Cutter Flank Wear Prediction Based on Physics-informed Machine Learning Model for the PHM-AP 2025 Data Challenge

Chao Wang

Vestas Wind Systems A/S, Aarhus, Denmark
caowg@vestas.com

Abstract
This report presents a hybrid physics-informed and data-driven methodology for per-cut flank wear estimation for the PHM-AP 2025 Data Challenge. A physics-based Usui-type wear model was developed to construct the missing per-cut wear labels. Vibration and acoustic emission signals were processed to extract a comprehensive set of statistical, spectral, and band-energy features, which were combined with controller-derived features to form the feature matrix. A Random Forest regression model was trained to learn the flank wear patterns. The proposed solution demonstrated good predictive capability both in cross-validation of the training dataset and the evaluation dataset.

1. Introduction

Tool wear is a critical factor determining machining efficiency, part quality, and tool replacement scheduling in modern manufacturing systems. Accurate wear prediction enables improved maintenance planning, reduced scrap rates, and avoidance of catastrophic tool failure. The PHM-AP 2025 Data Challenge provides time-series controller signals, multisensor recordings, and sparse flank wear measurements [1]. The dataset includes controller data (spindle speed, spindle load, feedrate, coolant status), vibration signals (X, Y, Z accelerations), and acoustic emission (AE) measurements. Each machining set contains up to 26 cuts. However, the provided training data contains cumulative flank wear measurements only at sparse anchor cuts (1, 6, 11, 16, 21, 26), which prevents direct supervised learning on per-cut wear increments. This work develops a method combining physics-informed wear modeling, sensor data and control parameter-based feature extraction, and machine learning modelling to estimate the flank wear.

2. Methodology

The workflow contains three main sections: (1) physics-based creation of per-cut wear labels, (2) feature engineering from controller and sensor signals, and (3) machine learning model training through cross-validation. Each section is summarized below.

2.1 Physics-Informed Wear Label Generation

The physics-based wear model computes instantaneous wear intensity using controller data based on Usui's wear formulation [2,3]. Pressure, sliding velocity, temperature surrogate, and coolant state are incorporated to estimate the wear intensity. The parameters are calibrated using the wear measurement from the anchor cuts (1, 6, 11, 16, 21, 26) from each trainset. The estimated wear rate for cuts 22-26 in trainset_01 and the cumulative wear for all trainsets after label generation are demonstrated in Fig.1 and Fig.2, respectively.

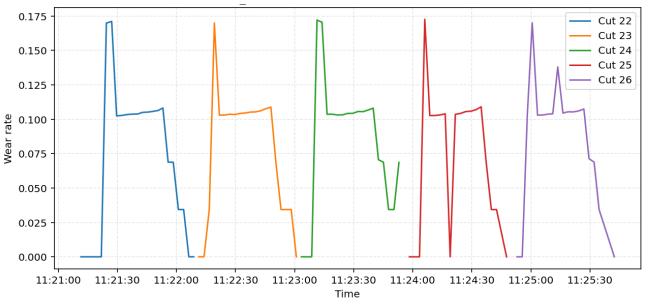

Fig.1. The estimated wear rate for cuts 22-26 in trainset_01.

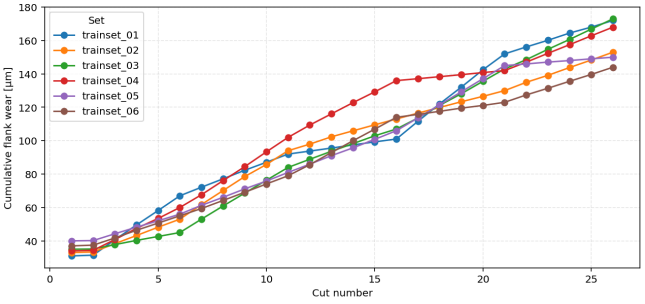

Fig.2. The cumulative wear for all trainsets after label generation.

2.2 Feature Engineering

Features are computed separately for each sensor channel (Acceleration X, Y, Z, and AE), and then combined with controller-derived statistics. The selected features includes time-domain statistics (mean, RMS, skewness, kurtosis), spectral features (spectral centroid, dominant frequency),

band energies (0–1 kHz, 1–5 kHz, 5–10 kHz, 8–12.8 kHz, 10–12.8 kHz), band ratios, controller parameters, cut duration, etc. The summary of the extracted features are in Tab. I.

Tab. I. Summary of Extracted Features

Category	Feature Group	Definition	Description
Time-Domain Features	Basic statistics	μ, σ, RMS, min, max, P2P	Central tendency, variability, and amplitude range.
	Distribution features	P_{10}, P_{50}, P_{90}, IQR	Percentile-based amplitude properties.
	Shape descriptors	Skewness, kurtosis, crest factor, shape factor, impulse factor, clearance factor	Measures waveform asymmetry, impulsiveness, and peak characteristics.
Frequency-Domain Features	Spectral descriptors	Spectral centroid, dominant frequency	Global characteristics of frequency content.
	Band energies (grouped)	$BE_{f_1-f_2} = \sum_{f=f_1}^{f_2} S(f)$	Energy integrated over vibration/AE-related frequency bands (0–1, 1–5, 5–10, 8–12.8, 10–12.8 kHz).
	Band ratios (grouped)	$\frac{BE_{HF}}{BE_{LF}}$, $\frac{BE_{HF}}{BE_{Mid}}$	Relative contribution of high-frequency AE energy to lower bands.
Controller Features	Spindle-related	mean/std of spindle speed and spindle load	Cutting force and cutting-speed indicators.
	Feed & axis loads	mean/std of feed rate and X/Y/Z axis loads	Material removal rate and mechanical loading.
	Coolant usage	% ON time	Thermal control indication.
Metadata Features	Cut duration	$t_{end} - t_{start}$	Time spent machining the cut.
	Cutting distance	Feed rate * duration	Approximate machined path length.

2.3 Machine-Learning Model Development

A Random Forest (RF) regression model [4,5] was developed to predict per-cut flank wear growth using multi-modal features extracted in section 2.2. The RF model was selected due to its robustness against nonlinear behavior, multicollinearity, and noisy sensor measurements. It also provides stable performance without requiring strict data normality assumptions. The RF Regressor with 800 trees was trained using the extracted features and the filled wear labels. Cross-validation is carried out using Group K Fold, with each machining set assigned to a separate group. This ensures that all cuts from a given set are contained entirely in either the training or validation partition, preventing leakage of information and providing a realistic estimate of performance on unseen tools.

3. Results

Model performance was evaluated using out-of-fold predictions. The Random Forest achieved low RMSE and MAPE across sets. Predicted per-cut wear and cumulative wear curves closely followed the generated wear labels and the ground-truth anchor measurements. Feature importance analysis showed that vibration spectral energies and controller spindle load statistics were the most influential predictors.

The Random Forest model demonstrated strong predictive capability both in cross-validation and external evaluation. All cross-validation folds achieved high R^2 values (0.82–0.98) when evaluated on flank wear, indicating stable generalization across tools.

The overall out-of-fold performance achieved:

- **RMSE:** 10.14
- **MAPE:** 7.50%
- **R^2:** 0.896

These results confirm that the model accurately reconstructs wear trends and captures tool-specific degradation patterns.

When submitted to the PHM-AP 2025 Data Challenge portal, the model achieved:

- **RMSE:** 15.338
- **MAPE:** 14.88%
- **R^2:** 0.776

The performance reduction on the data challenge evaluation set is attributable to covariate and operational-condition shift relative to the training dataset. Even under this shift, the model delivers robust wear prediction performance.

The physics-informed label generation enables realistic interpolation of wear progression between measured anchor points, and the engineered features provide robustness against sensor noise and operational variability. The physics model depends on approximate parameter settings, and discrepancies between assumed and actual cutting conditions may introduce bias into the generated labels. Moreover, while the RF is robust, its predictions may still degrade when evaluated under operating conditions that differ significantly from those seen in the training set.

4. Conclusion

A hybrid wear prediction solution was developed for the PHM-AP 2025 Data Challenge. The combination of physics-derived wear labels and data drive model enabled good per-cut wear estimation. Future work will explore jointly optimizing physics-model parameters and machine-learning model hyperparameters, incorporating temporal models (e.g., recurrent or transformer-based networks) to exploit sequential cut information, and domain-adaptive models.

References

[1] https://phmap25.org/datachallenge.html

[2] Usui, E., Shirakashi, T., & Kitagawa, T. (1978). *Analytical prediction of cutting tool wear.* Wear, 100(1–3), 129–151.

[3] Zhang, S., Li, J. F., & Deng, J. X. (2011). *Tool wear model based on Usui model considering tool–chip contact area.* International Journal of Advanced Manufacturing Technology, 52(5–8), 573–581.

[4] Breiman, L. (2001). *Random forests.* Machine Learning, 45(1), 5–32.

[5] Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). *Damage propagation modeling for aircraft engines using random forests regression.* IEEE Aerospace Conference.