Artificial Intelligence techniques and Internet of things sensors for tool condition monitoring in milling: A review

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Abstract. Milling is a machining process that involves removing material from a workpiece using a rotating cutting tool. During the milling process, the cutter is affected by a progressive degradation due to the grinding of the workpiece which results in a decline in product quality and a sharp increase in energy consumption and production costs. For these reasons, Tool Condition Monitoring has emerged as the essential approach in the machining industry. The application of Artificial Intelligence (AI) systems that incorporate the use of various Internet of Things sensors (IoT) to support the tool condition monitoring in the milling process has recently been a subject of great interest to researchers. It helps to achieve goals required in the modern manufacturing industries in terms of sustainability, cost reduction, and quality improvement. This review article focuses on the application of IoT sensors for recording acoustic emissions, to conduct tool condition monitoring of the milling cutting tools based on AI techniques. The discussion includes an analysis of the principal sensory systems and their main advantages and disadvantages for the milling process. Moreover, trends and problems of applied AI techniques for tool condition monitoring are highlighted.

Introduction

Milling process is a machining method in which a tool, called milling cutter, advances into a workpiece to remove materials. Due to friction between the cutting tool and the workpiece, degradation of the cutting tool occurs, resulting in tool surface wear, deformation, and even tool breakage [1]. Monitoring the tool condition is crucial to making timely decisions about replacing the tool before the failure condition, avoiding premature replacement, which reduces tool life and increases machine downtime, or delayed replacement, risking product quality and escalating production costs. In modern industry, Tool Condition Monitoring (TCM) systems can be constructed with the use of sensors that can do tasks such as "seeing, hearing, smelling, and touching" [2]. These sensors can be classified as direct or indirect [3]. The sensor is defined as direct if data are collected directly from the tool response to the contact with the workpiece, while it is defined as indirect if data are collected from a response external to the cutting interface. Examples of indirect TCM systems include cutting force, vibration, acoustic emission (AE), image, thermal, and other sensors [4]. Among them, AE exhibits high sensitivity to the sequence of events during tool contact, chip formation, and disengagement, as evidenced by the increasing trend in the averaged root mean squared (RMS) energy with flank wear growth [5-7]. Also, the variation of the AE frequency with various forms of tool wear was demonstrated [8].

The integration of AI techniques in the TCM is a hot research topic [9]. It allows to predict the state of wear of the tools and thus determine the best process parameters for increasing their useful life as well as for identifying the best time for replacement, also preventing damage to the processed materials. This can lead to huge savings in terms of materials consumed and therefore

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production waste, as well as the reduction of resources (time, energy, materials, etc.) necessary to re-manufacture the damaged products.

Given the heightened interest in this topic, several literature reviews have emerged, offering insights into commonly employed sensor monitoring signals and diverse signal processing methods across machining processes like drilling, turning, and milling [10-14]. Still, the artificial intelligence techniques applied to detect faults and monitor equipment status in real-time are delved [15]. Furthermore, considerations regarding the estimation of the Remaining Useful Life (RUL) of the tool are explored in the reviewed literature [14].

The purpose of this review is to study and analyze the use of AE sensor systems, investigating their advantages and disadvantages, for TCM in the milling process. Special focus is placed on the different resolution approaches adopted for the TCM problem. A thorough literature search to identify relevant papers in the last ten years related to the topic of AI techniques for AE in the milling process is conducted on Scopus and Web of Science databases. The keywords used for the search are: “artificial intelligence”, “machine learning”, “deep learning”, “milling process”, “audio signal”, “sound signal”, “acoustic emission”, “tool condition monitoring”, “tool wear” and “remaining useful life”. The outline of the survey goes as follows. In Section AE sensors in the Milling process the use of AE signals to monitor the tool conditions is explained, highlighting advantages and disadvantages. Section Resolution approach surveys the different ways in which the TCM problem can be addressed. In Section Artificial Intelligence models the popular decision-making algorithms used for monitoring and prediction are discussed. Section Multi-sensor approach reviews some works that have combined the AE signals with others, and the subsection Benchmark dataset is dedicated to surveying few papers that have used public datasets. Finally, Section Conclusion and Future Work provides recommendations for future work and gives the conclusion of the review paper.

AE sensors in the Milling process

Milling is considered the most versatile machining process [16]. The input machine parameters provided are essential for describing the milling process and determining the quality and efficiency of the operation. The three parameters that have the greatest effect on the success of a machining operation are:

- Depth of Cut (*p*): it represents the thickness of material being removed in a single pass;
- Feed Rate (*a*): it determines how fast the milling cutter advances into the workpiece;
- Cutting Speed (*V*): it is the linear speed of the tool through the workpiece, based on the spindle speed and cutter diameter. A higher cutting speed can lead to more efficient material removal [17].

Analyzing the tool condition has a crucial role in the milling process to optimize the cutting parameters and replace the damaged tool at the appropriate moment. The modern industry requires an online method that continually observes tool conditions while the process continues. In the indirect online TCM, three phases must be executed, as is shown in Figure 1: acquisition of signal, extraction and selection of features from the acquired signal, and construction of a predictive model for the tool wear [18]. After the signal acquisition, the extraction and selection phases are critical for identifying features relevant to the tool conditions [19]. Different types of sensors have been used in the literature to assess the tool conditions. Among them, AE sensors have demonstrated their relationship with the increase in tool wear. A similar sensor is microphone for the acquisition of sound during the process that can provide sensitive detection of tool breakage [20]. The AE states the acquisition of ultrasonic signals in a material subjected to an external load. The tool breakage generates high-amplitude AE signals, making the AE method useful in constructing a warning system to prevent failure. Instead, the sound is generated by the contact between the tool that proceeds with a high speed on the workpiece. In milling, a discontinuous sound is provided, due to the consecutive entry and exit of the tool on the workpiece.

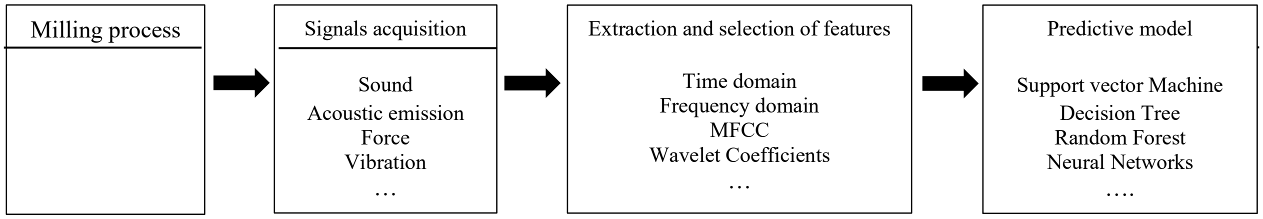

Figure 1 Framework of TCM

Advantages and disadvantages. An AE or sound method can reduce costs during manufacturing processes, increase tool life, and consequently improve the sustainability of the process. These types of sensors have demonstrated two advantages: measurement of the sound signal itself belongs to the non-contact measurement, data acquisition and measurement do not affect processing; formation of a sound signal measurement system is relatively simple and does not need to change the machine's structure and no need for more equipment [21]. However, the application of AE signal analysis to the milling process presents difficulties because of the magnitude of shock pulses during the entry and exit of each tooth from the workpiece, which may be equivalent to that generated during tooth fracture [22]. A practical method aimed at overcoming this difficulty is to utilize a multi-sensor approach, as discussed in the subsequent **Multi-sensor approach** Section. A disadvantage of both AE and sound sensors is that the capacity of identified changes in the tool wear is correlated to the position of these sensors in the machine. Kohuru et al. [23] acquired sound signals with the use of three microphones, positioned at different distances and angles from the cutting zone. They showed that the position of the microphone influences the prediction accuracy but by having more training data coming from different locations this positional error can be minimized. In addition, compared with an AE sensor, the reaction time of sound signals is very long, which makes the microphone less reliable.

Resolution approach

Regression and classification are the most commonly used approaches to solve the problem of TCM. In the case of a regression problem, the outcome variable can assume numerical real value. For TCM it can be the value of wear registered or the RUL [24-33]. A particular version is proposed, considering the tool wear as a percentage: if the tool is healthy the percentage is about 100%, working the percentage is reduced [34-35]. Another version considers the tool wear as a value from 1 to 3, if the predicted value exceeds three the tool should be changing [36].

Considering the classification problem, AI models were implemented to predict the tool wear status, classified into a certain number of classes. More research studies considered only two classes: a Good tool and a Worn tool [37-43]. The cutting tool during the milling process is considered a Good tool until wear reaches a maximum threshold, beyond which the tool must be replaced and thus is labeled as Worn. Other studies consider three classes [44-54], associated with the typical tool wear pattern that can be divided into three stages: rapid initial wear stage, normal wear stage, and severe wear stage [55]. In the initial stage, the rapid wear results from the impact of the cutting tool on the workpiece. In the second stage, the wear assumes a uniform pattern whose duration depends strongly on the cutting rate. Finally, in the last stage, tool wear increases rapidly, indicating that the cutting tool has reached the end of its effective lifespan and must be replaced. Most research, instead, defines multiple classes (up to six) based on thresholds on the recorded wear value [23,56-63].

Artificial Intelligence models

The use of AI in industrial processes has seen rapid growth over the past two decades and has become a major contributor to Industry 4.0 [64]. AI combined with the use of sensors can help, among other things, the achievement of sustainable industry by reducing waste and energy consumption in production processes with the introduction of technological solutions. AI application known as machine learning (ML) enables machines to learn from data without explicit programming. Many ML methods can be applied, and the correct selection is more important to achieve better performance. From the prominent methods, there are:

- Support Vector Machines (SVMs);
- Decision Trees (DTs);
- K-Nearest Neighbors (KNN);
- Artificial Neural Networks (ANN).

Support Vector Machines are supervised learning models with the primary goal of identifying a hyperplane that classifies the data points, maximizing the margin (i.e. the maximum distance between data points of different classes). In regression problems, it is called Support Vector Regressor (SVR). Kothuru et al. obtained good performance by applying an SVM model with input data features generated from the frequency domains of sound signals, acquired with the use of three microphones positioned in three different places [23,44,59]. In a comparative study, the SVM model outperformed the deep learning model of Convolutional Neural Networks (CNN) [60]. Li et al. [56] compared four different models (i.e. Classification and regression tree (CART), Random Forest, KNN, and SVM), concluding that SVM gave better performance. Krishnakumar et al. [46] tested the SVM model with different kernel functions to solve the classification problem, obtaining better performance with the Radial Basis Function (RBF).

Decision Trees are non-parametric supervised learning models that generate a tree with decision nodes, two or more branches from the decision nodes representative of the value of the attributes, and leaf nodes representative of a decision in the target. Twardowski et al. [38] compared three ML techniques (CART, multi-layer perceptron (MLP), and KNN) to solve the binary tool wear prediction problem, obtaining better performance with the CART. Other studies have demonstrated the efficiency of using DT model to solve the classification problem of tool conditions [45,62].

K-Nearest Neighbors is a popular algorithm used for both regression and classification problems, based on the nearest k neighbors. The principle behind the algorithm is that similar data points tend to have similar values. Yuan et al. [39] trained a KNN to predict the tool breakage conditions. The results showed good performance of the model (with an accuracy of 96.21%), demonstrating that the proposed method can effectively identify damaged cutters in milling operations.

Artificial Neural Networks are a series of algorithms that identify relationships between data points of datasets, inspired by the human brain. Their architecture comprises three layers: input, hidden, and output. In each layer, several neurons are present. The communication between nodes of different layers is permitted by patterns, characterized by weights that excite the signals during the communication. The output layer is characterized by one neuron in the case of binary classification or regression, and more neurons in the case of multi-class classification (one for each class). CNNs are the most widely used type of ANNs in TCM. They are a type of deep learning model used to process data with a grid pattern, such as images. Some studies convert sound signals into images, training CNNs for classification, showing high efficacy in detecting worn tools [37,47,63]. Khan et al [54] solve the classification problem with a Long Short-Term Memory Network (LSTM), achieving a prediction accuracy of over 98%. Zhou et al. [25] introduced the Two-Layer Angle Kernel Extreme Learning Machine (TAKELM) for tool wear regression. This algorithm, implemented in a single hidden-layer feedforward neural network, sets random values for weights and biases, keeping them fixed during training. By utilizing two-angle kernel functions without hyperparameters, TAKELM simplifies the model and outperforms existing methods, showcasing remarkable predictive accuracy with minimal error compared to state-of-the-art approaches in tool wear prediction.

Multi-sensor approach
To overcome the limitations of the use of AE or sound signals, the multi-sensor fusion method has become a hot research direction of TCM [65]. Combining various types of signals can improve the robustness of the method and reduce the sensitivity to noise and transient faults associated with using audio signals alone. A combination of vibration and sound signals (or AE signals) was adopted in more research work [34,35,43,57,61]. Vibrations can be acquired with the use of piezo-electric sensors and occur in the milling process due to the interaction between the material surface and the tool at particular spindle rotation frequencies. They are detrimental to tool life and workpiece surface finish. Zhu et al. [58] combined the use of all three types of signals (vibration, sound, and AE) to predict the tool conditions, fusing all three in a 2-D image with the angular matrix imaging method. The results demonstrated that vibration signals incorporated with sound signals outperform other combinations of signals to solve the tool wear classification problem. Yan et al. [29] combined the three types of signals, constructing a condition-adaptive hidden semi-Markov model for evaluating the wear condition and estimating RUL. Some studies demonstrated, instead, that the use of the only vibration sensor against the sound sensor allows to reached better performance for both regression and classification problems [24,48]. Cutting force signals, highly correlated with tool wear, offer another avenue for signal combination [36]. An increase in tool wear determines an increase in cutting force during milling operations, without changing the machine parameters. Dynamometer can be used to acquire cutting force signals, requiring a relatively simple installation in the machining process. A big disadvantage of using this type of signal is the need to reduce the noise content. Some research work used the current signal in combination with vibration and sound signals [26,41]. Letford et al. [27] combined the use of the four sensors (vibration, AE, cutting force, and spindle motor current) to solve the regression problem of tool wear prediction. Good performance was achieved by applying an artificial neural network model.

Other combinations are carried out in various research work. Sun et al. [49] conducted various experiments to determine optimal sensors and feature combinations for monitoring tool wear. Accelerometers, microphones, current transformers, and AE sensors are considered in the experiments and 29 features are selected from the time and frequency domain of the signals and the machine parameters. Results demonstrated that the use of all sensors, if not appropriate for the examined problem, can achieve poor performance. In addition, the use of only one type of sensor is preferred because it allows a considerable reduction in associated costs. Other studies used the axial load signals, combined with sound and spindle power signals, to solve the three-classes classification problem [50-51]. Chen et al. [53] used an online tool image acquisition method combined with the collection of AE signals to monitor the milling process. The images collected were processed to obtain the tool wear while AE features were used to train four ML models, achieving a recognition accuracy of 96.11%. McLeay et al. [40] developed a fault detection system for predicting tool replacement, utilizing an unsupervised learning model based on multiple sensors (AE, two microphones, two accelerometers, and a spindle power sensor).

Benchmark dataset. Two are the public benchmark datasets for the tool condition problem of a milling process: NASA and PHM 2010. These datasets are intended to check the accuracy of the RUL prediction models. More research work solved the problems using different approaches, where tool wear prediction or tool wear condition classification has been proposed. NASA dataset [66] was provided by the UC Berkeley Emergent Space Tensegrities (BEST) Lab. Experiments

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were carried out with the Matsuura Machining Center MC-510, cast iron and steel material as workpiece, and a 60mm face mill with six KC710 inserted tools. Various combinations of machine parameters were tested, including variable depth of cut, variable feed rate, and a constant cutting speed. Data sampled by three different types of sensors (acoustic emission, vibration, and current sensors) were acquired at several positions. PHM 2010 [67] is provided for the PHM Data Challenge, a competition open to all the participants of the 2010 PHM Society Conference. Three types of sensors (dynamometer, accelerometer, and acoustic emission) were used to capture relevant signals from high-speed CNC milling machine operations, in which a workpiece made of Inconel 718 and a 6mm ball nose tungsten carbide cutter were used. Constant input machine parameters are set during the experiments and three training sets (named C1, C4, and C6) are provided to construct the predictive model. Table 1 shows the results obtained by different research work, solving the proposed problems.

Table 1. Literature results for benchmark datasets

Benchmark Dataset	Type problem	Decision-Making Models	Results			Study
PHM 2010	Regression	Temporal Convolutional Network (TCN)	MAE			[28]
			C1: 9.5	C4: 10.9	C6: 8.5	
		Gated Recurrent Unit Convolutional Neural Network	MAE			[32]
			C1: 0.95	C4: 1.02	C6: 0.84	
		Condition-adaptive hidden semi-Markov model	MAE			[29]
			C1: 6.25	C4: 17.73	C6: 18.90	
		TAKELM with binary differential evolution	MAE of $3.52 * 10^{-6}$ (for C6)			[30]
	Classification	KELM with bandpass filter	Accuracy of 89% on 20 experiments			[42]
		CNN- ResNet-50 and EfficientNet-B0	Accuracy of 100%			[52]
		Condition-adaptive hidden semi-Markov model	Accuracy (%)			[29]
			C1: 92.46	C4: 90.79	C6: 93.02	
NASA	Regression	Neural Networks	Mean RMSE of about 0.10			[31]
		1D-CNN	RMSE of 0.09			[33]
	Classification	CNN- EfficientNet-B0	Accuracy of 100%			[52]

Conclusion and Future Work

In the last decades, more attention has been paid to the use of AE or sound sensors to monitor the milling process and the application of ML techniques to construct a TCM system. This system enables the prediction of cutting tool wear, allowing for the optimization of process parameters to increase tool life and identify optimal replacement times preventing, moreover, damage to the machined materials. In addition, the acquisition of sound signals has proven to be the cheapest compared to other types of signals. The conclusions that can be drawn from the analysis performed are:

- both approaches, regression and classification, were found to perform well for the TCM problem in the milling process;
- the most widely used and best-performing ML models for the problem under consideration are SVM and CNN.

Despite the presence of numerous works, many challenges remain. The works conducted were all performed in laboratories, including public benchmark datasets, and neglected real-world production challenges like background noise affecting sound signals. Another important limitation is due to the rather small number of observations within the datasets which considered few scenarios in terms of variation in the materials adopted for both tool and workpiece and machine input parameters for which different combinations can be set. Addressing these issues, intelligent datasets, comprising selected instances from larger sets, could offer a more comprehensive representation of wear process behaviors. Future progress should be based on the implementation of ML techniques in combination with reliable and inexpensive sensors, acquisition and communication systems that are better suited to real production settings, facilitating more effective monitoring of instrument conditions in real-world environments.

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