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Feature-Optimised Machine Learning Framework for Intelligent CNC Grinding Tool Monitoring

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ABSTRACT

Tool Condition Monitoring (TCM) is vital in CNC grinding to ensure dimensional precision, surface quality, and process efficiency. This study introduces a machine learning-based TCM framework that integrates vibration signal analysis, feature extraction, and metaheuristic optimization. Vibration data from industrial CNC grinding were processed to extract time- and frequency-domain features, which were then applied to tool wear prediction using Support Vector Regression (SVR). To improve accuracy and robustness, the Marine Predators Algorithm (MPA) was employed for hyperparameter tuning. The MPA-optimized SVR achieved the lowest mean squared error (0.0028), outperforming autoregressive (0.0088) and power-law (0.0084) models. These findings demonstrate the potential of combining vibration analysis with metaheuristic-optimized machine learning for intelligent, scalable, and real-time TCM. The proposed framework aligns with Industry 4.0 objectives by reducing downtime, improving reliability, and enabling adaptive monitoring in precision manufacturing.

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INTRODUCTION

In precision manufacturing, Computer Numerical Control (CNC) grinding is essential for achieving dimensional accuracy, surface integrity, and process efficiency. However, the reliability of CNC operations is often limited by tool wear, which contributes to quality degradation, unexpected downtime, and increased costs. Traditional Tool Condition Monitoring (TCM) methods—based on force, current, or acoustic emission sensors—have provided valuable insights but frequently fall short in robustness, adaptability, and cost-effectiveness for industrial-scale deployment. In recent years, vibration-based TCM has gained prominence due to its sensitivity to tool–workpiece interactions, ability to capture dynamic tool wear behaviour, and suitability for real-time monitoring. Despite this progress, key challenges remain in extracting discriminative features from vibration signals and developing predictive models that generalize across varying machining conditions. Classical machine learning methods depend heavily on handcrafted features and manually tuned hyperparameters, often resulting in limited scalability and reduced accuracy. To overcome these limitations, metaheuristic optimization has emerged as a promising approach for both feature selection and model parameter tuning, offering automated exploration of high-dimensional search spaces while mitigating the risk of local minima.

The main objective of this paper is to propose and evaluate a vibration-based TCM framework that integrates metaheuristic-driven feature selection and model optimization for precise tool wear prediction in CNC grinding. Specifically, the study focuses on three key components:

i. vibration signal processing to extract time- and frequency-domain features,
ii. selection of informative features using the Marine Predators Algorithm (MPA), and
iii. predictive modelling with Support Vector Regression (SVR), enhanced through metaheuristic hyperparameter tuning.

By combining these elements, the framework aims to achieve high predictive accuracy, adaptability to diverse machining conditions, and real-time decision-making capabilities aligned with Industry 4.0 initiatives.

Early surveys on Tool Condition Monitoring (TCM) provided comprehensive insights into the evolution of monitoring methods and their limitations. Rehorn *et al.* [1] outlined state-of-the-art methods as early as the mid-2000s, highlighting traditional approaches based on force, vibration, and acoustic emission signals combined with statistical and heuristic models. Their review underscored the challenges of signal nonlinearity, machine variability, and the need for models that could generalize across tools and machining conditions. Similarly, Ambhore *et al.* [2] revisited TCM developments a decade later, emphasizing the growing reliance on sensor-based data acquisition, feature extraction in time, frequency, and time–frequency domains, and the role of artificial intelligence techniques. Both works concluded that while TCM had achieved significant progress, gaps remained in real-time adaptability, robustness, and scalability.

Building on this foundation, Serin *et al.* [3] provided an extensive review of modern TCM research with particular emphasis on opportunities for deep learning. Their analysis pointed out the limitations of handcrafted features and traditional machine learning algorithms when dealing with high-dimensional, noisy, and non-stationary machining data. They identified convolutional and recurrent neural networks as powerful alternatives capable of directly learning representations from raw vibration or acoustic signals. Importantly, the review stressed the need for large, diverse datasets, transfer learning techniques, and edge-deployable architectures to make deep learning viable in industrial settings.

More recently, Kaliyannan *et al.* [4] explored advanced machine learning paradigms by integrating deep learning with reinforcement learning for tool condition monitoring in milling. Their study demonstrated that reinforcement learning could dynamically adapt tool state predictions by incorporating feedback from machining outcomes, while deep neural networks handled feature representation from sensor data. This combination was shown to improve prediction accuracy and adaptability under variable machining conditions, marking a step toward intelligent, autonomous TCM systems. Synthesizing these works, it is evident that the field is moving from traditional feature-engineered models toward data-intensive deep and reinforcement learning frameworks. However, industrial deployment is still challenged by data scarcity, variability across machines, and the need for explainable, lightweight solutions. In this context, the present study positions itself as a bridge: it leverages vibration signals with engineered features but enhances prediction accuracy and robustness through metaheuristic optimization of Support Vector Regression (SVR). This approach combines the interpretability and efficiency of classical machine learning with the adaptability of modern optimisation, offering a pragmatic path for scalable, real-time TCM in precision manufacturing.

RESEARCH METHODOLOGY

The proposed research methodology is summarized in the flowchart presented in Figure 1. The study begins with vibration data acquisition from CNC grinding operations using high-resolution accelerometers under diverse machining conditions. The raw vibration signals are pre-processed through band-pass filtering, segmentation, and normalisation to reduce noise and ensure consistency across datasets. In the feature engineering stage, statistical descriptors from both time and frequency domains are extracted to capture tool wear signatures. To enhance model generalisation and reduce redundancy, the Marine Predators Algorithm (MPA) is applied for feature selection [5]. This metaheuristic approach identifies the most informative feature subsets by optimizing predictive performance criteria while avoiding overfitting.

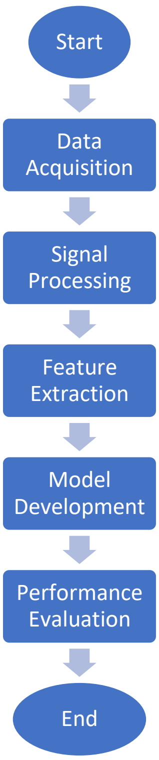

Figure 1. The flowchart of proposed approaches.

Subsequently, model development is conducted using Support Vector Regression (SVR), with the Marine Predators Algorithm (MPA) employed to optimise key hyperparameters (C, γ, and ε) to enhance predictive robustness. The optimised SVR models are then trained, validated, and benchmarked against baseline Autoregressive (AR) and Power-

Law models developed in [6]. Model performance was evaluated using standard statistical metrics including Mean Squared Error (MSE) and coefficient of determination (R^2) to assess prediction accuracy and consistency. This integrated methodology ensures a rigorous evaluation of the proposed metaheuristic-driven Tool Condition Monitoring (TCM) framework, assessing its predictive accuracy, adaptability, and suitability for industrial deployment in real-world CNC grinding environments.

The experimental data were acquired from a CNC grinding machine operating under real industrial conditions, as illustrated in Figure 2. Data acquisition was performed using a high-precision NI DAQ 9234 module with integrated signal conditioning to ensure accurate and reliable capture of vibration and acoustic responses. Two Dytran tri-axial piezoelectric accelerometers (sensitivity: 100 mV/g) were mounted near the grinding wheel and workpiece to record vibrations along the X, Y, and Z axes, while a GRASS microphone (sensitivity: 50 mV/Pa) was used to capture acoustic emissions related to tool wear, grinding wheel offsets, and other process anomalies. The signals were sampled at 12,800 samples per second, covering a frequency range up to 6,400 Hz, sufficient to capture dominant vibration and acoustic components. The grinding wheel operated at a constant speed of 3,000 RPM (50 Hz), and each measurement cycle lasted 468 seconds (approximately 7.8 minutes), enabling the analysis of both steady-state behaviours and transient dynamics during startup and shutdown phases. A total of 38 experimental runs were conducted using the same type of grinding tool to ensure consistency and repeatability in the collected data, thereby minimising variability in tool condition and process parameters across trials.

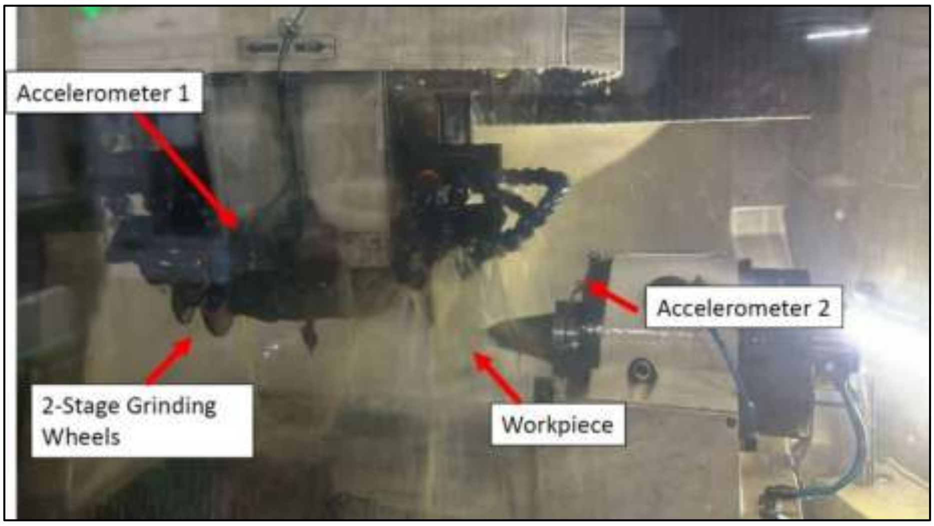

Figure 2. The experimental setup for data collection.

For the MPA optimiser initialisation, a population of 30 search agents and 200 iterations were employed to optimise the Power Law, Autoregressive (AR), and SVR models. The optimisation process was guided by minimising the mean squared error (MSE) between predicted and experimental data. The AR model required tuning of nine parameters, while the Power Law and SVR models involved optimisation of three parameters each. The search boundaries for the MPA were defined as $[-10,10]$ for the Power Law and AR models, and $[0.001,10]$ for the SVR model to ensure feasible parameter convergence within their respective domains. In Figure 3, the representative dataset (Observation No. 18) is presented in the frequency domain, illustrating vibration responses from the five axes of the two accelerometers used during the experiments. These datasets formed the foundation for subsequent analysis using an image embedding approach, where time- and frequency-domain vibration signals were transformed into image representations to reveal distinctive patterns related to tool condition and wear progression. The generated images were processed using the VGG-19 image embedder within the Orange Data Mining environment, producing 4,096 high-level features [7]. To enhance computational efficiency and improve model generalization, the extracted features were further refined using a feature selection technique optimized by the Marine Predators Algorithm (MPA) and Principal Component Analysis (PCA). Although the signal-to-image transformation inevitably introduces a minor degree of information loss, primarily due to discretisation and spatial encoding. However, the process preserves the essential frequency and amplitude characteristics required for accurate tool wear analysis. The combination of optimised feature selection and PCA ensures that only the most informative and discriminative attributes are retained, effectively mitigating the impact of this loss while maintaining strong predictive fidelity.

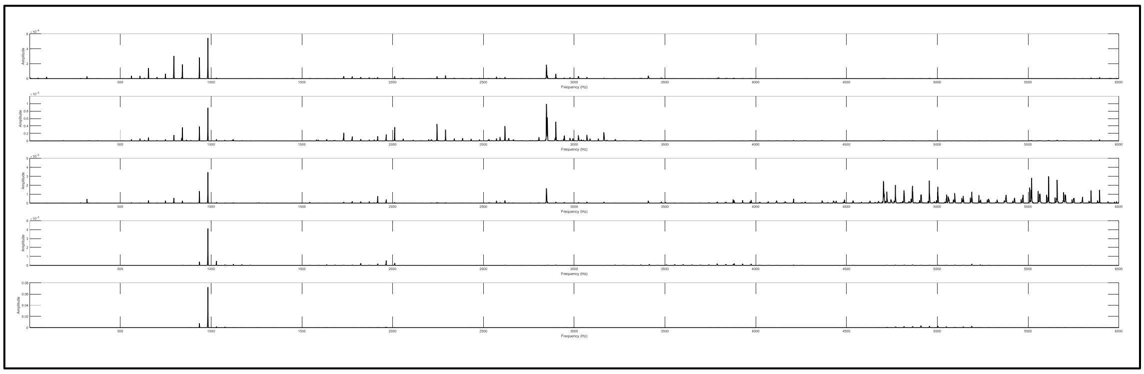

Figure 3. The exemplar dataset in the frequency domain for Observation No. 18, showing vibration responses from the accelerometer axes.

RESULTS AND DISCUSSION

All numerical analyses were carried out using MATLAB R2024b and Orange Data Mining software, taking advantage of their robust toolsets for signal processing, feature extraction, and model development. Computations were performed on a DELL workstation equipped with an Intel® Core™ i9-14900K CPU (3.20 GHz), 64 GB RAM, and Windows 11 (64-bit), ensuring efficient handling of large datasets and computationally intensive algorithms. Figure 4 presents the comparative performance of three modelling approaches—Power-Law, Autoregressive (AR), and Support Vector Regression (SVR)—against the real vibration-derived tool wear data, expressed through the normalized first principal component across 38 samples. The Power-Law model captures the overall degradation trend smoothly but fails to reflect local fluctuations, particularly in the mid-life region (samples 10–25), thereby limiting its suitability for adaptive monitoring. The AR model shows greater responsiveness than Power-Law but still deviates significantly in transitional wear phases, reflecting sensitivity to noise and limited robustness under variable operating conditions.

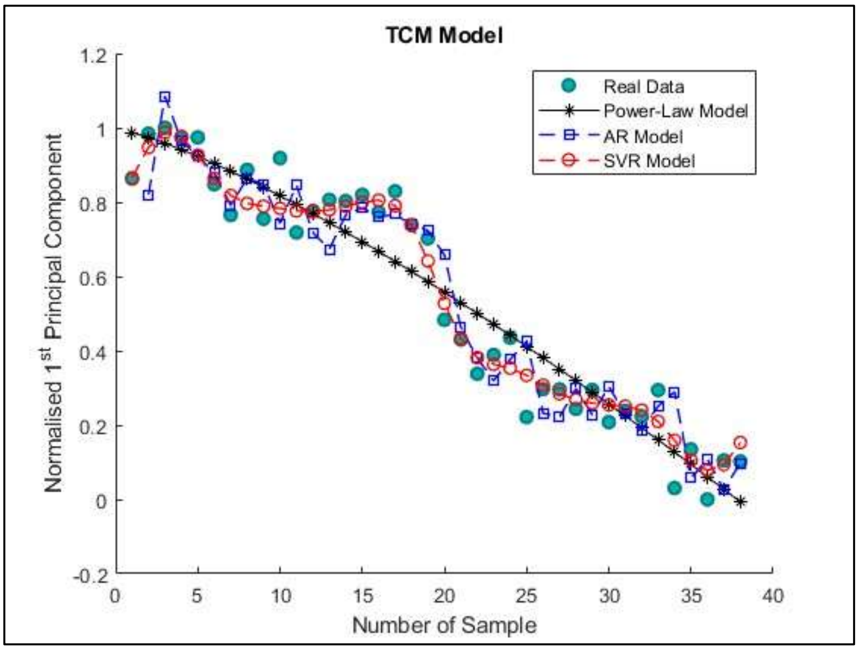

Figure 4. The performance of developed models.

By contrast, the Support Vector Regression (SVR) model optimized using the Marine Predators Algorithm (MPA) achieved the closest alignment with the experimental data, effectively capturing both the overall wear progression and local fluctuations. This superior performance is validated by its lowest mean squared error (0.0028) compared to the Autoregressive (AR) model (0.0088) and the Power-Law model (0.0084), as well as its highest coefficient of determination ($R^2 = 0.9716$) versus AR (0.9109) and Power-Law (0.9154) models. The optimised SVR model produced the best-performing hyperparameters of $C = 0.6360$, $\gamma = 3.5605$, and $\varepsilon = 0.0206$, providing a well-balanced trade-off between model complexity, generalization ability, and sensitivity to nonlinear tool wear patterns. Although computational time was not compared among the models in this study, the primary focus was placed on evaluating the accuracy and robustness of the developed predictive framework. Overall, the findings demonstrate that vibration-based modelling enhanced with metaheuristic optimization provides a more accurate, adaptive, and scalable framework for Tool Condition Monitoring (TCM). Unlike traditional models that either oversimplify or overfit wear behaviour, the proposed approach delivers the predictive precision and robustness required for real-time industrial deployment in precision manufacturing.

CONCLUSIONS

This study presented a vibration-based Tool Condition Monitoring (TCM) framework for CNC grinding that integrates advanced feature extraction with metaheuristic-optimized Support Vector Regression (SVR). By employing the Marine Predators Algorithm (MPA) for feature selection and hyperparameter tuning, the proposed approach effectively addressed the limitations of conventional mathematical models and traditional machine learning methods. Experimental results demonstrated that the MPA-optimized SVR outperformed both the autoregressive and power-law models, achieving the lowest mean squared error (0.0028) and the highest R^2 value (0.9716). Unlike baseline models, which either oversimplify or show sensitivity to noise, the optimized SVR model successfully captured both global wear progression and local fluctuations, proving its robustness under variable machining conditions. The findings confirm that metaheuristic-driven machine learning combined with vibration analysis offers a practical, scalable, and intelligent solution for real-time TCM. Beyond predictive accuracy, the framework directly supports Industry 4.0 objectives by reducing downtime, enhancing process reliability, and enabling adaptive monitoring in precision manufacturing environments. Future work will extend this study to multi-sensor fusion, cross-machine generalization, and edge deployment, advancing toward autonomous, data-driven manufacturing systems.

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