [79,83–87,91,92]; (vi) signal power [77,87,91]; (vii) peak-to-peak, range, or peak-to-valley amplitude, [69,73,75,79,83,87]; (viii) crest factor [69,79,84,85,87]; and (ix) ratios of the signals, signal increments [69,93].

4.2.1.2. Acoustic emission time domain features. Some features are applicable only to vibration and AE signals: (a) ring down count or pulse rate: number of times AE_{raw} signal crosses the threshold level [68,71,89,90,94]; (b) pulse width: the percentage of time during which AE_{raw} remains above the threshold level [71,94]; (c) burst rate number of times AE_{RMS} signal exceeds preset thresholds per second [68,71,87]; and (d) burst width – percentage of time AE_{RMS} signal remains above each threshold [71,94]. Kannatey-Asibu and Dornfeld [95] assumed that AE_{RMS} signal has a β distribution. They showed that skew and kurtosis are sensitive to both the stick-slip transition for chip contact along the tool rake face and progressive tool wear on the flank of the cutting tool. Jemielniak and Otman [80,96] applied these parameters to catastrophic tool failure detection.

4.2.1.3. Time series modeling. Three main time series modeling techniques are frequently used in machining monitoring: Auto Regressive (AR), Moving Average (MA) and Auto Regressive Moving Average (ARMA) [21,68,79,84]. Early research work developed AR models of high order, up to the 28th order [21]. These were considered of little practical use because of the high computing load inadequate for online process monitoring. Thus, the 1st or the 1st and the 2nd AR, MA or ARMA coefficients were used as features [68,79,84]; sometimes higher AR coefficients of the 3rd–5th order [97]. Recently, Suprock et al. [97] applied the 100th order AR model for failure prediction in endmilling. They noticed that, while lower-order models may achieve "adequacy", as defined in statistical terms, higher-order models produce more stable trends.

4.2.1.4. Principal component analysis. Principal component analysis (PCA), also known as the Karhunen–Loeve transformation, has been widely used in system identification and dimensionality reduction in dynamic systems. Shi and Gindy [98] investigated the PCA technique to extract features from multiple sensory signals treated as a high-dimensional multivariate random matrix, composed of several vectors formed by the signals. By implementation of PCA, the signals can be reduced to a new reduced-size feature vector. Shi and Gindy used two perpendicular cutting force signals for tool wear monitoring in broaching. The pattern of cutting forces in the 2D space orbit diagram (Fig. 7) formed as

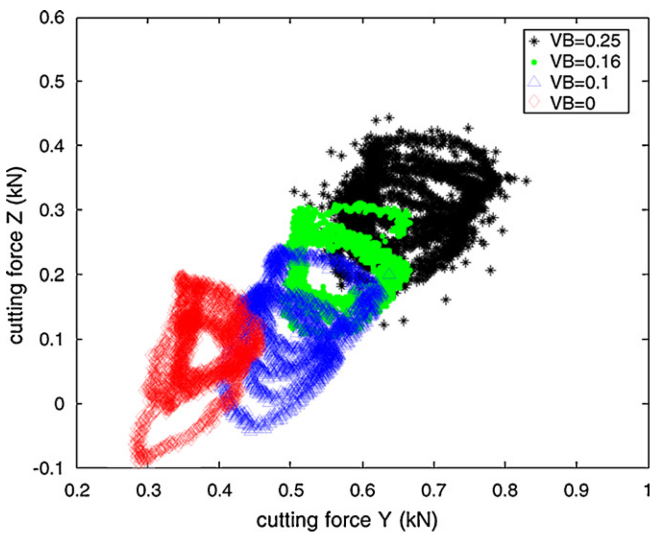

Fig. 7. Orbit diagram of cutting force signals in dual directions measured by integrated force sensors for different level of tool wear [98].

scatter ellipse and was closely related to tool wear. This relation was quantitatively evaluated by PCA through the length of the major/minor axes (a/b) and the ellipse inclination angle (β). Moreover, the origin (F_y, F_z) of the scatter ellipse was related to the average value of the cutting force in two orthogonal directions and could also be included in the feature set. Finally, the feature set normalized elements were specified as $\{F_y, F_z, a, b, \beta\}$ and fed to the tool wear prediction model. Abellan-Nebot and Subirón [99] extracted several standard SFs from cutting force signals, applied PCA to reduce the number of SF and constructed a new set of features that were a combination of the original SFs.

4.2.1.5. Singular spectrum analysis. Singular spectrum analysis (SSA) is a non-parametric technique of time series analysis incorporating the elements of classical time series analysis, multivariate statistics, multivariate geometry, dynamical systems and signal processing [83]. SSA decomposes a given time series into the sum of three independent components: a slowly varying trend representing the signal's local mean, the difference between the original signal and the trend, called detrended signal or oscillatory component, and a structureless noise presenting no latent structure. Basically, the method projects the original time series onto a vector basis obtained from the series itself, following the procedure of PCA. Salgado and Alonso [83] applied SSA to vibration signals from a turning process to extract information correlated with the tool state or for in-process prediction of surface roughness [100]. They decomposed two vibration signals (longitudinal and transverse) into the trend and the detrended signals, and extracted from them several statistical features. It appeared that only the RMS and variance of the detrended signals showed a monotonic behavior with tool wear, which meant that the information in the vibration signals about flank wear was mostly contained in the high-frequency components. Later, they extended their technique by applying cluster analysis to group the SSA decomposition of the vibration signals [101]. This time, they found that only the RMS and standard deviation of the medium and high frequency signals of the longitudinal vibration and the RMS and standard deviation of the high-frequency components of the transverse vibration showed a monotonic behavior with tool wear. Salgado and Alonso [102] also used SSA to extract information correlated with tool wear from audible sound signals.

4.2.1.6. Permutation entropy. Another relatively new parameter of time series complexity measure applied in machining monitoring is permutation entropy [76]. For time series $\{x_t,\ t = 1\ldots T\}$ of n different signal values, there are $n!$ permutations π of ordered patterns. The permutation entropy for the time series is defined as:

$$H_p(n) = -\sum_{i=1}^{n!} p(\pi_i)\ \ln\ p(\pi_i) \tag{1}$$

where $p(\pi_i)$ is the relative frequency of permutation π_i.

The normalized permutation entropy is then:

$$H_p = \frac{H_p(n)}{\ln(n!)} \tag{2}$$

and the smaller the value of H_p, the more regular the time series.

Li et al. [76] used permutation entropy as a feature of feed-motor current signals to detect tool breakage in endmilling. Fig. 8 shows long-term feed-motor current signals and the matching normalized permutation entropy. The feed-motor current during normal cutting conditions is similar to a regular periodic signal. Thus, the H_p values were small: from 0.75 to 0.8 between the 8th and the 38th second of experiment. This meant that the feature values were insensitive to noise influences such as different effects of friction coefficients at diverse positions. When a cutter flute was broken, the regular periodic quality of the motor current was disturbed and the H_p values increased.

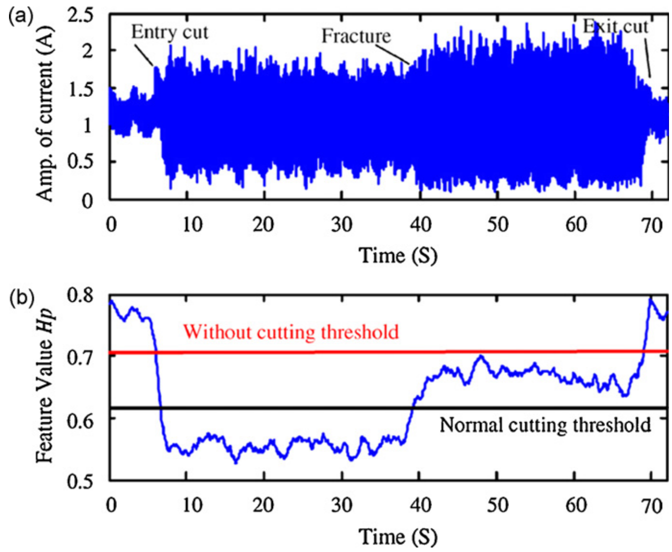

Fig. 8. A long-term feed-motor current signal and its permutation entropy H_p during normal cutting and tool breakage [76].

4.2.2. Frequency and time–frequency domain

4.2.2.1. Fast Fourier transform. The determination of SFs in the frequency domain is usually based on a discrete windowed Fourier transform. Discrete Fourier transform (DFT) maps a discrete–time sequence of N samples $x[n]$ ($n = 0\ldots N-1$) into a discrete–frequency representations $X[m]$ ($m = 0\ldots N-1$). Practically, one of the several commonly known fast Fourier transform (FFT) algorithms is used. For example, if tool wear influences the frequency contents of the sensor signal, FFT gives an inside view of this process. El-Wardany et al. [92] investigated spectral maps of vibration signals for TCM in drilling and observed that the signal magnitude in the frequency range 2–5 Hz increased sharply just before drill breakage. Verl et al. [103] applied frequency and distance domain parameters to quantify the wear of feed drives.

The use of single Fourier coefficients $X[m]$ is not practical due to leakage effects. Thus, further SFs are usually considered: (i) amplitude of dominant spectral peaks [69,78,87,90,92,104]; (ii) signal power in specific frequency ranges [69,71,85,87,105,106]; (iii) energy in frequency bands [72,78,84]; (iv) statistic features of band power spectrum such as mean frequency, variance, skewness, kurtosis of the power spectrum distribution [87]; and (v) frequency of the spectrum highest peak [69,89,107].

Even though the sensor signals detected during machining are essentially nonstationary, the FFT averages the frequency composition over the duration of the signal with fixed resolution of the entire frequency spectrum. To address this issue, a time–frequency analysis as the short time Fourier transform (STFT) can be applied. STFT uses a window $w[n]$ sliding along the time axis to characterize the change of frequency components at different time intervals. Spectral coefficients are calculated for this short length of data; the window is then moved to a new position k and the calculation repeated. Thus, STFT provides the time information by computing different FTs for consecutive time intervals, and then putting them together. Marinescu, and Axinte [78,108] studied the effectiveness of AE signals to detect tool and workpiece failures in milling operations and applied STFT to precisely determine the moment when the inserts are in contact with the workpiece in milling.

4.2.2.2. Wavelet transform. The STFT is a form of joint time–frequency analysis but it has a major drawback: the window width which decides on both time and frequency resolution. Both time and frequency resolutions cannot be arbitrarily high (Heisenberg's uncertainty principle). To overcome the preset resolution problem of the STFT, the wavelet theory was developed in the late 1980s by Mallat [109] and Daubechies [110]. The wavelet transform (WT) uses windows of different lengths for different frequencies: high frequencies are analyzed with narrower windows for better time resolution, while at low frequencies wider windows are used for better frequency resolution. Thus, the WT can extract more information in the time domain at different frequency bands. The WT decomposes a signal through the wavelet scale function and scaled and shifted versions of the mother wavelet. Practically, it can be reduced to filtering the signal by high-pass and low-pass filters derived from the wavelet and the scaling function. The discrete wavelet transform (DWT) decomposes the signal into the scaling coefficients (approximations A) and the wavelet coefficients (details D) by convolution of the signal and impulse response of the low-pass and high-pass filters.

Another type of WT is the wavelet packet transform (WPT) where both approximations and details are decomposed, generating many more frequency bands. This provides more opportunities to find useful SFs. On the other hand, for n levels of decomposition, the DWT produces $2n$ sets of coefficients as opposed to $(2^{n+1}-2)$ sets for the WPT. Thus, the computational cost of the DWT is much less than for the WPT.

WT have been used in machining monitoring for more than decade [111–117]. Kamarthi and Pittner [113], who used force and vibration signals for flank wear estimation in turning, compared the performance of FFT and WT. They noticed that, differently from FFT, short time delays of the signal can cause large changes in WT coefficients, especially at fine scales. According to the results, they recommended WT for force signals, while FFT seemed better matched to vibration signals.

It is worth noting that, in general, the type of wavelet is arbitrarily selected without any explanation. Occasionally, statements such as "the coiflet 3 wavelet was chosen for analysis because it yielded the best results after experimenting with a number of different wavelets" [84] can be found.

Sometimes, especially in earlier works, the wavelet coefficients were applied directly. Tansel et al. [114] used them as inputs to neural networks for tool failure detection in milling based on cutting force measurements. Xiaoli [115] and Tarng and Lee [116] applied wavelet coefficients of AC servo motor current signals directly for drill breakage detection. Kwak [117] did the same for tool failure detection based on cutting force measures.

As the WT outputs have relatively large size, informative features must be extracted from the coefficients. WT coefficients are usually treated as separate signals, each characterized by features used for time domain signals: average value [111,112,118], RMS [118], standard deviation or variance [104,112,118,119], crest factor [84,112], peak-to-valley or peak-to-peak value [112,118], kurtosis [84,112,118,119].

Wu and Du [112] introduced an automatic feature extraction and assessment procedure using WPT for machining monitoring. They selected the wavelet packets according to their energy, as such packets contained large amounts of information. To identify the effectiveness of the selected features, four criteria were proposed: cross-correlation and cross-coherence of the signal and the reconstructed signal, correlation of the residue and power spectrum of the residue. Scheffer and Heyns [84] used a similar method but applied Shannon entropy to choose the optimal packets. On the other hand, wavelet packets energy itself can be used as a SF [86,113,119,120]. Kamarthi and Pittner [113], using force and vibration signals for flank wear estimation in turning, first grouped the wavelet coefficients into clusters; then, the wavelet coefficient energy in the cluster was used as single robust feature. This method was later applied in [120] for tool wear estimation in turning based on AE signals. Rene et al. [93] used asymmetry of compressed cutting force signals in milling for catastrophic tool failure detection. During normal milling with both inserts in good conditions, cutting force signals are alike and asymmetry is close to zero. When breakage takes place, cutting force signals of the inserts are different and the waveform is asymmetric. The asymmetry was calculated as the point-to-point variance between detail level-5 DWT coefficients of the cutting force signals for each insert in a full tool revolution:

$$A=\sum_{i=1}^{4}(B_{i+4}-B_i)^2 \tag{3}$$

where B_i – DWT coefficient for the first insert, B_{i+4} – DWT coefficient for the second insert. Fig. 9 shows the normalized asymmetry data from the tool breakage detection system plotted for each milling tool revolution. A similar method was applied later to the motor current signal [121].

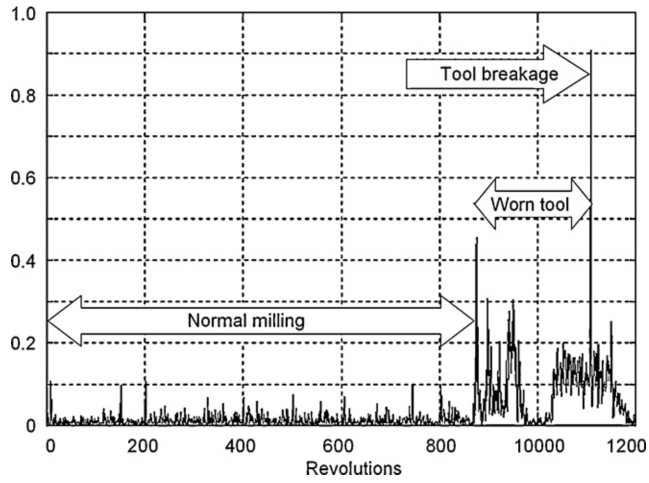

Fig. 9. Cutting force detail level-5 DWT at each spindle revolution during normal, worn tool and tool breakage conditions in milling [93].

Mori et al. [122] noticed that the breakage of small drill bits is characterized by two transient types ('sawtooth' and 'screeching') in the cutting force signal. To detect such transients they applied DWT coefficients reduced to three indices: energy, waviness, and irregularity. When chipping or tool breakage occurs, the signals often contain abrupt changes or a sudden shift to a different level, which are singularity points. Local singularity can be estimated from the regularity of function $f(x)$ at a certain point x_0 and the rate of decay of the coefficients near this point using Lipschitz exponents from equation [123]:

$$|f(x)-f(x_0)|\leq A|x-x_0|^{\alpha} \tag{4}$$

where $A>0$, $(x, x_0)\in[a, b]$, and $0\leq a\leq 1$.

The function $f(x)$ is called uniformly Lipschitz α over the interval $[a, b]$. The larger the value of α the smoother the function $f(x)$. The exponent a indicates the degree of singularity and is often used as a feature in TCM [124]. Chen and Li [125] applied this method to detect singularities in wavelet coefficients by looking for time points where the Lipschitz exponent drops from positive values towards zero or below. Zhu et al. [86], who applied singularity analysis to detect tool wear in milling, noted that, with wear increase, force signal singularities and singularity ranges increased too. They also stressed that particular attention should be given to choosing the mother wavelet type for this kind of analysis. The wavelet should be the 1st order differentiation of a certain smooth function (i.e. Gaussian). The selected wavelet must be also sufficiently regular, i.e. a larger vanish moment, otherwise singularities could be overlooked. WT is sometimes used for signal de-noising before applying another signal processing technique [76,117,126]. It is based on the rule that wavelet expansions tend to concentrate data energy into a relatively small number of large coefficients. Wavelet-based de-noising is done by first transforming the data into the wavelet domain, zeroing all the wavelet coefficients below a threshold and inverse transforming back into the time domain. An interesting review of WT applications in tool condition and process monitoring can be found in [124].

4.2.2.3. Hilbert–Huang transform. A further new method of time–frequency analysis recently applied to extract the key features of sensor signals for machining operation monitoring is the Hilbert–Huang transform (HHT) [127], especially designed for nonstationary and nonlinear signals. Unlike spectrograms, wavelet analysis or Wigner-Ville Distribution, the HHT is more like an algorithm applied to a data set (empirical approach), rather than a theoretical tool. It consists of two steps: the Empirical Mode Decomposition (EMD) to decompose a signal into a set of monocomponent signals, called Intrinsic Mode Functions (IMFs), and the application of the HHT to the IMFs. The Hilbert Spectral Analysis (HSA) examines the IMFs instantaneous frequency and generates effective time–frequency distributions called Hilbert spectra.

Peng [128] used this method for tool breakage detection based on cutting force signal during milling. The tool breakage could be detected directly in the Hilbert spectrum or by means of the energies of the characteristic IMFs associated with characteristic frequencies of the milling process. When tool breakage occurs, the energies of the associated characteristic IMFs change in opposite directions, which is different from the effect of changes of the cutting conditions, e.g. depth of cut and spindle speed (Fig. 10). Thus, they were not only able to capture the significant information on the tool condition but also reduced the sensitivity to the effect of diverse uncertainties.

Bassiuny and Li [126] applied HHT analysis to detect end mill flute breakage via feed-motor current signals (Fig. 11a). They noted that some IMF components have higher amplitude in case of tool breakage than the matching components in case of normal cutting. The instantaneous energy of the most informative IMFs was combined to form a new signal for further analysis (Fig. 11b). Then, the energy signal was processed by the Smoothed Nonlinear Energy Operator (SNEO) emphasizing the breakage-waves that corrupt the pure feed-motor current signals (Fig. 11c). The SNEO output was thresholded to separate breakage regions from background signal regions (Fig. 11d).

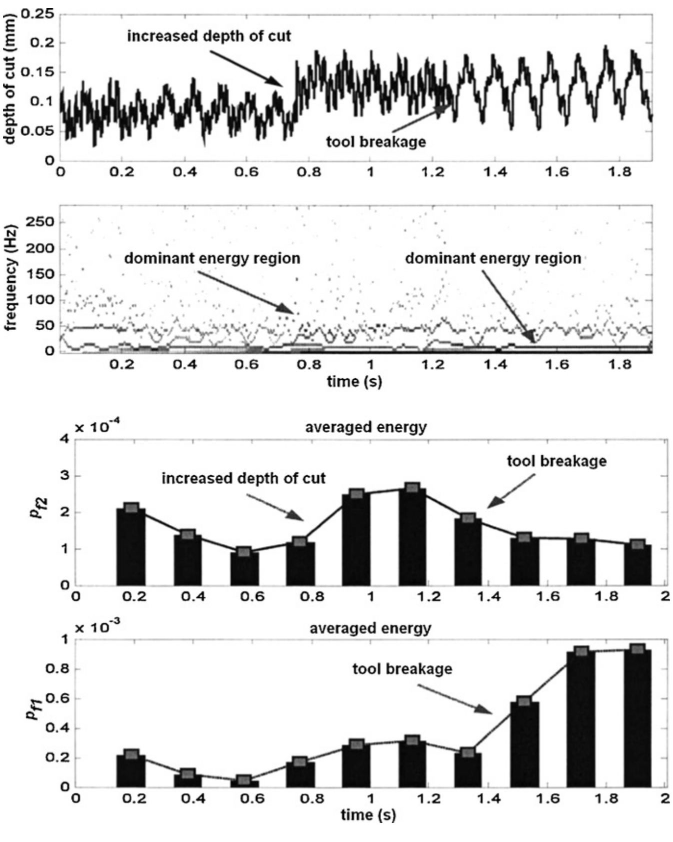

Fig. 10. Milling process with increased depth of cut and tool breakage; (a) cutting force signal, (b) instantaneous frequency, and (c and d) average energies of two dominant frequency regions f_1 and f_2 [128].

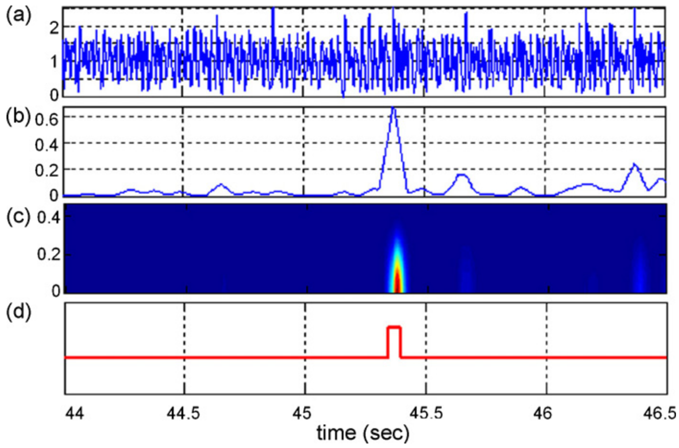

Fig. 11. Feed-motor current signals and detection results for small cutting edge fracture: (a) original signal, (b) combined instantaneous energy, (c) SNEO output and (d) threshold results [126].

4.3. Signal feature selection

The number of features originating from one or more signals can be very large but most of them are very distorted or indifferent to process conditions, whereas the selected SFs should be relevant and sensitive to process or tool conditions. However, even the well correlated SFs can be sometimes randomly disturbed. Hence, the number of SFs should be high enough to cover the possible random disturbances of any single SF. On the other hand, especially in neural network based systems, the more the features, the more training samples are needed [111]. If the system is supposed to work already after the first training session, the amount of training samples may not be large enough to properly train a complex neural network necessary for large numbers of SF inputs [71]. Thus, the second objective of signal processing is to preserve as much of the relevant information as possible by removing redundant or irrelevant SFs. In industrial applications, feature selection should be automatically carried out, without operator intervention. Sick [69] presented an interesting classification of feature selection procedures for tool wear estimation in turning. In 38% of 138 papers, SFs were selected without any reason (or based on literature review), in 26% SFs were defined after analyzing the measured signals, in 21% the most appropriate SFs were selected without considering the behavior of the subsequent tool wear model. Only in 15% of the papers, the optimal set of SFs was found after analyzing of the influence of the diverse SFs on tool wear estimation.

Quan et al. [129] applied the Pearson correlation coefficient r to find the features that can best characterize tool wear conditions. The correlation coefficient between a selected feature x and a tool wear value y can be expressed as follows:

$$r^2 = \frac{\left(\sum_i (x_i - \bar{x})(y_i - \bar{y})\right)^2}{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2} \tag{5}$$

where $\bar{x}$ and $\bar{y}$ are the mean values of x and y, respectively. The correlation coefficient r is a measure of the strength of linear dependence between x and y. Also Scheffer and Heyns [73,84] used this coefficient for SF selection, assuming that with lower r, the lower the chance for the selected feature to show any trend towards tool wear. They ignored the fact that, even if the SF is perfectly correlated with tool wear, the correlation is not linear and the correlation coefficient is <1.

To avoid any uncertain assumption about the SF dependence on tool wear, Jemielniak et al. [94] used the coefficient of determination which is a statistical measure of how well any SF-tool wear model approximates the real data points:

$$R^2 = \frac{\mathrm{RSS}}{\mathrm{TSS}} = \frac{\mathrm{TSS} - \mathrm{ESS}}{\mathrm{TSS}} = \frac{\sum_i (y_i - \bar{y})^2 - \sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{6}$$

where $\mathrm{TSS} = \sum_i (y_i - \bar{y})^2$, total square sum; $\mathrm{ESS} = \sum_i (y_i - \hat{y}_i)^2$, residual square sum; RSS = TSS − ESS, regression square sum; $y_i, \bar{y}$, single and mean values of the SF; $\hat{y}_i$, SF value evaluated based on any SF-tool wear function.

They proposed to group the SF values into four ranges of tool wear KT and to replace the $\hat{y}_i$ values with mean group values.

Jemielniak et al. [70,81] evaluated the correlation between SFs and used-up parts of tool life (ratio of cutting time to tool life $\Delta T = t/T$). Each SF was correlated with ΔT, using a 2nd order polynomial approximation, and the RMS error of this correlation was a measure of the SF applicability to tool wear monitoring. Later, the method was improved by substituting the polynomial approximation by low-pass filtering of the time series representing the SF [130]. Al-Habaibeh et al. [91] extracted "sensory characteristic features" sensitive to cutter conditions. They applied average dependency values, obtained from Taguchi's orthogonal arrays, as indicators of the usefulness of a combination of specific sensor and characteristic SFs for cutter fault prediction (the higher the dependence, the more appropriate the sensor for fault prediction). Sun et al. [85] identified the most effective SFs using a Bayesian framework and Support Vector Machine (SVM). They evaluated the error between the tool condition modeled with a candidate feature and the actual tool condition (fresh or worn): the worst SFs were deleted.

Another method to verify the quality of the selected SFs proposed by Scheffer and Heyns [73] is the Statistical Overlap Factor (SOF), determining the degree of separation of a feature between the new and worn tool conditions (the higher the better). The SOF is defined by:

$$\mathrm{SOF} = \left| \frac{\bar{x}_1 - \bar{x}_2}{(\sigma_1 - \sigma_2)/2} \right| \tag{7}$$

where $\bar{x}_1, \sigma_1, \bar{x}_2, \sigma_2$ is the mean and the standard deviation of data collected from new (1) and worn (2) tools. The authors noticed that automated feature selection paradigms often select SFs that are too similar or dependent on one another, and thus cannot achieve the goal of actual sensor fusion. In these cases, they recommended "engineering judgment" rules entailing automatic feature selection suspension and scientist manual intervention. Such procedure is hardly acceptable in shop floor situations, making this monitoring system a purely laboratory solution. Nevertheless, they raised the important issue of removing the similar features that do not contain additional information. Jemielniak et al. [70,81,130] applied RMS error calculation of the best selected SFs and all others. Those with RMS errors higher than a threshold were rejected. From the remaining SFs, again the best one is chosen and the SFs correlated with it are rejected, etc.

Dong et al. [79] applied neural networks to select relevant features and design neural estimators for tool wear estimation in face-milling. First, they extracted 16 features from the force signals in one spindle rotation. Then, they used a neural network based on Bayesian Multilayer Perceptrons (BMLP) for feature selection. 16 hyperparameters $(a_1, a_2, \ldots, a_{16})$ were assigned to the 16 extracted features, respectively, representing the inverse variance of the prior distribution of the weights on the connections from this feature to hidden neurons. A smaller value of a means that larger weights are allowed and the corresponding feature is relevant; a larger a value means that the weights are near zero and the corresponding feature is less relevant. Based on these values, the relative importance of inputs is decided. They also applied a neural network based on Bayesian Support Vector Machines for Regression (BSVR) with similar SF selection results. The comparison between the tool wear estimation results showed that the BSVR method was more accurate than the BMLP one, but at the cost of higher computing load. Zhu et al. [86] applied WPD of cutting force signals (5 levels, 62 packets) and an algorithm to reduce the SFs number. They used Fisher's linear discriminant analysis for ranking features (mean energy of the packets) according to their class-discriminability. The selected top discriminant SFs were modeled and recognized by Hidden Markov Models. Binsaeid et al. [87] presented a correlation-based feature selection method which evaluated the SF relevance taking into account the level of correlation of individual SFs with the predicted class (tool condition) and the level of inter-correlation among SFs. High scores were assigned to SFs that were highly correlated with the class, yet had low inter-correlation with each other. The merit coefficient was:

$$m = \frac{N\bar{r}_{\mathrm{cf}}}{\sqrt{N + N(N-1)\bar{r}_{\mathrm{ff}}}} \tag{8}$$

where N, number of features; $\bar{r}_{\mathrm{cf}}$, $\bar{r}_{\mathrm{ff}}$, average feature–class and feature–feature inter-correlations, respectively. The correlation was evaluated by entropy measures.

5. Monitoring scopes

In this section, a survey of applications related to the main goals of advanced monitoring of machining operations is presented and a summary of viable solutions as a function of the monitoring scopes is reported in Table 2.

5.1. Tool conditions

Kuljanic et al. [131] focus on the application of AE for tool wear estimation in milling using WPD to build an automatic tool wear classification system. Axinte and Gindy [132] try to correlate broaching tool conditions to output signals of multiple sensors: AE, vibration, cutting force and broaching machine hydraulic pressure. In [14], they assess the use of spindle power signal for TCM in milling, drilling and turning: this method is successful for continuous turning and drilling while it shows low sensitivity for discontinuous milling. Teti and Baciu [133] apply an intelligent monitoring system based on audible sound energy for in-process tool state recognition in band sawing of Al alloy and low C steel. Lee et al. [24] present a real-time tool breakage monitoring system for milling based on cutting force indirect measurement through feed drive AC motor current, whose sensitivity is sufficient to identify tool breakage. Ryabov et al. [57] develop an online tool geometry measurement system based on a laser displacement meter. Ahn et al. [134] build up a vision system to detect small diameter tap breaks hardly perceived by indirect in-process monitoring methods as AE, torque and motor current; in [135], they propose an online drill wear estimation method based on spindle motor power signal during drilling. Arrazzola [136] uses micro-scale thermal imaging to identify effects of steel machinability change on cutting zone temperature and related tool wear mechanisms. In [137], he analyses and compares cost effective methods for tool breakage detection by performing trials on an ultra-precision micro-milling machine.

5.2. Chip conditions

Govekar et al. [105] use filtered AE spectrum components for chip form classification. Kim and Ahn [82] propose a method of chip disposal state monitoring in drilling based on spindle motor power features. Teti et al. [118,119,138] apply WPT and spectral estimation of cutting force signals for chip form recognition. Venuvinod et al. [139] use a variety of sensors to obtain stable clusters of chip form under varying dry cutting conditions through geometric transformations of the control variables: they aimed at recognising chip entanglements, chip size (including continuity), and chip shape. Andreasen and De Chiffre [140] develop and test a laboratory system for automatic chip breaking detection via frequency analysis of cutting forces.

5.3. Process conditions

Brophy et al. [141] classify drilling operations as 'normal' or 'abnormal' (tool breakage or missing tool) using spindle power

Table 2
Summary of machining operations monitoring scopes and related viable solutions.

Monitoring scope	Sensor system	Signal analysis	Machining process
Tool conditions: tool wear [14,131–133,192,193–197, 200,203–205,210,211,227], tool breakage [14,24,134, 192,227], tool geometry [57], tool temperature [136]	AE [131–133,193,194,204,205], vibrations [132,133,195–197], cutting force [24,133, 192,195–197,203,210], hydraulic pressure [133], motor power [14,135], laser [57], camera [134], thermal imaging [136], audible sound [133,200], multiple sensors [210,211,227]	Wavelet transform [131,193,197], time and frequency domain analysis [133,192,200, 203–205,210,227], image analysis [134,136,227], histogram method [57], thermal analysis [136], fractal dimensions [195,196]	Milling [14,24,57,131,227], band sawing [133], broaching [132,192], drilling [14,135], turning [14,136,193–197,200,203–205,210], tapping [134]
Chip conditions: chip form [105,118,119,138,139], chip disposal [82,199], chip breakage [140]	AE [105], motor power [82,141,199], cutting force [118,119,138,140], multiple sensors [139]	Wavelet transform [118,119,138], spectral estimation [105,118,119,138], frequency analysis [140], statistics [199]	Drilling [82,199], turning [105,118,119,138,139,140]
Process conditions: process fault [141,142], process variations [144–146], process state [143,147–149, 215–219], cutting variables [150], process simulation [143]	Motor power [141,143], torque and forces [142], audible sound sensor [144–146], internet-based process optimisation and monitoring [147], AE [148,149], high speed photography [150], multi-sensor fusion [215–219,225,226]	Frequency analysis [144–146,215–219,225,226], cross-correlation [143], short time Fourier transform [143], statistical analysis [143,148]	Drilling [141], tapping [142], broaching [143], turning [143,150,215–219,225,226], milling [143–147], slicing [148], polishing [149]
Surface integrity: surface finish and roughness [88,89, 100,107,151,152,154,160], white layer formation [89], surface integrity [89,90,153,155–159], plucking and smearing [158,159], delamination [160]	Cutting force [88,151,153,155–157,160], vibrations [100,107,152,153,157], AE [89,90,153,155,156,158,159], spindle motion displacement [154], temperature [160]	Statistical methods [88,151], spectrum analysis [100], time series [152], frequency and time domain analysis [89,90,107,153,156], linear regression model [154]	Turning [100,107,151], broaching [153,155–157], hard machining [89], grinding [90], milling [88,155,156], drilling [160]
Machine tool state: feed drives wear [103], fault diagnosis and maintenance planning [161], spindle bearings [162]	Motor current [103], power [161], AE [162], vibrations [161,162], temperature [161], pressure [161], shock pulse [162]	Time and frequency domain analysis [103,161,162]	Turning [162], diverse machining processes [103,161]
Chatter detection: chatter state [163–166,198], chatter onset [105,106], chatter vibration [90]	Multi-sensor system [163,198], cutting force [105,106, 164,165], AE [90,106,166]	Wavelet transform [164,165], entropy rate [105], power spectrum density [106], FFT analysis [163,166]	Turning [105,106,164], grinding [90,166], milling [163,165,198]
Other monitoring scopes: work material heat treatment conditions [167–169], workpiece mass, tool-workpiece contact [170], workpiece diameter [172], cutting force measurements [173,174,176,177], product conditions [175], process, tool and workpiece states [177], ultra-precision machining conditions [178–180], collision detection [29], machining environment monitoring [59]	AE [167–169,171,178–180], vibrations [170], optical fibers [172], rotating dynamometer [173], spindle-integrated force sensor [174], virtual maintenance system [175], cutting force [29,167–169], tool integrated strain gauges [176], capacitive displacement sensor [177], multi-sensing [59,167–169], micro-thermosensor [178–180]	Time and frequency domain analysis [167–169,171,174,176]	Turning [167–169,172,176], grinding [171], milling [173,174,177], drilling [29]

signals. Mezentsev et al. [142] develop a method for fault detection in tapping based on torque and radial force; the method allows to identify typical faults of tapping operations: axial misalignment, tap runout, tooth breakage both singly and in a combined way. Axinte et al. [143] develop an online machining monitoring system based on PXI and LabVIEW platforms experimentally validated for broaching, turning and milling of aero engine materials. Teti et al. [144–146] use a process monitoring system based on inexpensive sound energy sensors, audible sound frequency analysis and neural network processing of audible sound SFs to identify variable process conditions in Al alloy milling. Chen et al. [147] implement a generalised internet-based process monitoring facility to provide clients with a virtual manufacturing process optimisation facility combining process simulation software with a Remote Machine Monitoring System (RMMS). In [148], state monitoring in the slicing of quartz glass ferrules is studied using AE detected during normal and abnormal states and extracting SFs for each symptom: a monitoring algorithm is proposed to reliably discriminate abnormal from normal states even under noisy circumstances. In [149], a polishing expert system integrated with sensory information is proposed which can modify even the polishing conditions initially recommended by the system itself, depending on the on-site polishing status; a real system using AE signals is developed. Pujana et al. [150] report on a new method to assess cutting variables (shear angle, chip thickness, tool vibration amplitude, strain, strain rate) and chip topology by means of high speed photography combined with laser printed square grid patterns on the workpiece at industrial cutting speeds and feeds.

5.4. Surface integrity

Azouzi and Guillot [151] apply cutting parameters and two cutting force components for online estimation of surface finish and dimensional deviations. Huang and Chen [88] employ a statistical approach to correlate surface roughness and cutting force in endmilling operations. Abouelatta and Madl [107] develop a method of surface roughness prediction in turning based on cutting parameters and FFT analysis of tool vibrations. Salgado et al. [100] use singular spectrum analysis to decompose the vibration signals for in-process prediction of surface roughness in turning. Song et al. [152] investigate time series analysis of vibration acceleration signals measured during cutting operations for real-time prediction of surface roughness. Axinte et al. [153] try to correlate the quality of the machined surface after broaching, in terms of geometrical accuracy, burr formation, chatter marks and surface anomalies, and the output signals from multiple sensors: AE, vibration, cutting force; the former proved efficient to detect small surface anomalies such as plucking, laps and smeared material. Guo and Ammula [89] investigate the sensitivity of a broad range of AE parameters to white layer, surface finish and tool wear in hard machining: AE_{RMS}, frequency and count rate have good correlation with white layer formation and may be used to monitor surface integrity factors. Kwak and Song [90] apply AE signal analysis to recognise grinding burns in cylindrical plunge grinding processes. Chang et al. [154] develop a method for in-process surface roughness prediction based on the displacement signal of spindle motion. Axinte et al. [155,156], using AE signals backed up by cutting force data, report on process monitoring to detect surface anomalies when abusively broaching and milling difficult-to-machine aerospace materials. In [157], they report on the dynamics of broaching of complex part features: force and acceleration signal analysis revealed that damped coupled vibrations, resulting in tilted chatter surface marks, occur due to specific geometry of cutting edges that enable coupling of 3D vibrations. In [158,159], the detection of workpiece surface discontinuities, plucking, and smearing is attempted through an array of 3 AE sensors during multiple cutting edge machining. Rawat and Attia [160] investigate the effect of cutting speed and feed rate on the quality features of drilled holes in carbon fibre composites (delamination, geometric errors, surface finish) by recording cutting forces with a dynamometer and inserting two K type thermocouples inside the drill.

5.5. Machine tool state

Verl et al. [103] propose a system for feed drives wear monitoring based only on signals available in controlled drives: position, speed and motor current. The algorithm compares current characteristic parameters with those detected when the machine is new. Zhou et al. [161] introduce a systematic method to design and implement an integrated intelligent monitoring system, with modular and reconfigurable structure, to monitor power, vibration, temperature and drive and spindle pressure for condition monitoring, fault diagnosis and maintenance planning in flexible manufacturing cells. Saravanan et al. [162] present an analysis of failure frequency and downtime of critical subsystems in a lathe: it can be seen from Fig. 12 that the highest number of failures took place in electrical and headstock subsystems. The latter however has suffered more downtime than the former. By analysing the failure modes in the headstock subsystem, they observe that gear and bearing elements are the most significant components. Thus, they focus on spindle bearings condition monitoring techniques like vibration, AE, shock pulse and surface roughness monitoring for fault identification.

5.6. Chatter detection

Kuljanic et al. [163] analyse chatter identification methods used in research and investigate an industrial chatter detection system by comparing several sensors: the best results were given by a multi-sensor system using an axial force sensor and two accelerometers. Berger et al. [164] apply wavelet decomposition of cutting force signals to discriminate between chatter and non chatter states. Govekar et al. [105] use entropy rate of resultant cutting force signals to detect broken chip formation and chatter onset in turning. Kwak and Song [90] develop a method based on AE signals to recognise chatter vibration in grinding. Yoon and Chin [165] apply wavelet transform of cutting force signals for real-time detection of chatter in endmilling operations. Griffin and Chen [166] propose a multiple classification of AE signals to obtain signatures for both chatter and burn phenomena in grinding. Tangjitsitcharoen [106] utilizes power spectrum density of dynamic cutting forces during machining to detect continuous chip formation, broken chip formation, and chatter onset.

5.7. Other monitoring scopes

Teti et al. [167–169] apply sensor monitoring during turning of annealed and tempered Al alloys using AE time and frequency domain features, backed up by cutting force data, for in-process, real-time identification of work material heat treatment conditions independently of cutting parameters variations. Klocke et al. [170] study the impact of the workpiece mass on the piezoelectric force sensor dynamic behaviour by taking into account not only the natural vibration of the sensor but also the vibration characteristics of the whole machinery; methods to improve the measurement system's dynamic accuracy are proposed. Oliveira and Dornfeld [171] apply fast AE RMS analysis to monitor grinding events such

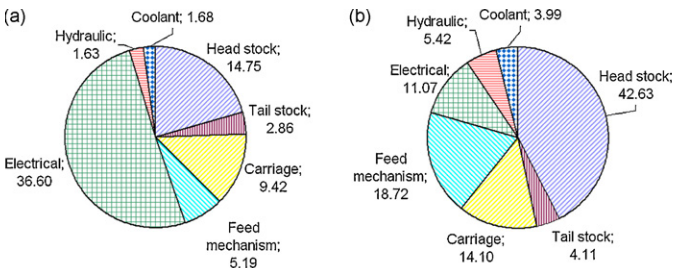

Fig. 12. Percentage values of (a) failure frequency and (b) downtime [162].

as contact, spark out, and dressing in the presence of process disturbances. Choudhury [172] apply an optical fiber transducer and a predictive system based on a neural network for online monitoring of tool wear and control of workpiece diameter. Klocke et al. [173] develop a new rotating dynamometer to measure milling forces acting at each cutting edge separately and with good dynamic characteristics. The design of the "intelligent cutter", composed of a telemetry system, a cutter body and integrated 3D force sensors for each cutting edge, is illustrated. Altintas and Park [174] present a dynamically compensated spindle-integrated force sensor system to measure milling forces for tool breakage monitoring, adaptive process control and optimization of cutting conditions. Van Houten and Kimura [175] develop a virtual maintenance system to relate predicted product behaviour and specific signals which can be detected by sensors and used to avoid catastrophic failures. This system is applied for condition-based maintenance and design for maintainability. O'Donnell et al. [29] integrate two piezoelectric force sensor rings in a direct driven motor spindle for online process monitoring of machining, encompassing TCM, spindle condition monitoring and collision detection. Santochi et al. [176] develop a new concept of cutting tool using strain gauges for the measurement of forces in turning by integrating the sensor within the tool shank. Kim et al. [177] build up a cylindrical capacitive displacement sensor to monitor endmilling and propose a mechanistic model considering tool deflection for quantitative estimation of dynamic cutting forces. Shinno and Hashizume [59] propose a multi-functional in-process monitoring method based on simultaneous multi-phenomena sensing to monitor the complete machining environment: process, tool and workpiece states. In [178–180], they report on an online process monitoring and adaptive control system for ultra-precision machining. First, a sensorless process monitoring method is studied; then, a sensor based approach, using a new micro-sized Pt temperature sensor mounted on the single crystal diamond tool rake face, is developed to keep constant the cutting point temperature by cutting parameters adaptive control. Finally, a multi-sensor system comprising the micro-thermosensor and an AE sensor to monitor ultra-precision machining conditions with high sensitivity and reliability is proposed.

6. Decision making support systems and paradigms

In monitoring and control activities for modern untended manufacturing systems, the role of cognitive computing methods employed in the implementation of intelligent sensors and sensorial systems is a fundamental one [181]. A conspicuous number of schemes, techniques and paradigms have been used to develop decision making support systems functional to come to a conclusion on machining process conditions based on sensor signals data features. The cognitive paradigms most frequently employed for the purpose of sensor monitoring in machining, including neural networks, fuzzy logic, genetic algorithms and hybrid systems able to synergically combine the capabilities of the various cognitive methods, are briefly reviewed before presenting their applications relevant to the scopes of this paper.

6.1. Neural networks

6.1.1. Neural network paradigms

An artificial neural network (NN) is a computational model of the human brain that assumes that computation is distributed over several simple interconnected processing elements, called neurons or nodes, which operate in parallel [182]. A NN provides a mapping through which points in the input space are associated with corresponding points in an output space on the basis of designated attribute values, of which class membership can be one. NN can capture domain knowledge from examples, do not archive knowledge in an explicit form such as rules or databases, can readily handle both continuous and discrete data, and have a good generalisation capability. NN can be employed as mapping devices, pattern classifiers or patterns completers. For more information on NN, see [183,184].

Knowledge is built into a NN by training. Some NN can be trained by feeding them with typical input patterns and expected output patterns. The error between actual and expected outputs is used to modify the weight of the connections between neurons. This method is known as supervised training.

Other NN are trained in an unsupervised mode where only the input patterns are provided during training: the NN learns automatically to cluster them in groups with similar features.

6.1.1.1. Supervised learning. Among supervised learning paradigms, backpropagation (BP) NN, which are multiple-layered feedforward (FF) NN [182], have been very popular for their performance. Jemielniak et al. [94] noticed that conventional training of FF BP NN very soon leads to overtraining and deterioration of the NN response. Training of these NN depends very much on the initial weight values. A good way to obtain satisfactory results is to introduce random distortions to the weight system, which efficiently push the NN out of local minima of testing errors. An even more effective method is to employ temporary shifts in the weights, alternately negative and positive. This brings the NN to a balance between training and testing errors and enables a notable reduction in the number of hidden nodes.

Further supervised NN approaches are also considered here due to their use in decision making during monitoring of machining: probabilistic NN (PNN) [185], recurrent NN (RNN) [186–188], artificial cellular NN (ACNN) [189], fuzzy logic NN (FLNN) or neuro-fuzzy systems (NFS) combining NN and FL methods to integrate the benefits of both paradigms [190].

6.1.1.2. Unsupervised learning. In unsupervised learning, only input stimuli are shown to the NN that organises itself internally so that each hidden processing element responds strongly to a different set or closely related group of stimuli. These sets of stimuli represent clusters in the input space which typically stand for distinct real concepts. Among unsupervised learning paradigms, the self-organising map (SOM) NN has been largely used for their performance [191]. The SOM NN creates a 2D feature map of input data so that order is preserved: if two input vectors are close, they will be mapped to processing elements that are close together in the 2D layer that represents the features or clusters of the input data.

6.1.2. NN applications to sensor monitoring of machining

The use of PNN for automated classification of broaching tool conditions utilising cutting force data is described in [192]. Trials with short broaching tools that simulate the roughing stage of industrial broaching were carried out to produce square profile slots while detecting cutting force signals. To reproduce real industrial tool failures, where both tool wear and single tooth chipping or breakage may randomly occur, the broaching tools had cutting teeth in different conditions: fresh, worn, chipped tooth, broken tooth. The push-off force F_y was selected as the most sensitive to tool conditions. Tool failure recognition was based on the extraction of a set of *N* characteristic points from the F_y plot by repetitive selection of local maxima to construct *N*-elements feature vectors (pattern vectors). Pattern vectors for different tool conditions were used as inputs to a PNN with 4 tool state classes: fresh, worn, chipped, broken. The success rate achieved was as high as 92%. A scheme of the tool failure recognition paradigm is shown in Fig. 13.

Recurrent NN with simple architecture were used in [193–197] for the evaluation of tool wear in turning. In [193], features from wavelet representation of AE signals were related to flank wear. Using RNN data processing, accurate flank wear estimations were obtained for the operating conditions adopted in the experimentation [194]. In [195], fractal dimensions were used as input features to a RNN for flank wear land estimation [196]. The development of this estimator comprised four stages: (i) signal representation, (ii)

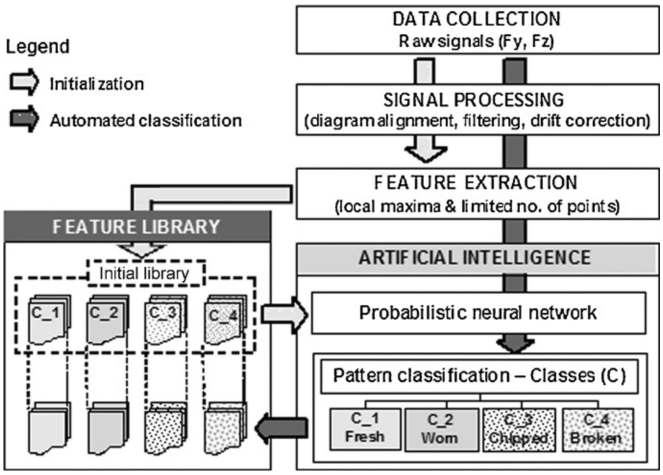

Fig. 13. . Schematic of the tool condition recognition system.

signal separation, (iii) feature extraction, and (iv) state estimation (flank wear land). In stage (i), a compact Suboptimal Wavelet Packet Representation (SWPR) [194], superior to other wavelet-based signal representation schemes, was used. In stage (ii), a method for suppressing noise components from measured time series data, called Modified Wavelet Method (MWM) [197], was selected for signal separation due to its high performance. The capacity, correlation and information fractal dimensions were extracted as features of a 4D time series vector formed by combining cutting force and vibration signals. The extracted features were related to flank wear land using a trained RNN that out-performed earlier tool wear estimators in terms of architecture simplicity and estimation accuracy. Due to the high signal sampling rate, this estimator may be used for real-time flank wear estimation at time epochs of few milliseconds, which can help with early detection of undue tool wear and related machining process faults [195].

In [198], an intelligent multi-sensor chatter detection system for milling using two accelerometers and one axial force sensor embedded in the milling machine was investigated (Fig. 14). Particular attention was paid to industrial needs: (a) no reduction in machine stiffness; (b) compatibility with pallet and tool changers; (c) no restriction on tools, parts and cutting parameters; (d) robustness against sensing units failures; and (d) independence from cutting conditions and system dynamics. To evaluate the system capability for a broad application range, different test set-ups with diverse milling machines, toolings, sensor systems and work materials were used. A NN approach was used for decision making, comprising an ACNN [189] applied to acceleration signals and a fuzzy NN [190] for axial force signals. Good levels of NN accuracy were obtained with all single sensor signals.

To realise the concept of multi-sensor chatter detection, the NN outputs for each single sensor signal were combined through: (i) linear combination of single sensor chatter indicators; (ii) a separate NN for multi-sensor classification; (iii) fuzzy logic classification (Sugeno fuzzy model); and (iv) statistical inference classification based on conditional probability, i.e. the probability that the system is unstable for a specific combination of single chatter indicators. The accuracy of the first three approaches was very high: 95–96%. But residual accuracy in case of sensing unit malfunctions dropped notably: 50–75%. The behaviour of the forth approach was quite different: accuracy was slightly lower, 94%, but insensitivity to malfunctions was extremely robust: 90–92%. Thus, the statistical inference multi-sensor chatter indicator, combining NN data processing and statistical methods to achieve both high accuracy and high robustness, was assessed as the most suitable for industrial milling applications.

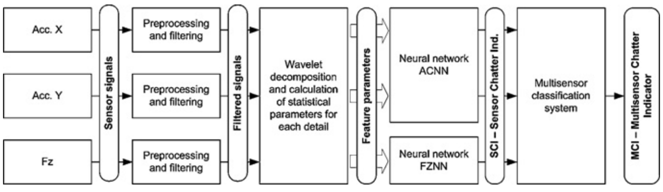

Fig. 14. Outline of the multi-sensor chatter detection system.

In [199], a sensor monitoring method, based on spindle motor power sensing and NN processing, was evaluated for chip disposal state detection in drilling. Spindle motor power measurements have the advantage of being easily realised during machining. From them, selected features such as variance/mean, mean absolute deviation, gradient, and event count were calculated to form input vectors to a FF BP NN for decision making on chip disposal state. The selected features were experimentally shown to be sensitive to changes in chip disposal state and relatively insensitive to changes in drilling conditions. So, the proposed monitoring system could effectively recognize chip disposal states over a wide range of drilling parameters, even if training was carried out under diverse process conditions.

Among the various sensing techniques, audible sound energy appears as one of the most practical ones since it can replace the traditional ability of the operator, based on his experience and senses (mainly vision and hearing), to determine the process state and react adequately to any machine performance decay [200]. This monitoring technology, however, has not been exhaustively investigated for process monitoring in machining, even though it is extensively used by machine tool operators for real-time decision making. In [133,144–146], audible sound energy generated by milling and band sawing of Al alloy and C steel under different process and tool conditions was analysed in the frequency domain by a real-time spectrum analyser to develop an automatic process monitoring system based on inexpensive sound sensors. Signal analysis was carried out by suppressing the noise generated by the machine and the environment from the sound emitted during machining. Classification of audible sound SFs was performed by a NN approach that could successfully identify the process and tool conditions solely on the basis of sound sensor monitoring.

6.2. Fuzzy logic

6.2.1. Fuzzy logic paradigms

Fuzzy logic (FL) has two different meanings. In a narrow sense, FL is a logical system, which is an extension of multivalued logic. But in a wider sense, which is in predominant use today, FL is almost synonymous with the theory of fuzzy set [201]. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. A fuzzy set defines a mapping between elements in the input space (sometimes referred to as the universe of discourse) and values in the interval [0,1]. A membership function is a curve that defines how each point in the input space is mapped to a membership value (degree of membership or truth degree) between 0 and 1. The membership function can be any arbitrary curve, the shape of which can be defined as a function suitable from the point of view of simplicity, convenience, speed and efficiency. Typically employed membership function shapes are triangular, rectangular, trapezoidal, gaussian, sigmoidal, etc. The processing core of a FL is based on a collection of IF-THEN rules, where the IF part is called the “antecedent” and the THEN part is called the “consequent”. Fuzzy rule sets usually have several antecedents that are combined using fuzzy operators. The combination is called a “premise” and it generates a single truth value that determines the rule’s outcome. In general, one rule by itself does not do much good. What’s needed are two or more rules that can play off one another. The output of each rule is a fuzzy set, but in general the output for an entire collection of rules should be a single number. Thus, first the output fuzzy sets for each rule must be aggregated into a single fuzzy set. The most common aggregation methods are: MAX (maximum), PROBOR (probabilistic or) and SUM (sum of each rule’s output set).

Fig. 15. Fuzzy logic data processing.

Then, the resulting set is defuzzified or resolved to a single number. The most popular defuzzification methods are: centre of area, bisector, middle of MAX, largest of MAX, and smallest of MAX. The process of mapping from input to output using FL is called fuzzy inference, involving all that was discussed above. Thus, a fuzzy inference system calculation comprises the 5 steps illustrated in Fig. 15. This global inference method, due to [202], is the most popular one.

6.2.2. Fuzzy logic applications to sensor monitoring of machining

In [203], the application of a Fuzzy Decision Support System, (FDSS "Fuzzy Flou") is presented for tool wear estimation during turning using cutting force components measurements. The architecture of the FDSS consists of a knowledge base, an inference engine and a user interface. The knowledge base has two components: the linguistic term base and the fuzzy production rule base. The linguistic term base is divided into fuzzy premises and fuzzy conclusions. Knowledge is represented by a set of if-then rules which specify a relationship between observations (causes) and conclusions (effects). The knowledge base can be created directly from the monitor using the tree view (see below) or can be written in a text editor and loaded into the FDSS. For tool wear estimation using cutting force components, the FDSS database comprised 3 premises (f, F_c, F_f), 2 conclusions (a_p, VB), and 18 if-then rules (Fig. 16). The results showed that the accuracy of tool wear assessment through the FDSS is sufficient for online tool wear monitoring.

In [204,205], in-process monitoring during quasi orthogonal cutting of metal alloys was attempted through sensor fusion of frequency features extracted from AE signals through diverse forms of signal analysis. These features were processed by a FL based pattern recognition method to develop a multi-purpose intelligent sensor system for classification of tool wear level and workpiece heat treatment state for two work materials: low C steel and 7075 Al alloy. The obtained results were considered positive for both monitoring scopes as, in the worst classification cases, a success rate not lower than 75% was obtained from the FL based decision making system, capable to take many factors into account without incurring in undue complexity.

6.3. Other methods (genetic algorithms, hybrid systems, etc.)

Genetic algorithms (GA) belong to a branch of computer science called "natural computation" where programmers, inspired by phenomena in the biological world, create models of these systems on a computer. This technique can solve complex problems by imitating Darwinian theories of evolution on a computer [206,207]. The first step in the use of a GA is building a computer model to represent a given problem [208]. Interacting variables in the problem are first combined and encoded into a series of binary strings (rows of ones and zeros) to form numerical "chromosomes". The computer randomly generates an entire "population" of these chromosomes and ranks them based on a "fitness function" which determines how well they solve the problem. Those strings which are deemed the "fittest" are allowed to "survive" and "reproduce" with other chromosome strings, through genetic operators such as "crossover" and "mutation", to create "offspring" chromosomes. This population of strings evolves by continuously cycling the genetic operators [209] (Fig. 17). A powerful search engine is thus available which inherently preserves the balance between exploitation (take advantage of information already obtained) and exploration (search new areas). The result is then decoded back to its original value to reveal the solution. Although simplistic from a biologist's viewpoint, these algorithms are sufficiently complex to provide robust and powerful search mechanisms.

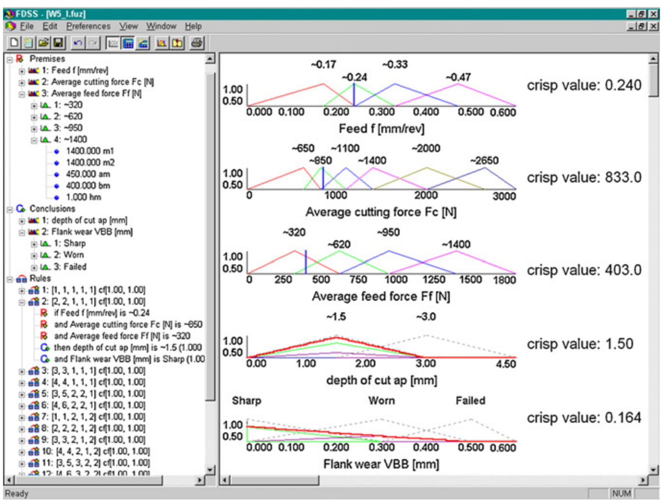

Fig. 16. Screen view of the FDSS "Fuzzy Flou" with knowledge base structure (left) and complete evaluation of depth of cut and flank wear (right).

Fig. 17. Structure of genetic algorithms and genetically based operators.

In [210], GA are utilised to automatically construct a FL knowledge base (KB) from a set of experimental data on tool wear monitoring during turning without requiring any human expert intervention. The performance of this FL-GA system is compared with the performance of classical FL and NN systems for application to tool wear estimation. The construction of a FL KB necessitates skills and expertise. The operator has to analyze the dependence of F_c on VB so that the experimental results have to be presented in a conveniently understandable form. This makes FL systems rather difficult for practical implementation in their human manual form. This problem can be solved using a GA to automatically construct the FL KB (Fig. 18).

The operator no longer needs to analyze the experimental data. He only needs to select the maximum level of complexity he wants to consider. The learning time of the GA method was the shortest among the considered methods, making it very convenient for shop floor use. Moreover, one can specify the maximum complexity level

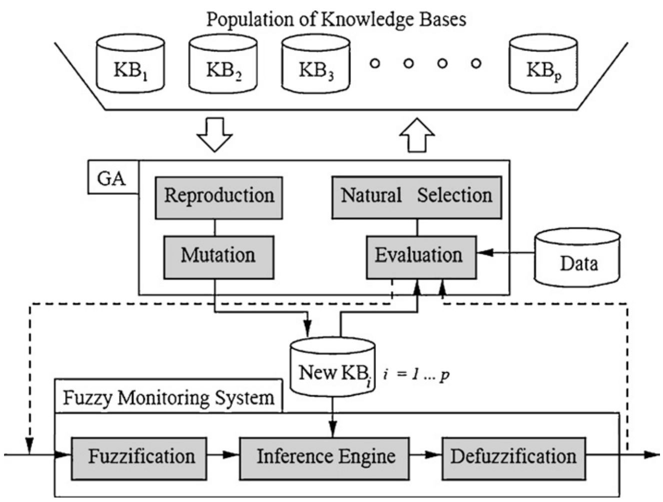

Fig. 18. GA learning process of the FDSS Fuzzy Flou knowledge base.

together with how much emphasis the GA must place on accuracy increase versus complexity reduction. There are definite advantages for practical applications since the GA provides more generality to the KB.

6.3.1. Hierarchical algorithms

In general, when a single NN is used for sensor monitoring of machining, several SFs are fed to the NN input nodes, while the process or tool conditions estimation is obtained at the NN output. However, the use of several SFs as input to a single NN requires a large number of experimental data that are usually not available if the monitoring system is supposed to be trained during the first tool life period and be ready for monitoring during the next ones [81]. A different approach is presented by Kuo and Cohen [211], who proposed a hierarchical monitoring system for tool conditions consisting of two modules: the first estimates the tool wear using all the SFs from one sensor and the cutting parameters using a NN with single radial-basis function. The results are then integrated in the final system's response in the second module, where a fuzzy NN is used. Jemielniak et al applied a strategy based on a large number of AE and cutting force SFs and a hierarchical algorithm for tool wear monitoring in conventional turning [70] and micro-milling [81]. In the 1st stage of the hierarchical algorithm, the tool wear is estimated separately for each SF using a 3rd degree polynomial approximation. In the 2nd stage, the results obtained are integrated (averaged) in the final tool condition evaluation. In [70], the efficiency of the TCM strategies based on a single NN with several input signals and on a hierarchical algorithm was analyzed. The latter proved to be much more efficient, which was attributed to insufficient NN learning data (collected during the first tool life) in relation to the necessary network size. Decomposition of the multi SFs tool wear estimation into hierarchical algorithms shows the considerable advantage of the hierarchical models over the single-step approach. A higher number of SFs can be used, since the SF-tool wear relationship for a single feature is simple, easy to model, and easy to reverse, while direct determination of the tool wear dependence on many SFs requires copious learning data and long learning times.

6.4. Sensor fusion technology

6.4.1. Sensor fusion concepts and paradigms

When measuring a particular variable, a single sensory source for that variable may not be able to meet all the required performance specifications. A solution to this problem is sensor fusion that combines sensory data from disparate sources so that the resulting information is better than would be possible when these sources are used individually. The term "better" can mean more accurate, more complete, more dependable, more robust, or refer to the result of an emerging view, such as stereoscopic vision that calculates depth information by combining 2D images from two cameras at slightly different viewpoints. One can distinguish direct fusion, indirect fusion and fusion of the outputs of the former two. Direct fusion is the fusion of sensor data from a set of heterogeneous or homogeneous sensors, soft sensors, and history values of sensor data, while indirect fusion uses information sources like a priori knowledge about the environment and human input [212–214].

6.4.2. Reconfigurable monitoring system for sensor fusion research

Sensor fusion for machining process monitoring has been extensively investigated in [215–219] within a multi-annual project aiming at the implementation of a reconfigurable multi-sensor monitoring system (Fig. 19), endowed with cutting force, vibration, AE, motor current, audible sound and optical sensors, for application to diverse machining processes (orthogonal cutting, turning, milling, drilling, and broaching), work materials (steels, composite materials, Ti alloys, Ni alloys, Ni–Ti alloys) and monitoring scopes (tool wear, chip form, process conditions, work material state, and machinability assessment).

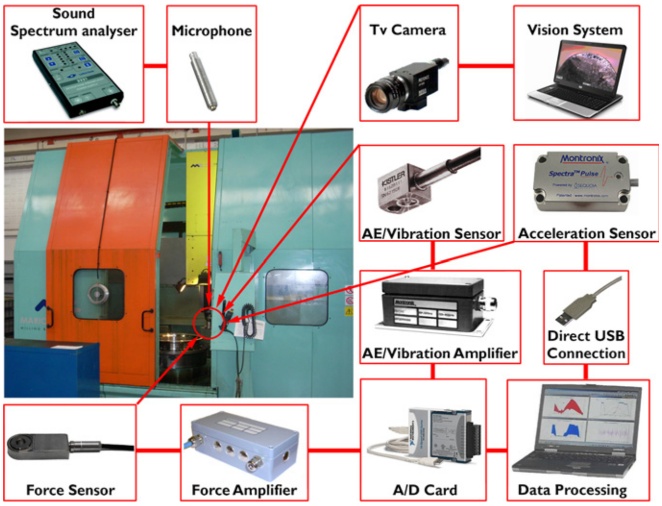

Fig. 19. Reconfigurable multi-sensor monitoring system.

Sensor signal characterisation is based on frequency domain analysis, accomplishing sensor signal spectral estimation through a parametric method that allows for feature extraction from the signal frequency content [4]. In this procedure, the signal spectrum is assumed to take on a specific functional form, the parameters of which are unknown. The spectral estimation problem, therefore, becomes one of estimating these unknown parameters of the spectrum model rather than the spectrum itself [220]. From each signal specimen (measurement vector), p features $\{a_1, \ldots, a_p\}$ (feature vector), characteristic of the spectrum model, are obtained through Linear Predictive Analysis (LPA) by applying Durbin's algorithm [221]. The details of this procedure are given in [222]. Feature vectors are used to construct input pattern vectors for pattern recognition paradigms [223]. If single signal specimens are utilised as inputs, the feature vector and pattern vector coincide. If signal specimens' inputs come from two or more diverse sensor signals, input patterns are complex vectors integrating sensory data from diverse sources to realise the concept of sensor fusion. Pattern recognition and decision making in the reconfigurable multi-sensor monitoring system is carried out by three layers FF BP NN whose architecture is automatically configured as a function of the monitoring application. The constructed input pattern vectors are the input of the first NN layer that, accordingly, assumes a number of nodes equal to the number of input pattern vector elements. The hidden layer takes up a number of nodes as a function of the number of input nodes. The output layer contains one or more nodes, yielding coded values associated with the monitored process variables that need to be recognised. For NN learning, the leave-k-out method, particularly useful when dealing with relatively small training sets, is typically utilised [224]: one homogeneous group of k patterns, extracted from the training set, is held back in turn for testing and the rest of the patterns is used for training. The NN output is correct if the actual output, O_a, is equal to the desired output, O_d, ±50% of the difference between the numerical codes for different process conditions. By setting error $E = (O_a - O_d)$, process conditions identification is correct if $-0.5 \le E \le +0.5$; otherwise, a misclassification case occurs. The ratio of correct classifications over total training cases yields the NN success rate.

6.4.3. Sensor fusion application to machining process monitoring

The NN pattern recognition paradigm of the reconfigurable multi-sensor monitoring system proved able to effectively realise the concept of sensor fusion for a broad range of machining process monitoring applications, yielding satisfactory results also under unfavourable situations by synergically combining the knowledge extracted from multiple sources of information. In [217,225,226] the system was applied to process condition and machinability evaluation during cutting of difficult-to-machine materials such as

Ti alloys and NiTi alloys, using cutting force and acceleration signals through both single signal and sensor fusion data analysis. Training sets with input pattern vectors of different size and nature were built: (a) signal specimen feature vectors of single cutting force or acceleration component: F_x, F_y, F_z, a_x, a_y, a_z; (b) integrated pattern vectors of the 3 cutting force or acceleration components: $[F] = [F_x \quad F_y \quad F_z]$; $[A] = [a_x \quad a_y \quad a_z]$; (c) sensor fusion pattern vectors combining cutting force and acceleration pattern vectors: $[S] = [F \quad A] = [F_x \quad F_y \quad F_z \quad a_x \quad a_y \quad a_z]$. The NN outputs were coded values to evaluate process condition and machinability. Results showed that the use of single component signal data as pattern inputs provided acceptable accuracy: 78–85%. If the integrated 3 acceleration or 3 cutting force components signal data are used as inputs, accuracy improves notably: 92–97%. By applying sensor fusion technology to fully combine information from cutting force and acceleration signal data, a very high accuracy is obtained: 99–100%.

In Teti and Segreto [216], sensor monitoring during cutting of plastic matrix fibre reinforce composites was performed for consistent and reliable identification of tool state. AE and cutting force signals were subjected to the NN based sensor fusion paradigm. The superior classification results found by merging cutting force and AE data stressed sensor fusion aptitude for data analysis enhancement and decision making reinforcement [5,118].

It is worth noting that the above results were achieved via sensor fusion of multimodal data which is far less common than fusion of data from the same sensor type. This highlights the NN ability to efficiently realize the concept of sensor fusion as well as to deal with incomplete or noisy data sets, yielding satisfactory results also under adverse situations by synergically combining knowledge extracted from multiple sources of information.

In [227], the combination of a direct sensor (vision) and an indirect sensor (force) is proposed to create an intelligent integrated TCM system for online monitoring of tool wear and breakage in milling, using the complementary strengths of the two types of sensors. For tool flank wear, images of the tool are captured and processed in-cycle using successive moving-image analysis. Two features of the cutting force, which closely indicate flank wear, are extracted in-process and appropriately pre-processed. A SOM network is trained in a batch mode after each cutting pass, using the two features from the cutting force, and measured wear values obtained by interpolating the vision-based measurements. The trained SOM network is applied to the succeeding machining pass to estimate the flank wear in-process. The in-cycle and in-process procedures are employed alternatively for the online monitoring of flank wear. To detect tool breakage, two time domain features from cutting force are used, and their thresholds are determined dynamically. Again, vision is used to verify any breakage identified in-process through cutting force monitoring. Experimental results show that this sensor fusion scheme is feasible and effective to implement online TCM in milling and is independent of cutting conditions.

7. Industrial initiatives, experiences and applications

The development and growth of precision machining applications to a wide field of mechanical products (from medical devices to automotive drivetrain, power systems and aerospace) due to the demand for higher performance, better energy efficient and more complex products has pushed the "commercialization" of precision machining. This requires highly reproducible processes in spite of work material properties variability, tool wear, thermal distortion, etc., and thus has called for the increased use of sensors in precision machining. Recent CIRP Keynotes [228] highlighted the challenges in this field requiring advanced sensors. Simple tasks such as "finding the part" are complicated in precision micromachining due to the small tool size (<few 10s of μm), complex part shapes, and small work areas. As a result, attention is directed to the use of sensor technology to aid in part setup and machinining [229]. A comprehensive review of the challenges to precision machining monitoring and applications in typical processes (e.g. grinding, wheel dressing, abrasive polishing, and ultraprecison turning/diamond turning) is given in [230].

An additional area of development focuses on the communication between sensors, machines and the outside world. With the increase in complexity of manufacturing systems and processes, there is a growing need to bring together advances from different realms of manufacturing research and application. It is no longer adequate for manufacturers to focus on particular aspects of their process for improvement: rather, they need to use a holistic approach. Since sensors and sensing systems play an integral part in the operation and control of most of these systems and processing, they need to be included as well. Clearly, to harness and process information across different levels, robust methods for communication and interoperability in and between the levels are needed [231]. Interoperability is defined as "the ability of two or more systems or components to exchange information and to use the information that has been exchanged" [232]. The Association for Manufacturing Technology recently launched MTConnect, an open software standard for data exchange and communication between manufacturing equipment [233]. Currently, MTConnect has been adopted primarily by machine tool manufacturers and their end-users who see immense value in being able to interoperate with other equipment. The MTConnect protocol defines a common language and structure for communication in manufacturing equipment, and enables interoperability by allowing access to manufacturing data using standardized interfaces. It does not define methods for data transmission or use, and is not intended to replace the functionality of existing products and/or data standards. It enhances the data acquisition capabilities of devices and applications, moving towards a plug-and-play environment that can reduce integration costs. MTConnect is built upon prevalent standards in the manufacturing and software industry, which maximizes the number of tools available for its implementation and provides a high level of interoperability with other standards and tools. MTConnet's messages are encoded using XML (eXtensible Markup Language), widely used as a portable way of specifying data interchange formats. Fig. 20 shows a data gathering setup using MTConnect: data are collected in near-time from a machine tool and thermal sensors attached to it. Other sensor inputs can be easily added, e.g. TCM or power monitoring. Software tools can be developed which operate on the XML data from the agent. Since the XML schema is standardized, the software tools can be blind to the specific equipment configuration from where the data is gathered. An added benefit of XML is that it is a hierarchical representation, and this is exploited by designing the hierarchy of the MT Connect schema to resemble that of a conventional machine tool.

The schema itself functions as a metaphor for the machine tool and makes the parsing and encoding of messages intuitive. Data items are grouped based on their logical and not on their physical organization. Although temperature sensors operate independent

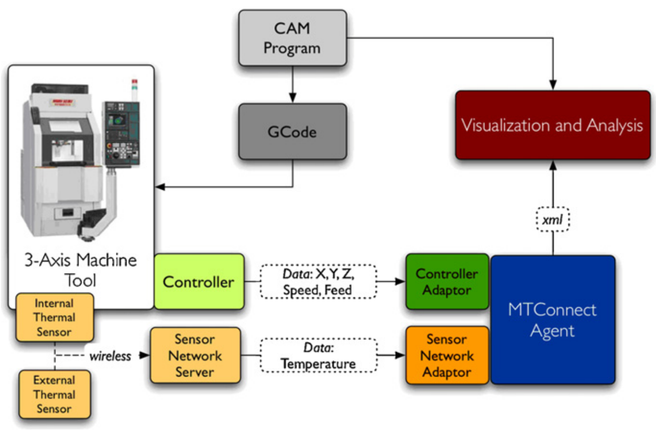

Fig. 20. MTConnect setup.

of the machine tool, sensory data are associated with specific machine tool components, and hence temperature data is part of the machine tool hierarchy. This simplifies data analysis, e.g. to observe and control thermal distortion of a machine component and relate it to a specific part geometry. Major machine tool builders have recognized the need for better integration of their hardware. Seiki [234] developed the Mori-Net system, which allows remote monitoring of machine tool status over the internet while simultaneously logging data for post processing. Mazak [235] has similar systems (Cyber Monitor and Cyber Tool Management) that help remotely track the machine tool status in a factory. While these technologies are very robustly integrated into the respective machine tool systems, they are proprietary "walled" systems. Only specific machine tools can be used with them, which limits their applicability. Also, since these are not extensible systems, they are limited by their inherent capabilities and cannot be modified by the users. MTConnect does not aim to replace these methods but provides the basic tools needed to "talk" to a machine tool. Value added applications can be built on the MTConnect layer. So the benefits that advanced systems, such as Mori-Net, bring to newer machine tools can be applied in older systems as well. MTConnect interacts similarly with existing interoperability standards used in industry and works in conjunction with other standards such as the NIST IEEE 1451 standard for sensors and transducers [236]. As shown by MTConnect, interoperability standards and their application offer tremendous potential to use advanced sensor system outputs, especially for reconfigurable systems, and building high speed decision making and control capability on existing sensor signal processing techniques.

A notable instance of industrial initiative in the area of sensor monitoring of machining can be found in the aerospace industry. Following the Pensacola catastrophic event in 1996, the Aerospace Industries Association (AIA) felt the urgent need of a research effort to respond to accidents caused by manufacturing induced anomalies in critical rotating parts. The 1997 Report of the AIA Rotor Integrity Sub-Committee stated that about 25% of rotor failure events are caused by manufacturing induced anomalies. It was projected that, given the expected increase in air travel and the evidence of component failures due to such anomalies, the resulting loss of aircraft would be unacceptable. Accordingly, three large industry led international research projects on machining process monitoring were launched in the last decade: AIA and FAA "ROMAN" project; EC FP5 "MANHIRP" project; and EC FP7 "ACCENT" project.

By responding to the US Federal Aviation Administration (FAA) initiative on critical rotating part manufacturing, the AIA and FAA project on Rotor Manufacturing (ROMAN, 1998–2000) was started by the main aero engine makers in USA and Europe.

The European aero engine manufacturers in the ROMAN project joined in the ensuing EC FP5 project on Integrating Process Monitoring and Control in Manufacturing to Produce High Integrity Rotating Parts (MANHIRP, 2001–2005), to investigate the use of sensor monitoring for machining induced anomaly detection and evaluate the resulting loss in performance.

Today, also on the basis of the MANHIRP issues, the main European aero engine manufacturers (Rolls Royce, UK; Snecma, France; MTU, Germany; Volvo AC, Sweden; Avio SpA, Italy; Turbomeca, France; ITP SA, Spain) join in the EC FP7 project on Adaptive Control of Manufacturing Processes for a New Generation of Jet Engines (CP 213855 ACCENT, 2009-11) involving leading university research centres in the field of sensor monitoring of machining (WZL-RWTH Aachen, Germany; University of Naples Federico II, Italy; ENIT Tarbes, France; Mondragon University, Spain; ENSAM Cluny, France; TUKE Kosice, Slovakia) [237]. This initiative sets off from the fact that critical aero engine components manufacturers are faced with machining highly complex parts from difficult-to-machine superalloys, with large part variability and small batch quantities. Stringent controls are placed on safety critical component manufacture to ensure that parts will function correctly and safely to a declared service life. Thus, the manufacture of these parts is very conservative and process parameters are often reduced or tools changed early to ensure part integrity. In this situation, machining processes can never be fully optimised. The industry method is to "freeze" the process following qualification to first article inspection and part validation via laboratory tests. Once frozen, no process condition change is allowed without time consuming, costly re-validation. In the ACCENT project (Fig. 21), multi-sensor monitoring, using cutting force, AE, vibrations and motor power, is being applied for process optimisation in turning, milling, drilling and broaching of aero engine parts made of Ni and Ti alloys. The initial results reveal the feasibility of process adaptation to changing tool and component states while operating in industrially approved multi-dimensional process windows warranted by relevant sensor SFs.

The noise from disturbance sources that usually contaminate the desired signal can be minimized using AE sensors, as AE propagates at frequencies well above the characteristic ones in machining, e.g. spindle RPM or natural frequencies. AE is more advantageous than force or vibration, especially at the ultra-precision scale, due to its relatively superior signal/noise ratio and sensitivity. Hence, AE is very well suited to detect micro-scale deformation mechanisms within a relatively 'noisy' machining environment [238] (Fig. 22). In [238], the application of AE and cutting force signals for TCM in micro-milling was presented. The obtained results showed, that despite the small material removal rate in micromachining, AE was strong, easy to record and had a very short reaction time to tool-workpiece contact, making it an ideal means of contact detection and integrity monitoring in the cutting process (Fig. 23). Though the cutting force signals were severely disturbed by the dynamometer resonance vibrations, the measurements still appeared useful for TCM. New tasks of TCM appearing in micro-machining, such as cutting edge offset [239] (Fig. 24) and material structure, necessitate new approaches.

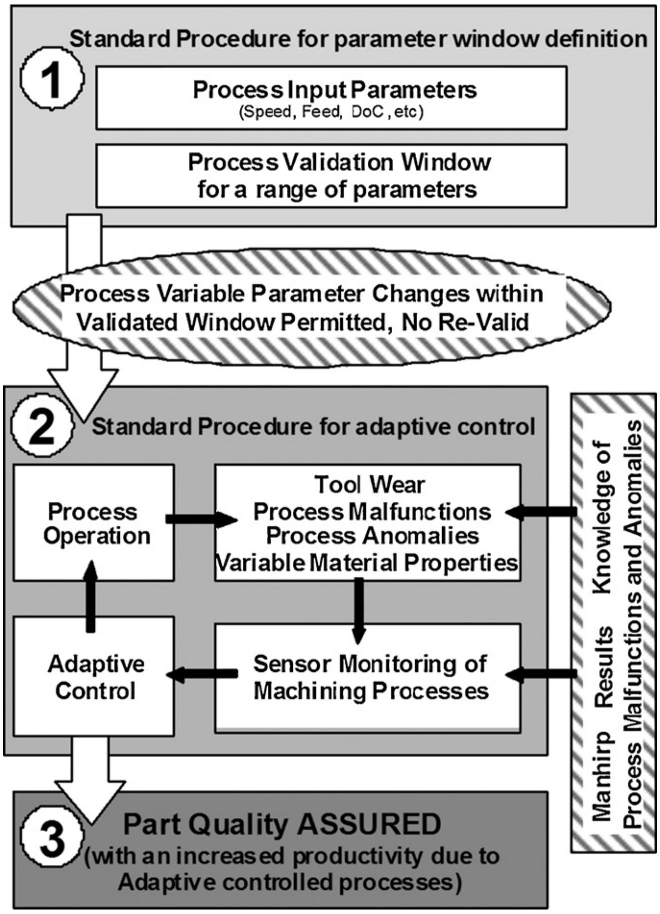

Fig. 21. Scheme of the EC FP7 CP 213855 "ACCENT" project [236].

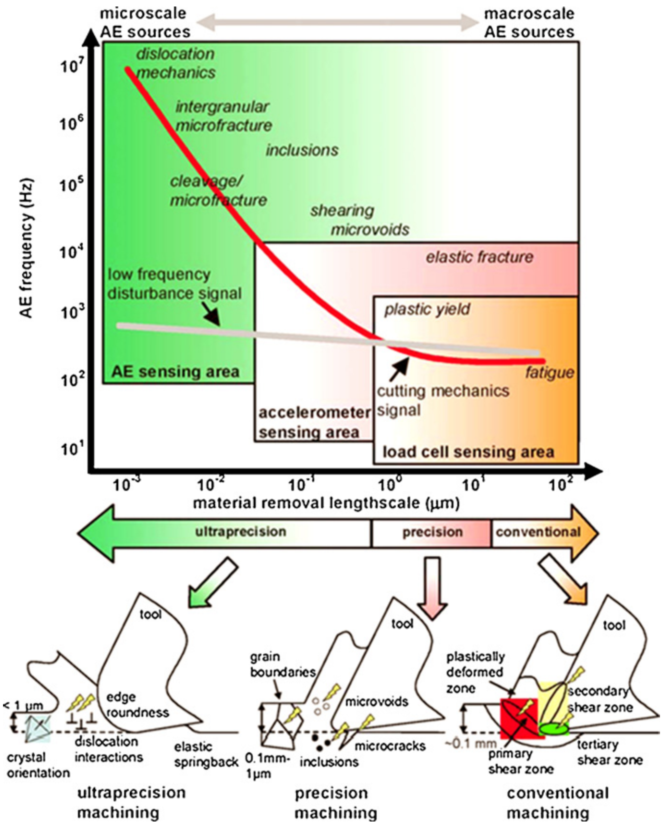

Fig. 22. Sources of AE at different stages of material removal [238].

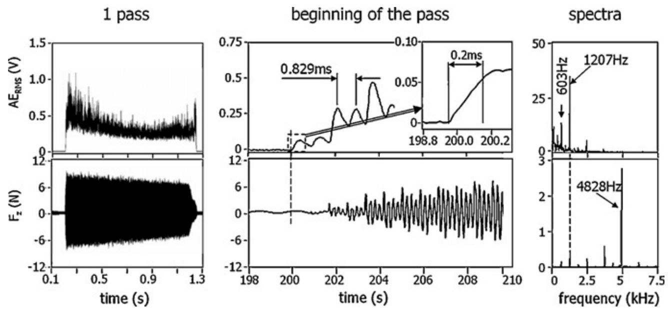

Fig. 23. Examples of AE and cutting force signals detected during tests; 1207 Hz: tooth passing frequency, 4828 Hz: 4th harmonic of tool passing frequency, the closest to the dynamometer natural frequency (5080 Hz) [238].

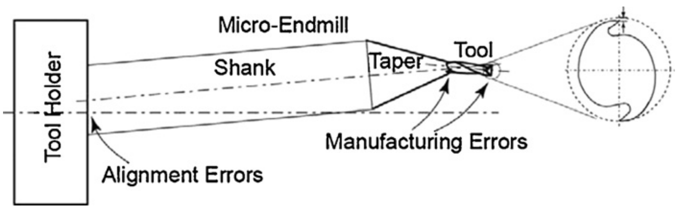

Fig. 24. Micro-end mill with associated errors [239].

8. Outlook on future challenges and trends

The EC FP6 Network of Excellence on "Innovative Production Machines and Systems – I*PROMS" (2004–2009) [240], organised by Prof. D.T. Pham, Cardiff University, with participation of 30 European research partners, comprised in its activities on Production Automation and Control the task, coordinated by Prof. R. Teti, University of Naples Federico II, of identifying and proposing a roadmap of recommended research to solve the needs and provide the key enabling technologies for "Intelligent Sensor Technology in Manufacturing" by 2017.

The future challenges for ISTM were identified as the targets of the following main key enabling technologies (KETs): (a) new sensors and sensor systems; (b) advanced sensor signal data processing; and (c) intelligent sensor monitoring.

8.1. New sensors and sensor systems

Targets: transformation of stand-alone sensors, used primarily as diagnostic devices in a manufacturing process, to sensors that are a part of an intelligent system for process, tool and machine monitoring and control. *Recommended measures*: (i) more basic and applied research in new sensors, (ii) more basic and applied research in sensor system intelligence, and (iii) academia and industry collaboration to identify the real needs for new sensors and sensor systems.

8.2. Advanced sensor signal and data processing

Targets: innovative signal and data processing techniques, assisted by cognitive tools and methods, to develop and apply sensing systems for manufacturing monitoring. *Recommended measures*: (i) more applied research in advanced signal and data processing, (ii) more basic and applied research in decision making systems, (iii) more manufacturing and ITC interdisciplinary research, and (iv) training and formation of skilled operators.

8.3. Intelligent sensor monitoring

Targets: intelligent sensor monitoring systems including, as part of their packaging, abilities for self-calibration and self-diagnostics, signal conditioning, and decision making. *Recommended measures*: (i) more applied research in intelligent sensor monitoring applications to manufacturing, (ii) development of high performance equipment, (iii) efforts towards standardisation, (iv) promotion with industry, (v) robust pattern recognition paradigms; and (vi) training and formation of skilled operators in intelligent sensor monitoring.

The next and most important step in the roadmap compilation is the definition of "development trajectories", i.e. logical/temporal connections among KETs and gaps till 2017. Finally, the visionary targets of the KETs after 2017 were identifies as: (i) intelligent sensors and sensor systems technology achievement; (ii) smart sensors integration; (iii) Ambient Intelligence (AmI) in manufacturing; (iv) strengthening the European Sensor System Suppliers (SMEs) in their market position by developing smart sensors platforms; and (v) less machine down time, less scraps, higher productivity, easier system operability, less false alarm, higher product quality and better knowledge about manufacturing processes. For details on associated challenges to achieve the visionary targets see [240].

9. Conclusions

The future enhancement of machining systems and their operation performance will vitally depend upon the development and implementation of innovative sensor monitoring systems. These novel systems will need to be robust, reconfigurable, reliable, intelligent and inexpensive in order to meet the demands of advanced manufacturing technology. These demands include increasingly small, precision and complex products for applications in biomedicine, transportation, MEMs devices, etc., as well as ubiquitous sensor systems for machine and system monitoring to reduce resource requirements and insure that manufacturing systems operate efficiently with minimal energy consumption and environmental impact. Luckily, today's sensor systems are becoming increasingly dependable and low-priced and the signal processing capabilities of advanced algorithms and decision making strategies are also rapidly progressing.

There are numerous techniques and methods of signal processing (feature extraction, selection and refinement) and feature integration (decision making) developed in laboratories worldwide, most of them really effective for sensor monitoring of machining operations: the main achievements were reported in Sections 3 and 5. Despite industrial data availability or industrial conditions adoption in many studies, very few of these achievements found actual application in the shop floor or in commercially available tool and process conditions monitoring systems. The main reason seems to be the difficult, sophisticated usage of these techniques and methods. Usually, author's tuning of "hand made" configuration is inevitable, making the procedure hardly applicable in industry. Accordingly, one of the main challenges in future machining process monitoring systems is the development of algorithms and paradigms really autonomous from machine tool operators, who are not required to know about methods like wavelet transform, neural networks, etc., with signal feature extraction and decision making performed without intervention of the operator, who should provide only very simple (the lesser, the better) input and information.

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