Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 133 (2025) 78–83

www.elsevier.com/locate/procedia

20th CIRP Conference on Modeling of Machining Operations

Prediction of Cutting Tool Condition in Milling Using Optimization and Non-Optimization Techniques

Amirmohammad Jamali[1], Volker Schulze[1]

[1]wbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), Kaiserstr, 12, 76131 Karlsruhe, Germany

* Corresponding author. Tel.: +49-173-267- 2698;. *E-mail address:* Amirmohammad.jamali@kit.edu

Abstract

In an automated machining environment, monitoring tool conditions is essential. In this study, experiments were conducted to classify tool conditions during high-speed machining of AISI4140. During the machining process, vibration and force signals were continuously monitored in situ using an accelerometer and a dynamometer, respectively. In addition, tool wear was measured ex-situ after every 10 cutting passes using a microscope. Features were extracted from the vibration and force signals, and a set of prominent features was selected using the ANOVA-Whale optimization technique. These selected features were then fed into a classification algorithm to determine the condition of the tool. The tool condition classification was performed using machine learning algorithms, specifically the Support Vector Machine (SVM). The results obtained using the ANOVA-Whale optimization technique were compared with those obtained using the ANOVA technique without the optimization method. The methodology used in this study is expected to be beneficial for online tool condition monitoring.

Keywords: Tool condition classification; Wear;Maschine learning;

1. Introduction

The Tool Condition Monitoring (TCM) system becomes very important in modern manufacturing quality assurance and extension of tool life. If un-monitored, the tool wear decreases the precision, surface quality, and productivity [1]. Traditionally, TCM relied on vibration, temperature, and force data. However, with the development of machine learning, it is possible to achieve real-time prediction and improve operational efficiency [2]. Algorithms like SVMs (Support Vector Machine) and ANNs (artificial neural network) have been carried out with great success in the accurate classification of tool wear based on sensor data analysis, while some models have more than 90% accuracy in real-time prediction [3]. By leveraging advanced machine learning techniques, such as self-configuring systems, tool condition monitoring can achieve high accuracy and adaptability across varying cutting conditions and platforms [4].

One of the major problems in TCM is to select features that improve the accuracy of the models while reducing the computational burden. Statistical methods, particularly analysis of variance (ANOVA), are widely used in feature selection and can obviously improve the performance of machine-learning models by keeping only relevant features [5]. When combined with Whale Optimization Technique (WOA), the ANOVA provides a higher efficiency of feature selection, especially for high-dimensional data contexts, which can improve the accuracy and stability of tool wear monitoring models [6]. Advanced monitoring techniques utilizing sensor fusion and feature extraction have proven effective in correlating signal features with tool wear progression across various machining operations, as highlighted in Teti et al. [7].

Thus, sensor-based monitoring systems, by using accelerometers and dynamometers, have become an integral part of TCM. More specifically, the detailed vibration and force signals are captured and then processed in order to extract, by

2212-8271
10.1016/j.procir.2025.02.015

using advanced techniques such as wavelet analysis, features indicative of tool wear [8]. The integration of statistical techniques such as ANOVA with optimization algorithms such as WOA offers significant advantages for predictive performance in complex, feature-rich environments. By exploiting the strengths of both methods, this approach improves model accuracy and robustness through probabilistic optimization of key parameters. This allows researchers to develop response surfaces that improve predictive reliability by accounting for the inherent variability in these complex systems [9]. However, few studies have combined this hybrid feature selection (FS) method with an SVM classifier specifically tailored for tool condition monitoring (TCM).

Accordingly, the present work develops a novel hybrid method that combines the potential of ANOVA, WOA and SVM to meet the unique TCM requirements in high-dimensional data scenarios. The strengths of statistical feature selection and metaheuristic optimization are further leveraged in the proposed method to refine feature subsets toward better accuracy, thus making tool wear prediction more robust under different operating conditions. This approach provides a valuable opportunity to provide the TCM with an improved framework that enables better reliability and efficiency for real-time tool wear monitoring, so that proactive maintenance strategies can reduce downtime and extend tool lifetime.

Nomenclature

F	F-statistic (between-class/within-class variance)
VB_{max}	Maximum Flank wear width
a_p	Axial depth of cut
a_e	Radial depth of cut
C	Penalty parameter in SVM
FRF	Frequency Response Function

2. Methodology:

The proposed multi-sensor-based tool wear monitoring system consists of four main components: sensors that measure force and vibration during the machining process, a feature extraction module that derives relevant time-domain and frequency-domain indicators of tool wear, a feature selection method based on ANOVA with Whale Optimization Algorithm (WOA) to identify the most significant features, and a Support Vector Machine (SVM) model for classifying tool wear conditions using these selected features. This system structure is illustrated in Figure 1.

2.1. Experimental conditions

In order to validate the proposed method for monitoring tool wear conditions, tool life tests have been conducted on a Heller MC16 4-axis milling machine. The workpieces employed in the present study were square-shaped blocks of AISI4140 steel.The material AISI4140 was selected (in the quenched and tempered condition) due to its good machinability, hence quite suitable for studying tool wear in a context relevant to industrial practice. Each block had dimensions of 300 mm in length, 100 mm in width, and 100 mm in height. The mechanical properties of the 42CrMo4 material are as follows: tensile strength of 1000 MPa, yield strength of 650 MPa, and hardness of 300 HB [8].

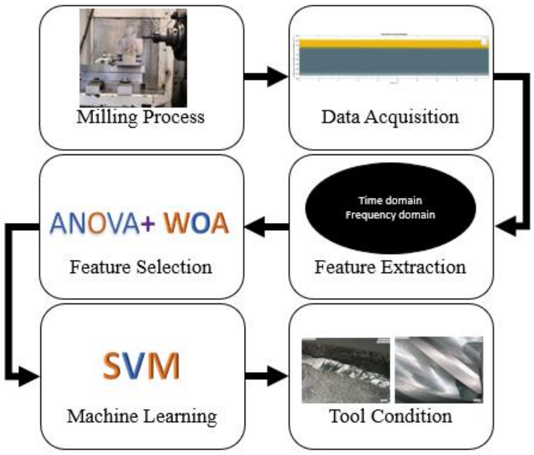

Fig.1. Illustration of TCM system

The milling tool employed in this experiment is the Gühring RF 100 Diver. The diameter of the tool is 12 millimeters, the number of cutting edges is four and the overall length of the tool is 83 millimeters. The helix angle is 38°, the corner radius is 0.24 mm and the cutting-edge rounding is 0.02 mm. The tools were evaluated under a range of milling parameters to ascertain their wear characteristics and performance. All milling operations were conducted in a dry environment without the use of cutting fluid.

Table 1 presents five different cases of an experimental design to analyze tool wear for different intensities of cutting. In each case, axial depth of cut ($\boldsymbol{a_p}$) was maintained at 6 mm, the spindle speed at 3000 RPM, and feed rate at 0.042 mm per tooth, while the cutting speed $\boldsymbol{Vc}$ and the radial depth of cut $\boldsymbol{a_e}$ were varied.

Table 1. Cutting parameters

Case No.	Vc [m/min]	a_e [mm]
1	500	3
2	500	6
3	375	4.5
4	250	6
5	250	3

Cutting force measurements were obtained using a Kistler triple-component piezoelectric dynamometer® with a 10 kHz sampling rate charge amplifier, which was securely mounted between the workpiece and the worktable. A Kistler PiezoBeam® 8692C50 triaxial accelerometer, sampling at 12 kHz, was mounted on the spindle for the purpose of monitoring vibration. The vibration signals were then transmitted to a computer through a Kistler 4-channel coupler (Type 5134A). For each tooth, flank wear was quantified using a Keyence® digital microscope following the completion of a cutting path of 300 mm. The mean wear value across all teeth was then calculated and used as the representative tool wear value for each interval. The resulting data was stored in an Excel file for subsequent feature extraction. Figure 2 illustrates the experimental setup.

2.2. Data collection and preprocessing

Tool wear data, including vibration and force signals, were collected using multiple sensors throughout the machining process. A modal analysis using a Kistler impact hammer (sensitivity: 0.234 mV/N) and a PCB triaxial accelerometer (sensitivity: 9.98 mV/g in x-direction, 10.28 mV/g in y-direction and 10.42 mV/g in z-direction) identified the natural frequencies. Using Simcenter SCADAS hardware and the Simcenter Testlab Impact Testing module, a Frequency Response Function (FRF) analysis isolated the resonant frequencies, allowing the selection of frequency intervals with high coherence and minimal noise interference.

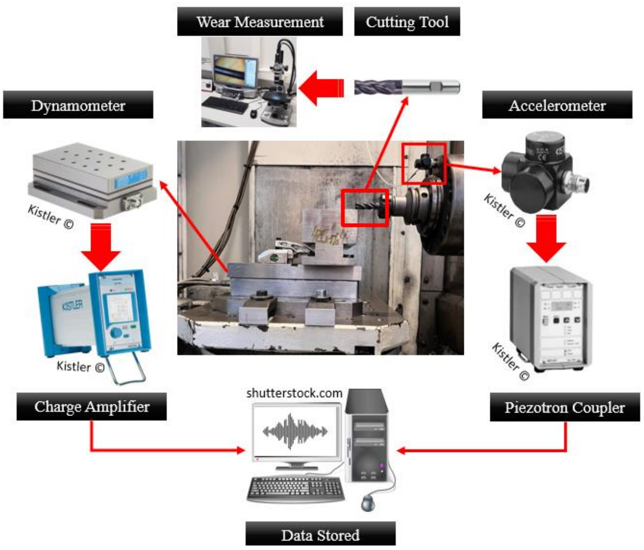

Fig.2. Experiment setup

2.3. Classes of tool wear

In this study, tool wear is divided into three different stages: New Tool, Mid-Life and Worn Tool. These stages are defined based on the maximum flank wear width (VB_{max}) as follows:

New tool: $VB_{max} < 50\mu m$

Mid-Life tool: $50\ \mu m \leq VB_{max} \leq 200\ \mu m$

Worn tool: $VB_{max} > 200\mu m$

These classifications are consistent with ISO standards (ISO 8688-2:1989) [10] and provide a reliable framework for monitoring tool condition. The thresholds represent critical stages in the tool life cycle and reflect progressive wear that can significantly affect machining performance. This segmentation also forms the basis for statistical analysis, such as ANOVA, to identify features that effectively discriminate between these wear stages.

2.4. Feature selection using ANOVA

ANOVA calculates an F-statistic for each feature (both time-domain and frequency-domain features extracted from vibration and force signals) by comparing the variance between tool wear classes (New Tool, Mid-life, and Worn Tool) with the variance within each class. The independent variables are the extracted features, while the dependent variable is the tool wear condition, categorized into these three defined wear stages.

Features with high F-statistics and low p-values ($P < 0.05$) are considered statistically significant, as they demonstrate meaningful differences between the wear classes. The threshold for the F-statistic is determined by the degrees of freedom and the significance level ($\alpha = 0.05$). This filtering step selects features that effectively distinguish between wear levels, reducing computational complexity and noise in subsequent analyses. From this process, the 10 most relevant features are chosen as input for the model, ensuring the feature set remains both concise and informative for classification.

2.5. Whale optimization algorithm for feature selection

Further refinement of feature selection after preliminary filtration using the ANOVA test is done by the Whale Optimization Algorithm. The inspiration for WOA comes from the bubble-net hunting behaviour of humpback whales; hence, it can balance exploration and exploitation to scan the feature space very effectively. In this algorithm, each "whale" represents a feature subset, and WOA performs three main actions: encircling the best solution, simulating a spiral bubble-net attack, and exploring randomly to avoid local minima. These steps enable WOA to focus on features that improve model accuracy while discarding irrelevant ones. The integration of ANOVA and WOA is very apt for this study. While ANOVA provides an initial filtering based on the statistical relevance that reduces noise and computational load, WOA adapts to nuanced patterns in tool wear data. Unlike RFE, which is computationally expensive and sensitive to feature correlations due to its greedy approach, the global search nature adopted by WOA helps avoid local minima with a high probability of returning impactful features, thus boosting predictive performance [11]. After running WOA, the 10 most informative features are selected in order to optimize the model interpretability and reduce noise so as to have reliable tool wear predictions.

2.6. *SVM model training and parameter tuning*

The best features were then obtained by using an ANOVA-Whale Optimization Algorithm, and classification for the tool wear states was performed using an SVM classifier with the Radial Basis Function kernel (RBF). The proposed model of SVM was then implemented in Python code for tuning the penalty parameter C and kernel parameter γ to achieve the best accuracy for classification using GridSearchCV. In this respect, the RBF kernel had been selected, being appropriate for mapping the data into a higher-dimensional space and effectively separating the wear states by capturing nonlinear relationships that play an important role in varying machining conditions. This method will exploit the generalization powers of the support vector machines for the classification of wear states with small quantities of training data, the method being pretty well suited to this application.

3. Results and analysis

3.1. Tool wear pattern

Figure 3 illustrates the progression of tool wear width (VB_{max}) over time for five cases, each utilizing different cutting speeds and radial depths of cut. As shown in Figure 3, cutting speed and radial depth of cut have an influence on the wear process. The transition to the worn stage occurs at a faster rate when higher cutting speeds are employed (500 m/min in Cases 1 and 2) compared to lower speeds (250 m/min in Cases 4 and 5). Higher speeds result in increased friction and temperature, which intensify the tool wear [11]. Similarly, an increase in radial depth of cut (6 mm in Case 2 and 2) results in a greater magnitude of cutting forces and vibration due to an expanded contact area, which accelerates the wear progression. A reduction in depth of cut (3 mm in Cases 1 and 4) has the effect of reducing contact stress and slowing down the wear progression. It can be seen that both speed and depth have a significant impact on tool life.

Figure 4 gives in detail how tool wear develops for Case 1 through three successive stages: new tool, mid-life, and worn tool. Each stage has characteristic visual marks which signify the type of wear involved. The three stages in the tool wear are determined by the flank wear measurements, where for the new tool stage VB_{max} < 50 µm, the mid-life stage 50 µm < VB_{max} < 200 µm, and for the worn tool stage VB_{max} > 200 µm.

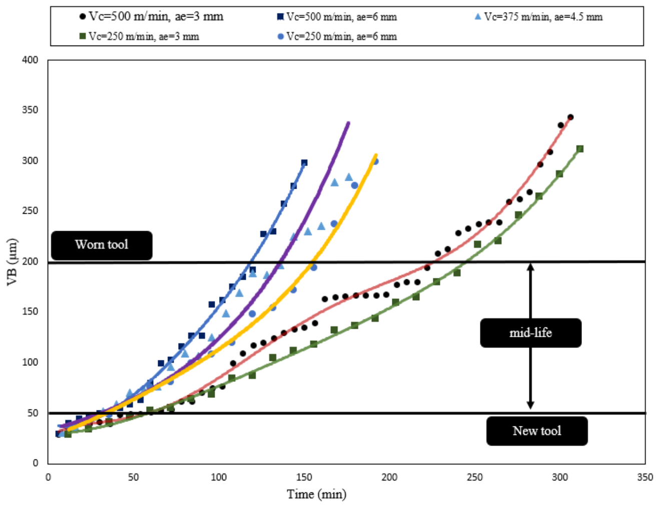

Fig.3. Tool wear progress

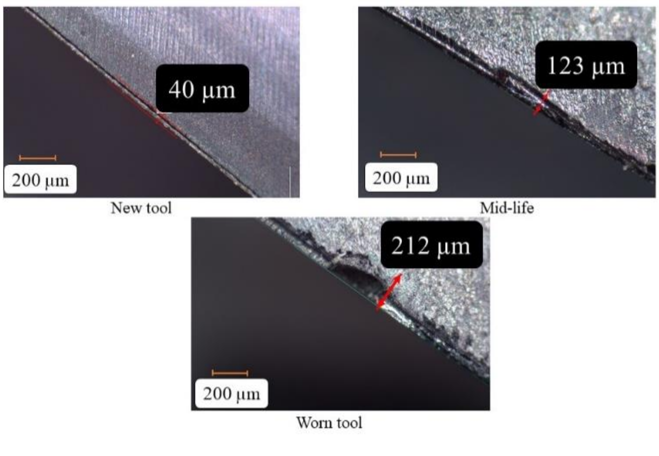

Fig.4. Microscopic wear patterns in case 1 at New (VB_{max} = 40µm), Mid-life (VB_{max} = 123 µm), and Worn Tool (VB_{max} = 212 µm) stages

3.2. Force and vibration progression throughout the machining process

As shown in Figure 5, the cutting force in the cutting direction increases progressively as machining time advances, aligning with the findings in Figure 3. Initially, in the new tool stage ($VB_{max} < 50\,\mu m$), the cutting forces remain relatively low due to the sharpness of the tool edge, which minimizes friction and ensures a smooth cut. As the tool progresses to the mid-life stage ($50{-}200\,\mu m$ wear), the cutting forces increase steadily due to the gradual blunting of the cutting edge, resulting in higher friction and contact stresses at the tool-workpiece interface [12,13,14]. To generate the data in Figure 5, Time Synchronous Averaging (TSA) was applied to the force signals to isolate periodic cutting forces and reduce noise, and the average of the maximum cutting force in the Fz direction was calculated at each time step to represent the cutting force progression over time.

At the worn tool stage (VB_{max} > 200 µm), cutting forces increase more significantly. Severe tool degradation and increased resistance at this stage require significantly higher cutting forces, often resulting in unstable cutting conditions. The trends observed in the figure confirm that cutting speed and radial depth of cut play a critical role in the progression of forces. For example, high cutting speeds (500 m/min in cases 1 and 2) and larger radial depths of cut (6 mm in case 2) accelerate the force increase, indicating that aggressive parameters accelerate wear and increase cutting loads. Conversely, lower cutting speeds (250 m/min in Cases 4 and 5) and reduced radial depths of cut (3 mm in Case 4) show slower force growth, demonstrating the mitigating effect of less aggressive machining settings on wear and force escalation.

Figure 6 illustrates the frequency spectrum of vibration for Case 3 across wear stages. The spectrum excludes frequencies in the noise band, which are primarily influenced by external machine vibrations, such as those from the Kistler force measurement platform or spindle. Notably, distinct peaks for each wear stage—new tool (3850 Hz), mid-life (4700 Hz), and worn tool (4950 Hz)—indicate that as wear progresses, the dominant frequency shifts upwards. This trend is consistent across all cases, with vibration frequency rising as wear increases.

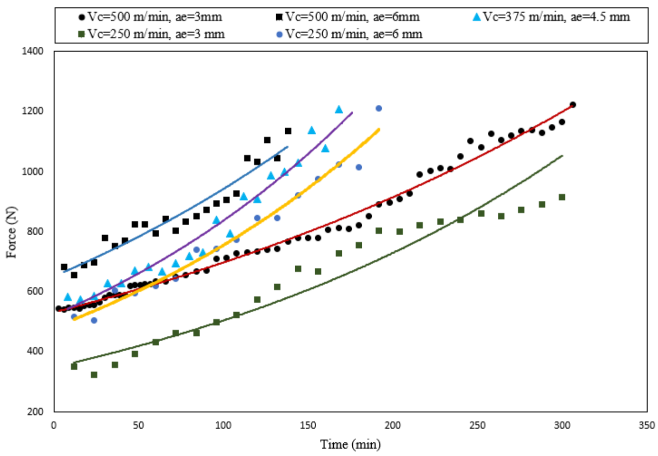

Fig.5. Cutting force progression in z Direction (Cutting direction)

Additionally, the amplitude of vibration exhibits decreases as the tool wears. This phenomenon could be attributed to a damping effect induced by severe wear, where increased material removal and surface degradation dampen vibration transmission, effectively dissipating energy and reducing amplitude despite higher frequency. This aligns with the hypothesis that excessive wear can lead to loss of vibrational coherence due to inconsistent material contact and tool instability [15,16].

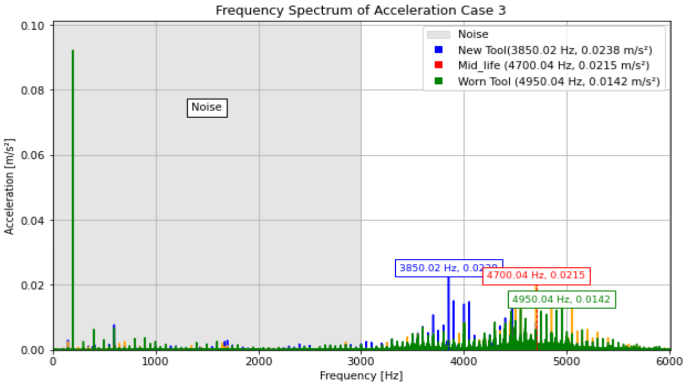

Fig.6. Vibration spectrum for case 3

3.3. Performance analysis of SVM model for tool wear classification using ANOVA and ANOVA + WOA feature selection

The performance analysis, illustrated in Figures 7, and 8 provides a detailed comparison of the Support Vector Machine (SVM) model's accuracy in classifying tool wear stages when employing two feature selection approaches: (1) ANOVA and (2) ANOVA enhanced with the Whale Optimization Algorithm (WOA). For model development, data from Cases 1, 2, 4, and 5 were utilized for training and testing, while Case 3 was exclusively reserved for prediction to evaluate the model's generalization capability. The dataset was partitioned with 80% allocated for training and 20% for testing. Additionally, hyperparameter tuning using GridSearchCV optimized the SVM parameters, selecting a penalty parameter C=10, a radial basis function (RBF) kernel, and a gamma value set to "scale." These parameters were instrumental in enhancing the classification performance, ensuring precise predictions of tool wear stages across diverse cases.

Figure 7 illustrates the evaluation matrix such as accuracy, precision, recall, and F1-score of the models using both feature selection methods. The ANOVA + WOA method demonstrated superior performance compared to ANOVA, achieving an accuracy of 94.28% versus 90.07%. Precision, recall, and F1-score metrics also showed notable improvements, highlighting WOA's effectiveness in refining feature selection. Both methods retained 10 features; however, while ANOVA predominantly selected features in the time domain, such as amplitude and peak values of vibration and force signals, the ANOVA + WOA approach prioritized frequency-domain features, such as dominant frequencies and spectral energy. Frequency-domain features are particularly sensitive to wear variations, capturing periodic patterns and resonance shifts that time-domain features may not fully reflect. Literature underscores the significance of frequency-domain analysis in detecting progressive mechanical condition changes, especially in rotating systems like milling tools, where vibration spectra shift with tool degradation [17, 5].

Figure 8 presents the confusion matrix for model predictions, comparing ANOVA and ANOVA + WOA methods. The ANOVA + WOA method shows fewer misclassifications, particularly between adjacent stages such as "worn tool" and "mid-life," which is essential for precise tool wear monitoring and timely maintenance. Studies have shown that hybrid feature selection methods reduce class overlap by introducing diverse features that offer unique insights into class boundaries, thereby improving classification precision and operational efficiency [5, 17].

Specifically, the ANOVA + WOA model achieves an accuracy of 92.09%, compared to 88.84% for ANOVA. The improved precision (91.73%) and recall (90.21%) reflect the ANOVA + WOA method's ability to reduce false positives and to capture a broader range of actual wear conditions accurately, thus enhancing the model's reliability and robustness.

4. Conclusion

Thus, the paper presented good performance of the ANOVA-WOA technique on feature selection in the monitoring of tool wear to outperform traditional methodologies. This approach, combining an ANOVA filtering step with the refinement by WOA, enhances the accuracy and interpretability of the model by considering only those features strongly related to the wear progression, reducing its dimensionality and computational complexity.
The experimental results demonstrate that an increase in cutting speed and radial depth of cut significantly accelerates tool wear. In other words, there is a need to optimize these parameters. Due to their high intensity, tools undergo significant deterioration from mid-life onwards, reaching a state of severe wear. It can therefore be concluded that achieving an equilibrium between the various machining parameters may result in an extended lifespan for the tool, thereby ensuring its continued effectiveness.

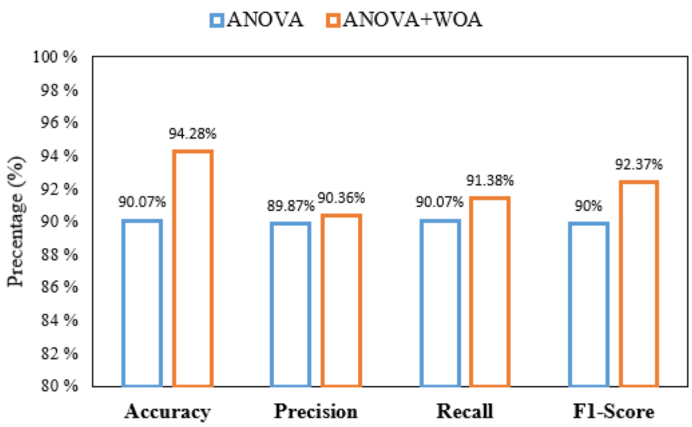

Figure 7. Machine learning model accuracy for tool wear prediction

Overall, the ANOVA + WOA approach offers a more robust and accurate solution for tool wear classification than ANOVA. This method demonstrates the value of combining statistical and metaheuristic techniques for feature selection in machine learning applications for tool condition monitoring.

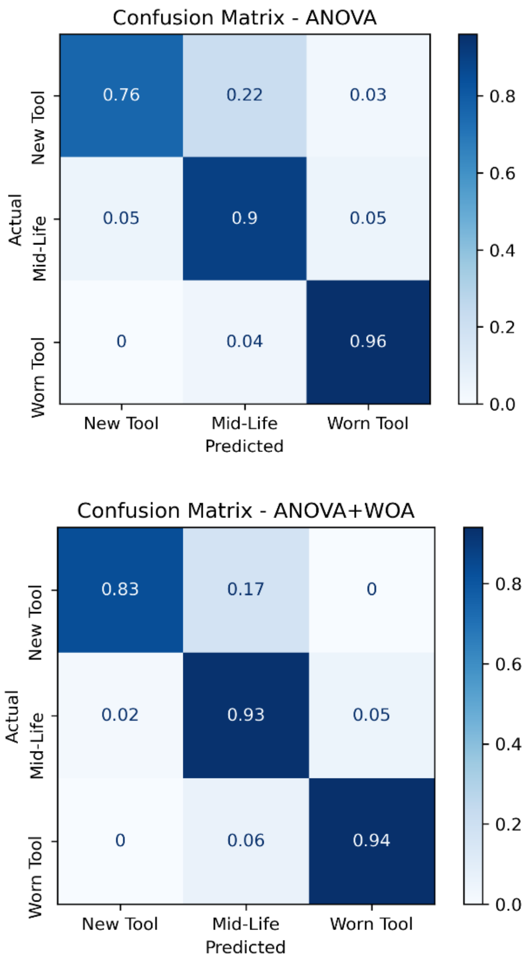

Figure 8. Performance metrics comparison of SVM model using ANOVA and ANOVA + WOA feature selection

The hybrid ANOVA-WOA and SVM approach demonstrated significant improvements in tool wear monitoring and is suitable for all types of end-milling operations, including rough and fine milling. By leveraging vibration and force signals, it effectively captures tool wear progression patterns across diverse machining conditions. However, the method was validated under specific dry machining conditions of AISI 4140 steel, limiting its generalizability to other materials or machining environments, such as those involving coolant or multi-axis operations. Additionally, WOA is sensitive to initial conditions, requiring fine-tuning for different datasets, and the exclusive reliance on vibration and force signals excludes other valuable modalities like acoustic emissions or thermal imaging. Furthermore, while SVM offers robust classification, its computational expense during hyperparameter tuning may challenge real-time applications.

Future work will address these limitations by validating the method across varied machining environments, incorporating additional sensor modalities, and exploring alternative optimization techniques. Testing for ANOVA assumptions, such as normality and variance homogeneity, will also be conducted, with non-parametric alternatives like the Kruskal-Wallis test considered where necessary. Despite these challenges, the proposed method holds significant potential to enhance tool condition monitoring, enabling more reliable and proactive maintenance strategies.

5. References

[1] Sun, X. Milling tool condition monitoring based on an integrated wireless vibration sensing tool holder. International Journal of Precision Engineering and Manufacturing, 2024, 1-13.

[2] Mäkiaho, Teemu; Vainio, Henri; KOSKINEN, Kari T. Wear parameter diagnostics of industrial milling machine with support vector regression. Machines, 2023, 11. 3, 395.

[3] Qin, Bo, et al. A tool wear monitoring approach based on triplet long short-term memory neural networks. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2024, 238 11, 1610-1619.

[4] Hassan, M., Sadek, A., & Attia, H. In-process self-configuring approach to develop intelligent tool condition monitoring systems. CIRP Annals - Manufacturing Technology, 2024, 73(1), 81-84. https://doi.org/10.1016/j.cirp.2024.04.049.

[5] Mohamed, Ayman, et al. Tool condition monitoring for high-performance machining systems—A review. Sensors, 2022, 22. Jg., Nr. 6, S. 2206.

[6] Cheng, Yaonan, et al. A new method based on a WOA-optimized support vector machine to predict the tool wear. The International Journal of Advanced Manufacturing Technology, 2022, 121. 9, 6439-6452.

[7] Teti, R., Jemielniak, K., O'Donnell, G., & Dornfeld, D. Advanced monitoring of machining operations. CIRP Annals - Manufacturing Technology, 2010, 59(2), 717–739. https://doi.org/10.1016/j.cirp.2010.05.010

[8] Nouioua, Mourad; Bouhalais, Mohamed Lamine. Vibration-based tool wear monitoring using artificial neural networks fed by spectral centroid indicator and RMS of CEEMDAN modes. The International Journal of Advanced Manufacturing Technology, 2021, 115. 9, 3149-3161.

[9] Babouri, Mohamed Khemissi, et al. Prediction of Optimal Lifetime of the Tool's Wear in Turning Operation of AISI D3 Steel Based on the a New Spectral Indicator SCG. In: Computational Methods and Experimental Testing In Mechanical Engineering: Selected Papers from the 6th Algerian Congress on Mechanics, CAM 2017, November 26-30, 2017, Constantine, Algeria. Springer International Publishing, 2019. 87-100.

[10] DIN, E. N. 10083-3. Vergütungsstähle–Teil 3: Technische Lieferbedingungen für legierte Stähle; Deutsche Fassung EN 10083-3: 2006. Deutsches Institur für Normung, 2006

[11] Mirjalili, Seyedali; Lewis, Andrew. The whale optimization algorithm. Advances in engineering software, 2016, 95. 51-67.

[12] ISO 8688–2:1989(en). Tool-life testing in milling—Part 2: End milling. International Organization for Standardization; 1989.

[13] Ur Rehman, Atiq, et al. Chip Analysis for Tool Wear Monitoring in Machining: A Deep Learning Approach. IEEE Access, 2024

[14] Grzesik, Wit. Advanced machining processes of metallic materials: theory, modelling and applications. Elsevier, 2008.

[15] Clough, Ray W.; Penzien, Joseph. Dynamics of structures. Berkeley. CA: Computers and Structures, 2003.

[16] Diniz, Anselmo E., et al. Evaluating the use of a new type of impact damper for internal turning tool bar in deep holes. The International Journal of Advanced Manufacturing Technology, 2019, 101. 1375-1390.

[17] Peng, Defeng; LI, Hongkun. Intelligent monitoring of milling tool wear based on milling force coefficients by prediction of instantaneous milling forces. Mechanical Systems and Signal Processing, 2024, 208. 111033.