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Assessment of Cosine Similarity for Acoustic Emission-Based Tool Condition Monitoring in Milling Processes †

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Abstract: Tool Condition Monitoring (TCM) systems have become increasingly important in industrial automation due to the need to improve efficiency and reduce manufacturing costs. These systems use advanced sensors to capture signals during machining processes, allowing for early detection of faults and prediction of tool life. This study explores the potential of using the Cosine Similarity (CS) method as a practical technique for analyzing acoustic emission (AE) signals and monitoring tool wear during milling operations. Acoustic signals were applied to the CS method under reference conditions and after potential damage. We used 9000 samples of the milling cutter passing over the workpiece, collected from experiments with milling machines using the AE sensor WD925 at a frequency of 100 kHz. The CS method tracked wear proportionally in each case. As the tool wore down, its similarity to the intact tool decreased, proving to be an effective indicator for condition monitoring. However, the change in CS calculation was not as pronounced as the tool wear observed, suggesting that having enough data is crucial for this methodology in condition monitoring. A longer sampling period is necessary to capture significant signal variations and effectively detect losses in similarity. This provides a significant amount of data and, as a result, leads to more conclusive findings for the process in question.

Keywords: tool condition monitoring; acoustic emission; feature extraction; cosine similarity; industrial automation

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1. Introduction

Tool Condition Monitoring (TCM) systems have become essential in driving the transformation of industrial automation, particularly in the context of Industry 4.0. Their importance stems from the increasing demand to boost production efficiency while reducing costs in today's highly competitive manufacturing landscape [1,2]. By incorporating state-of-the-art sensors and sophisticated data analysis, TCM enables continuous, real-time monitoring of tool conditions and predicts their remaining useful life (RUL), marking a significant leap forward in the management of industrial assets [3].

In precision machining processes like milling operations, TCM plays a critical role in ensuring quality and reliability by providing accurate, real-time monitoring of tool conditions. This allows for the early detection of issues such as abnormal wear, breakages, cracks, micro-cracks, and even catastrophic failures. By identifying these problems in advance, TCM helps maintain the integrity of manufacturing processes while optimizing production, enhancing operational efficiency, and reducing waste [4].

Moreover, the ability to adjust operations in real-time not only improves product quality but also fosters sustainability by minimizing resource consumption and waste generation. TCM also enables precise forecasting of maintenance needs, shifting traditional corrective or preventive maintenance practices toward more advanced predictive and prescriptive strategies. This extends the lifespan of equipment and tools, ensuring uninterrupted production and boosting the competitiveness of companies in the global market [5,6].

The use of acoustic emission sensors and piezoelectric transducers has become increasingly popular in the context of TCM [7]. These devices capture acoustic signals generated during machining processes, providing critical information about tool conditions. This allows for the early detection of failures by analyzing acoustic activity and the behavior of corresponding electrical signals.

Advanced digital signal processing techniques, such as time series analysis [8], time-frequency analysis [2,9] and wavelet transform [10], are applied to analyze data from these sensors. These methods enable the extraction and selection of relevant features related to the phenomenon under study. Such approaches are essential for isolating critical information that aids in interpreting the acoustic data captured [11].

Unlike traditional acoustic emission (AE) signal analysis methods, which focus on specific parameter values, the cosine similarity (CS) method emphasizes the similarity in the waveform of the AE signal. This approach suggests that under normal operating conditions, AE signals demonstrate high similarity and stability, indicating the absence of anomalies [12]. However, when tool failures or wear occur, the signals become unstable and show lower similarity. Therefore, irregularities in tool conditions can be efficiently identified by calculating the cosine similarity between AE signals, facilitating continuous monitoring [13].

The objective of this study is to explore the potential and feasibility of applying distance-based metrics, such as condition indicators based on the cosine similarity method, to monitor tool wear during milling operations. The milling process is essential in modern manufacturing due to its versatility in creating complex shapes, precision in meeting tight tolerances, and ability to achieve high-quality surface finishes. This research is expected to increase productivity, reduce manufacturing costs, optimize tool life, minimize the risk of significant damage during milling, and enable prompt corrective actions when damage is detected.

2. Material and Methods

2.1. Dataset

The dataset used in this study is based on the work of Goebel [14], and contains information from experiments conducted on milling machines under various operational conditions. Structured in Matlab, the dataset comprises 16 cases, each representing a distinct combination of cutting parameters, such as depth, feed rate, and material type. It is important to note that each case has a variable number of tool passes, depending on the degree of flank wear (VB), measured in centimeters. Additionally, each pass includes 9000 samples collected by an acoustic emission sensor of the model WD925, with a sampling frequency of 100 kHz.

2.2. Application of Cosine Similarity in AE Analysis

For this study, the Cosine Similarity (CS) method will be employed to correlate events present in acoustic emission (AE) signals with tool wear during the milling process. CS is one of the most widely used metrics for measuring similarity [15]. This technique effectively measures correlations or variations between windows of different signals in the time domain, offering the advantage of computational simplicity, which eliminates the need for complex mathematical operations. This makes it particularly suitable for real-time applications. The fundamental concept behind this method is to calculate the cosine of the angle between two vectors to assess their similarity [16,17]. Assuming there are two different vectors of the same dimension, $X^T = \{x_1, x_2, x_3, \ldots, x_n\}$ and $Y^T = \{y_1, y_2, y_3, \ldots, y_n\}$ the cosine similarity between X^T and Y^T is defined as follows:

$$CS(X,Y) = \frac{\sum_{i=1}^{N} x_i \cdot y_i}{\sqrt{\sum_{i=1}^{N} {x_i}^2} \cdot \sqrt{\sum_{i=1}^{N} {y_i}^2}}$$

The value of cosine similarity (CS) ranges from −1 to 1. Specifically, a CS value of −1 indicates that two vectors point in opposite directions, while a value of 1 indicates that they are aligned in the same direction. The closer the CS value is to 1, the more similar the vectors are [13,18]. Notably, the CS method emphasizes the directional difference between two vectors rather than differences in magnitude. This characteristic makes CS an effective alternative for detecting mutation points in AE signals. The application of the CS method in this study for analyzing acoustic emission signals in the milling process involves the following steps: (i) acquisition of AE signals using a data acquisition system; (ii) pre-processing the signals to remove noise by applying a low-pass filter with a cutoff frequency of 40 kHz, as the acoustic emission signals have a bandwidth of 0 to 40 kHz; (iii) dividing the signals from each tool pass into segments of 9000 samples, followed by vectorization of the data; and (iv) calculating the cosine similarity between vectors, where vectors X and Y represent the acoustic signals under reference conditions (baseline signal, related to the intact tool) and after potential damage, such as tool wear.

3. Results

Based on the entire study conducted up to the drafting of this document, the results obtained for the signals captured under the parameters of one of the cases from the previously mentioned dataset will be presented. Cosine similarity was calculated using the vector corresponding to the tool without flank wear, in comparison to signals exhibiting a progressive wear pattern. The results generated for these samples, applied in the CS calculation, are presented in Figure 1.

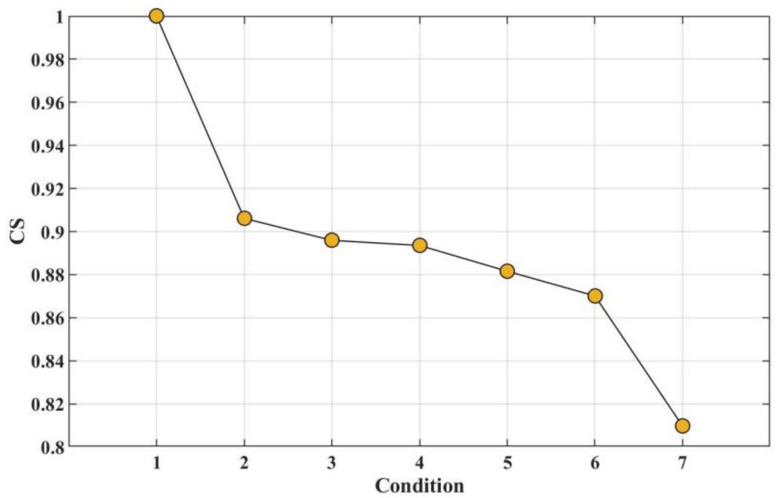

Figure 1. Cosine Similarity Calculation for the Samples of the Tool Passes on the Workpiece.

For comparison purposes, the degree of flank wear (VB) measured for each sample is shown in Figure 2.

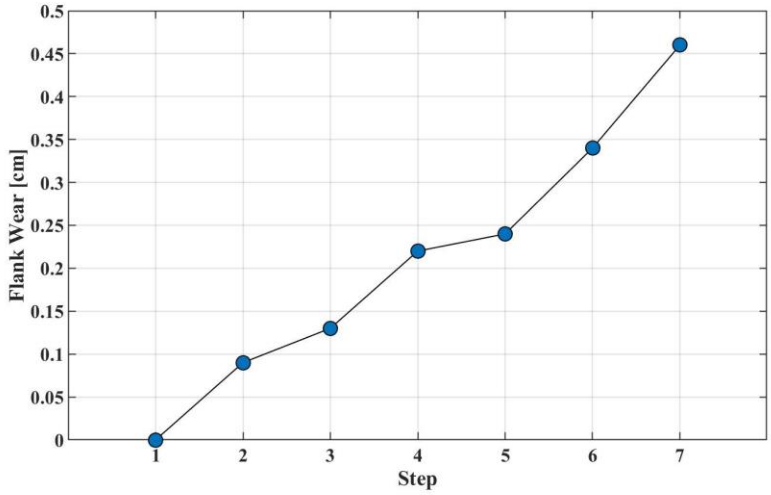

Figure 2. VB Flank Wear.

By analyzing Figures 1 and 2, it can be observed that as flank wear (VB) increases with each tool pass, the corresponding CS calculation decreases, as expected. This occurs because the tool progressively wears out, reducing its similarity to the intact tool. However, it is important to note that the two curves do not always vary with the same intensity at every point. For example, between passes 3 and 4, the flank wear curve shows a noticeably steeper incline, indicating more abrupt deterioration compared to the previous state. In contrast, the CS curve exhibits a more gradual decline during the same interval, reflecting a less drastic change. This suggests that despite greater tool wear in this period, the CS calculation did not vary proportionally, as the acoustic signal emitted during this short time frame—i.e., between passes—did not fully capture the more acute wear of the tool.

An alternative approach to analyzing the CS method is to compare each signal with its immediately preceding sample, rather than with a single reference signal. When recalculating the CS using this approach, the results presented in Figure 3 are obtained.

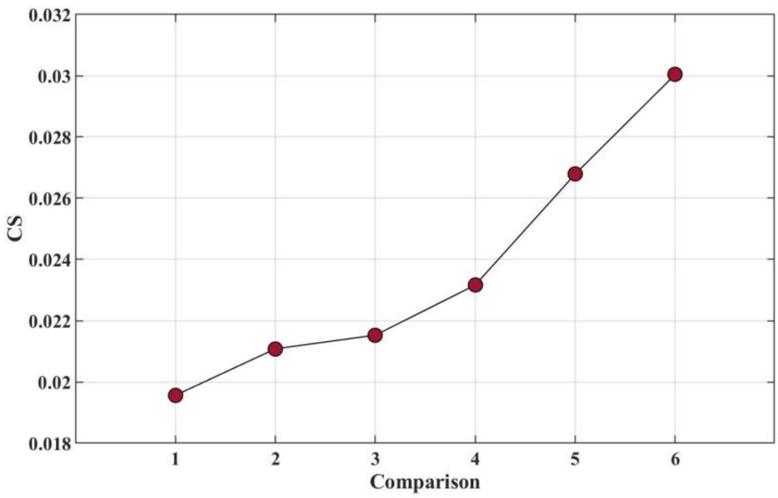

Figure 3. Alternative Approach for Cosine Similarity Calculation.

As shown in the figure above, the tool wear for each signal is compared with the previous signal. With each new pass, the changes in the acoustic signal resulting from the contact between the milling tool and the workpiece become less significant compared to the immediately preceding pass. This indicates that, under acoustic analysis, the deformations in an initially intact tool are more abrupt and intense than the wear observed in an already deteriorated tool. Consequently, the CS curve may eventually trend toward a saturation region after many cycles of comparison.

4. Conclusions

To apply the cosine similarity (CS) method, the acoustic emission signals were preprocessed and trimmed to stable, noise-free regions, ensuring coherent and undistorted results. With the processed signals, the CS calculation was performed, producing a similarity curve that reflected the wear measured with each pass of the tool over the workpiece. As tool deformation increased, the similarity curve decreased, indicating that the similarity between the worn tool and its initial, undamaged condition progressively diminished with each tool pass.

Using this same methodology, a second curve was generated by comparing the current tool condition with its immediately preceding state. This resulted in an increasing curve that tends toward a saturation region after several comparison cycles. This suggests that, under acoustic analysis, deformations in an initially intact tool are more abrupt and pronounced than the wear observed in a previously deteriorated tool.

Based on these results, it can be inferred that the cosine similarity method is an effective indicator for condition monitoring, as it proportionally tracked tool wear in each case. However, it was noted that within the same interval, the CS calculation does not vary with the same intensity as the tool wear. This underscores the importance of having sufficient data for this methodology to be effective in condition monitoring analyses. A sufficiently long sampling period is required for the signal to exhibit significant variations, enabling the detection of similarity loss. This ensures a substantial data set and, consequently, more conclusive results regarding the tool wear process.

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Abbreviations:

The following abbreviations are used in this manuscript:

AE Acoustic Emission; CS Cosine Similarity; RUL Remaining Useful Life; TCM Tool Condition Monitoring.

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