Review Article

Tool condition monitoring techniques in milling process — a review

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\textbf{A B S T R A C T}

The most important improvement in metal cutting industry is the continuous utilization of cutting tools and tool condition monitoring system. In the metal cutting process, the tool condition has to be administered either by operators or by online condition monitoring systems to prevent damage to both machine tools and workpiece. Online tool condition monitoring system is highly essential in modern manufacturing industries for the rising requirements of cost reduction and quality improvement. This paper summaries various monitoring methods for tool condition monitoring in the milling process that have been practiced and described in the literature.

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1. Introduction

Recently, high speed machining (HSM) has received great attention owing to high accuracy and precision during the machining process. The degradation of product quality due to wear and increasing product cost owing to frequent replacement of tool is the major issue in HSM. The deformation or damage of sharp edge of a cutting tool during machining due to the interactions between the tool and workpiece is called tool wear. Prediction of tool life and tool changing policies are based on the estimation of tool life from the tool wear data obtained from past experiments. In manufacturing industries, the cost and maintenance time is increased and production rate is decreased due to the failure of cutting tools [1]. The condition monitoring system (TCMs) is directly useful to the manufacturing industries as this reduces the down time and increases the productivity. The monitoring process helps to (a) avoid damages on tool and workpiece, (b) improves the productivity and quality of the machined product, and (c) predicts the tool wear.

The estimation of cutting tool condition is a difficult process since every manufacturing process is a non-linear time variant system. Moreover, signals acquired from various sensors during cutting depends on machining conditions and tool wear and difficult to model and predict the wear. Early finding and monitoring of wear progress are necessary for cost optimization of machining processes. The tool wear can
be minimized by using the optimal process parameters in machining process. Hence, TCMs is used to monitor the tool condition and reduce the product cost. This paper outlines the various indirect tool condition monitoring techniques, feature extraction techniques and machine learning algorithms for monitoring the tool condition.

2. Tool condition monitoring system

The major constraint for manufacturing industries is to reduce the cost and improve the production. Manufacturing industries used computer numerical control machines with automatic tool changers and mainly focused on tool changing procedures. During 1980’s to 1990’s, the cutting tool was replaced based on wear of the cutting tool [1]. Conventionally, a cutting tool was replaced for the development of machining process to meet new process requirements. To replace a cutting tool when the tool was dull, online tool wear monitoring was required. The demand for monitoring in a manufacturing process includes monitoring the machine and dynamics of machining process, workpiece and machine tools to assure optimal performance [2]. Hence, the objectives of TCMs can be considered as:

- Early detection of cutting tool wear,
- Maintaining a machining accuracy by providing a corrective action for tool wear
- Prevention of cutting tool from breakage.

Without TCMs the deficiencies like, excessive power consumption, dimensional inaccuracies, poor surface roughness of workpiece and failure of cutting tool may occurred [1]. To a greater extent, research was conducted regarding to the growth of consistent TCMs. A number of factors have obstructed the progress in the development of TCMs including improper selection of sensors and their operation [1]. The frame work of TCMs [3] is shown in Fig. 1.

A simple layout for online milling TCMs was presented in Fig. 2. Tool wear can be measured with direct or indirect methods. In direct method, cutting tool has to be removed from machine and Tool Makers Microscope or Optical Microscope is generally used to measure the wear [4]. It takes more time and increases the machine down time. On the other hand, indirect method utilizes various sensor signals (acoustic emission, milling force, tool/workpiece vibration, sound, spindle torque, spindle motor current and power, temperature, vision system, stress, and chip formation) for estimating the tool wear. The sensor signals were correlated with tool wear. Indirect methods support on-line tool condition monitoring without affecting the production rate. Different methods for tool condition monitoring was reviewed [5]. Current challenges and issues in TCM was discussed and suggested to measure the remaining useful time of the tool instead of measuring the tool wear [6]. This paper outlines the methods used in TCMs.

2.1. Acoustic emission

Acoustic Emission (AE) is the phenomenon of radiation of acoustic waves in material that occurs when subjected to deformation, metal cutting or fracture. It is generally accepted that AE is correlated to plastic deformation process during formation of chip, due to the interface between workpiece and cutting tool. Liu and Liang [7] found that plastic deformation and rubbing of work material was responsible for generation of AE signal during milling process. AE signal was used to predict the tool wear. The experimental results proved that AE signal parameters namely ring down count and rise time were used to categorize the dull from new tool [8].

An experiment was conducted to measure the tool wear and results were used to train the Neural Network (NN) to predict the tool wear. Based on the results, optimum cutting parameters for minimum tool wear were selected. The current shop floor practices for tool replacement was improved by this method [9]. Sundaram et al. [10] used AE signals to monitor the tool wear during machining process. The acquired signals had a frequency range from 100 to 2 MHz, and tool condition monitoring had a significant effect above 200 kHz. AE RMS values were used to indicate the gradual progress of tool wear. Tool wear was analysed by capturing the signals from AE transducer where coolant was used as a transmission medium. Initially, signals for fresh and worn out tool were considered. Based on AE RMS, the tool wear was predicted [11]. In face milling process, the tool breakage was detected with cutting sound. It was found that both proposed Empirical Mode Decomposition (EMD) and Independent Component Analysis (ICA) methods were capable to separate the cutting sound of fresh and dull tool from other sounds. The results were effectively used to detect the tool breakage [12].

The tool life in end-milling of H13 mould-steel was monitored using emitted AE signals and found that tool life was decreased with increased in cutting speed [13]. Additionally, researchers found that AE signals can be effectively used to monitor the tool condition during end milling process [14]. Recently, a novel TCM was developed based on spindle motor current and AE signal to monitor the wear in form milling process. It was found that AE signals provide comprehensive information about the cutting tool [15]. In milling process, tool condition was monitored using AE and vibration signals with various machine learning algorithms. The tool condition was monitored with AE and vibration signals with different machine learning algorithms and found that the performance of SVM was better than decision trees, naive bayes and artificial neural network [16] due to its ability of the kernel function to solve complex problems, and the performance of ANN in time-frequency domain was better than SVM, decision trees, and naive bayes [17]. The application of AE in machining process was discussed by Kishawhy et al. [18]. The relationship between flank wear and AE burst signals were recognized by clustering of AE energy. The flank wear can be monitored by the total energy of AE burst signals induced by fracture and plastic deformation [19].

The very near field acoustic sensor, which can directly measure the acoustic particle velocity. The use of particle velocity sensor offers a significant advantage over traditional testing techniques, providing all measurements that can be carried out in the proximity of vibrating surface [20]. This sensor is suitable to measure the particle velocity during the machining process and it can differentiate the signals of good and faulty tool significantly.
In material removal process, the mechanism of AE signal generation was studied. The plastic deformation during machining emits distinct AE signals. Therefore, these signals can be used to understand the quality of machining and to measure the tool wear. Tool wear has a significant effect on AE parameters. The AE signal discriminate the cutting action between sharp and worn-out tool. By using the qualitative assessment, AE signals provided the wide range of tool condition regarding flank wear, crater wear, crack propagation and severe adhesive wear.

2.2. Cutting force

Generally, cutting force measurement is one of the indirect method used for on-line tool condition monitoring [21]. In milling process, flank wear was monitored using the changes in magnitude of cutting force harmonics. Based on the immersion ratio and number of tooth in the cutter, the cutting force harmonics were varied. The features selected from harmonics were used to design the on-line TCMs [22]. The cutting parameters, workpiece geometry, and cutting force were considered as input to train NN and tool wear was considered as output. Additionally, the developed regression model from cutting force signal was used to predict the flank wear [23].

Tool wear in milling process was monitored by measuring the average cutting force and reported that variation in cutting force increased continuously during the machining process. These results confirmed that cutting tool continuously lost their sharp edge and became worn out [24]. ANN based TCMs in milling process was designed using cutting force signals to predict the flank wear and surface roughness and found that cutting force signals increased with tool wear [25]. Tool wear in face milling was estimated using Normalized Cutting Force indicator (NCF) and Torque-Force Distance indicator (TFD). It was concluded that TFD method was better than NCF. Since TFD was not affected by cutting parameters and its interaction [26].

The wear propagation and variation in cutting force was analysed for coated carbide tool. It was found that flank wear was the leading failure mode and affects the tool life [27].
The tool wear in milling process was monitored using cutting force as monitoring signal and Continuous Hidden Markov Model (CHMM) as a diagnostic method [28]. The tool wear was monitored by tracing the tangential and radial cutting force coefficients during end milling process. The behaviour of cutting force coefficients was independent of cutting conditions and correlated with tool wear. This method was used to monitor the tool wear [29]. TCMs during end milling of Glass Fibre Reinforced Plastic (GFRP) composite was developed using cutting force signals and Adaptive Network based Fuzzy Inference System (ANFIS). The results confirmed that tool wear was predicted with feed force data using ANFIS predictor [30].

The cutting force signals were analysed in time as well as frequency domain and results showed that the magnitude of cutting force in time domain was increased and in frequency domain was decreased with increase in flank wear and cutting speed [31]. The cutting condition also affects the cutting force signal along with tool wear. The average tool life can be monitored and predicted with high accuracy of 98.5% using cutting force model [32]. The remaining useful life time of the cutting tool was estimated using cutting force with HMM [33]. The cutting force components are linked well with the progress of wear land and cutting tool failure. Most of the literature reveals that an increase in flank wear leads to increase in cutting force due to increase in contact area between cutting edge and workpiece [34].

2.3. Vibration signals

During milling process, the flank wear was measured by monitoring the spindle shaft vibration. It was found that forced frequency component increased with increase in tool wear and power spectral ratio of natural and forced vibration frequency components gave a measure of flank wear [35]. When tool wear increased gradually, the time domain features of vibration signals like RMS, peak to peak, and kurtosis values were increased significantly [36]. The vibration signals during end-milling process were acquired through low cost microcontroller based data acquisition system. The frequency domain features were extracted and found that frequency level had a significant variation for various tool conditions [37]. TCMs was designed using Singular Spectrum Analysis (SSA) of tool vibration signals. The frequency spectrum was divided into different frequency ranges. It provides a methodology to separate the variation of spectrum due to wear [38]. The tool wear was evaluated with the aid of fractal dimension change of vibration signals. It was confirmed that vibration signals were consistent with tool wear [39]. The vibration frequency was slightly varied due to the geometrical change of the cutting tool.

Tool condition was monitored in micro-milling process using vibration signals. The frequency domain features were extracted and features were selected based on class mean scatter criteria. The Backpropagation Neural Network (BPNN) was used to classify the tool condition. It was found that the combination of Z axis vibration signals along with X or Y axis signals provide better results [40]. Wang et al. [41] measured the vibration signals during milling of Ti6Al4V alloy. Various time and frequency domain features were extracted and the tool condition was monitored. Vibration signals were used to monitor the tool condition in face milling process. The vibration signals were acquired for good and various fault tools during machining of 42CrMo4 steel alloy. K-star algorithm was used to classify the tool condition [42].

Recently, vibration signals were acquired during milling process and Hybrid Healthy Condition Monitoring (HHCM) method was used, which combines the Variational Mode Decomposition (VMD) with Genetic Algorithm based Backpropagation Neural Network (GA-BPNN). The developed model was used to detect chatter and tool condition. The experimental results confirmed that proposed HHCM method was used to identify the chatter and tool condition [43]. The conventional machines have been integrated with vibration sensors and vibration signals were used to predict and monitor the tool life with ANN [44]. The vibration signatures have significant variations with tool state. The filtering and denoising is required to differentiate cutting vibration with machine vibration. The vibration signatures like mean, RMS, and peak to peak was increased with increase in flank wear [44].

2.4. Sensor fusion technique

In general, sensors for monitoring the process was specifically planned to evaluate a selected feature (example dynamometer) and then related to process of interest (cutting force). If the signal to noise ratio is high then the measuring feature yields meaningful correlation to the desired quantity, if it is low; then the opposite is true. In industrial applications, the feature was predicted with more than one sensor usually called as sensor fusion [1]. The effect of process parameters and tool wear on AE and cutting force signals were studied during face milling operation [45,46]. It was found that flank wear was correlated with both AE and cutting force signals. Also, a real-time tool fracture sensing system was studied using sensor fusion concept in machining process. The utilization of several sensors improves the performance and provides the tool condition [47].

Cutting force and vibration signals were used to monitor the milling tool condition. Various data fusion methods like Comparison Group (CG), Index Multiplication Group (IMG), Indices Summation Groups (ISG), Indices Multiplication and Division Group (IMDG) and Vectors in Mapping Space Group (VMSG) were used to integrate the extracted features and various NN architectures were used to classify the tool wear. Finally, it was concluded that IMDG and IMG fusion methods significantly improved the classification accuracy [48]. The cutting force, vibration and AE signals were acquired during HSM of GGG40 steel. It was found that time and frequency domain analysis confirmed the importance of cutting force and vibration signals for TCM in HSM process. Also, concluded that tool wear was sensitive to AE signals, with rising amplitude of up to 160 kHz for dull tool [49]. During tool breakage, the significant fall of cutting force was followed by an AE signal burst which then occurred. This system could easily identify the tool breakage within 0.02 s [50].

TCM with sensor fusion model based on NN was developed. The various signals from cutting zone, namely cutting force, spindle vibration, spindle current, and sound pressure were acquired. All these signals were fused to estimate the average flank wear of main cutting edge [51]. The integration
of direct (vision sensor) and indirect (cutting force) measurement was used to design TCMs along with Self-organizing map (SOM) as an estimator. The tool breakage was detected by cutting force features in time domain and experimentally verified using vision sensor. This integration overcomes the drawbacks occurred in single sensor based TCMs and can be implemented in machining industries [50]. The cutting force and AE signal during micro-milling process were measured to monitor the tool wear. It was found that AE signal demonstrated a very small reaction time for the tool to get in touch with workpiece, which made easier for detecting this contact and monitoring the reliability of the machining process. Finally, it was concluded that better results were attained using cutting force and AE signals, which were in micro-milling process [52].

Tool condition was monitored by measuring the cutting force, vibration and cutting sound signals which were captured from dynamometer, accelerometer, and microphone respectively. These sensor signals were used as an input for fuzzy inference system (FIS) and output of this FIS was given as an input to sensor fusion model. The tool condition was estimated from the output of sensor fusion model [53]. Multi-sensor based TCMs was developed with cutting force, vibration, AE, and spindle power signals. The signals were acquired during end-milling of 4340 steel and effectively used to monitor the tool condition [11].

On-line TCMs was developed with cutting force, torque, vibration, and AE signals. A range of statistical features were extracted from the measured data and these features were used to train the Support Vector Machine (SVM). The output of SVM was used to estimate the tool condition. Genetic Algorithm (GA) was used to select the features which give the most useful information and remove the irrelevant information. Hence the prediction accuracy was improved from 89 to 100% [54]. TCMs for machining process was designed using AE and sound signal. The wavelet decomposition and reconstruction was used to extract the features and SVM was used as decision-making algorithm to predict the tool wear. The experimental results illustrated that prediction accuracy of tool wear was better due to the combined effect of AE and sound signals [55].

In milling process, AE, cutting force and vibration signals were used to predict the tool wear and tool life with support vector regression (SVR). Also, the operator can start a suitable maintenance action based on the obtained result [56]. In high-speed milling process, various clustering methods were employed for on-line TCM and fault diagnosis. Cutting force, vibration and AE signals were acquired and wavelet features were extracted. It was found that fuzzy clustering method performs better than other clustering methods [57].

In end-milling process, AE and cutting power signals were measured during machining of VP80, tool condition was monitored with AE and cutting power signals used Probabilistic Neural Network (PNN) with an accuracy of 91% [14]. Stavropoulos et al. [58] considered the limitations of tool wear prediction in milling of CGI 450 plates, during the measurement of vibration and spindle current signals. It was found that, vibration signals had a significant effect on tool wear prediction. Recently, in milling of AISI 1045 steel, tool condition was monitored with cutting force, spindle current, spindle vibration, and machining sound signals. These signals were fused together in FIS, tool condition was evaluated and a decision was made to replace the cutting tool or change the cutting conditions [59].

In milling process, vibration, cutting force and power signals were used to predict the tool wear. It reveals the relationship between the machining condition and tool wear [60]. Tool wear was sensitive with cutting force and vibration signals [61]. AE and cutting force signals were closely linked with flank wear and provide the useful data about tool condition. The combined effect of sound and AE signals provides better results in machining process.

2.5. Thermal imaging

The cutting tool temperature increases with increasing the cutting speed, feed and depth of cut owing to the generation of large amount of frictional heat produced at the interface between tool and workpiece [62]. In general, cutting tool temperature increases with increase in cutting speed [63]. The tool condition has to be monitored using the cutting tool temperature [64,65]. Hence, online monitoring of tool temperature in machining process is required to avoid the unpredictable tool failure. During machining process, different contact and non-contact methods were used to monitor the temperature of the tool and workpiece [66,67]. The commonly used contact method utilizes the thermocouple (embedded thermocouple, tool-work thermocouple, thin-film thermocouple and single-wire thermocouple) sensor to measure the temperature.

The contact method has some drawbacks like limited access, location for placement of sensor, and high response time. In contrast, non-contact methods like radiation pyrometer [68] and infrared thermography (IRT) [62,69] have smaller response time and cutting zone temperature is measured easily in non-contact and remote manner. IRT is relatively novel non-contact temperature measurement method, where the IR rays emitted by an object are detected using a suitable IR sensor and temperature of the object is measured from the intensity of emitted rays using Stefan–Boltzmann’s Law [70]. The application of IRT and IR cameras were reviewed by Bagavathiappan et al. [71]. IRT is more accurate, reliable and cost effective method for temperature measurement [72].

2.6. Miscellaneous methods

The other methods like surface image, spindle torque / current and power [73], stress [74], machine vision system [1], chip formation and workpiece dimension were also employed to monitor the tool condition.

**Vision system:** A new on-line tool wear measuring algorithm was proposed using the machine vision system. The tool images were captured before and after the machining process and detection algorithm with sub-pixel accuracy was used to measure the tool wear [75]. Voronoi tessellation method was used to extract the number of polygons with zero cross moment and total void area of the Voronoi diagram from the machined surface images. The number of polygons with zero cross moment had a linear relationship with flank wear than the total void area [76]. Gray level co-occurrence matrix, Voronoi tessellation, and discrete wavelet transform were
used to extract the various features from the images to estimate the flank wear using SVM based models [77].

An indirect TCMs based on the image processing technique was used for analyzing the surface images of the machined surface. This technique attained high importance due to its non-tactile and flexible nature [78]. Tool wear was directly measured and monitored by a CCD camera. The influence of cutting conditions on tool wear was studied [79]. Tool wear images were processed and tool wear was predicted using the percentage of white pixel [80]. But it requires a costlier machine vision camera and complex image processing algorithms to predict the tool wear.

**Motor current and power:** The power consumption of tool drives was used for online detection of tool breakage. This signal exposed the best signal-to-noise ratio and used to predict the tool wear [81]. In the face milling process, tool life was predicted by an adaptive procedure. AC and DC portions of spindle motor current were used to predict the tool wear [82]. Spindle power is a comprehensive signal, which contains cutting force components and direct factor which determine tool breakage, Coulomb friction, and viscous damping forces, inertial forces which are thermally sensitive and nonlinear. Tool breakage can be accurately predicted from the spindle power signal. The spindle power had a linear relationship with the tool condition [83]. The feed motor current was used to monitor the tool breakage [73,81]. It requires complex signal processing techniques to separate the required components from the entire signal.

**Stress:** A stress analysis of three-dimensional loading was used to analyze tool failure. From finite element analysis, the location of tool deformation and failure mode of cutting tool was predicted [74]. The online measurement of cutting tool stress is a difficult task and it can be estimated from cutting force signals.

**Chip formation and workpiece dimension:** During the face milling process, tool wear, cutting force, and chip morphology were studied. The chips collected during face milling process were examined for their shape and texture. It was found that chip morphology was not changed with cutting conditions [84]. The measurement of the workpiece dimension was affected by various parameters such as vibration, deflection, and misalignment [1]. Hence, one is unable to quantify the tool wear with chip morphology and workpiece dimension.

### 3. Data acquisition and feature extraction

Data acquisition is a method to acquire the signals and store the data for further analysis and future access. The various sensors like dynamometer, microphone, AE, accelerometer, ultrasonic sensor, spindle power, and spindle current sensors have been used to acquire the signals. From the acquired signals, time [34], frequency [40], and time-frequency domain [3] features were extracted. In the course of feature extraction, most suitable features that correlate well with tool wear and not inflated by cutting conditions were extracted from the acquired signals.

#### 3.1. Time-domain and frequency domain analysis

In time-domain analysis, the response was demonstrated as a function of time. Time-domain features were mostly established for AE [85] and cutting force signals. Occasionally, it was feasible to develop the mathematical model for the dynamic system based on the fundamentals of physics, which enable us to estimate the value of varying quantity at any particular instant of time. A model that constructs precise calculation would be exclusively deterministic. Conversely, few dynamic systems were entirely deterministic due to the effect of several factors during the machining process. Hence it was suitable to construct a stochastic model that can express the dynamics of the system from a probabilistic point of view. A time-series modeling technique was used to build a stochastic model with discrete samples of input/output data of a physical system. In this fashion, essential system physics can be studied from the behavior of experimentally measured data [86]. The time series model consists of Auto-Regressive (AR), Moving Average (MA) [29] time domain & statistical features [87,88].

The time-domain data were transformed into a frequency domain through the FFT algorithm to analyze the frequency components. Features of vibration [89] and sound signals were usually extracted using frequency domain analysis. The benefit of frequency domain analysis over time-domain analysis was its capability to simply recognize and segregate the definite frequency components of interest. The foremost thought of spectrum analysis is to look at the entire or at distinct frequency components of interest. The wavelet analysis deals with time-frequency domain features. Most of the researchers followed the time-frequency domain analysis [55].

The wavelet transform is able to decompose a signal into various components in various time windows and frequency bands through scale, and mother wavelets. The discrete wavelet transform (DWT) decomposes a signal into scaling coefficients (approximations A) and wavelet coefficients (details D) by the complex signal and impulse response of band-pass filters. More details about DWT was discussed in the literature [3]. Kurtosis appeared as the most efficient wavelet feature. The other signal processing techniques like Empirical Mode Decomposition (EMD), Hilbert transformation (HT) [55,90,91] and Continuous wavelet transformation (CWT) [92] were also used for feature extraction.

#### 4. Decision-making algorithms

The various time domain, statistical data, and time-frequency domain features were extracted from the experimental data. Tool condition was predicted from the extracted features with different decision-making algorithms. Decision-making algorithm plays an essential role in the development of TCMs. Numerous techniques have been considered to automate the TCMs, including Probabilistic Neural Network (PNN) [14], Support Vector Regression (SVR) [56], Support Vector Machine (SVM) [54], pattern recognition, Artificial Neural Networks (ANN) [93,94], fuzzy logic [95,96], and genetic algorithm [54]. Recently researchers used the Hidden Markov model [28], ANFIS [30] and Decision trees [97] to predict the tool condition.
4.1. **Artificial neural network (ANN)**

ANN consists of an input layer, hidden layer, and an output layer, each layer has the number of neurons. All the neurons in each layer were interconnected. The weight and bias were used to enhance the strength of the connection between the neurons. These values were tuned automatically to reduce the output error during the training of NN. The network was trained based on the training data and training algorithm. The relationship between the sensor signals and flank wear were non-linear in nature. Hence ANN is a suitable model with fault tolerance and eliminates the noise [5]. Different studies reported that ANN had excellent performance [30,98,99]. Shankar et al. [34] monitored the flank wear using cutting force and sound signals with ANN and ANFIS and found that the performance of ANN was better than ANFIS in terms of mean squared error (MSE). On the other hand, ANN models have few disadvantages like, it requires a large number of training samples, selection of number of hidden layers and number of neurons in hidden layer [100,101].

4.2. **Support Vector Machine (SVM)**

The functioning of SVM is based on statistical learning theory, which is used to classify and predict the results with minimum number of samples and non-linear signals that are suitable for the milling process. SVM non-linearly maps the input samples in original space to high-dimensional space using a kernel function, and make a linear algorithm in high-dimensional space that corresponds to the solution of non-linear problem in original space [5]. SVM attracts more interest in TCM and used to monitor the tool condition [11,54,78,102]. Earlier researchers reported that the classification accuracy of SVM was better than ANN [11,42]. Also, SVM has some problems, like the selection of kernel function and its parameters which were selected based on a trial and error approach [103,104].

4.3. **Hidden Markov Model (HMM)**

An HMM is a Markov process with entailed unknown parameters. An HMM allows two stochastic processes: one is a Markov process, which describes the transition sequence of hidden states, and the other is a random process that builds the observation sequence of hidden states [33]. In HMM, the state of a system was influenced only by the earlier state and not depends on all other states, which is consistent with the progression of tool wear [33]. An HMM can be used to represent the milling process as a dynamic model to a certain extent than a static model. HMM have few drawbacks such as it requires a large number of training data as similar to ANN, and duration of the state.

4.4. **Fuzzy logic**

Fuzzy logic (FL) is a well-established approach for decision making in the presence of ambiguity. Essentially, fuzzy logic allows for considering the logic that is fairly accurate rather than the exact one. The fuzzy inference system (FIS) is a mapping process from a given input to an output using FL. The FIS includes input and output membership functions, fuzzy logical operators, and if-else rules. The steps involved in the implementation of FL are Fuzzification of input, fuzzy rules, and defuzzification of output. During fuzzification, input and output values are converted into fuzzy crisp sets. If-then rules are formulated based on the knowledge base with fuzzy logic operators [105]. In defuzzification, the fuzzy system returns an output as the response. Few studies employed FL in TCMs [21,53,59,96,106,107].

4.5. **ANFIS**

ANFIS is ANN-based Takagi - Sugeno fuzzy interface system which incorporates both ANN and FL in a single structure. The objective of ANFIS is to identify the model, which correctly relates the inputs to its output [34]. In FIS modeling, output signals from each layer were processed by the node functions. The ANFIS architecture includes a number of interconnected nodes, which are defined by tunable parameters. ANFIS supports only for single response system and it takes more time for processing the data compared to ANN. Also, the performance was substantial than ANN [34]. The following studies used ANFIS for the prediction of tool condition in the machining process [27,107].

5. Discussion

TCM in milling is a very complex process due to the influence of many parameters, such as cutting conditions, work-piece material, and process parameters. The tool condition was assessed based on sensor data, selected features, and decision-making algorithms. Based on the extracted features, a decision-making algorithm was trained and used to test the data and predict the tool wear. The commercially available TCMs are based on cutting force components or quantities related to cutting force (power, torque, distance/displacement, and strain). The dynamometer can be fixed with machine vise of the existing machines and do not influence the machine dynamics [108]. Online TCMs was implemented in M/s. Flen-dor (Ind.) Ltd., Kharagpur, India and M/s. TATA Bearings Ltd., Kharagpur, India. The system was implemented in real-time and able to predict the tool wear in 0.85 s with the tool wear prediction error of less than 25 μm [51]. The spindle motor current based system was implemented in the plant floor for machine tools used in mass production lines of car parts [81]. Though much progress has been made in TCM research for the milling process, still the following issues have to be solved.

- The cost of the designed TCMs has to be minimized as much as possible. The cost of the sensor (Dynamometer, AE, accelerometer, etc.) has a major role in implementing the TCMs in small scale enterprises.
- The measurement of cutting force using a strain gauge based dynamometer is an invasive one. So, the cutting force can be measured with spindle motor current signals.
- During the measurement process, the environmental and electrical noise has to be properly removed using filters.
- The use of multiple sensors can achieve better results than the results achieved with a single sensor. However, the utilization of multiple sensors increases the dimensions of
signal, noise and increases the complexity of signal processing. This leads to reduce the accuracy of results. Result accuracy can be enhanced by selecting the significant features from the acquired data.

- Therefore, it is necessary to optimize the multiple sensor signal features to obtain the best performance of TCMs.
- The signal features can be optimized by using decision trees, principal component analysis, Ant colony optimization, and sequential forward floating selection methods.
- In the decision-making algorithm, machine learning and deep learning algorithms like naive Bayes, K-Nearest Neighbors algorithm, deep recurrent neural network, deep belief network, stacked auto-encoder, convolution neural network, and recurrent neural network can be used to predict the tool condition without any misclassification.
- Current TCMs will monitor and predict the state of the tool. In contrast, the future system may predict the remaining useful lifetime of a cutting tool.
- The remaining useful lifetime of a tool can be estimated with a prognostics module by mapping the relationship between product quality and tool degradation.
- When the degradation curve of a tool reaches the critical zone, the remaining useful life can be evaluated immediately.
- Predicting the remaining useful lifetime is more important than monitoring the tool condition. Since the remaining useful lifetime and failure probability of a tool is more significant than the diagnosis of tool wear.

6. Significance of the study

Prediction of tool life and tool changing methods are based on the conventional estimation of tool life from tool wear history. In an automated operation, the tool must be changed from the cutting process before it failed, otherwise the part produced becomes faulty. Therefore, monitoring the tool wear during the cutting process is an important process in industries. The utilization of multiple sensors can be replaced by a single sensor that is well suited for the industrial environment.

As a Non-Destructive Testing (NDT) method, the sound particle velocity sensor offers a simple and reliable method for TCM during the machining process with better accuracy. In the future, TCMs with a single sensor along with Industry 4.0 concepts can be effectively implemented in manufacturing industries. With the aid of Industrial Internet of Things (IIoT), the tool condition and the remaining useful lifetime of the tool can be easily estimated and monitored from anywhere through the cloud.

7. Summary

Tool wear is one of the major problem in manufacturing industries. Direct measurements of tool wear lead to an increase in the machine idle time and reduce the production rate. In order to enhance the production rate, on-line TCMs is required, which utilizes the indirect measurement of tool wear. Indirect methods are easy to implement and monitor the tool condition. The selection of appropriate sensors and features plays a vital role in the design of TCMs. The different sensor signals like cutting force, vibration, AE, spindle motor current, torque, and the cutting sound were utilized to access the cutting tool condition. While increasing the number of sensors to monitor the tool wear, the system cost is increased and also the processing of the acquired signal is a tedious process. The progress of flank wear had a significant effect on cutting force, vibration, and cutting sound signals. This can be used to monitor the tool condition in the machining process.

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Conflict of interest

The authors declare no conflicts of interest.

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