Development of a resource-efficient real-time vibration-based tool condition monitoring system using PVDF accelerometers

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Abstract

Sustainable machining demands efficient tool condition monitoring (TCM) to maximize tool utilization and reduce environmental impact. Existing TCM solutions range from high-cost multi-sensor systems to ultra-low-cost alternatives with limited accuracy. This research bridges the gap with a resource-efficient, standalone TCM system for on-site tool wear estimation. The system integrates a PVDF-based accelerometer, Raspberry Pi 4, and a data acquisition card. A multi-level software architecture is designed to fully leverage this hardware, optimizing real-time signal processing while supporting both machine learning model training and inference. The proposed method employs two elementary models: k-means clustering for machining phase segmentation and ridge regression for tool wear estimation. A case study on an industrial lathe established a linear correlation between tool wear and surface roughness. Data from three tool inserts over their lifetimes proved sufficient for training machine learning models, achieving promising prediction accuracy. This research advances standalone TCM solutions tailored for manufacturing sectors seeking a balance between affordability and performance.

Keywords: tool condition monitoring, surface roughness, tool vibration, turning, tool used life

1. Introduction

Context and Motivation

The demand for sustainable, high-precision machining continues to grow across industries. While machining is renowned for its precision and consistency, the quality and performance of the final product heavily depend on effective cutting tool management. Traditional approaches replace tool inserts based on fixed production metrics rather than actual wear, typically setting replacement intervals at 50–80% of the tool's mean time to failure, determined through preliminary cutting tests [1]. Overly conservative intervals lead to unnecessary tool waste and higher costs, as inserts represent a significant expense. Conversely,

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overly optimistic intervals increase the risk of tool failure, with up to 20% of total downtime attributed to tool failure [2], or subpar product quality, both contributing to productivity losses and increased costs. The unnecessary tool or product waste, inefficient resource utilization, and an increased environmental impact of traditional tool/insert replacement methods has driven the research in tool condition monitoring (TCM) systems [3, 4].

The lifespan of a cutting tool is limited as it either gradually deteriorates machining performance and product quality due to wear mechanisms such as flank wear, crater wear, corner wear, and notch wear, or it fails abruptly through chipping, fracture, or breakage [5]. Among these, flank wear is the most widely monitored tool-condition indicator [6, 7], as it results from abrasion between the tool and the workpiece [8] and directly affects surface finish quality. In practice, tool life is typically evaluated using a productivity metric, most commonly defined by the number of parts produced or the volume of material removed.

The objective of TCM systems is to maximize tool life utilization while minimizing the risk of damage to the workpiece and machine through accurate wear state estimation. A typical TCM system consists of three key steps: data acquisition, data processing, and tool wear estimation. In the data acquisition stage, TCM methods are categorized as direct or indirect. Direct methods primarily rely on optical techniques to assess tool condition [9]. However, these approaches require an unobstructed line of sight, making them impractical in industrial environments due to cutting fluids and mounting constraints. As a result, numerous researchers focus on indirect TCM methods, which utilize sensors to monitor one or more relevant physical parameters near the cutting zone. These include cutting force, vibration, acoustic emission, temperature, and electric current, among others. Following data acquisition, TCM systems employ signal processing and feature extraction to refine the collected data. The extracted features are then used for tool wear estimation, with an increasing reliance on artificial intelligence (AI)-based models for enhanced prediction accuracy [10].

Literature Review

An important factor in extending tool life is the optimization of machining parameters, with significant research focusing on key variables such as cutting speed, depth of cut, and feed rate [11, 12, 13]. Beyond parameter optimization, recent studies have explored the effects of advanced tool coatings and lubrication techniques. Mahapatra et al. investigated the impact of AlTiSiN-coated carbide tools under environmentally conscious nanofluid minimum quantity lubrication (MQL) in the hard turning of AISI H13 steel [14]. Nanofluid MQL has also been studied in combination with AI-driven optimization techniques, as demonstrated by Pradhan et al., who applied genetic algorithms (GA) to optimize machining conditions in hard turning of functionally graded specimens [15]. A similar multi-objective GA approach was successfully applied in non-traditional hot abrasive jet machining (HAJM) of engineering ceramics, optimizing process parameters [16]. These studies emphasize the role of advanced coatings, lubrication strategies, and AI-driven optimization in improving machining efficiency, tool longevity, and sustainability.

Recent advancements in TCM have increasingly leveraged AI-driven tools and other advanced signal processing techniques. Mahmood et al. developed a tool wear detection system for milling, drilling, and turning, utilizing cutting force measurements and a deep learning approach for wear classification [17]. Their method included singular spectrum analysis (SSA) for noise reduction and principal component analysis (PCA) for feature selection, improving model efficiency. Similarly, Han et al. investigated tool temperature in turning using a fiber-optic multi-spectral method, demonstrating a positive correlation between cutting temperature and tool wear [18]. Their system enabled real-time temperature monitoring and used sparse autoencoders with k-means clustering for tool wear recognition. Bahador et al. explored predictive maintenance in Industry 4.0, discussing sensor integration, data acquisition, and machine learning (ML) techniques for remaining useful life (RUL) prediction in manufacturing systems [19]. K"ullaç et al. analyzed close-up images of the workpiece after turning, identifying a linear correlation between machining time and discrete Fourier transform amplitudes [20]. Their study examined entire surface images as well as individual features such as feed marks, crests, and troughs. Further integrating predictive modeling into machining strategies, Amigo et al. investigated high-feed turning of a Nimonic C-263 superalloy, analyzing cutting force changes in relation to tool wear [21]. Their study also evaluated cutting tool geometry modifications and the effects of cooling strategies on tool life.

State-of-the-art indirect TCM data acquisition remains an active area of research. While industrial solutions often rely on multi-sensor systems to enhance reliability, this approach introduces high costs and increased hardware complexity [22]. Additionally, many TCM decision-making models leverage advanced machine learning algorithms, such as artificial neural networks (ANNs) and convolutional neural networks (CNNs), which demand substantial training data and computational resources [10].

These models, however, struggle with generalizability, as their performance deteriorates when applied to different machines or varying machining parameters, primarily due to overfitting [19]. Research efforts have focused on improving training data generation to mitigate this issue [23, 24], but the high demands for hardware, data storage, and real-time processing remain significant barriers. As a result, the cost and complexity of multi-sensor TCM systems hinder widespread adoption, particularly in industries with tight profit margins.

While high-cost multi-sensor systems remain the dominant approach in industrial TCM applications, some research has explored low-cost alternatives. Failing et al. proposed an ultra-low-cost TCM system using current and sound sensors with Arduino-based computing, enabling basic tool wear classification while maintaining affordability and ease of installation [25]. However, such low-cost solutions often face trade-offs in accuracy, robustness, and adaptability, particularly when applied to diverse machining conditions. Despite these challenges, cost-effective TCM development remains crucial, especially for small and medium-sized enterprises (SMEs) that must balance tool life optimization with financial feasibility.

Research Gap

Significant research has focused on high-end, resource-intensive AI models and complex multi-sensor TCM systems, while the opposite end of the spectrum has been explored with ultra-low-cost solutions that prioritize affordability over accuracy and adaptability. However, a notable research gap exists in the development of cost-effective yet capable TCM solutions that offer reasonable performance on standard, widely available computing platforms. Bridging this gap requires systems that are affordable, deployable on conventional computing hardware, and effective with a single sensor, providing a viable alternative for industries that cannot justify the expense of high-end systems but need better reliability than ultra-low-cost alternatives.

Contributions and Novelty

This paper addresses the identified research gap by proposing a cost-effective, complete hardware and software TCM system designed for standalone on-site operation. The system is intended for estimating the used life (UL[1]) of turning inserts and offers a single-sensor approach as an alternative to conventional multi-sensor setups.

It employs a uniaxial polyvinylidene fluoride (PVDF)-based accelerometer, strategically placed near the cutting tool insert, eliminating the need for modifications to tool mounting while ensuring reliable vibration measurements. The system's processing and decision support framework is built around a Raspberry Pi 4 microcomputer and a Digilent MCC 172 data acquisition card. A novel multi-level software architecture is proposed, fully utilizing the available hardware capabilities for real-time data preprocessing, compression, and storage. The entire software runs locally, without external data processing, making it standalone and easy to deploy in diverse machining environments. The system integrates two elementary machine learning techniques: k-means clustering [27] to distinguish different stages of the machining operation and ridge regression [28] to efficiently estimate the used life of the tools. With these resource-efficient algorithms, the system can be retrained on local hardware and adapted almost instantly to changes in machining parameters or different machines.

The system is validated on an industrial lathe, demonstrating a strong correlation between TCM-based tool life estimates and surface roughness. A predefined critical surface roughness level serves as a benchmark for tool life assessment. Using only the first three tool states (from new to worn), the system accurately predicts remaining tool life, achieving high estimation accuracy despite its moderate hardware capabilities.

The proposed system bridges the gap between high-cost multi-sensor TCM systems and ultra-low-cost alternatives by offering a balance between affordability and capability. Unlike high-end systems, it relies on a single sensor and a standalone computing unit, eliminating

[1]Some researchers describe tool life as the amount of work done by the tool (e.g. cut distance in [26]), which increases with machine time. Remaining useful life (RUL) of the tool is more commonly used in this context, as the remaining amount of work which can be done by an already used tool is typically of interest. In this study, the term "used life" (UL) is used to represent the percentage of the total number of parts to be machined that have already been produced. (E.g. if the tool is expected to produce 10 000 parts in total and 2000 parts have already been produced, then UL = 20%. Therefore, RUL would amount to 80%.) Our main criterion for determining whether a tool has reached its service life is the surface roughness of the workpiece. Therefore, the tool condition is indirectly characterized by the surface roughness of the workpiece after turning.

the need for complex integration. Compared to ultra-low-cost solutions, it provides superior acquisition capabilities and computational performance, ensuring better adaptability and transferability across different machining setups without excessive retraining.

Organization of the Paper

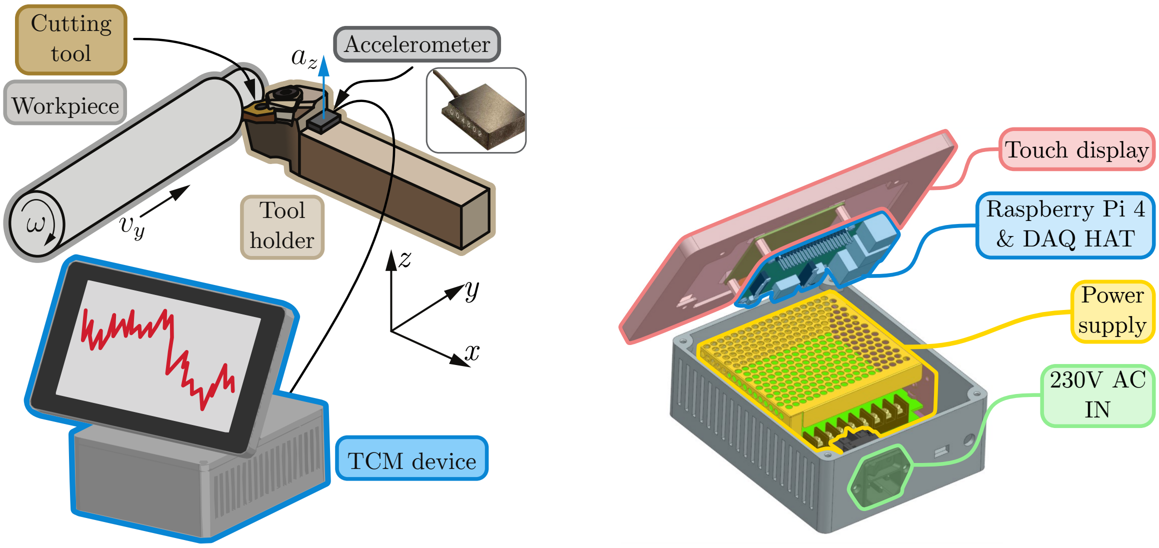
The remainder of this paper is structured as follows: Section 2 describes the TCM hardware setup, detailing the sensor selection, data acquisition system, and processing framework. Section 3 presents the methodology for tool used life estimation, including data preprocessing, feature extraction, and the machine learning model used for prediction. Section 4 reports the results, comparing estimated tool life with reference data and evaluating model performance. Finally, Section 5 concludes the paper, summarizing key findings, discussing limitations, and outlining directions for future research.

2. TCM Hardware Setup

The first objective of this study is to propose a standalone TCM hardware setup that balances affordability and performance for efficient tool condition monitoring. The proposed design adopts a single-sensor approach to reduce complexity compared to multi-sensor systems. Vibration monitoring is selected for its straightforward sensor installation, eliminating the need for modifications to tool mounting, unlike force measurement systems. To achieve a balance between performance and reliability, the proposed setup incorporates a PVDF-based accelerometer, which offers a low noise floor and high-frequency range while remaining cost-effective compared to traditional Integrated Electronics Piezoelectric (IEPE) accelerometers.

The processing unit of the proposed system is a Raspberry Pi 4 microcomputer, chosen for its affordable yet sufficient computational capabilities, comparable to low-to-mid-range personal computers. Data acquisition is handled by the Digilent MCC 172 HAT, which directly integrates with the Raspberry Pi and supports two input channels with a sampling frequency of 51.2 kHz. Additionally, the proposed hardware package incorporates the Raspberry Pi Touch Display, enhancing usability and real-time monitoring.

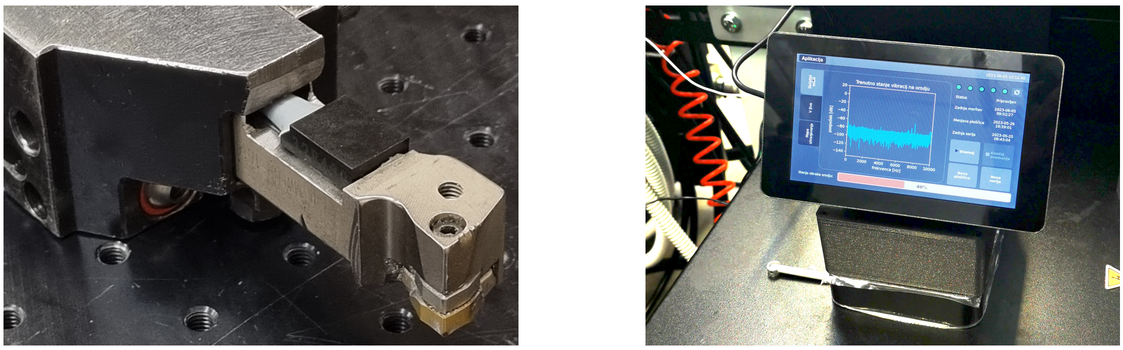
The schematic representation of the proposed TCM hardware package is shown in Fig. 1a. A uniaxial PVDF accelerometer is strategically mounted on the tool holder near the cutting tool, measuring vibrations in the cutting direction (z-direction, as defined in Fig. 1a). To support efficient data handling and analysis, a custom-developed graphical interface enables seamless measurement execution, real-time signal monitoring, model training, and tracking of estimated tool life. A CAD model of the proposed device components (excluding the DAQ HAT) is illustrated in Fig. 1b.



(a) (b)

Figure 1: TCM device: (a) schematic representation of the TCM device connected to the accelerometer during turning; (b) rear view of the TCM device model without housing top.

The accelerometer was mounted on the tool holder as shown in Fig. 2a. A protective tube was used to protect the cable from potential damage caused by sharp chips. The TCM device in the real setting is shown in Fig. 2.



(a) (b)

Figure 2: TCM system in the real setting: (a) accelerometer mounted on the tool holder; (b) TCM device.

3. Methodology for Tool Used Life Estimation

The second objective of this study is to establish a reliable method for estimating the used life of the cutting tool. To ensure clarity, the proposed methodology is presented in parallel with the actual case study. First, we empirically establish the relationship between surface roughness and the number of produced parts. Next, we outline the signal processing strategy, followed by the implementation of machine learning tools, covering both theoretical foundations and practical application. The flowchart summarizing the use of vibration measurements for used life estimation is given in Fig. 3

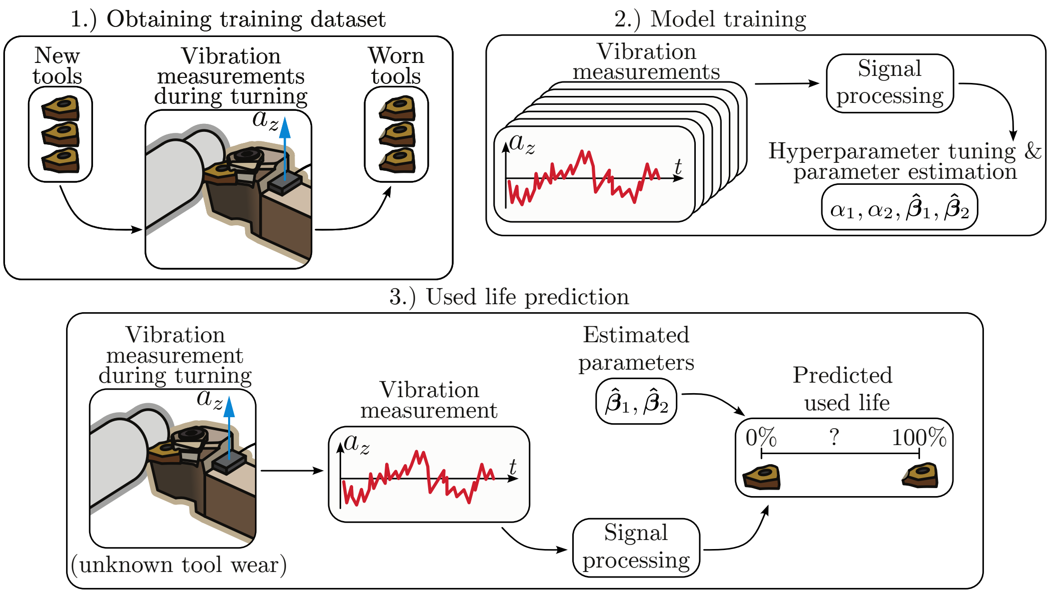


Figure 3: Flowchart describing the use of vibration measurements for used life estimation.

Empirical relation between surface roughness and tool life

A common criterion for tool replacement in machining is machined surface roughness, while tool life is typically expressed as a quantitative metric, such as the number of produced parts.

The first step in our methodology involved a preliminary test conducted on an industrial lathe in a local manufacturing facility during serial production. Over the full lifetime of the cutting insert (defined by the acceptable roughness limits for the specific product), we measured the surface roughness of the workpiece from a new to a completely worn tool state, as surface roughness was considered the tool wear criterion.

Both Ra and Rz roughness parameters were measured at intervals of 25 produced parts using a Mitutoyo SJ 400 device. The measured roughness parameters in relation to the number of produced parts are shown in Fig. 4. Both Ra and Rz exhibit a strong linear relationship with the number of produced parts, as the coefficient of determination R^2 exceeds 0.9 for both parameters.

Based on these results, for our specific application, we assume a linear relationship between surface roughness and the number of produced parts (i.e., tool life). Therefore, in subsequent experiments, roughness measurements were not conducted; instead, only vibration measurements were performed while monitoring the number of produced parts.

Data acquisition and signal processing

In the following case study, the same lathe was used, equipped with a revolver head holding three tools, and employed in serial production. One of the tools was monitored using

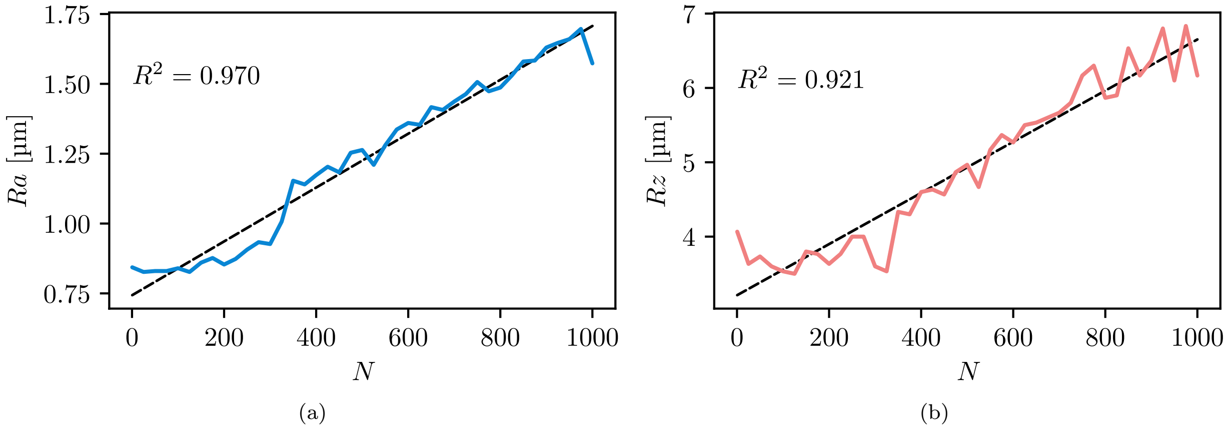


Figure 4: Surface roughness with respect to the number of produced parts N using a single tool: (a) Ra, (b) Rz.

the proposed TCM system, executing two distinct turning operations on each workpiece. Tool vibrations were measured in the cutting direction for each individual part with the sampling frequency of 51.2 kHz. In our experimental setup, data acquisition was conducted for four tools, from new until reaching a state of complete wear.

A typical time series of measured vibrations is shown in Fig. 5. The first step in the signal processing procedure is to identify and extract high-amplitude regions where the monitored tool is actively cutting. The signal clearly shows distinct high-vibration regions corresponding to periods when the monitored tool is performing turning operations. Additionally, several lower-amplitude regions appear due to vibration transfer through the revolver head when other unmonitored tools are in use. To isolate only the relevant high-amplitude segments, an amplitude-based filtering algorithm was developed. Note that this step does not determine the number of segments but simply retains the signal subsets with high amplitudes.

It is common for a single tool to perform multiple turning operations, each producing distinct vibration patterns. To enable a consistent comparison of signals across a series of operations, it is crucial to efficiently distinguish specific signal subsets corresponding to different turning operations. This grouping process was performed using the k-means clustering algorithm [27], which can be applied universally regardless of the number of turning operations. k-means clustering is an unsupervised machine learning algorithm with the ability to split the data into k clusters (i.e. groups), such that the within-cluster variance is minimized. The vibration measurements were accurately split into two clusters based on the length of the turning operation and the average vibration amplitude. The vibrations corresponding to the first and second turning operation are labeled as s_1 and s_2, respectively. A separate instance of the chosen statistical model is built for each machining operation to estimate used life, which are combined in the final stage of the analysis.

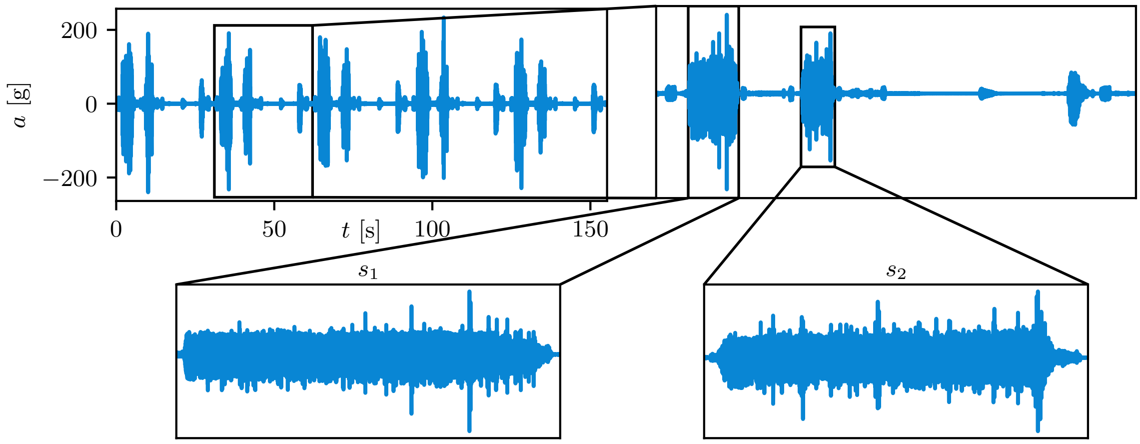


Figure 5: Isolation of vibration time series for s_1 and s_2 operations.

Feature extraction and labeling

Each isolated time series $s(t)$ was transformed to the frequency domain using the discrete Fourier transform, denoted as $S(\omega)$. Since the first resonant frequency of the PVDF accelerometer used is 13 kHz, the frequency range was limited to 10 kHz for further analysis. After this transformation, an averaging process was applied to the amplitude spectrum to achieve a frequency resolution of 10 Hz. Each frequency bin was considered as an independent feature or input variable, which were normalized to improve the performance of ridge regression (used in later stage). Each feature $|\bar{S}(\omega)|$ was therefore rescaled to achieve a zero mean value and a unit variance. The normalized feature vector is denoted by $\boldsymbol{x}$. Each time series was assigned a label indicating the number of parts manufactured using the monitored cutting tool. Upon tool replacement, the used life y was computed for each sample by dividing the number of parts produced up to that sample by the final number of parts produced using that tool.

A design matrix $\mathbf{X}$ was constructed by stacking the normalized feature vectors $\boldsymbol{x}$ into the rows of the design matrix $\mathbf{X}$. Similarly, a target vector $\boldsymbol{y}$ was constructed by stacking the target values y (i.e. used life) in the same sequence. The proposed machine learning approach requires a large sample size for reliable estimation. Out of the four conducted experiments, data from three were used to construct the design matrix and target vector. For each turning operation, the design matrix had dimension 3280×1000, comprising 1080 samples from the first experiment, 1050 from the second, and 1150 from the third. The fourth experiment, consisting of 1000 samples, was reserved for validation and will be used to assess the model's performance.

ML-based tool used life estimation

The ridge regression model was selected for estimating the tool used life. Ridge regression establishes a linear relationship between features ($\mathbf{X}$) and targets ($\boldsymbol{y}$) [29, 28], as described by Eq. (1):

$$\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{1}$$

where $\boldsymbol{\beta}$ represents the regressor coefficients, which must be calculated, and $\boldsymbol{\varepsilon}$ represents the error term. Standard linear regression calculates $\boldsymbol{\beta}$ by minimizing the sum of squared errors $\|\boldsymbol{\varepsilon}\|_2^2 = \sum_{i=1}^{N} \varepsilon_i^2$. However, this approach may lead to overfitting, particularly when Eq. (1) is not sufficiently overdetermined. A more accurate estimate can often be attained by introducing a term associated with the magnitude of the coefficients to the minimization problem. In ridge regression, this involves scaling the sum of squared coefficients by a hyper-parameter α and modifying the minimization problem to include the new term [29]:

$$\hat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \left(\|\boldsymbol{\varepsilon}\|_2^2 + \alpha \|\boldsymbol{\beta}\|_2^2 \right) = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \left(\|\boldsymbol{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \alpha \|\boldsymbol{\beta}\|_2^2 \right), \tag{2}$$

where $\hat{\boldsymbol{\beta}}$ denotes the value of $\boldsymbol{\beta}$ which minimizes the cost function in Eq. (2). One of the advantages of ridge regression lies in its closed-form solution [29], described by Eq. (3):

$$\hat{\boldsymbol{\beta}} = \left(\mathbf{X}^\top \mathbf{X} + \alpha \mathbf{I} \right)^{-1} \mathbf{X}^\top \boldsymbol{y}. \tag{3}$$

In contrast to standard linear regression, ridge regression introduces an additional hyper-parameter, denoted by α. An established approach for determining appropriate hyperparameter values involves the integration of a grid search (GS) algorithm with cross-validation (CV). Initially, a set of α values is generated for the GS algorithm. For each α, a distinct model instance is constructed, and the value of α, yielding the highest prediction accuracy, is selected. The prediction accuracy for each α is estimated using CV.

It is common to apply k-fold CV, where the training data is first split into k groups. Subsequently, k instances of the chosen model are created. The i-th model instance considers the i-th data group for test data and the remaining $k-1$ groups for training. The performance of each model instance is evaluated on its assigned test set by evaluating an error metric, e.g. mean squared error. This procedure is repeated for every hyperparameter value (or combination of hyperparameter values in case of models with multiple hyperparameters). The selection of hyperparameters involves identifying values that optimize performance in the CV procedure. In this context, both 5-fold CV and leave-one-out cross-validation (LOOCV) were explored to determine the values of α_1 and α_2. While the final prediction error was similar for both CV approaches, LOOCV was ultimately implemented in the final application due to a more efficient implementation. The combined GS and CV approach is facilitated by the Python library scikit-learn for machine learning [30]. The regressor coefficients are computed independently for s_1 and s_2 operations, yielding two distinct used life estimates for each workpiece.

Postprocessing

The final used life estimation is calculated as the moving average used life estimation based on the last 5 produced parts[2]. The methodology is schematically depicted in Fig. 6. It is important to note that prior to training, in the data preparation step, the mean feature values and standard deviations are stored and used for variable standardization during model inference.

[2]The value 5 is recommended as a balanced compromise between averaging and accuracy. However, it remains a variable parameter, and in the Results section, alternative values are also considered and discussed.

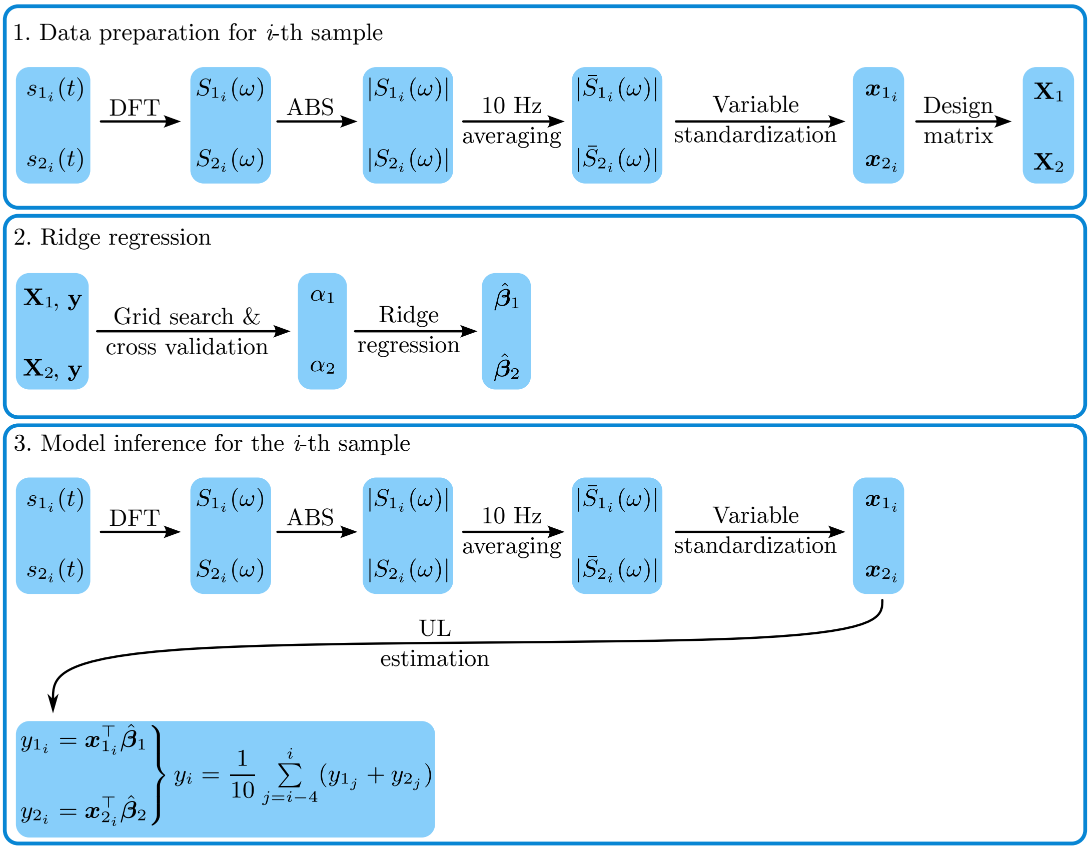


Figure 6: Used life estimation methodology.

4. Results

ML models were trained on vibration measurements collected throughout the lifetime of three cutting tools. Since two distinct turning operations were identified through clustering, separate ML models were trained for s_1 and s_2 signal groups. We then applied the proposed methodology to estimate the used life of a fourth tool, validating the predictions against the actual number of produced parts.

Fig. 7 presents the direct estimates from ridge regression for s_1 and s_2 separately. While the models capture the overall trend well, both predictions exhibit significant outliers and noticeable noise. Although the estimates for s_1 and s_2 follow a similar trend, there are notable differences between them. By applying the proposed post-processing techniques, the results can be significantly improved. Even a simple averaging of the s_1 and s_2 estimates shown in Fig. 7 demonstrates a higher correlation with the true used life (UL). This improvement is expected, as incorporating more diverse vibrational data helps enhance overall prediction accuracy and may better capture underlying patterns related to tool wear.

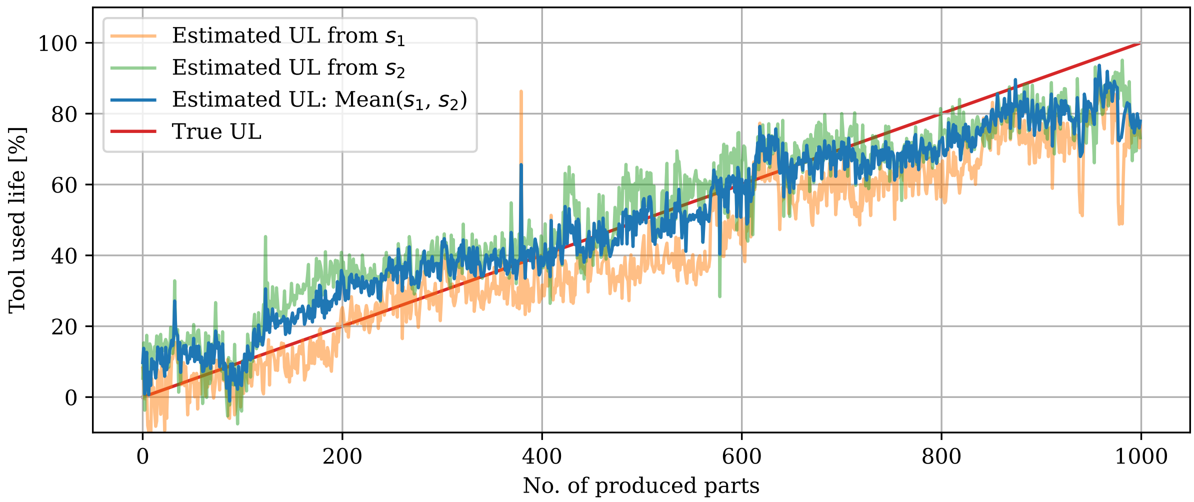


Figure 7: Tool used life estimation.

Additionally, since the raw estimates exhibit noisy behavior, a moving average filter can be applied to further smooth the results. Fig. 8 compares the original unfiltered curve with moving averages over 5 and 10 instances, demonstrating a significant reduction in noise, with the level of smoothing increasing with the averaging window size. However, excessive smoothing can reduce accuracy, so we generally recommend a window size of 5 as a compromise between noise reduction and predictive accuracy.

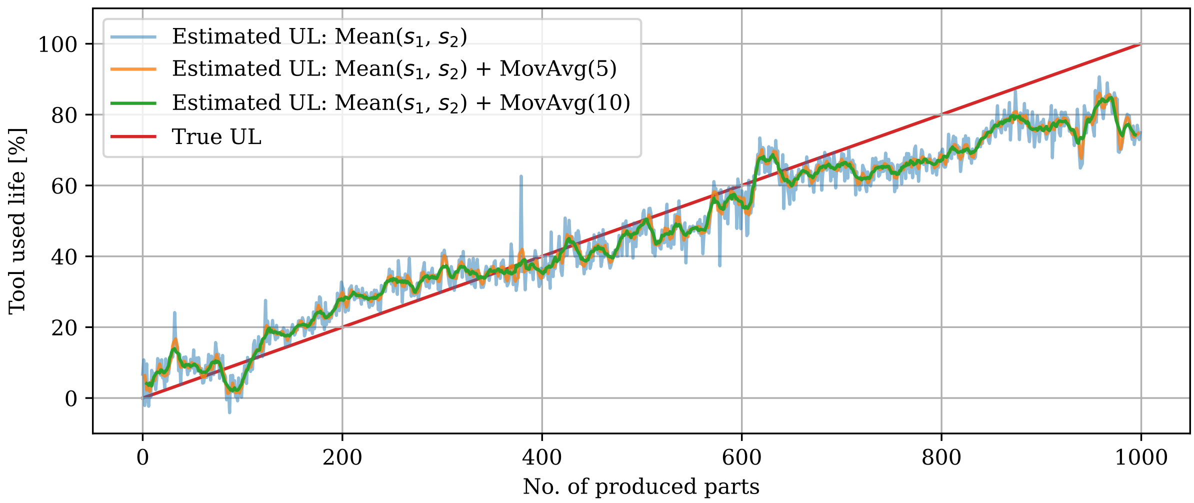


Figure 8: Tool used life estimation with moving average.

It is observed that as tool life approaches 100%, the accuracy of the used life estimation slightly decreases. To ensure reliable tool replacement, the system should alert the operator before this decline becomes significant. A practical approach is to set an alert threshold at around 80% of the tool's estimated life, ensuring timely replacement while maintaining prediction accuracy.

The computational efficiency of the proposed TCM system is achieved through ridge regression. One of its key advantages is its closed-form solution, which eliminates the need for iterative computations during model fitting, making the system lightweight and suitable for real-time implementation.

The proposed TCM system effectively adapts to varying machining conditions despite limited hardware resources. By requiring vibration measurements from only three tools, from new to worn state, the system efficiently learns tool wear patterns and predicts used life with minimal data. This reduces the need for extensive training datasets and enables rapid adaptation to different machining setups. A strong linear correlation ($R^2 > 0.9$) between tool life estimates and surface roughness validates the use of roughness as an indirect wear indicator. Defining a critical roughness threshold as a wear benchmark ensures timely tool replacement, balancing cost and surface quality. The combination of a multilevel software architecture and computationally efficient ridge regression allows real-time tool life estimation without expensive multi-sensor setups.

5. Conclusion

In this paper, a low-cost TCM system running on the Raspberry Pi single-board computer was developed to detect tool wear. The main criterion for when the tool has reached its service life is the surface finish of the workpiece after turning. In a preliminary study, the surface finish measurements were conducted across the tool's lifecycle and it was concluded that there is a linear relationship between the number of produced parts (or used life) and surface roughness. Surface roughness was therefore not monitored in the following test and was only measured near the end of tool life to determine whether it has reached its service life.

The proposed approach estimates tool life based on vibration measurements near the cutting insert, which is advantageous to force measurement, as no modifications of the tool holder mounting are needed. Ridge regression is chosen as the statistical model for estimating tool life due to several favorable characteristics for our application. Although ridge regression is based on a linear model, it is significantly less prone to overfitting due to the regressor coefficient regularization. Moreover, the closed-form solution of ridge regression ensures computational efficiency in model fitting, eliminating the need for iterative computations.

The monitored tool was involved in two distinct turning operations during the production of each workpiece. Individual instances of the regression model were built for the time series corresponding to each operation. These models are combined in the final step for a more robust used life estimate. This approach presents a computationally efficient and cost effective method to alert the operator about the cutting tool reaching its service life.

The system currently relies on a predefined critical roughness threshold for tool wear detection. Future research could explore automated methods to dynamically adjust this threshold based on real-time surface roughness trends, ensuring optimal tool replacement timing. In addition, extending this approach to other turning operations or machining processes with similar vibration-based wear characteristics (e.g., finishing vs. roughing operations) could validate its applicability across a wider range of industrial scenarios.

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