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Data-Driven Prediction of Remaining Useful Life for Milling Tools Using Machine Learning Models

Nguyen Trong Minh*

Faculty of Engineering, Vietnam National University of Agriculture, Hanoi 12400, Vietnam

Abstract

In the context of precision machining, predicting the remaining useful life (RUL) of cutting tools plays a critical role in optimizing production processes and reducing maintenance costs. This study proposed and developed four machine learning models for predicting tool RUL in milling operations, namely exponential Gaussian process regression (GPR), fine tree, linear regression, and quadratic support vector machine (SVM). The input dataset was constructed from sensor signals and key process parameters, including three-axis vibrations (vibration_x, vibration_y, vibration_z), acoustic emission signals, spindle load, cutting speed, feed rate, material hardness, and tool wear. The models were trained and evaluated using standard performance metrics, namely the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Experimental results indicated that the linear regression model outperformed the other models, achieving an R^2 value of 1 and extremely low prediction errors (RMSE = 4.1×10^{-8}; MAE = 3.2×10^{-8}). The findings suggest that the proposed framework is both effective and highly applicable for tool condition monitoring, while also supporting the optimization of cutting parameters in milling processes.

Keywords

Remaining useful life (RUL), linear regression, exponential Gaussian process regression, fine tree, quadratic support vector machine, milling tool

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Correspondence to
Nguyen Trong Minh
ntminh@vnua.edu.vn

ORCID
Nguyen Trong Minh
https://orcid.org/0000-0002-3904-9392

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Introduction

Milling is widely employed in modern manufacturing industries due to its flexibility and its capability to produce complex geometries. However, the performance and quality of machining processes are highly dependent on the tool condition, as tool wear directly affects surface integrity, dimensional accuracy, and overall production efficiency (Nguyen *et al*., 2026). In practice, tool degradation may lead to unexpected failures, increased energy consumption, and

substantial downtime costs, thereby highlighting the necessity for reliable tool condition monitoring and prognostics (Qin *et al*., 2022). Beyond conventional manufacturing applications, tool wear prediction is also highly relevant to agricultural engineering and agro-processing systems. Equipment such as biomass shredders, feed milling machines, forage choppers, and harvesting machinery are continuously exposed to abrasive materials and demanding operating conditions, leading to progressive tool degradation. Excessive wear can reduce processing efficiency, increase energy consumption, deteriorate product quality, and result in unexpected equipment downtime. Therefore, the accurate prediction of tool wear and the remaining useful life (RUL) can support predictive maintenance strategies, improve equipment reliability, and enhance the operational sustainability of agricultural production and processing systems (Lee *et al.*, 2021; Wang *et al*., 2023).

Traditional approaches to tool condition monitoring (TCM) and remaining useful life (RUL) prediction are typically physics-based or based on empirical models that describe tool wear mechanisms under specific cutting conditions (Li *et al*., 2022; Liu *et al*., 2022; Zhang *et al*., 2024). These methods generally rely on strong assumptions regarding wear behavior, material properties, and cutting dynamics, which limits their generalizability in complex and variable machining environments. Furthermore, the inherently nonlinear and stochastic nature of tool wear-driven by the interaction of multiple factors, such as cutting parameters, material characteristics, and machine dynamics, poses significant challenges for conventional models in achieving a robust and consistent performance across diverse operating conditions.

In recent years, rapid advancements in sensor technologies and data acquisition systems have enabled the collection of large volumes of high-resolution machining data, including vibration signals, acoustic emissions, cutting forces, and spindle load measurements. This data-rich environment has facilitated the adoption of data-driven approaches, particularly machine learning, for tool condition monitoring and prognostics. Unlike traditional methods, machine learning models are capable of learning complex relationships directly from data without requiring explicit physical formulations, making them well suited for capturing the nonlinear and multivariate characteristics of tool wear and degradation processes.

A wide range of machine learning (ML) techniques have been extensively investigated for predicting the remaining useful life of machining tools, especially cutting tools in milling operations. Deep learning models such as long short-term memory (LSTM), convolutional neural networks (CNN), and hybrid CNN-LSTM architectures have demonstrated superior performance due to their ability to automatically extract temporal and spatial features from sensor data. This capability is often further enhanced by attention mechanisms, which enable the models to quantify the relative importance of features and time steps (Chen *et al*., 2021; Sayyad *et al*., 2023; Wang *et al*., 2023). Probabilistic approaches, such as convolutional neural networks integrated with variational inference, allow for the quantification of predictive uncertainty, thereby supporting more informed maintenance decision-making (Wang *et al*., 2020). Hybrid methodologies that integrate data-driven deep learning models with physics-based degradation models, for example, Wiener processes updated within a Bayesian framework, have been shown to improve both prediction accuracy and robustness under varying operating conditions (Li *et al*., 2024). Comprehensive reviews have also identified key challenges, including data quality, model interpretability, and generalization across different machines and operating conditions. These studies further emphasized the increasingly important role of Industry 4.0 technologies, such as the Internet of Things (IoT) and cyber-physical systems (CPS), in enabling effective predictive maintenance through ML-based RUL estimation (Sayyad *et al*., 2021; Zhou *et al*., 2024; Refaie *et al*., 2025).

Despite significant advances in the application of machine learning to tool wear prediction, several challenges remain. First, many existing studies rely on a limited set of

input features, often neglecting the combined effects of multi-source sensor data and machining parameters. Second, the comparative performance of different ML models under identical experimental conditions is not always systematically investigated, making it difficult to identify the most appropriate model for a given application. Third, issues such as overfitting, data leakage, and limited model generalization are frequently overlooked, particularly when models exhibit unrealistically high predictive accuracy. These challenges underscore the need for comprehensive and rigorous studies that evaluate multiple models using consistent datasets and robust validation strategies.

In milling processes, tool wear progression is governed by the interplay of mechanical, thermal, and tribological factors. Vibration signals along multiple axes (vibration_x, vibration_y, vibration_z) provide valuable information regarding the dynamic interaction between the tool and the workpiece. Acoustic emission signals, typically represented by the root mean square value (acoustic_rms), capture high-frequency energy released during cutting and are sensitive to micro-scale wear mechanisms. In addition, process parameters such as spindle load, cutting speed, and feed rate directly influence cutting forces and temperature, thereby affecting the rate of tool degradation. Material hardness also contributes to wear behavior, while direct measurements of tool wear offer critical information on the current degradation state. Integrating these heterogeneous features into a unified data framework is essential for improving the accuracy and reliability of remaining useful life predictions.

Motivated by these considerations, this study proposed a data-driven approach for predicting the RUL of milling tools using multiple ML models. Specifically, four representative models were developed and evaluated, namely exponential Gaussian process regression (GPR), fine tree, linear regression, and quadratic support vector machine (SVM). These models were selected to span a broad spectrum of modeling paradigms, ranging from simple linear relationships to complex nonlinear and probabilistic frameworks. Furthermore, they provided a suitable balance between predictive capability, computational efficiency, and model interpretability, which are important requirements for industrial tool-condition monitoring applications. In addition, the available dataset was of moderate size; therefore, conventional machine learning approaches were considered more appropriate than deep learning architectures, which generally require substantially larger datasets and higher computational resources to achieve reliable generalization performance. By comparing their performance under identical conditions, this study aimed to provide systematic insights into the strengths and limitations of each approach in the context of milling tool RUL prediction.

The main contributions of this study can be summarized as follows. First, a comprehensive data-driven framework was developed for predicting the remaining useful life in milling processes, integrating multi-source sensor data with machining parameters. Second, a systematic comparison of four machine learning models was conducted under consistent experimental conditions, providing valuable insights into their relative performance. Finally, the proposed approach demonstrated strong potential for practical deployment in smart manufacturing systems, supporting predictive maintenance and process optimization.

Materials and Methods

Dataset

The dataset employed in this study emulates a realistic industrial milling environment and was specifically designed to support tool wear estimation and remaining useful life prediction. It comprised a total of 1,400 samples, each corresponding to a distinct machining condition and tool state. The dataset integrated information from multiple sources, including sensor-acquired signals, operational parameters, and material properties, thereby providing a comprehensive foundation for data-driven modeling (Kaggle, 2025.).

In terms of sensory inputs, vibration signals were recorded along three orthogonal directions

(X, Y, and Z axes), capturing the dynamic interactions between the cutting tool and the workpiece. Additionally, acoustic emissions were represented through root mean square (RMS) values, which reflect high-frequency energy variations associated with tool degradation mechanisms (Kaggle, 2025.).

The dataset also incorporated key machining parameters that directly influence tool wear progression, including spindle load, cutting speed, and feed rate. These variables characterized the mechanical and thermal conditions of the cutting process. Furthermore, material hardness was included as an input feature to account for variations in workpiece properties that may affect wear behavior.

Figure illustrates the histogram distributions of all the input and target variables, offering insights into their variability and distribution patterns. The corresponding descriptive statistics, including central tendency and dispersion measures for each variable, are summarized in **Table 1**.

In this study, a Monte Carlo simulation framework was employed to evaluate model robustness. For each Monte Carlo run, the entire dataset was randomly partitioned into 70% training samples and 30% testing samples using random hold-out sampling. This random splitting procedure was repeated 600 times, generating different train-test combinations for model development and evaluation.

Exponential Gaussian process regression (GPR)

In this study, an exponential Gaussian process regression (GPR) model was proposed to predict the remaining useful life of cutting tools based on data-driven inputs. Exponential GPR is a variant of Gaussian process regression, a nonparametric Bayesian regression framework, in which the covariance function (kernel) is

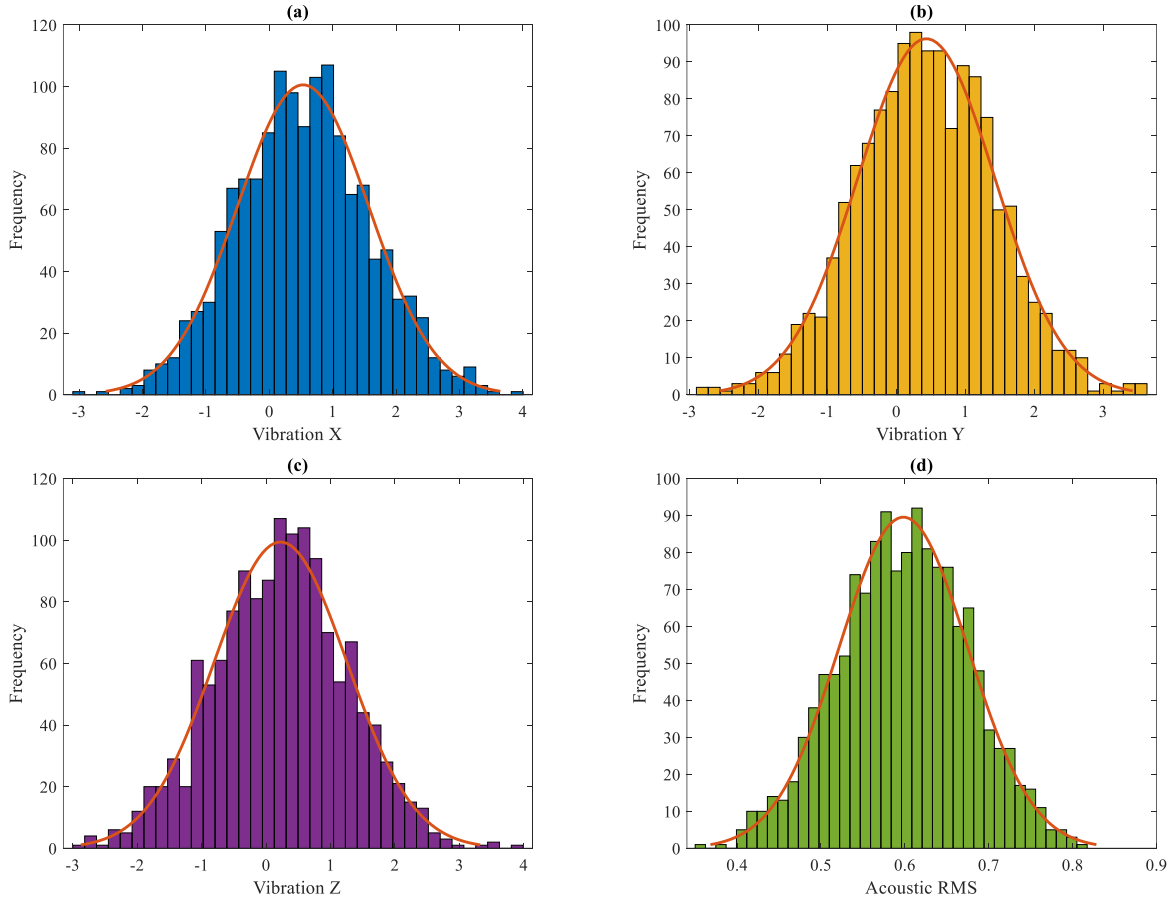


Figure 1. Statistical distributions of the input features and target variable used in the study

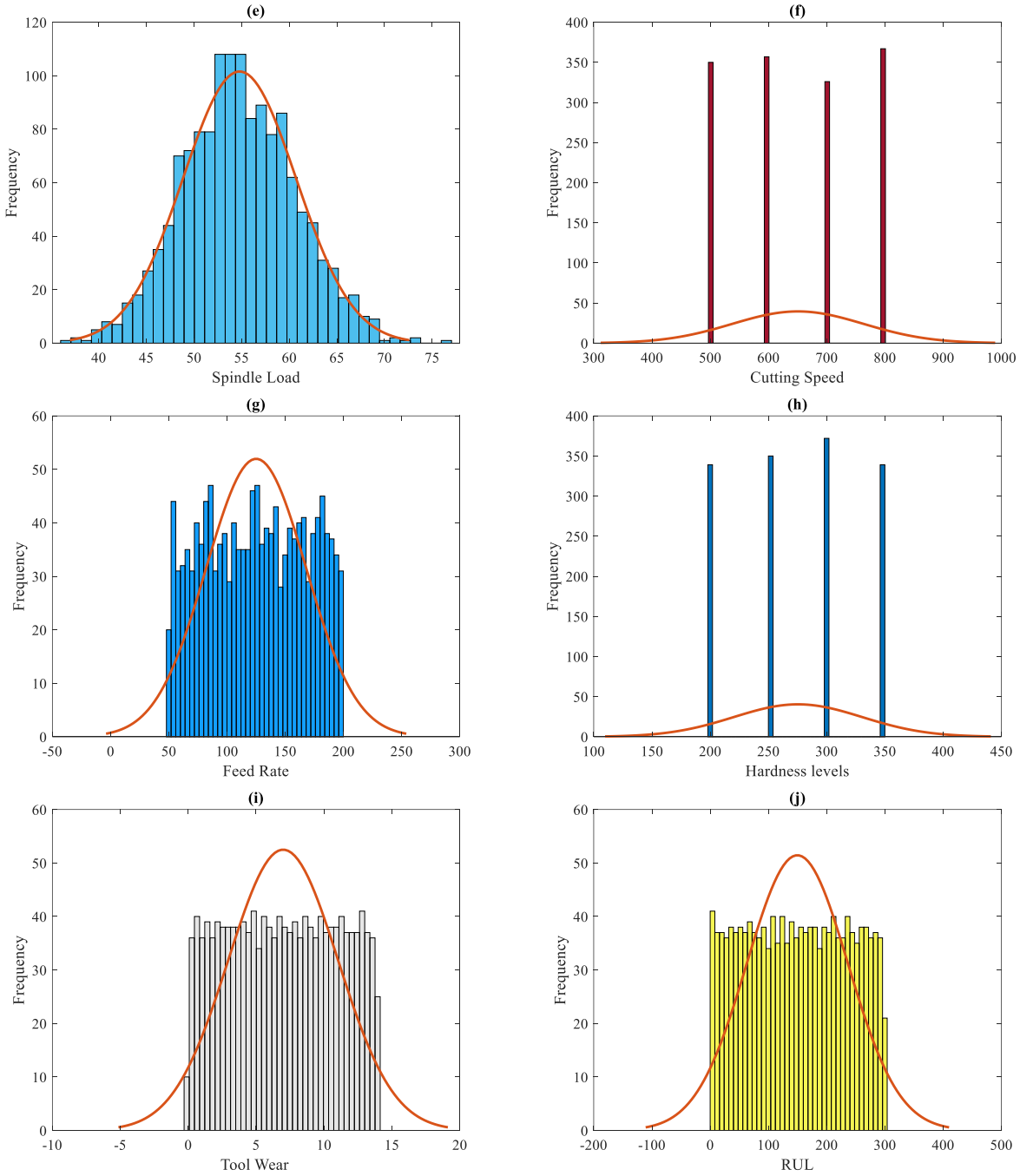


Figure 1. Statistical distributions of the input features and target variable used in the study (cont)

specified as the exponential kernel (also referred to as the Matérn-1/2 kernel or the Ornstein-Uhlenbeck kernel) (Bareth *et al.*, 2023; Yadav *et al.*, 2024). This kernel selection is well justified, as tool wear evolution and RUL degradation typically exhibit irregular ("rough") behavior and a near-exponential decay pattern with respect to cutting time. Furthermore, GPR inherently provides predictive uncertainty quantification through confidence intervals, which is a critical requirement in prognostics and health management (PHM).

A Gaussian process (GP) is fully specified by its mean function m(x) and covariance function k(x,x′):

$$f(x) = GP(m(x), k(x, x')) \quad (1)$$

In the regression setting, the observations are modeled as follows:

Table 1. Summary statistics (minimum, quartiles, mean, maximum, standard deviation, and coefficient of variation) of the dataset variables

Parameter	Min	Q25	Q50	Mean	Q75	Max	Std	CV%
Vibration X	-3.0540	-0.1880	0.5301	0.5337	1.2035	4.0021	1.0372	194.3545
Vibration Y	-2.8121	-0.2285	0.4334	0.4352	1.1326	3.6274	0.9977	229.2505
Vibration Z	-2.9386	-0.4939	0.2403	0.2249	0.8994	3.9602	1.0338	459.6050
Acoustic RMS	0.3583	0.5456	0.5997	0.5983	0.6516	0.8159	0.0767	12.8195
Spindle load (%)	36.1351	50.7060	54.6143	54.7858	58.7999	76.8733	5.9370	10.8368
Cutting speed (m min^{-1})	500	575	600	650.7143	800	800	112.9223	17.3536
Feed rate (mm min^{-1})	50.0361	87.3214	125.2646	125.0783	162.5366	199.9510	42.9872	34.3682
Material hardness (HB)	200	250	300	275.3929	300	350	55.2128	20.0487
Tool wear (10^{-2} mm)	-0.0168	3.4983	6.9805	6.9947	10.4887	13.9662	4.0430	57.8012
RUL (min)	0	74.6974	150.0562	149.7517	224.8561	300.3602	86.8453	57.9929

$$y = f(x) + \varepsilon,\ \varepsilon \sim N(0, \sigma_n^2) \quad (2)$$

Given n training samples, with $D = \{(X, y)\}$, $X \in R^{n.d}$ and $y \in R^n$, the posterior distribution at a test point x_* is Gaussian:

$$p(f_* \mid X, y, x_*) = N(\bar{f}_*, V[f_*]) \quad (3)$$

Here, the posterior mean and posterior variance are computed as follows:

$$\bar{f}_* = k_*^T (K + \sigma_n^2 . I)^{-1} . y$$
$$V[f_*] = k(x_*, x_*) - k_*^T (K + \sigma_n^2 . I)^{-1} . k_* \quad (4)$$

Here, K denotes the covariance matrix of the training inputs, $K_{ij} = k(x_i, x_j)$, and k_* represents the covariance vector between the test point x_* and the training inputs.

The kernel employed in this model is the exponential kernel:

$$k(x, x') = \sigma_f^2 \exp\left(-\frac{\|x - x'\|}{l}\right) \quad (5)$$

where σ_f^2 is the signal variance and l is the length-scale.

The exponential kernel is equivalent to the Matérn kernel with $\nu = 1/2$, enabling the model to represent non-smooth functions with rapid decay characteristics—properties that are consistent with tool wear behavior, particularly the transition from steady wear to accelerated degradation. This kernel was selected after comparison with the squared exponential (RBF) kernel through correlation matrix analysis and cross-validation experiments, demonstrating superior capability in capturing RUL degradation patterns from sensor-derived features.

Model fine tree regression

The fine tree model belongs to the family of decision tree algorithms and is well recognized for its ability to capture complex nonlinear relationships between sensor signals and RUL, while offering fast training and high interpretability. Decision tree regression constructs a binary tree structure by recursively partitioning the dataset at each node based on threshold values of input features, with the objective of minimizing impurity at the leaf nodes. The fine tree configuration is a high-resolution (fine-grained) variant, typically allowing the tree to grow with a large number of leaf nodes, minimal restrictions on maximum depth, and locally optimal split criteria at each step (Yang *et al*., 2017). This configuration enables the model to learn detailed patterns in the data, making it particularly suitable when the relationships between features (e.g., acoustic RMS, spindle load, and vibration) and RUL are highly nonlinear and exhibit sharp transitions characteristic of the accelerated wear phase of cutting tools.

Model linear regression

To establish a baseline for comparison with more complex nonlinear models, this study

employed multiple linear regression (MLR), a classical linear regression approach. Although the relationship between sensor signals and the remaining useful life (RUL) is typically nonlinear, linear regression is utilized to assess the extent to which the data can be explained by linear relationships, while also providing a foundation for analyzing the contribution of individual features.

The multiple linear regression model assumes a linear relationship between the dependent variable y (RUL) and the independent variables $x = [x_1, x_2, \ldots, x_p]^T$, expressed as follows (Montgomery *et al*, 2021):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_p x_p + \varepsilon \quad (6)$$

where β_0 is the intercept; $\beta_1, \beta_2, \ldots \beta_p$ are the regression coefficients; and ε denotes the random error term.

For n observations, the model can be expressed in matrix form as follows:

$$y = X.\beta + \varepsilon \quad (7)$$

The estimates of the coefficients β are obtained using the ordinary least squares (OLS) method, which minimizes the sum of squared errors:

$$\hat{\beta} = (X^T X)^{-1} X^T y \quad (8)$$

Model quadratic support vector machine (quadratic SVM)

To capture the nonlinear relationships between sensor signals and the remaining useful life (RUL) of cutting tools, this study employed quadratic support vector regression (quadratic SVR). This approach is a variant of support vector regression (SVR) that utilizes a quadratic kernel, enabling the model to learn more complex patterns than linear regression while maintaining robustness and strong generalization capability (Smola *et al*., 2004).

Support vector regression (SVR) maps the input data into a high-dimensional feature space via a kernel function, and subsequently constructs an ε-insensitive tube such that most data points lie within this margin. The objective is to minimize a loss function that balances prediction error and model complexity (Smola *et al*., 2004):

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} L_\varepsilon(y_i, f(x_i)) \quad (9)$$

where the ε-insensitive loss function is defined as follows (Smola *et al*., 2004):

$$L_\varepsilon(y, f(x)) = \begin{cases} 0 \\ |y - f(x)| - \varepsilon \end{cases} \quad (10)$$

with C being a regularization parameter that controls the trade-off between minimizing the prediction error and maintaining the flatness (smoothness) of the regression function.

In this model, a quadratic kernel is employed to perform the nonlinear mapping:

$$k(x, x') = (x^T x' + c)^2 \quad (11)$$

where c is a free constant (typically set to 1). The quadratic kernel enables the model to capture second-order relationships and interaction effects among features without requiring explicit feature space expansion. This kernel is particularly suitable for RUL prediction, as tool wear processes often exhibit strong nonlinear effects.

Model Evaluation Metrics

To quantitatively assess the predictive performance of the proposed model, three widely adopted metrics, namely the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE), were employed. These metrics are defined as follows (Nguyen & Le, 2026):

$$R^2 = 1 - \left[\frac{\sum_{1}^{n} \left(m_i - \hat{m}_i \right)^2}{\sum_{i}^{n} \left(m_i - \bar{m} \right)^2} \right] \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n} \left(m_i - \hat{m}_i \right)^2} \quad (13)$$

$$MAE = \frac{1}{n}\sum_{1}^{n} \left| m_i - \hat{m}_i \right| \quad (14)$$

where n is the number of predicted data points, m_i is the observed value, and $\hat{m}_i$ is the prediction value of $\bar{m}$, which is the average of the actual values of the dependent variable.

From an interpretative perspective, RMSE and MAE evaluate the magnitude of prediction errors, with lower values indicating higher predictive accuracy. In contrast, R^2 measures the proportion of variance in the observed data explained by the model, where values closer to unity indicate a better fit. A model is generally considered reliable when it simultaneously achieves low RMSE and MAE along with a high R^2, reflecting both accuracy and generalization capability. In addition to these metrics, the slope of the linear regression between predicted and observed values was also examined to further characterize the agreement between model outputs and actual data.

Results and Discussion

Table 2 presents a comparative evaluation of four machine learning models: exponential Gaussian process regression (GPR), fine tree, linear regression, and quadratic support vector machine (SVM), revealing a pronounced disparity in predictive performance. Among these, linear regression clearly outperformed the others, achieving $R^2 = 1$, RMSE = 4.0635×10^{-8}, and MAE = 3.21062×10^{-8}, which indicates an almost perfect fit to the data. This exceptionally high performance suggests that the target variable was strongly correlated with the predictor variables and could be represented almost entirely by a linear combination of the input features. Therefore, the outstanding results obtained by linear regression are likely attributable to the intrinsic characteristics of the dataset rather than the universal superiority of linear models for all tool wear and RUL prediction tasks. It should be noted that such near-perfect predictive performance is rarely observed in real machining environments, where measurement noise, sensor uncertainty, and operational variability are unavoidable. Consequently, the present result should be interpreted as a reflection of the highly structured nature of the dataset rather than evidence of a universally perfect prediction model. This result suggests the presence of a highly strong and purely linear relationship between the input and output variables, rendering the simplest model the most optimal choice. Both fine tree and GPR exhibited excellent performance, with R^2 values of approximately 0.9999 and 0.9998, respectively, demonstrating their capability to capture nonlinear patterns. However, the RMSE and MAE of the fine tree model (0.5266 and 0.6344) were notably lower than those of GPR (1.1322 and 0.439), reflecting a trade-off between global bias and local error characteristics. In contrast, the quadratic SVM was the weakest model in this comparison, with $R^2 = 0.995$, RMSE = 5.0976, and MAE = 6.15. Although its performance remained within an acceptable range for many practical applications, the relatively high absolute error indicates limited suitability for the current data structure. Overall, the results confirm that when the underlying data exhibit strong linearity, more complex models do not necessarily provide additional benefits. Selecting a model that aligns with the intrinsic characteristics of the data remains a critical factor in the development of effective machine learning systems.

Figure 2 illustrates the relationship between the predicted and actual values of the linear regression model for both the training set (a) and the testing set (b). The data points were observed to lie almost perfectly along the ideal y = x line, indicating exceptionally high predictive accuracy. The RMSE values for both datasets were extremely small, demonstrating that the discrepancy between predicted and actual values was negligible. Notably, the near-identical performance on\ the training and testing sets suggests that the model not only fits the data effectively but also exhibits strong generalization capability, with no evident signs of overfitting. Overall, these results confirm the model's superior performance and high reliability in the prediction task.

Figure 3 illustrates the evolution of RMSE and MAE as the number of Monte Carlo simulations (NMC) increases for both the training and testing datasets. At low NMC values

Table 2. Performance comparison of different regression models based on evaluation metrics

Model	R^2	RMSE (min)	MAE (min)
Exponential Gaussian Process Regression (GPR)	0.9998	1.1322	0.439
Fine Tree	0.9999	0.5266	0.6344
Linear Regression	1	$4.0635E^{-08}$	$3.21062E^{-08}$
Quadratic Support Vector Machine (SVM)	0.995	5.0976	6.15

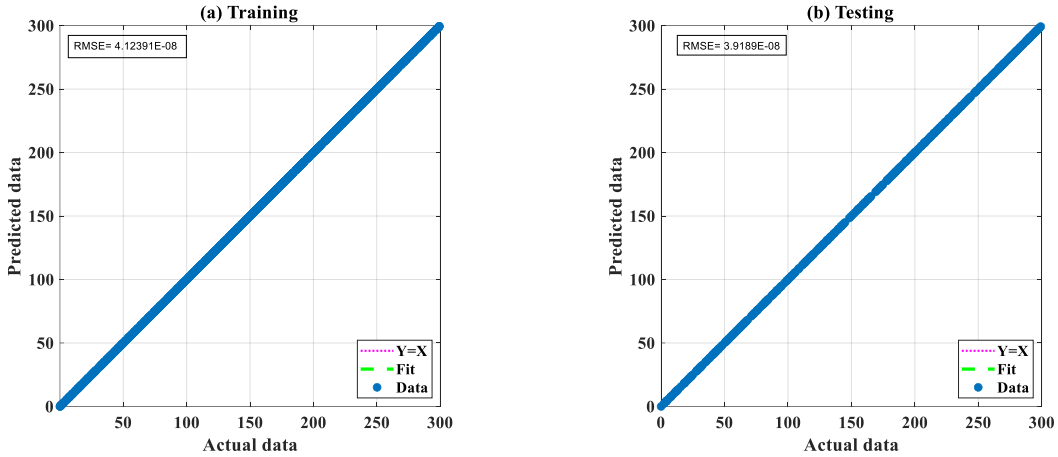


Figure 2. Comparison between predicted and actual values of the linear regression model for (a) training and (b) testing datasets

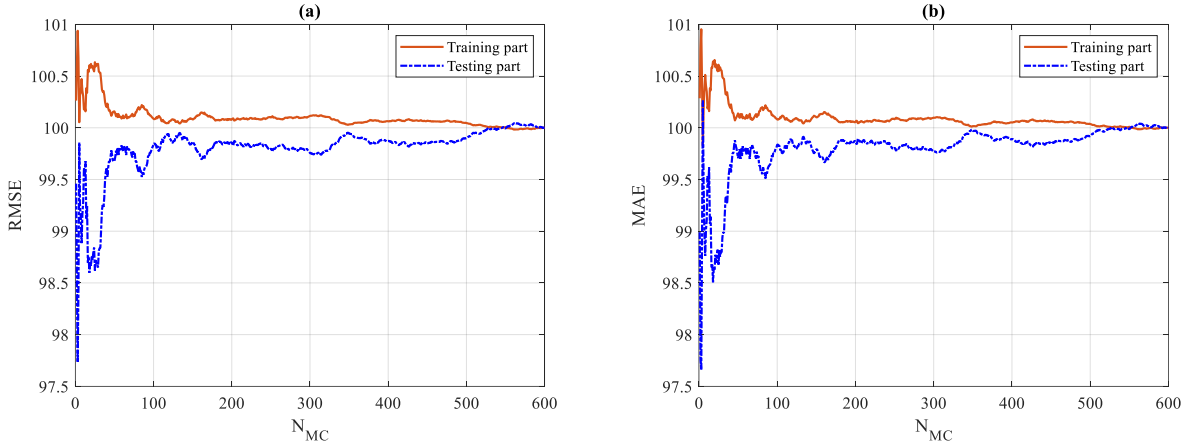


Figure 3. Convergence analysis of the linear regression model in terms of (a) RMSE and (b) MAE over Monte Carlo runs

both error metrics exhibited noticeable fluctuations, particularly for the testing set, indicating sensitivity to random data partitioning. However, as the NMC increased, the curves gradually stabilized and converged toward consistent values, demonstrating improved reliability of the performance estimates. Notably, the training and testing errors remained closely aligned throughout the simulation process, suggesting that the model maintained good generalization capability without evident overfitting. Beyond a certain threshold (approximately NMC $\approx$ 200 $\div$ 300), further increases in simulations yielded only marginal changes in RMSE and MAE, indicating that the evaluation results have reached convergence. This behavior confirms the robustness and stability of the proposed modeling approach under repeated random sampling conditions.

Figure 4 presents the histograms of RMSE and MAE obtained from 600 Monte Carlo simulations for the linear regression model. Both

error distributions exhibited a narrow spread and were concentrated within a limited range, indicating low variability in model performance across repeated random data partitions. The distributions appeared approximately unimodal and close to symmetric, suggesting stable estimation behavior without significant skewness or extreme outliers. Furthermore, the consistency of the RMSE and MAE values across simulations implies that the model's predictive performance was not sensitive to data partitioning. Overall, these results indicate that the linear regression model provides reliable and stable predictions under repeated Monte Carlo sampling conditions.

Figure 5 presents the feature weights obtained from the linear regression model. The results showed that tool wear was the dominant predictor of RUL, with an absolute coefficient of 86.353, while the coefficients of all other variables were close to zero. This finding indicates that tool wear contributes most significantly to the prediction of tool remaining useful life, whereas vibration signals, acoustic RMS, spindle load, cutting speed, feed rate, and material hardness have negligible influence within the linear regression framework. The negative coefficient of tool wear further confirmed the expected inverse relationship between tool wear progression and RUL.

Conclusions

In this study, four machine learning models, exponential Gaussian process regression (GPR), fine tree, linear regression, and quadratic support vector machine (SVM), were developed and comparatively evaluated for predicting the remaining useful life (RUL) of cutting tools in milling operations. The results indicated that the linear regression model achieved the highest predictive accuracy, with very low error metrics, suggesting that the relationship between the

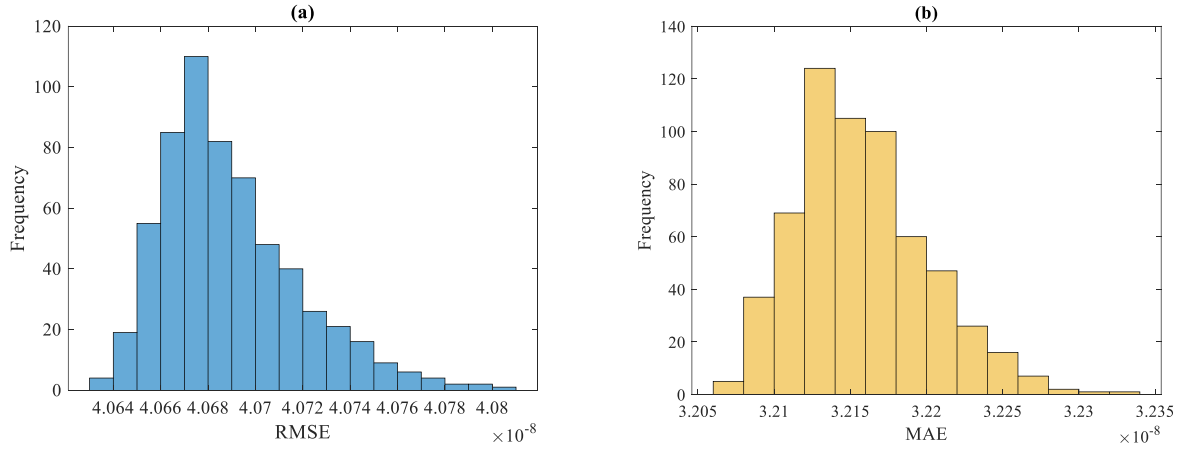


Figure 4. Statistical distributions of RMSE and MAE based on repeated Monte Carlo simulations for the linear regression model

========== FEATURE WEIGHTS ==========

Feature	Coefficient	AbsoluteWeight
{'Tool Wear (10^-2 mm)' }	-86.353	86.353
{'Vibration X' }	-3.1259e-09	3.1259e-09
{'Vibration Y' }	-2.0799e-09	2.0799e-09
{'Material Hardness (HB)'}	1.5992e-09	1.5992e-09
{'Spindle Load (%)' }	-1.3941e-09	1.3941e-09
{'Vibration Z' }	1.0236e-09	1.0236e-09
{'Cutting Speed (m/min)' }	-9.7721e-10	9.7721e-10
{'Feed Rate (mm/min)' }	2.6436e-10	2.6436e-10
{'Acoustic RMS' }	-9.1228e-11	9.1228e-11

Figure 5. Feature weights obtained from the linear regression model for RUL prediction

selected input features and tool wear progression were effectively approximated by a linear model. Fine tree and GPR also demonstrated strong predictive performance, although slightly lower than that of linear regression, while quadratic SVM showed comparatively reduced accuracy.

These findings suggest that simpler models can outperform more complex approaches when they are well aligned with the underlying data structure. In addition, the proposed multi-sensor framework, which integrated vibration, acoustic emission, and machining parameters, provides a comprehensive basis for tool condition monitoring. From a practical perspective, the low computational cost and stable performance of the linear regression model make it a promising candidate for real-time implementation in smart manufacturing environments, supporting timely tool replacement, reduced downtime, and improved process efficiency.

However, this study had several limitations. The dataset may have lacked sufficient diversity, and its structured nature could have affected the generalizability of the results. Furthermore, the publicly available dataset employed in this study may not have fully captured the stochastic noise, measurement uncertainty, sensor drift, and environmental disturbances typically encountered in real-world machining systems. As a result, the predictive performance reported herein may be more optimistic than that achievable under actual industrial operating conditions. Therefore, future work should focus on validating the proposed approach under more complex and heterogeneous machining conditions, incorporating additional sensor modalities, and exploring advanced or hybrid models, such as deep learning architectures, to further improve robustness and scalability.

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