A Course project (IT307M) Report on

Predictive Maintenance of CNC Milling Machine

undergone at

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under the guidance of

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Abstract

This project develops a predictive-maintenance pipeline for a high-speed CNC milling machine using the PHM dataset. The goal is to estimate tool wear from multi-sensor measurements (dynamometer force, accelerometer vibration, and acoustic emission) and thereby enable timely maintenance actions. The work is organized into three implemented stages: exploratory data analysis (EDA) to characterize signal properties and failure modes; feature engineering to extract robust time- and frequency-domain descriptors from raw sensor streams; and regression modeling where a sparse linear model (Lasso) is trained and evaluated to predict wear. Results demonstrate that carefully engineered features combined with regularized linear regression provide a competitive, explainable baseline for wear estimation and form a foundation for later experimentation with deep models and dashboards. This report documents the methodology, data preprocessing steps, feature set, model training, and evaluation strategy implemented.

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1 Introduction

Predictive maintenance has become a central component in modern industrial systems, enabling manufacturers to prevent unexpected breakdowns, improve productivity, and prolong machine life. In machining environments such as CNC milling, tool wear is one of the most critical factors affecting product quality, surface finish, energy consumption, and overall operational efficiency. The availability of high-frequency sensors—such as force, vibration, and acoustic emission—provides opportunities to detect wear progression before critical failure occurs. Using data-driven approaches, this project focuses on developing a baseline tool-wear prediction pipeline based on exploratory analysis, feature construction, and regression modeling.

1.1 Background and Motivation

In machining operations, a tool gradually deteriorates due to friction, heat generation, chip removal forces, and mechanical fatigue. If wear is not monitored effectively, it can lead to dimensional inaccuracies, poor surface finish, machine downtime, and costly scrapped parts. Traditional wear monitoring relies on manual inspection or fixed replacement schedules, which are either inaccurate or economically inefficient. With the rise of Industry 4.0 and IoT-driven sensing technologies, continuous monitoring using data analytics offers a more precise and economical method to understand tool health. This motivates the exploration of sensor-based tool wear prediction using structured data processing, feature engineering, and interpretable machine-learning models.

1.2 Problem Statement

Despite the availability of multiple sensor channels, raw signals are often noisy, high-dimensional, and influenced by cutting speed, feed rate, and material properties. Direct interpretation of these signals is difficult, and traditional thresholds do not generalize well across different operating conditions. The core problem addressed in this project is how to transform multi-sensor measurements into meaningful features and how to build a baseline regression model capable of estimating the amount of tool wear. The challenge includes handling heterogeneous sensor data, extracting relevant statistical and frequency-domain features, and identifying modeling approaches that provide stable predictions while remaining computationally efficient.

1.3 Objectives

The key objectives of this work are:

1. To perform exploratory data analysis (EDA) on the machining sensor dataset to identify trends, correlations, and wear-related signal patterns.

2. To preprocess and engineer informative features from force, vibration, and acoustic emission signals using statistical, temporal, and spectral descriptors.

3. To develop and evaluate a baseline regression model—using regularized linear regression—to estimate tool wear from engineered features.

1.4 Related Work

Prior work in tool-wear monitoring spans statistical approaches, signal processing methods, and machine-learning models. Traditional research emphasized hand-crafted features from vibration and acoustic signals, using methods such as RMS, kurtosis, FFT-based spectral energies, and wavelet transforms. With the evolution of machine learning, models like support vector regression, random forests, and neural networks have been employed to capture nonlinear relationships between sensor data and wear progression. Many studies highlight the importance of combining well-engineered features with interpretable models to create robust monitoring systems suitable for industrial deployment. The present project aligns with this trend by focusing on engineered features and a lightweight regression model to form a clear and interpretable baseline for tool-wear prediction.

1.5 Literature Survey

Table 1: Literature Survey

Title	Author	Work done	Limitations
Tool wear prediction based on multisensor data fusion and machine learning	Jones, T. & Cao, Y. (2025)	Collected force, vibration, AE data from CNC milling; extracted 28 statistical features; used three-level data fusion (raw, feature, decision); trained RF, XGBoost; best result with (RF+XGBoost) achieving RMSE = 58 m.	Requires manual feature engineering; not fully end-to-end; ensemble is computationally heavier for deployment in real-time.
Tool Wear Prediction Based on Multi-Scale CNN with Attention Fusion	Huang, Q. et al. (2022)	Developed multi-scale CNN with attention-based feature fusion for tool wear regression; showed that combining multi-resolution feature maps improves prediction robustness.	Performance sensitive to kernel size choices; may overfit on small datasets without regularization.
Survey: Deep Learning Models for Predictive Maintenance	Serradilla / Zugasti et al. (2020–2022)	Reviewed CNN, RNN, Autoencoder, VAE-based approaches for predictive maintenance tasks, highlighting benefits of multimodal fusion and hybrid models.	Mostly descriptive; no experimental results; does not give direct implementation details.
Deep learning-based tool wear prediction using multi-scale feature fusion	Xu, X. et al. (2021)	Proposed multi-scale CNN with channel attention mechanism for learning features from multi-sensor signals; improved accuracy by capturing tool wear patterns at multiple scales.	Increased network complexity; computationally more expensive for real-time use.

Table 1 presents a comprehensive overview of recent research in tool wear prediction. Jones and Cao [1] developed a multisensor data fusion approach, while

Xu et al. [2] proposed a multi-scale CNN architecture. Huang et al. [3] further advanced this with attention fusion mechanisms. Serradilla et al. [4] provided a comprehensive survey of deep learning models for predictive maintenance.

2 Methodology

This study follows a structured methodology consisting of data understanding, exploratory data analysis, feature extraction, and baseline model development. Each stage is described below.

2.1 Data Collection and Understanding

The project uses sensor data from a CNC milling machine, consisting of multimodal measurements recorded during controlled machining operations. These include force measurements from a dynamometer, vibration signals from accelerometers in three axes, and acoustic emission readings. Tool wear values were periodically measured to serve as the target variable. All raw files were loaded into unified dataframes, validated for consistency, and prepared for analysis.

2.2 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed to understand the behavior of sensor signals across different wear levels. Summary statistics such as mean and variance were computed, while plots of force, vibration, and acoustic signals helped visualize temporal trends. Correlation analysis identified sensor channels sensitive to wear progression, and outliers were filtered to improve data quality.

2.3 Feature Engineering

To convert raw high-frequency sensor signals into meaningful descriptors, three categories of engineered features were extracted. These features capture statistical behavior, frequency composition, and acoustic characteristics that evolve with tool wear.

(a) Time-Domain Statistical Features

Time-domain features describe the amplitude and variability of the signal over time. Metrics such as mean, RMS, standard deviation, peak-to-peak, skewness, and kurtosis summarize overall energy, spread, and shape of the waveform, providing insight into force and vibration behavior as wear increases.

(b) Frequency-Domain Features

Frequency-domain features quantify how signal energy is distributed across frequencies using the Fast Fourier Transform. Wear progression often introduces high-frequency components due to increased friction and chatter. Features such as dominant frequency, spectral centroid, and band-power efficiently represent the vibration spectrum.

(c) Acoustic Emission Features

Acoustic emission features capture transient events like micro-fractures, rubbing, and cutting instabilities. Burst count, RMS, crest factor, and AE energy highlight sudden spikes and high-frequency disturbances that intensify as the tool deteriorates.

2.4 Model Development

A regularized linear regression model (Lasso Regression) was implemented to predict tool wear from the engineered features. Lasso shrinks unimportant coefficients to zero, helping identify the most informative descriptors. The model was trained and evaluated using train-test splits, with performance measured using MAE and RMSE. Coefficients were analyzed to interpret which sensor features most strongly correlate with wear.

3 Results and Discussion

The results of the analysis are organized into four key areas: sensor behavior, feature performance, model evaluation, and interpretation of Lasso-selected features. These elements collectively demonstrate the effectiveness of the data-driven approach for tool wear estimation.

3.1 Sensor Signal Behavior

The exploratory analysis revealed distinct patterns in force, vibration, and acoustic emission signals across different tool wear levels. Force signals exhibited increasing mean and peak values as the tool deteriorated, indicating greater cutting resistance. Vibration signals showed higher variability and more pronounced spikes, reflecting increased chatter and instability during machining. Acoustic emission readings displayed more frequent burst events and elevated high-frequency activity, characteristic of friction-induced micro-fractures. These trends confirm that the sensor channels carry measurable signatures of wear progression.

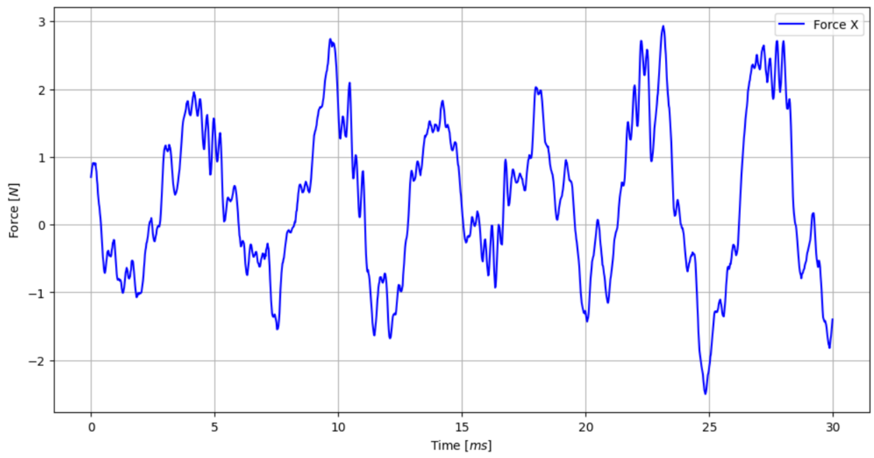

Figure 1: Time-series plots of cutting force X for different wear levels.

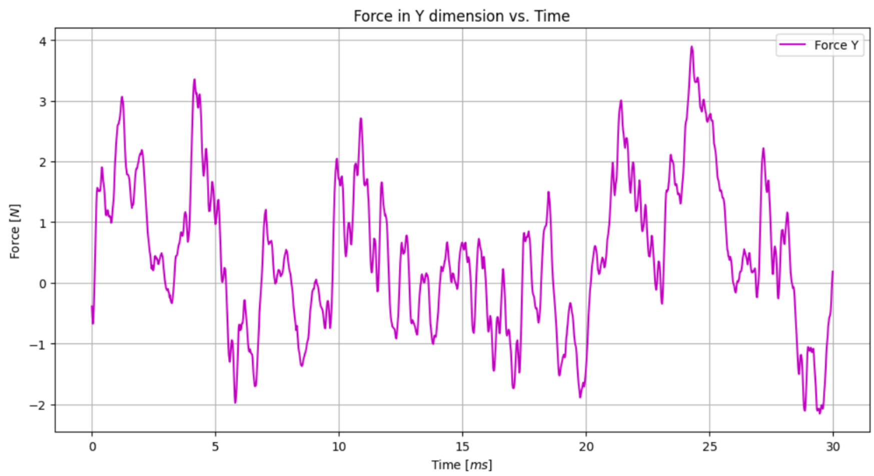

Figure 2: Time-series plots of cutting force Y for different wear levels.

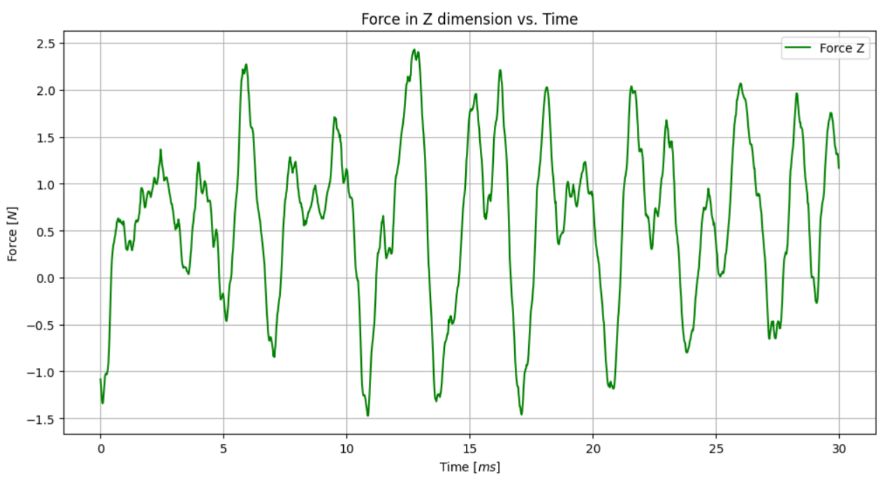

Figure 3: Time-series plots of cutting force Z for different wear levels.

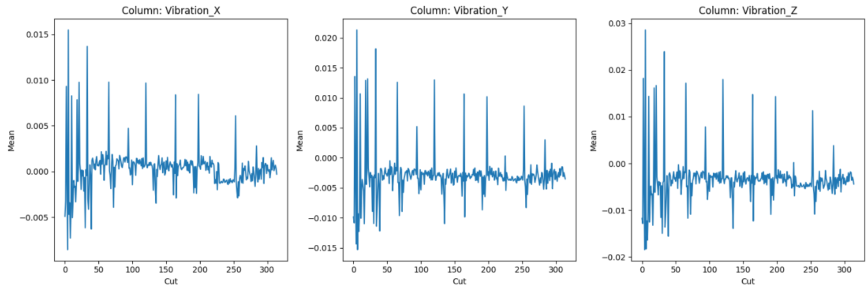

Figure 4: Vibration mean signal with respect to cuts.

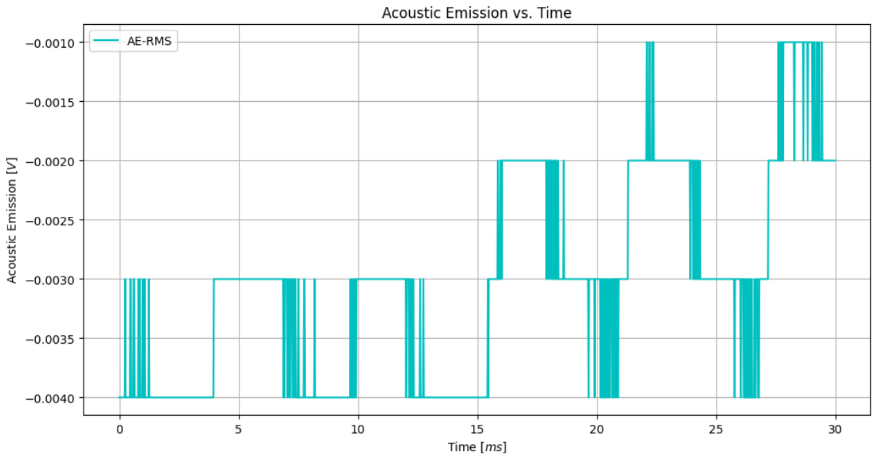

Figure 5: Acoustic emission with variation of time.

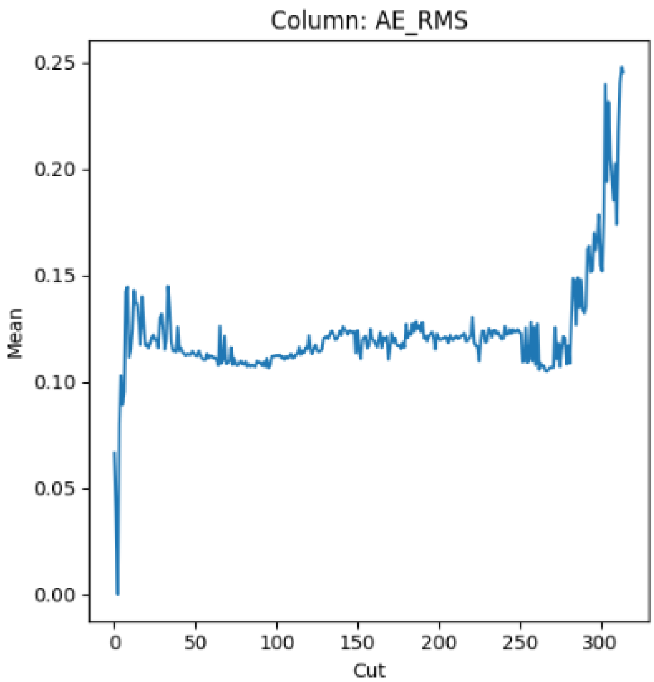

Figure 6: Acoustic mean emission with variation of cuts.

3.2 Feature Behavior and Correlations

The engineered features provided a stable representation of wear-related variations. Time-domain features such as RMS, standard deviation, and peak-to-peak amplitude increased consistently with tool degradation. Frequency-domain descriptors captured the shift of energy toward higher frequencies, particularly through spectral centroid and band-power metrics. Acoustic emission features—especially burst count and AE energy—showed the strongest relationship with wear. Correlation analysis validated these observations, identifying RMS force, vibration variance, spectral centroid, and AE energy as strong indicators of tool condition.

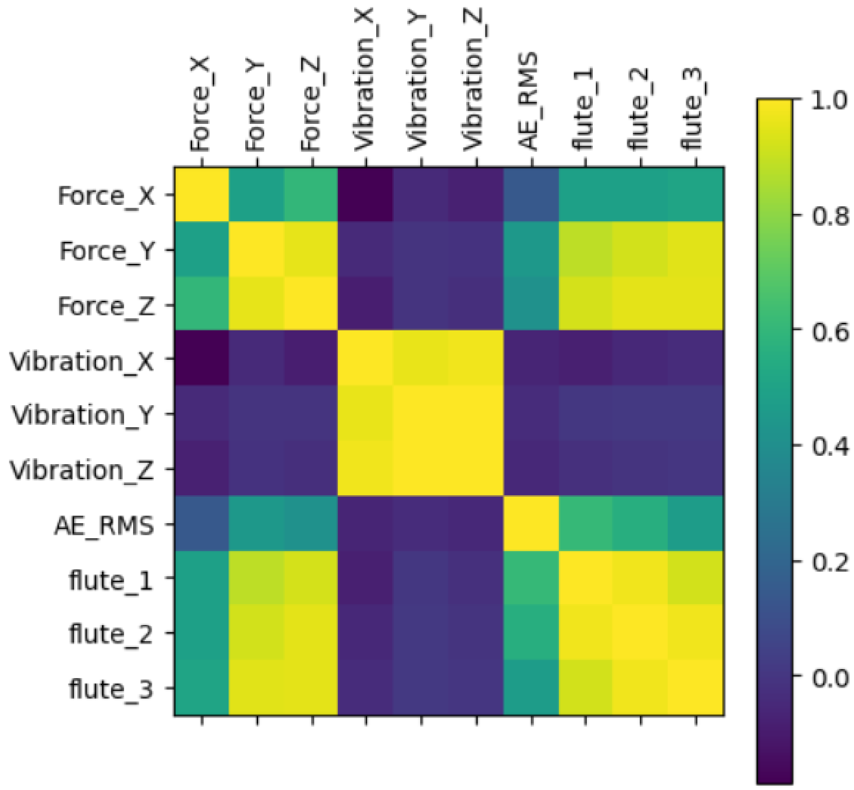

Figure 7: Correlation matrix showing relationships between sensor data and tool wear measurements.

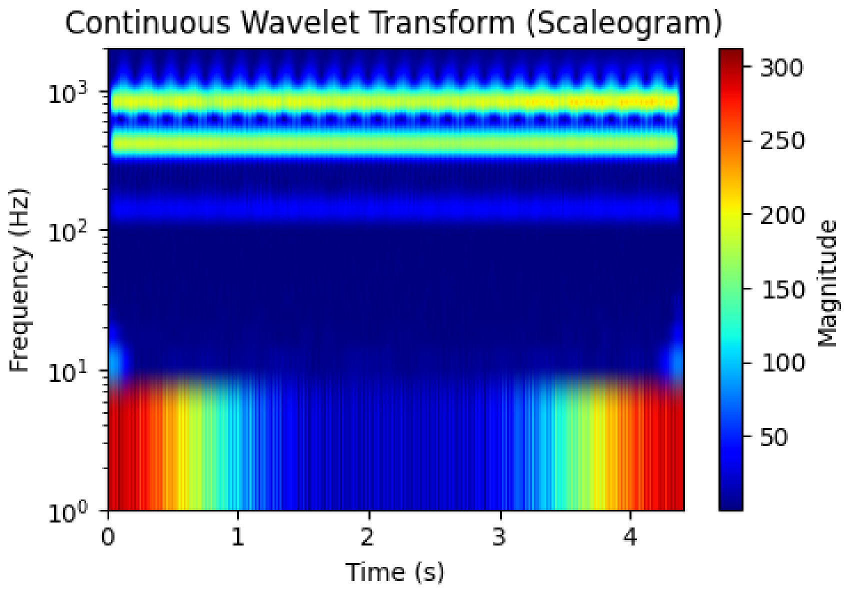

Figure 8: Continous wavelet patterns

3.3 Lasso Regression Model Performance

The Lasso regression model was used as an interpretable baseline for tool wear estimation. The model demonstrated stable performance, with predicted wear values following the general trend of the measured data. Although slight underestimation occurred at higher wear levels, evaluation metrics such as MAE and RMSE confirmed that the model captured the dominant wear-related behavior. Lasso's regularization effectively removed redundant features and improved generalization, demonstrating that a simple linear model can serve as a strong baseline for predictive maintenance applications.

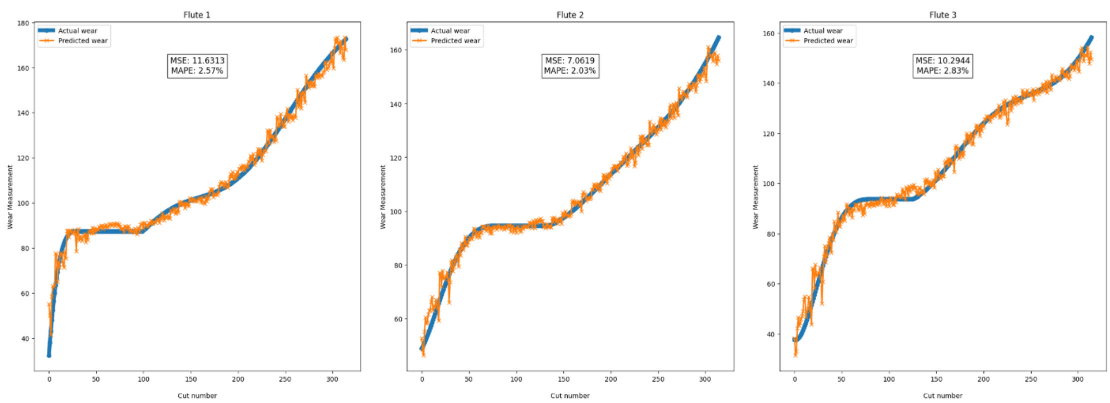

Figure 9: Plot of predicted tool wear vs. actual measured wear on test set.

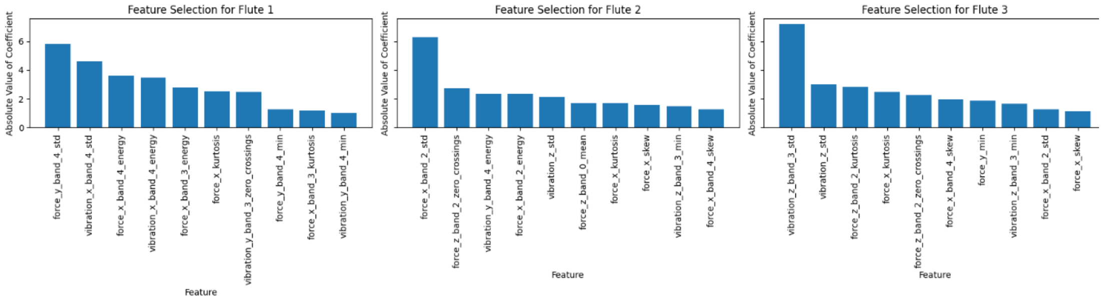

Figure 10: Feature selection for flutes

3.4 Interpretation of Informative Features

Inspection of the Lasso coefficients revealed that force RMS, vibration variance, spectral centroid, and AE energy were among the most influential features. These metrics align with physical machining phenomena: increased cutting resistance, elevated chatter, and intensified micro-fracture activity. The agreement between model-selected features and domain knowledge supports the validity of the engineered feature set and highlights the effectiveness of combining statistical, spectral, and acoustic descriptors for tool wear prediction.

3.5 CNN Model Performance

The CNN model demonstrated a strong correlation between the predicted and actual tool wear values for each flute, as shown in the graph of True vs Predicted Wear Values. The predicted wear trends closely followed the true measurements across successive cuts, indicating that the CNN effectively captured the nonlinear and dynamic characteristics of the milling process. Compared to linear and Lasso regression models, which assume linear relationships and often underfit complex machining data, the CNN achieved significantly better predictive accuracy.

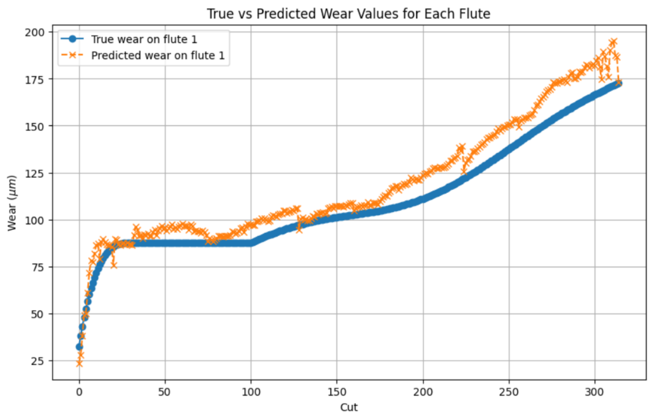

Figure 11: True vs Predicted Wear Values for Each Flute

4 Conclusion

The study developed a compact data-driven framework for tool-wear estimation using multi-sensor machining data. Systematic exploration of force, vibration, and acoustic-emission channels showed that each sensor carries distinct, meaningful signatures of wear progression; engineered time-domain, frequency-domain, and emission features provided informative representations that improved signal interpretability over raw measurements alone.

A simple regression model was established as an effective, interpretable baseline, capturing major wear-related trends and helping to identify the most relevant handcrafted features. Its transparency makes it useful for diagnosing which sensors and features drive predictions, and it delivers reliable, easily validated performance for early prototyping and demonstration.

To extend predictive power, convolutional neural networks (CNNs) were incorporated to learn hierarchical patterns directly from raw or minimally processed sensor streams. CNNs can capture local temporal and spectral structures that handcrafted features may miss, improving accuracy and robustness when sufficient labeled data are available; combining CNN outputs with engineered features or using hybrid models balances predictive performance with interpretability.

Overall, the results emphasize the value of fusing sensor-based monitoring, careful feature engineering, and modern data-driven models to enhance machining reliability. The methodology provides a solid foundation for further work on model interpretability, cross-machine generalization, uncertainty estimation, and real-time deployment in predictive-maintenance systems.

5 Future Work

Future work can focus on developing more advanced machine-learning models, such as ensemble methods, to better capture the nonlinear relationships between sensor signals and tool wear. Real-time monitoring can be enabled by implementing streaming data pipelines and sliding-window feature extraction to support online prediction during machining. Expanding the dataset to include different tool types, materials, and cutting conditions would also improve model generalization. Finally, evaluating additional signal-processing techniques, such as wavelet features or envelope analysis, may reveal more sensitive indicators of wear and further enhance prediction accuracy.

References

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