Tool Condition Monitoring System: A Review

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Tool condition monitoring system: A review

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Abstract

Increasing demands of process automation for un-manned manufacturing attracted many researchers in the field of on-line monitoring of machining processes. In view of this, extensive research work is taking place world-wide in the area of on-line tool condition monitoring system (TCMS). Tool wear is the most undesirable characteristic of machining processes as it adversely affects the tool life, which is of foremost importance in metal cutting owing to its direct impact on the surface quality of the machined surface, and its dimensional accuracy, and consequently, the economics of machining operations. Therefore, methods for cutting tool wear sensing are crucial in view of the optimum use of cutting tools. With an effective monitoring system, the damages to the machine tool, downtime and scrapped components can be avoided. This paper provides brief overview on tool condition monitoring.

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*Keywords:*Tool condition monitoring; signal and acquisition processing; acoustic emission; vibration signnals

1. Introduction

In any metal cutting process, tool wear means the gradual failure of cutting tools due to regular operation. As cutting proceeds, the amount of tool wears increases which directly affect the tool life. Carrying on the machining process with a worn tool, can increases the friction between the tool and the workpiece and also increases the power consumption.

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Worn tool produces a rough surface of workpiece, distortions in dimension and also causes vibration in the system. Early replacement of a workable tool or late replacement of a worn tool may cause time and/or production loss [1].

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Sometimes late replacement of worn tool may cause unpredictable machine breakdown at any time. Hence to avoid catastrophic tool failure, there is a real need to monitor the progression of cutting tool wear from the beginning of the cutting process. With an effective monitoring system, worn tool can be changed in time to avoid unexpected downtime and scrapped components [2-5]. In view of this, extensive research work is taking place world-wide in the area of on-line tool condition monitoring system. Tool wear sensing helps in the optimum use of tools and several methods have been proposed by researchers.

These are classified into two main groups: direct methods and indirect methods. Direct methods are based upon direct measurements of the tool wear using optical, radioactive, electrical resistance proximity sensors or vision system etc. The direct tool wear methods have the advantages of capturing actual geometric changes arising from the wear of tool. However, direct measurements are less beneficial because of the cutting area is largely inaccessible and continuous contact between the tool and the workpiece. This method is almost impossible in the presence of coolant fluids. Indirect methods are based on parameters measured during the cutting operation that can be correlated to wear state. In indirect method, tool condition is not captured directly but achieved from the measurable parameters through sensor signal output to predict the condition of cutting tool [5-8].

Table 1. Tools wear sensing methods.

Direct Methods	Indirect Methods
Electric Resistance	Cutting force
Optical	Vibration
Radioactive	Temperature
Measurement of tool geometry	Acoustic emission
Vision system etc.	Surface roughness
	Torque/current etc.

Commonly used parameters by various researchers include cutting forces [4-5], temperature [9], vibrations [5, 10], spindle motor current and power measured during cutting processes [11] and acoustic emission [12-13]. These indirect methods are popular among the researchers and extensively used. The detailed analyses of these methods have been carried out in the past twenty years.

2. Tool Condition Monitoring System(TCMS)

In modern manufacturing systems, machine tools are the major equipment and play a very important role. The malfunction of machine tools may result in the halt of the whole production and bring about tremendous financial losses. With an effective tool condition monitoring damages to the machine tool, unexpected downtime and scrapped components can be avoided [14].

Typically advanced TCMS is consist of sensors, signal conditioners/amplifiers, monitor. Sensor is a key element and have to be placed as close as possible to the target location (close to the tool tip) being monitored. Signal processing is then carried out to obtain useful information from the signals received through the sensors. The monitor is display unit used to analyze signal from the sensor.

In general any indirect TCMS consists of four steps: (i) collection of data in terms of signals from sensors such as cutting force, vibration, temperature, acoustic emission and/or motor current, (ii) signal processing and extraction of features from the signals, (iii) classification or estimation of tool wear using pattern recognition, fuzzy logic, neural networks, or regression analysis, and (iv) development of decision making technique to control the machining process based on information from the sensors [16, 18]. The block diagram and schematic of TCMS showing elements of TCMS is shown in Figs. 1 and 2 respectively.

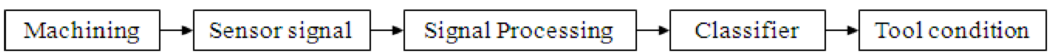

Fig.1. Block diagram of TCMS.

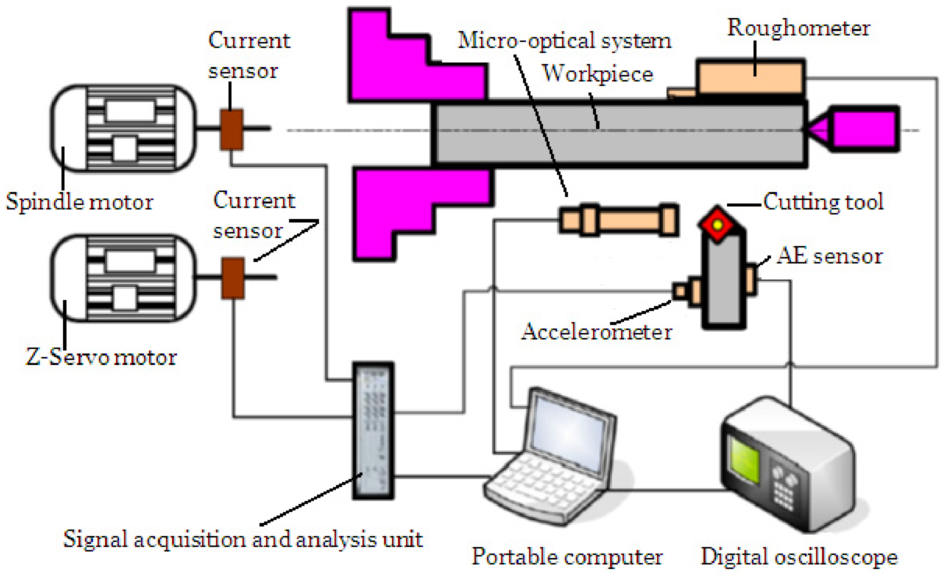

Fig.2. Schematic of tool condition monitoring system.

3. Process parameters measurement

From the literature it is seen that variety of process parameters can be detected and used to predict the cutting tool state. The process parameters mainly include force, vibration, acoustics signals, current, temperature etc. In this section a brief overview of process measurement is presented.

3.1 Measurement of cutting force

Gradual increase in tool wear during the cutting process causes the cutting forces to increase. Therefore cutting force is generally considered one of the most significant indicators of tool wear in the metal cutting process. Many Researchers uses cutting force to establish the relation with tool wear. Dimla and Lister [5] developed an on-line tool wear monitoring system for turning operation. They have used tool-post dynamometer as a force sensor to measure all three mutually perpendicular components of the cutting force. These parameters are investigated for tool wear monitoring through time series and fast Fourier transform (FFT) analyses. The determined characteristics showed that the sensor signals were affected by the different wear modes occurring simultaneously on the tool insert. The results indicated that the magnitudes of the static cutting forces were overwhelmingly dependent on the cutting conditions especially the depth of cut and feed-rate. Authors suggested that the vertical components (z-direction) of both cutting forces and the vibration signatures were the most sensitive to tool wear, with nose wear being the most useful indicator of eminent tool failure.

Ghasempoor et al [17] experimentally verified the feasibility of using different force component for on-line tool condition monitoring system for turning operations. Authors correlate the feed and cutting force components to flank wear and observed that these parameters are more sensitive to changes in the cutting condition. The crater wear predictions were less accurate partly because of the opposing effects of crater and flank wear components on cutting force components. Muhammad et al [4] presented the application of 2-D methods to interpret the cutting force signal for detection the tool wear progression in turning process. These results reveal that feed force is very significant due to flank wear and I-kaz 2-D is suitable to visualize any changes in the signals.

Force signals correctly reflect the frictional conditions between cutting tool flank and the workpiece. In view of this, Sikdar and Chen [20] described the relationship between flank wear area and cutting forces for turning operations. The experimental results showed that there is an increase in the three directional components of the cutting force with increase in flank wear area.

3.2 Acoustic emission (AE)

During metal cutting process, workpiece undergoes plastic deformation as the tool penetrates in it. Due to deformation, the transient elastic waves are generated by the rapid release of energy from a localized source or sources within a material. This released energy is commonly referred to as acoustic emission [21, 22].

According to Li [21], an AE is a sound wave or, more properly, a stress wave that travels through a material as the result of some sudden release of strain energy. Other sources of AE include phase transformations, friction due to tool-workpiece contact, crack formation, chip breakage, collision between chip and tool and tool fracture [21-24]. AE is one of the most effective for sensing tool wear. 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 [21]. Researchers have employed different strategies and sensors for capturing signals. Kakade et al [25] used AE analysis to predict tool wear and chip-form in face milling. AE parameters and flank wear are measured at fixed interval and also chips are simultaneously collected at fixed interval. Analysis of the results concluded that AE parameters namely ring-down count, rise time, event duration, frequency and event rate increases with tool wear.

Ravindra et al [24] used AE signals generated during machining of C-60 steel with a multilayer coated carbide tool. Many quantifiable characteristics of the AE signal, viz. rise time, energy, ring down counts, events, peak amplitude, rms voltage etc., have been studied and an attempt was made to correlate the above parameters with tool wear and cutting conditions. The results of study suggest that AE signals are a sensitive tool for tool failure prediction and can be used for on-line monitoring of the failure of a cutting tool. Bhuiyan et al [26-27] measured AE signals from a turning process to monitor tool wear, surface roughness and chip formation. It was found that the tool wear, the plastic deformation of work material and the chip formation are the key source of the AE signal. The investigation has shown that the AE and vibration components can effectively respond to the different occurrences in turning including tool wear and surface roughness. The AE has shown a very significant response to the tool wear progression. AE has been successfully used by many researchers in milling [12], drilling [29-30].

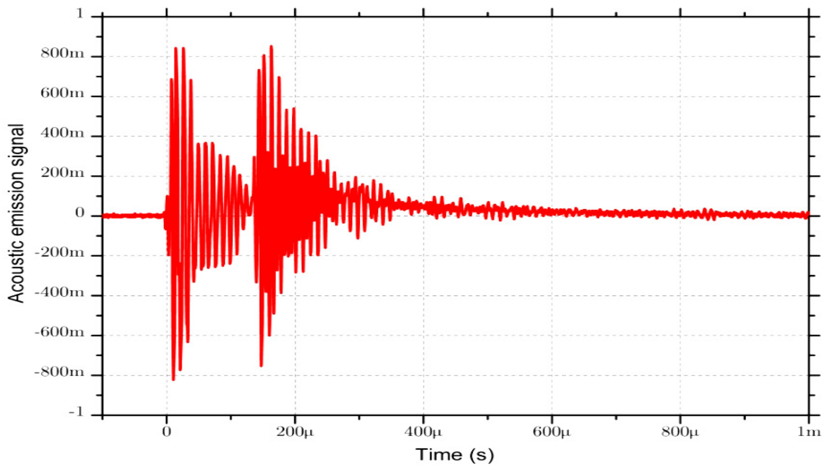

Fig.3. Typical AE signals in turning.

3.3 Vibration

Vibration signals are one of the most widely used by many researchers because they provide thorough insight in metal cutting process. Accelerometer is used as the sensing elements device to measure vibration response. Mechanical vibrations are produced by the cyclic variations in the machine components and due to the dynamic interactions between the cutting tool and the work piece. Tool vibration reduces the performance of machining operations also results in poor surface quality, tool wear and reduced tool life and creates unpleasant noise. Teti et al [31] categorizes vibration during the metal cutting process into dependent and independent. Vibration independent of metal cutting include forced vibration caused by other machines or machine components, e.g. vibration transmitted through foundations, unbalance of rotating parts, inertia forces of reciprocating parts and kinematic inaccuracies of drives. Vibration dependant on metal can be due to a number of characteristics as a function of the process, e.g. interrupted cutting.

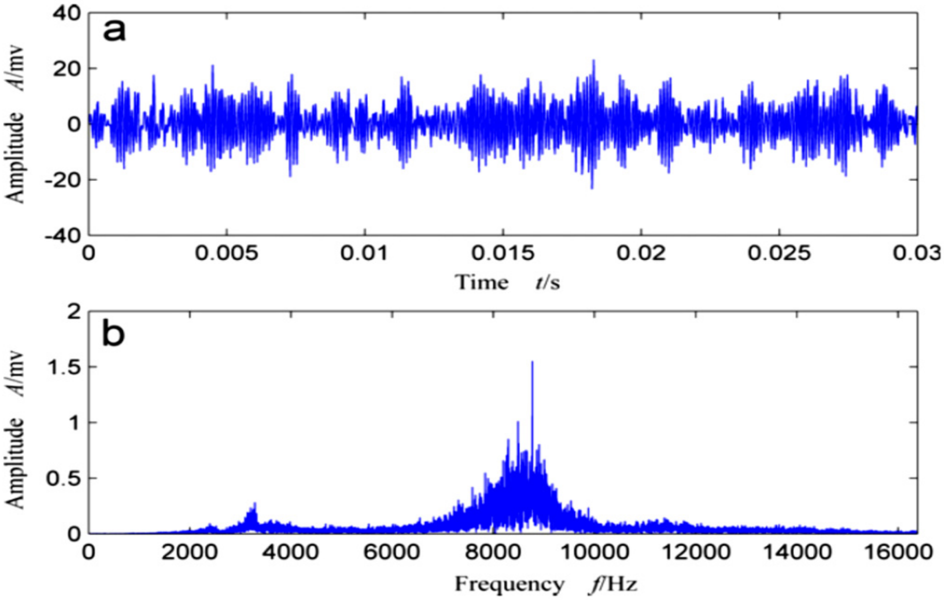

Fig.4. Vibration signals in frequency and time domain.

Vibration analysis for tool condition monitoring is presented by many researchers. Dimla and Lister [5] used tri-axial accelerometer to measure vibration signals in three mutually perpendicular directions. Time and frequency domain analysis is carried out to predict too wear. They observer that vibration signal are most sensitive to tool wear. Abouelatta and Madl [32] used vibration signals to established the correlation between surface roughness and cutting vibration during turning. The surface roughness has been measured using Surtronic 3+ measuring instrument. FFT analyzer used to measure tool vibration in radial direction and feed direction. Findings of the investigation showed that the proposed model gives accurate and convenient result for the prediction surface roughness which mainly depends on tool vibration. Alonso and Salgado [11], developed tool condition monitoring based on tool vibration signals using singular spectrum analysis (SSA) and cluster analysis. SSA is a non-parametric technique of time series analysis that decomposes the acquired tool vibration signals into an additive set of time series. Cluster analysis is used to group the SSA decomposition in order to obtain several independent components in the frequency domain. It is shown that the use of SSA and cluster analysis to process the signal can give acceptable results in TCMS development.

Measurement of vibration is reported by most of the researchers. Aliustaoglu et al [1] measured vibration signal for drilling operation. Chen et al [29] used vibration signals to estimate reliability of cutting tool based on logistic regression model. Wang et al [33] monitored vibration signals and used them using *v* support vector machine to develop tool condition monitoring system. Elangovan et al [18] used vibration signal and along with SVM kernel function classifier for the prediction of single point cutting tool. Rao et al [34] measured vibration signals using

Doppler vibrometer to evaluate the tool life. Bhuiyan et al [26] captured vibration and AE signals in turning. It is found that vibration signals have most significant response to the change in feed, death of cut and cutting speed. Rajesh and Namboothiri [35] measured the vibration signals generated during the turning process and carried out nonlinear time series analysis. The phase space construction and computation of the correlation dimension is constructed. It is seen that as the flank wear increases the correlation dimension also shows a similar trend due to change in cutting dynamics owing to different degrees of tool wear.

3.4 Motor current and power measurement

Motor current is used by most of the researcher to define the cutting tool condition. A worn tool requires more cutting forces than a sharp tool thus resulting in more input power [23]. Researchers have shown more interested in motor current measurement due to its low costing and non disturbance to machining process. In addition, the current sensor does not require a pre-assembly for signal acquisition. Salgado and Alonso [36] used motor current to estimate cutting forces and used them to developed tool condition monitoring system. Al-Sulaiman et al [37] reported tool wear by monitoring the signal of electrical power consumption for drilling process. In this technique the power for running spindle motor is nullified and only the power required for actual drilling process is recorded. From the investigation, it is found that the power consumption can be used to correlate flank wear of the drill. Ghosh et al [38] also used different machining parameter including spindle motor current to estimate tool wear. Li et al [39] monitored current signals in order to developed tool condition monitoring system.

From the literature, it is observed that the measurement of current is a simple and inexpensive. However there is a difficulty in detecting the relatively small change in the current caused by the cutting process compared to the current needed to rotate the spindle for big motors. Hence this method can only be used for small machines [37, 40].

3.5 Temperature

In metal cutting processes, heat generation is normal phenomenon and it is unavoidable. The resulting high temperature around the cutting tool tip damages the cutting tool. Tool wear rate is depends upon the cutting tool temperature. Many attempts have been made to correlate cutting edges temperatures to tool wear. Davis et at [19] presented the methods of measurement of temperature during material removal and showed how they can be applied to temperature monitoring during material removal. Authors have outlined the physics of each method, detailing the sources and evaluation of uncertainty. However they have not focused on suitability of methods for particular application. Kulkarni et al [41] presented tool-work thermocouple method to determine the thermal electromagnetic field signals generated at a hot junction produced by the interaction between the top layer of the coating and the workpiece. In the investigation, it is observed that high temperatures are generated in the region of the cutting tool edge, and these temperatures have a controlling influence on the rate of wear of cutting tool and on the friction between chip and cutting tool. Korkut et al [42] developed regression analysis (RA) and artificial neural network (ANN) model for prediction of tool-chip interface temperature and validated it experimentally. It was observed, proposed model have good accuracy and suitable for predicting the tool-chip interface temperature. Cutting temperature may give a good indication of tool wear but accuracy of these methods is questionable as it depends upon the thermal properties of the workpiece and tooling material [9].

3.6 Surface Roughness

Roughness is surface irregularities which result from the various machining process. Surface roughness is a widely used index of a machined product quality which indirectly indicates the tool condition. The cutting condition has a considerable effect on the tool wear and surface roughness. Abouelatta et al [32] reported the measurement and prediction of surface roughness. They have used Surtronic 3+ instrument for the measurement of surface roughness. In addition, FFT analyzer used to measurement tool vibration in radial and feed direction. From the investigation it is observed that cutting parameters and tool vibration gives accurate results in view of predicting surface roughness.

Rao et al [34] have monitored tool condition by analyzing surface roughness. They have measured surface roughness on Talysurf after machining. It is concluded that feed rate is the significant parameter for affecting surface parameter. Ozel and Karpat [43] measured surface roughness and tool flank wear over the machining time for variety of cutting conditions in finish hard turning. Regression models are also developed in order to capture process specific parameters. The result 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 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. Siddhpura and Paurobally [23] that the regenerative vibration or chatter accelerates tool wear resulting in poor surface finish and in turn reduces tool life. From the literature it is concluded that surface roughness is good indicator to estimate tool wear condition.

3.7 Other Methods

Varieties of methods have been employed in various attempts in monitoring the tool condition. Some of the methods have been reported by various researchers which mainly include optical methods [29, 44], sound [36], stress/strain measurement [10], methods based on measuring the workpiece dimension [22], ultrasonic method [45, 50], Torque [58], and chip formation [27].

4. Data Acquisition and Processing

Data acquisition is a process of collecting and storing useful data from targeted physical assets for obtaining meaningful information. Different types of sensors such as accelerometer, AE sensors, ultrasonic sensors etc., have been used for collecting various types of signals [47]. The signals captured from the machine can be vibrational signals, acoustic signals, temperature, current, etc. Generally captured signals are raw signals and required processing to extract significant features out of them. During the feature extraction stage, the most appropriate features which correlate well with tool wear and not affected by process conditions are extracted from the captured signals [7]. The analysis of signal can be done in time domain, frequency domain, time-frequency domain, statistical domain. Most of the researchers have focused on these domains in order to obtain useful parameter for tool monitoring [10, 26, 46].

4.1 Time domain and frequency domain analysis

Time domain analysis refers to a display of response parameter as a function of time. Features in the time domain are mostly determined for force signals. More advanced approaches of time-domain analysis apply time series models to waveform data. The main models include Auto Regressive (AR), Moving Average (MA) and Auto Regressive Moving Average (ARMA) [31]. Dimla and Lisetr [5] and Wang et al [33] reported time domain in order to predict the tool wear.

Frequency domain analysis is based on the transformed signal in frequency domain. Features of the vibration and sound signals are generally extracted using the frequency domain. For this purpose, fast Fourier transform (FFT) is the most widely used. The advantage of frequency-domain analysis over time-domain analysis is its ability to easily identify and isolate certain frequency components of interest. The main idea of spectrum analysis is to either look at the whole spectrum or look closely at certain frequency components of interest and thus extract features from the signal [46].

4.2 Time-frequency domain analysis

Time-frequency analysis is used for analysis of non-stationary signals. The feature extraction in the time frequency domain is usually performed with the help of wavelet transforms. Wavelet transform provides information about localization of a signal in the time domain and the frequency domain at the same time. Feature extraction with wavelet transform largely reduces the processing time [7]. Wavelet transforms has been employed by many researchers with great success [39, 47]. Three types of wavelet transforms viz. continuous wavelet transform, discrete wavelet transform and stationary wavelet transform are generally used.

4.3 Hilbert and Hilbert-Huang Transform

Hilbert–Huang transform (HHT) is new signal processing method used to monitor tool wear and tool fault. HTT application provides some additional information about an amplitude, instantaneous phase and frequency of vibrations. Thomas [48] carried out tool condition monitoring using HTT. The HHT has been successfully applied to nonlinear and nonstationary data. A details analysis about HHT is presented by some researchers [48-50].

4.4 Statistical domain

Statistical method generally used to detect faults. Faults which produce short term impulses such as tool breakage may not significantly alter the overall vibration level but may cause a statistically significant change in the shape of the signal. Thus, the shape of the signal is a better indicator of tool damage than the overall vibration level [46, 56]. This domain includes the features which describe the probability distribution of the random process such as mean, variance, skew, kurtosis, and standard deviation and coefficients of time series signals such as autoregression, moving average, and Auto Regressive Moving Average [7, 31, 52]. From statistical analysis can understood which variables selected has important changes in the mechanical behavior of the processes. In the statistical analysis not only were the control variables considered separately but a specific treatment was also carried out to find possible interactions between variables that could affect the processes negatively [52].

5. Decision Making Techniques

Decision making strategies plays very important role in the development of automated machining process and tool condition monitoring. They process incoming signals features to predict tool condition. Artificial Intelligent based techniques have been increasingly applied to machine diagnosis and have shown improved performance over conventional approaches. Several different approaches have been proposed to automate the tool monitoring function including pattern recognition [41], neural networks [10, 36, 43, 53-54], fuzzy logic [8, 13], and genetic algorithms. Recently researchers reported Artificial Neural network [42], Hidden Markov model [6], Singular Spectrum Analysis [11], Decision tree [51] and Support Vector Machine [2, 33, 55, 57] and successfully applied in many cases. Siddhpura and Paurobally [7] reported neural network classifiers and have been employed by many researchers due to its merits such as high fault tolerance and adaptability, noise suppression capability, and data-driven nature.

6. Conclusion

In today's high speed machining and competitive market, continuous monitoring of tool condition is essential to maintain the quality of finished product. With an effective monitoring system, worn tool can be changed in time to avoid unexpected downtime and scrapped components. In view of this, extensive research work is taking place world-wide in the area of on-line tool condition monitoring system (TCMS). In acquiring the process parameter, sensors plays very important role. Many researchers have used sensors to increase the confidence limit of machining process. However research should be carried to in the direction of smart sensor. Most of the researcher used variety of techniques to carry out each phase of tool condition monitoring. Such phases include, choice of the parameters to be captured, feature extraction, feature selection and feature classification. Many researchers have contributed toward condition monitoring studies that are computationally simple, effective and robust. However there is a need to develop advanced signal acquisition and processing technique to carried feature extraction without being affected process parameters and tool workpiece material combination. Artificial intelligent base models and proper decision technique could develop reliable, robust tool condition monitoring system.

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