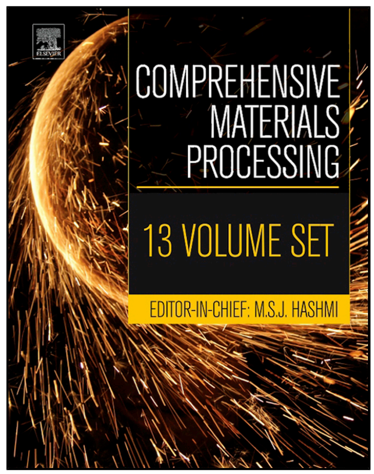

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13.22 Review of Sensor Applications in Tool Condition Monitoring in Machining

MSH Bhuiyan and IA Choudhury, University of Malaya, Kuala Lumpur, Malaysia

13.22.1 Introduction

Tool condition monitoring (TCM) can be defined as a process of watching the performance of a cutting tool during machining to observe the damages occurred to it by the responsible process mechanics. A machining process is usually accomplished through a series of complex change of process dynamics. Wide ranges of occurrences are involved with the process of metal cutting; they are mostly damaging for the cutting tool condition and workpiece surface roughness. The uncontrolled machining operation creates chatter, vibrates the system, and disturbs the machining process stability, which eventually do affect the state of cutting tool and product quality. According to Oraby and Hayhurst (*1*), though, machining time has been appreciably reduced using high-speed machining technique, however, machining of high-strength aerospace alloys, composites, and ceramics so far demand a significant improvement. Machining such materials causes high tool temperatures and fast wear of cutting edges, lacks dimensional accuracy, and requires considerable amount of coolants. These entire deficiencies from various machining methods result in the tool breakage, tool failure, and other kind of catastrophe during machining. Even though a cutting tool is traditionally changed to meet the demand of a new process (e.g., differing tool geometry and material) or to fit the kind of cutting (roughing, finishing, and profiling), however, it also requires to be replaced when it is worn or broken. To change a tool when worn necessitates monitoring the tool wear. This is primarily because the tool wear is a complex phenomenon that manifests itself in different and diverse ways. An effective TCM, therefore, can keep the cutting tool under surveillance to safeguard the cutting tool and protect the workpiece from damage. Though TCM was not pronouncedly taken up at the very early states of machining, this has always been done by users during operation either intentionally or unconsciously. With the change in time, the TCM has become very useful and achieved users appeal to be used during all types of machining operations.

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13.22.2 Factors Monitored during TCM

In machining, the phenomena which affect the state of the cutting tool are essentially generated from the process of metal cutting. The entire phenomena in machining (see Figure 1) could be categorized into two types, i.e., avoidable and unavoidable events. Despite some of the happenings being avoidable, however, most of the phenomena in machining are intrinsically involved with the process of metal cutting to remove the unwanted material from the workpiece and thus to make the machining effective.

To develop a professional machining process, one has to be more concerned about the factors, which influence the progressive tool wear, tool breakage, tool breakdown, surface roughness, and other final outcomes of the process. A great improvement could be achieved to the performance of machining operation by minimizing the effect of different factors that damage the condition of the tool. It is a primary requirement to know the details about the entire tentative occurrences taking place in machining to minimize their effect.

13.22.2.1 Unavoidable Occurrences

The tool wear, tool fracture, chip formation, chip breakage, chip removal, tool breakdown, etc. are the fundamental occurrences inseparably involved with machining which damage the effectiveness of cutting tools. A tool may fail in different ways like progressive flank wear, crater wear, notch wear, built-up-edge (BUE), frittering, thermal crack, fracture, plastic deformation, and breakage. The different happenings during machining damage the tool condition and disturb the process stability. The entire phenomena have their particular effect on the process and also on the state of the tool. The effect on the tool might be mechanical, chemical, thermal, and abrasive. However, all of them come up with tool wear, tear, and breakdown. The tool wear mechanism during metal cutting and its corresponding effects have been thoroughly described by Li (2).

Tool wear is a progressive failure mechanism, generally comprising the predominant wear mode, dependent upon the cutting conditions, workpiece and tooling material, and the tool insert geometry. For a particular cutting tool and workpiece material combination, the tool wear progression may depend exclusively on the cutting conditions, principally the cutting speed, v, and the undeformed chip thickness, t, and a combination of different wear mechanism. With the increase of depth of cut, the swept area is considerably increased and that causes to decrease the tool life significantly. Tool wear at low cutting speeds is predominantly influenced by rounding-off of the cutting point and subsequently loses sharpness. As the cutting speed increases, the wear-land pattern alters to accommodate the resulting change with extremely high values leading to plastic flow at the cutting point. At slow cutting speeds, adhesion and abrasion are the main wear mechanisms. Abrasion and chemical wear are essential at high cutting speeds, especially in continuous chip formation (3).

For single-point cutting tools, the nose, flank, notch, and crater wear are identified as more predominantly occurring and principal types of wear in turning. Nose wear or edge rounding occurs primarily through the abrasion wear mechanism on the cutting tool's major edges resulting in an increase in negative rake angle. At high cutting speed, the edge deforms plastically and may result in the loss of the entire nose. Besides an intensive dependency on cutting conditions, this type of wear can also take place through plastic or elastic deformation (4,5). The BUE formation is one type of damaging incidence very common to cutting tool,

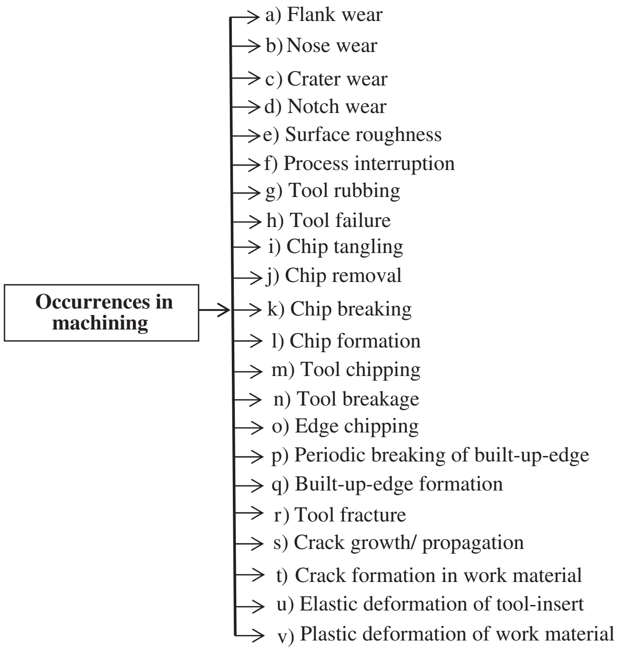

Figure 1 Various phenomena involved in machining.

which breaks periodically through chipping and cracking in interrupted cutting, in particular, with the tool with brittleness and thermal fatigue. The use of inappropriate cutting conditions and brittle tool (e.g., ceramics and cemented carbide) can end up in a considerably worn tool with catastrophic tool failure (CTF).

Notch wear is another form of tool wear, which occurs at the depth of cut line as the tool rubs against the shoulder of the workpiece. This occurrence leads to abrasion on tool surface and chemically affects the cutting tool that possibly causes failure of the cutting tool. However, the intense rubbing action between the clearance face of the cutting tool and the newly formed surface of the workpiece triggers both the adhesive and abrasive mechanisms in contact area and followed by flank wear. Flank wear deteriorates surface quality, enlarges the contact area, and thus increases heat generation (*6*).

The cutting temperature, on the other hand, influences the crater wear more than the cutting speed (*7*). The rake face affected by cutting temperatures and high shear stresses results in the crater wear some distance away from the tool edge, which can be quantified by depth of cut and cross-sectional area. The mechanism of crater wear includes adhesion, abrasion, and diffusion all together. The tool may fail catastrophically at cutting point due to various depths of the crater. However, results from a considerable amount of research recommended the flank and nose wear as better indicators of tool wear than any other types of wear (*6*).

Chip formation is another factor in metal cutting, which has an unavoidable effect on the cutting tool. The chip formation has a major influence on the cutting tool condition depending on the formation mechanism and its geometry. During the chip formation at different cutting conditions, the tool flank and rake face experience different level of continuous effect (mechanical, thermal, and abrasive). The tool wear due to the chip formation occurrences depends on several things: how does the chip form, its type, how does it separate, how (speedily/slowly) is it removed, the level of energy content, the quantity of temperature content, how intensely does it strike the tool face during disposal, etc. Chip formation involves a complicated interaction of plastic and elastic deformations within a small region, which is known as the shear zone. This interaction in the shear zone ultimately defines both the geometry and motion of the chips that are generated from metal cutting (*8*). The chip types are essentially important to tool wear, whereas the chip formation is dominated by cutting conditions. The increase in cutting speed produces thin chips. As in high cutting speed, the controlled chip region is decreased; the thickness of the chip is reduced (*9*). However, the cutting speed affects the shape and dimensions of the chip formation zone or the extent of the region of plastic deformation ahead of the cutting tool (*8*). The steady-state and the cyclic types of chips are typically generated from machining. The steady-state or continuous-type chips generate from the blunt tool-tip and contain concentrated, pie shaped, and extended shear zone in it (*10*). The generation of a continuous chip during turning is undesirable, due to its adverse effect on surface roughness. Furthermore, a continuous chip tends to cause problems by tangling around the tool.

It has been reported that the chip formation produces the maximum amplitude of the dynamic component of cutting force (*11*). The segmented chip formation force was recorded to be less whereas the generated heat was more than the continuous chip formation (*12*). Among the entire chip types, the segmented chip is essentially produced from conventional turning and damages the cutting tool more seriously. Shaw and Vyas (*13*) have demonstrated that for certain geometry, the cutting speed typically controls the onset of strain localization and thus the segmented chip formation. Kishawy and Wilcox (*14*) in another investigation have pointed the periodic cracking as the root cause of saw-tooth chip formation, not the adiabatic shear. With the thinning of microcrack region, the chip moves up the tool face and thus gives rise to a cutting ratio(s) greater than one. The consequent effect would influence the cutting tool and the workpiece surface finish. The effect of steady-state/continuous-type chip formation comes up with progressive wear on tool faces. Since the chip and tool have interrupted contact during the chip removal, it has a different extent of discontinuous effect on the tool face depending on the chip types (*15*). The chip formation incidence affects the tool state whatever be its types.

The chip removal generated from material cutting is another damaging factor for the tool state. Depending on the cutting conditions and tool geometry, the chips flow in different directions to dispose. Chip flow in a grooved tool basically consists of side-flow and back-flow, while the chip curl consists of up-curl and side-curl (*16*). Based on the residual shear stresses and subsequent elastic recovery, it is reported that the chip is born straight in the shear surface until it reaches the end of the contact zone of rake face (*17*). The chip flow direction or the flow angle is obtained by summing the flow angle of small elements along the length of the cutting edge (*18*). With the change of chip flow angle, the stress–strain concentration in the chip is varied and also its geometry. It is empirically established that the residual shear stresses and strains are maximum at the tool–chip contact surface and minimum at the free surface (*19*).

During the chip removal, the tool–chip contact occurs which causes friction at the interface and thus produces tool wear. The initial part of the interface is considered as sticking zone, where intense plastic shearing of weaker (chip) material occurs, and the rest of the contact zone is represented as sliding zone with relatively fewer severe frictional conditions. It is assumed that the uniform shear stress in the sticking region decreases with a power law in the sliding zone (*19*). The cutting tool is thereby affected from the sticking and sliding of chips during removal. The sticking regions are the most heat-affected regions due to the intense contact and thus for the friction between the underside of the chip and the tool's groove (*17*). For the assumption that all energy produced by friction is dissipated in the chip ($J = 1$), it is seen that the frequencies of cutting force increase; however, the mean value and the bandwidth remain unaffected. Therefore, the tool material should have high wear resistance and endurance to the specific cutting forces and generated high temperature (*14*).

13.22.2.2 Avoidable Occurrences

The tool breakage and process interruption, though very common occurrences in machining, are avoidable by proper monitoring. Tool breakage is one kind of tool failure that typically happens in extreme cases when the cutting force applied on tool insert exceeds its strength limit. It also occurrs in case of no corrective actions taken in the early stages of crater or notch wear development.

Different investigations have shown that about 50% cases of tool life expire just because of the tool fracture. It has also been reported that about 15% of tool breakage is the result of the wrong choice of cutting parameter (20). The use of worn cutting tools leads directly to reduced process capabilities and product quality. Eventually, the process stability is being disturbed. As a result, toothed cutting tool's tooth breakage may result in either a small chipping of the cutting edge or a complete breakage of cutting tooth, which is a more dangerous failure mode and causes severe disruption of the machining process and product quality. Even though the failure relating the cutting tool accounts for up to 6.8% of the downtime of machining in its entirety, the tool wear and breakage are the most predominant failure modes appearing in a machining process (18). Process interruption would be a resulting effect of tool breakage. This may also generate due to machine trouble, change in cutting conditions, and sometimes it is being incorporated intentionally to produce the desired object.

The different potentially damaging occurrences in machining, including the tool wear, chip formation, tool breakage, etc., are required to be monitored to avoid any kind of unexpected catastrophe during operation. The tool wear causes extra power consumption; tool breakage interrupts the process; and chip formation accelerates the tool wear and disturbs the surface integrity (21). All are unexpected and impede achieving an efficient machining and to have cost-effective manufacturing. Even though the tool wear, tool fracture, tool breakdown, chip formation, chip breakage, chip removal, surface roughness, change of cutting condition, vibratory effect, process interruption, etc. are involved with the process of metal cutting, however, some of the extreme occurrences can be avoided by proper monitoring. Especially, the tool breakdown, process interruption, workpiece surface derogation, and consequent vibratory effect are avoidable events in machining. The effects of all the aforementioned occurrences disturb the smooth progression of process and spoil the consequent time and money as well. Therefore, to safeguard the cutting tool, ensure a safe machining operation, and confirm the good-quality product, the employment of TCM is obligatory. It is since the tool monitoring in machining got viral of importance to assure continuity of operations and to improve overall effectiveness of the machining process (22). A number of TCM techniques are being used to materialize the objective; however, the sensor-based TCM techniques are being preferred more by the users for their ease of manipulation and deployment as well. The different occurrences involved in machining have some certain effect on the state of cutting tool and incite the different sensors according to their frequency range and mode of sensing. It is very important to select the best suitable sensor for a particular application and to choose the more pertain processing method for a sensor-based monitoring.

13.22.3 Sensor-Based TCM

Historically, human operators, using a combination of sight and sound, have performed the TCM during machining. They have used heuristic rule to explain their observation. With the changing demand of time through a number of stages of development, TCM has been reached at a very compatible and easy use state now. The gradual improvement of TCM system has been accomplished through a number of steps. **Figure 2** shows different stages of evolution of TCM. The TCM started using human sensing faculties, followed by the direct measurement technique by taking the tool off, and eventually the use of sensors in monitoring the tool condition has been introduced and being used extensively in modern manufacturing application.

These sensor-based monitoring techniques have been developed based on the theme of imitating the human sensing faculties. However, it is impossible to develop a sensor that can mimic exactly the human operator, who is subjective and flexible but inaccurate. Implementing such a sensor that can adequately meet the requirement of online TCM is still an unresolved challenge. This shortcoming has been circumvented using some descriptive parameters of the cutting process that show sensitivity to tool wear, thus precluding the need for a unique sensor. Designing an advanced sensor-based monitoring system expedites gathering information from the cutting process enabling adequate measurements. Depending on the type of application, scope, and suitability, various types of sensors have been used to make the monitoring useful and reliable. Martin (23) carried out a survey on the application of sensor in diagnosing faults in cutting tool. Kilundu et al. (24) administered a thorough study on some commonly used sensing and signal processing technique prior to investigate the tool condition in machining. Zhu et al. (25) have reviewed a large number of articles focusing on the application of different signal processing techniques to monitor the cutting tool condition using sensor. Teti et al. (26) have compiled a database of TCM literature containing over 500 publications from 1960 to 1995. Dimla (6) has reviewed 83 articles on available methods for sensor-based TCM. Particular attention was paid to the manner in which sensor signals from the cutting process have been harnessed and used in the development of tool condition monitoring systems (TCMSs). A huge volume of literature in this field suggests a variety of process parameters in the metal-cutting environment that can be tapped and used to predict the cutting tool state. Some typical techniques of sensor-based TCM prior to their application in machining are acoustic emission (AE), cutting force, vibration signature, optical measurement/vision monitoring, laser monitoring, thermal imaging/tool temperature measurement, electrical measurement, etc. Some other less frequently used methods are ultrasonic, workpiece surface finish quality, workpiece dimensions, stress/strain analysis, spindle motor current, etc. as means of monitoring the tool condition (6). **Figure 3** shows a chart of commonly used sensor-based TCM techniques.

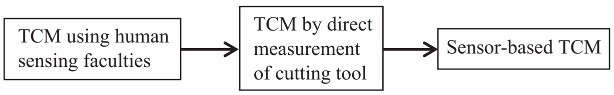

Figure 2 Advancement of tool condition monitoring techniques.

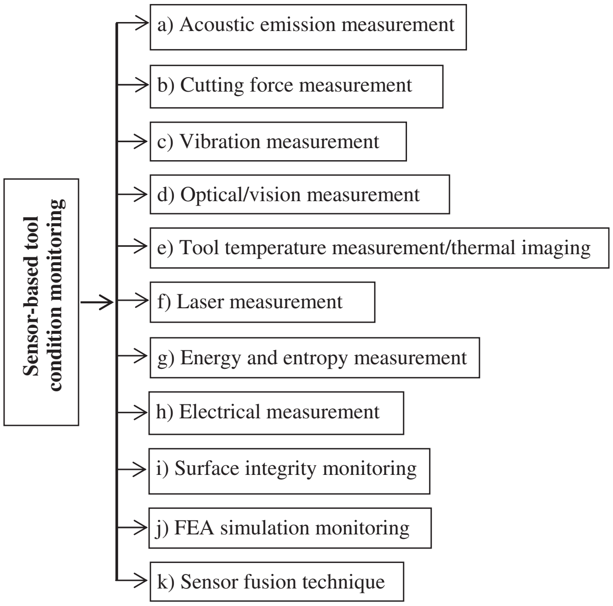

Figure 3 Mostly used sensing techniques in tool condition monitoring.

Although wide ranges of sensors are available to make the monitoring effective, however, choosing the right sensor for the right application is still a matter of discretion.

Babel et al. (27) have identified different occurrences, including tool damage using the AE sensor. Kalvoda and Hwang (28) have used vibration signature to detect wear and fault of cutting tool in milling. Kirby and Chen (29) have measured vibration of cutting to predict the surface roughness of workpiece. Chiou and Liang (30) have jointly deployed AE and cutting forces to locate the tool fracture and tool breakage during turning. The chip formation and surface integrity were thoroughly investigated by Balaji and Ghosh (17) using force measurement. Song et al. (31) have used AE sensor, vibration sensor, and force dynamometer together to observe the effect of cutting speed, feed rate, and depth of cut on the cutting tool.

A sensor-based TCM is usually accomplished in three steps: (1) data/signal acquisition, (2) signal processing and analyzing, and (3) tool status reporting. A typical method of indirect (sensor-based) TCM is illustrated in Figure 4.

The signal processing is a major part of sensor-based TCM that comprised of another two steps, i.e., preprocessing and post-processing. The preprocessing of signal is usually performed using the different hardware modules like amplifier, filter, etc. A wide range of methods like root mean square (RMS), fast Fourier transformation (FFT), time–frequency domain (TFD), statistical analysis, etc. has been used to postprocess signals from the sensor(s).

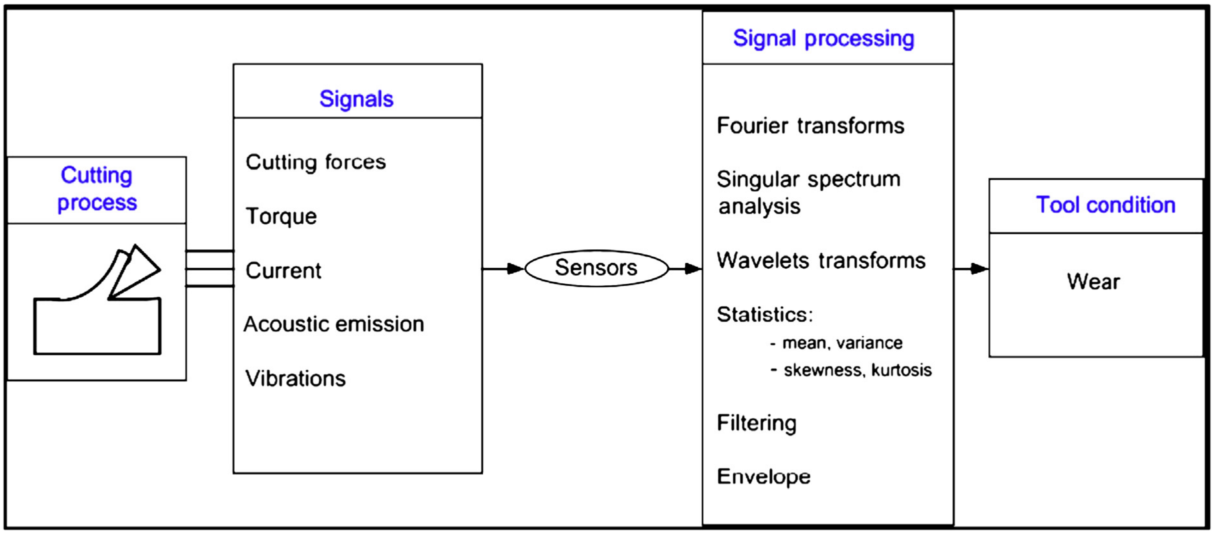

Figure 4 Indirect methods of tool condition monitoring. Reproduced from Martin, K. F. A Review by Discussion of Condition Monitoring and Fault Diagnosis in Machine Tools. *Int. J. Mach. Tool. Manuf.* **1994,** *34* (4), 527–551.

13.22.3.1 Signal Processing and Analyzing Methods

The process of metal cutting is accomplished through a change of energy of different form like mechanical, thermal, abrasive/frictional, chemical, vibratory, etc. Therefore, a more appropriate sensor(s) with pertinent processing method is required to represent all the changes into a common readable output. Usually, the entire sensing systems used in TCM display their output into electric voltage (V). The signals from a conventional tool setup are very stochastic and squiggle in look; therefore, it is required that the signals are synthesized to make them comprehensive. The signal is complex, and it contains numerous frequencies from different occurrences in machining. The captured raw signals from different sensors are processed following the logical scheme schematically illustrated in Figure 5.

A number of signals generated from different sources are included in the same raw signal. The raw signals are illegible and demand processing to extract the significant feature(s) out of them. The signal parameters are used to correlate the cutting conditions, tool wear, tool geometry, tool breakage, chip formation, and other occurrences involved in machining with the captured signal. The entire features need to consider recognizing a change in sensing the tool condition to make the monitoring more effective. Usually the pattern recognition analysis is used to characterize the signal pattern and thus to monitor the tool failure arising from wear and fracture. Before adopting the pattern recognition system, feature reduction is done by selecting only the best features using feature selection criteria, i.e., class mean criteria *(26)*. Best features are the ones that carry more information regarding the status of the cutting tool, cutting condition-speed, feed, and depth of cut are also taken as parameters to make the diagnostic system more universal *(32)*. For best performance of the monitoring system, only those features which show a high sensitivity to tool wear and low sensitivity to process parameters should be utilized *(33)*. Wide ranges of signal analyzing method are available to illustrate the significance of raw signal captured from sensors. However, choosing the best suitable method for the respective sensor signal is crucially important.

The raw signals that are captured by the sensors as well as recorded and then analyzed are usually time-domain signal. Usually two types of patterns are very obvious from a raw signal, either continuous or burst. The RMS signal represents the energy content of raw signal, which indicates the intensity level of occurrences *(34)*. The frequency analyses of time-domain signal, i.e., the Fourier transformation, can significantly expedite the TCM. This is one of the mostly used TCM techniques, due to relatively fast data collection and interpretation when compared to other available off-line methods. Since the data are collected as digitally sampled time-domain signals, the frequency analysis technique allows further manipulation using computers. The development of FFT reportedly allows the conversion of the time-domain data into frequency spectra with ease, as the data are already stored in a digital format *(35)*. Similar statement have been reported in another article published by Ebersbach and Peng *(36)*. The objective is to obtain a frequency decomposition of the original signal in which the features, best correlated with the tool wear, can be detected in a simple fashion *(37)*. The analysis results obtained from the peak detection, and knowledge base can be used to assess the cutting tool condition, to detect the faults present in a machine as well as some fault severity assessment *(36)*. The TFD signals are used to represent the occurrences both in the time and frequency extent concurrently. Wavelet is another pre-processing method that is used to analyze the local features of sensor's signals unlike the time–frequency distribution. The wavelet transform can accommodate simultaneously both the large and small scales in a signal, enabling the detection of both distributed and local faults. Some researchers have used Wigner–Ville distribution to analyze the sensor signals for the early detection of tool damage. The instantaneous power spectrum was successfully used to detect the local faults in cutting tool. The propagation of local faults is identified by monitoring variations in the features of the power spectral distribution *(38)*.

A common signal processing approach for tool wear monitoring is to generate many signal features and then use a feature selection strategy to identify the features most sensitive to tool wear. There are four domains from which features from sensor signals can be generated:

- statistical analysis;
- time-domain analysis;
- frequency-domain analysis; and
- joint time–frequency analysis (e.g., spectrograms and wavelet analysis) *(39)*.

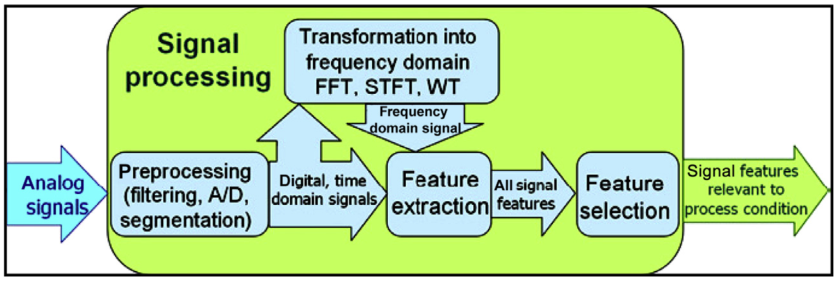

Figure 5 Signal processing logical scheme. Reproduced from Teti, R.; Jemielniak, K.; O'Donnell, G.; Dornfeld, D. Advanced Monitoring of Machining Operations. *CIRP Ann. – Manuf. Technol.* **2010,** *59* (2), 717–739.

Many signal processing methods have been used to analyze sensor signals, with the aim to extract the features of signals for monitoring. The main methods include time-series analysis, FFT, wavelet transformation, statistical analysis, and Gabor transformation (or window (local) Fourier transformation) (34). The different available signal processing and analyzing methods are listed in Table 1.

13.22.3.1.1 Time-Series Modeling

Time-series modeling technique is used to extract parameters from sensor's signals. A number of researchers have used time-series analysis whereas autoregressive (AR) parameters and AR residual signals were taken as features for monitoring tool wear condition (40).

An AR model can be set as follows:

$$\bar{x}(n) = a_1x(n-1) + a_2x(n-2) + \cdots + a_5x(n-5) \qquad [1]$$

$$R(n) = \bar{x}(n) - x(n) \qquad [2]$$

where $x(n)$ is the acoustic emission–root mean square (AE-RMS) time series; $\bar{x}(n)$ is the AR predicted value; a_1, a_2, …, a_5 are the AR model parameters; and $R(n)$ is the AR residual signal.

Table 1 Common signal processing methods

	Signal postprocessing methods		
Signal preprocessing methods	*Feature extraction methods*	*Feature selection methods*	*Decision-making methods*
Filter, piezotron, coupler, charge amplifier	1. General purpose time-domain feature: a. arithmetic mean, average value, magnitude, mean square error (MSE) counting; b. ring down count or pulse rate, pulse width, burst rate, burst width, rise time, peak, amplitude, signal energy (for AE), c. effective value (root mean square, RMS); d. variance (or standard deviation); e. skewness; f. kurtosis; g. signal power, h. peak-to-peak, range, or peak-to-valley amplitude; i. crest factor; j. ratio of the signal increment 2. Time-series modeling: a. autoregressive (AR), 1st, 2nd, 3rd, 4th, 5th order autoregressive AR, AR2, AR3, AR4, AR5, respectively; b. moving average (MA); c. autoregressive moving average (ARMA); d. principal component analysis (Karhunen–Loeve transformation); e. signal spectrum analysis (SSA); f. permutation entropy 3. Frequency analysis: a. Fast Fourier transform (FFT), b. Discrete Fourier transform (DFT), c. Short-time Fourier transform (STFT) 4. Time–frequency analysis: a. Wavelet transform, b. discrete wavelet transform (DWT), c. wavelet packet transform (WPT), d. Hilbert–Huang transform (HHT)	1. Random, 2. Neural network-based system, 3. Pearson correlation coefficient, 4. Group of signal feature (SF) value, 5. Polynomial classifier, 6. Taguchi orthogonal array, 7. Bayesian framework and support vector machine (SVM), 8. Statistical overlap factor (SOF), 9. Engineering judgment rule, 10. By setting up a threshold limit, 11. Neural network by using Bayesian multilayer perception (BMLP), 12. Group method of data handling (GMDH) Class mean criteria	1. Neural network: a. supervised learning (back propagation multilayer forward), b. unsupervised learning, 2. Fuzzy logic, 3. Genetic algorithm, hybrid system

The experimental results have found that the power of the AR residual signal of the AE increases with increases of the flank wear of the cutter in turning. Some other researchers have performed time-series analysis based on artificial neural network (ANN) in analyzing the sensors' signal (34).

13.22.3.1.2 Fast Fourier Transforms

A physical signal is usually represented by a time function $f(t)$ or, alternatively, in the frequency domain by its Fourier transform (FT), $F(\omega)$:

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega t} \mathrm{d}\omega \qquad [3]$$

and

$$F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-i\omega t} \mathrm{d}t \qquad [4]$$

where t is time and ω is angular frequency. Both functions, known as FT pair, contain exactly the same information about the signal, but from different and complementary focuses (41).

It is good enough to describe a stationary signal. However, if the frequency composition of nonstationary signals is being calculated by using FT, it averages the frequency composition over the duration of the signal. As a result, FT cannot describe adequately the characteristics of the transient signal in the lower frequency (34). However, some studies have been carried out successfully using FT to process signal captured from the cutting tools with different wear levels (42).

13.22.3.1.3 Time–Frequency/Wavelet Analysis

By analyzing the time–frequency spectrum of signals, a larger amount of information can be extracted than investigating a frequency spectrum only. Wavelet analysis is one such time–frequency analysis method. By using the wavelet function the localization complexity of the Fourier transformation can be eliminated. It is impossible to reduce both time and frequency localization arbitrarily. Wavelet analysis provides an interesting compromise on this problem.

Applying windows of different sizes can change the resolution of time and frequency. It allows the use of long intervals when more precise and low frequency information is needed or the use of shorter intervals when high-frequency information is required (43).

According to some researchers (25), this is achieved by generating a complete family of elementary functions by dilations or contractions and shifts in time, from a unique modulated window:

$$\psi(t) \Rightarrow \psi_{a,b} = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) \qquad [5]$$

where $\psi(t)$ is the mother wavelet function and $\psi_{a,b}(t)$ is a wavelet function, with $a \neq 0$ and b the scale and shift parameters. The function $\psi(t)$ must be located in time, of null average, and its function transform $\Psi(\omega)$ has to be a continuous bandwidth filter and strongly falling when $\omega \to \infty$ and $\omega \to 0$.

The wavelet functions are characterized into two ways. Some are attributed for the continuous signal whereas others are for discrete. Continuous wavelet transform (CWT) can be defined by

$$W_\psi s(a,b) = \int_{-\infty}^{\infty} s(t) \psi_{a,b}(t) \mathrm{d}t \qquad [6]$$

where $s(t)$ is limited-energy signal.

Assuming a real mother wavelet and a limited-energy signal (t), the wavelet discrete transform is defined by

$$DW_\psi s(j,k) = < s, \psi_{jk} > = \int_{-\infty}^{\infty} s(t) \psi_{jk}(t) \mathrm{d}t \quad j,k \in Z \qquad [7]$$

Kamarthi and Kumara (44) have studied the effectiveness of the wavelet analysis in estimating the flank wear and found it to be satisfactory. Li (45) has successfully used CWT, and the discrete wavelet transforms (DWTs) to detect real-time tool breakage in drilling.

13.22.3.1.4 Statistical Analysis

The statistical analysis technique attempts to recognize differences between signals through the study of the distribution of amplitudes. The distribution shape can be achieved by means of the central moments of the distribution function, in particular, by the third and fourth central moments which are called skew and kurtosis, respectively (41) and given by

$$S = \frac{1}{\sigma^3} \int_{-\infty}^{\infty} [x - E(x)]^3 f(x) \mathrm{d}x \qquad [8]$$

and

$$K = \frac{1}{\sigma^4} \int_{-\infty}^{\infty} [x - E(x)]^4 f(x) \mathrm{d}x \qquad [9]$$

where f is the function of the probability density of variable x and σ is the standard deviation.

The skew measures the symmetry of the distribution about its mean value while the kurtosis represents a measure of the sharpness of the peaks. A positive value of the skew generally indicates a shift of the bulk of the distribution to the right of the mean, and a negative one, a shift to the left. A high kurtosis value implies a sharp distribution peak, i.e., a concentration in a small area, while a low *kurtosis* value indicates essentially flat characteristics (46).

13.22.3.1.5 Gabor Transform

Gabor transformation, also called short-time Fourier transformation (STFT), is a time–frequency technique used to deal with nonstationary signals (34). A Gabor transformation has a short data window centered on time. Spectral coefficients are calculated for this short length of data; the window is then moved to a new position, and the calculation is repeated (41). Assuming an energy-limited signal, $f(t)$ can be decomposed by STFT, namely

$$G(w, \tau) = \int_R f(t) g(t - \tau) e^{-wt} \mathrm{d}t \qquad [10]$$

where $g(t - \tau)$ is called the window function.

Implementation of Gabor transformation for signal processing is efficient when it is used to locate and characterize events with many defined frequency patterns, not overlapping and long relatively to the window function (34).

13.22.3.1.6 Entropic Distance Method

The entropic distance method is based on the comparison of the obtained signal with a pattern signal used as reference. To do this, the signals are adjusted to an AR pattern of order p:

$$\sum_{t=0}^{p} a_i x_{t-i} = \varepsilon_t \quad a_0 = 1 \qquad [11]$$

where

$\{\varepsilon_t\}$ is a Gaussian random variable with $E[\varepsilon_t] = 0$.
$E[\varepsilon_i, \varepsilon_j] = \delta_{ij}\sigma_\varepsilon$ and a_i are the pattern coefficients.

The entropic distance is defined as

$$d = -2 \ln \lambda = \left(N'_R = N'_T\right) \ln\left(\widehat{\sigma}_p^2\right) - N'_R \ln\left(\widehat{\sigma}_R^2\right) - N'_T \ln\left(\widehat{\sigma}_T^2\right) \qquad [12]$$

where N_R and N_T are lengths of reference and test samples, respectively. 'σ_p' and 'a_p' are two parameters obtained when both sampling fit the same pattern, two sets of parameters (σ_R, a_R) and (σ_T, a_T) are two sets of parameters obtained when both sampling fit different patterns.

Under normal conditions, 'd' is a nonnegative number and is zero only if $\widehat{\sigma}_R = \widehat{\sigma}_T$ and $\widehat{a}_R = \widehat{a}_T$, i.e., if the patterns are the same (46).

13.22.3.1.7 Hilbert–Huang Transforms

Hilbert–Huang transform (HHT) is another type of signal processing method applied to decompose intrinsic mode functions (28). Each component has its Hilbert transform as

$$y_i(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{c_j(\tau)}{t - \tau} \mathrm{d}\tau \qquad [13]$$

With the Hilbert transform, the analytic signal is defined as

$$z(t) = x(t) + iy(t) = a(t) e^{i\theta(t)} \qquad [14]$$

where

$$a(t) = \sqrt{x^2 + y^2} \qquad [15]$$

and

$$\theta(t) = \arctan(y/x) \tag{16}$$

Here $a(t)$ is the instantaneous amplitude and θ the phase function, and the instantaneous frequency is simply

$$\omega = {}^{\mathrm{d}\theta}\!/_{\mathrm{d}t} \tag{17}$$

After performing the Hilbert transform on each component, the original data can be expressed as the real part '$\Re$' in the following form

$$x(t) = \Re\left\{\sum_{i=1}^{n} a_j(t)\exp\left[i\int \omega_j(t)\mathrm{d}t\right]\right\} \tag{18}$$

With the Hilbert spectrum defined, the marginal spectrum can be defined as

$$h(\omega) = \int_0^T H(\omega, t)\mathrm{d}t \tag{19}$$

The marginal spectrum offers a measure of the total amplitude (or energy) contribution from each frequency value. This spectrum represents the accumulated amplitude over the entire data span in a probabilistic sense. Further details of HHT can be found in Ref. *(47)*.

All the aforementioned methods have been used to perform the signal processing. Some other methods have been found to be used in decomposing the sensors' signals (AE, vibration, force, feed current, motor power, etc.) as well as extract the features out of them. Chiou and Liang *(30)* have used a fast block-averaging algorithm for features and patterns indicative of tool fracture during analyzing the recorded AE and force data. Similar work was conducted by Jonak and Gajewski *(48)*; they have used a statistical signal processing algorithm to identify the RMS, skew, and kurtosis of the recorded signals in the detection of CTF. In addition to RMS, Jemielniak and Otman *(49)* have measured average, variance, maximum, and minimum values of the signals to extract the significant features out. Scheffer et al. *(39)* have worked out a self-organizing method to identify a certain frequency range in FFTs that were sensitive to tool wear and independent of the type of the workpiece and machine type.

In addition to the above methods, the ANN, fuzzy neural network (FNN), fuzzy logic technique, AR method, linear regression (LR) method, polynomial classifier (PC), group method of data handling, ISODATA method, statistical overlap factor (SOF), random signal frequency analysis, and RMS have also been used to process the sensor signal.

13.22.3.2 Mostly Used Sensor-Based TCM Techniques

A number of sensor-based TCM techniques have been found in monitoring the cutting tool condition online as well as off-line during machining. Some of them have specific application whereas some others have commonplace application and are being used extensively. The following literature tersely presents some mostly used sensor-based TCM methods and about their scopes of application.

13.22.3.2.1 AE Measurement

The AE is the transient elastic wave generated by the rapid release of energy from a localized source or sources within a material. During the AE process, a stress wave is generated and propagated through the material. This effect appears as plastic deformation, phase transformations, vacancy coalescence, and decohesion of inclusions and fracture, which are sources of AE. **Figure 6** shows the different sources of AE in machining. However, only the plastic deformation and fracture have major significance in metal cutting *(32)*.

Dornfeld *(40)* pointed out the possible AE sources referring to stress waves generated by the sudden release of energy in deforming material during metal cutting: (1) plastic deformation of the workpiece during cutting process, (2) shearing of the chip, (3) frictional contact between the tool flank face and the workpiece resulting in flank wear, (4) frictional contact between the tool rake face and the chip resulting in crater wear, (5) collisions between chip and tool, (6) chip breakage, and (7) tool fracture. The AE derived from turning of metals consists of continuous and transient signals, which have distinctly different characteristics. Continuous signals are associated with shearing in the primary zone and wear on the tool flank and rake face, while burst or transient signals result from either tool fracture or from chip formation (chip breakage, chip–tool collision). Therefore, the sources of AE of (1)–(4) do generate continuous AE signal's frequency, while sources of (5)–(7) produce transient frequency of AE signals *(34)*. Factors like tool breakage and chip breakage are easily identifiable by sudden bursts of AE, followed by large changes in AE intensity *(50)*. Similar results were obtained from another investigation carried out by Hase et al. *(51)*. On the other hand, the tool wear is more difficult to detect because of the low intensity of the signal and dependency of AE signals on process parameters. It is generally agreed that the continuous-type AE signal components are associated with plastic deformations and tool wear during metal cutting; however, the burst-type signals are observed during crack growth inside the material. The occurrences of tool fracture, chip breaking, chip tangling, and chip impact also generate the frequency of burst-type AE signals *(52)*.

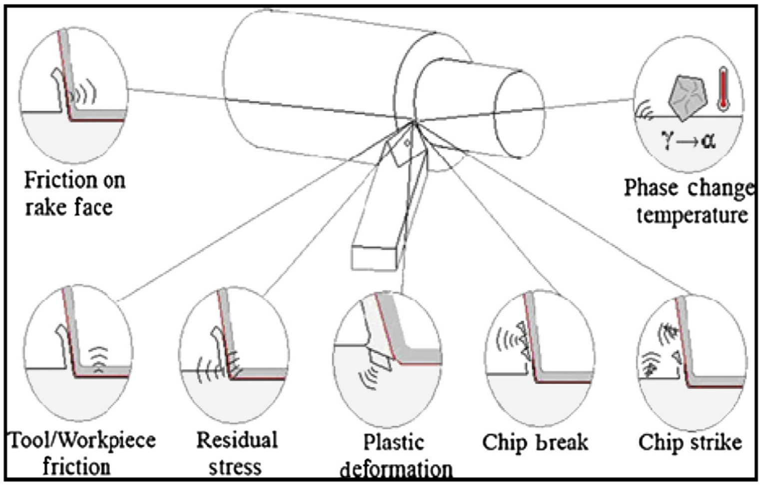

Figure 6 Sources of AE produced during machining. Reproduced from Teti, R.; Jemielniak, K.; O'Donnell, G.; Dornfeld, D. Advanced Monitoring of Machining Operations. *CIRP Ann. – Manuf. Technol.* **2010,** *59* (2), 717–739.

AE is a very high-frequency signal and generated from the object's internal structure changes. The possibility of the signal disturbance by surrounding noise is considerably less. The major advantage of using AE to monitor the tool condition is that the frequency range of the AE signal is much higher than that of the machine vibrations and environmental noises, and does not interfere with the cutting operation. The AE sensor of frequency range 30 kHz to 2 MHz are mostly used in TCM *(43)*. Dornfeld *(53)* presented a compelling review on the application of AE sensing techniques in manufacturing processes, in particular, detecting the tool wear during machining.

Rabani et al. *(54)* have monitored a water-jet milling process using AE sensor. They have captured the AE signal from the workpiece surface using a self-developed program in a LabVIEW environment. The time-domain signal was processed using Welch's power spectral density (PSD) and FFT methods. The transfer rate of energy was found to have a significant response to the change of cutting process, cutting condition, and cutting tool condition. A success rate of 73–75% was obtained from the results of their trials. Yen et al. *(55)* have captured AE signal from a micromilling process to monitor the cutting tool condition. FFT has been used to process raw AE signal, which was further processed using a self-organizing approach to extract the features out of them. The class scatter criterion has been used to select the feature where bandwidth size and scatter level of spectral components were utilized to distinguish the sharp and worn tool. The fluctuation of bandwidth for the sharp tool was found to be less, within a band of 95.7–99.5 kHz; whereas it was recorded to be high for the worn tool where it varied between 73.9 and 99.9 kHz. This method could obtain 99% classification of the tool wear reliably and thus reduced the effects of noise and variation on system performance.

Marinescu and Axinte *(56)* have employed AE sensor to monitor the state of cutting tool, surface anomalies, and other critical moments like entrances/exits of individual cutting edge into workpiece material during milling. The detection has been performed in TFD using some advanced processing methods like STFT, Choi–Williams, or Zhao–Atlas–Marks distributions on AE signals. From the observation of AE signal, the results started at a slightly increased value of 50 peaks per second when most of the cutting edges were fresh and sharp. Even though the result was pretty promising in detecting the surface anomalies, this was not good enough to investigate the state of cutting tool accurately. The accuracy of the results was also not tested. Gómez et al. *(57)* have used AE sensor to assess cutting tool in drilling. They have measured mean power (MP) and torque of AE signal, which were then plotted on the moving average (MAMP) and moving variance of a mean power (MVMP) graph. From the observation, the MP and torque were found not to be sensitive enough to the tool wear at a low level of tool wear. However, it was significantly high for increased damage of tool wear. From MVMP vs MAMP series, relatively small cluster of data was observed for low damage condition and became larger when damage of the cutting tool edge increased. Manipulation of signal data was another time elapsing procedure, which would impede to develop an online monitoring system following this method.

Gómez et al. *(58)* have recorded AE signal to correlate with torque and degree of tool wear measured in drilling. They have discovered a linear relationship between MAMP AE and torque. However, it was found that with the increase of chip breakage (more damaged tool edge), the resultant data became more scattered. The main downside was the long processing time required for handling a huge number of data to report the tool condition. Despite a good agreement between the results from the experiment and data from AE signals, the success rate of investigation was not estimated.

Babel et al. *(27)* have investigated the actual wheel-work contact length using AE sensor in surface grinding. The raw AE and its RMS have been measured to describe the entry and exit incidences. They have also underlined the significance of using AE as a tool for detecting grinding damage in a wide range of workpiece materials, and for characterizing the dynamic response of a grinding process. The study could identify three major frequency bands apparently damaging the grinding wheel; however, the frequencies were not correlated with the tentative responsible occurrences.

Warren Liao *(59)* studied some feature extraction and selection methods being used to analyze AE signal to monitor the grinding wheel. Two feature extraction methods, i.e., discrete wavelet decomposition and AR modeling, have been used whereas three feature selection methods – sequential forward search ant colony optimization (ACO-S), random search ant colony optimization (ACO-R), and sequential forward floating selection (SFFS) – have been used to extract and select the optimum features from the AE signal. For wavelet energy feature, the lowest classification error was recorded to be 7.81% with either one of the three feature selection methods. For AR coefficient, the lowest classification error was 6.88%, where ACO-R was seemed to be outperformed by both the ACO-S method and the SFFS method. Bhuiyan et al. (60) have taken up a self-organized approach to monitor the tool condition using AE by separating the chip formation frequency from the entire bands. The authors have utilized raw AE, its RMS, and FFT to analyze the captured signals and thus investigate the rate of flank wear, surface roughness, and the effect of chip formation on tool state during turning. Both the time- and frequency-domain signals were found to have a significant response to the change of tool condition. Both the amplitude of time-domain AE signal and the signal frequency were observed to increase with the increase of tool wear. Their tool wear assessment using AE signal was more qualitative that quantitative. Nonetheless, the different pattern and frequency of signals were correlated with the respective occurrences; the estimation of tool wear from the amplitude of signals was remained uninvestigated. In another investigation, Bhuiyan et al. (61) have monitored the effect of chip formation on the cutting tool using the AE signals. Similar signal processing techniques were followed to extract the features from the captured signals. Investigation showed that the chip formation occurrences damage the cutting tool severely as the cutting speed, feed rate, and depth of cut increased except at the optimum cutting condition where it had a sudden drop.

Kalogiannakis et al. (62) have used AE sensor to identify the wear mechanism of glass/polyester materials during machining. They have used wavelet analysis to extract the feature from the captured AE signal. Some other researchers (63) have used AE sensor to monitor the tool wear and to determine the workable and worn tool in turning. The sensitivity of AE signal to tool fracture has been studied using quantifiable characters like rise time, RMS voltage, peak amplitude, ring down count, events, energy, etc. Jemielniak (64) has captured the AE raw and AE-RMS signal from the system to observe the behavior of AE signal corresponding to different occurrences. From their investigation, the continuous AE signal has given information on tool wear, which reportedly generated from the friction between workpiece and cutting tool during machining. The captured AE signals have been analyzed using statistical analysis where kurtosis was measured as the indicator of CTF. In the following year in a separate investigation, he has conducted a test lead pencil to observe the AE features at lead breakage. The raw AE and its RMS were used to describe the signals. Their investigation results recommended using AE-RMS signal for AE bursts' analysis in cutting when the integration time constant should not exceed about 0.1 ms (65). Haili et al. (66) have captured the AE signal in turning to investigate the tool breakage. The time–frequency analysis (TFD) and AR model of order 2 (ART2) methods were used to analyze the captured AE signals. From the method of ART2, the correct recognition rate of tool breakage was observed to be a constant at 95% when the vigilance parameter was 0.97. Axinte et al. (67) have carried out an investigation to find out the uneven events using an array of three AE sensors in a milling operation. The Matlab environment has been used to locate the sources of the AE signal.

Dornfeld et al. (68) have used AE signal to monitor the surface finish of workpiece and thus the corresponding tool condition in turning and grinding tests. The AE-RMS signal was measured and was found to be sensitive to material defects. Even though that defect could not be visualized during machining, it was possible to observe the shape and position of these defects with AE. Kang et al. (69) have performed a frequency study to monitor the surface of a lens during machining. Dolinsek and Kopac (70) have employed a water-jet AE sensor to monitor a finish machining (turning) process and to predict the tool wear. The captured AE signal was analyzed using power spectrum and their frequency bands. The SEM pictures of different tool wear have also been taken to investigate the tool wear and the corresponding surface roughness of workpiece. Guo and Ammula (71) have conducted a number of cuts in dry turning to monitor the surface finish of the workpiece using AE signal. They have used the count rate of signal to evaluate surface roughness and the corresponding tool wear.

From the above literature, AE is found to be extensively used to investigate the tool wear, tool breakage, chip formation, and variation in cutting condition during machining. Among a number of processing techniques, AE events (e.g., rise time, peak), RMS, AR parameter, power spectral distribution and PSD are identified to be more pertinent to investigate the tool wear progression whereas FFT and TFD are recorded to be good for sensing the chip formation occurrences and the change of cutting condition, and statistical analysis can spot the CTF more accurately.

13.22.3.2.2 Cutting Force Measurement

Cutting force is associated with cutting and removing material from the workpiece in machining. The different directional cutting forces fluctuate with the change of cutting conditions and at different stages of tool life. In effect, the cutting forces vary with the alteration of process dynamics, which has a significant effect on the state of cutting tool. The existence of a correlation between cutting force and tool wear has been widely recognized (72). Aknouche et al. (73) also observed a correlation between the tool wear and the computed angle (θ), between the tangential and cutting forces. The variation of angle (θ) was found to be unstable in the running period and stable in the linear wear zone. The cutting force can be used significantly to investigate the state of the worn tool due to the variations generated from the friction between the flank face of cutting tool and workpiece (74). During material removal in machining (turning), three-directional cutting force acts simultaneously (75), which is illustrated in **Figure 7**.

By equating the external work rate to the sum of the internal work rates in cutting (i.e., plasticity, friction, and surface formation), Rosa et al. (75) have shown that the force F_c exerted in the direction of cutting is

$$F_c = \left(\frac{\tau_y \gamma_w}{Q}\right) t_0 + \frac{Rw}{Q} \qquad [20]$$

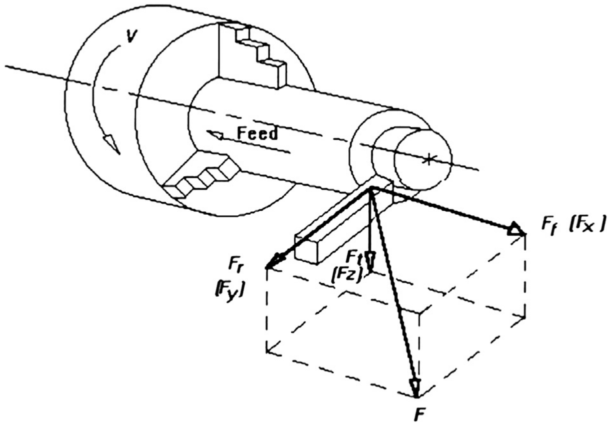

Figure 7 Cutting force components on a single point tool during turning. Reproduced from Dimla, D. E. Sensor Signals for Tool-Wear Monitoring in Metal Cutting Operations–A Review of Methods. *Int. J. Mach. Tool. Manuf.* **2000,** *40* (8), 1073–1098.

where τ_y is the rigid-plastic shear yield stress (it is possible to include work hardening (75)), γ is the shear strain along the shear plane inclined by an angle Φ, t_0 is the uncut chip thickness, w is the width of the orthogonal cut, β is the friction angle, α is the tool rake angle, R is the fracture toughness, and Q is a friction correction factor given by

$$Q = \left[1 - \left(\sin\beta \sin\varphi / \cos(\beta-\alpha)\cos(\varphi-\alpha)\right)\right] \quad [21]$$

F_f, F_r, and F_t are the components of the cutting force R defined in the fixed rectangular coordinate system of unit vectors x_0, y_0, and z_0:

$$R = F_x x_0 + F_y y_0 + F_z z_0 \quad [22]$$

where x_0 denotes the cutting speed-direction ($V = Vx_0$, with V the work material velocity with respect to the tool); y_0 is in the plane of the newly machined surface; and z_0 is perpendicular to this plane (76).

It is reported by Dimla (6) that the different forms of tool wear have been responded differently by the three components of the cutting force. According to him, the crater wear is affected intensively by feed force where both the feed and radial forces are influenced more by tool wear than the main cutting force.

Both the static and dynamic components of cutting forces have substantial importance in the process dynamics and thus on the tool state. According to Dimla (6), the development of TCMs is largely based on the static and dynamic cutting forces. The components of the static force signals are often used for wear monitoring purposes. The dynamic component of the force signal also contains very useful information about the tool wear. The reason is that the tool wear causes increasing vibration amplitudes in certain frequency ranges owing to the larger frictional forces when the tool is worn (39). The time domain, on the other hand, demonstrates the nature and level of static force magnitude transformation while frequency analysis illustrates the response of dynamic force corresponding to cutting conditions and accrued wear levels. The more concise elements of tool wear, the progressive tool wears to catastrophic failure would be observed better in the frequency domain (77).

Kaya et al. (78) have monitored as well as predicted the tool wear by capturing the three-dimensional force components (F_x, F_y, and F_z) and torque (M_z). They have used linear and multiple regression model to process the data to monitor the tool wear whereas ANN was used to predict the tool wear from the captured signals. From their observation, the components of torque, M_z, and cutting force, F_z, were revealed to be more sensitive to flank wear than that of the force components F_x and F_y. However, it was still unrealized that which particular components need to be measured to monitor as well predict the tool wear accurately. A linear relationship with 95% of confidence level was established between the variables using the regression model, where the ANN could predict flank wear with a great accuracy of 94.58% from the experimental data.

Ghani et al. (79) have measured cutting force to monitor the tool wear and to predict the flank wear online in turning. A two-channel strain gauge was employed to measure the cutting force where regression method was utilized to process the data and a graphical user interface in Matlab environment to monitor the tool condition. The regression trend of correlation between flank wear and raw signal showed a power–law curve with the R-square values of the regression coefficient between 0.938 and 0.991. The applied method was capable of predicting the flank wear with very minimum RMS error of 5.91–16.03%. However, the major drawback was the long time requirement to analyze the data.

Zhu et al. (25) have recorded the cutting force from a micromilling process to monitor the tool condition. They have used hidden Markov model to identify the flank wear, where the average recognition rates of 92.5 and 90.5% were obtained for copper and steel, respectively.

Kious et al. (52) have investigated the state of flank wear by measuring the cutting force in a high-speed horizontal milling process. Features from the force signals were extracted both in time and frequency domains and correlated with the measured flank wear under various cutting conditions to ascertain the state of tool condition. Poor performance of their proposed method urged to obtain a fusion sensing method to monitor the tool condition more accurately.

Devillez et al. (80) estimated the magnitude of cutting and feed forces' components and calculated cutting force ratio during an orthogonal cutting test to investigate the tool condition. Two types of methods, the neural network (NN) models and analytical models, were applied to assess the tool condition. A comparison between the methods showed the NN models to produce less error of 5.2% than that of the analytical models of 5.9%. From the experiment of Coelho et al. (81), the cutting force was recorded to be the highest when the tool wear was highest, which had a slight drop after cutting a certain length of cut of 14 km. Szecsi (82) has measured the cutting force and calculated the force ratio to estimate the tool flank wear. He has applied ANN and LR models to monitor the cutting tool condition. From the analysis, NN model has been observed to be more accurate than the LR method; however, none of them were satisfactory.

A thorough investigation of tool wear was carried out by Dimla (83) to monitor the tool state in turning. He used fresh and worn tools in his experiment to assess the nature of tool wear with changing the cutting parameters. From the observation of both the static and dynamic force components, the cutting force has shown the corresponding changes with the change of cutting speed, feed, and depth of cut. The magnitudes of static force signal from worn tool were notably higher than those from the sharp tool; however, for dynamic forces, the relationship was found to be reverse. Astakhov (10) has assessed the state of tool wear by capturing the cutting force signal and plotting the data into correlation curves in turning. The experiment has shown that the minimum tool wear occurred at the optimum cutting speed (v_{opt}); the apparent friction coefficient reached its lowest value at this speed. The result showed a marked increase in tensile strain to fracture (about 0.018–0.25), and also in the work of fracture, at the melting point temperature. As the cutting speed was increased to 4 m s^{-1}, this material was found to lose its cutting ability. The proposed correlation curve–based approach was identified to be very potential due to its independency over material properties, where the only downside was its demand of considerable time consumption to produce the correlation curve. Scheffer and Heyns (77) have monitored a turning process by capturing the force signal from the system. The NNs were used to extract the feature from the recorded signal and SOF was employed for selecting the feature during the investigation. The results showed that the frequency of interruption was exactly 50 Hz. The high-pass filtering showed the most energy around 3 kHz, which indicate the tool-holder cantilever resonance in the direction of feed force component (F_x). The method followed to estimate the tool wear was investigated to be capable of obtaining 92% of accuracy on average, and in extreme cases with an accuracy of not lower than 70%. The accuracy of this technique was limited to the training range of the static NNs, and was not able to produce accurate results if the machine is operated beyond that range.

Using force signal, the elastic deflection of work material was characterized by Benardos and Vosniakos (84) in turning. The captured force signals were processed using ANN where the analytical equation was used for elastic line. The mean relative error was equal to 11.99%, which was very satisfactory while there was a maximum difference of only 2.5 mm between the measured and predicted elastic deflection values.

Tansel (85) used force signal and Daubechies-type wavelet equation to investigate the tool breakage in milling. The result showed a sudden increase for tool breakage whereas an almost continuous constant level of the graph appeared from the tool wear. Jemielniak and Otman (86) have detected the CTF by measuring the passive force in turning. The skews and kurtosis of the β distribution (a statistical analysis) were the main measures employed to perform the monitoring.

Choudhury and Rath (87) have measured the cutting force to estimate the tool wear and investigate the chip formation in milling. Kim et al. (88) have estimated the tool life by measuring the cutting and feed force using a force dynamometer in turning. The tool life has been estimated under different sets of cutting parameters using the equation $VT^n = C$, where 'V' was the cutting speed, 'T' was the tool life, and 'n' and 'C' were constants. The results from the detection unit and direct measurement are found to be in good agreement with a minimal error. Oraby and Hayhurst (1) have taken up a test to predict the tool condition using force signal in turning. The captured force signals were analyzed using a nonlinear multiple regression analyzing method to extract the features. The tool condition was predicted using the force ratio measured by the strain gauge. The force ratios were found to vary at different stages of tool life depending on the cutting conditions. The tool life estimation using two different tool life equations were observed to maintain a substantial coherence with the experimental results.

The above literature shows that the measurement of triaxial cutting force components (F_x, F_y, and F_z) and torque (M) have been used to monitor the cutting tool condition since early period of time. Main cutting force component, F_z, and torque, M_z, and measurement of static force are identified to be more sensitive to the tool wear whereas dynamic force measurements are capable of investigating process interruption even more properly. Even though the magnitudes of force components are increased with the increase of tool wear, and it is notably higher for the worn tools than any sharp one, it is still difficult to decide which force component(s) needs to be measured for monitoring what phenomenon. Among a number of processing methods, regression model is found to be mostly used to investigate the tool wear, whereas ANN is observed to be used to predict the tool wear. FFT, on the other hand, appeared to be successfully used to spot the process interruption in machining.

13.22.3.2.3 Vibration Measurement

Vibrations are produced by cyclic variations in the dynamic components of the cutting forces. Usually, these vibratory motions start as small chatter responsible for the serrations on the finished surface and chip thickness irregularities, and progress to what has come to be commonly termed vibration. Uncontrolled chatter causes the rough surface end and dimensional inaccuracy of the workpiece, along with unacceptably loud noise levels and accelerates tool wear. During chatter, the cutting force becomes periodically variable, reaching considerable amplitudes, and the machined surface becomes undulated (89). Chatter is a self-excited vibration that can occur during machining operations and become a common limitation to productivity and part quality. This regenerative effect is reportedly the most important cause of chatter. The primary, secondary, frictional, and thermo-mechanical mode coupling chatter are the major types of chatter vibration taking place during metal cutting (90). Physically, different types of chatter are caused by a number of sources such as friction on the rake and clearance surfaces, chip thickness variation, shear angle oscillations, and regeneration effect (91). The cutter vibrations leave a wavy profile on the workpiece surface (92). Song et al. (31) have observed the amplitude of acceleration signal at the axial cutting depth of 30 mm that is recommended by tool manufacture in an end-milling process. This is understood for the reason that the cutting resistance increases as the depth of cut increases and consequently, the amplitude of vibration acceleration wave increases, and inversely when the depth of cut decreases, the tool itself vibrated more largely due to the increasing force on the edge of the cutting tool. On the other hand, from the result of the power spectrum obtained from frequency analysis, the change in the power of the peaks in the frequency domain with the axial depth of cut was hardly observed. It is therefore considered that the time-series model analysis is more effective in monitoring the machining state due to the change of cutting condition.

Dimla (83) has measured the tool holder vibration and correlated them with the tool wear to assess the state of cutting tool. The observation has shown that at different cutting speed, the magnitudes of vibration signal spectra were higher along the z-axis and lower along the x-axis, which was observed to be significantly small along the y-axis. However, the frequency of vibration signal corresponding to chip formation recorded to be consistent and peaked at around 600–800 Hz. The trend of worn tool spectra behaved similarly along all three planes and exhibited the same characteristics those for the sharp tool. Orhan et al. (93) have evaluated the tool wear by vibration analysis in milling. Both the time and frequency analyses was performed to describe the vibration signal during the investigation. Song et al. (31) have carried out an investigation to monitor the cutting tool condition in a high-speed end milling by measuring the vibration. The signals captured from the system were processed using the AR method. The surface roughness and stiffness of machined parts were estimated by time series model parameter under the experimental cutting conditions. However, performance of the approached method was limited to some extent of surface roughness of 3–5 μm.

Alonso and Salgado (37) have conducted a tool wear investigation using the vibration signature in turning. The time-domain acceleration signals captured from the system were processed in Matlab 6.1 environment. The results showed that the high-frequency components of vibration signal of above 3 kHz have provided more significant information about the flank wear. A comparative analysis showed the results to contain an RMS error of 13–25%. Kilundu et al. (24) have measured the vibration of the tool holder as the index of tool condition. They have used data mining and pseudo-local singular spectrum analysis (SSA) to extract the features which were sufficiently sensitive to tool wear evolution. The features were defined, in some frequency bands, from the sums of Fourier's coefficients of reconstructed and residual signals obtained by SSA. Four feature classification methods, i.e., decision trees, Bayesian networks, k-nearest neighbor, and NN, were tested with the data to obtain relatively better monitoring. Tool wear condition was recognized with good rate whereas cutting process anomalies as chip stuffing and unproductive pass were detected poorly. They have reported from their observation that there was a strong relevance of information in 'high frequency' vibration components. The success rate of tool wear recognition was found to vary between 50 and 67% depending on the signal classification methods applied. However, the methods required a wide range of data to trial the system, and that was time consuming.

Elangovan et al. (94) have monitored tool wear by applying data mining approach to probe into the structural information hidden in the vibration signal acquired during turning. Different occurrences in machining were investigated using Naïve Bayes and Bayes Net classifier methods; the accuracy levels of those methods were checked by comparing with the histogram features. The classification accuracy of statistical feature using Bayes Net was found to be 86.34% while with Naïve Bayes, it was found to be 85.28%. Again, the classification accuracy of histogram features using Bayes Net was found to be 73.61% while with Naïve Bayes, it was found to be 64.72%. Although the model-building time was minimum, the classification accuracy was relatively low that, consequently, decreased the accuracy of tool wear identification.

Siddhpura and Paurobally (95) have reviewed a large number of articles on regenerative vibration or chatter during machining. They have discussed the phenomenon of chatter, its effect on cutting tool, and workpiece surface finish, and also investigated the influences of cutting parameters (cutting speed, federate, depth of cut, etc.) on the chatter formation. A theoretical relationship between chatter vibration and tool wear has been identified in order to predict tool wear and tool life in the presence of chatter vibration. The effect of vibration on the life of single-pointed cutting tools can be theoretically expressed as a ratio given by

$$T_d/T_0 = 2/[1 + (A\omega/\nu_0)]^n + [1 - (A\omega/\nu_0)]^n \qquad [23]$$

where 'T_d' is the tool life under vibrating conditions, 'T_0' is the tool life under vibration-free conditions, 'A' is the amplitude of vibration, 'ν_0' is the nominal cutting speed in m min^{-1}, 'ω' is the frequency of vibration in radian s^{-1}, and 'n' is the constant for a given set conditions.

Kalvoda and Hwang (28) have detected wear and fault of cutting tool in milling by measuring the vibration. The captured signals were processed using HHT which were then compared with the results from FT to validate the output. The problem of nonlinearity and nonstationary could be overcome by presenting the results obtained from HHT both in frequency and TFDs. The best performances were recorded for the x-axis and z-axis, while the y-axis was less sensitive for TCM. Even though the proposed method made the investigation clearer, the reliability of information about the frequency was questioned due to the fact that by using average Fourier's transformation, it might overlook some frequency, which was significant for damaging the cutting tool.

Abu-Mahfouz (33) has measured vibration of cutting tool in drilling to monitor the flank wear. A multiple layer NN has been applied to twist drill wear detection and classification using supervised learning with experimentally obtained vibration data.

The signals, collected from extensive experimentation, were analyzed using the discrete harmonic wavelet transform, Burg PSD, and four statistical measures of the time domain. The ANN algorithm successfully mapped the vibration signals to the appropriate classes of drill wear. During the testing phase, a success rate of 100% was obtained for detection of the existence of drill wear, and a rate greater than 80% for success in drill type classification was realized. For some ANN configurations, the rate of accurate classifications was greater than 90%. The results also revealed that without a proper training from before, the NN could not classify and recognize the pattern of signal to investigate the tool condition reliably.

The literature above shows that vibration measurement of the tool holder is another potential way to investigate the cutting tool condition in machining. Among three vibration components (V_x V_y, and V_z), the magnitude of V_z component is reportedly the most, which gradually decreases for the components of V_x and V_y and therefore have a minimal response to the change of tool wear. Time-domain signal and time-series analysis are more effective in monitoring the tool wear whereas the frequency-domain signal has good relevance with the occurrence of chip formation. The high-frequency vibration components provide more significant information about flank wear.

13.22.3.2.4 Optical Measurement/Vision Monitoring

Optical measurement or vision monitoring is usually performed by capturing the images of different occurrences that take place during machining using a charge-coupled device (CCD) camera on real time.

Pfeifer and Wiegers (96) have reported various available methods for vision monitoring and represented a comparative study among these methods. They have reported various machine integrated optical monitoring techniques, including the illumination, image capturing, and processing methods. They discussed about the requirements like quality of measurement results, integration close to the machine, tool handling, and advanced techniques of adaptive illumination for obtaining optimized camera images even for varying types of cutting tools. The information obtained from their article is really significant and helpful for one who is interested to monitor the tool condition using optical measurement. They have demonstrated a vision monitoring technique with an image-processing technique called the degree of overlap (DOV) that helped to assess the tool by counting the pixel of contour. Despite achieving an accuracy of 70–90% for some tools to identify the flank wear, it was impractical for some tools like boring bit, HHS milling cutters, throwaway tool tips, etc. due to their complex geometry.

Lanzetta (97) carried out a vision monitoring system in turning and milling using tool imaging CCD camera. The segmentation method which is based on texture analysis was used to process the image into the frequency domain. The graph plotted from the recorded data showed high amplitude of frequency for worn-out area of the tool and drop of amplitude for burnt area and medium amplitude for undamaged area. Thus, the method was capable of recognizing a large range of parameters unlike the other available methods using an algorithm developed. This method, on the other hand, was demanding some specific test to determine the algorithm parameters. Barreiro et al. (98) have captured the image of flank wear to monitor the tool condition in turning. The captured images were analyzed using descriptors based on moments. The linear (LDA) and the quadratic (QDA) discriminant analyzing methods were utilized to analyze and plot the data. Though no descriptor was found to be adequate for monitoring the level of tool wear, the statistical moment parameter used as the image descriptor named after the pioneer Hu seemed to be considerably better. The first Hu descriptor, h_1, was observed to be responsible for 99.88% of the discrimination among wear levels, which was remarkable. However, plotting the image descriptors on the LDA and QDA to describe the tool condition required a lot much effort. Niranjan and Ramamoorthy (99) monitored the tool wear by capturing the image of cutting tool using a CCD monochrome camera in turning. They have measured the flank wear width and the crater wear depth from the deflection data between tool and the camera for each strip. The ANN was used to analyze the data, to estimate and predict the tool wear. The method was found to be capable of investigating the pattern of three-dimensional tool wear with less trial. The NN-based monitoring was required to train in a supervised manner, which was unpleasant. Castejón et al. (100) have investigated the level of tool wear during turning to avoid under use as well as to prevent overuse of cutting tool. They have captured 1383 flank wear images using CCD camera and employed several preprocessing and segmenting methods to analyze the captured images. Nine geometric descriptors and clustering analyses were used to describe the images; however, from linear descriptor analysis (LDA), three (eccentricity, extent, and solidity) out of nine descriptors were found to carry out 98.63% of necessary information regarding the tool wear. A drawback of this procedure was that the amount of acquired images were not enough to provide a smooth evolution, which sometimes produced an abrupt transition among classes. Ji et al. (101) monitored the tool condition by capturing the images of cutting tool where an unusual method called Mahalenobis distance feature method was used to analyze the captured images. The Mahalenobis method was identified to be very sensitive to tool wear and breakage. The only limitation was the prerequisite of maintaining the light source invariable for during the entire period of taking image. A new vision technique to monitor the flank wear without shutting down the machine was developed by Wang et al. (102) during milling. It was done by capturing the successive image of cutting tool at a low spindle speed of 20 rpm instead of stopping the system totally. The images were processed dynamically on real time; the results from the image analysis were found to be very promising with the direct measurement values of flank wear. However, the technique was unsuitable for high-speed machining.

A new technique of monitoring cutting tool condition using optical measurement was approached by Sortino (103). He used a CCD camera to capture the images of flank wear, which were then processed and analyzed using an own developed software assisted method called 'WEARMON' method. The method could automatically calculate the flank wear land from the wear pattern unless the extent of wear was very low, and that was a limitation of the proposed technique. The result was found capable of calculating maximum wear land in about 92% of cases. Yan et al. (104) employed the vision monitoring system to measure front and corner wear of a tool in an electrodischarge machining. An image-processing program was linked to the Matrox image library

(MIL 8.0, Matrox) using Borland C++ Builder 5 programming to process captured monochrome images of 640 × 480 pixels. From the processed images, it was observed that the front and corner wears were increased rapidly during drilling and milling, respectively. With the aid of image-processing software, this developed vision system could reduce 40% of machining time compared to the uniform wear method. This was observed having very minimal measurement error of 3% when compared with the results using a tool microscope.

Kurada and Bradley (105) carried out a thorough study on vision TCMS. The images of tool insert have been captured during operation whereas the NN was used to process the recorded images to estimate the tool wear. The technique was observed to repeatably estimate the tool wear and at the same time determine the surface roughness; however, it was limited to the investigation of lower roughness range.

From the literature above, vision or optical method is another popular method used by different researchers to monitor the cutting tool condition in machining. The images of cutting tool captured at distinct stages of tool life are usually analyzed using texture analysis method in the domain. The amplitude of frequency from worn-out area is high, which drops for the burnt area and becomes medium for undamaged area. Genetic descriptor, cluster analysis, ANN, and some self-developed software-based method can estimate tool wear as well as predict the tool condition. The main downside of vision monitoring is the image resolution which does affect the accuracy of information from the sensor; however, the major advantage of this monitoring is its easy implementation.

13.22.3.2.5 Laser Monitoring

Laser is a special type of beam having a long wavelength that has been extensively used in laboratory application. Recently, laser has reportedly been employed in monitoring the machining process, including the tool wear, chip formation, surface roughness of workpiece, and so on. Some researchers have employed laser sensor combined with the high photographic camera to investigate tool wear and chip formation occurrences in machining under different cutting speeds and feeds (106). Ryabov et al. (107) have used a commercially available laser displacement sensor for an in-process tool geometry measurement during milling. The failure of tool geometry has been monitored by reconstructing and displaying the 3-D image of a milling tool via a hybrid laser sensor measurement method. They have used laser displacement measurement and distribution of light intensity techniques simultaneously to detect and locate the chipped part and to determine the length of flank wear. Their developed system has allowed them to measure the flank wear to an accuracy level of 40 μm. However, the accuracy of the measurement system has a great dependency on the sensor distance resolution and striking angle of the laser beam, and thus was very prone to get some error in the results due to a little deflection of the beam.

Wong et al. (108) performed TCM using laser sensor and CCD camera by measuring the surface roughness of workpiece. The surface of the workpiece was illuminated with a coherent beam of laser, and a CCD camera was used to capture the reflected light. The captured images of workpiece surface roughness were analyzed using laser scattering method to predict the tool condition. According to their observation, using the optical parameters, mean value (μ_{op}) of the gray level distribution, and standard deviation (σ_{op}) of the gray level distribution, there was no definite relationship between the surface roughness of the machined workpiece and the intensity distribution of the scattered light pattern. However, for most of the workpiece, a quite good correlation between tool wear and intensity distribution of the scattered light pattern was observed. The only downside was to require a judicious selection of cutting condition to obtain reliable damage detection. Jurkovic et al. (109) have monitored the cutting tool condition by capturing the image of tool surface. A CCD camera was used to capture the image(s) while a laser diode was employed to determine the deepness of profile by projecting laser raster lines onto the tool surface. The maximum wear land width, wear land area, wear land perimeter, and the slope of tangent in particular points were estimated to get the profile deepness. A software 'UTHSCSA Image Tool' was used for analyzing the parameters on JPG or GIFF files formats. The tool wear was measured from the profile of the cutting tool surface successfully. But this method was still considerably expensive because of its demand of costly additional software and scanning camera and requirement of the skilled operators.

Although the laser sensor is not a widely applied TCM technique, it is found to have good skills to monitor the tool wear, surface roughness, and chip formation occurrences in different investigations conducted by several researchers. Laser displacement measurement sensor is used to capture the images from an object which are analyzed using laser scattered method to predict the tool condition. A quite good correlation was observed between tool wear and intensity distribution of the scattered light pattern for most investigations.

13.22.3.2.6 Tool Temperature Measurement/Thermal Imaging

Heat generation is an unavoidable phenomenon during the process of metal cutting, which is the major damaging factor for the cutting tool condition. A big portion of energy consumed to cut the material is converted into heat energy and dissipated in cutting tool, workpiece, and chip forming during machining. The heat accelerates the tool wear mechanism; the crater wear, notch wear, and BUE formation are more importantly influenced by the tool temperature during machining. Therefore, measurement of cutting tool temperature has reportedly been used as a means of tool wear monitoring. According to Toh (110), about 80–90% of total heat generated during metal cutting is removed with the chip disposal whereas about 10–15% of heat dissipate into the workpiece. He measured the chip surface temperature during milling, which would indirectly describe the cutting tool condition. The temperature was recorded using infrared technique, and its corresponding effects on tool wear were studied thoroughly. From his investigation, the chip temperature was observed to increase with the increase of flank wear and axial depth of cut. Investigating tool condition based on the chip color and shape analysis was required to inspect trivial changes in chips with substantial respect, and to perform this always accurately was difficult.

An infrared thermography has been used by Lebar et al. (*111*) to monitor a water-jet cutting process. The captured images were analyzed in a Matlab environment and thus to extract the significant features out of them. Their proposed monitoring system was capable of shortening the tedious experimentation procedures during a particular investigation. Pujana et al. (*112*) measured the temperature of drill tip using infrared radiation to monitor the several parameters of an ultrasonic-assisted drilling process. It was done by high-speed imaging and thermal measurement. The main focus was not to measure the tool wear; however, it was recommended to investigate the tool wear from the thermal effect. Though the accuracy of the monitoring technique had not been tested by the researchers, it was expecting to shorten tedious experimentation procedures.

The effect of machinability on the thermal field during an orthogonal high-speed cutting of AISI 4140 steel was carried out by Arrazola et al. (*113*). They captured thermal data from the system using a custom infrared microscope. The recorded infrared spectrums were then processed using FT to extract the emissivity parameter. The maximum heat-affected area on chip and cutting tool were clearly investigated from their investigation. Nevertheless, there was some prevalent source of uncertainty like the emissivity of the materials and its variation with wavelength/temperature, finish, oxidation, camera focus changes, etc., which might affect the accuracy of the TCM technique. Davies et al. (*114*) have reviewed a good amount of work on the thermal measurement during the process of material removal. They have evaluated some widely used temperature measurement techniques prior to showing their methods of application in monitoring the cutting tool condition and the process of material removal. The physics of different methods was outlined detailing the sources of uncertainty, and they have compared among the measuring methods they discussed. That study was helpful to gather knowledge on the available thermal measuring techniques. However, determining the suitable one for the appropriate application was still left unadvised.

In summary, the infrared technique is used to capture the thermal images from the cutting tool and chip formation, which are analyzed using FT and Matlab environment to extract the significant features out of them. The maximum heat-affected area on cutting tool, and chips were clearly investigated by thermal imaging method. The temperature is increased with the increase of flank wear axial depth of cut. As 80% of total energy consumed in metal cutting is converted into heat, therefore, thermal measurement is a very much potential mean to monitor the tool condition in machining.

13.22.3.2.7 Energy and Entropy Measurement

Every single change in the process of metal cutting is accomplished through a certain change in entropy, enthalpy, and simply the energy associated with that system. The measurement of entropy and energy is, therefore, a potential mean to evaluate the state of cutting tool. Chungchoo and Saini (*115*) investigated the cutting tool condition by measuring the total energy and total entropy of force signal that was captured under the different cutting conditions during turning. The correlation between the measured parameters, tool wear, and a wide range of cutting conditions was examined. The experimental results showed that the energy of force signal could be reliably used to monitor tool flank and crater wear over a wide range of cutting conditions. However, the total entropy of forces did not appear to be sensitive to feed rate, rake angle, and tool wear. As the energy and entropy measurement was representing the energy consumption and distribution pattern of signal for different occurrences in the frequency domain, the monitoring had been more accurate. However, this method was identified to be unresponsive to the change of cutting conditions, which was also required to be investigated.

Pérez-Canales et al. (*116*) proposed a new method to investigate the dynamic instability of a milling process based on approximate entropy (ApEn) measurement of vibration signals. The ApEn approach was capable of dealing with nonlinear and nonstationary signal's data, required a relatively small number of observations, and could be used for noisy signals. From their investigation, the time–frequency ApEn monitoring method has shown that unsteady chattering was associated with entropy increment for a frequency range. The natural dynamics of the cutting tool during stable milling led to an entropy pattern where high-entropy values were concentrated at high frequencies. The applied ApEn method was observed to detect the different irregularity spontaneously, but its performance in monitoring the regular tool wear progression was not commendable. Pérez-Canales et al. (*117*) carried out an investigation of machine chatter vibration by measuring the entropy randomness index during turning. Their experiment has shown that the instability of a cutting machine under different depth of cut and spindle speed conditions could be effectively identified through increments of the entropy randomness content.

The permutation entropy of feed motor current signals was measured by Li et al. (*118*) to detect the tool flute breakage in an end milling process. The detection method was composed of the estimation of permutation entropy and wavelet-based denoising. The affectivity of the employed method was verified by performing some typical experiments under different cutting conditions, including the entry/exit cut. The tool flute breakage during the entry/exit cut was detected successfully, and the method was found insensitive to the run out, entry/exit cut, and variations of axial or radial depth of cut during end milling. However, the proposed technique was not trusted as a tool for monitoring the normal progressive tool wear.

Above research shows that energy and entropy measurement of different signal components could potentially describe the cutting tool condition and process stability. Total energy and entropy of cutting force signal are measured to investigate the tool wear and cutting condition, whereas approximate entropy of vibration signal is used to measure the chatter developed in machine under different cutting condition. Permutation entropy of feed motor current signal is measured to investigate the flute breakage of cutting tool. Time–frequency analysis and randomness indexes are used to process the data and to extract important information from the recorded signals. The total energy is found to correspond to tool wear (flank wear, crater wear) and cutting conditions where the total entropy is insensitive to those parameters. Increase in entropy of vibration signal indicates to the instability of cutting process.

13.22.3.2.8 Electrical Measurement

The process of metal cutting is carried out by a system that comprised of some mechanical and electric hardware and peripherals. The electric components of the system are basically the modules for power supply to the system; these have respective change to the change of process dynamics what depicts on the state of cutting tool. The electrical measurement, therefore, has been taken as common mean in monitoring the process and cutting tool condition in machining.

Szecsi (119) has measured current supply to main DC motor of CNC lathe machine was to monitor the cutting tool condition in turning. The recorded current supply signals were filtered and amplified before storing, which were then manipulated using a genetic algorithm–based fuzzy rule set. The experiment has shown that the armature current of the main motor could successfully be used to define the cutting tool condition during turning. The developed and trained monitoring system was capable of defining the average flank wear of the cutting tools with an accuracy of ± 0.2 mm in about 80% of the situations. Though a good level of accuracy was obtained using the proposed method, there were still 5% of the training examples that did not satisfy the monitoring system and were identified to be contradictory to the results.

Choi et al. (120) investigated the tool condition in drilling by measuring the feed motor current where the NN was used to process the recorded data. From the experimental results, the drill state index (DSI) value was found near to 0.1 at normal state and near to 0.9 at the failure state. Drill failure was predicted by monitoring the number of times that DSI exceeded the threshold DSI value. Experiments showed that the proposed algorithm could accurately identify impending failure before drill breakage regardless of cutting conditions and machine tool types. As the prediction of tool failure was carried out by counting the number of time the DSI values exceeded the threshold of feed motor current what had to be set randomly; therefore, a number of trials were required to get an appropriate threshold value for investigation.

Rogante (121) assessed tool wear by measuring input electrical power consumption by lathe motor, measuring level of vibration, and by checking the surface roughness of workpiece in semifinishing and rough-shaping turning processes. He has used the optical microscope to measure the flank and nose wear where the crater wear was measured using a dial gauge. Tool holder vibration was measured using an accelerometer while the machining time has been recorded by a high-precision chronometer. A DC ammeter and a DC voltmeter were connected directly in series and parallel, respectively, to the lathe motor terminal to measure the power consumption. Finally, Taylor's equation was utilized to assess the tool life under different cutting conditions. The results were found to be directly influenced by the degree of the tool wear and also give indications when the tool insert has reached the end of its life. Coated inserts permitted approximately 50% longer machining time, a higher wear mark width, and reduced applied power consumption, compared with uncoated inserts. The end of tool life in the semifinishing processes, when compared to the rough-shaping processes, refers to the higher power range used in the latter stage. Despite the system that was appointed to measure the tool condition achieving a great success, an additional DC motor setup of 0.110 kW power was required to develop the measurement system. The power consumption by that DC motor was merely an extra consumption of energy, which was not even used to cut the material.

Xiaoli (122) detected the real-time tool breakage by measuring the current supply of AC servo motor in drilling. Both the continuous and DWT were used to decompose the spindle and feed AC servo motor current signals, respectively. That approach was found to have an excellent online monitoring capability and a low sensitivity to change of the cutting conditions and high success rate for the detection of the tool breakage. Using their proposed technique, the occurrence of tool breakage was clearly spotted but assessment of progressive tool wear appeared to become hardly possible. A qualitative assessment of cutting tool was obtained using the technique, an automatic method for tool–workpiece contact detection was developed by Kakinuma and Kamigochi (123) using a cutting force observer in drilling. The thrust force was measured recording the current supply of a linear motor connected to the system. Tool–workpiece contact detection became very conspicuous when the difference between the current cutting force and moving average was monitored. Their proposed algorithm with the aid of cutting force observer was capable of drilling automatically without having any difficult tool setting. Though that electrical monitoring scheme could effectively investigate the occurrence of tool touching the workpiece, it was not capable of monitoring the progressive tool wear and tool breakage.

It can be observed that the measurement of electrical power consumption of machine's main DC motor, feed motor is capable of investigating tool wear as well as to predict the cutting tool condition, whereas current measurement of feed motor and AC servo motor can identify the tool breakage during machining. Fuzzy logic technique is used to perform the analysis of electrical signal to investigate the tool wear, whereas NN is used to predict the tool failure/breakage beforehand. Wavelet transformation, on the other hand, is employed to analyze motor power to investigate tool breakage and tool–workpiece contact.

13.22.3.2.9 Surface Roughness Monitoring

The surface roughness is an indirect index of tool condition; the tool wear, tool breakage, tool breakdowns, etc. are reflected in the surface roughness profile of workpiece during machining.

The measurement of surface roughness of workpiece to investigate the tool wear was reported by Kang et al. (124). They have employed a new fractal analysis where the fractal characteristics of machined surfaces were utilized to monitor in-process tool wear. From their investigation, the fractal dimension and the surface roughness (R_a) showed similar tendencies depending on various cutting conditions. The increase in the fractal dimensions with cutting length (tool wear) showed a similar tendency associated with the increase in surface roughness. From the images obtained using light scattering method, the fractal dimension was found to increase regularly as with the increase of tool wear. A qualitative investigation of tool wear was conducted by measuring surface roughness and fractal dimensions; no quantitative assessment could obtain from the experiment results. Benardos and Vosniakos

(84) have reviewed a number of methods that have been employed to monitor the surface roughness of workpiece and therefore, discussed the relationship of tool geometry/tool wear with the surface roughness, tool vibration, and cutting force in machining.

Costes and Moreau (125) measured tool deflection to relate with the workpiece surface roughness during flank and end milling processes, which would help to report the state of cutting tool condition during machining. A noncontact displacement sensor was used to assess the surface topography of the workpiece to relate the tool wear. The investigation showed the predicted R_a values were better correlated with measurements in flank milling than in end milling. However, a considerable amount of error of 12 and 23% were calculated for the flank and end milling tests, respectively. Kassim et al. (126) investigated the tool condition by measuring the surface roughness of workpiece in end milling and face milling, and both for roughing and semifinishing operations. A CCD camera with appropriate focusing has been used to capture the image of surface roughness, and the images of machined surfaces were analyzed using structural and statistical-based approaches. From their observation, the run-length statistics-based method was fast and reliable in differentiating tool conditions, while the structure-based Hough transform method was computationally intensive. Though a considerable accuracy was obtained, some fitting error was still in the results. For instance, some total fitting error of 61 and 189 were counted for the sharp and dull tool, respectively, from the Hough transformation method.

The prediction of surface roughness and flank wear was performed by Özel and Karpat (127) for variety of cutting conditions during turning. They have developed and utilized a NN model to investigate tool wear and surface roughness where the regression model was used to capture process parameters. A comparison has been carried out between results from NN model and regression model analyses. The developed prediction system is found to be capable of accurate surface roughness and tool wear prediction for the range it has been trained. The results have shown that a decrease in the feed rate resulted in better surface roughness but slightly faster tool wear development, and increasing cutting speed resulted in a significant increase in tool wear development but resulted in better surface roughness. Increase in the workpiece hardness resulted in better surface roughness but higher tool wear. Despite a significant rate of success, the result was obtaining some minimal error of 10 and 9% for flank wear and surface roughness identification, respectively.

It is reported from Siddhpura and Paurobally (95) that the regenerative vibration or chatter accelerates tool wear resulting in poor surface finish and in turn reduces tool life (95). Kotaiah et al. (128) employed the surface roughness of workpiece with other parameters to estimate the tool condition in inward turning operation. They used NN model to relate surface roughness with tool wear and cutting conditions. The crossover probability was considered as 98%, and the probability of mutation was taken as 1%. Chae et al. (129) have monitored the tool condition by measuring the surface roughness in a micromilling process and thus investigated the difference between the theoretical and experimental results. Their developed model was based on single variable method, which would be more potential if all three variables, i.e., cutting speed, feed rate, and depth of cut, are considered changing simultaneously. Kirby and Chen (29) have measured vibration of cutting to predict the surface roughness of workpiece which was then processed using a fuzzy-net model to correlate with the tool life. An accuracy of 95% was obtained from their proposed model in predicting the surface roughness and thus the tool life. However, the five steps fuzzy networking method and dealing with a wide range of data have made the monitoring and predicting process considerably complex.

Although the surface roughness measurement is carried out for the long-term perspective, there is no unified methodology to measure, evaluate, and represent the surface roughness in relation to metal-cutting tools (130).

Above research has shown that surface roughness measurement have been used to investigate the tool condition indirectly. Fractal analysis, light scattered method, and statistical and structural analyses are used to analyze captured surface roughness images to correlate with the tool wear. Regression model, NN, and fuzzy logic techniques are utilized to predict the tool wear from surface roughness values. A decrease in feed rate results in better surface roughness, which causes slightly faster tool wear; an increase in cutting speed produces better surface roughness and higher tool wear. Regenerative vibration accelerates tool wear resulting in poor surface roughness and tool life.

13.22.3.2.10 Power-Based Monitoring

Power-based TCM is another indirect method to invigilate the health of cutting tool, which is getting preference due to its low costing and trivial arrangement requirement. This is usually performed by measuring the spindle motor power. Al-Sulaiman et al. (131) have carried out TCM in a drilling operation by measuring the differential electrical power consumption. They nullified the power consumed for running the spindle before recording the actual drilling power. From the investigation, the method of measuring the differential electrical power consumption could monitor the tool wear by sensing minute change in drilling power even on a large powered drilling machine of 10 kW effectively. This method was also successfully used to determine the maximum possible wear in drilling material. The differential power detector box used was designed only for the three-phase machine, its performance for single-phase machine was not tested. The signal of drilling power, on the other hand, was required to amplify and further processing to assess any appreciable change, and that was demanded some extra power consumption what was preferable.

A cutting power model based on continuously updating monitoring threshold of mean cutting power was developed by Shao et al. (132) to monitor the tool wear in a face milling operation at variable cutting conditions. The spindle motor with the intermittent cutting load has been simulated, which was then verified with experiments. An inherent fluctuation due to intermittent cutting load was observed in the cutting power signals measured. These fluctuations made the model very difficult to use to predict instantaneous power signal. The experimental results showed that the simulated power signals could predict the mean cutting power better than the instantaneous cutting power. The mean cutting power of measured and simulated power signals demonstrated good agreements. To deal with variable cutting conditions, the proposed method was investigated to be very robust than the traditional constant threshold power monitoring strategies. In particular, setting up threshold of the mean cutting power was very much prone to get inappropriate for the given cutting conditions and thus could produce some error into the results. In another investigation, Shao et al. (*133*) have identified the possible causes of power signal contamination and thus tried to extract only the features relevant to cutting tool out of the signals. A modified blind sources separation (BBS) technique that developed on wavelet transform and independent component analysis was applied to isolate those pertinent signal sources from a single-channel power signal. The experiments with different tool conditions illustrated that the separation strategy could successfully identify the signal components from milling cutter and spindle from others. The milling cutter information could not be identified directly from the measured power signals with STFT. They could be investigated from the separated ones with STFT when the measured power signals for separation were carefully selected with severe tool breakage (rupture). However, the frequency relating to milling cutting was pointed to be insignificant for minor breakage or wear of a cutting tool and thus was not capable of monitoring progressive tool wear.

Heinemann and Hinduja (*134*) have adopted a power-based TCM strategy to predict the imminent tool failure in drilling. This has been done by recording spindle power and AE-RMS signals over the tool life. The recorded signals were then subdivided into small sections to monitor those sections with the most significant change(s). The important features were extracted using wavelet transformation in a LabVIEW environment from the significant signal sections, which helped to identify the final tool life stage successfully and thus could replace the worn-out tool shortly before fracture occur. The experiment showed that the tool wear has a smaller effect on the mean values of the spindle power, which increased to different extent by 140 and 36% for two different amplification factors of SPmp2 and SPm22, respectively. However, it has significantly higher influences on the AE-RMS mean (AEmp2) and variance (AEvp2) as well as on the spindle power variance (SPvp2), which exhibited changes of between 200 and 3000%. Based on the entire drilling cycle, the average value of the spindle power was found to increase by a mere 32% over the tool's life. The features mean value and variance of both the spindle power and AE-RMS show a good correlation to tool wear progression, and they exhibit the strongest change close to the end of the drilling cycle. Of 24 drills tested, the TCM system was able to utilize an average of 84% of the tool life; in only one case it failed to detect tool breakage. Their proposed strategy achieved considerable success to identify the tertiary stage of tool wear; however, tool failure due to other unexpected occurrences before reaching its final stage was unable to detect with this method applied. Kordonowy (*135*) has categorized the energy consumption in machining into three major groups and thus estimated them separately. According to them, 65.8% of total energy consumption is spend as a variable machining energy for material removal, 20.2% of energy is a constant energy used for running the machine, and remaining 13.2% of energy is consumed for starting up the process. A new online energy efficiency monitoring model based on energy consumption by machine tool was proposed by Hu et al. (*136*) to monitor the cutting tool condition. The energy consumption was measured in advance and stored in database, and the variable energy consumption was derived from cutting power that could be estimated online according to power balance equation and additional load loss function. In order to reduce the mistakes in identifying the machine tool's operating state and errors from estimating the cutting power, moving average filtering of power signal was applied. The additional load loss function was identified off-line through input power and cutting power of the machine tool spindle.

The total power flow of the spindle system was reported to be into three parts, namely idle power, cutting power, and additional load loss (eqn [24]).

$$P_{\text{in}} = P_u + P_c + P_a \qquad [24]$$

In terms of cutting power, the additional load loss was identified to be a quadratic function and that can be expressed as

$$P_a = P_0 P_c + a_1 P_c^2 \qquad [25]$$

From eqns [24] and [25], the following equation can be obtained:

$$P_{\text{in}} = P_u + (1 + a_0) P_c + a_1 P_c^2 \qquad [26]$$

Based on the proposed approach, an online energy efficiency monitoring (OEEM) software was developed to monitor the tool condition. Several experiments were performed on a CNC machine tool CJK6136 to assess the effectiveness of the proposed method. Energy-saving analysis was taken using several experiments of different cutting parameters. Six rough bar turning experiments (material of C45E4 steel, 60 mm in length, and 59 mm in diameter) were conducted, and the result showed that the energy efficiency was improved by changing the cutting parameters. The results showed that the condition at a spindle speed of $s = 400$ rpm, cutting depth of $a_p = 0.153$, and feed rate of $f = 2$ mm rev^{-1} has the least energy efficiency $\eta = 25.7\%$; moreover, the depth of cut was changed to two cases when the spindle speed and feed rate were invariable: $a_p = 0.198$ mm (condition #2) and 0.243 mm (condition #3). Thus, the energy efficiency was improved to 33.6 and 42.8%, respectively. Similar result could be obtained when the spindle speed was 800 rpm. Furthermore, the conditions at the spindle speed of $s = 800$ rpm, cutting depth of $a_p = 0.243$, and feed rate of $f = 2$ mm rev^{-1} has the highest energy efficiency $\eta = 54.8\%$. Comparing condition #6 to condition #1, the energy efficiency could be improved by 29.1%. As the efficiency was subjected to change with the varying cutting conditions, unoptimized cutting conditions might cause some drop in the efficiency of proposed technique. The empirical results from some other researchers (*137*) showed the similar results that setting the optimized cutting parameters could lead to a shorter cycle time and in turn reduce the total power consumption. Though an application example of OEEM system on a CNC lathe was given, it was reportedly able to be extended easily to other kinds of machine tools. However, the only limitation of this method was the requirement of cutting experiment for the identification of additional load loss function, which needed well-designed cutting parameters and vast materials. Rajemi et al. (*138*) have classified the machining power consumption into three categories, i.e., power for machining, power of machine module, and idle power. This has been done to investigate the tool condition based on the

Table 2 Comparison among different tool wear sensing techniques

Methods	*Direct measurement*	*Cost*	*Reliability*	*Flexibility*	*Sp. testing setup*	*Time consuming*
Optical system	√	Low	Very high	√	X	√
Mechanical power	X	High	High	X	√	X
Acoustic emission	X	High	Low (30%)	√	√	X
Vibration signature	X	Low	High	√	√	X
Neural networks	X	High	Low	X	√	X
Vision sensors	√	High	High	√	√	√
Electrical power	X	Low	High (80%)	√	X	X

Reproduced from Al-Sulaiman, F. A.; Baseer, M. A.; Sheikh, A. K. Use of Electrical Power for Online Monitoring of Tool Condition. *J. Mater. Process. Technol.* **2005,** *166* (3), 364–371.

machining power consumption. The power for machining was estimated to be 31–39%, power of the machine modules fluctuated between 36 and 26%, and idle power was found to remain at 33–34% depending on the different cutting condition used. The work clearly identifies critical parameters in minimizing energy use and thus could identify the cutting tool condition.

From the above literature, the power-based TCM is considerably inexpensive due to its minimal setup requirement. Some are found to manage measuring the energy of chip removal solely by nullifying the energy required for running the machine. Some others estimated intermittent power signal and thus pointed the significant sections of it to extract the important features out to monitor the tool condition. The mean value and variance of power signal were observed to be commonly used as measuring parameter where a little extent of wavelet transformation was also found to be applied. Some researchers were found to monitor the tool condition by estimating the power consumption by their own developed cutting power equations. Various results from literature indicated that the optimized cutting parameters could lead to a shorter cycle time and in turn reduce the total power consumption. The application of this technique is observed to be limited in shop floor drilling and milling operations rather to use in monitoring any turning process. This TCM technique is also not much reliable because of its inability to stand alone from other dwelling sources of signals. The signal from the spindle motor usually contains components of material removal, machine running, machine starting up, and some other anonymous disturbances, which are unavoidable and required additional setup to free it from contamination. It can be concluded from the above observation that the power-based TCM can be used to identify the final state of tool life; however, not good enough to spot the tool breakage and similar other sudden occurrences effectively. **Table 2** shows comparison among different tool wear sensing techniques.

13.22.3.2.11 Sensor Fusion Technique

As the working principle of various sensors is different, the use of multiple sensors in monitoring the tool condition is capable of investigating a particular event in the system from the different perspective. If the outputs from different sensors indicate a common incidence or state of cutting tool, the investigation becomes even more reliable and unambiguous. Fusion application of sensors and signal analyzing methods would aid to overcome all the difficulties incorporated with an independent use of sensor in TCM. For engineering process monitoring, the sensors are typically designed to measure a targeted parameter, which are later correlated to the process of interest. As a cutting process is involved with a wide range of complex and diverse occurrences, to investigate the entire events with a single sensor application is apparently marginal. The TCM techniques with single sensor application are, therefore, less robust, unreliable, and generally incapable of 'total' TCM's ability to recognize incipient, partial, or complete CTF *(139)*. Application of more than one sensor at a time to investigate some particular occurrence or process is commonly termed as sensor fusion. **Figure 8** shows the different scopes of various sensors to be used in fusion application to monitor the tool condition in machining.

The decision as to which sensor and how many to use in a TCMS is indeed a difficult one to make. To develop a more efficient TCM, the cost-effectiveness and practicality of sensor to obtain significant signals are equally important. Special attention has to be paid to the facts that the chosen sensors are suitable for such application and provide adequate shielding to the machining environment. Distinct care and consideration must be taken to ensure that measuring apparatuses are not disturbing or interfering with the machining process *(6)*. Besides choosing the most suitable type(s) of sensors, pointing the best appropriate location for the sensor where the concentration of specified signal and its reproducibility is considered to be the highest. Information from a variety of different sensors, therefore, has to be collected and these signals of varying reliability integrated. The fusion of sensor could provide with more substantial information about the underlying wear level and thus improve the reliability of TCM technique by offsetting the lose of sensitivity of one signal by other *(139)*. The fusion application of sensor would add some more advantages by expanding the power of calculation for cutting process in machine *(140)*. Three types outcome from results of data fusion technique could possibly come; these are competitive, complementary, and uniquely independent outputs. When the data from each fused sensors increase in value or repudiate with other, it is called competitive fusion. Independent data fusion is simply when one sensor is used to sense a particular feature. The complementary sensor extracts relatively different information from different sensors employed and thus complement the lacking of individual sensors. Besides the sensor level fusion, decision level fusion is also performed on the captured data/signal by employing two or more data analyzing methods for a particular investigation in monitoring tool condition. The process of fusion monitoring is schematically presented in **Figure 9**.

Jemielniak et al. *(141)* have carried out an investigation to monitor the tool condition by measuring the cutting force and AE signals during rough turning, where the wavelet packet transformation was used to extract the useful features from the signals.

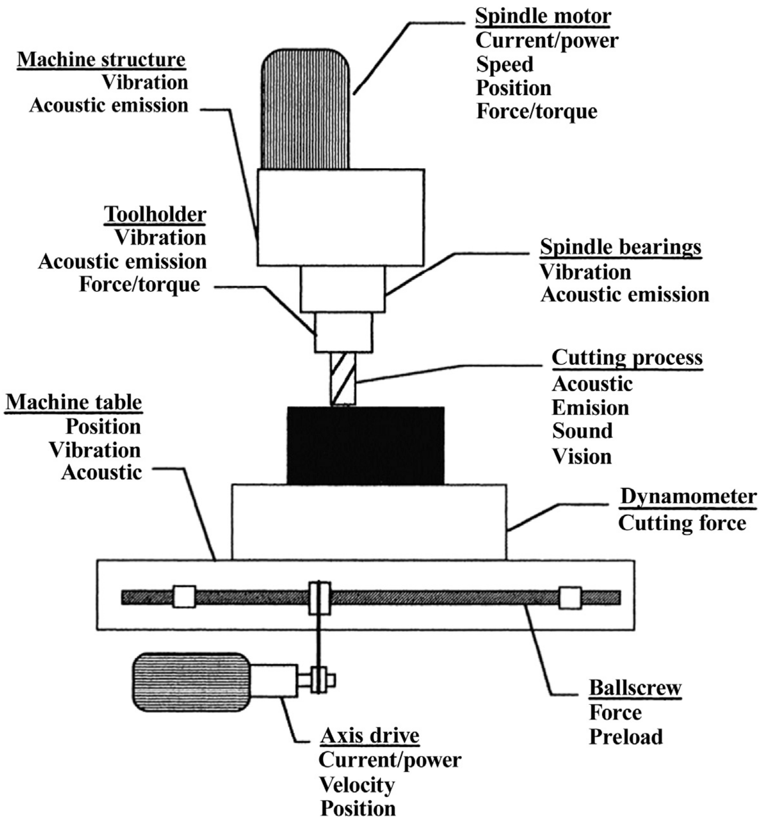

Figure 8 Multisensor cutting tool monitoring options. Reproduced from Girardin, F.; Rémond, D.; Rigal, J.-F. Tool Wear Detection in Milling—An Original Approach with a Nondedicated Sensor. *Mech. Syst. Signal Process.* **2010,** *24* (6), 1907–1920.

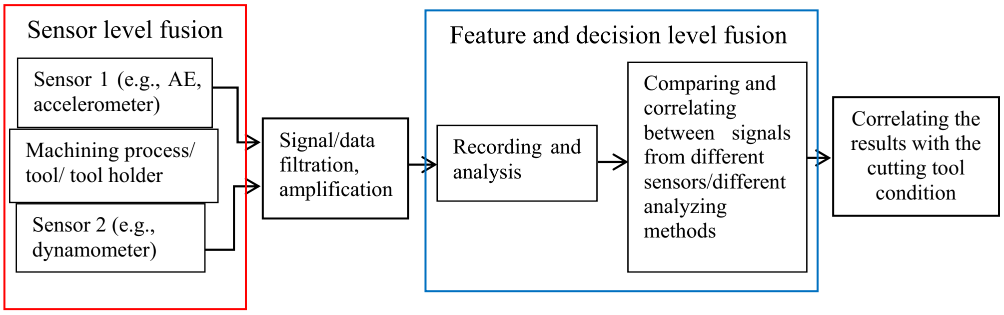

Figure 9 Fusion (sensor, feature) technique for tool condition monitoring.

The AE signal was investigated to be very good in detecting tool–workpiece contact and monitoring the cutting process integrity, whereas cutting force was identified to perform considerably well in monitoring tool wear. However, selecting the significant features from the captured signals was the most difficult part and wrong selection of features might produce poor results or even could divert from the real tool condition. Chung and Geddam *(142)* employed the same sensor to capture the signal from a milling process; however, the FFT and spectrum analysis were utilized as the tool of signal processing. The cutting force was identified to be capable of monitoring dimensional accuracy and surface finish of the workpieces and wear of the cutting tools. The frequency peak of the AE-RMS and torque, on the other hand, are found to be more sensitive to the variation of the flank wear than the force. Identifying the effective peak frequency appeared difficult sometimes. Arul et al. *(143)* recorded the AE and force signals to find out the best possible cutting condition for a drilling process. The AE was identified to be very sensitive to the tool wear, a minor influence of AE power was observed with a minimum change in flank wear. The thrust force, on the other hand, was found to fluctuate with the change of cutting conditions, which was drastically increased with the increase of feed rate. The accuracy of the experimental results was not tested.

Some researchers have measured AE and cutting force signals to monitor the tool wear in turning. They have used NN and FFT as the signal processing tool. The measurement revealed strong influence of tool wear on AE signal, providing acceptable results even while used separately. The cutting force signals acquired in this study were severely disturbed by resonance vibrations in the dynamometer. In spite of this, the signals still appeared having dependences on tool wear thus becoming very useful in TCM (144). Some others have approached a fusion sensing method comprising AE and force sensors, where prediction of cutting tool wear has been made using ANN and PC and been compared with the real measure of tool wear. The results have shown that the average accuracy of predicted results of 89.02% for ANN was higher than the results for PC. Though the reduced features' sets in cutting force and AE required 70% less computational time compared to the full features' sets, overlooking some features indicated to ignorance of some effect that resultantly influenced the cutting tool hazardously in the long run (145).

The AE and force signals were applied together by Chungchoo and Saini (146) to monitor the tool wear in turning. The FNN and Matlab software based (MLSB) methods were used to process the recorded AE signal during operation. The results from the experiment were indicated to a variation in AE-RMS and mean cutting force depending on the tool wear and cutting conditions. Chiou and Liang (30) employed an AE sensor and an accelerometer together to monitor the flank wear of cutting tool in turning by measuring the corresponding change in RMS amplitudes of signals. Frequency analysis with fresh and worn tools under cutting conditions at the stability boundary was performed on the captured signals. The experiments have shown that the fluctuation of AE-RMS amplitude and tool vibration increased as the flank wear increased. The TCM technique was qualitative and the accuracy assessment of that method was not tested. An experimental investigation was carried out by Dimla (83) to identify and isolate the effects of cutting conditions on cutting forces and vibrations due to tool wear. The depth of cut and feed rate was found to affect the signal characteristics significantly, and a specific band of vibration signal of frequency ≈ 5 kHz, and another band of frequency of 4–6 kHz of force signal were deemed most sensitive to the changes identified. Even though the cutting force and vibration signals offered excellent separability between sharp and worn tool, no quantitative assessment of tool wear was obtained from the investigation. Dimla and Lister (147) have undertaken a thorough experimental investigation into the development of an online TCM system with a fusion application of cutting force and vibration signatures in metal turning. The sensitive features to tool wear were pointed out after extracting the mean and oscillatory components of signals by analyzing them in time and frequency domains, respectively. Measurements of flank, nose, and notch wear lengths were made immediately preceding recording the online data. The vertical components (z-direction) of both cutting forces and the vibration signatures were found to be most sensitive to tool wear, with nose wear being the most useful indicator of eminent tool failure. The static force in this case was the most sensitive indicator of cutting condition changes such as DOC and feed rate while the dynamic sensors were good at tracking changes in the sensors from accrued wear. To distinguish the static and dynamic components of the force and vibration components from such transient signals was critical which have made the investigation difficult.

In some investigations, the cutting force, vibration, AE, and spindle power were observed to measure both in the time and frequency domains to monitor the tool condition during end milling. The machine learning and machine ensemble approaches were employed to investigate the effectiveness of multisensor fusion technique. The feature level fusion with the best multiple sensors was also carried out and thus the effectiveness of several decision-making methods was evaluated. An accuracy of 94.43% was obtained for the $(V + F)$ multisensor combination with feature level fusion method of support vector machine (SVM) whereas it was counted to be 88.84% and 91.01% under no fusion constraint for individual vibration and force sensor models, respectively. On the other hand, $(F + P)$ has no improved accuracy levels compared to their individual models. The stacked generalization ensemble was found capable of ensuring the highest accuracy of 97% in TCM. However, selecting a feature subset of 25 features out of 138 explanatory features was the great difficulty with that method, which had to increase the computational performance of the TCM system (148). Cho et al. (149) have carried out another separate investigation with the purpose of developing a multisensor fusion-based monitoring. The same machining environments under the similar cutting condition were used to investigate the efficiency of the applied monitoring technique. No exception, the results of that experiment showed almost equal levels of accuracy like the previous investigation.

The tool wear has been estimated by Aliustaoglu et al. (150) by capturing the different signals of force, vibration, and machine sound (AE) in drilling and milling experiments. The statistical parameters were derived from the measured signals to be used in developing a fuzzy-logic-based sensor fusion method. A fusion has been made between the results from different sensor using a double-phase fuzzy model comprising a Mamdani fuzzy model and a Takagi–Sugeno fuzzy model. Mean value, standard deviation, RMS, and maximum value of various signals have been used as input for the fuzzy model. Though TCM using a fuzzy model is simply complicated and a number of uncertainties existed, the Mamdani model was found to be more promising than Takai–Sugeno model in monitoring the tool condition.

Boud and Gindy (151) have monitored the tool condition and surface anomalies using AE, cutting forces, vibration, hydraulic pressure, and table displacement technique in broaching. From their experiments, the tool wear was identified by the cutting force, pressure, and table displacement signals while the machine sound signals with the double-phase fuzzy method outperform others in detecting tool breakage. The AE signals were found to be efficient in detecting surface anomalies such as smearing, scoring, and overheating. The double-stage fuzzy technique has made the decision-making process slightly lengthy and difficult. The acousto-optic emission signals were captured by Prasad et al. (152) to predict the tool wear using a piezoelectric accelerometer and a laser Doppler accelerometer in face turning. The recorded signals were processed using a high-speed FFT analyzer to extract the features. Vibration displacement in the feed direction consistently produced two peak amplitudes just prior to rapid tool degradation. The vibration amplitudes were identified to be very promising to investigate the tool wear and found to increase along with the tool wear progression throughout the experimental investigation. However, there was always some possibility of disturbance in monitoring process by any obstacle coming between laser Doppler accelerometer and the cutting tool, and that has decreased the reliability of the monitoring technique.

Table 3 Sensor-based TCM techniques and their applications

TCM techniques	*Processing methods*	*Applications*
Acoustic emission measurement (AE)	Root mean square (RMS); fast Fourier transformation (FFT); time–frequency domain (TFD); autoregression method 2 (ART2); statistical analysis (skew, kurtosis); Matlab environment; power spectrum; event: rise time, peak amplitude, and ring down count; signal energy	Flank wear estimation; crater wear investigation; wear mechanism monitoring; identifying different occurrences during machining; investigating chip formation type; chip breakage monitoring; tool breakage identification; catastrophic tool failure detection; material defect identification; surface roughness/integrity monitoring; process monitoring
Cutting force measurement	Force ration, neural network; linear regression; cutting coefficient; force ratio; wavelet transformation; artificial neural network (ANN); mean square error (MSE); FFT	Tool wear (flank, crater, notch, and nose wear) monitoring; monitoring the change of cutting conditions/parameters; catastrophic tool failure (CTF) monitoring; monitoring the chip formation mechanism; machinability observation; tool breakage identification; predicting the elastic deformation of work material; process monitoring
Vibration measurement	Power spectrum; FFT; ANN; power spectral distribution; PSD; autoregression (AR); Matlab; singular spectrum analysis	Chatter monitoring; monitoring the chip formation type; surface profile of workpiece; tool wear and breakage monitoring; monitoring the surface roughness of workpiece; investigating the process anomalies during machining
Vision monitoring/optical measurement	Neural network (NN); segmentation method; structural- and statistical-based approaches; Hough transformation method; linear (LDA) and quadratic (QDA) discriminant analyses; geometric descriptor analysis; software-assisted method (Wearmon)	Online and off-line tool wear (flank wear) monitoring; 3D tool wear measurement; detecting the tool damage; surface roughness monitoring
Laser measurement	Laser displacement and distribution of light intensity techniques (simultaneously); laser scattering method; laser raster line projection on the tool surface	Tool geometry/tool geometry failure measurement; flank wear monitoring; monitoring the profile of cutting tool surface; surface roughness monitoring; chip formation monitoring
Tool temperature measurement/thermal imaging	Matlab environment; fuzzy ARTMAP neural network (to analyze image)	Tool (flank, crater) wear monitoring; investigating the thermal effect on tool tip; measurement of temperature from different heat sources; tool condition monitoring (TCM); monitoring the process of material removal
Energy and entropy measurement (of signal)	Time–frequency approximate entropy (TF ApEn); entropy randomness index; estimation of permutations entropy and wavelet-based-de-noising	Tool (flank, crater) wear monitoring; investigating the dynamic instability of process/natural dynamics of cutting tool; detecting chatter vibration of machine; investigating the flute breakage of cutting tool during entry/exit
Electrical measurement	Motor power and current measurement; NN; autoregressive (ART1); developing a relationship between motor current and motor power; square of stator current of induction motor; differential electrical measurement; fuzzy rule set (genetic algorithm–based method); armature current of main motor; TFD; discrete wavelet transformation (DWT); average value; standard deviation of feed motor current; FFT of spindle frequency; state index (e.g., DSI (drill state index))	Tool (flank) wear monitoring; predicting tool condition; detecting tool breakage (real time); tool failure investigation
Surface integrity/roughness measurement	Image of surface roughness; fractal dimension and light scattering method	Monitoring tool wear and breakage; investigating the change of cutting condition
Power-based TCM	Mean value; variance; RMS; wavelet transformation; short-time Fourier transform (STFT); cutting power equation	Tool failure identification; power efficiency monitoring; optimization of the cutting condition
Sensor fusion		
AE and cutting force measurement	RMS; FFT; wavelet packet transform; spectrum analysis; neural network; polynomial classifier; fuzzy neural network, fuzzy logic; Matlab software based (MLSB); expert system, model-based system, fractal, chaos theory, genetic algorithm	Tool wear estimation; locating the tool fracture and breakage; cutting process integrity measurement

Table 3 Sensor-based TCM techniques and their applications—cont'd

TCM techniques	*Processing methods*	*Applications*
AE and vibration measurement	RMS; FFT	Tool (flank) wear monitoring; finding the best possible cutting condition; effect of cutting condition (cutting parameter)
Cutting force and vibration measurement	RMS; FFT	Online tool condition monitoring
AE, cutting force, and vibration measurement	RMS; FFT; machine learning; machine ensemble method	Tool condition investigation (in time and frequency domain); monitoring surface roughness of workpiece; observing the effect of changing the cutting condition
Cutting force, vibration, and machine sound measurement	RMS; standard deviation; mean/max values; fuzzy system	Tool wear measurement
AE, cutting force, vibration, hydraulic pressure, and table displacement	RMS	Monitoring the tool condition and surface anomalies
AE, vibration, cutting force, and spindle power measurement	RMS; FFT; two-level fusion (decision level, feature level)	Tool condition monitoring
Acousto-optic measurement	RMS; FFT	Monitoring tool wear progression
AE and feed electric signal measurement	DWT	Investigating the tool breakage

An investigation was conducted by Malekian et al. (*153*) to find out the factors affecting the tool wear using accelerometers, force, and AE sensors together in a micromilling process. The signals were fused through the neuro-fuzzy method, which then determines whether the tool is in good shape or is worn out. A qualitative assessment of cutting tool was achieved using that approach. The result from fusion method was found to be capable of determining the tool condition much more accurately than using one sensor at a time. Some special attachment was required to locate the sensor in the right position. In addition, it was also difficult to define certain boundaries between different tool conditions, due to the uncertainties involved, trapezoidal membership functions have been chosen for signal processing. As a result, the tool condition could be defined with a certain percentage of two different conditions in the intersection regions, what was somewhat dubious. However, that would be more effective if the method can be extended to estimate the measure of tool wear.

Girardin et al. (*154*) have designed and implemented a self-organizing approach to detect the tool wear and breakage during milling. Cutting force and spindle rotational frequencies were recorded using both time and angular sampling methodologies. The cutting force was often found as the best indicator of tool breakage and tooth wear detection, but maximum slow-down was shown to be more suitable information. The most worn tooth of the tool slowed down the spindle less than the least worn tooth. The rotational frequency has been shown to be very useful comparing with cutting force; however, the only limitation concerns the bandwidth of the method, which was limited to about 600 Hz.

Heinemann and Hinduja (*134*) measured spindle power and AE signal during drilling and thus extracted features out of them to identify tool fracture and in turn to predict the imminent tool failure. They have identified the most significant subdivision of drilling cycle and monitored them. The method approached was found to be able to utilize 84% of tool life where one case of 24 tests was failed to detect the tool breakage. Another difficulty relating to the moving window with a volatile memory was that the small dynamic window and noisy signal components would make some data hidden and thus make the monitoring inaccurate.

It can be concluded from the above literature that the fusion of multiple sensors in monitoring the tool condition is capable of demonstrating a particular occurrence from a different perspective. In this case, the message from one sensor is verified by other, the result from cross checking can potentially determine various occurrences even more reliably. Besides the sensor level fusion, the decision and feature level fusions can significantly improve the accuracy of the tool condition classification. It has also investigated that the highest accuracy could achieve using force, vibration, and AE sensor together with correlation-based feature selection method. The different sensor-based TCM techniques reviewed in this chapter are summarized in **Table 3**.

From the above literature, fusion application of two or more sensors to monitor a particular machining process and cutting tool is even more informative and reliable than that of using single sensor at a time. Depending on the scope, machining environment, objectives, importance of accuracy, etc., the various available sensing methods are observed to apply in different combinations to monitor the tool condition in machining. AE and cutting force sensors with the aid of FFT, wavelet transform, and RMS can investigate tool wear and best possible cutting condition; whereas using FFT and ANN and FNN, the tool wear prediction can potentially be done. AE and vibration signal's measurement with the assistance of RMS amplitude and FFT could identify different types of wear (e.g., flank wear, notch wear). Force, vibration, AE, and spindle power measurement with the aid of statistical parameter, mean value, standard deviation, fuzzy logic model, e.g., Mamdani fuzzy and Takagi–Sugeno fuzzy models, are capable of estimating tool wear and surface anomalies. Some other sensing technique like acousti-optic emission measurement with the help of FFT and neural fuzzy model can identify sharp and worn tool. The measurement of cutting force and spindle rotational frequency in time and angular sampling can investigate the tool breakage. The application of spindle power and AE, on the other hand, can predict tool failure/tool breakage. The results from different investigations show a strong influence of tool wear on AE signal, providing acceptable results even while used separately. The experiments have shown that the fluctuation of AE-RMS amplitude and tool vibration increased as the flank wear increased.

13.22.3.2.12 Miscellaneous

Some other discrete methods have been found to be used in monitoring the tool condition which are very particular in application. Though a variety of other sensing techniques have been reported from different researches, the following methods are observed to have considerable potential in monitoring the tool condition and the process parameters:

- stress/strain measurement,
- methods based on measuring the workpiece dimension,
- magnetic flux cut measurement, etc.

13.22.4 Concluding Remarks and Challenges

13.22.4.1 Concluding Remarks

Even though a large number of tool condition monitor techniques are available and persisting to make the monitoring more significant, there is no such method informative enough to describe the entire occurrences involved in machining properly. In case of sensor-based monitoring, choosing the right sensing technique for the appropriate application is the major issue of concern. Choosing the most pertinent signal processing method is another important decision to be made for the best possible result. Despite all the above difficulties, the signals from the sensor(s) are capable of describing the different occurrences taking place in machining within its range.

The application of various sensors in monitoring tool condition is investigated to be very random and is chosen based on the desired parameter and machining types as it is to apply. However, some trends based on their success rate and frequency of use are identified. To spot the CTF, application of AE is more appropriate; force and electrical measurement, and power-based monitoring are efficient to investigate the effect of changing the cutting condition. Vibration measurement is capable of identifying different discrete occurrences like process interruption, tool displacement, etc. more proficiently than others. The application of laser, thermal imaging, and optical monitoring techniques perform considerably well to investigate the chip formation and tool wear when cutting tool is completely enveloped by workpiece. The energy and entropy measurement of signals is preferable to understandably spot the incident of entry and exit (engagement and disengagement) of cutting tool. In high-speed machining, thermal imaging is recommended to investigate the tool wear, however, not to measure the tool wear. Surface roughness is good to monitor any change in tool geometry and to identify the tool failure due to tool wear progression. Though the AE and force are identified to be most effective for monitoring turning operation, the vibration and surface roughness measurements are also used for such application. The AE and vibration, on the other hand, are found to be potentially used for monitoring milling operation; the optical, laser, and energy and entropy measurement are observed to be slightly used for TCM in milling too. Despite the tool temperature measurement and power-based monitoring being widely appreciated in monitoring drilling, the AE, vibration, and electrical measurement are also marginally applied. The fusion application of sensor is identified to be more effective than any single sensing method. The combinations of AE and force sensor are applied to investigate the tool wear, where AE and vibration are applied to identify the fresh and worn tool, and force and vibration to monitor the tool condition online. In addition to these methods, some other trivially used methods are also found to be applied in TCM depending on the desired parameter to be used. To monitor the tool condition and thus to check the unexpected and avoidable occurrences in machining, the application of sensor-based TCM is the best technique developed yet.

13.22.4.2 Challenges

Due to ease of application, nowadays the sensor-based monitoring techniques have become very popular. Even though they are capable of describing the tool wear, chip formation, chip breakage, tool breakdown, and process interruption, they are not good enough to distinguish the signal components according to their source of occurrences. Sometimes it becomes difficult to tell about the occurrences just seeing the signal; the signal patterns from the chip formation and tool breakage seem hardly distinguishable. This problem would be solved if the entire occurrences are investigated according to their frequency band(s). Then monitoring would become more effective, and information about the occurrences will be more accurate.

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