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STATE-OF-THE-ART IN METHODS APPLIED TO TOOL CONDITION MONITORING (TCM) IN UNMANNED MACHINING OPERATIONS: A REVIEW

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Abstract – The main scope of this paper is to present a summary of the monitoring methods, signal analysis and diagnostic techniques for tool wear and failure monitoring that have been proposed, tested or reported in literature up today. Initially, the necessity for planned tool condition monitoring in modern manufacturing is being discussed. Then, there is a discussion about the difference between soft and hard faults and the reason that they are used for prediction and diagnosis respectively. The paper, then, lists the basic parameters that are correlated with each type of fault. Both direct methods, such as computer vision, and indirect methods, such as vibration, that have been used to monitor the aforementioned parameters, are presented. Moreover, the paper summarizes the signal processing techniques that have been applied to each monitoring method, including e.g. statistical parameters and Wavelet Transform. Following this, a number of diagnostic tools, which have been developed for diagnosis of tool condition, are presented. The paper concludes that the area of condition monitoring and fault diagnosis is of increasing importance, stressing the fact that only few implementations have been achieved, as a consequence that all available techniques present drawbacks and limitations.

Keywords: Fault prediction; Fault diagnosis; Monitoring methods; signal processing; diagnostic tools

1. INTRODUCTION

Nowadays, conventional machining operations, such as turning, milling, grinding, and drilling, are among the most common activities in the manufacturing industry, playing a large role in supporting the economy of developed countries [1]. The main trend of the modern machining industry is towards production cost reduction by using higher cutting speeds and by reducing human resources. The necessity of the latter has lead to the development of unmanned machining systems. Condition monitoring and diagnosis systems, which are capable of identifying machining system defects and their location, are essential for unmanned machining. Thus, much research effort has been made in implementing "intelligent" systems to monitor directly or indirectly the machining conditions, utilizing signals from thermal, force, acoustic, acceleration and vision sensors.

One of the most important components in a machining system is the tool. Unmanned production is possible only if there is a method –or a combination of methods– available for tool condition monitoring (TCM). Tool wear influences the quality of the surface finish and the dimensions of the parts that are manufactured, whereas tool failure is a major cause of unplanned interruption in a machining environment [2]. Particularly, for modern machine tools, 20% of the downtime is ascribed to tool failure, resulting in reduced productivity and economic losses [1].

A reliable TCM system should allow optimum utilization of the tool's life cycle. Today, tool changes are made based on conservative valuations of tool life without taking into account sudden failures, e.g. tool breakage, and at the same time leading to a wastefully high number of changes because the full lifetime of tools is not considered. Consequently, valuable production time is lost.

Tool condition is strongly affected by faults that may occur during a machining operation. As shown in Figure 1, faults can be classified in two types [3].

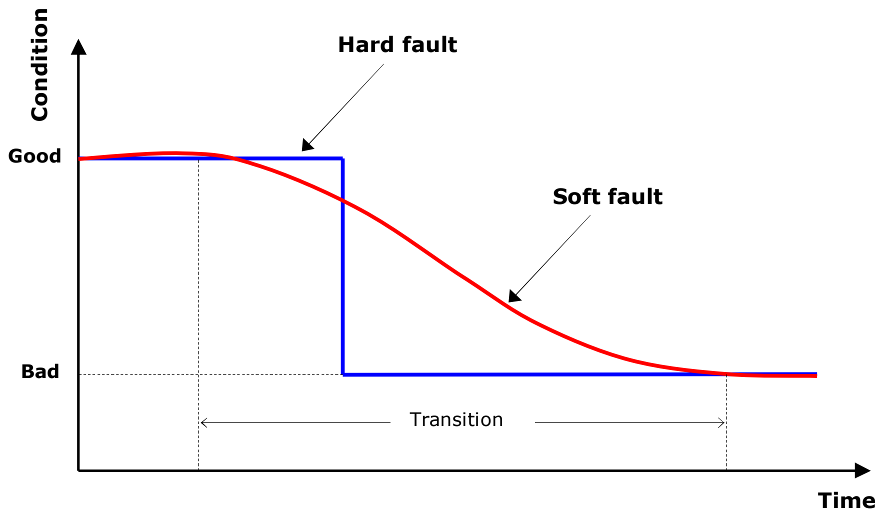

Figure 1 Hard and soft faults

Soft faults develop progressively with time creating a gradual degradation of the tool. On the other hand, hard faults take place instantaneously causing an abrupt cutoff of the operation. In other words, soft faults lead to a predictable situation, an attribute that makes them appropriate for condition monitoring, while hard faults are generally unpredictable and ineligible for this area of research. Consequently, the former type of fault can be used for prediction, while the latter is easier for diagnosis. Both hard and soft faults are strongly correlated with a number of monitoring parameters (Table 1).

Monitoring parameters for hard faults	**Monitoring parameters for soft faults**
• Tool breakage • Door closure • Tool presence • Workpiece presence	• Axis drive motor current/power • Feed drive current • Acceleration • Force • Surface texture • Temperature • Distance/Displacement

Table 1 The monitoring parameters

2. MONITORING METHODS

The mode that a fault is produced on a tool is a complex process and it is generally accepted that analytical models and numerical methods have limited accuracy as condition monitoring methods [4]. The remaining options are on-line monitoring, i.e. indirect estimation, and direct (generally off-line) measurement of the tool condition. Indirect monitoring methods include the measurement of the aforementioned soft fault parameters (Table 1, right column), while direct methods offer the potentiality of actual tool condition determination based on the examination of the hard fault parameters (Table1, left column).

Direct tool wear estimation systems are able to measure directly the tool wear by means of tool images, computer vision, etc. Their application is simple and the reliability is high. However, the automated application of a direct tool wear estimation system is difficult because the detection system should be able to detect the wear zone and measure it. On the other hand, the main advantage of indirect methods is that they are applied online. Unfortunately, these methods present limited reliability and design complexity due to the unpredictable impact of the wear process to the measured signal. Moreover, the sensor cost is generally high.

A synopsis of monitoring methods that have been reported in the available literature is presented in Table 2. There is an obvious trend among the researchers towards applying certain indirect methods such as spindle motor current, cutting forces, vibration, acoustic emission and direct methods including laser scatter pattern, scanning electron microscopy, surface texture/reflectance imaging and stereo, optical and optoelectronic imaging.

Monitoring methods	Reference number
Spindle motor current	[11, 12, 13, 37, 38, 49, 50, 53, 76, 78, 94, 99, 104, 108]
Feed rate	[26, 45, 48, 49, 50, 82, 104]
Cutting forces	[4, 5, 6, 19, 28, 31, 34, 35, 37, 38, 39, 45, 46, 48, 52, 53, 56, 57, 59, 61, 62, 74, 75, 76, 77, 78, 81, 83, 94, 96, 101, 103, 106, 107, 108, 110]
Cutting speed	[26, 45, 48, 50]
Vibration	[10, 24, 36, 38, 40, 49, 52, 53, 56, 57, 76, 77, 82, 83, 86, 95, 96, 101, 107, 108]
Cutting noise	[41, 94]
Ultrasound signals	[33]
Acoustic Emission	[5, 6, 8, 9, 21, 24, 27, 28, 29, 30, 31, 32, 38, 40, 46, 50, 51, 57, 75, 77, 85, 95, 101, 102, 105, 107, 110]
Displacement	[50, 53, 77, 85, 91]
Tool temperature	[26, 71]
Roughness	[41, 60, 79, 95]
Other indirect methods	[15, 53, 73, 80, 95]
Direct Methods (Vision-based)	[16, 17, 18, 19, 20, 23, 39, 42, 43, 44, 47, 55, 58, 60, 69, 70, 81, 91, 97, 100]

Table 2 A summary of monitoring methods that have been reported in the available literature

2.1 Cutting forces

Torque, drift and feed force together with strain measurement are all measures of cutting forces and are strongly correlated with the tool wear. The idea behind monitoring torque and feed forces is based on the fact that these dynamic parameters generally increase as the tool gradually wears due to the increasing friction between tool and workpiece.

In [5], Heinemann et al. notice that monitoring the torque and thrust force is the most common method to obtain information about the amount of tool wear in drilling. Although, from their work, it was concluded that the thrust force exhibited a very weak correlation with the progression of tool wear and is therefore an inappropriate parameter for monitoring tool wear. In contrast, torque appears to be much more suitable for tool condition monitoring in drilling.

On the other hand, Ertunc et al. in [6] note that cutting forces are affected by experimental conditions such as cutting conditions, workpiece material and type of the tool; for example, the faster feed rate, the higher cutting forces are measured, fact that may cause confusion about whether the increasing of cutting forces is due to tool wear or changes in the cutting conditions. It is concluded that the proposed method should be developed only under specific experimental conditions. Moreover, in [2], Jantunen notices that both torque and thrust measurements for monitoring drill wear should be attempted only after a very close tolerance has been obtained in the workpiece hardness making this monitoring method difficult to be achieved industrially.

2.2 Acoustic emission

Acoustic emission (AE) is a phenomenon which occurs when, for different reasons, a small surface displacement of a material surface is produced due to stress waves generated when there is a rapid release of energy in a material, or on its surface [2]. Hence, AE signal appear to be a promising candidate for tool wear monitoring.

In [7], Li reviews briefly the research on AE sensing of tool wear condition in turning noticing that the major advantage of using AE to monitor 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. In [8], Tansel et al. propose a wear estimation and tool breakage detection system using AE signals. It was concluded that both wear estimation and breakage detection methods were found to be acceptable for industrial application. However, the reliability of the tool breakage detection system was higher than the wear estimation method. It was also noticed that the main advantage of the AE is its independence from the cutting direction. Kim et al., in [9], developed an on-line tool life monitoring system using AE signals in gear shaping. It was suggested that the maximum RMS AE voltage value is an effective parameter to monitor tool life. The developed tool life monitoring system applied successfully to gear machining processes.

However, both Li [7] and Kim et al. [9] notice, that AE signals, like cutting forces, are heavily depended on process parameters, i.e. cutting conditions, tool material and tool geometry. Thus, a key issue is how to reduce these effects in intelligent tool wear and fracture monitoring using AE signals. Moreover, Jantunen in [2] reckons that AE is seen to suffer from severe attenuation and multi-path distortion caused by bolted joints commonly found in machine tool structures and restricting the mounting location of the AE transducer to somewhere very near the tool or workpiece.

2.3 Vibration

AE is no more than high frequency vibration signals. Consequently vibration signals present similar behavior to AE signals during a tool wear process. Thus, they are also widely used in literature as index of tool condition.

Against those who consider acoustic emission as a reliable indicator of tool wear, in [10], Dimla remarks that substantially little AE is generated during the tool wear process compared to the large amount which accompanies tool breakage and fracture, with as much depending on the cutting material (workpiece) structure as on the cutting tool. As the emphasis on any tool condition monitoring system would generally be on tool wear rather than tool fracture, AE is not suitable as tool wear indicator in monitoring applications, but it could be used with good effect in detecting tool tip breakage on machining centers. In the same paper, Dimla suggests vibration signatures as reliable, robust and applicable for TCM, in addition to the fact that vibration signatures require fewer peripheral instruments than AE for instance. Furthermore, vibration signals have the quick response time needed to indicate changes for on-line monitoring.

2.4 Spindle motor current

Spindle motor current monitoring features similar characteristics, and thus advantages and drawbacks, to cutting force signals. Lee et al., in [11], investigate a hybrid approach to cutting force regulation for tool wear signal extraction from the spindle motor current, which have been proved successful for monitoring of gradual tool wear. In [12], Constantinides and Bennett examine the use of the measurements of spindle motor power for the estimation of wear and the detection of the end of effective tool life for a vertical milling machine. Their work has shown that the changes in spectral energy in the fluctuating part of the spindle motor power consumption are linearly related to the wear rate of the tool. Finally, Franco-Gasca et al. in [13] conclude that spindle motor current can be related to the dynamics of drilling process and to monitoring the cutting tool condition.

2.5 Other indirect methods

In [14], Abukhshim et al. present a review of previous research on heat generation and temperature prediction in metal cutting and implications for high speed machining. They noticed that prediction of cutting temperatures is a major challenge in metal cutting due to numerous practical difficulties involved in the process. It was concluded, however, that for temperature measurement of the high speed cutting process, the most promising candidates are the fibre-optic pyrometers and infrared thermography techniques.

An active method in which the damping ratio of the tool vibration and its behavior with tool wear development in the feed direction after impact excitation were discussed by Gong et al. in [15]. It was concluded that the tool wear states can be quantitatively estimated in machining at any time.

2.6 Direct methods

A direct method includes measurement of flank or crater wear using a vision-based system. Vision-based systems are generally much more suitable for off-line inspection and diagnosis of hard faults, such as tool-breakage detection.

Several researchers have examined the use of machine vision for the measurement of tool's surface texture. In [16], Bradley and Wong present a direct tool condition measurement method. The objective was to extract the surface texture signature component due to tool wear from the other texture components, using three different image processing techniques, and employ it as an indicator of the tool condition. It was concluded that the approach is shown to indicate the change in the surface structure with progressive tool wear. Karthik et al., in [17], propose a non-contact method that provides visualization of the tool wear geometry using a pair of stereo images and generates the volume of crater wear as a new parameter for inspection. The results demonstrated that the volume of crater wear can be effectively used to measure the amount of the tool wear. Jurkovic et al., in [18], introduced a new approach in tool wear measuring technique using CCD vision system consisting of a light source to illuminate the tool, a CCD camera, a laser diode with linear projector, a grabber for capturing the picture and a PC. In [19], Yeo et al. presented a novel approach for the estimation of tool wear using the reflectance of cutting chip surface and a back propagation neural network. Results showed that the prediction was in good agreement with the flank wear measured experimentally. The authors, however, noticed that the major problem faced in that method was the hostility of the cutting environment. The dust and chip particles accumulated on the optical instrument result in false indication of tool wear.

Finally, in [20], Kerr et al. described the use of digital image processing techniques in the analysis of images of worn cutting tools in order to assess their degree of wear and thus the remaining useful life. It was concluded that, although all the textural analysis methods tested showed some potential for the direct assessment of tool wear condition, they are subject to changes in illumination and viewing conditions, as well as to contamination of the tool by dirt, cutting fluid, etc. In any practical TCM system, these problems (whilst not insurmountable) would need to be overcome before computer vision could be used as a robust indicator of tool wear.

3. SIGNAL PROCESSING TECHNIQUES

The importance of signal processing lies on the fact that it is essential to acquire the meaningful information out of the mass of information of an obtained signal. In many cases the dilemma is that the more sophisticated techniques are slow to use and, consequently, not suitable, e.g. for tool breakage detection [2]. In addition, the results with a sophisticated analysis function are sensitive to the cutting conditions, making the diagnosis more demanding. On the other hand, very simplistic techniques are fast and often not influenced from changes in cutting conditions. Unfortunately, at the same time they are not so sensitive to tool wear either. A summary of signal processing techniques that have been tested in the literature is given in Table 3. Statistical parameters, time domain, Fourier transforms and wavelet analysis appear to be the most prevalent signal processing techniques amongst the researchers.

3.1 Statistical parameters and time domain

A time domain signal is not very informative as such, or at least it is very time consuming. Especially, force sensor signals in the time domain do not show any correlation with drill wear [2]. Although the utilization of statistical parameters along with time domain signal can be proved promising:

- The gradient of the thrust force has been identified to be suitable process parameter for prediction of tool failure.
- As the tool wears, the torque requirement increases and correspondingly the spindle motor current also increases. The RMS value of the spindle motor current becomes a valuable feature for wear prediction.

Signal processing techniques	Reference number
Time series	[27, 77, 85, 103]
Fourier transforms (FFT, STFT, DFT)	[10, 13, 15, 31, 46, 49, 51, 56, 57, 73, 77, 82, 83, 94, 95, 96, 108, 110]
Spectral analysis	[4, 12, 80, 82, 86, 96, 108]
Time domain	[4, 5, 10, 24, 28, 29, 30, 31, 35, 36, 39, 40, 48, 51, 60, 75, 77, 82, 83, 85, 94, 99, 108]
Standard histogram analysis / stretching	[20, 70]
Thresholding, Image segmentation	[20, 44, 97, 100]
Statistical parameters & ARMA	[4, 5, 6, 9, 11, 12, 18, 24, 26, 28, 29, 30, 31, 35, 37, 38, 39, 40, 42, 46, 51, 53, 56, 62, 64, 74, 75, 77, 82, 83, 85, 94, 96, 99, 105, 106, 108]
GLCM analysis, Gray level distribution	[20, 60]
Wavelet transform / analysis	[4, 13, 21, 31, 33, 34, 42, 51, 57, 77, 82, 101, 102, 104]
Edge detection, enhancement	[23, 43, 97]
Cross-correlation function	[56, 97]
Fast Hough Transform	[58, 97]
Taylor diagrams / log-log analysis	[91]
Other signal processing techniques	[12, 16, 17, 18, 20, 44, 51, 53, 62, 65, 74, 78, 95, 100]

Table 3 A summary of signal processing techniques that have been reported in the literature

3.2 Fourier transforms

Fourier transforms, including Fast Fourier transforms (FFT), short-time Fourier transforms (STFT) and discrete Fourier transforms (DFT), provide a means to find out the frequency content of a measured signal. In particular, power spectrum of the drift force changes from a band limited process to a wide band process when the tool is worn. The power content of the high frequencies of the cutting forces increases as the tool approaches failure, providing thus a useful index to detect the failure of the cutting tool [2].

3.3 Wavelet analysis

It is suggested that wavelets might be the perfect tool for many applications requiring automated monitoring of manufacturing operations [2]. However, not enough comparison to FFT or statistical parameters has been made yet. Chen and Li, in [21], present a technique based on AE signal wavelet analysis for tool condition monitoring. The results showed that TCM cannot depend on Fourier transform solely because of its limitation. They concluded that their method can be used as a valuable tool for TCM, suggesting several approaches to be tested, including the threshold value selection function and new broadband sensors application. Franco-Gasca et al., in [13], analyzed the sensorlessly obtained driver current signal to estimate the tool condition by using the discrete wavelet transform (DWT). The DWT was found helpful and the whole method provided an accurate estimation of drill wear under different drilling conditions.

3.4 Other signal processing techniques

Several other signal processing techniques have been studied in the literature. The majority of them have been used for image processing, in direct methods. In [16], Bradley and Wong concluded that all three image analysis methods (Histogram Analysis, Frequency Domain Analysis, Texture Domain Analysis) that were used are shown to indicate the change in the surface structure with progressive tool wear. In particular, the frequency domain technique can also identify the onset of tool wear, an important factor in any automated tool monitoring system. Kerr et al., in their work [20] confirmed the results of Kurada and Bradley [22], who found the thresholded variance operator to be a good indicator of wear. Although, the tests that carried out showed generally disappointing results; only the inertia and entropy statistics gave the expected monotonic trends with wear and only in a particular gray level co-occurrence matrix search direction (GLCM analysis). Finally, in [23], Sortino presented an innovative algorithm for tool wear zone identification and a detection system based on statistical filtering of images of the cutting edge. The statistical filter proved to be very efficient in comparison to standard filters for edges detection.

4. CLASSIFICATION/DIAGNOSTIC TOOLS

Last but not least, diagnostic tools play the important role of classifying the previously acquired and processed signals in a TCM system and taking quick and precise decisions about the extent of the tool wear. A summary of classification/diagnostic tools that have been tested in the literature is given in Table 4. It can be said that, it is a clear trend among the researchers towards using Fuzzy Logic and Neural Networks.

4.1 Fuzzy Logic

Fuzzy Logic (FL) reasoning has been successfully applied in many different fields. Among others, fuzzy logic systems (fuzzy inference systems, FL systems) were tested for machine monitoring and diagnostics.

In [24], Sokolowski deals with some specific aspects of FL system implementation in machine tool and cutting process monitoring. The main scope of his research was to work out a cutting tool wear monitoring strategy which makes possible far reaching independence of the wear symptoms from the cutting conditions. He noticed that the FL system led to poor tool wear classification. Some crucial disadvantages were pointed out; the FL systems are much more sensitive to quantity and quality of information provided as an input. For example, results obtained with the FL systems depend on applied data selection methods. In addition, the performance of the systems can deteriorate with increasing number of inputs or increasing number of fuzzy rules. Lower learning ability of the considered systems was revealed, as well. However, Sokolowski concluded that the above facts do not stand for neglecting the FL systems for data integration. He focused on potential problems and difficulties that could be faced while applying such systems for machine tool and cutting process diagnostics, but this does not mean that for other applications the FL systems may not perform better than, for example, neural networks.

Classification / diagnostic tools	Reference number
Pattern recognition	[27, 38, 77, 94]
Adaptive Resonance Theory (ART2)	[8, 110]
Neural Networks	[4, 19, 24, 25, 26, 28, 31, 33, 36, 41, 45, 47, 48, 77, 82, 84, 96, 107, 108, 109, 110]
Sensor / Data fusion	[6, 77, 94, 108]
Microcomputer-based	[30, 74, 78, 97, 106]
Linear Regression (LR)	[12, 20, 34, 37, 57, 59, 77]
Fuzzy Logic (FL)	[24, 35, 37, 39, 48, 76, 77, 85, 104]
Hidden Markov Models (HMM)	[4, 49, 61, 103]
Support Vector Machine (SVM)	[51, 75, 105]
Knowledge & Rule-based	[52, 53]
Other diagnostic tools	[8, 13, 25, 26, 34, 42, 48, 61, 66, 67, 70, 71, 77, 81, 94, 97, 100]

Table 4 A summary of classification/diagnostic tools that have been reported in the literature

4.2 Neural Networks (NN)

Currently, it is generally accepted that the indirect sensor-based approach is the best practical solution to reliable TCM [4]. Furthermore, in recent years, neural networks (NNs) have been shown to model successfully the complex relationships between input feature sets of sensor signals and tool wear data. NNs have several properties that make them ideal for effectively handling noisy and even incomplete data sets. Another powerful method of modeling noisy dynamic systems is by using hidden Markov models (HMMs), which are commonly employed in modern speech-recognition systems.

In [4], Scheffer et al. aim at presenting a comparative evaluation of the performance of NNs and HMMs for a TCM application describing the advantages and disadvantages of both methods. The advantage of NNs is their ability to perform continuous estimations (although HMMs can also be employed to achieve this). The disadvantages of NNs are their relative complexity compared with HMMs and also the fact that great deal of experience and trial-end-error work are required for successfully implementing an NN-based monitoring strategy. The advantages of HMMs are that if the problem is well understood it is fairly easy to initialize and implement an HMM-based monitoring strategy, since computer implementations of HMMs are readily available. However, HMMs typically contain a large number of parameters and therefore need large amounts of data to estimate the HMMs parameters properly. Lastly, HMMs are not generally used for making continuous estimations, but rather for carrying out classification tasks. In [25], Ojha and Dixit used Neural networks to predict lower, upper and most likely estimates of the tool life. The comparison, which is made in the same paper, between neural networks and multiple regression, shows the superiority of the former. In [26], Choudhury and Bartarya focused on the comparison of Neural Networks (NN) against Design Of Experiments (DOE). The results showed that neural networks come ahead of the DOE in nearness of the predictions to the experimental values of flank wear as the average errors in the flank wear in case of NN are less than that obtained using DOE.

5. CONCLUDING REMARKS

A summary of monitoring methods, signal processing techniques and diagnostic tools applied to tool condition monitoring (TCM) has been presented. Nowadays, unmanned machining operations are possible only if there is a method –or a combination of methods– available for TCM. It is essential to distinguish between sudden and progressive failure. Methods that utilize cutting force, vibration or spindle motor current signals appear to be more effective in monitoring the latter type of failure, i.e. for fault prediction. On the other hand, acoustic emission signals and the majority of direct (vision based) methods are generally used for diagnosis of hard, unpredictable faults, such as tool breakage. Signal processing is the part of a TCM system that acquires the meaningful information out of the mass of information of an obtained signal. For this scope, time domain and statistical techniques, Fourier transforms and wavelet analysis are widely used by a number of researchers. However, it is suggested that wavelets might be the perfect tool for many applications requiring automated monitoring of manufacturing operations. Neural Networks and Fuzzy Logic are generally accepted as ideal diagnostic tools which could take quick and precise decisions about the tool condition. The expediency of the application of the latter, with the use of infrared thermography (IR) imaging, is of further interest and under investigation by the current research team, in the area of failure prognosis.

It is unobjectionable, that the area of condition monitoring and fault diagnosis is of increasing importance. Unfortunately, only few implementations have been achieved, such as Wearmon software [18], ESPRIT Project P2255 with TOPMUSS toolbox [3], Caron TMAC System (CNC Engineering Inc.) and NC4 (Renishaw Corp.).

In conclusion, it must be noticed that all available methods present drawbacks and limitations; most effective and reliable methods for tool wear monitoring are so slow in practice that they are not suitable for the detection of sudden failures. Generally speaking, the simpler a TCM system is, the less likely it is to fail. Reliability was rated as being the most important concern by those actually using some form of TCM. Thus, it is obviously vital to minimize the complexity of any future TCM system [1].

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